Hierarchical Electricity Demand Forecasting by Exploring the Electricity Consumption Patterns

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Keywords: Hierarchical Forecasting, Aggregate Constraints, Consumption Pattern.

Abstract: Accurate electricity demand forecasting is necessary to develop an efficient and sustainable power system. Total demand of the whole region can be disaggregated at different levels, thus producing a hierarchical structure. In the hierarchical demand forecasting, the prediction accuracy and aggregate consistency between levels are two important issues, however in the previous works the prediction accuracy is often affected by conducting the aggregate consistency. In this work, we propose a novel pattern-based hierarchical time series forecasting (PHF) method which consists of two aggregation stages. In the first aggregation stage, by exploring the electricity consuming patterns with clustering method, the bottom level electricity demand forecasting is improved, and in the second stage the region level aggregation is conducted to achieve the whole level forecasting. The experiments are conducted on the Energy Demand Research Project (EDRP) datasets, and the experimental results show that compared with the previous state-of-the-art methods, our method improves the prediction accuracy in all hierarchical levels with keeping aggregation consistency.

1 INTRODUCTION

Due to the existing problem of inconvenience electricity storage, excess electricity would cause unnecessary waste. Accurate forecasting is helpful to guide the electric power companies to make decision. Thus, electricity demand forecasting is one of the most important problems in the field of electric power management. With the rapid growth of smart grid, more and more meter data are becoming available, which brings potential of improving the prediction of the power demand with more delicacy.

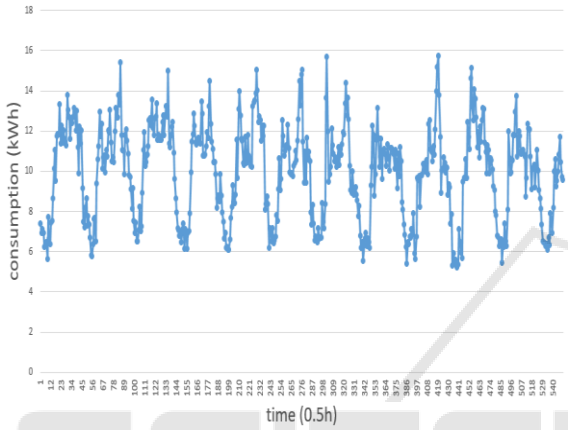
Recently, hierarchical electricity demand forecasting attracts more and more research attentions (Taieb et al., 2017). Total consumption in the whole geographic region can be geographically disaggregated into several sub-regions, and these sub-regions can be further disaggregated into regions at lower level. For example, electricity consumption in countries can be disaggregated into provinces, cities, districts, etc. That is, electricity time series can be represented in a hierarchical structure. From top down, the structure contains series at top level, high level, low level and bottom level. According to the above geographic disaggregate strategy, the time series in different levels must obey the aggregation constraints, i.e. the demand in different levels should be summed consistently. Most of the state-of-the-art hierarchical predication methods estimate initial forecasts and then reconcile them to ensure aggregate constraints. However, it is noticed that the regional aggregation consistency cannot improve the whole level prediction accuracy (Hyndman et al., 2011).

The electricity consuming pattern can be found by clustering analysis on the time series of electricity usage with the similarity measurements. Figure 1 illustrates the aggregation time series of electricity consumption by clustering and random selection. We notice that in this Figure the aggregated time series obtained by clustering of similar time series shows more stable and regular than the series aggregated by randomly selected ones. The experience and some previous work (Wijaya et al., 2015) show that the stable and regular time series are very good (or ideal) for prediction or regression. Therefore, we are motivated to exploit the time series clustering to improve the bottom level electricity demand prediction and manage to improve the regional hierarchal predication accuracy.

