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Abstract

Against the background of climate change, increasingly more extreme weather is expected, and the energy demand which is sensitive to weather is also expected to be affected accordingly. Meanwhile, short-term fluctuation in weather and temperature can still occur due to natural climate variability, posing challenges to electricity load forecasting which may have implications in energy resources deployment.

In this study, the Hong Kong Observatory (HKO) and the Hongkong Electric Company, Limited (HK Electric) jointly investigated the feasibility of improving electricity load forecast using long-range temperature forecasts. The temperature forecasts were generated by the HKO using a handful of calibration/post-processing methods, comprising monthly forecasts up to six months ahead. The temperature forecasts were then fed into a load demand model developed by HK Electric which used to operate based on historical temperature observations. Initial verification results for 2007-2017 showed that by utilizing the long-range temperature forecasts, a reduction of 18.5% in the mean absolute error of the load forecasts could be achieved.

长期温度预报对预测用电量的影响

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摘要

在气候变化的背景下，预料极端天气会越来越多，与天气相关的能源需求亦预计会受影响。同时，因气候系统的自然变率而产生的短期天气和温度波动仍会发生，为用电量预测带来挑战，亦会影响能源资源调配。

在这研究中，香港天文台和香港电灯有限公司（港灯）连手探讨利用长期温度预报以改善用电量预测的可行性。天文台利用多种订正方法或后处理方法制作未来六个月的逐月温度预报，港灯把这些温度预报放进由他们研发、原本根据历史温度观测数据的用电量预测模型。2007-2017 年的初步验证结果显示，利用长期温度预报可以把用电量预测的平均绝对误差减少 18.5%。

1. Introduction

Load forecast is crucial in electricity business as it directly affects the operation of the electricity generation system and informs various planning activities. In particular, load forecast is essential in financial monitoring, generation planning and fuel planning. Many studies have investigated relationship between weather elements such as temperature and humidity and electricity consumption [1]. Lee *et al.* [2] also found a significant correlation between cooling degree-days and electricity consumption in warm months in Hong Kong.

Against the background of global warming, it is anticipated that the mean temperature as well as the frequency of occurrence of extreme weather events will increase [3]. Meanwhile, short-term fluctuation in weather and temperature could still occur due to natural climate variability. These projected changes pose challenges to electricity load forecasting and call for better and more efficient energy resources management in future at all time scales from days to months.

Given the significant influence of weather fluctuation on electricity load, it is not surprising to see previous attempts to include short-term weather forecast as one of the predictors in short-term electricity load forecast [4-7]. For longer term electricity load forecast, some previous studies employed climatological information as an input [8]. However, studies to investigate the impact of long-range forecasts on electricity load forecast are relatively scarce. In the present study, the Hong Kong Observatory (HKO) and the Hongkong Electric Company, Limited (HK Electric) collaboratively investigate the impact of long-term temperature forecasts on electricity load forecast. This paper will document the methodology and discuss the impact of long-range forecasts on electricity load forecasting. Data and methodology will be described in Section 2. Results will be presented in Section 3, followed by a discussion and conclusion in Section 4.

2. Data and Methodology

2.1 Existing electricity load forecast method

In the existing load forecast method developed by HK Electric, a multiple regression model based on data of the most recent year is established using daily electricity load as the predictand and daily mean temperature and other meteorological variables (e.g. daily mean relative humidity) as the predictors. The forecast is generated by feeding the values of the predictors in the previous ten years into the regression model, summing up the daily forecasts for a target forecast period, e.g. January–June 2017, then taking average of the ten forecasts. To illustrate how the method works, let's consider the example of forecasting electricity load for January–June 2017 with the following procedures.

(a) A multiple regression model is established using the observed daily electricity load and daily meteorological data from January to December 2016.

(b) The observed daily mean temperatures together with other meteorological data in the past ten years (January–June, 2007–2016) are fed into the regression equation to obtain ten forecasts of 6-month electricity load for January–June 2017.

(c) The average of the ten forecasts is then taken as the final forecast for January-June

2017.

