A Framework for Short-Term Activity-Aware Load Forecasting

Yong Ding
TECO, KIT
Karlsruhe, Germany
yong.ding@kit.edu

Martin Alexander Neumann
TECO, KIT
Karlsruhe, Germany
martin.neumann@kit.edu

Per Goncalves Da Silva
SAP Research
Karlsruhe, Germany
per.goncalves.da.silva@sap.com

Michael Beigl
TECO, KIT
Karlsruhe, Germany
michael.beigl@kit.edu

ABSTRACT

In this paper, we present a framework for implementing short-term load forecasting, in which statistical time series prediction methods and machine learning-based regression methods, can be configured to benchmark their performance against each other on given data of smart meters and other related exogenous variables. Besides the prediction methods, forecasting performance also depends on the quality of training data. This is addressed by two characteristics of our framework on data collection and preprocessing. The first one is to introduce a human activity variable as an additional load influencing factor which reflects anomalous load patterns by aperiodic human activity. The second characteristic is to wavelet transform training data during the preprocessing stage to better extract redundant information from meter data. To investigate the feasibility of the proposed framework, a preliminary case study for predicting daily power consumption of several individual smart meters, using real-world data, is presented. The results indicate that, in general, the aggregation level of meter data and activity data matters.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; I.5.4 [**Pattern Recognition**]: Applications—*signal processing, waveform analysis*

General Terms

Design

1. INTRODUCTION

Power load forecasting can have significant effects on power system planning and operation, in particular short-term load forecasting (STLF) [23]. Many operational decisions such as generation scheduling, load management and system security assessment are based on short-term forecasts. STLF refers to load forecasts of power system loads with lead times ranging from a few minutes to seven days ahead. The aim of STLF is to predict future power consumption based on historical consumption data and other exogenous variables, in order to make the best use of electric energy and relax the conflict between supply and demand [20].

Inaccurate load forecasts would not only lead to monetary losses but also to grid security losses for the supply industry. Bunn and Farmer have already estimated in 1984 that an increase of 1% forecasting error would imply a 10 million pounds increase in operating costs per year [2]. Therefore, accurate STLF models are required. In order to achieve this, a lot of research has been done using statistical methods [11, 24, 17, 27], such as autoregressive moving average, linear regression, stochastic time series, exponential smoothing, state space methods with Kalman filtering; and machine learning-based methods, such as artificial neural networks (ANNs) [12], support vector regression (SVR) [20], random forest (RF) [6], etc.

Anomalies are ubiquitous in energy load at different distribution levels. Being able to recognize anomalies in short-term is relevant to all stakeholders of the power grid [7, 15]. Human activity is an important contributor to local energy consumption, particularly in urban areas [22, 13, 18]. Therefore, we expect insights into human activities and their correlation with energy consumption to help energy suppliers in more accurately estimating power demands, especially in the short-term. Consumption anomaly prediction is vital for grid stability, security and efficiency [7, 15], as well as energy trading [10]. This is becoming particularly important when considering the high fluctuations in distributed renewable energy generation.

An important problem in load forecasting is to select the relevant variables and features on training data sampling these variables, and then including them appropriately in STLF models. We research the correlation between diverse human activities (incl. personal & social group activities, as well as urban activities, especially aperiodic ones) and energy consumption, in order to augment load forecasting models.

The paper is structured as follows: a review of the state of the art in load forecasting, in particular short-term load forecasting, is provided in Sect. 2. In Sect. 3, we present our proposed short-term load forecasting framework and describe the system architecture representing the functional modules. In Sect. 4, we afterwards evaluate a real-world use case to assess the relation of urban-scale human activities on home-scale demand prediction. Finally, Sect. 5 concludes the paper.

2. RELATED WORK

In recent years, energy load forecasting has become one of the major areas of research in electrical engineering, especially short-term load forecasting has become increasingly important since the rise of competitive energy markets [12]. Load forecasting is, however, challenging, due to the influence of many important exogenous variables. A wide variety of procedures has been tried for short-term load forecasting in the literature. These procedures can typically be classified into two categories of forecasting models [12]: time series (univariate) models, in which the load is modeled as a function of its past observed values, and causal models, in which the load is modeled as a function of some exogenous factors, particularly weather and social variables. More recently, machine learning techniques have been applied to the problem with specific focus on probabilistic inference modeling [30], support vector machine or regression [20] and artificial neural networks [32]. Also random forest [6] and deep learning [3] have proved their worth for the short-term load forecasting.

