Short-Term Load Forecasting Methods for Maritime Container Terminals

Norman Ihle

OFFIS, Institute for Information Technology, Oldenburg, Germany
norman.ihle@offis.de

Abstract. Procurement of electricity gains more and more focus in enterprises especially with the introduction of electric mobility. At a maritime container terminal the electricity consumption is highly related to the number of container movements of each day. Short-term load forecasting (STLF) methods have not yet been systematically researched when applied to container terminals. Therefore it seems reasonable that the inclusion of knowledge about the number of next day's container movements might improve the forecasting of next day's electricity demand of the container terminal. One way to include this knowledge in the forecasting process is to use Case-Based Reasoning methods. In this thesis a concept for a corresponding system is outlined and implemented. In addition, also further concepts for using established STLF-methods are described and implemented. Besides the system based on Case-Based Reasoning, naive methods, time-series models, artificial neural networks and simulation are being implemented and compared to each other. The implementations are tested with data from the use-case Container-Terminal Altenwerder in Hamburg, Germany. Goal of the thesis is to evaluate, which method is best suited in what situation.

1 Introduction

Rising energy prices and fluctuating power generation from decentralized sources into grids that were not designed for this purpose are controversially discussed topics nowadays. With the introduction of E-Mobility to maritime container terminals new possibilities for the terminal operator arise to optimize the energy demand which have not been possible before. Not only does the relevance of energy demand rise in the operational strategies but also for the first time flexibility in regard to the time of the energy demand can be achieved. This flexibility results from the fact that there is a possibility to control, within a certain range, the point in time when the battery of the vehicle is recharged. The flexibility can be used in several use-cases to gain economic benefits. For example, balancing energy can be offered to the grid or peak shaving of the load curve can be applied. The basis for the use of this flexibility is the knowledge about the expected power demand of the container terminal, especially the demand for the next day as time-series of 15-minute values. This forecast is widely referred to as short-term load forecasting (STLF). STLF methods have been a topic in scientific research for a long time. Several methods have been established by now.

Most of them are applied to complete grids or to larger groups of electricity consumers. Reviews on established methods can for example be found in [3], or [5]. In the course of scientific research none of the discussed methods have been applied for a single container terminal. Therefore this thesis researches concepts on how STLF-methods can be applied to maritime container terminals and which method fits best in which situation. Since it can be shown that

Method	Accuracy	Portability	Implemen-tation effort	Computa-tional effort	Based on historical data	Includes knowledge about terminal processes	Applicable for STFL at a container terminal
Equivalent day approach	-	++	++	++	Yes	No	?
Time series models	+	+	+	+	Yes	No	?
Artificial neural networks	+	o	-	+	(Yes)	No	?
Simulation	++	--	--	--	No	Yes	Yes
Case-Based Reasoning	***?***	***Within the domain***	***One time modelling***	+	***Yes***	***Yes***	***?***

Scale: ++ = very good/very low effort; + = good/low effort; o = medium; - = bad/high effort; -- = very bad/very high effort

Fig. 1. Assumptions on different forecasting methods

the energy demand of the container terminal is highly dependent on the number of container movements of each day, it seems reasonable that an inclusion of knowledge might improve the forecasting. This thesis introduces a concept for a short-term load forecasting system using Case-Based Reasoning methods to include this knowledge. Case-Based Reasoning (CBR) methods have hardly been used in the area of STLF. A concept for CBR methods applied to STLF at a container terminal is outlined and implemented. Besides the concept of a CBR-based system also the use of further methods is researched. Concepts for a equivalent day approach from the class of naive methods, time-series models from the class of mathematical methods, artificial neural networks from the class of artificial intelligent approaches and an already implemented simulation model are presented. Each concept is implemented and results of the forecasting process are compared based on historical data from the Container-Terminal Altenwerder (CTA) in Hamburg, Germany. From a mere literature review assumptions about the different methods can be made as shown in figure 1. The goal of this thesis is to systematically research the different categories for each of the forecasting methods and to provide an according table with proven values.

In the following the single methods are shortly introduced, each with a brief introduction how they can be applied for forecasting the load of a container terminal. After that, the current state of work is described and a short outlook on the further work is presented.

2 Short-Term Load Forecasting methods

2.1 Equivalent day approach

From the class of naive methods the equivalent day approach is commonly used by utility companies to predict next days load curves. Equivalent day in this case means to take the data of the same day of the week before as forecast for the same day (according to the calendar) in the future [1]. If the load curve of a Monday is supposed to be forecasted the load curve of last Monday is used as forecast. This method fits particularly well in domains with recurring processes and corresponding regular load curves. The method can be improved by using a number n of past equivalent days to smooth the load curve and to avoid errors. Each chosen equivalent day can be weighted with a different share. Usually earlier equivalent days are weighted less than more recent days. For the application of this method the usage of five past reference days yields the best results. For special days, the previous years value of the equivalent special day is used as reference day.

