Probabilistic Forecasts of the Magnitude and Timing of Peak Electricity Demand

Patrick E. McSharry, Sonja Bouwman, and Gabriël Bloemhof

***Abstract*—Adequate capacity planning requires accurate forecasts of the future magnitude and timing of peak electricity demand. Electricity demand is affected by the day of the week, seasonal variations, holiday periods, feast days, and the weather. A model that provides probabilistic forecasts of both magnitude and timing for lead times of one year is presented. This model is capable of capturing the main sources of variation in demand and uses simulated weather time series, including temperature, wind speed, and luminosity, for producing probabilistic forecasts of future peak demand. Having access to such probabilistic forecasts provides a means of assessing the uncertainty in the forecasts and can lead to improved decision making and better risk management.**

***Index Terms*—Load forecasting, load management, management decision making, power demand, power generation peaking capacity, power system planning, simulation, temperature, time series.**

I. Introduction

ELECTRICITY demand is one of the most important variables required for estimating the amount of additional capacity required to ensure a sufficient supply of energy. Demand forecasts can be used to control the generation and distribution of electricity more efficiently. From an operational point of view, the key question is whether there will be problems in meeting the peak demand; failure to meet this peak demand could result in blackouts. In addition, forecasts of demand have become even more important because they are also required for estimating future electricity spot prices [1], [2].

Network operators could benefit from accurate forecasts of electricity demand due to i) the need to support investment decisions more objectively, ii) higher utilization and, thus, smaller margins in the network, and iii) increasing uncertainties regarding demand and supply. Furthermore, in some countries, there is an obligation to submit capacity plans to the regulator (as is the case of the Dutch regulator, DTe). Having access to accurate forecasts of electricity demand provides the manager with the ability to reduce risk and minimize costs.

The range of approaches for generating forecasts includes semiparametric regression [3], [4], time series modeling [5], exponential smoothing [6], Bayesian statistics [7], [8], time-varying splines [9], neural networks [10], [11], decomposition techniques [12]–[14], transfer functions [15], grey dynamic models [16], and judgmental forecasting [17]. These forecasts may be characterized by their time horizon i) short-term forecasts (five minutes to one week ahead) for ensuring system stability, ii) medium-term forecasts (one week to six months ahead) for maintenance scheduling, and iii) long-term forecasts (six months to ten years ahead) for capital planning.

While a point forecast provides an estimate of the expected value of the future demand, probabilistic forecasts contain additional valuable information. Having access to prediction intervals, such as a lower and upper boundary of the forecast distribution [16] or a prediction density [18], would inform the decision maker of the uncertainty inherent in the forecast. Quantification of this forecast uncertainty is essential for managing the risk associated with decision making. Despite their value for grid companies, probabilistic forecasts of the peak demand have not received adequate attention in the literature.

Electricity demand (which equals the electricity load in the absence of blackouts or load shaving) is highly inelastic since it is a necessary commodity and has a strong deterministic component due to seasonal effects on daily, weekly, and yearly time scales. The strongest source of variation (after seasonality has been removed) is temperature [3], [15], [19], [20]. The relationship between demand and temperature is nonlinear, with demand increasing for both low and high temperatures. Other important weather factors include wind speed and luminosity. Demand is also affected by special calendar days and socioeconomic effects. For long-term forecasts with lead times of a couple of years, the socioeconomic factors play the largest role in determining the future electricity demand.

The aim of this paper is to construct a model for generating probabilistic forecasts of both the timing and magnitude of the peak demand for lead times of one year. Ensemble weather forecasts [21], [22] with prediction skill out to two weeks ahead [23], [24] can be used to generate accurate short-term forecasts of electricity demand [18]. Given that weather forecasts are not available for lead times of one year, the daily weather is simulated using a novel technique that replicates both the distribution and autocorrelation (equivalent to the power spectrum) of each weather variable, such as temperature, wind speed, and luminosity. Furthermore, the cross-correlations between these weather variables are preserved.