Existing literature points out that besides climate and seasonal factors, social activities are primary influence factors on load forecasting. The STLF publications not only in the 90's [25, 29, 26, 16] but also in the recent research [20, 21] focus on load forecasting for special days. They interpreted the social activities performed by humans as different day types, such as weekdays, weekends and public holidays. These approaches employed special event and day types as input variables to adequately map the causality between the hourly or daily load patterns and social activities. But all these load forecasts and events information have been focused on a high aggregation level, see Figure 1.

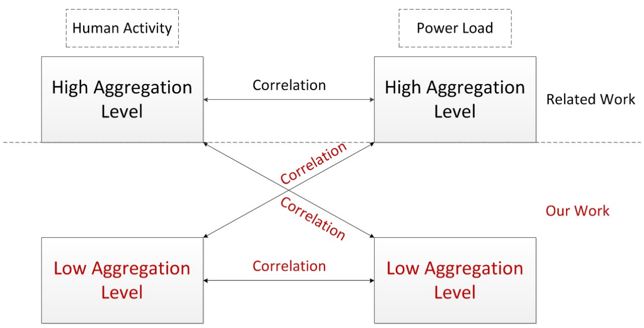

Figure 1: Comparison of our work with related work

In order to explore the aperiodic human activity influences on load forecasting, we propose to incorporate human activities on different scales into short-term load forecasting. Firstly, we need to identify human activities, like situations and events on different scales, which have relevant short-term energy load impact, and quantify their impact scales. Then, our work will focus on a correlation study as depicted in Figure 1, between: 1) low-level activity information and low-level load information; 2) low-level activity information and high-level load information ; 3) high-level activity information and low-level load information.

3. FORECASTING FRAMEWORK

Our STLF framework follows a number of systematic procedures. In general, there are five basic steps: (1) collecting data, (2) preprocessing data, (3) building the forecasting model, (4) train, and (5) test performance of model as shown in Fig 2.

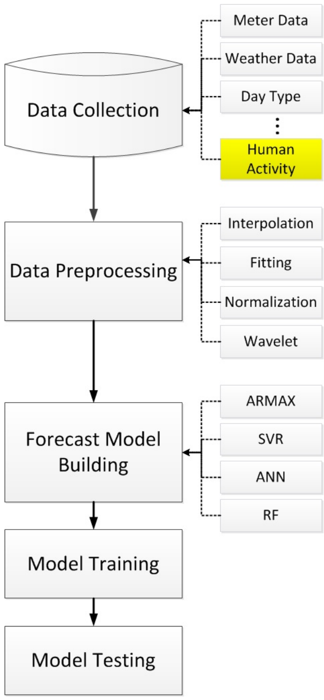

Figure 2: Basic flow of our load forecasting framework

3.1 Data Collection

Collecting and preparing input sample data is the first step in designing load forecasting models. Historical measurement data of smart meters is considered as the primary input data: for hourly and daily load forecasting, we use load information of last 24 hours and last seven days as inputs respectively. Hourly or daily weather conditions, such as wind speed, cloud cover, temperature and humidity, are optionally introduced to STLF models on the input side. On the one hand, data on weather variables, except temperature, can not always be available. On the other hand, the inherent difficulty in weather forecasting, for instance the temperature prediction, can actually decrease the accuracy of the load forecasting [5]. Another state-of-the-art influencing factor, which we include in the input sample entries, is weekday type. The weekday type input indicates the calendar information (weekdays or weekends).

Since we propose a human activity enabled load forecasting framework, the novelty on data collection is to integrate the recognized or predicted aperiodic human activities. In order to integrate automatically the aperiodic human activities, such as sports events, concerts, traffic jams, etc., as an additional input variable into this STLF framework, we utilize human activity recognition systems [31, 8, 19] to detect relevant human activities, which cause the anomalous load patterns. Since the anomalous load pattern scales from different distribution levels, such as from personal level to urban level, human activity information at each level is then required. Thus, we employ the following sensors for the whole activity recognition services: *temperature sensor*, *weather radar*, *calendar*, *cell tower*, *GPS*, *humidity sensor*, *light sensor*, *accelerometer* and *social media*.

