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Time-series modeling and prediction of weather-driven system-level electrical load – Case of Abu Dhabi

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Abstract

Load forecasting has long been used in operations and planning of the electric power system. In this study, weather variables were used for modeling and prediction of the system-level electrical load of the city of Abu Dhabi, UAE. A Transfer Function (TF) model was developed and its accuracy was compared to that of an Autoregressive Integrated Moving Average (ARIMA) model. We also tested an Artificial Neural Network (ANN) model based on the same weather variables that were used in the TF model.

Assuming perfect knowledge of the weather variables over the forecasting horizon, the TF model was more accurate for forecast horizons of up to 48 hours. The ANN model, on the other hand, was more accurate for one-week ahead forecasts.

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Assuming imperfect knowledge of the weather variables (i.e., they are not known over the forecasting horizon and have to be forecasted first), the TF model was more accurate than the ANN model in all cases. Average accuracy of the best TF method does not exceed 1.5% for 24-hour horizon, 2.5% for 48-hour horizon and 4% for 168-hour horizon. With the added uncertainty of forecasted weather drivers, the accuracy of the proposed method degrades only slightly, while the ANN model is much less robust and becomes unusable beyond a two-day horizon.

Mathematics Subject Classification: 62M10

Keywords: short-term load forecasting; time series modeling; ARMA; transfer function; artificial neural network

1 Introduction

Load forecasting is essential for operations and planning of power systems. Inaccurate forecasts increase the operating cost of power companies [1]. Broadly speaking, 4 categories of forecasts can have been investigated, each catering to its own application niche. Long-term forecasts (1 to 20 years ahead) are used for strategic planning and construction of new infrastructure capacity as new projects in these areas usually take years to complete [2]. Mid-term forecast (1 month to 1 year ahead) are used for maintenance scheduling and planning of power sharing agreements as well as generation of ex post baseline in demand-side management measurement & verification [3]. Short-term load forecasts (from 1 hour to a few weeks ahead) are used in plant scheduling, fuel purchase plans, security capacity, short-term maintenance as well as short-term storage usage [4]. The last category, very short-term forecasts (from a few minutes to an hour ahead) are used for real-time control [5]. In this study, we are specifically investigating short-term load forecasting (STLF) of system-wide hourly electricity demand in Abu Dhabi. We consider forecasting horizons varying in length from one day to one week.

Two approaches have emerged targeting STLF: statistical methods and machine learning methods. Despite differences in model structure and forecasting, both approaches rely on historical data of load and other impacting factors as seasons, day-types and weather. A popular machine learning method is based Artificial Neural Networks (ANN) modeling. This type of model usually consists of a black-box input-output mapping where no physical correspondence with the underlying physical systems is sought. Alternatively, expert information, system's structure and the underlying physical phenomena can be incorporated, in one way or another, to increase the forecast's accuracy or robustness.

The models presented in this study use the relationship between load and weather. The impact of each of weather variable was analyzed individually, and they were included in the final model based on their overall cross-correlation with load. The statistical models were compared to an ANN model using the same measured weather variables as inputs.

2 Literature Review

A comprehensive review of methods and model propositions applied to load forecasting is presented in [6], including techniques such as ARIMA, support vector machine, genetic algorithms, and neural networks. Some recent studies have employed the combination of two or more of the aforementioned methods. [7] describes the combination of an Autoregressive Integrated Moving Average (ARIMA) model for the forecast of the daily load, combined with Support Vector Machines (SVM). [8] uses the combination of Support Vector Regression (SVR) with Kalman Filter, while [9] combines Empirical Mode Decomposition (EMD) and Support Vector Machines (SVMs). The main disadvantage of using ARIMA models is that the important relationship to weather variables [10] is not accounted for. In order to overcome this limitation, a transfer function model (also called ARIMAX, X representing the "exogenous" weather variables) has been successfully applied in other scenarios [11, 12] and is the model developed in this study. A series of studies have been published based on artificial intelligence models. Data mining has been used in [13] to forecast weather sensitivity to load. A short-term load prediction in buildings using feedback ANN is presented in [14]. In [15] two adaptive ANN models are proposed and tested for online consumption forecasting. Other examples of ANN applied to building electricity forecasting can be seen in [16], [17] and [18]. A comparison study between neural networks and hybrid neuro-fuzzy system is presented in [19].