The model is constructed using daily electricity demand from a province of the Netherlands. An analysis of the last decade of electricity demand data shows (see Fig. 1) that the peak demand

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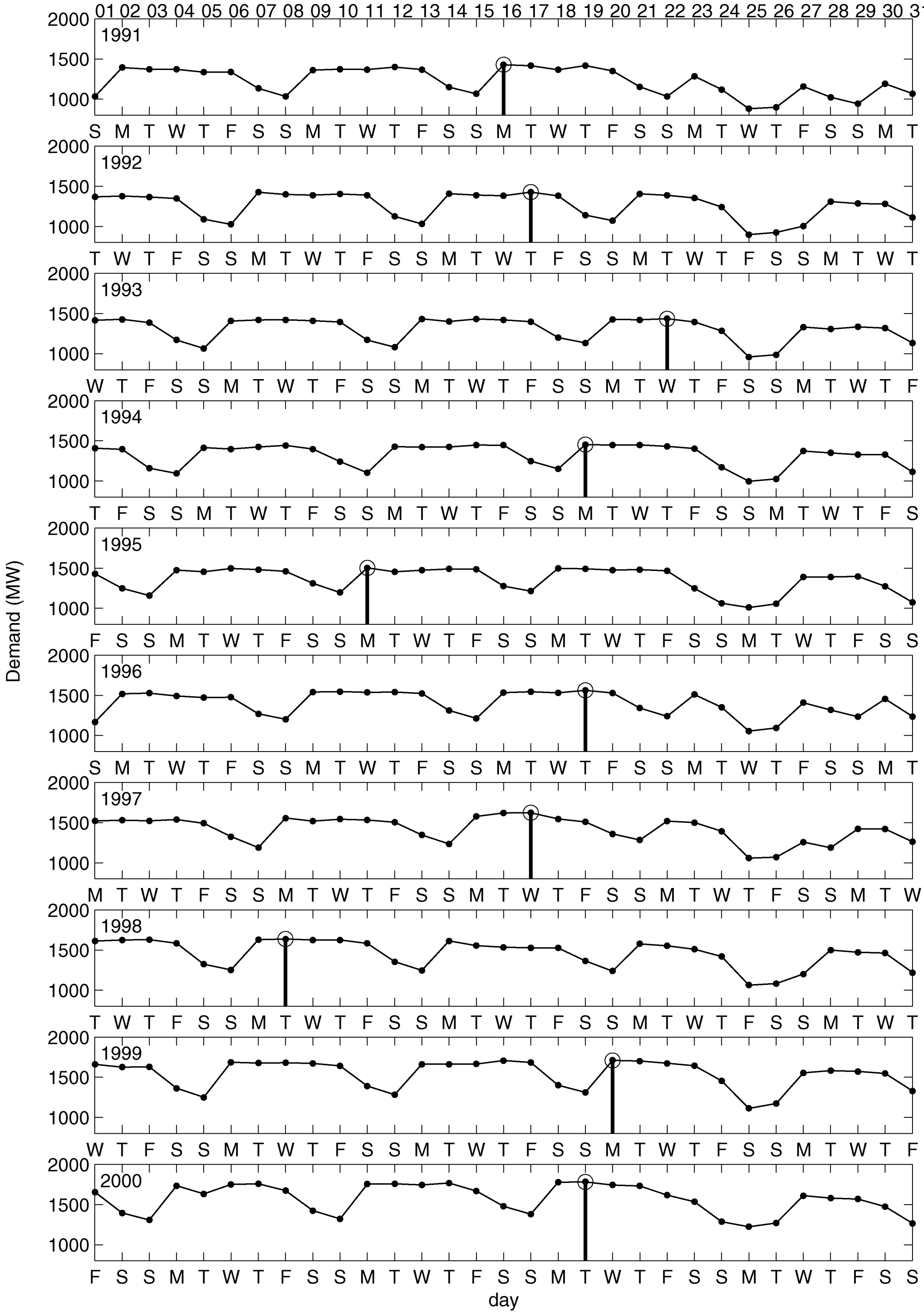

Fig. 1. Peak demand (in Megawatts) during December for the years 1991 to 2000. A circle and vertical line indicate the peak demand for each year.