3.2 Data Preprocessing

After data collection, data preprocessing for the load data is needed to "clean" data through: (1) solving the problem of data outliers or missing data, (2) normalizing data and (3) transforming data.

Firstly, the data outliers or missing data will be interpolated, for instance, replaced by the average of neighboring values during the same day (for hourly forecasting) or the same week (for the daily forecasting). Since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [28], the input sample data and the corresponding target vector for the forecasting models will be then normalized. Finally, the normalized load data are wavelet transformed during the preprocessing stage, since wavelets are able to extract redundant information and periodic behavior from load data and improve forecasting accuracy [1].

3.3 Building Forecasting Models

After the input sample data in terms of time series is normalized with or without wavelet transformation, diverse models are built in this framework for the STLF. For each forecasting algorithm, a set of necessary configuration parameters for each algorithm can be specified individually and properly by users.

- **A Common Parameter:** parameterization for load of how many previous hours or days included for one training dataset.
- **Autoregressive Moving Average Model with Exogenous Inputs (ARMAX) Model:** parameterization for the number of autoregressive terms, the number of moving average terms and the number of exogenous inputs terms.
- **Support Vector Regression (SVR):** parameterization for the cost of error C, the width of the ϵ-insensitive tube, the mapping function ϕ.
- **Artificial Neural Network (ANN):** parameterization for the number of hidden layers, neurons in each layer, activation function in each layer, training function, number of training epochs, mean squared error goal and spread of radial basis function.
- **Random Forest (RF):** parameterization for the number of regression trees and the randomly selected feature ratio.

3.4 Training Forecasting Models

Since the forecasting model building above is a departure from more traditional time series prediction methodologies in the sense that there is no "model" in the strict sense. Therefore, the data drives the forecasting. During the training process, the parameters of each forecasting model will be estimated based on the training set of time series. In order to avoid overfitting, cross-validation is applied. The input sample dataset is split into a training set and a validation set.

3.5 Testing Forecasting Models

The last step is to test the performance of each trained forecasting model. At this stage, we validate and test the models with the above split validation set. The criteria used for defining the measure of error between the actual and predicted load are the Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE), which measure the overall performance of the load forecasting model. MAPE is a standard for examining the quality of load forecasting models. MSE provides information on the short term performance which is a measure of the variation of predicated values around the measured data. The lower the MSE, the more accurate is the estimation.

4. CASE STUDY

In order to test the proposed load forecasting framework, we firstly use the LIBSVM dataset from National Taiwan University for the Eunite 2001 competition [4]. The given dataset includes power load and day types (i.e. weekdays, weekends and holidays) information from 1997 to 1998 and is applied to predict daily maximum load in January 1999. Due to the good quality of the given dataset, we can reproduce the prediction results based on our STLF framework, see Figure 3. The framework reaches an average MAPE value of 2.15% and the *ARMAX* method outperforms the other AI-based ones with a MAPE value of 1.69%.

