Electricity Demand Modeling and Forecasting in Singapore

Xian Li, Qing-Guo Wang, Jiangshuai Huang, Jidong Liu, Ming Yu, Tan Kok Poh

Abstract—In power industry, accurate electricity demand forecasting for a certain leading time is important for system operation and control, etc. In this paper, we investigate the modeling and forecasting of Singapore's electricity demand. To the end, several standard models, such as HWT exponential smoothing model, the ARMA model and the ANNs model, have been proposed based on historical demand data. We applied them to Singapore electricity market and proposed three refinements based on simulation to improve the modeling accuracy. Compared with existing models, our refined model can produce better forecasting accuracy. It is demonstrated in the simulation that by adding forecasting error into the forecasting equation, the modeling accuracy could be improved greatly.

Keywords—Electricity demand, Modeling, Forecasting.

I. Introduction

In power industry, electricity is generated in power plants and transmitted and distributed through grid to load terminals [1]. Since electricity cannot be stored efficiently, the physical essence of power system stability is the power balance between electricity generation and consumption. Thus, accurate demand forecasting in a range of leading times contributes a lot to the producers and consumers. With accurate electricity demand forecasting, power plants (producer) can better schedule their electricity generation to reduce wastage. Likewise, consumers can also gain superiority in electricity transactions as electricity price fluctuation also depends much on the electricity demand. They both would eventually get increasing profits in the game [2]. Besides, accurate electricity demand forecasting also benefits a lot for system security assessment, grid automatic control and maintenance [3], [4].

Recently, extensive studies on electricity demand modeling and forecasting had been reported in the literature and the researches mainly focus on parameter-based models [5]–[7] and intelligence-based models [8]–[11]. Holt-Winters (HWT) exponential smoothing model [5], [6]and autoregressive moving-average (ARMA) model [5], [7] are popular approaches in the former method for their good capacities in handling seasonal time series, while Artificial Neural Networks (ANNs) [8], [9], Radical Bias Function Network (RBFN) [10], [11] and expert systems [12], [13] work for latter method. Besides, Kalman filter [14] and wavelet transform techniques [15] are also extended to this field from their respective perspectives.

In this paper, we focus on electricity demand modeling and forecasting of Singapore energy market. Four standard models were firstly studied including the naive model, the HWT exponential smoothing model, the ARMA model and the ANNs model. Based on their simulation results on historical electricity demand data from Singapore electricity market, the standard HWT exponential smoothing model is selected as the base model for its simplicity and robustness. Then three refinements are proposed for better model quality. It is shown in simulation results that with our refinements, the forecasting error could be reduced.

The rest of this paper is organized as follows. Section 2 presents four standard electricity demand models, while their simulation studies are in Section 3. In Section 4, three refined models and their simulation studies are presented. Finally, we concludes this paper in Section 5.

II. Standard Models

A. The Naive Model

According to the time series analysis on historical electricity demand from Singapore Energy Market Company, strong daily, weekly and yearly seasonal patterns exist. Thus, we firstly proposed a benchmark model, whose future demand is forecasted by the same time of its last seasonal period, and its general form is

$$\hat{d}(t) = d(t-s), \tag{1}$$

where $\hat{d}(t)$ and $d(t)$ are the forecasting demand and actual demand at time t, while s is the length of selected seasonal pattern, which may be daily pattern with length s_1, weekly pattern with length s_2, yearly pattern with length s_3. As it is the benchmark model, any proposed models should at least beat it and those inferior to it are meaningless.

B. The HWT Exponential Smoothing Model

The HWT exponential smoothing model was first proposed by Brown, R.G. and Holt, C.C. to describe the seasonal time series with trends [16], [17], and then extended by J. W. Taylor to double seasonal patterns [6]. Its robustness and accuracy has led to widespread application in seasonal time series forecasting. Since the electricity demands are greatly different in day and night, weekdays and weekends, summer and winter, daily pattern, weekly pattern and yearly pattern seasonality are usually considered as seasonal pattern candidates in HWT

