Incremental Adaptive Time Series Prediction for Power Demand Forecasting

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Abstract. Accurate power demand forecasts can help power distributors to lower differences between contracted and demanded electricity and minimize the imbalance in grid and costs resulting from causing it. We propose a forecasting method that is designed to process continuous stream of data from smart meters. The focus is on the incremental processing and adaptivity of the prediction model to the concept drifts in power demand. Our method identifies drifts using a condition based on an acceptable daily imbalance of a distributor. Using only the most recent data to adapt the model (in contrast to all historical data) and adapting the model only when the need for it is detected (in contrast to creating a whole new model every day) enables the method to handle stream data. The proposed model was evaluated on two data sets and shows promising results.

Keywords: Power demand forecasting · Stream mining · Time series analysis · Concept drift

1 Introduction

Processing of streams coming from smart meters is nowadays one of the biggest challenges in the data analytics area. The directive 2009/72/EC of the European parliament and of the Council states that EU members shall equip at least 80 % of the consumers with intelligent metering systems by 2020. The smart meters send the measurements of power consumption regularly, e.g., every 15 minutes. Power distributors collect this vast amount of measurements from all of their customers. The responsibility of the distributor is to effectively utilize information from these data to prevent imbalance in power grid (i.e. to minimize online gap between contracted energy supplies and actual power demand) and to minimize regulation costs resulting from the grid imbalance. The accurate short-term forecast of the aggregated power demand of all distributor's customers for the next 24 hours is important for trading energy on the liberated electricity market where the electricity can be contracted even one hour ahead.

The important aspect of this very specific type of data, except its streaming properties, is the fact that their typical characteristics change over time and are affected by many external factors. The power consumption depends on the season, day of the week, time of the day, the type of the consumer (e.g., household, factory), weather, social activities, public events, and others [1]. Some of these factors are periodical, and one

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can predict them easily, e.g., seasonality, while others are quite unpredictable because there is often a lack of information about them, such as consumer behavior. Because the measured data are influenced by many factors, that sometimes cannot be foreseen, it is very important to take sudden changes in power demand into account. That is why stream change detection mechanisms are so important. The purpose of the fast change detection is to identify the ongoing changes in the monitored data – also called the concept drifts [2].

Detection of a change in data stream can help to correct (or to adapt) the prediction model that can no longer (because of the drift) predict the values correctly. The challenge is to perform these model adaptations online. The parameters of the forecasting model are usually determined based on the data in a training set. But in the large online stream processing, there are usually no such data available nor there is enough time or memory to train new models from scratch. The aim of this paper is to propose a method for power demand forecasting with respect to the two main requirements for this type of predictions – *incremental computing* and *adaptivity to concept drifts*.

The rest of the paper is organized as follows: In section 2 we present the related work concerning stream mining, power demand forecasting and concept drift. Sections 3 describes the proposed method for power demand forecasting that is able to quickly adapt to concept drifts. The performed experiments, their evaluation and the ideas for future work are outlined in section 4. The last section is the conclusion.

2 Related Work

Data streams can be described as the ordered sequence of samples transferred at the stable (high-speed) rate. The two basic properties of stream (volume and velocity) determine the way it is processed. The third important property of the stream is *variability*. It refers to the constantly changing data over time and the dynamic environment that affects the data. The ideal stream mining method [3]:

- requires a short constant time per stream sample;
- uses a fixed amount of memory;
- builds a model by using a single scan over the data;
- is able to deal with concept drift;
- produces a model with accuracy nearly identical to the accuracy of a batch learner.