Herein, a transfer function model was developed and its performance compared to an ANN model that fits the same dataset.

3 Method

While some earlier studies only relied on the autoregressive characteristics of load to generate forecasts, load models gradually evolve to account for observable external drivers of the load. Transfer Function models are one class of models that use the causal information represented by external drivers. This paper presents the process of data analysis and model estimation where temperature, specific humidity, GHI and wind speed data are integrated into a model for load forecasting.

3.1 Data description

We used substation-level hourly electricity data measured by the SCADA system of Abu-Dhabi Emirate's electricity utility, as well as hourly weather data, including global solar irradiance (GHI) and wind speed, monitored by Masdar City's weather station over a 2-year period from July 1st, 2009 until June 30th, 2011. Only electricity consumption within the Abu Dhabi municipality, mostly imputable to buildings (residential, commercial and institutional), is considered. A subset of substations representing the targeted downtown area was selected, thereby eliminating industrial & agricultural loads. This subset constitutes, in aggregate, a better proxy for the total system load within the municipality. Hourly electricity consumption data from 29 low-voltage was used. This subset includes all substations that directly supply street transformers serving final customers in residential/business areas within the Abu Dhabi municipality. The aggregate demand of the selected substations during this period peaks at 2,040 MW in 2011, presenting a growth over 2009 and 2010. Figure 1 presents the plot of electricity demand (MW) for each hour over the 2-year period of analysis. This data was used for model training and testing. A plot of each exogenous variable is presented in Figure 2, namely, temperature, specific humidity, GHI and wind.

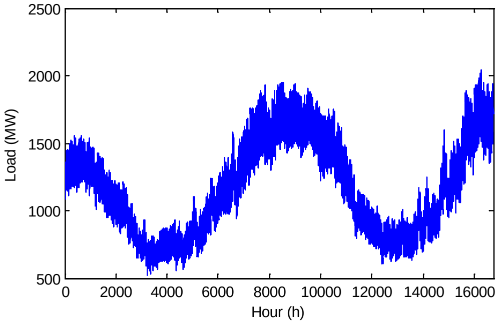

Figure 1: Electricity demand

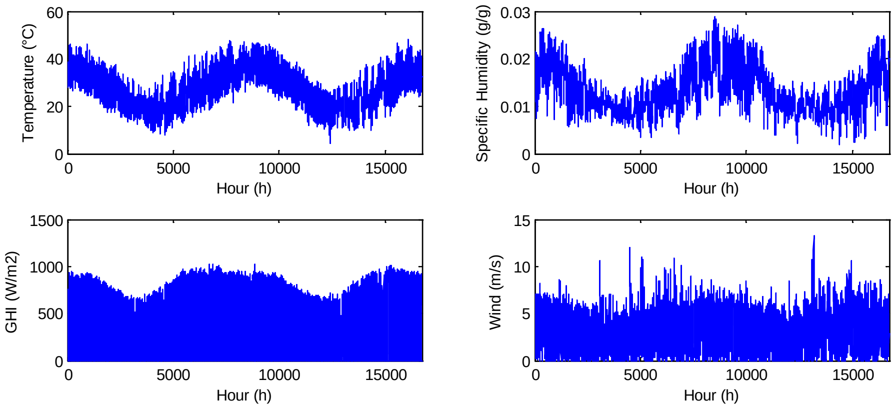

Figure 2: Exogenous variables(temperature, specific humidity, GHI and wind speed)

3.2 Data pre-processing

As can be seen in Figure 1, the load presents a trend as well as a daily seasonality (24-hour periodicity) and a weekly seasonality (168-hour periodicity). Following the Box–Jenkins time series modeling approach, the first step is to stationarize the time series under study. Considering Y_t the measured electricity consumption, first order differencing was used to eliminate the trend (growth). 24-hour and 168-hour differencing was applied in order to eliminate the seasonality components not driven by exogenous variables. The transformed series is represented by y_t (1). Annual differencing did not improve the model and because the annual seasonality is mostly captured by the exogenous variables and also because our longest forecasting horizon (one week) is significantly shorter than one year. Similarly, defining X_t as the matrix with the time series representing hourly measured values of temperature, specific humidity (SH), GHI and wind speed, 1-hour and 24-hour differencing was applied. Equation (2) presents this transformation, where x_t represents the transformed matrix of exogenous variables. All five time series were stationary after the differencing process.