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$$L(t) = \alpha\left[d(t) - (T(t-1) + S_1(t-s_1) + S_2(t-s_2) + S_3(t-s_3))\right] + (1-\alpha)(L(t-1) + T(t-1)), \tag{2}$$

$$T(t) = \beta\left[L(t) - (L(t-1) + T(t-1))\right] + (1-\beta)T(t-1), \tag{3}$$

$$S_1(t) = \gamma\left[d(t) - (L(t-1) + T(t-1) + S_2(t-s_2) + S_3(t-s_3))\right] + (1-\gamma)S_1(t-s_1), \tag{4}$$

$$S_2(t) = \lambda\left[d(t) - (L(t-1) + T(t-1) + S_1(t-s_1) + S_3(t-s_3))\right] + (1-\lambda)S_2(t-s_2), \tag{5}$$

$$S_3(t) = \delta\left[d(t) - (L(t-1) + T(t-1) + S_1(t-s_1) + S_2(t-s_2))\right] + (1-\delta)S_3(t-s_3), \tag{6}$$

$$\hat{d}(t,k) = L(t) + kT(t) + S_1(t-s_1+k) + S_2(t-s_2+k) + S_3(t-s_3+k), \tag{7}$$

exponential smoothing model. The general form of triple HWT exponential smoothing model is described by (2) to (7), where L is smoothed level electricity demand, T is trend of electricity demand, S_1, S_2, S_3 are the seasonal terms of daily pattern, weekly pattern and yearly pattern, s_1, s_2 and s_3 are defined similar to that of the naive mode, while $\alpha, \beta, \gamma, \lambda, \delta$ are their respective smoothing parameters. $d(t)$ is the actual electricity demand at time t, while $\hat{d}(t,k)$ is the k step ahead demand forecasting at time t. Besides, omitting all terms about yearly pattern, the double seasonal HWT exponential smoothing model can be derived.

The initial values of all model terms, including smoothed level L, trend T and seasonal terms S_1, S_2, S_3, were estimated from first four years data, while smoothing parameters $\alpha, \beta, \gamma, \lambda, \delta$ were selected with training data through a standard genetic algorithm (GA) [18], [19] and the last four years data was used as testing data to evaluate this proposed model.

C. The ARMA Model

Another widespread method in seasonal time series modeling is the autoregressive moving-average (ARMA) model. In this model, the future electricity demands are predicted by autoregressive models of demand and white noise term of previously measured data. Due to the multi-seasonal property in electricity demand, the ARMA model is extended to multiplicative seasonal ARMA model, and its general form with triple seasonal patterns (daily, weekly and yearly) is

$$\begin{aligned}\phi_{p1}\left(L^{s1}\right)\phi_{p2}\left(L^{s2}\right)\phi_{p3}\left(L^{s3}\right)(d(t) - a - bt) \\ = \psi_{q1}\left(L^{s1}\right)\psi_{q2}\left(L^{s2}\right)\psi_{q3}\left(L^{s3}\right)\varepsilon(t),\end{aligned} \tag{8}$$

where $d(t)$ is the demand data in period t, a and b are the level term and trend term respectively, while L is the lag operator, and ϕ_{p1}, ϕ_{p3}, ϕ_{p3}, ψ_{q1}, ψ_{q2}, ψ_{q3} are polynomial functions of back-shift operator with orders $p1$, $p2$, $p3$, $q1$, $q2$, $q3$ respectively, $\varepsilon(t)$ is the white noise. The efficiency of this proposed model depends largely on the election of appropriate variables in polynomial functions. Thus, the main work in this model is selecting useful inputs and forming specific outputs. Time series analysis on electricity demand provides some basic principles in order determination and input selection. For example, electricity demand has strong correlation with their adjacent demands, corresponding demands of adjacent days and corresponding demands of adjacent weeks. Besides, [19] presented some more useful feature selection methods for time series modeling.