(largest daily demand) throughout the year usually occurs in the winter, during the weeks before Christmas. Factors causing this increase in electricity demand include the cold weather (increased use of electrical heating devices) and pre-Christmas activities.

The paper is organized as follows: Section II discusses the available data set, Section III describes the model and explains its various components, Section IV introduces a technique for simulating daily weather time series over a year and presents the probabilistic forecasts for electricity demand, Section V provides a discussion of the results, and Section VI concludes the paper.

II. Electricity Demand Data

The data considered here consists of the daily electricity demand from a province of the Netherlands during the years 1991–2000. While the demand on work days is roughly similar, the demand on weekends is distinctly different. Saturday and

Sunday display lower demands than work days, with Sunday having the lowest demand. A closer inspection of the data reveals that there are also slight variations during the work days (see Fig. 1). There is generally less demand on Fridays than other work days.

In order to understand when the peak demand is likely to occur, it is useful to examine the historical patterns of peak demand during December for all the years between 1991 and 2000. Fig. 1 illustrates that while there is relatively normal intraweek variability in demand during the first half of December, there is a dramatic decrease in demand during the Christmas holiday period. The vertical lines and circles indicate the position and magnitude of the peak demand, showing that there is a large amount of variability in its position. While the peak usually occurs in the weeks leading up to Christmas Day, it is difficult to determine the exact date. The peak is determined by a complex combination of effects, which the following model attempts to describe.

III. Model Description

The construction of a model for predicting the peak demand for one or more years ahead requires the incorporation of a diverse range of factors that cause variations in the electricity demand. Electricity demand D_t at time t measured in days may be expressed as

$$\begin{aligned} D_t =& a_0 + a_1 t + a_2 t^2 + \sum_{i=1}^{3} b_i \delta_{t,i} \\ &+ \sum_{i=1}^{4} \alpha_i \tau^i + \sum_{i=1}^{3} \delta_{t,i} \sum_{j=1}^{4} \beta_{ij} \tau^j \\ &+ \sum_{k=1}^{11} \gamma_k \delta_{t,\mathrm{feast}_k} + \gamma_{12} \delta_{t,\mathrm{summer}} + \gamma_{13} \delta_{t,\mathrm{christmas}} \\ &+ c_1 T_t + c_2 {T_t}^2 + c_3 C_t + c_4 I_t + \varepsilon_t. \end{aligned} \quad (1)$$

The four lines of (1) represent i) growth of demand represented by a quadratic dependence on time and intraweek seasonality, ii) yearly seasonality, iii) special calendar events, and iv) weather-induced effects. The $\delta_{t,i}$ $(i = 1, 2, 3)$ are dummy variables for Friday, Saturday, and Sunday, respectively. A time of year variable $0 \leq \tau < 1$ is employed to deterministically model the intrayear seasonality using a fourth-order polynomial [18]. Separate seasonality expressions for Friday, Saturday, and Sunday are included. The dummy variables $\delta_{t,\mathrm{summer}}$ and $\delta_{t,\mathrm{christmas}}$ describe days falling in the summer and Christmas periods (excluding feast days and weekends). Eleven feast days (New Year's Day, Carnival, Easter Day, 2nd Easter Day, Ascension Day, Queen's Day, Whit Sunday, Whit Monday, Christmas Day, Boxing Day, and New Year's Eve) are described by $\delta_{t,\mathrm{feast}_k}$.