$$y_t = (1 - B)(1 - B^{24})(1 - B^{168})Y_t \tag{1}$$

$$x_t = (1 - B)(1 - B^{24})X_t \tag{2}$$

where: $X_t = [X_{Temperature}\ X_{SH}\ X_{GHI}\ X_{Wind}]$

Since exogenous variables (input series) are often auto-correlated, the direct cross-correlation function between the input and response series would give a misleading indication for model specification. One solution to this problem is to apply “pre-whitening”. Pre-whitening consists in fitting an ARMA model to the input series in order to account for the autocorrelation of the series and applying that same model to the response series (hourly load in this case). This analysis was conducted for all four input series. By analyzing the auto-correlation function ACF), the partial autocorrelation function (PACF) and the inverse autocorrelation function (IACF) of the differenced series, as shown on Figure 4, an autoregressive model was fit to each of the input series reducing the residuals to white-noise, and the same model was then applied to the differenced response series.

3.3 Model selection

Model selection was based on the fitting performance of typical model structures available in the literature for each exogenous variable isolated.

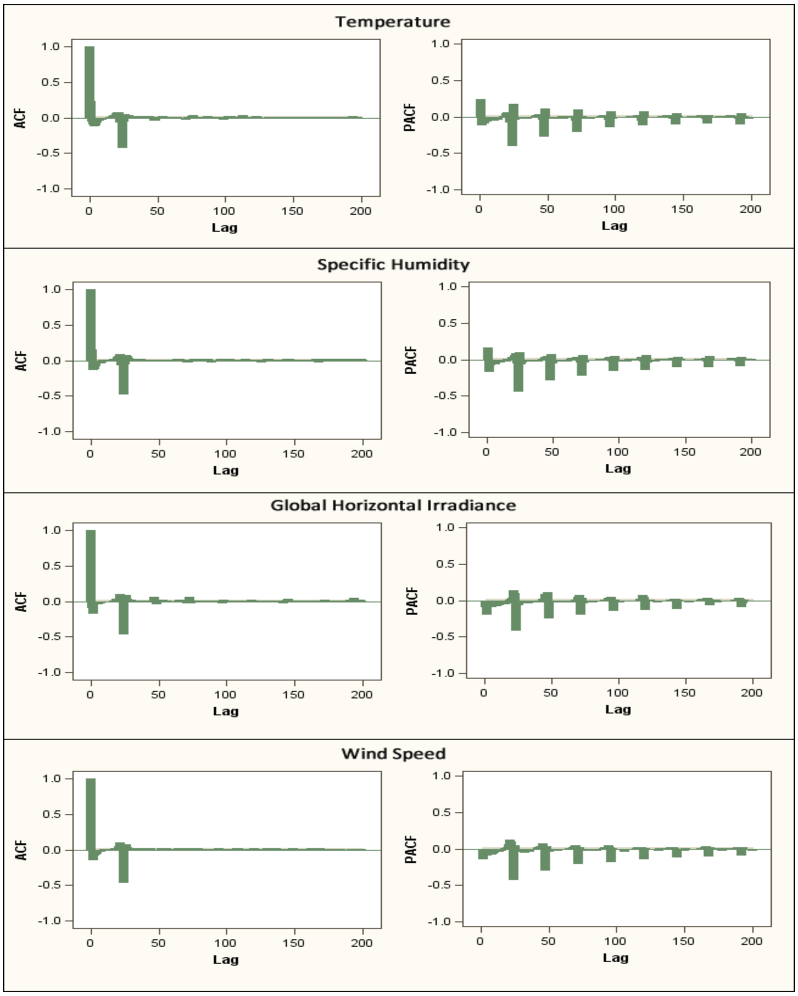

Figure 3: Trend and correlation analysis for 1-lag/24-lag differenced temperature (a), specific humidity (b), GHI (c) and wind speed (d)

After pre-whitening, a cross correlation analysis was performed. The cross correlation plots obtained after the pre-whitening were compared to the typical models structures presented in literature for transfer function models. Given b the delay (shift) term, s the order of the numerator, and r the order of the denominator in the transfer function model, Table 1 summarizes the most likely model structures for each exogenous variable being modeled.