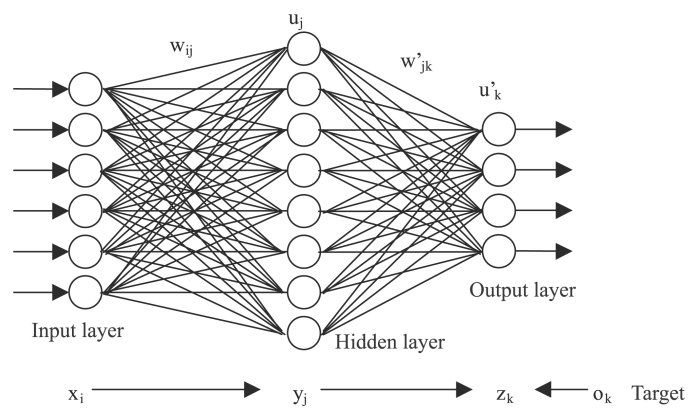

Fig. 1. The architecture of a three-level ANNs model

D. The Artificial Neural Networks Model

Artificial neural networks (ANNs) has been widely used in machine learning and pattern recognition. Besides, it is also a powerful nonlinear approximator and widespread used in time series modeling and forecasting. Through no general principles exist in its architecture design, the three-level back-propagation configuration, shown in Fig. 1, is usually adopted as the ANNs model structure in complex nonlinear time series modeling. Its neurons number in hidden layer is chosen based on try and error, while the numbers of neurons in input and output levels are same with that of inputs and outputs. Its general mathematical form is

$$z_k = \varphi_2\left(\sum_{j=1}^{M} w_{jk}^{(2)}\varphi_1\left(\sum_{i=1}^{N} w_{ij}^{(1)}x_i + b_j^{(1)}\right) + b_k^{(2)}\right), \tag{9}$$

where x and y are the inputs and outputs of ANNs model, i, j, k are the numbers of neurons of three layers, w, b are model parameters that are trained, φ_1, φ_2 are activation functions of hidden layer and output layer. Theoretically, a three-level ANNs model is adequate to mimic any nonlinear function,

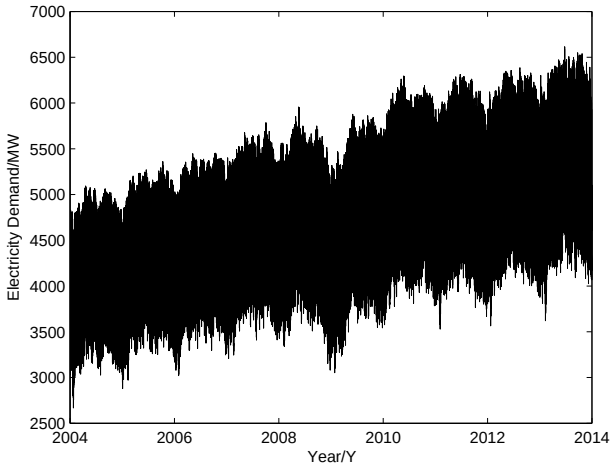

Fig. 2. Electricity demand time series of Singapore (Jan, 2004-Dec, 2013)

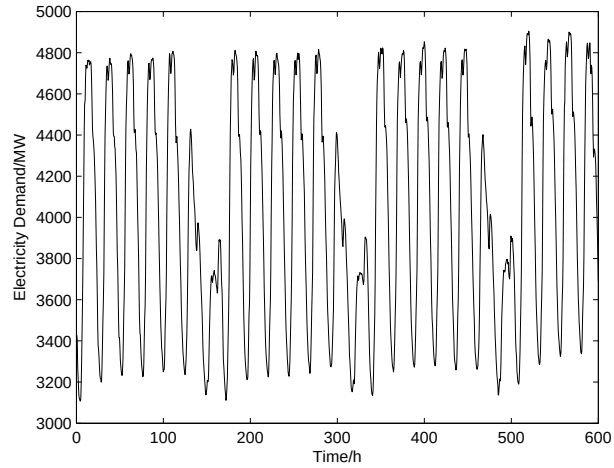

Fig. 3. Partial electricity demand time series of Singapore in normal days

however, similar to ARMA model, its model accuracy also depends much on the inputs and outputs selection. Thus, our main work in this approach is selecting useful inputs and forming specific outputs. In this model, we chose same inputs and outputs with that of ARMA model. Besides, to guarantee model quality, a large number of electricity demands are needed in model training and validating. Specifically, the first 70% of data is used for model training and validating, while the remainder 30% data is used for model testing.