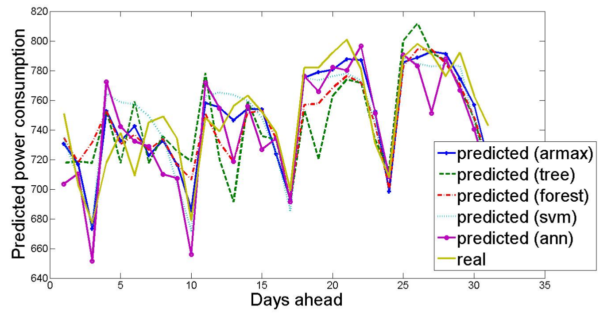

Figure 3: Comparison of the load forecasting results using LIBSVM dataset

The main part of our case study is to make use of the database of smart meter measurements taken in the NOBEL `http://www.ict-nobel.eu` project. The database includes 15-minute interval measurements for about 5000 meters taken between November 2010 and February 2013 in the project's field trial in Alginet, Spain. The raw dataset contains outliers, as well as missing meter readings due to downtimes or other infrastructural issues. For the STLF task, data of about $2/5$ meters, i.e. about 2000 meters, can be used. Furthermore, due to European Data Protection Regulation and privacy concerns, the NOBEL dataset can not provide our desired level of quality in terms of forecasting service. In addition, the anonymization process performed on this dataset has further eliminated some useful features for prediction purposes, including *location*, *consumer type*, etc. Based on the aforementioned issues, it seems reasonable to filter the dataset and also select those meters which contain 'sufficient' readings, i.e. consumption data ranging from November 2010 to the beginning of February 2013. Nevertheless, an accurate load forecasting on just one smart meter can contribute not only to a future local power market [14] but also to customer clustering for tariff design [9], since data obtained from individual smart meters at household's level reflects customers' time-based consumption behavior. We, therefore, propose here to consider only 10 smart meters in order to evaluate the STLF framework.

The meter readings are interpolated into hourly and daily power consumption and subsequently wavelet transformed. Then, we employ the *ARMAX*, *SVR*, *ANN* and *RF* respectively combining them with independent influencing factors, such as different weather conditions (incl. *temperature*, *humidity*, *pressure* and *wind speed*), weekday types (weekdays and weekends) and big events. We have not collected human activity data from the proposed activity recognition systems. Therefore, instead of fine granular human activity information, we consider the big events (e.g. sport events, concerts, etc.) as an additional influencing factor, which are more related to aperiodic human activity than the weekday types and holidays, and can be derived from special calenders of Alginet as well as social media. Finally, we train the load forecasting models with a two years dataset and test the models with the rest of the data.

We separate the evaluation of the forecasting results through the following combination cases of influencing factors: 1) without any influencing factor; 2) weekday types only; 3) temperature only; 4) humidity only; 5) pressure only; 6) wind speed only; 7) big events only.

For the above 7 cases, we evaluate not only individually the selected 10 smart meters but also the aggregation of 10 smart meters. The prediction metrics in Table 1 indicate the average MAPE and MSE of the selected 10 meters, while Table 2 shows the MAPE and MSE of the aggregated power consumption prediction. Since we reconstruct the consumption data from the normalized and wavelet transformed one, which ranges in the real life from about $40Wh$ to about $650Wh$, see e.g. Fig. 4 and 5. That's why the MSE of each approach reaches at least 10^2 (one meter scenario) or 10^3 (aggregation scenario) for 36 days ahead forecasting. We notice that in general the forecasting results at the aggregation level are more accurate than the ones for a individual smart meter. Moreover, the MAPE values in Table 1 show that the influencing factors except *wind speed* (case 6) and *big events* (case 7) can lightly improve the prediction accuracy for the single smart meter scenario. However, the influencing factor *big events* contributes to the accuracy improvement for the aggregation scenario, see case 7 in Table 2. Big events, which correspond to human activity at the higher aggregation level, show an impact on the load forecasting of aggregated metering data. In order to prove our hypothesis that the aggregation level of meter data and activity data matters, we will collect the human activity data at household level in future work to show its impact on the load forecasting for one individual smart meter.

Moreover, Figure 4 and 5 depict the prediction results for one representative smart meter of the 10 selected meters and the aggregation of 10 metering data, regarding case 7) with the influencing factor *big events*, respectively. From the predicted load curves in both scenarios, we can recognize that *RF* and *ARMAX* approaches both delivered promising load forecasting. By means of the only influencing factor *big events*, the comparison of both figures shows again that high-level human activity information influences the power consumption at higher aggregation level rather than at individual meter level.

5. CONCLUSION

A STLF framework combining different influencing factors, data preprocessing methods as well as forecasting algorithms was proposed and developed. The proposed forecasting framework has been validated based on the given LIBSVM dataset and used for daily load forecasting with a NOBEL project dataset. In this paper, rather than selecting the most existing relevant feature subsets, we introduced a new possible relevant exogenous variable, i.e. aperiodic human activity, into the proposed framework. After normalization and wavelet transformation preprocessing, four forecasting approaches, i.e. Autoregressive Moving Average Model with Exogenous Inputs (ARMAX) Model, Support Vector Regression, Artificial Neural Network and Random Forest, have been trained for the STLF.

In the performance evaluation of the daily consumption prediction, it was noticed that the big events—the aggregation level of human activity data—have no impact on load forecasting at the individual smart meter level, but at the aggregation level. In order to investigate the human activity impact on load forecasting of individual smart meters, we will collect more activity data (aperiodic) at household level in future.