Based on the assumption that the exogenous variables are not correlated, transfer model structures were tested for each exogenous variable separately and compared based on the AIC (Akaike information criterion) and Standard Error Estimate. Table 2 presents the best transfer function model for each exogenous variable. These models were then combined to form a full transfer function model for load.

After applying the transfer function model only with the exogenous variables, the residuals (difference between the predicted and the measured data) were auto-correlated, meaning that some information presented in the data was not being fully captured by the model tested. Figure 5 presents the ACF and PACF of the residuals.

Table 1: Transfer function model structures investigated

Temperature	s: 0,1 r: 1,2
Specific Humidity	s: 0,1,2 r: 1,2
GHI	s: 1,2
Wind	b: 0,1 s: 0,1,2

Table 2: Best models based on AIC and Standard Error Estimate

Input	Model	AIC	Standard Error Estimate
Temperature	$\frac{\omega_0}{1-\delta_1 B}$	*137828.3*	*15.52848*
Specific Humidity	$\frac{\omega_0}{1-\delta_1 B}$	*137856.5*	*15.54216*
GHI	$\omega_0 - \omega_1 B - \omega_2 B^2$	*138013.7*	*15.61563*
Wind	$(\omega_0 - \omega_1 B - \omega_2 B^2)B$	*138107.4*	*15.6599*

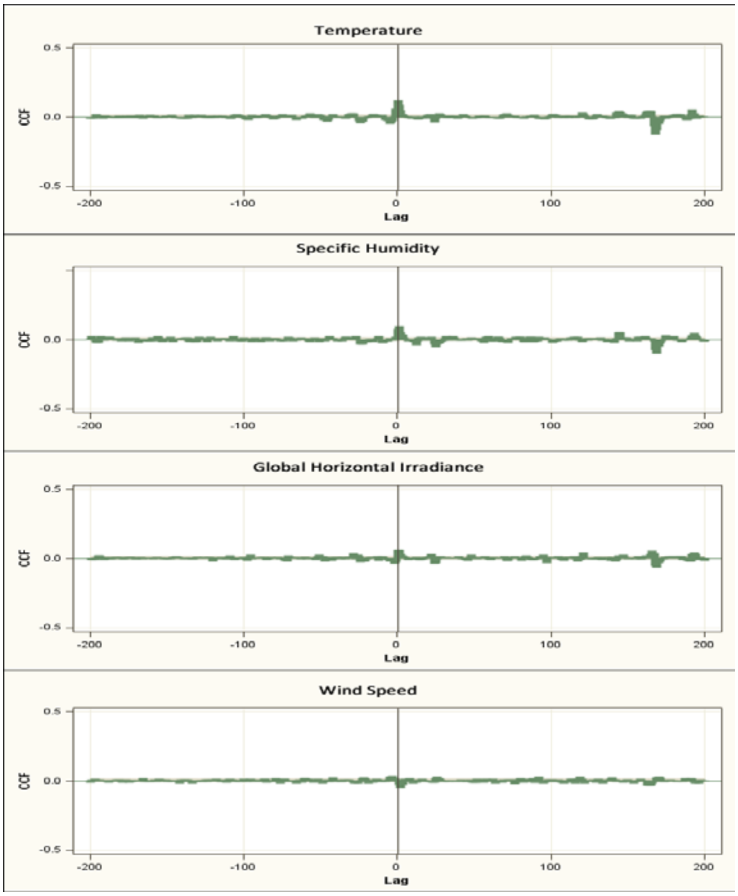

Figure 4: Cross-correlation between 1-lag/24-lag/168-lag differenced load and 1-lag/24-lag differenced temperature (a), specific humidity (b), GHI (c) and wind speed (d)

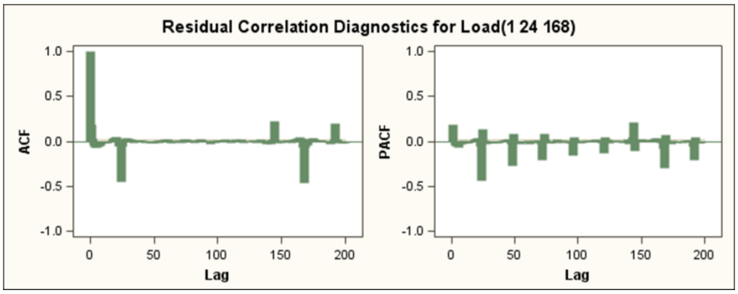

Figure 5: Residual analysis after the estimation of the transfer function model without any ARMA component