III. Simulation Studies

A. Data

In this study, the historical electricity data is downloaded from Energy Market Company (EMC) of Singapore, including historical electricity demand (MW) and historical electricity price (S$/MWh). These data lasts from January 2004 to December 2013 with half hourly sampling time. The visualization of historical electricity demand and its zoom in are in Fig.2 and Fig.3, respectively, where strong daily, weekly and yearly seasonality exist.

As shown in Fig.4, unusual electricity demands is presented during the public holidays (third day of second week) compared with normal days, which bring an obstacle for our electricity demand modeling. To eliminate their influence, the electricity demand data in public holidays is replaced by that in corresponding days of previous week. However, according to our study, a more useful approach is proposed. Demand data in public holidays can also be replaced by its forecasting demand based on proposed model. This is assumed to be more reasonable since the forecasting accuracy in proposed model is usually better than that in naive model. Besides, it is also verified from simulations, that the overall model forecasting error decreases slightly in all models when using the new method to replace the electricity demand in public holidays. Specifically, in standard HWT exponential smoothing model, the average forecasting error decreases from 1.24% to 1.18% in double one, while from 1.31% to 1.24% in triple one.

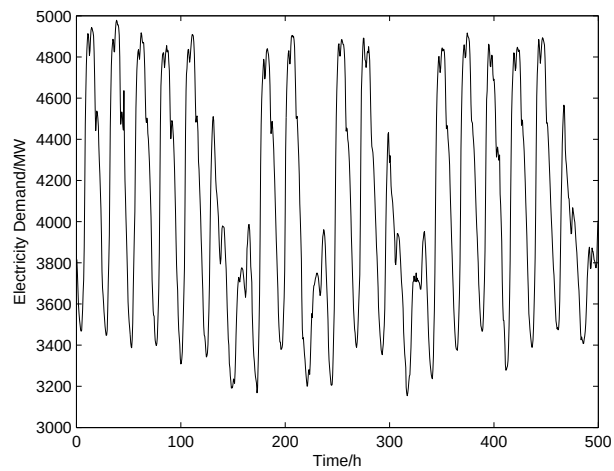

Fig. 4. Partial electricity demand time series of Singapore in public holidays

B. Model Evaluation Criterions

All proposed models forecasting next-day electricity demand only for perform normal days, and the next-day electricity demand forecast occurs at midnight from half hour ahead to one day ahead. To evaluate the proposed models, the forecasting accuracy is evaluated by the absolute percentage error (APE). It is

$$APE_i = \frac{1}{n}\sum_{j=1}^{N}\left|\frac{d_{ij}-\hat{d}_{ij}}{d_{ij}}\right|, i = 1\cdots 48, j = 1\cdots N, \quad (10)$$

where d_{ij} is the actual electricity demand of ith half hour of the jth day, while $\hat{d}_{ij}$ is its corresponding forecasting demand. In power system, huge economic loss would also results from large demand forecasting error in a particular time period. Thus, another model evaluating criterion is the maximal absolute percentage error (MAPE) and it is

$$MAPE_i = \frac{1}{10}\sum_{m=1}^{10}\left|\frac{d_{im}-\hat{d}_{im}}{d_{im}}\right|, i = 1\cdots 48, m = 1\cdots 10, \quad (11)$$