The concept drift can be formally defined by the equation 1, where p_{t_i} denotes the joint probability distribution at time t_i between the set of input variables X and the target variable y. The changes in data can be then seen as changes in the components of the relation, i.e. the input data characteristics or the relation between the inputs and the target variable [4]:

$$\exists X: p_{t_0}(X, y) \neq p_{t_1}(X, y). \tag{1}$$

There are different patterns of drifts in data (see Figure 1). In power demand, the abrupt drift can be caused by replacement of a sensor with a differently calibrated one. The incremental change can be caused by a sensor that is breaking down and loses its precision. The gradual change represents the presence of two states (before and after change) at once. For example, a power demand in a household before and after the introduction of a new tariff when the household gradually changes its habits in power consumption. The reoccurring concepts represent the events that are repeated over time but in contrast to the seasonality they are not periodical. Therefore, we don't know when exactly they will happen, e.g., a power demand during holidays, sport events, etc.

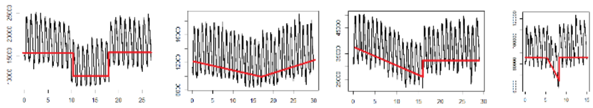

Fig. 1. Different patterns of concept drifts in power consumption (reoccurring, incremental, abrupt). The x-axis represents the time and the y-axis the consumption in kWh.

The drifts make the prediction more challenging. The prediction methods should therefore be able [2]: to detect the concept drift as soon as possible and adapt the prediction model to it if needed; to distinguish drifts from noise; and to operate in less than stream sample arrival time and use a fixed amount of memory. The procedure of changing the prediction model over time is referred to as the *adaptive learning* and consists of these three steps:

- prediction – after arrival of a sample a prediction is made with the existing model;
- *diagnose* – after arrival of the next sample (the true value), the loss is estimated;
- update – the last sample can be used to adapt the prediction model.

During the diagnostic step the loss estimate is calculated (usually as a difference between the predicted and the actual values). By monitoring the losses, the changes in data can be detected. The update step of the procedure can be then carried out as an *informed* decision based on the detected changes (cf. [2, 5]).

The power demand forecasting methods have been developed since the 19th century but the intense research in this area and the short term forecasting started in 1980s [6]. The methods for the power demand forecasting can be divided into two groups – statistical and artificial intelligence (AI) based methods. The examples of the statistical methods are the linear regression and the time series analysis methods, such as ARIMA [7], and exponential smoothing [8]. The advantages of these methods are the solid theoretical foundations and simple, robust and explainable prediction models. On the other hand, these methods usually model only linear relations between the input variables and the target variable. In general, it is assumed that the linear model is sufficient for the short term forecasting without weather variables (the relation between weather variables and power demand is usually nonlinear) [6]. The most used AI method is the neural network but the others, e.g., expert systems, fuzzy logic, support vector machines, are exploited as well. The advantages of the AI methods are the ability to model the nonlinear relationships between the inputs and the target variable and the low requirements for domain or statistics' knowledge.

The adaptive power demand forecasting methods we encountered in the literature usually use *blind adaptation* to cope with continually changing data. The most commonly utilized approach is the *regular batch training*. The prediction model is created from scratch with the arrival of a new batch of data, e.g., once a day/hour/15 minutes. The new batch is appended at the end of the existing data and the new model is built from all available data. Sometimes, instead of all available data, only a part of data (i.e. a window) is used to speed up the training process, e.g. the last few (similar) days.

Another popular approach is to create a large group of context-specific models, e.g. separate models for each day of the week, each hour of the day, each holiday. A proper model is chosen from this group according to current circumstances. Dannecker et al. [9] dwelled on this idea and incorporated other factors apart from time into the context, e.g., weather, calendar or economic factors. They created a repository of context-model pairs. Whenever a new context appears, the new model parameters are searched for in the repository. The most similar context is selected.

Similar to regular batch training, *periodical model parts' updates* assure the currency of the prediction model by updating its (all or a part of) parameters or weights regularly to minimize prediction error. The variations of the least squares' algorithm are employed for this purpose [10]. On the other hand, some *adaptive models* are designed in a way, so their parameters do not need to be updated. Instead of constants, the parameters are defined as functions. A typical representative of this group is the smooth transition exponential smoothing (STES) by Taylor [11], which has an adaptive parameter that exploits the one-step ahead prediction error.