Three variables—temperature T_t, wind speed W_t, and luminosity I_t—are used to describe the influence of weather on demand. A new variable, cooling power C_t, is defined to describe the influence of draught on demand using a nonlinear function of temperature and wind speed [18]

$$C_t = \begin{cases} W_t^{1/2}(18.3 - T_t), & \text{if } T_t < 18.3\ ^\circ\mathrm{C} \\ 0, & \text{if } T_t \geq 18.3\ ^\circ\mathrm{C}. \end{cases} \quad (2)$$

TABLE I
Training and Testing Forecast Accuracy of Year-Ahead Daily Demand Forecasts for Actual and Simulated Weather Data. Accuracy of Year-Ahead Forecasts for (a) In-Sample on Three Previous Year, (b) Out-of-Sample Using Actual Weather Data, and (c) Out-of-Sample Results Averaged Over 1000 Runs of Simulated Weather Data

Forecast	Training		Testing		Testing	
Weather	Actual		Actual		Simulated	
Year	NRMSE	MAPE	NRMSE	MAPE	NRMSE	MAPE
1995	0.17	1.87	0.25	2.25	0.27	2.39
1996	0.20	1.87	0.23	2.56	0.22	2.39
1997	0.22	1.87	0.22	2.26	0.24	2.55
1998	0.22	1.93	0.23	2.48	0.25	2.75
1999	0.20	1.89	0.22	2.49	0.23	2.52
2000	0.19	1.90	0.30	3.11	0.27	2.81
Average	0.20	1.89	0.24	2.52	0.25	2.57

The nonlinear dependence of demand on the weather variables enters through the T_t^2 and C_t terms in (1). Finally, the prediction error is represented by ε_t.

For each year between 1995 and 2000, the four previous years were used to fit the model parameters and then to generate out-of-sample predictions for that year. These year-ahead forecasts start from 31 December of the previous year. The accuracy of the point forecasts were evaluated using the root-mean-square error (RMSE) defined by

$$\mathrm{RMSE} = \sqrt{\langle (\hat{D}_t - D_t)^2 \rangle} \quad (3)$$

where $\hat{D}_t$ is the forecasted demand at time t, and $\langle \cdot \rangle$ denotes the average. In order to allow for comparison between different years, the normalized root-mean-square error $\mathrm{NRMSE} = \mathrm{RMSE}/\sigma$, where σ is the standard deviation of demand, was employed. The mean absolute percentage error (MAPE)

$$\mathrm{MAPE} = \left\langle 100 \frac{|D_t - \hat{D}_t|}{D_t} \right\rangle \quad (4)$$

was also calculated. Both the NRMSE and MAPE are reported in Table I for three different forecasting scenarios. The first is the in-sample forecasts on the training data of the previous four years, the second is the forecasts of the testing data set using the actual weather that occurred, and the third is the out-of-sample forecasts of the testing data set using simulated weather. The latter results were averaged over all the simulations.

The average values of model parameters are given in Table II. An inspection of the values γ_k for $k = 1, \ldots, 11$ corresponding to the eleven feast days shows that Queen's Day $(k = 7)$ produces the largest decrease in demand, whereas New Year's Eve $(k = 11)$ produces the smallest decrease. The quadratic dependence of demand on temperature implies a minimum demand at $T = -c_1/2c_2 \approx 15^\circ\mathrm{C}$.

IV. Simulation and Forecasts

Using the model in (1), it is possible to forecast one year ahead given values for the weather variables T_t, C_t, and I_t. These values for the weather variables cannot be forecasted one year ahead and, therefore, must be simulated using historical records.

TABLE II
AVERAGE VALUES OF MODEL PARAMETERS TO PROVIDE YEAR-AHEAD DAILY DEMAND FORECASTS USING (1)