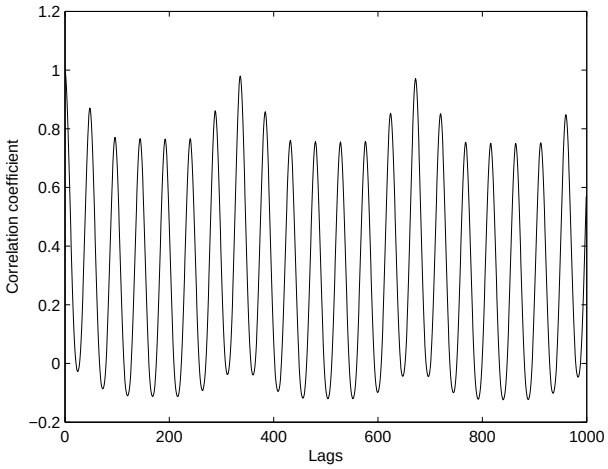

Fig. 5. The autocorrelation analysis of electricity demand series

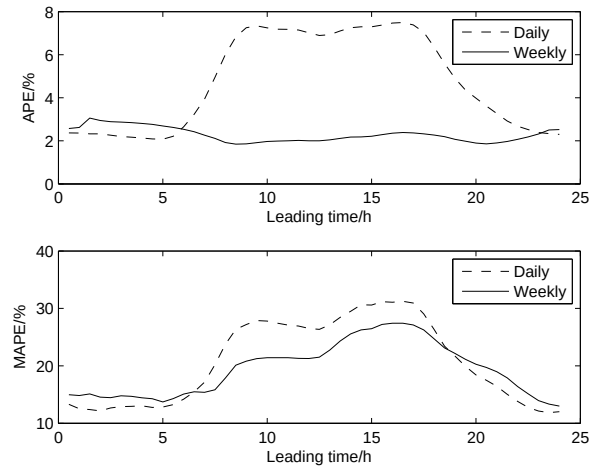

Fig. 6. Forecasting APE and MAPE in naive model

where m is the No. of specific days whose ith half hour are with top 10 largest demand forecasting errors.

C. Simulation Results and Discussion

Time series analysis about Singapore historical electricity demand was done before modeling and its autocorrelation analysis is shown Fig.5, where the electricity demand presents high correlation to electricity demand with lag s_1 and electricity demand with lag s_2, which are the seasonal lengths of daily pattern and weekly pattern, respectively. Thus, all of them can work as the selected seasonal pattern in naive model. However, weekly pattern should be adopted as its correlation coefficient is higher than that of daily pattern, which is also verified by their forecasting performance in Fig.6. The weekly pattern naive model produces lower forecasting demand APE and MAPE than daily pattern, whose average APEs are 2.29% and 4.77% respectively. Thus, the weekly seasonal pattern should be selected for naive model. However, the daily pattern naive model performs better during 11:00 pm to 5:00 am. Then a refined naive model is proposed by combining daily and weekly pattern naive models, where electricity demands during 11:00 pm 5:00 am are forecasted by daily pattern naive model, while other electricity demand are forecasted by weekly pattern naive model, and its average APE is 2.15%.

Generally, the triple HWT exponential smoothing model should perform better than the double one as it includes more seasonal properties. This was verified in their simulation results shown in Fig.7, where triple HWT exponential smoothing model presents 1.17% average APE while the double one with 1.19% average APE. Though they perform similar in forecasting APE, the triple one performs much better in forecasting MAPE.

In modern city, heating, ventilation and air-conditioning (HVAC) system and lighting system contribute nearly half electricity consumption in hot and humid regions [20], [21]. However, their electricity consumptions are influenced significantly by weather conditions. Besides, weather conditions influence the self-generation capacity of photovoltaic (PV)

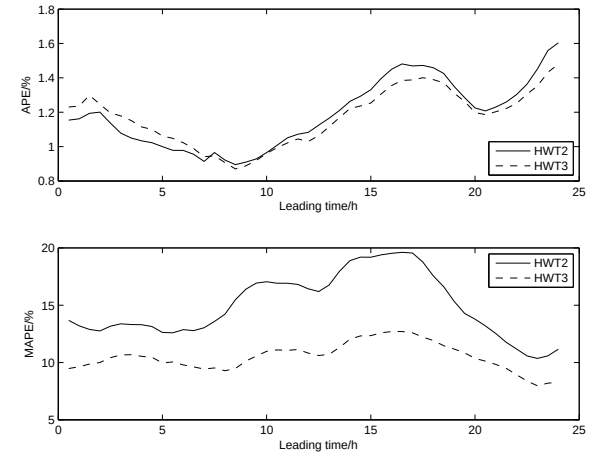

Fig. 7. Forecasting APE and MAPE in HWT exponential smoothing model

system [22], [23]. Thus, the yearly pattern seasonality should be involved to reflect year-round climate change, therefore the triple HWT exponential smoothing model suits more for regions with explicit seasons, but suits less for regions without obvious seasons.

