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Long-term peak load forecast in the Greek power system

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Abstract: This paper presents a novel approach for long-term electric power load forecasting. A 15-year peak load forecast is performed concerning the Greek interconnected system. The peak loads of the past twenty six years (from 1980 to 2005) are used as data sample and are analyzed in order to forecast the maximum power demand in the Greek interconnected system until 2020. In order to receive better forecasting results, the General Modified Exponential (GME) is applied in four different ways. The results from these methods are evaluated and the modified logistic is considered as the best, by which the final load forecasts are calculated. The results demonstrate the efficiency of the method, since the load forecasts have a mean absolute error of only 1.88%.

Key-Words: peak load, long-term forecasting, sigmoids, GME, modified Logistic

1 Introduction

It is well known in the scientific community that peak load forecasts play an important role in the planning of power systems. Load forecasting is the motivation under various plans and decisions on investment in the power market. As a result, an accurate power demand forecast in the long run (five to twenty years), motivates companies to construct power plants and/or plan power production for future utilization in order to cover the growth in the power demand.

In general, load forecasting problems can be broadly divided into three main categories: (i) short-term forecasts (a few minutes, hours or days to a few weeks ahead), (ii) mid-term forecasts (a few months to 5 years ahead), and (iii) long-term forecasts (up to twenty years ahead) used for system planning, scheduling construction of new generating capacity, as mentioned above. The last case is studied in this paper.

The structure of this paper is as follows: in Section 2 the literature on load forecasting is presented. Section 3 describes the method used for long-term peak load forecasting in this paper, and Section 4 presents the results of the analysis concerning the next years, until 2020. Finally, in Section 5 the results are evaluated and useful conclusions are drawn.

2 Literature review

A variety of methods have been employed for load forecasting, ranging from simple extrapolation methods to more complex time-series techniques, optimization methods, or even hybrid models that use a combination of relevant parameters for the purposes of the forecasting. Until now there is no consistent methodology to determine the relevant parameters to be used as independent variables in load forecasting. In most cases these variables are chosen using a linear correlation analysis with respect to the past load values, expressing a particular past situation, and with only this linear correlation criterion some validity questions to further future implications are raised.

All models applied to forecast the short, medium or long–term load are greatly influenced by the characteristics of the past load observations. So, a fair comparison of an old one and a new one method would have to be based on the respective errors when applied to the same years as data selected. That, however, is not provided by a direct reading of the literature, especially in the recent past, in which there is no particular data consistence in the received research results. To this context, several past methods are presented in this section.

Melamed, Morzhin, Timchenko, Tsvetkov and Zharkin, (1989) [1] described methodological approaches to solving long-term and short-term electrical power system load-forecasting and operational planning problems existing in the USSR, as well as information and system technological aspects of these problems. Their observations and future directions of methodological and program elaborations in this field were also discussed. The load-forecasting methods used in the USSR, which began to be used in the Soviet Union electric power system from the early 1970s, are presented. The authors argue that in order to improve forecasting and planning methodologies it is expedient to consolidate efforts of researchers from different countries through exchange of experience gained from investigations and elaborations.

Stutz (1990) [2] resumed the reasons for a shift in the long-term forecasting of electric loads, from an econometric to an engineering end-use approach, as well as ways in which econometric analysis were used to supplement end-use analysis. In his work, he implied that load prediction using end-use forecasting scenarios constructed by other means was better than from the endogenous modelling of consumer preference, and this important questioned preference stand in need of further discussion.

Kermanshahi (1998) [3] examined two artificial neural networks, a recurrent neural network (RNN) and a three-layer feed-forward back-propagation (BP), for long-term load forecasting until 2005 in Japan at national level. The RNN was designed to forecast the loads of one year ahead and the BP was used to forecast the next five and ten year's loads. The actual data of the survey was loads received from the past twenty years (from 1975 to 1994) and were tested for target years from 1995 to 1997, 2000, and 2005. The research results have demonstrated that the proposed RNN gave relatively accurate load forecasts, while the forecasted results were strongly influenced by the past and present economic situations and power demand. They also provide evidence that mid-term or long-term forecasts are not always accurate, and should be considered as a reference or rough forecasting and then be corrected by new coming information.

Al-Saba and El-Amin (1999) [4] developed an application of Artificial Neural Networks (ANN) for long-term load forecasting. They applied the ANN model to forecast the annual peak demand of a Middle Eastern utility up to 2006, and they argued that the uncertainty that characterizes such forecasts was very large making long-term load forecasting an extremely challenging computational problem. The concluding remarks demonstrate that ANNs can be used for long-term forecasting with minimum errors and better results than other forecasting techniques, providing a useful option for effective resource planning.

Hirschhausen and Andres (2000) [5] investigated several scenarios of electricity demand in China until 2010, at a national, a sectoral and a regional level. They took into account the recent macroeconomic downturn in the Chinese economy and the potential effects of deregulation and price increases in the power sector. They applied a simple Cobb-Douglas function, and they assumed constant income and price elasticity's, as well as, an autonomous increase in energy efficiency. They concluded that the large industrial areas in eastern China and the Central region are likely to face overcapacity, whereas North China and the peripheral regions may face deficits.