a_0	1.52e+03	β_{33}	1.52e+04
a_1	1.06e-01	β_{34}	-7.90e+03
a_2	1.48e-05	γ_1	-4.30e+02
b_1	8.67e+00	γ_2	-3.25e+02
b_2	-2.32e+02	γ_3	-5.03e+02
b_3	-3.24e+02	γ_4	-4.44e+02
α_1	-6.31e+01	γ_5	-4.66e+02
α_2	-5.20e+02	γ_6	-4.71e+02
α_3	8.98e+02	γ_7	-5.16e+02
α_4	-2.71e+02	γ_8	-3.97e+02
β_{11}	-1.78e+02	γ_9	-5.02e+02
β_{12}	1.00e+02	γ_{10}	-4.70e+02
β_{13}	6.49e+02	γ_{11}	-3.15e+02
β_{14}	-6.39e+02	γ_{12}	-1.43e+02
β_{21}	1.65e+02	γ_{13}	-9.48e+01
β_{22}	-2.65e+03	c_1	-3.14e+00
β_{23}	5.01e+03	c_2	1.08e-01
β_{24}	-2.52e+03	c_3	2.58e-01
β_{31}	1.01e+03	c_4	-1.01e-01
β_{32}	-8.37e+03		

Realistic weather time series for a year ahead can be simulated using the method of surrogates [25]–[27]. These surrogates aim to preserve both the distribution and the autocorrelation function of the original time series. The distribution is maintained by shuffling the original time series. The autocorrelation is preserved by taking the Fourier transform of the original time series, keeping the amplitudes fixed, randomizing the phases, and transforming back to the time domain. Since all the linear correlations are contained in the amplitudes of the Fourier series, this procedure preserves the power spectrum and autocorrelation function. Only the nonlinear correlations are lost since these are contained in the phases of the Fourier series. Given the multivariate weather data, consisting of temperature, wind speed, and luminosity, it is possible to also preserve the cross-correlations. The entire record of weather data, between 1991 and 2000, was used as the original time series. The phase of the yearly seasonality was replicated by using the time shift that maximized the correlation between each temperature surrogate and the original temperature time series. An example of the yearly temperature for 1991 and four different surrogates are shown in Fig. 2. Each of the surrogates provides a realistic simulation of temperatures for an entire year.

A simulation using 10 000 runs with different weather surrogates and different error realizations was used to forecast the distribution of electricity demand for each day during each year between 1995 and 2000. By sampling from the in-sample forecast errors, ε_t in (1), obtained from the previous four years, it is possible to incorporate the uncertainty due to model inadequacy in the probabilistic forecasts. Two examples of the forecasted daily demand for 2000 are shown in Fig. 3. Note that the different weather surrogates give rise to peaks on different dates and days of the week.

This simulation describes the model's estimates of the date and magnitude of the peak demand. Fig. 4 shows the probability of the peak demand occurring on different dates in December. For each year, the actual timing of the peak demand falls on a date that was assigned a relatively high probability by the model. This simulation also provides forecasts of the magnitude of the peak demand for each year. Fig. 5 displays the probability density function (PDF) of the size of the demand for each of the years between 1995 and 2000. These PDFs are constructed so that the area under the graph is equal to unity. Table III summarizes each forecast PDF by providing its mean, standard deviation, skewness, kurtosis, median, and values at different percentiles. Each PDF is asymmetric with positive skewness and platykurtic (positive kurtosis less than three). In each case, the Bera–Jarque test rejected the null hypothesis of the forecast PDF being normal with unspecified mean and variance ($P < 0.0001$). These results emphasize the benefit of simulations over assuming a normal distribution for the forecasts.

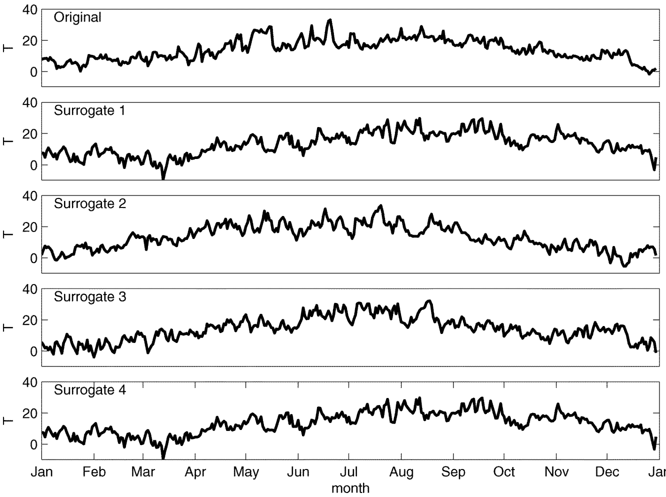

Fig. 2. Original temperature time series for 2000 and four surrogates, which were constructed to preserve the distribution, autocorrelation, and cross-correlations of the weather data between 1991 and 2000.