A series of ARMA models were tested in order to account for the autocorrelation of the residuals *a(t)* until a balance between the number of parameters (complexity of the model), significance of the coefficients (given by the t-statistics) and the probability of white noise of the residuals after applying the ARMA model was achieved. The final model obtained for the ARMA presented in (3).

$$\frac{(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3)(1-\theta_{24}B^{24})(1-\theta_{48}B^{48})}{(1-\phi_1 B-\phi_2 B^2-\phi_3 B^3)(1-\phi_{24}B^{24})(1-\phi_{48}B^{48})(1-\phi_{168}B^{168})}a_t \tag{3}$$

After applying the full model (4), the residuals presented no further seasonality and no significant autocorrelation as shown in Figure 6.

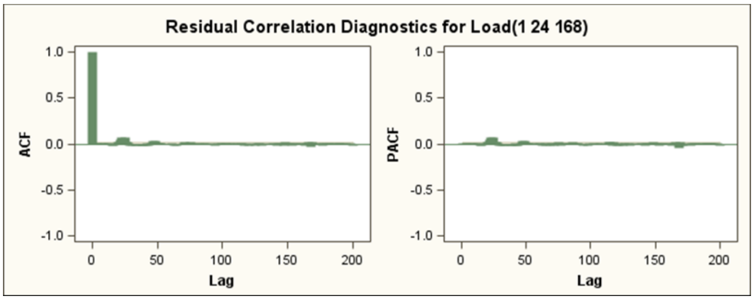

Figure 6: Residual analysis after the estimation of the transfer function model including an ARMA component

$$y_t = \frac{\omega_0}{1-\delta_1 B} x_{Temperature_t} + \frac{\omega_0}{1-\delta_1 B} x_{SH_t} + (\omega_0 - \omega_1 B - \omega_2 B^2) x_{GHI_t} + (\omega_0 - \omega_1 B - \omega_2 B^2) B x_{Wind_t} + \frac{(1-\theta_1 B - \theta_2 B^2 - \theta_3 B^3)(1-\theta_{24} B^{24})(1-\theta_{48} B^{48})}{(1-\phi_1 B - \phi_2 B^2 - \phi_3 B^3)(1-\phi_{24} B^{24})(1-\phi_{48} B^{48})(1-\phi_{168} B^{168})} a_t \tag{4}$$

where:

$y_t = (1-B)(1-B^{24})(1-B^{168})Y_t$

$x_t = (1-B)(1-B^{24})X_t$

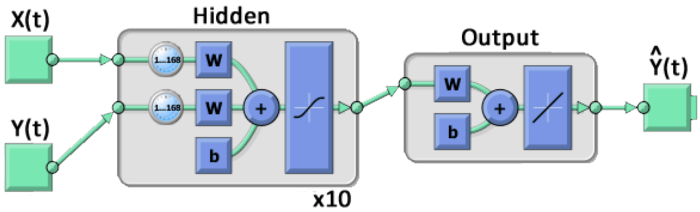

Figure 7: Artificial Neural Network architecture

4 Forecasting

4.1 Accuracy assessment

In order to test the model's accuracy, load was forecasted from one hour ahead to one week ahead (168 hours) starting every day at midnight for 30 consecutive days, resulting in 30 forecasts of one week each. The results from each forecast $\hat{Y}_t$ were compared against actual data Y_t and the accuracy was measured using the Mean Absolute Percentage Error (MAPE) according to (5). At this stage, comparative forecasting accuracy being the main focus, perfect knowledge of the exogenous variables was assumed over the forecasting horizon.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|Y(t)-\hat{Y}(t)|}{Y(t)} * 100 \quad (5)$$

4.2 Model comparison

In order to compare the proposed model's forecasting accuracy for STLF, an ANN model using the same input parameters was considered. Modeling and training was conducted using Matlab's Neural Net Time Series Application. An ANN model composed of one input layer, one hidden layer and one output layer was used similarly to [20]. Due to the strong autocorrelation and cross correlation between load and the exogenous variables, lagged variables of each series was considered for lags 1, 2, 3, 6, 12, 24 and 168. Figure 3 presents the ANN architecture used during the training period. Once the model is used for forecasting, $\hat{Y}_t$ is fed back to the input layer so that only information prior to the start of the forecast is used, and subsequent terms in the future are based on forecasted values.