According to literature, the quality of ARMA model highly depends on the model structure and inputs selection. Their model forecasting accuracy usually differs a lot with various model structure or input features. In this paper, inputs for specific output are selected based on time series analysis. Through a trade-off between model complexity and model efficiency, a 6-order model with selected inputs is adopted and its simulation result is shown in Fig.8, where its average APE is 1.52%, which is worse than HWT exponential smoothing model. Summarily, due to uncertainties in model structure and inputs selection, the ARMA model is less efficient in multi-seasonal time series modeling.

In standard ANNs model, a three-layer structure with 20 hidden neurons is selected to process same inputs and outputs formats with the ARMA model. The first 70% electricity

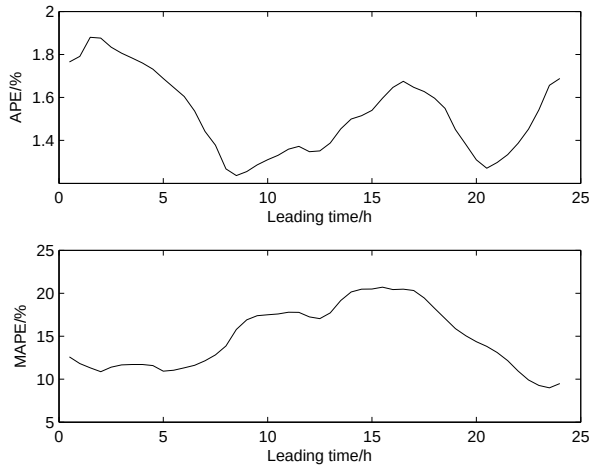

Fig. 8. Forecasting APE and MAPE in ARMA model

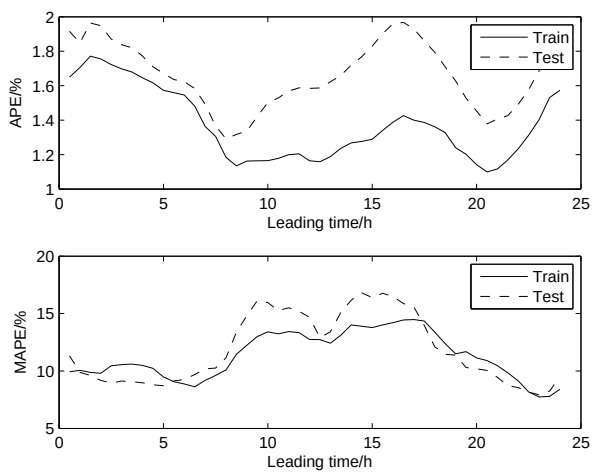

Fig. 9. Forecasting APE and MAPE in ANNs model

demand data is used for model training and validation, while the remainder 30% electricity demand data is for model testing. Fig.9 shows its simulation results, where the average APE is 1.37% for training data, while 1.66% for testing data. Its training data performs better than the ARMA model, while worse in testing data. Besides, the ANNs model brings large computation load during model training. Thus, it is not a good choice in electricity demand modeling.

Summarily, the HWT exponential smoothing model, the ARMA model and The ANNs model can beat the naive model in our simulation studies. According to their simulation results, the HWT exponential smoothing model resulted in the best forecasting accuracy and it will be the base mode our following studies.

IV. Refined Models

According to the simulation studies in Section 3, the HWT exponential smoothing model performed best. In the following section, three refinements are proposed to improve its performance. These refinements are parallel and all based on the

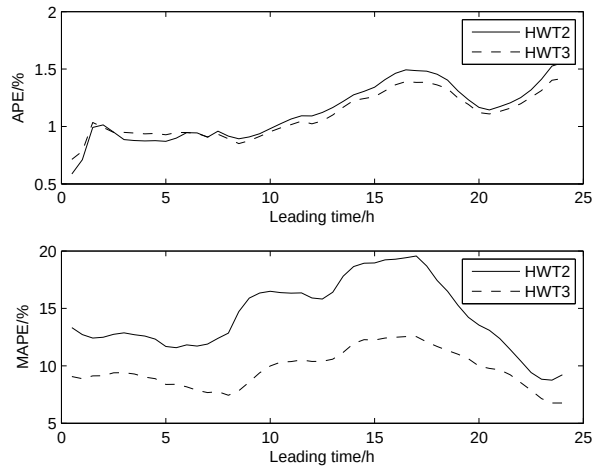

Fig. 10. Forecasting APE and MAPE in HWT model (Refinement 1)

standard HWT exponential smoothing model.