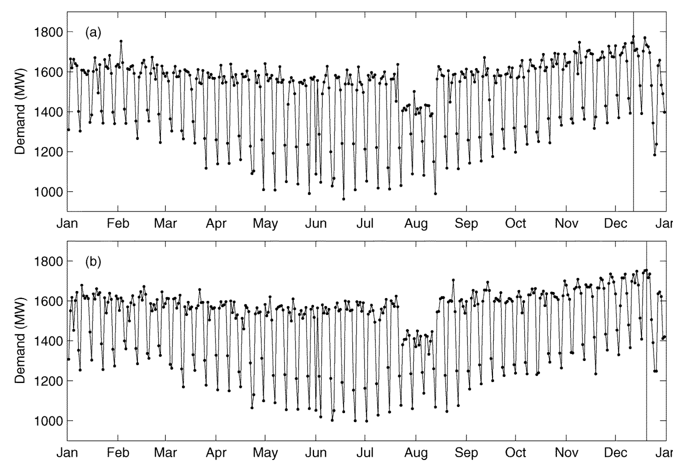

Fig. 3. Forecasted daily electricity demand for 2000 using two different weather surrogates (a) and (b). The peak demand for each simulation occurs in December and is indicated by a vertical line.

V. DISCUSSION

The model described in (1) provides a relatively accurate fit to the data during the period 1991–2000, with an average in-sample NRMSE of 0.22 and a MAPE of 1.89. The average out-of-sample forecasts for one year ahead using actual weather

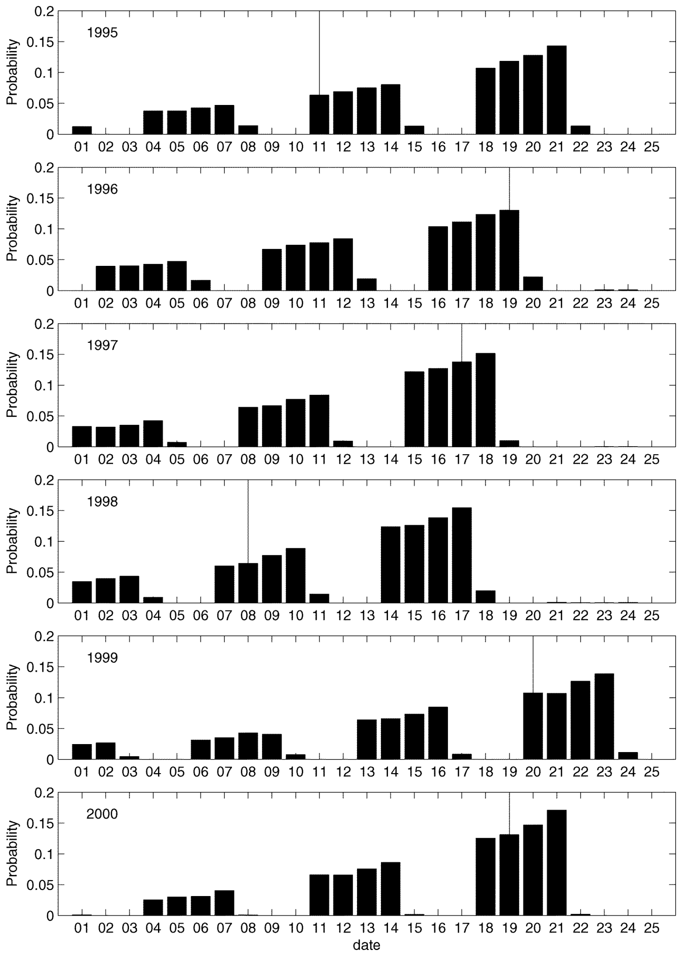

Fig. 4. Probability that peak demand will occur on various dates in December for years 1995–2000. A vertical line reflects the date of the actual peak demand.