Generally, the blind adaptive prediction methods are more common. They try to update the prediction model on each arrival of a new sample from a stream. The *informed adaptive prediction methods* utilize a concept drift detector and monitor the accuracy of the prediction model. Only when a drift is detected, they update the model. This way, the possibility of overfitting is reduced and computing and memory resources can be spared. It has been shown that concept drift detector can improve the prediction model accuracy [12]. In the next section we propose a power demand forecasting method that addresses these issues and is built on the incremental adaptive learning.

3 Adaptive Power Demand Forecasting Method

The proposed method is able to predict the power demand of a group of consumers. We predict the aggregated electricity for the next 24 hours. The power demand is affected by multiple external factors. Some of them are incorporable into the prediction model, such as seasonality (intraday cycle, intraweek cycle and intra-year cycle), weather (particularly temperature and humidity) and calendar or social events (holidays, summer leaves in factories, nation-wide TV broadcasts, etc.).

Figure 2 depicts the essence of our method for power forecasting that is based on adaptive learning scheme. We assume that an initial prediction model exists. The first step – *prediction* – is executed on arrival of new data. The next step – *diagnostics* – happens after the arrival of actual value of power consumption for the predicted horizon. The error is evaluated and it is sent to change detection mechanism module. If the prediction error increases over time or some external factor significantly changes (e.g., temperature, humidity, day type), the alarm is setoff and the third step – *update* – is triggered. The parameters of the prediction model are re-estimated from the sliding window of the most recent data.

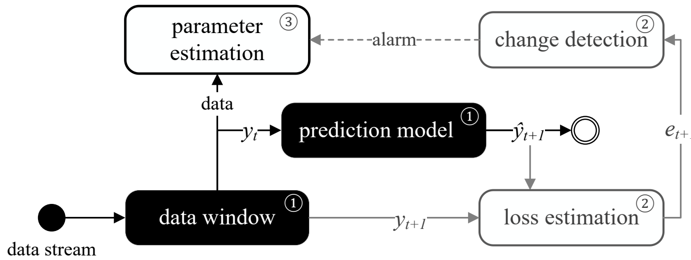

Fig. 2. Power forecasting method consists of three steps: predict (1), diagnose (2) and update (3), (y_t is the actual value of power consumption at time t, $\hat{y}_t$ is the predicted value of power consumption at time t, e_t is the error of prediction at time t).

To complete our method, we had to:

1. choose a proper prediction model with possible and effective parameter re-estimation, that can operate in the streaming environment, and
2. design a proper change detection mechanism to timely spot changes in the power demand.

3.1 Prediction Model and Parameter Estimation

The main criteria for the prediction model selection were simplicity, robustness, the ability to model the multiple seasonal cycles of the power demand, the possibility to compute the predictions incrementally and easy parameter re-estimation.

Therefore, we decided for the exponential smoothing (ES) method. Its original version – Holt-Winters' ES [8] is able to model only a single seasonality so we used its extension by Taylor with double seasonality – Holt-Winters-Taylor (HWT) ES [13], which was shown to have very good accuracy [14]. The HWT method is simple and calculates the predicted value recursively in a constant time utilizing the past results, so it is very suitable for incremental computing. The parameters of this method are estimated by the least squares method. It is defined by the equations (2) [13]:

Level $$S_t = \alpha \frac{y_t}{D_{t-s_1} W_{t-s_2}} + (1-\alpha)(S_{t-1} + T_{t-1})$$

Trend $$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$$

Seasonality 1 $$D_t = \delta \frac{y_t}{S_t W_{t-s_2}} + (1-\delta)D_{t-s_1}$$

Seasonality 2 $$W_t = \omega \frac{y_t}{S_t D_{t-s_1}} + (1-\omega)W_{t-s_2}$$

$$\hat{y}_{t+k} = (S_t + kT_t)D_{t-s_1+k}W_{t-s_2+k} + \phi^k(y_t - (S_{t-1} + T_{t-1})D_{t-s_1}W_{t-s_2}) \quad (2)$$

