Short Term Load Forecasting for Individual Consumers based on Markov Chains

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***Abstract*—Emerging smart-grid applications in low-voltage systems generate a need to forecast not only aggregated load profiles, but individual, consumer specific profiles in a high temporal resolution. These load profiles are noisy and volatile, which makes forecasting them challenging. A short term load forecasting (STLF) model, based on Markov chains, is presented in this paper. It is designed for continuous training during operation and can be pre-trained, making it universally applicable. Its performance is evaluated at a synthetic dataset of individual households. The predictive accuracy of the model is investigated for different forecasting resolutions and levels of load aggregation. The results show that the general characteristics of individual, high resolution load profiles is modelled reasonably well, outperforming a naive prediction, utilizing a scaled standard load profile.**

***Index Terms*—STLF, smart-grid, residential, low-voltage, Markov chain, forecast, time-series**

I. Introduction

The continuing increase of distributed generation, as well as emerging smart-grid applications in low-voltage systems generate a need to forecast not only aggregated load profiles, but individual, consumer specific profiles in a high temporal resolution. These load profiles are a lot noisier and also more volatile than the highly aggregated load curves used in transmission systems for load flow calculations and predictions. Forecasting models typically used in high-voltage and extra-high-voltage systems are therefore ill suited to predict individual consumer profiles accurately [1]. Load profiles of individual consumers show large power spikes for short periods of time with a low base consumption during the rest of the time. Due to the stochastic nature of these power spikes STLF for individual households is challenging [2]. However, reoccurring events and load patterns can be predicted by analysing historical data.

There are not many sources dealing with the forecasting of individual, residential load profiles. In [3] a Long Short Term Memory (LSTM) Neural Network is used. In [1] a Non-linear Auto-Regressive eXogenous (NARX) model is evaluated. In [4] the "impact of calendar effects and forecast granularity" is investigated for different forecasting techniques like Support Vector Machine (SVM), Multiple Linear Regression (MLR), Regression Trees and Neural Networks. However, in the aforementioned sources no high resolution load profiles were used, but 30 minute mean values instead, which show a highly skewed frequency distribution, in comparison to one minute profiles [5]. Moreover, the prediction models based on neural networks are often difficult to implement in real operation scenarios with continuous training, due to the high training durations. Most research seems to be focused on the prediction of aggregated load profiles at the mv/lv transformer level, ignoring the characteristics of the individual profiles, which they consist of.

The goal of STLF in this paper is to forecast representative, high resolution load profiles for each household in a low-voltage network in order to perform (probabilistic) system analysis - e.g. state prediction. The forecasted profiles should have the same characteristics as the real data, mainly the amount of power spikes and the time of their occurrence should match within a reasonable error margin. Furthermore the accumulated predictions of all households within the same low-voltage network should at least match the predictive accuracy of a naive prediction, described by a scaled standard load profile. The H0 profile from [6] is used as the naive prediction in this paper.

In order to achieve these goals, a forecasting model based on Markov chains was developed. It utilizes high resolution smart-meter measurements as training data. The model is designed for continuous training with individual smart-meter data. The major benefit of this approach is that over time a model pre-trained with synthetic data will adjust to the consumer specific behaviour of one household, or a cluster of similar households, and therefore increase its predictive accuracy. The model is of limited complexity and therefore easy to use. At the same time the model is universally applicable, because of its pre-training. It can be applied without any measurements from the field, but at the cost of severely reduced accuracy.