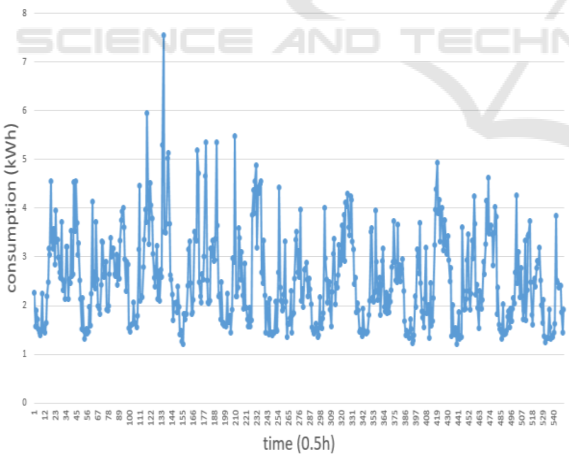
In this paper we propose a novel pattern-based hierarchical demand forecasting (PHF) method which consists of two aggregation stages. The proposed

Pang, Y., Jin, C., Zhou, X., Guo, N. and Zhang, Y.
Hierarchical Electricity Demand Forecasting by Exploring the Electricity Consumption Patterns.
DOI: 10.5220/0006715005760581
In *Proceedings of the 7th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2018)*, pages 576-581
ISBN: 978-989-758-276-9

method improves the whole level regional demand prediction accuracy by exploring the electricity consuming clustering and the aggregation consistency. Specifically, at the first aggregation stage, the proposed method constructs a hierarchical structure based on electricity consuming pattern by clustering analysis. Then, the bottom-level series are then reconciled appropriately through the aggregation constraints in the hierarchy. At the second aggregation stage, we aggregate the refined individual predication to improve the regional demand prediction.



(a) The aggregated series of electricity consumption of 7 households by time series clustering.



(b) The aggregated electricity consumption of 7 random selected individual households.

Figure 1: Aggregated electricity consumption series by clustering and random selected households on real datasets.

To our best knowledge, this is the first work of forecasting hierarchical regional electricity demand by using electricity consumption pattern analysis. The experiments are conducted by using real electricity dataset. The experimental results demonstrate that our proposed method not only satisfies consistency relationship between different levels, but also improves the prediction accuracy in all regional levels. Compared with the previous methods, our method achieves 0.07 and 0.03 lower prediction error in the evaluation measurements of Mean Absolute percentage Error (MAPE) and Mean Square Error (MSE) respectively.

2 RELATED WORK

The related works of forecasting demand in hierarchical structure mainly include classical forecasting and optimal combined forecasting.

2.1 Classical Forecasting

Classical forecasting is also called base forecasting (BASE) (Hyndman et al., 2011). It forecasts time series in all levels independently. The common forecasting models used in BASE forecasting are: Exponential Smoothing State Space (ETS), Autoregressive Integrated Moving Average (ARIMA) and ETS with Box-Cox Transformation, ARMA Errors, Trend and Seasonal Components (TBATS) (De Livera et al., 2011). The merit of BASE is that forecasts in different levels do not influence each other, resulting in high prediction accuracy at all levels. But the shortcoming is that the forecasts usually do not satisfy the aggregation consistency.

2.2 Optimal Combined Forecasting

Optimal combined forecasting (OPT) method firstly obtains initial forecasts in all levels using BASE (Hyndman et al., 2011). According to the aggregation constraints, optimal combined forecasts are then obtained by revising series in all levels. The key process of OPT is to estimate covariance matrix of forecast error. Two common methods of estimating covariance matrix are optimal combined forecasting based on ordinary least square and weight least square (OPT-OLS and OPT-WLS). Owing to the revision, OPT has the advantage of satisfying aggregate constraints over BASE. However the excess revising may affect the overall prediction accuracy.

(1) OPT-OLS

In 2011, Hyndman et al. estimates covariance matrix using ordinary least square (Hyndman et al., 2011). Optimal-OLS assumes that covariance matrix can be equivalent to a coefficient matrix multiple identify matrix.