In this definition, $\hat{y}_{t+k}$ is the predicted value for the kth horizon of a time series, S_t is the level of the series and is smoothed by the smoothing parameter α, T_t is the trend of the time series and it is smoothed by the parameter γ and D_t and $W_t$reflect the double (daily and weekly) seasonality. The seasonality is smoothed by the parameters δ and ω, respectively. s_1 and s_2 are seasonal periods, e.g., for 15-minute measurements $s_1 = 96$ (one day) and $s_2 = 672$ (one week). The smoothing parameters α, γ, δ and ω come from the interval (0,1). Taylor [13] further improved the accuracy of the prediction by the inclusion of the AR(1) model for the residuals with parameter ϕ. It is estimated together with the smoothing parameters.

We assume that the seasonal smoothing parameters (δ and ω) do not change significantly over time and the concept drifts affects only the level of the time series and can be managed by adjusting the level smoothing parameter α and the parameter ϕ of the residual autoregression adjustment. When the concept drift is detected, the values of the parameters are re-estimated by the minimization of the sum of squared errors in a sliding window with the most recent stream data. We have used the last two weeks of data. The length of the window was determined experimentally. It had to be long enough to reflect the double (daily and weekly) seasonality and short enough to provide the most recent information about the ongoing concept drift.

3.2 Change Detection

The timely warnings about the changes in the stream gives the distributor the opportunity for flexible reaction, e.g., to sell or to buy the energy on short-term market. We propose a change detection mechanism that monitors the prediction errors, i.e. the differences between the predicted and the real values of power consumption. In the future, the deviations in external factor variables like temperature or humidity can be incorporated. The inclusion of the external factors in the change detection mechanism and not in the predictive model itself, makes the predictor more robust and able to operate even when the data about external factors are not accessible.

The concept drift should be signalized when a change in mean (ideally, it is zero) or a change in variance (only increasing variance should be alarmed, the decreasing variance indicates improvement of prediction accuracy) of the prediction errors occurs.

The utilization of one of the methods for concept drift detection in a stream environment e.g. sequential analysis [15, 16]or statistical process control [17], seemed to be a straightforward solution. These methods usually assume that the monitored stream has a Gaussian distribution. Though we monitor prediction errors, because of the many external factors that influence the power demand and that are not included in the prediction model, we cannot make any assumptions about the residuals' distribution. Therefore we tried to use a non-parametric change detection – several statistical distribution-free tests presented by Ross et al. [18, 19] (namely the Mood statistic for the detection of changes in variance and Lepage, Kolmogorov-Smirnoff and Cramer-von-Mises statistics to detect more general distributional changes). Initial experiments showed that these tests did not detect the concept drifts soon enough or alerted the drifts also in (for us) undesirable cases like the drop in variance of prediction error.

We propose our own simple method for concept drift detection in power consumption data based on the acceptable daily deviation of a power distributor in the power engineering domain. The difference between contracted and demanded electricity of a power distributor should not be higher than 5 % a day.

The prediction error is calculated as the difference between the true value and the predicted value, i.e. $e_t = y_t - \hat{y}_t$. We evaluate the percentage absolute error over the past day (e.g., in case of quarter-hourly measurements it is the last 96 observations). The percentage error is computed as the quotient of the sum of absolute prediction errors and the sum of the true values (the actual power consumption):

$$pe_t = \frac{|e_{t-95}| + \cdots + |e_{t-1}| + |e_t|}{y_{t-95} + \cdots + y_{t-1} + y_t} \quad (3)$$

We used the absolute errors to penalize both higher and lower power supply. When the percentage error exceeds the defined threshold, we assume that the accuracy of the prediction model over time lowers and the concept drift is detected. The re-estimation of the model's parameters is triggered. We set the threshold to be 5 % ($pe_t > 0.05$).