II. Methodology

A. Dataset

The dataset used in this paper is taken from [7]. It consists of 74 synthetic load profiles for individual households in Germany with a time resolution of one second. The synthetic data is based on smart-meter measurements from the year 2010 with a temporal resolution of 15 minutes. In a second measurement campaign, lasting two weeks, the power

consumption of 30 households in Austria was recorded with a resolution of one second. Each 15-minute interval of the base profiles was replaced by a section of the one second data corresponding in their energy demand [7].
In order to decrease computation time, the data used in this paper is averaged for each minute and only 20 of the 74 load profiles are considered. This is also the amount of households assumed in this paper to represent one feeder in a low-voltage network. An example of a 15-minute base profile and the corresponding one minute synthetic power consumption is shown in Fig. 1.
Because of the synthesizing method chosen in [7] electrical devices with the same energy consumption but different characteristics can get mixed up. This could affect forecasting accuracy negatively, because time dependent correlations would get lost. E.g. the usage of clocked hotplates is in reality limited to certain times of the day. During the process of synthesizing in [7] the very distinct characteristics of hotplates could also be used for time periods outside of their real operating times, if the energy consumption is equally high. This needs to be considered when comparing the results of this paper with other works, performing STLF on real measurements.

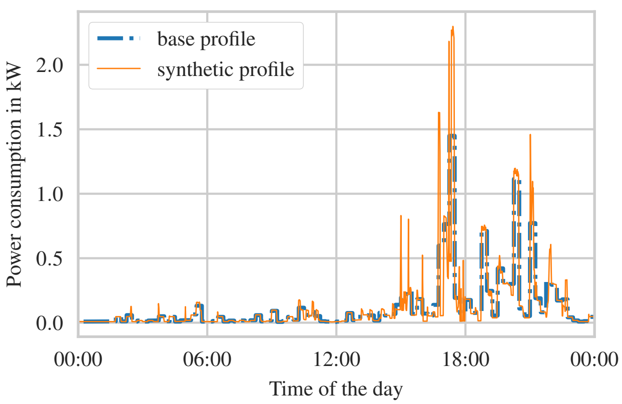

Fig. 1. Synthetic load profile example from the dataset taken from [7]

B. Forecasting model based on Markov chains

The STLF model used in this paper is based on [8] and [9] and utilises Markov chains. The model is designed for continuous training with individual smart-meter data. Therefore some modifications were made to the model in [8], in order to enable continuous training.
First, the training data is discretized into 100 bins, from 0W to 15kW, resulting in a resolution of 150W. The maximum of 15kW was chosen because it is the physical limit for a single phase power consumption, assuming a 64A fuse in a low-voltage network ($230V \cdot 64A = 14.72kW$). Each transition from the power consumption P_{t_n} into the value of the next time point $P_{t_{n+1}}$, is counted inside a transition matrix, according to the power values of the transition, as depicted in the transition matrix below. E.g. a change in power demand from $P_{t_n} = 315W$ to $P_{t_{n+1}} = 100W$ would result in incrementing $f_{3,1}$ by one, because $315/150 = 2.1$ and $100/150 = 0.66$.

$$\begin{array}{c c} & \begin{array}{cccc} P_{1,t_{n+1}} & P_{2,t_{n+1}} & \cdots & P_{100,t_{n+1}} \end{array} \\ \begin{array}{c} P_{1,t_n} \\ P_{2,t_n} \\ \vdots \\ P_{100,t_n} \end{array} & \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,100} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,100} \\ \vdots & \vdots & \ddots & \vdots \\ f_{100,0} & \cdots & \cdots & f_{100,100} \end{pmatrix} \end{array}$$

The transition matrix now stores the training data's frequency distribution, from which the transition probabilities are not calculated, as would be usual with a Markov model. This way new observations can be added to the already trained model, instead of having to re-train it with all of the values. When using the transition matrix in a random walk, the transition probabilities are calculated on the fly, by dividing the entries of each row in the transition matrix by its cumulative sum.
Not all transitions are stored in the same matrix. Instead, the time of day in steps of 15 minutes ($t = 96$), the month ($m = 12$), the season ($s = 4$) and whether it is a working or a non-working day ($w = 2$) is considered during training. Furthermore the training is carried out separately for each household ($h = 20$). Therefore $t \cdot m \cdot s \cdot w \cdot h = 184320$ different 100x100 transition matrices are created and stored inside a NoSQL database during the training phase.
When performing a forecast, the appropriate transition matrices are loaded from the database for each step within the random walk. If a less specific subset of training data is to be considered, e.g. all summer workdays, the corresponding matrices can be added together, because they store the training data's frequency distribution instead of the transition probabilities. This enables many different approaches in combining the transition matrices. Five approaches are compared in this paper:

- Daytype
- Daytype & Season
- Latest 1 months
- Latest 2 months
- Latest 3 months

The "Daytype" method is used as a basis and only differentiates between the households, the type of day (working day - non-working day) and the time of day. The data of the entire year is therefore taken into account in this method. The method "Daytype & Season" also takes the season into account, reducing the amount of data being accounted for. The "Latest X months" methods differentiate between the type of day, while taking only the latest X months into account, starting with the month of the forecasting date. So when forecasting the 28^{th} November with the "Latest 2 months" method, only the training data of October and November is being considered.
All forecasts are carried out in a temporal resolution of one

minute with a forecasting horizon of 24 hours. Forecasts are repeated 100 times for each of the 20 synthetic load profiles. In the final evaluation, the results are aggregated to different temporal resolutions, in order to compare the results with other papers like [1].

C. Evaluation Criteria

There are two main criteria for evaluation used in this paper.

a) Mean Absolute Percentage Error: The Mean Absolute Percentage Error (MAPE) is described as:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{R_t - P_t}{Z_t}\right|$$
$$with \quad Z_t = \begin{cases} P_t, & \text{if } R_t = 0 \\ R_t, & \text{otherwise} \end{cases} \tag{1}$$

where R_t is the recorded and P_t the predicted power consumption at the time t.

b) Theil's inequality coefficient U_2: In order to compare the STLF model with a naive prediction Theil's inequality coefficient U_2 is used:

$$U_2 = \frac{\sqrt{\frac{1}{T}\sum\limits_{t=1}^{T}(R_t - P_t)^2}}{\sqrt{\frac{1}{T}\sum\limits_{t=1}^{T}(R_t - N_t)^2}} \tag{2}$$

where R_t is the recorded, P_t the predicted and N_t the naively assumed power consumption at the time t.
In case of a perfect prediction R_t is equal to P_t, thus $U_2 = 0$. If the forecast is as good as the naive prediction $\sum\limits_{t=1}^{T}(R_t - P_t)^2$ is equal to $\sum\limits_{t=1}^{T}(R_t - N_t)^2$, resulting in $U_2 = 1$.
For $U_2 > 1$ the forecast accuracy is not as good as that of the naive prediction. $U_2 < 1$ indicates a better accuracy than the naive approach. In order to justify the use of any STLF model its forecasting accuracy should be higher than that of the naive prediction.
The standard load profile H0 from [6] is used as the naive prediction. It is scaled according to the amount of energy consumed on the previous day.

III. Results

The presented results refer to a forecast for one workday (Monday 29.11.2010) and one non-working day (Sunday 28.11.2010). Some load profiles are more difficult to predict than others, as can be seen in Fig. 2.
This is different depending on the forecast date, as consumer behaviour includes random variations and can therefore only be modelled for average days, not for times of unconventional consumer behaviour.
The boxplots in the upper subfigure of Fig. 2 each include 100 forecasts for the working day, comparing two different

