IMPROVING THE EFFICIENCY OF ENERGY CONSUMPTION IN SMART GRIDS WITH APPLICATION OF ARTIFICIAL INTELLECT

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Energy saving accuracy estimates are important for development of energy efficient projects and for demonstrating their cost-effectiveness. Increasingly, commercial buildings have an advanced measurement infrastructure, which has led to the availability of high-frequency interval data. These data can be used in a number of energy efficiency tasks, including anomaly detection, control and optimization of heating, ventilation, and air cooling systems. All it makes possible the application of artificial intellect methods and therefore leads to more accurate estimates of energy savings. In this paper, we proposed the method for modeling the consumers energy profile based on the clustering analysis, exactly, modified K-means algorithm. Extended computer simulations have been shown that it improves the accuracy of energy consumption forecasts considerably.

Keywords: energy consumption, smart meter data, smart grids, forecasting, cluster analysis, gradient boosting.

1. Introduction

The development of the intelligent networks in industry, finance and services creates new opportunities for the development and application of effective methods of machine learning and data analysis. Smart technologies for collecting, recording and monitoring data on energy consumption create a huge amount of data of different nature. These data can be used for optimal network management, improving the accuracy of the forecasting load, detection of abnormal effects of power supply (peak load conditions), the formation of flexible price tariffs for different groups of consumers [1, 2, 3]. One of the most important issues in this area is to predict the power load consumption as accurately as possible. Consumption have a rather complicated stochastic structure, which are difficult for modeling and prediction. Nevertheless, when different methods of aggregation are applied to the group of consumers having similar statistical characteristics of time series of power consumption, it is possible to count on considerable progress in the solution of objectives. However, in order to improve the accuracy, our goal is to investigate the possible benefit of combining clustering procedures with forecasting methods. We have used several known approaches such as Holt-Winters exponent smoothing, ARIMA model, Support Vector Regression and some others. Also most effective machine learning algorithms were applied, exactly, random forest, gradient boosting and bagging.

2. Machine learning algorithms applications for energy consumption modeling

The problems of application of clustering methods to the time series of electricity consumption are mainly in high dimension and high noise level of the data, which can be solved with the use of machine learning methods [4,14]. Our method consists of three steps: the first one is to normalize the data and calculate the energy consumption model for each consumer. In the future, the study uses four different models based on the representation of time series, which serve as inputs to the clustering method. The second stage consists of calculating the optimal number of clusters for the given time series representation and the selected data training period. The third stage is clustering and aggregation of consumption within clusters. For each cluster, the forecast model is trained and the forecast for the next period is run. Then the forecasts are aggregated and compared with the real consumption data. Next, we construct a forecast for received representations of the clusters using the methods, that we will describibied as follows.

2.1. Modeling of the energy consumption time series

The time series X is an ordered sequence of n real variables

$$\boldsymbol{X} = (\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_n}), \boldsymbol{x_i} \in \boldsymbol{R}. \quad (1)$$

The main reason for using time series presentation is a significant decrease in the dimension of the analyzed data, respectively, reducing the required memory and computational complexity. Four different model-based representation methods were chosen: (a) Robust Linear Model (RLM), (b) Generalized Additive Model (GAM), (c) Holt-Winters Exponential Smoothing (Ho-W), and (d) Kalman linear filter. The first presentation is based on a robust linear model (RLM) [6]. Like other regression methods, its aim to model the dependent variables (1) by independent variables

$$\boldsymbol{x_i} = \boldsymbol{\beta_1 u_{i1}} + \boldsymbol{\beta_2 u_{i2}} + \dots + \boldsymbol{\beta_s u_{is}} + \boldsymbol{\varepsilon_i}, \quad (2)$$

where i = 1, ..., n, x_i– is energy consumption of i-th consumer, $\beta_0, \beta_1, \dots \beta_s$ - regression coefficients, u_{i1},..., u_{is} - binary variables, ε_i is a white noise. Extensions for regression model (2) are generalized additive models (GAM) [8]

$$\boldsymbol{E(x_i)} = \boldsymbol{\beta_0} + \sum_{\boldsymbol{l=1}}^{\boldsymbol{L}} \boldsymbol{\beta_l f_l(u_{il})}, \quad (3)$$

where f_l are B-splines [8,14], L – rank of regression model.

2.2. Cluster analysis for energy consumption in smart grids

Utility services have been differencing their consumers into industrial, commercial and residential sectors based on some internal information on them. It may be nominal demand, the whole consumption, etc. This empirical approach could be applied to define the sets of customers load profiles and each user will be assigned to one of these profiles. The great problem to do this is, firstly, that the consumption data of customers, who have installed smart meters, are now accessible. So , they could change their profile dynamically. Secondly, the time period of measurement is not restricted and usage information for some successive years is available. Thus, as the smart meters data are continuously reported, they can have possible applications of real-time operation and control of energy systems. All these factors stimulate the need to develop new clustering methods to characterize energy consumption.