A. Refinement 1

Since the current demand value and its forecast would have been known before next-day demand forecasting, the forecasting error can be used to improve the modeling accuracy. In this refinement, the latest forecasting error is assumed to affect future demand forecasting exponentially, and (7) becomes

$$\begin{aligned}\hat{d}(t,k) = {} & L(t) + kT(t) + S_1(t - s_1 + k) + S_2(t - s_2 + k) \\ & + S_3(t - s_3 + k) + \phi^k \left[d(t) - (L(t-1) + T(t-1) \right. \\ & \left. + S_1(t - s_1) + S_2(t - s_2) + S_3(t - s_3)) \right],\end{aligned} \tag{12}$$

where ϕ is the base while leading time k is the power in exponential propagation of current forecasting error. The value of $\phi \in (0, 1)$ can be also selected together through genetic algorithm(GA). This refinement brings slightly forecasting accuracy improvement as shown in Fig.10, and their average APE decreases from 1.19% to 1.13% for double HWT exponential smoothing model while from 1.17% to 1.09% for triple HWT exponential smoothing model.

B. Refinement 2

Though the HWT exponential smoothing model performs well in electricity demand series modeling, periodical fluctuation still exists in its forecasting residuals, which brings possibility to improve the modeling accuracy. As the relationship between future forecasting residuals and previous forecasting residuals in HWT exponential smoothing model is unclear, the ANNs model is adopted here to mimic the forecasting residual series. In this simulation, three groups of inputs are formulated for next-day forecasting residuals modeling. In group 1, the ANNs model trains each next-day forecasting residual with all current days residuals, while the inputs changed to corresponding forecasting residuals in past several daily periods and past several weekly periods in group 2. In group 3, the model inputs are the inputs combination of group 1 and group 2. The input-output pair in group 1 results in the

best forecasting and its simulation results are shown in Fig.11, where its forecasting accuracy is slightly improved in refined double HWT exponential smoothing model, which decreases the average APE from 1.19% to 1.17%, while worse in the refined triple HWT exponential smoothing model. Besides, compared with final results from normal HWT exponential smoothing model in Fig.7, its forecasting errors fluctuate drastically.

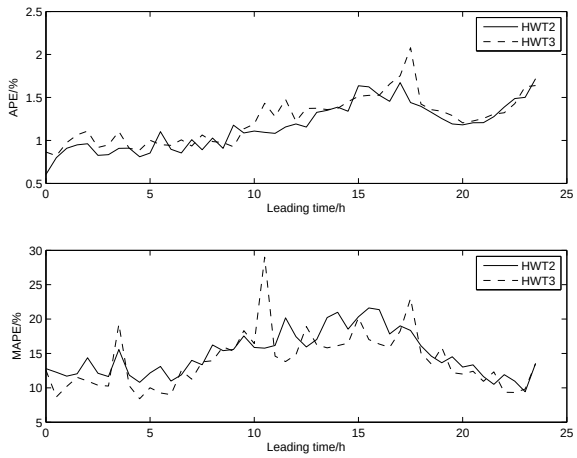

Fig. 11. Forecasting APE and MAPE in HWT model (Refinement 2)