2.2 Modified electricity load forecast method

Using the 6-month temperature forecasts (i.e. monthly temperature forecast for six consecutive months) provided by HKO as described in Section 2.3, the way to generate the electricity load forecast is modified by incorporating a "monthly temperature offset" in the daily temperature values. For illustration, we apply the "monthly temperature offset" to the example shown in Section 2.1 (a)-(c). The procedures are as follows:

(a) For each month under consideration (January to June), the observed daily temperatures are aggregated into monthly mean temperatures (T_{month_obs}). The observed monthly temperatures are then compared against the monthly temperature forecast for the corresponding month (T_{fc}) to obtain the "monthly temperature offset", $T_{month\_offset} = T_{fc} - T_{month\_obs}$.

(b) The observed daily mean temperatures (T_{daily}) would then be adjusted by adding the corresponding "monthly temperature offset" to them, $T_{daily\_adjusted} = T_{daily} + T_{month\_offset}$.

(c) The adjusted daily temperatures, together with other meteorological data as described in Section 2.1(b), are fed into the regression model established in Section 2.1(a) to generate ten electricity load forecasts.

(d) The average of the ten forecasts is then taken as the final forecast.

2.3 6-month temperature forecasts

Generally speaking, systematic bias exists in long-range forecast directly produced by climate models and hence calibration or post-processing is needed. The ensemble mean of hindcasts of European Centre for Medium-Range Weather Forecasts (ECMWF), National Centers for Environmental Prediction (NCEP) and Japan Meteorological Agency (JMA) climate models are employed to calibrate their corresponding forecasts. Details of the hindcast and forecast data are listed in Table 1.

For the sake of simplicity, all the hindcasts/forecasts will be termed forecasts hereafter. For each of the three climate models, monthly temperature of Hong Kong is extracted using bi-linear interpolation of the direct model output of the four nearest grid points around Hong Kong. Three calibration methods are applied to the ensemble mean for each of the model forecasts, namely quantile-quantile mapping (QQM), standardized anomaly mapping (SAM) and linear regression. In QQM, the relative position of the predictor (direct temperature output given by models) in a training data set is first determined. The value of the predictand (temperature at HKO) with the same position in the predictand's training data set is then taken as the forecast. In SAM, the standardized anomaly of the predictor is taken as the standardized anomaly forecast of the predictand. The basic training period is 1979/1981/1982-2006 (depending on the climate model) and the verification period is 2007-2017. As the verification year progressed from 2007 to 2017, the training period would extend year by year accordingly. With three climate models and three calibration methods, there are a total of nine forecasts. The final temperature forecast is the average of these nine forecasts. As JMA provides only 3-month forecasts for some of the months in the year, the final forecast will be the average of six forecasts from ECMWF and NCEP when JMA forecast is not available.

3. Results

3.1 Verification of 6-month temperature forecasts

The 6-month temperature forecasts with initial forecast month from January 2007 to January 2017 are verified. There are a total of 121 sets of 6-month temperature forecasts. The climatology is used as a reference forecast. For year 2007-2010 (2011-2017), the average of 1971-2000 (1981-2010) is taken as the climatology. Figure 1 shows the root mean squared error (RMSE) of the temperature forecasts with different lead times ranging from one to six months. The RMSE of the forecasts regardless of lead time are generally smaller than that of climatology in June to September, indicating that the forecasts are generally skillful in warm months. Performance in certain months of the year such as March, April and December is not satisfactory with RMSE higher compared to the case of climatology.

3.2 Comparison of the existing and modified electricity load forecast methods

Mean absolute error (MAE) is employed as the metric to compare the performance of the existing and the modified electricity load forecast methods. Without incorporating the "monthly temperature offset", the MAE of the load forecast is 90.27 Gigawatt hours for the period of January-June 2007 – January-June 2017. With the "monthly temperature offset" incorporated, the MAE is reduced to 73.57 Gigawatt hours, a reduction of 18.5% (Table 2). For more recent years from January-June 2011 to January-June 2017, the reduction of MAE of the load forecasts could reach 38.7% (Table 3).