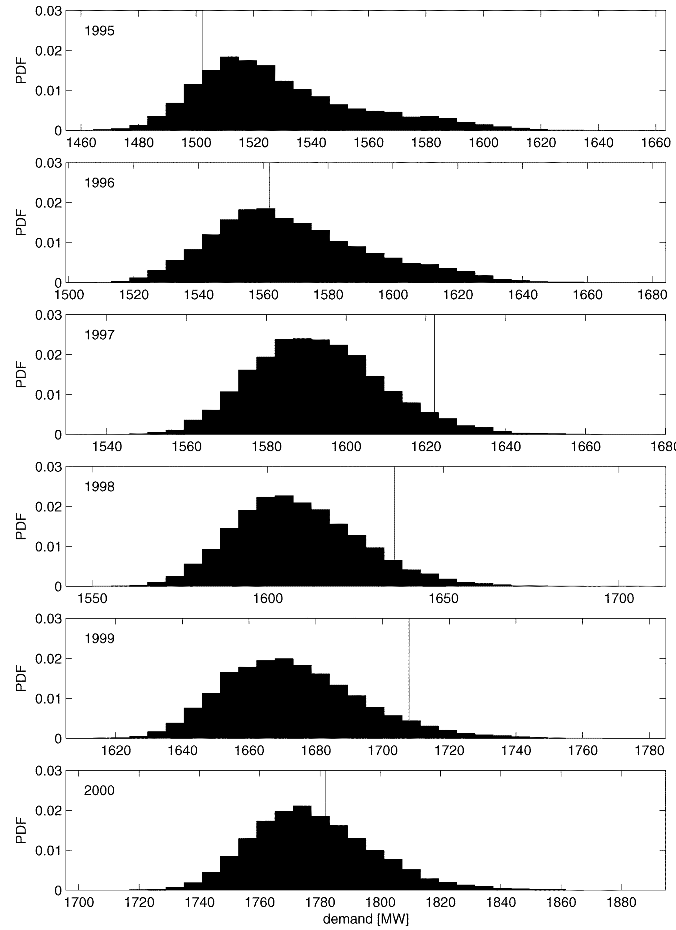

Fig. 5. PDF for the forecasts of and actual (vertical line) peak electricity demand for years 1995 to 2000.

values had a NRMSE of 0.24 and a MAPE of 2.52. Taking averages over the results achieved using simulated weather values gave a NRMSE of 0.25 and a MAPE of 2.57. While five years is insufficient to provide a formal analysis of the accuracy of the forecast densities of the timing and magnitude of the peak demand, these appear adequate for describing the position and uncertainty of the peak demand forecast.

The model assumes that the quadratic growth experienced during the training data of the previous four years will continue throughout the following year. While this has been a reasonable assumption during the last decade, an inspection of the annual percentage growth of the total energy consumption over the last four decades in the Netherlands shows that while there is generally an upward trend, this is not always the case (see Fig. 6). A period of decay between 1980 and 1982 was associated with an economic recession, since the Gross Domestic Product (GDP) strongly influences the amount of energy consumption. Moreover, the annual growth (see Fig. 6) demonstrates that the latter period (1984–1998) has been much more stable than the earlier period (1960–1983). Long-range forecasts with lead times between a year and ten years should incorporate socioeconomic information, such as predictions of GDP and demographics.

All these observations point to the fact that electricity demand is extremely dependent on the economy and that statistical forecasts, such as those provided by (1), should only be used for decision-making in the light of additional knowledge about the state of the economy. Indeed, the intervention of human intuition is often necessary to incorporate this additional information.