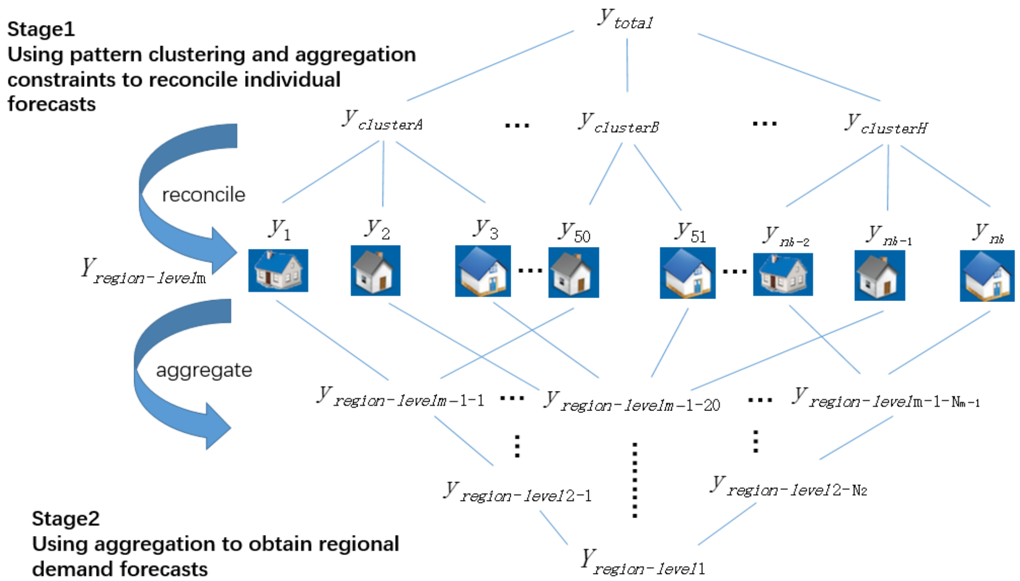


Figure 2: The strategy of PHF.

(2) OPT-WLS

In 2016, Hyndman et al. estimates covariance matrix using weight least square (Hyndman et al., 2016). Optimal-WLS assumes that covariance matrix can be equivalent to a coefficient matrix multiple diagonal matrix. The diagonal matrix is constructed using sample variance of BASE forecasts errors.

3 PATTERN-BASED HIERARCHICAL TIME SERIES FORECASTING

Electricity time series can represent the consumption behaviour of residential user, namely electricity consumption pattern. Compared to time series aggregated by randomly selected, consumption pattern obtained by clustering of similar ones shows more stable and regular, hence reduces the difficulty of series prediction. A novel pattern-based hierarchical time series forecasting (PHF) is proposed in the paper. The idea is illustrated in Figure 2.

For convenience, we define some symbols. n denotes the number of series at all levels. Y_t denotes an n-length vector with observations at time *t* and all levels. n_b denotes the number of series at bottom level. b_t denotes an n_b-length vector with observations at time *t* and bottom levels. S denotes an $n \times n_b$ summing matrix constructed from the hierarchical structure. According to hierarchical structure constructed from geographic data, these symbols can be associated through equation (1) (Taieb et al., 2017).

$$Y_t = Sb_t \tag{1}$$

PHF mainly includes two stages of aggregations, the specific procedures are as follows.

(1) Stage 1

Electricity consumption patterns of all individual time series are extracted by k-means clustering. The process of k-means clustering can be defined with equation (2) (Hartigan and Wong, 1979).

$$\arg\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\| \tag{2}$$

where μ_i is the mean of all points in cluster C_i. According to the results of clustering, hierarchical structure based on electricity consumption pattern and the corresponding summing matrix S_c are obtained.

We let $\hat{Y}_t(h)$ be an n-length vector of h-step ahead initial forecasts estimated with historical observations at time t and all levels. $\hat{Y}_t(h) = \begin{bmatrix} \hat{y}_{total} \\ \hat{y}_{clusterl} \\ \hat{y}_i \end{bmatrix}$, $l = A, \ldots, H$, $i = 1, \ldots, n_b$. $\hat{Y}_t(h)$ is obtained by BASE. And we use classical models to forecast series. For example, equation (3) is the forecast equation of simple exponential smoothing model (Hyndman et al., 2002).

$$\hat{y}_{t+h|t} = \sum_{j=1}^{t} \alpha(1-\alpha)^{t-j} y_j + (1-\alpha)^t \ell_0 \quad (3)$$

where α is smoothing parameter, $0 \le \alpha \le 1$. ℓ_0 is the first forecast value of y_1.

In order to improve the predication accuracy of bottom level series, we reconcile initial forecasts at bottom level according to the higher level cluster aggregation predication. The bottom revised forecasts can be estimated by solving the following regression as shown in equation (4) (Hyndman et al., 2011).

$$\hat{Y}_t(h) = S_c \beta_t(h) + \varepsilon_h \quad (4)$$

where $\beta_t(h)$ is the mean of forecasts at bottom level. ε_h is the reconciled error, whose mean and variance is zero and covariance matrix W_h.

$$W_h = E[(y_{T+h} - \hat{y}_{T+h}) * (y_{T+h} - \hat{y}_{T+h})^T] \quad (5)$$

where y_{T+h} and $\hat{y}_{T+h}$ are real and estimated value of h-step ahead forecasts with historical observations at time T separately.