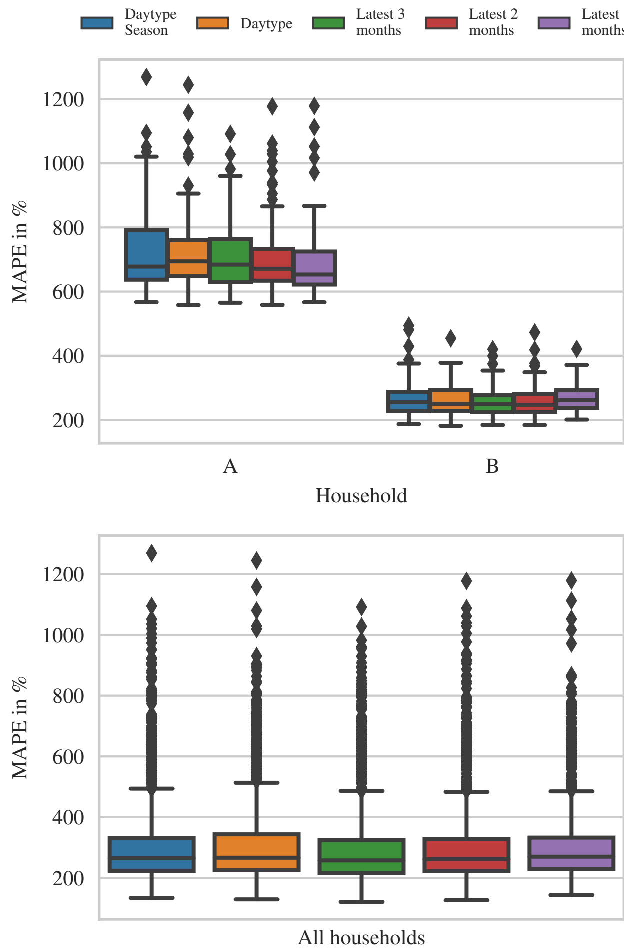

Fig. 2. Comparison of the prediction error for the working day with a time resolution of one minute for different households

households A and B. The lower subfigure includes all forecasts of the 20 households. None of the five methods has a significantly better prediction accuracy, when forecasting individual load profiles at a time resolution of one minute.
When aggregating the 20 individual load profiles to represent the power consumption of a whole feeder, the forecasting accuracy is much better, as can be seen in Fig. 3. Theil's inequality coefficient indicates a better performance than the naive prediction, with $U_2 < 1$ for all five methods. In contrast to the naive prediction, the waveform corresponds very well with the measured values, as can be seen in Fig. 4. It shows one of the 100 predictions for the working day with the method "latest 3 months". The 20 load profiles were forecasted separately and then aggregated.

In the next step, the one-minute forecasts were aggregated in different temporal resolutions. Fig. 5 shows the results at feeder level with a resolution of 30 minutes. The shown forecast example and the scatter plot belong to the "latest 3 months" method. The red line in the scatter plot indicates

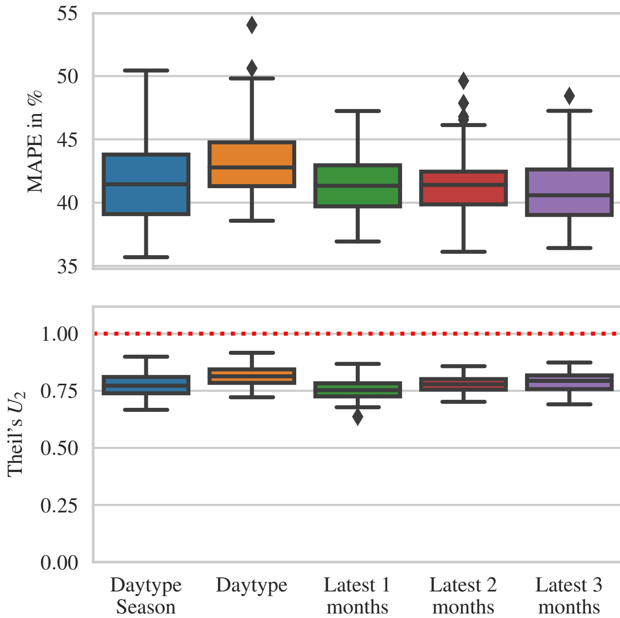

Fig. 3. Forecasting accuracy at feeder level with a time resolution of one minute for a working day