For classification consumers into groups (clusters), we used the centroid based clustering method K-means [4,5,7]. The advantage of the K-means method is based on carefully seeding of initial centroids, which improves the speed and accuracy of clustering [10]. Before applying the K-means algorithm the optimal number of clusters k must be determined. For each representation of a data set, we have determined the optimal number of clusters to k using the internal validation rate Davies-Bouldin index [10,13]. It works as follows. Let $d(x)$ denote the shortest Euclidean distance from a data point x to the nearest centroid we have already chosen. Choose an initial centroid K_1 uniformly at random from X. Choose the next center $K_i = \hat{x} \in T$, selecting with probability $d(\hat{x})^2 / \sum_{x \in X} d(x)^2$. Repeat previous step until we have chosen a total of K centers. Each object from data set is connected with a centroid that is closest to it. New centroids are then calculated. Last two steps are repeated until classification to clusters no longer changes. In each iteration we have automatically determined the optimal number of clusters.

2.3. Energy consumption time series forecasting

We used three methods to improve forecasting energy consumption time series: Support Vector Regression (SVR) [6], a method based on a combination of STL decomposition, Holt-Winters exponential smoothing and ARIMA model [9]. Seasonal decomposition of time series based on LOESS regression is a method, which decomposes seasonal time series into three parts: trend, seasonal component and remainder (noise). For the final three time series any of the forecast methods is used separately, in our case either Holt- Winters exponential smoothing or ARIMA model [12]. Random Forest (RF) algorithm is suitable for classification and regression [15]. The method constructs the large number of decision trees at training time. Its output is the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Gradient Boosting Machine (GBM) is an efficient and scalable implementation of gradient boosting framework by Friedman [15]. The GBM was first proposed for classification problems. Its basic principle is that several simple models, called weak learning models, to be merged into one iterative scheme for the selection of parameters with the aim of obtaining the so-called strong learning model, i.e. models with better prediction accuracy. Thus, the GBM algorithm iteratively adds a new decision tree (i.e. “weak learner”) at each step, which best reduces the loss function. Specifically, in a regression model, the algorithm starts with model initialization, which is typically a decision tree minimizing the loss function (RMSE), and then at each step, a new decision tree is adjusted to the current residual and added to the previous model to update the residuals. The algorithm continues to run until the maximum number of iterations is reached or the specified precision is reached. It means that at each new step, the decision trees added to the model in the previous steps are fixed. Thus, the model can be improved in those parts of it where it still does not assess the residuals.

Bagging (Bagg) predictors generate multiple versions of predictors and use them for determination an aggregated predictor, so the aggregation is an average of all predictors [16]. The bagging method gives substantial gains in accuracy, but the vital element is the instability of the prediction method. In the case that perturbing the learning set has significant influence on the constructed predictor, the bagging can improve accuracy. The accuracy of the forecast of electricity consumption was measured by MAPE (Mean Absolute Percentage Error). MAPE is defined as follows:

$$\boldsymbol{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - \bar{x}|}{x_i}100\% \tag{4}$$

where x_i is actual consumption, $\bar{x}$ – load forecast.

3. Computer experiments for energy consumption forecasting

We performed advanced computer experiments to evaluate the profit of using clustering procedures on four time series representation methods for one day ahead forecast. Table 1 shows average daily MAPE forecast errors of 6 forecasting methods. Each forecasting method was evaluated on 5 datasets; 4 datasets are clustered with different representation methods (Kalman, Ho-W, GAM, RLM) and 1 dataset is aggregated electric load consumption (Aggr). The following conclusions can be derived from Table 1. Optimized clustering of consumers significantly improves accuracy of forecast with forecasting methods SVR, Bagging, GBM. Despite this, clustering with LOESS+ARIMA, RF, R-Tree does not really improve accuracy of forecast. Robust representation methods of time series Kalman, GAM and RLM performed best among all representations, while Ho-W was the worst in most of the cases. The best result of all cases achieved by GBM algorithm with optimized clustering using GAM representation with mean daily MAPE error under 3,44%.

Table 1. Mape(%)-error forecasting methods for aggregated load consumption. repres.: model-based presentations of consumption time series. meth.: forecasting methods applied with clustering

METH.\REPRES	Kalman	Ho-W	GAM	RLM	Aggr
LOESS+ARIMA	4.873	4.947	4.423	4.674	4.854
SVR	4.073	4.072	4.42	4.216	4.621
Bagging	3.438	3.475	4.23	3.34	4.34
GBM	3.78	4.036	3.44	4.21	4.46
R-Forest	4.479	4.476	4.36	4.62	4.72
R-Tree	4.42	4.476	4.33	4.26	4.63

3. Conclusion

Improving the accuracy of electricity consumption forecasts is an essential direction in the development of intelligent energy systems. Machine learning methods such as cluster analysis, boosting and others were used to implement this task. The main purpose of this work was to show that the application of the consumer clustering procedure to the representation of time series of energy consumption can improve the accuracy of their energy consumption forecasts. Robust linear model, generalized additive model, exponential smoothing and Kalman linear filter were used as such representations. In this paper we applied a modified K-means++ algorithm to more accurately select centroids and the Davis-Boldin index to evaluate clustering results. Numerical experiments have shown that the methods of forecasting such as LOESS+ARIMA, SVR, RF, Bagging considered in the paper are more effective for improving forecast accuracy if used together with clustering. Prediction methods performed the best reliable representations of RLM, GAM, and Kalman filter. The lowest prediction error is obtained by GBM algorithm with the GAM presentation. Among the perspective applications of clustering for smart grids are benefits for individual tariffs design, compilation smart demand programs, improvement of load forecast, classifying new or non-metered consumers and other tasks.

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