Model	ARMAX	SVR	ANN	RF
1) MAPE	20.98	22.53	22.58	19.45
MSE	175.87	213.28	210.23	166.54
2) MAPE	20.78	22.38	25.17	18.85
MSE	172.05	212.04	252.21	156.40
3) MAPE	21.26	21.90	22.88	18.44
MSE	180.17	198.55	211.71	146.75
4) MAPE	20.88	22.49	22.70	19.54
MSE	173.22	212.71	246.74	163.75
5) MAPE	20.76	22.54	25.46	19.35
MSE	173.42	213.60	322.21	160.99
6) MAPE	21.33	22.94	24.65	19.78
MSE	179.60	219.58	253.03	169.61
7) MAPE	21.08	22.58	26.27	19.55
MSE	177.63	213.93	285.86	163.91

Table 1: Average MAPE (%) and MSE of 10 smart meters for different forecasting models in different cases

Model	ARMAX	SVR	ANN	RF
1) MAPE	12.32	12.94	11.15	10.51
MSE	$5.61 \cdot 10^3$	$6.60 \cdot 10^3$	$4.74 \cdot 10^3$	$4.42 \cdot 10^3$
2) MAPE	12.69	13.06	14.65	10.04
MSE	$5.44 \cdot 10^3$	$6.57 \cdot 10^3$	$7.72 \cdot 10^3$	$4.57 \cdot 10^3$
3) MAPE	12.67	12.90	12.39	9.57
MSE	$5.54 \cdot 10^3$	$6.54 \cdot 10^3$	$5.62 \cdot 10^3$	$4.25 \cdot 10^3$
4) MAPE	12.25	12.94	18.93	11.51
MSE	$5.36 \cdot 10^3$	$6.61 \cdot 10^3$	$2.32 \cdot 10^4$	$5.81 \cdot 10^3$
5) MAPE	12.76	12.94	57.43	11.04
MSE	$5.80 \cdot 10^3$	$6.60 \cdot 10^3$	$1.09 \cdot 10^5$	$4.71 \cdot 10^3$
6) MAPE	12.39	12.94	13.96	10.75
MSE	$5.40 \cdot 10^3$	$6.59 \cdot 10^3$	$7.68 \cdot 10^3$	$4.50 \cdot 10^3$
7) MAPE	12.20	12.51	10.92	10.37
MSE	$5.26 \cdot 10^3$	$6.51 \cdot 10^3$	$4.13 \cdot 10^3$	$4.39 \cdot 10^3$

Table 2: MAPE (%) and MSE of aggregated metering data for different forecasting models in different cases

6. ACKNOWLEDGMENTS

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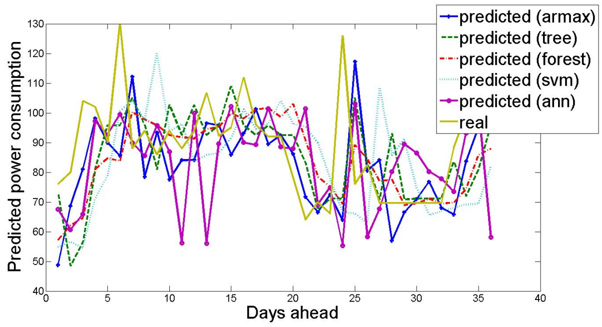

Figure 4: Comparison of the load forecasting results with influencing factor *big events* for one smart meter

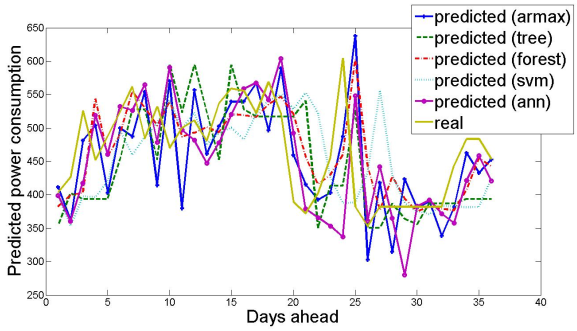

Figure 5: Comparison of the load forecasting results with influencing factor *big events* for aggregated metering data

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