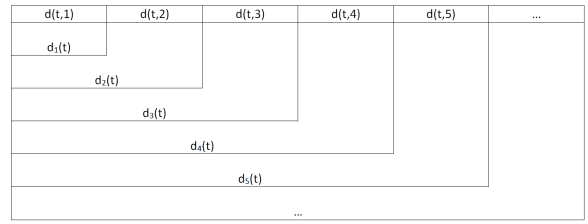

Fig. 12. Schematic diagram for data preprocess and recovering

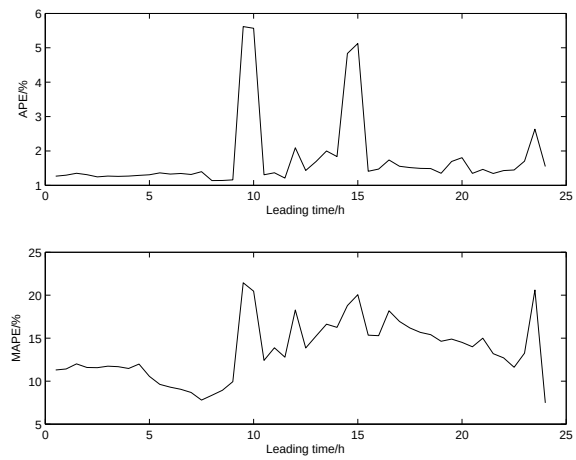

Fig. 13. Forecasting APE and MAPE in HWT model (refinement 3)

C. Refinement 3

According to simulation studies on standard forecasting models, forecasts of next-day electricity demands usually present higher forecasting accuracy with short leading time than that with long leading time. Thus, the refinement 3 is a data preprocessing and recovering method. As shown in Fig.12, the demand series is firstly translated to 48 scales by

$$d_s(t) = \frac{1}{s}\sum_{j=t}^{t+s-1} d(j), t = 1\cdots N, s = 1\cdots 48, \tag{13}$$

where d_s is the electricity demand in scale s. Then these 48 models work on their own scales independently, and the next-day demand forecasts of 48 sampling periods can be recovered from all 1 step-ahead demand forecasts of these independent models. Specifically, 1 step-ahead demand forecasts of all 48 models are conducted in their own scales and actual demand forecasts of future 48 sampling periods are recovered through

$$d(t,s) = sd_s(t) - (s-1)\, d_{s-1}(t), t = 1\cdots N, s = 1, \cdots, 48. \tag{14}$$

This data preprocessing and recovering approach can be applied on any methods discussed before. In this section, we only apply it on the double HWT exponential smoothing model and its performance is shown in Fig.13, where it produces lower forecasting accuracy than the standard HWT exponential smoothing model.

The simulation presents opposite results to our expectation. Though theoretical analysis, the reasons can be summarized as follow. The electricity demands in future 48 sampling period are $d(t,1), d(t,2), d(t,3), \cdots, d(t,48)$ at time t while 1 step-ahead electricity demands of 48 scales are $d_1(t), d_2(t), d_3(t), \cdots, d_{48}(t)$ at time t. Given that all 1 step-ahead demand forecasting errors are $e_1, e_2, e_3, \cdots, e_{48}$, then the forecasting errors of recovering demand forecasts are

$$\left|\frac{d(t,1)-\hat{d}(t,1)}{d(t,1)}\right| = e_1, \left|\frac{d(t,2)-\hat{d}(t,2)}{d(t,2)}\right| \le e_2 + \frac{d(t,1)}{d(t,2)}(e_1+e_2),$$
$$\left|\frac{d(t,n)-\hat{d}(t,n)}{d(t,n)}\right| \le e_n + \sum_{i=1}^{n-1}\frac{d(t,i)}{d(t,n)}(e_{n-1}+e_n), n = 3, \cdots, 48. \tag{15}$$

where it is obvious that this data preprocess and recovering method cannot guarantee the recovering forecasting demand of future 48 sampling periods with high forecasting accuracy though all 48 independent models in 48 scales have high forecasting accuracy. Thus, the forecasting accuracy cannot be improved through this refinement. Even through this refinement does not improve the forecasting rate, it can still provide a guideline for designing forecasting algorithm.

V. Conclusions

In this paper, we first studied four standard electricity demand models, which are the naive model, the HWT exponential smoothing model, the ARMA model and the ANNs model. The HWT exponential smoothing model results in the best forecasting accuracy and adopted as the base model of following refinements. According to their simulation results, the modeling accuracy is improved in refinement 1, slightly improved in refinement 2 and deteriorated in refinement 3. Besides, the failure reason of refinement 3 was analyzed in its

subsequent theoretical analysis. In summary, our HWT exponential smoothing model combined with genetic algorithm in parameter selection presents highest modeling accuracy. Currently, electricity demand modeling using weather conditions is under study and new findings will be reported later.

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