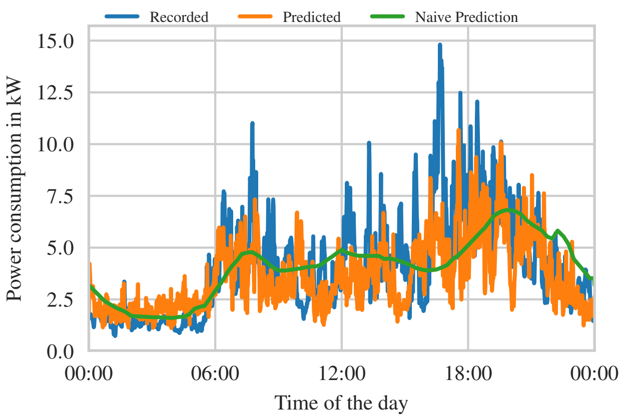

Fig. 4. Example of a one minute forecast with the “latest 3 months” method at feeder level for a working day

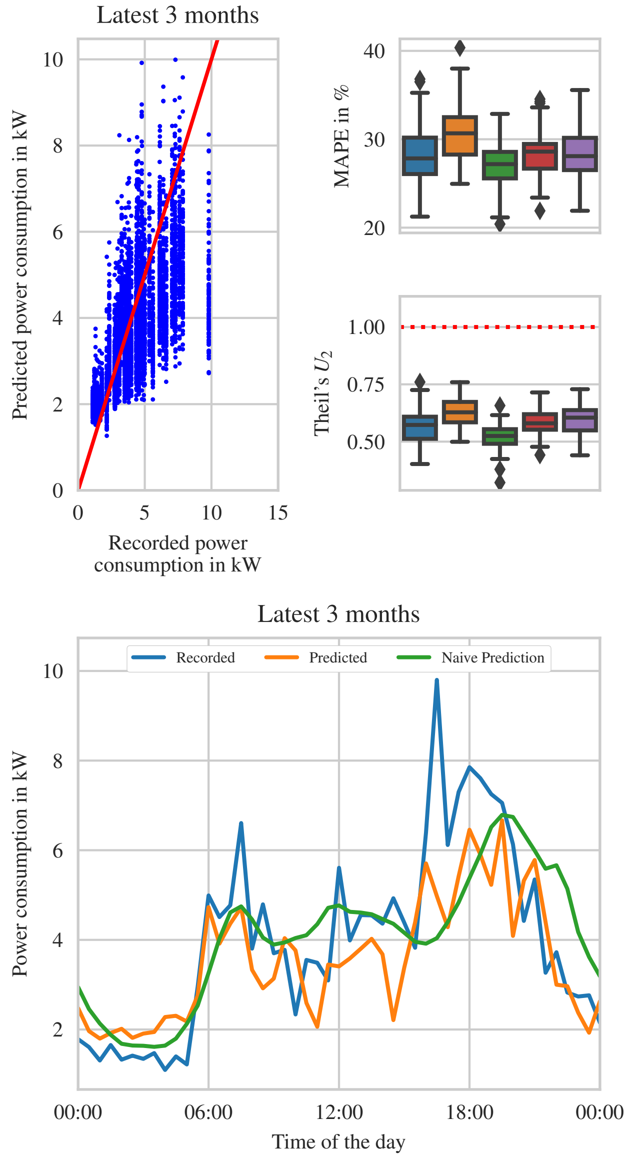

Fig. 5. Results for the working day forecast with a time resolution of 30 minutes at feeder level using the “latest 3 months” approach

a perfect prediction. Other time resolutions were evaluated, showing an increase in accuracy with lower time resolutions. The error values (MAPE) indicate a reduced predictive accuracy of the STLF model, compared to those in [1]. It should be mentioned, however, that in [1] half-hourly and hourly mean values of real load profiles were used as the data basis, instead of synthetic, minutely averaged profiles. Although the amount of training data available for non-working days is greatly reduced in comparison to working days, the presented STLF model achieves similar accuracy for the analysed non-working day. The results are summarized in Fig. 6 at feeder level with a time resolution of 30 minutes.