4 Evaluation

We performed a set of experiments to pursue the answers for the following questions:

1. Can be the informed adaptation be as accurate as blind adaptation? i.e., can the forecasting method utilizing the change detection be as accurate as the periodically created prediction model from scratch?
2. Does informed adaptation require more time or memory resources? Is it suitable for stream processing?
3. Does the change detection improve the demand forecasting? If so, to what extent?

4.1 Data

We performed the experiments on two datasets. Since we have used the double exponential smoothing method to create our prediction model, the initial experiments were executed on the same British data that Taylor used in his paper [13]. We can directly compare the results of our incremental approach to the original method. The dataset comes from the National Grid company, which is responsible for the power transmission in England and Wales. The power consumption is measured in the half-hour intervals. The data contains 12 weeks (from Monday 5 June to Sunday 27 August 2000).

The second dataset comes from Slovak smart meters. Our goal was to design the method that would be applicable and suitable for these data. Slovak smart meters measure the power consumption quarter-hourly. We used the data from 6 regions in Slovakia. The measurements were performed for a period of more than one and a half year (from 1 July 2013 to 16 February 2015). We aggregated the data to predict the power demand of the whole region. For our experiments we chose the 12 weeks (8 for training, 4 for testing) that contained concept drifts (from 19 May to 10 August 2014) and 12 that didn't (from 13 January to 6 April 2014).

4.2 Experiments

Firstly, we applied our informed adaptive method on Slovak dataset and evaluated the prediction accuracy on data with and without concept drifts. We trained the initial double seasonal exponential smoothing model on the first 8 weeks of data. The remaining 4 weeks were used to sequentially analyze the residuals and improve the model's accuracy on the fly. To the accuracy evaluate, we used the *mean absolute percentage error (MAPE)*, which is the widely used measure in power demand forecasting. Furthermore, we recorded how many times was a concept drift detected and the model was adapted (α and ϕ had to be re-estimated from a sliding window).

Secondly, we computed the predictions on the same data by application of the blind adaptive batch learning. After each day the prediction model was created from scratch on all available data (the first 8 weeks of data plus the days that have passed until actual point in time) to predict the next day's consumption. We used the 4 weeks long test set (28 models were created). We evaluated the MAPE of the test set like in the first part of the experiments. In the end, we compared the blind and the informed adaptive approaches with respect to the accuracy and the needed resources for the prediction calculations. We repeated the experiments on the British dataset as well to find out how the change detection affected the original double seasonal exponential smoothing method results. The British dataset did not contain any concept drifts. The results of both parts of the experiments are summarized in the next section.

4.3 Results

In this section we answer the evaluation questions we stated at the beginning of the section 4. Table 1 contains the results of the experiments.

The accuracy of both blind and informed adaptive approaches was comparable. We observed that MAPE was slightly worse when the concept drift was present in data in both approaches (the difference was cca 1 %). When we compared MAPE of blind and the informed approach on the same datasets we found out that the informed adaptation had on average 0.36 % higher error. Wilcoxon signed rank test confirmed that this is not a significant difference. In several cases the accuracy of the informed approach was better. Therefore, we point out that the informed adaptation can be as accurate as the blind adaptation (in spite of the fact that it adapts the two model parameters only in cases of concept drift and the learning is based only on the sliding window).

The second evaluated aspect represents the amount of resources used for the computation. We recorded the number of times the prediction model needed to be adapted during the test period. The informed adaptation required on average 55.35 % less updates than the blind adaptation. With the respect to the memory usage, the informed adaptation needed only the two last weeks of the data in comparison with the blind adaptation that recomputed the model every day from all the available data. Since both approaches had the similar accuracy results, we consider the informed adaptation more suitable for the stream processing.