5 Results & Discussion

5.1 Ex post forecast

Perfect knowledge of the weather variables over the forecast horizon (1 week) is assumed. Forecasting accuracy was compared between the ARIMA model, the TF model and the ANN model. Thirty forecast of one week each were generated, starting at midnight, for 30 consecutive days covering the period from the last week of May until the last week of June 2011. Table 3 presents the forecasting accuracy (MAPE) for the three models averaged over each of three different forecast horizons: first 24 hours (1:24), first 48 hours (1:48) and the full week (1:168).

For the ANN model, due to large number of parameters to be identified, the non-convex nature of the estimation problem and the random starting parameters utilized for the training, each run produced slightly different results. The ANN model with best performing cross-validation after 10 runs was used for comparison to ARIMA and TF.

Figure 8 presents the residuals for 30 forecasts of one week for the TF model. Residuals are centered around zero and, as expected, increase in variability as the forecasting horizon increases. For a given forecast, the residuals are often on-sided, meaning either over- or under-forecast consistently over the horizon.

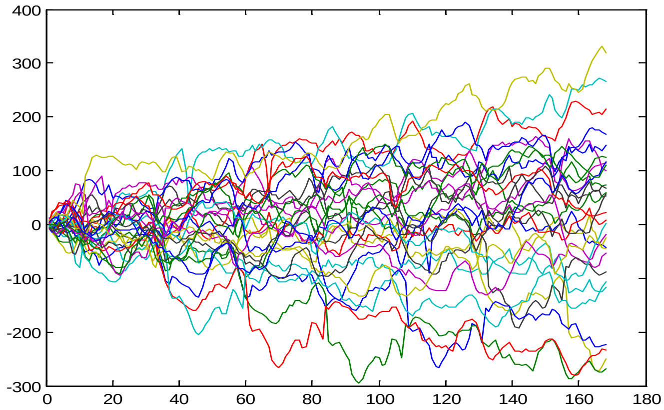

Figure 8: Residuals for 30 forecasts of one week

Table 3: Forecasting efficiency

	1:24	1:48	1:168
TF	1.47	1.97	3.92
ARIMA	1.53	2.06	4.13
ANN	1.97	2.48	3.18

The TF model produced the best results for 1:24 and 1:48 hours, while the ANN gave better forecasting performance for 1:168 hours. This can be justified by the fact that the TF has a significant autoregressive component, while the ANN is based mostly on the exogenous variables, which at this stage were considered to be known over the forecasting horizon.

5.1 Ex ante forecast

In the second stage of the study, in order to analyze the applicability of the models to a more realistic scenario, where the weather information for the future is not known, an ANN model was used for forecasting the weather parameters using lags 1, 2, 3, 6, 12, 24, 48 and two hidden layers with 5 neurons each (Figure 9). For the forecasting of the weather variables, the only input to the model was past weather information, as opposed to the load forecasting case where exogenous variables are present. Forecasted values of specific humidity, GHI and wind below zero were set to zero.

Weather was forecasted for the last week of June 2011, and the forecasted values were used in the load forecasting. Figure 10 presents the forecasted weather parameters against the measured ones, only for that week.

The TF model was compared with the ANN based on the forecasting performance for the last week of June 2011, using both the measured weather data and the forecasted weather data. The forecasting results between the two models for the three time ranges are presented in Table 4. For short horizons of up to 48 hours, the TF-based load forecasts using approximate (forecasted) weather is comparable to, even slightly better than, the one using actual (measured) weather. This is due to the good precision of the weather prediction up to two-days. Also, as mentioned previously, for a given load forecast based on actual (measured) weather, the residuals are often one-sided—either under-forecast or over-forecast, consistently over the entire horizon—so it can happen that the error of the approximate weather, itself often one-sided, accidentally cancels part of the bias of the original load forecast, resulting in a comparable or slightly better load forecast. It should be noted that we are looking, this time, only at a single forecast instance (i.e., only one week-long load forecast instead of 30 previously), so the results in Table 4 are to be interpreted only for comparative analysis. That being said, it is safe to infer that the TF-based load forecast is not very sensitive to uncertainty in the exogenous variables with a degradation of accuracy that does not exceed 0.25% over the week-long horizon. The ANN model on the other hand displays a severe lack of robustness to said uncertainties, even over a short 24-hour horizon.