IV. Discussion and Conclusions

From the results shown in section III it can be concluded that the STLF model presented in this paper can be used to predict load profiles of individual households with high temporal resolution within reasonable tolerances. The characteristics of individual load profiles are modelled realistically, even though the MAPE for individual forecasts is high. Due to the stochastic nature of individual load profiles, it is impossible to achieve the same level of forecasting accuracy for them, as for aggregated load profiles. It was found, that the MAPE is not a representative evaluation criteria for individual, high resolution load forecasting. For point-wise comparison methods, like the MAPE, “an observed

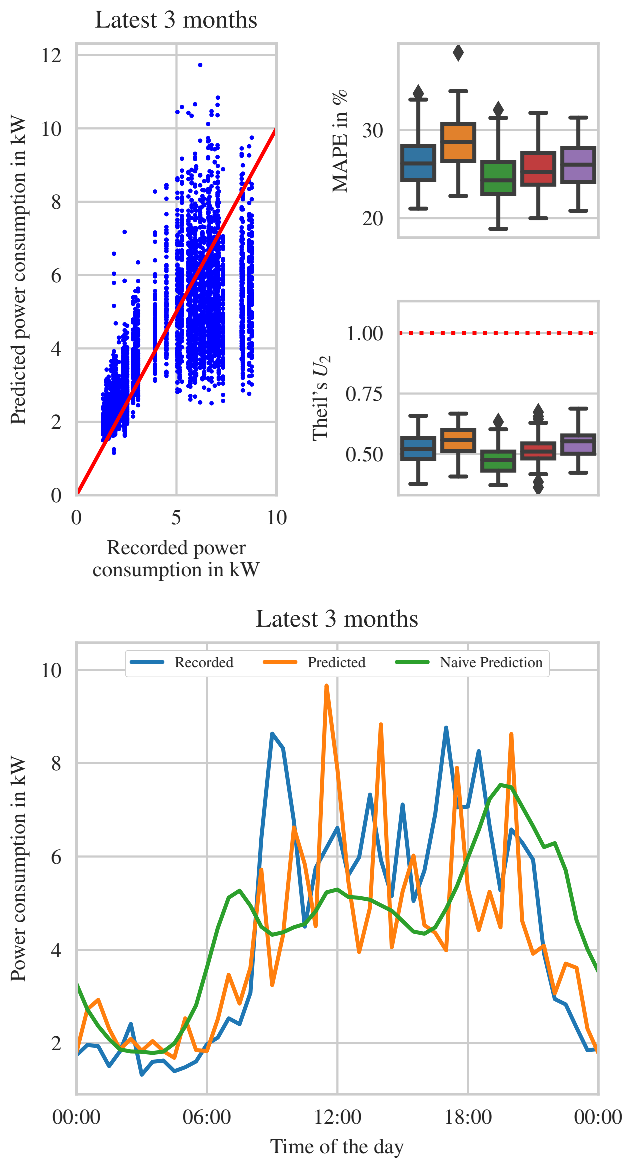

Fig. 6. Results for the non working day forecast with a time resolution of 30 minutes at feeder level using the "latest 3 months" approach

feature that is forecasted accurately in terms of size and amplitude, but displaced in time, incurs a double penalty" [10]. Therefore, new measures of the predictive accuracy need to be developed for future application to this kind of data [1] [10]. The predictive accuracy of the Markov based model increases for levels of higher aggregation, e.g. at a low-voltage feeder. It was shown, that the forecasts are superior to a naive prediction, utilizing the standard load profile for households H0 from [6]. No serious differences were found in the five different selection methods of the examined training data. One reason could be the use of synthetic data in this paper, as explained in section II-A. The load forecasts are sufficiently accurate to be used in further system analysis, like state estimation and state prediction. Furthermore, the design of the presented STLF model allows continuous training with measurements from the field in real time. The model can be pre-trained with historical data from different sources, making it universally applicable. The categorization and selection of the pre-training data needs to be investigated. The application of the presented STLF model to real high resolution data is necessary for a final evaluation. Unfortunately, the amount of high resolution data, available to the authors, is not sufficient at the point of writing this paper.

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