Table 1. The MAPE results of blind and adaptive approaches on 4-week test sets with and without concept drifts. The number next to the region name is the number of consumers in the region, #r denotes how many times the prediction model was adapted.

	with concept drift				without concept drift			
	blind		informed		blind		informed	
region	MAPE	#r	MAPE	# r	MAPE	#r	MAPE	# r
BA (1314)	4.439305	28	3.658986	12	5.202546	28	3.050979	9
ZH (773)	3.680101	28	4.142884	13	1.776970	28	3.202408	5
TT (733)	4.063877	28	3.948850	13	3.485590	28	3.744616	11
PN (706)	4.012653	28	6.133951	14	1.932296	28	2.764335	5
ZV (605)	4.086086	28	5.302434	16	3.813536	28	3.788003	10
PE (584)	3.979758	28	3.231175	7	2.878603	28	3.832020	11

We managed to further improve the accuracy of the informed adaptive method at the cost of the needed resources. Fig. 3 shows an example of the informed adaptation on data without (top) and with (bottom) the concept drifts. To detect the concept drift, the average percentage error of the last 96 observations is evaluated. When the prediction model is adapted, the next concept drift can be detected no sooner than after the next 96 observations arrive. We can't consider the prediction errors of the previous model in the concept drift detection, because those were already too high to trigger the model adaptation. The mean value of those errors with the error from the adapted model would instantly result in concept drift detection. Also, it would not reflect the accuracy of the current model. We noticed that sometimes it is too late to start monitoring the prediction errors again after the 96 observations. The percentage error can be too high then (e.g. in Fig. 3 bottom, error after the adaptation at day 70). We added a condition to detect the concept drift also in the case the percentage error of the last 48 observation exceeds 7.5 %. This modification helps to react to drift sooner preventing the higher absolute errors but also results in more frequent model adaptations. The informed adaptation had in this case on average the error smaller by 0.16 % than the blind adaptation and required on average 38 % less updates than the blind adaptation.

In the end, we compared the performance of blind and informed adaptation on the British dataset. This dataset did not contain any concept drifts. MAPE of the blind adaptation was 1.11 %. The model was retrained 28 times. The accuracy of the informed adaptation was 2.4 % with only 2 model updates needed.

To sum up, the concept drift detection significantly improved the power demand forecasting when considering time and memory resources needed during the computations. This feature is extremely useful in stream environment. In return, the accuracy of the predictions did not significantly drop and we managed to maintain the daily 5 % deviation that is acceptable in the power demand forecasting. Additional tests showed that if we would keep adapting the prediction model for another month (beyond the 4-week test set), the accuracy would drop on average by 0.86 %. In order to maintain the accuracy, a new "initial" model should be created from the longer chunk of data, once in a longer period of time, e.g. a few months. This model can be then maintained by the informed adaptation. We believe that even with this limitation, the informed adaptive forecasting is more suitable for the stream data than a blind adaptive approach.