5 Conclusions

A Transfer Function model was proposed for the short-term (up to one week) forecast of city-scale hourly electricity consumption. The model was validated using actual measurements of hourly system load for the city of Abu Dhabi, UAE. The influence of exogenous weather variables including not only temperature but also specific humidity, solar irradiation and wind speed was incorporated.

The performance of the TF model, assessed via the MAPE, was compared to an ARIMA model (not using exogenous variables) as well as an ANN model. The TF and ANN models had better performance than the ARIMA model in all tested forecasting horizons (1-day ahead, 2-day ahead and 1-week ahead). Considering perfect knowledge of the exogenous variables over the forecast horizon, the TF model obtained better results for up to 2 days ahead forecast (MAPE better than 1.5% for 24-hour horizon, better than 2.5% for 48-hour horizon), while the ANN model outperformed the TF model for the 1-week ahead forecast scenario (MAPE of 3.18% vs. 3.92%). The superiority of the ANN model for the 1-week ahead forecast is in part explained by the fact that the model is less dependent on previous forecasted load values, compared to TF. This results in a more stable forecast over the longer horizon, when actual values of the weather variables over the horizon are available.

We then switched to a more realistic scenario where weather variables are not known over the forecast horizon. Weather was forecasted, using ANN, over one week. All weather variables were estimated together (multivariate forecast) whereby the prediction of each variable was informed by past values of all 4 variables. These predicted values were then input to the load forecast model. The ANN approach proved superior for the forecasting of the exogenous weather variables while the TF model presented significantly better load forecasting performance for all forecast horizons. The uncertain nature of the predicted weather drivers had limited impact on the accuracy of the forecasted load.

The multivariate prediction of weather via ANN is surprisingly accurate over the horizon of interest (one week). The use of all 4 weather variables is shown to be advantageous when compared to the ARIMA model or the TF model with a single weather variable (temperature) [4]. A sophisticated TF model was derived for the forecasting of the hourly system load in Abu Dhabi using hourly values of 4 weather variables. This approach is promising and, in our opinion superior to alternatives, for this specific case.

Table 4: TF and ANN model comparison for last week of June 2011

		1:24	1:48	1:168
Measured weather	TF	2.19	2.46	3.28
	ANN	1.56	3.28	2.43
Forecasted weather	TF	2.18	2.43	3.42
	ANN	4.38	10.41	11.5

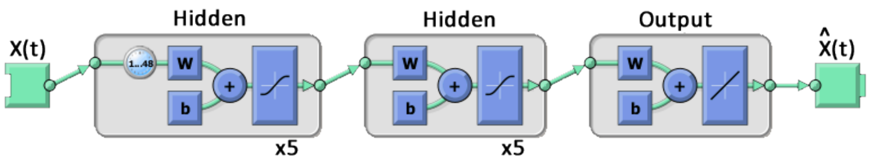

Figure 9: ANN for weather forecast

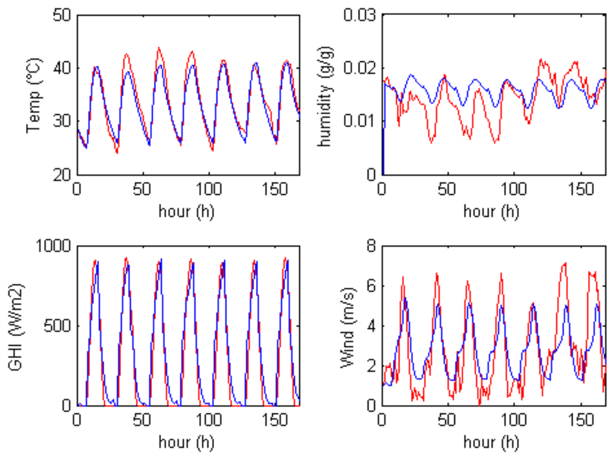

Figure 10: Predicted weather variables (blue) against measured (red)

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