We estimate $\beta_t(h)$ by MinT (Wickramasuriya et al., 2015). Its main idea is to minimize the trace of variance of forecast errors by equation (6).

$$\beta_t^{MinT}(h) = (S_c^T W_h^{-1} S_c)^{-1} S_c^T W_h^{-1} \hat{Y}_t(h) \quad (6)$$

where W_h^{-1} denotes the transpose of W_h.

(2) Stage 2

According to the geographic data, geography-based hierarchical structure and corresponding regional summing matrix S_r are obtained. Here, we assume the hierarchy contains m levels, and N_{m-1} indicates the number of series in levels m-1. Based on estimated bottom-level forecasts obtained at stage 1, the region demand forecasts $\tilde{Y}_t(h)$ are obtained according to equation (7).

$$\tilde{Y}_t(h) = S_r \beta_t^{MinT}(h) \quad (7)$$

So far, we obtain the final results $\tilde{Y}_t(h) = \begin{bmatrix} \tilde{Y}_{region-level1} \\ \tilde{Y}_{region-level2} \\ \cdots \\ \tilde{Y}_{region-levelm} \end{bmatrix}$.

4 EXPERIMENTS

4.1 Data

We use the public datasets from Energy Demand Research Project: Early Smart Meter Trials (EDRP), which is conducted by four energy suppliers in England (AECOM, 2011). EDRP datasets contains about 14000 electricity consumption of residential consumers during January, 2009 and September, 2010. The electricity consumed is measured during half-hour interval. We extract 2501 smart meters with data available between May 9th, 2009 and August 24th, 2009.

We obtain the information of regional division-based hierarchical structure from geographic data. The hierarchy contains six levels. The numbers of series at different level are: 1 (level 1), 7 (level 2), 12 (level 3), 21 (level 4), 44 (level 5) and 2501 (level 6).

4.2 Experimental Setup

We use data at the time interval from 1 to T as historical data to predict data at time T+h, where T ranges from 500 to 549 and h=1. In one experiment, we conduct 50 forecasting tasks and compute mean forecast accuracy for all tasks.

We compare PHF with the methods introduced in the related work (Section 2 in the paper). In PHF, the eight types of pattern are extracted by k-means clustering at the first aggregation stage. In comparison method, we choose BASE, OPT-OLS and OPT-WLS. In all the experiments, we use ETS, ARIMA and TBATS as the basic models of independent forecasting respectively.

4.3 Evaluation Metrics

In the experiment, we use Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) as the metrics for evaluating.

(1) MAPE

The definition of MAPE is (Wijaya et al., 2015):

$$\text{MAPE}(y, \hat{y}) = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (8)$$

where y_t and $\hat{y}_t$ are real and estimated value of forecasts at time t respectively, n indicates the number of series in all levels. First, compute the MAPE measurement of forecast error in every forecasting task. Second, compute average value of 50 tasks as the final evaluation measurement. When MAPE measurement is lower, the method has higher prediction accuracy.

(2) MSE

The definition of MSE is (Yang et al., 2017):

$$\mathrm{MSE}(\mathrm{y},\hat{y}) = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{9}$$

The procedure of computing the MSE measurement is similar to that of MAPE. Likewise, the method has higher prediction accuracy when its MSE measurement is lower.

4.4 Experimental Results

According to the experimental results of aggregate consistency, both OPT and PHF do satisfy the geographic aggregate constraints, but BASE does not. In term of prediction accuracy, the experimental results are shown in following tables.

Table 1: The comparison of prediction accuracy by methods based on ETS (all levels).