2.2 Time-series models

From the class of mathematical models originate different time-series analysis and regression models. ARMA describes a number of linear models that can be used for stationary, time-discrete stochastic processes. For this case autoregressive processes (AR) are combined with moving average models (MA). The term autoregressive describes stochastic models, that explain an output variable y_t by the linear combination of past values and a current error term ϵ. Moving-Average Models explain future values by the error terms of the past values. The error terms are referenced as the deviation of a past value from the average. An ARMA model can be written as

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{p-1} + \epsilon_t - \beta_1 \epsilon_{t-1} - ... - \beta_q \epsilon_{t-q}$$

α describes the weights of the autoregressive part and β the weights of the Moving-Average part. p refers to the order of the model that describes how far values date back in the past. The challenge of the model is to estimate the weights. Methods like Least Squares or Maximum-Likelihood can be used for this purpose. Pre-condition is that the time series is stationary, that means that trend and seasonality have been removed, and the average of the remaining series is about zero. This can be reached by component analysis and integrating the time series (ARIMA-Models). For the use of ARIMA-Models for forecasting purposes at the container terminal the Hyndman-Khandakar algorithm [4] for automatic model estimation can be used. A component decomposition has to be applied before using the algorithm.

2.3 Artificial Neural Networks

Artificial Neural Networks (ANN) are inspired by the structure of the human brain. They consist of a large number of parallel processing units. These neurons are quite simple units that are connected to each other. These connections can be activated using given rules. Each connection from neuron i to neuron j has a individual weight $w_{i,j}$ that is adjusted during the training process that is needed to prepare the network for its task. Each network consists of an input-layer, which receives the input data, a number of hidden layers that are responsible for the computation, and an output-layer for the result. Each neuron has an activation function that is responsible for taking the weighted sum of the inputs and calculating the corresponding output for the neuron. Different ANN-structures and training algorithms have been proposed over time. For the use of an ANN for forecasting purposes the number of container movements per quarter hour can be used as input. A network with one hidden layer yields promising results when trained using a common back-propagation algorithm.

2.4 Simulation

Simulation is a problem solving method which replicates a system in an executable model as exact as possible. The advantage of simulation in comparison to analytical methods is the modeling of system-specific dynamic dependencies and reciprocal effects over time. Stochastic effects can be observed [6]. In the energy sector, simulation is often used to calculate medium or long term forecasts. [2] propose a discrete event-driven simulation model for short-term load forecasting. They modeled the Container Terminal Altenwerder and its logistic processes. Each process is connected to different energy consumption values depending on their current state in the process chain. The energy consumption values are constantly monitored. Using the list of ship arrivals and departures of the next day as basis for the simulation, a load curve for the next day can be forecasted. This simulation model of CTA is used to represent the simulation based approaches.

2.5 Case-Based Reasoning

Case-Based Reasoning (CBR) is a method from the field of Artificial Intelligence that is based on the assumption that similar problems have similar solutions. If a similar problem to the current problem has been found, the corresponding solution is adapted to fit the current problem situation. In a general approach the problem description as well as the solution build up a case. A number of cases is stored in the case-base from which cases similar to the current problem are retrieved. CBR uses domain knowledge for case modeling and adaptation. In order to use this method for forecasting the electricity demand load curve of a container terminal the case can be composed of attribute-value data, so a structural CBR-method is used. The problem description is based on the list of ship arrivals and departures which also includes the number of containers to be handled per ship. It is part of the operating plan for the terminal. All information about ship handling and influencing external factors like the weather for exactly one day build up a case together with the load curve of that day. Based on next day's list of ship arrivals and departures a similar day can be found. The corresponding load curve of that similar day can be adapted regarding differences in the container numbers, weather influences or seasonal effects to compute the corresponding forecast.

3 Current state and further work

The research on this thesis began in spring 2015. For the implementation and the evaluation ship arrival and departure data as well as electricity consumption data for 4 years from the Container-Terminal Altenwerder is available. Currently, a concept for the load forecasting process for each of the described methods has been described and corresponding prototypes have been implemented. First forecasting results of each method are available. The next step will be to adapt the prototypes to improve the forecasting results based on knowledge gained from the first results. For example, the CBR-system constantly underestimates the real consumption. This is due to the fact that the average consumption of the terminal increases each year. So a factor to regard this average raise can be introduced and cases from dates closer to the current date might get weighted higher. After this a systematic evaluation of all methods against each other will be performed. This evaluation is supposed to not only regard the forecasting accuracy but also further factors like portability, computational effort or implementation effort. The research is supposed to be finished by summer 2017 so that the thesis can be completed within the year 2017.

References

1. Feinberg, E.A., Genethliou, D.: Load forecasting. In: Applied mathematics for restructured electric power systems, pp. 269–285. Springer (2005)
2. Grundmeier, N., Ihle, N., Hahn, A.: A discrete event-driven simulation model to analyse power consumption processes in container terminals. In: Simulation in Production and Logistics 2015. Fraunhofer IRB Verlag, Stuttgart (2015)
3. Hong, T.: Short term electric load forecasting. North Carolina State University (2010)
4. Hyndman, R., Khandakar, Y.: Automatic time series forecasting: The forecast package for r. Journal of Statistical Software 27(1), 1–22 (2008), https://www.jstatsoft.org/index.php/jss/article/view/v027i03
5. Singh, A.K., Ibraheem, S.K., Muazzam, M., et al.: An overview of electricity demand forecasting techniques. Network and Complex Systems 3(3), 38–48 (2013)
6. Wenzel, S., Collisi-Bhmer, S., Rose, O.: Qualitaetskriterien fuer die Simulation in Produktion und Logistik: Planung und Durchfuehrung von Simulationsstudien. Springer-Verlag (2008)