TABLE III

ACTUAL PEAK DEMAND AND A SUMMARY OF THE FORECAST DISTRIBUTION FOR THE PEAK DEMAND: MEAN, STANDARD DEVIATION, SKEWNESS, KURTOSIS, 1%, 5%, 10%, MEDIAN, 90%, 95%, AND 99% PERCENTILES

Year	1995	1996	1997	1998	1999	2000
Peak	1502	1562	1622	1636	1708	1782
Mean	1529	1569	1593	1609	1673	1778
S.D.	28.01	24.24	16.40	18.05	20.66	20.54
Skewness	0.83	0.58	0.40	0.46	0.55	0.57
Kurtosis	0.29	0.04	0.27	0.42	0.41	0.68
1%	1482	1525	1560	1572	1633	1737
5%	1493	1535	1568	1581	1643	1748
10%	1498	1541	1573	1587	1648	1753
Median	1523	1566	1592	1607	1671	1776
90%	1571	1604	1615	1632	1701	1805
95%	1585	1615	1622	1640	1710	1814
99%	1605	1631	1636	1656	1730	1835

VI. CONCLUSIONS

The model expressed in (1) has been shown to be capable of capturing the various factors that govern electricity demand, such as i) the day of the week, ii) intrayear seasonality, iii) the summer holiday period, iv) the Christmas holiday period, and v) feast days. Furthermore, this model is able to incorporate the

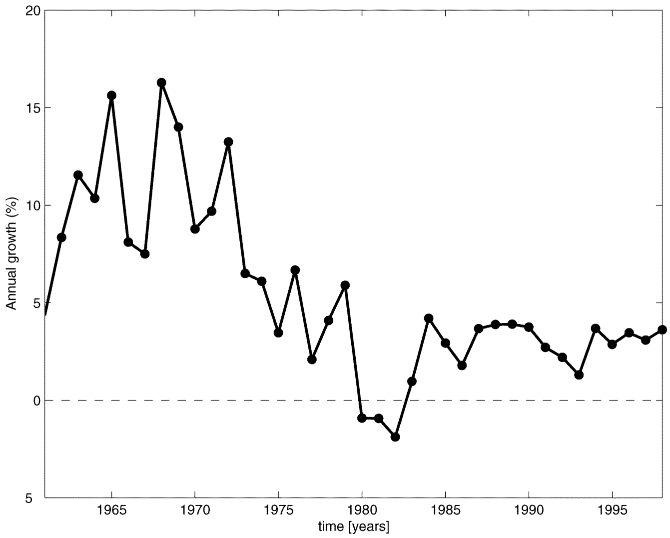

Fig. 6. Total energy consumption for the Netherlands: annual percentage growth during the years 1960 to 1998.

effect of weather on the daily electricity demand. For forecasts with a lead time of one year, where no weather forecasts are available, it is possible to use simulated weather data to generate probabilistic forecasts. Simulated weather data were produced by constructing surrogates of the original temperature, wind speed, and luminosity time series. These surrogates preserve the distribution, autocorrelation, and cross-correlations of these original weather time series. Model inadequacy [28] was incorporated in the probabilistic forecasts by sampling from the errors realized while training on the previous four years.

Probabilistic weather forecasts [21], [22] are currently available from the US-based National Centers for Environmental Prediction (NCEP) and the European Centre for Medium-Range Weather Forecasts (ECMWF). These probabilistic temperature forecasts have value for approximately two weeks ahead [23], [24] and could be used to replace the simulated temperatures and generate short-term forecasts of the daily demand [18]. In this way, the model could be used to provide superior forecasts of the magnitude and location of the peak demand up to two weeks ahead.

There are a number of practical applications for these probabilistic forecasts of daily electricity demand. Forecasts of the magnitude of the peak demand are useful for both capacity planning and investment decisions. In addition, the ability to forecast the timing of the peak demand is important for maintenance planning. These probabilistic forecasts can be used to improve decision making. In summary, these forecasts can reduce both costs and risks for those operating in electricity markets.

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