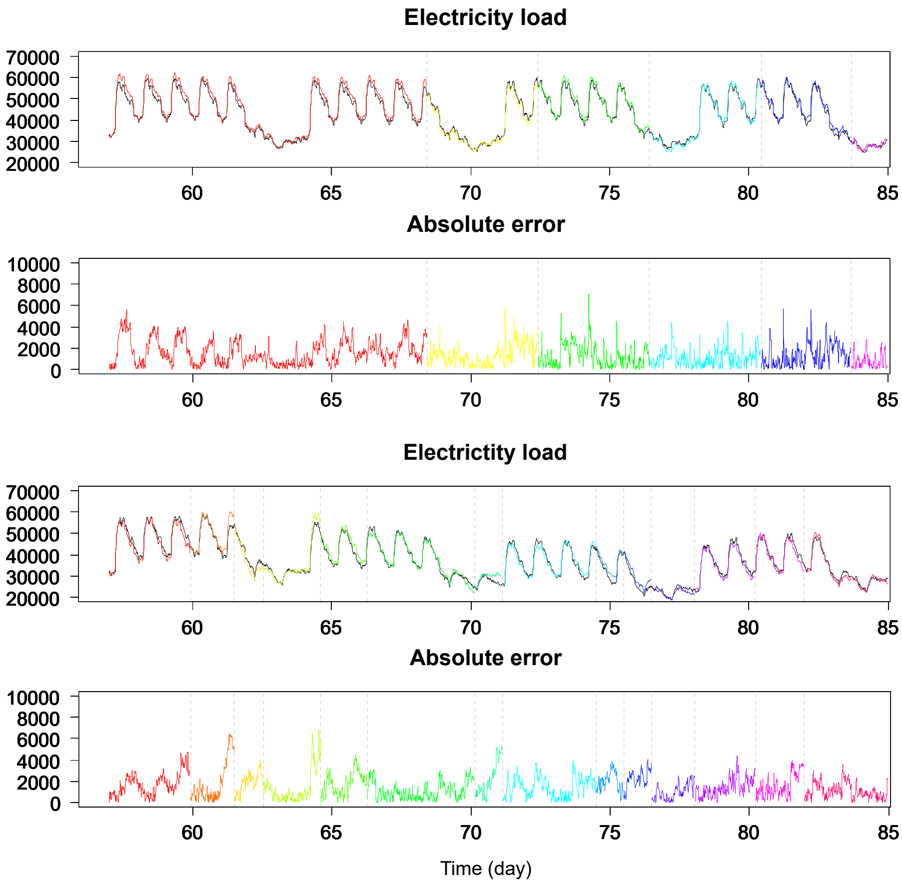

Fig. 3. Predictions and prediction errors for ZH region. Data without concept drift (top two) and with concept drift (bottom two). Measured in kW/15min. The grey lines denote the times when a concept drift was detected and the prediction model was adapted.

4.4 Future work

In the future, we would like to examine other prediction methods that are suitable for continual adaptation, such as support vector machines. The classic statistics, e.g., the exponential smoothing method, requires human reasoning and the analysis of data in comparison with the AI black boxes, which move experts far away from the understanding of the supervised process. Although, by employing machine learning, we may lose the simplicity and easy interpretability of the model, support vector regression has less parameters and so the parameter optimization (the most time-consuming step) could be improved.

A further improvement might be achieved if the adaptations were performed based on data from a dynamic-length window, not just the last two weeks. The shorter window is appropriate when a concept drift occurs, on the other hand, a longer window is more suitable when there are no concept drifts in the stream for a longer period of time.

5 Conclusion

We introduced an informed adaptive approach for predicting the values of power demand seasonal time series. The precise short term power demand forecasts are essential for minimizing the imbalance in power grid and resulting costs. They are an important input for operations on short term electricity market where the electricity can be contracted even an hour ahead of its consumption.

The prediction part of the method utilizes a simple, robust and easily interpretable statistical method – double seasonal exponential smoothing. The informed method employs a concept drift detector to identify changes in power demand. The detector monitors the daily percentage error. When it exceeds a defined acceptable threshold, the prediction model is adapted to the new concept in the data. The concept drifts in power demand are particularly caused by holidays, summer leaves and weather. They manifest mostly by level shifts of a power demand time series. When a drift is detected, the parameters concerning the level of the time series and residuals' correction are estimated based on a short window of recent values.

The proposed method is suitable especially for streams of numerical data with inherent seasonal dependencies. We applied the model to two electricity consumption datasets and made one-day ahead predictions of electricity demand. The method provided similar errors as the regular batch learning, which is a form of blind adaptation to concept drifts. The batch learner was trained every day and based on all historical data. With the informed adaptive method, the need of model adaptations decreased significantly, what can be considered a great benefit in the stream environment.

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