4. Discussion and conclusion

The impact of long-range temperature forecast on electricity load forecast was studied. Results showed that by utilizing 6-month temperature forecasts, the MAE of the load forecasts could be reduced by 18.5% for the period January 2007 – January 2017. It is not a surprising result because the existing electricity load forecast model only considers the observed temperature in the past ten years and the applicability of such approach may be limited in the context of a changing climate. Global warming has loaded the climate dice and altered the frequency of occurrence of extreme weather. This is where climate models can help to improve the electricity load forecast. With the advance of numerical climate modelling, global climate models are gradually improving in capturing month-to-month variation in short-term climate. Verification results of the 6-month temperature forecasts indeed showed that the forecasts are skillful in summer months when the electricity load is most sensitive to temperature [2]. As such, the incorporation of the long-range temperature forecasts can improve the performance of electricity load forecast. In addition to temperature, the electricity load may be sensitive to other meteorological elements such as relative humidity and precipitation. The impact of long-range forecast of these parameters on electricity load forecast could be explored in future studies.

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Table 1 Details of climate models used

Model	Horizontal resolution	Number of forecast months	Number of forecast ensemble members	The beginning year of hindcasts	Number of hindcast ensemble members
ECMWF	0.4 deg	6	51	1981	25
NCEP	~0.9 deg	9	52	1982	12
JMA	2.5 deg	6[1]	51	1979	15

Note 1: Number of forecast months is reduced to 3 for forecasts issued in Jan, May-Aug and Nov-Dec.

Table 2 Comparison of electricity load forecast for January-June 2007 – January-June 2017

Mean Absolute Error (Gigawatt hours)		
Without temperature adjustment	With temperature adjustment	Reduced by
90.27	73.57	18.5%

Table 3 Comparison of electricity load forecast for January-June 2011 – January-June 2017

Mean Absolute Error (Gigawatt hours)		
Without temperature adjustment	With temperature adjustment	Reduced by
92.47	56.67	38.7%

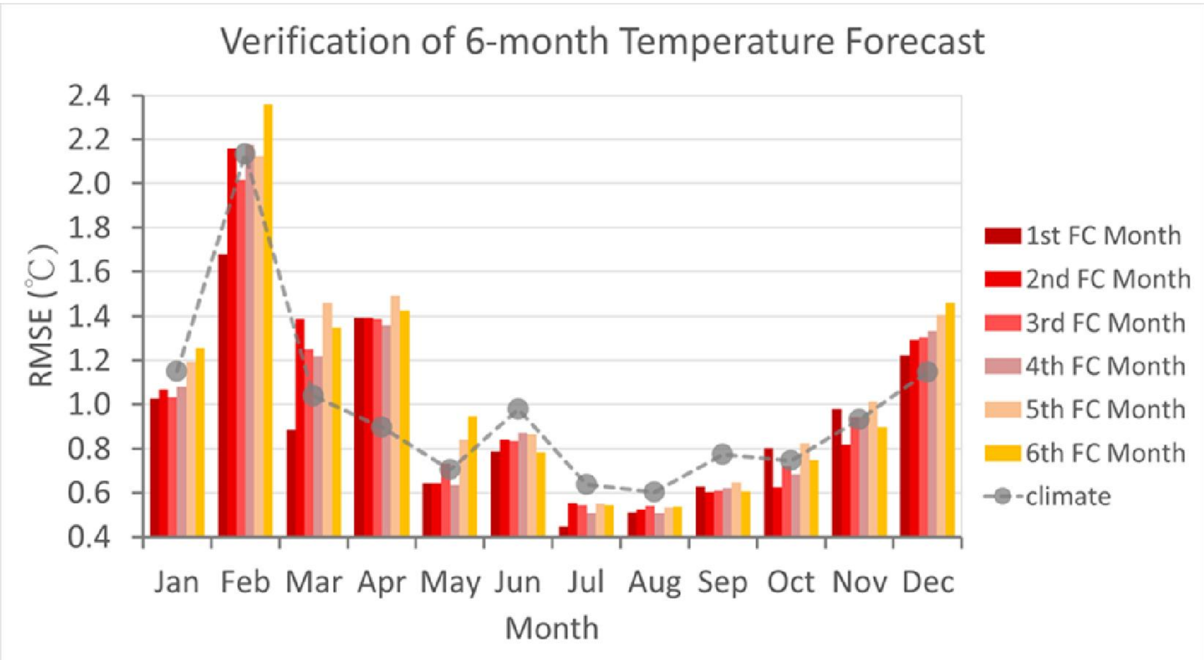

Figure 1. Root mean squared error (RMSE) of the 6-month calibrated temperature forecasts (coloured bars) with initial forecast month from January 2007 to January 2017 and with different lead times. RMSE of climatological forecasts are shown by the grey dashed line.