Method	MAPE	MSE
BASE-ETS	0.68	1.02
OPT-OLS-ETS	0.69	1.01
OPT-WLS-ETS	0.64	1.02
PHF-OLS-ETS	0.64	0.90
PHF-WLS-ETS	0.64	0.92

In first experiment, we use ETS model to forecast time series. The results are shown in Table 1. Under the measurement of MAPE, PHF (0.64) has higher prediction accuracy than BASE (0.68), while OPT-OLS (0.69) has lower prediction accuracy than BASE (0.68). This indicates that OPT-OLS meets aggregate consistency at cost of prediction accuracy. In contrast, PHF can improve overall prediction accuracy, as well as satisfy aggregation constraints. Under the measurement of MSE, although OPT-OLS (1.01) enhances predicting ability of BASE (1.02), PHF (0.90) has stronger predicting ability. It also means that PHF has higher forecasting accuracy on the premise of meeting aggregate constraints. In term of weight least square estimation, we come to the same conclusion. PHF-OLS-ETS has the highest prediction accuracy in consideration of both MAPE and MSE measurement.

Table 2: The comparison of prediction accuracy by methods based on ETS (bottom levels).

Method	MAPE	MSE
BASE-ETS	0.69	0.06
OPT-OLS-ETS	0.69	0.06
OPT-WLS-ETS	0.66	0.06
PHF-OLS-ETS	0.66	0.06
PHF-WLS-ETS	0.65	0.06

The forecasting accuracy for 2501 time series at bottom level using ETS model is shown in Table 2. Under the measurement of MAPE, PHF-OLS-ETS (0.66) achieves highest prediction accuracy, compared with OPT-OLS-ETS (0.69) and BASE-ETS (0.69). Under the measurement of MSE, all methods achieve the same prediction accuracy. It is because the values of bottom forecasts are very small, MSE is not enough for measuring the difference between methods. In consideration of both MAPE and MSE measurement, PHF-WLS-ETS achieves the best prediction accuracy. This demonstrates that PHF appropriately reconciles the series at bottom level through aggregation constrains at the first stage 1.

According to Table 1, the region forecasts by PHF have less errors compared to OPT. This is because that regional forecasts of series at all levels are computed through aggregation constraints based on the improved forecasts of bottom series.

In the next experiment, we use ARIMA model to forecast time series. The results are shown in Table 3.

Table 3: The comparison of prediction accuracy by methods based on ARIMA (all levels).

Method	MAPE	MSE
BASE-ARIMA	0.70	0.95
OPT-OLS-ARIMA	0.74	0.92
OPT-WLS-ARIMA	0.65	0.95
PHF-OLS-ARIMA	0.67	0.89
PHF-WLS-ARIMA	0.65	0.93

Similar to the above analysis, PHF (MAPE: 0.67/0.65, MSE: 0.89/0.93) achieves higher forecasting accuracy than OPT (MAPE: 0.74/0.65, MSE: 0.92/0.95) when using OLS or WLS. Especially, the MAPE measurement of forecasts obtained by PHF is 0.07 less than OPT, and the MSE measurement of forecasts obtained by ECPHF is 0.03 less than OPT.

In the last experiment, we replace ARIMA with TBATS model. The results are shown in Table 4. PHF-TBATS (MAPE: 0.62/0.62, MSE: 0.93/0.95) still forecasts more accurately than OPT-TBATS (MAPE: 0.73/0.62, MSE: 0.97/0.95).

Table 4: The comparison of prediction accuracy by methods based on TBATS (all levels).

Method	MAPE	MSE
BASE-TBATS	0.45	1.00
OPT-OLS-TBATS	0.73	0.97
OPT-WLS- TBATS	0.62	0.95
PHF-OLS- TBATS	0.62	0.93
PHF-WLS- TBATS	0.62	0.95

In conclusion, compared with the previous methods, our method achieves the best prediction accuracy on average of all the 2586 series in the hierarchy with keeping aggregation consistency.

5 CONCLUSIONS

We focus on hierarchical demand forecasting in the paper. Both the high prediction accuracy and aggregate consistency should be considered in the forecasting. However, in order to keep the aggregate consistency, prediction accuracy is usually affected (reduced) in the previous works. To deal with the problem, we propose a novel hierarchical demand forecasting method based on electricity consumption pattern analysis with a two stage algorithm. It reconciles forecasts of bottom series at first aggregation stage and further improves regional demand forecasts at second aggregation stage. The experimental results based on the Energy Demand Research Project datasets demonstrate that compared with the previous state-of-the-art methods, our method achieves the best forecasting accuracy while keeping aggregation consistency.

ACKNOWLEDGEMENTS

This work was supported by the National High Technology Research and Development Program (863 Program) of China (2015AA050203) and NSFC grant no. 61370157.

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