Jia, Yokoyama, Zhou and Gao (2001) [6] examined a flexible long-term load forecasting method based on a new dynamic theory - General

Simulation (GSIM) theory that can treat as a whole two kinds of logical and intuitive information simultaneously and integrally. In order to predict long-term load forecasting in power systems and improve the accuracy of forecasting, the applied method divided relations of factors correlated with power demand into functional relations and impact relations and showed the ability to learn the inter-dependencies between the affecting factors and deal with these two kinds of relations simultaneously. The simulation has used a twenty-year historical data of Tokyo area and its result for a five-year forecasted period was compared with traditional method-multiple linear regression, where the feasibility of the proposed method has been demonstrated.

Kermanshahi and Iwamiya (2002) [7] tried to forecast peak electric loads in Japan up to year 2020. They applied two artificial neural networks, a recurrent neural network (RNN) and a three-layer feed-forward back-propagation (BP), for long-term load forecasting until 2020 at nine Japanese power companies. Predictions were done for target years 1999, 2000, 2005, 2010, 2015, and 2020, and the data of the survey consisted of loads received from the past twenty one years (from 1975 to 1995) in Japan. The authors argue that, unlike short-term load forecasting, long-term load forecasting is mainly affected by economical factors rather than weather conditions. The research has focused on economical factors that seem to influence long-term electric load demands, which were: actual yearly, incremental growth rate from the previous year, and both together (actual and incremental growth rate from the previous year). The research results have demonstrated that the proposed BP and RNN gave relatively accurate load forecasts, while the changes in loads are referred as a reflection of the economy.

Al-Hamadi and Soliman (2005) [8] examined a mid or long-term electric load forecasting technique for forecasting hourly daily load demand for a lead-time of several weeks to a few years. They implemented the strong short-term correlations of daily and yearly load behaviour to predict future load demand. The load data of the survey was loads from one of a largest utility company in Canada for the years 1994 and 1995. Regression models were obtained from 1994 data and used to project load demand for 1995. The results demonstrate successful (one year ahead) load forecast with a mean absolute error of less than 3.8% and with a standard deviation of less than 4.2, which proved to some extent superior to other techniques published earlier in the related literature and with further applications to a longer forecasted period than was one year.

3 Data and Methodology

Time series models make efficient and sufficient use of available historical records for long-term forecasting [9]. Here, the observations (electricity load) are expressed purely as a function of time, rather than by relating it to other economic, demographic, and technological variables [10]. This function of time is obtained as the function that best explains the available data, and is observed to be most suitable for simple and accurate predictions [11]. One of the time series methods is the use of trend curves, polynomials, exponentials, and especially, sigmoids, like the General Modified Exponential model (GME or generalized logistic) [12]. The GME is determined by:

$$y_t = \frac{a}{[1+\phi \exp[-b(t-\gamma)]]^{1/\phi}} \qquad (1)$$

where α = upper asymptote, b = rate, $t = \gamma$ = point of inflection, and ϕ = power low parameter

Special cases of the GME are:

(i) ϕ = 1, which referred as Logistic model and (1) is transformed to:

$$y_t = \frac{a}{[1+\exp[-b(t-\gamma)]]} \qquad (2)$$

(ii) ϕ = 0, which referred as Gompertz model and (1) is transformed to:

$$y_t = a\exp[-\exp[-b(t-\gamma)]] \qquad (3)$$

(iii) ϕ = -1, which referred as Simple Modified Exponential model and (1) is transformed to:

$$y_t = a[1-\exp[-b(t-\gamma)]] \qquad (4)$$

The addition of a constant c in (1) results in the equation's shift vertically by the amount of constant c, so that (1) lies between the asymptotes (c) and (c + α). Thus, the extensions of the GME, if a constant c is added to (2), (3) and (4), respectively, are modified to:

(i) the five Parameter General Modified Exponential model
(ii) the Modified Gompertz model
(iii) the Modified Logistic model, which is equivalent to the Bass model (Extended Logistic), written as a function of time [*see Endnote (iii)*], given as:

$$y_t = \frac{a' + b' \exp(-bt)}{1 + \delta' \exp(-bt)} \tag{5}$$

where:

- $\alpha' = \alpha + c$, $b' = c \exp(b\gamma)$, $\delta' = \exp(b\gamma)$, and
- for $b' = 0$, equation (5) is transformed to the Logistic, and
- for $d' = 0$, equation (5) is transformed to the Simple Modified Exponential.

Table 1. Peak loads in the Greek power system, in MW

Year	Peak load	Year	Peak load
1980	3.554	1993	5.498
1981	3.654	1994	5.963
1982	3.788	1995	6.063
1983	3.813	1996	6.503
1984	3.940	1997	6.705
1985	4.109	1998	7.372
1986	4.260	1999	7.366
1987	4.445	2000	8.531
1988	4.576	2001	8.600
1989	4.738	2002	8.924
1990	4.924	2003	9.042
1991	5.460	2004	9.370
1992	5.371	2005	9.582

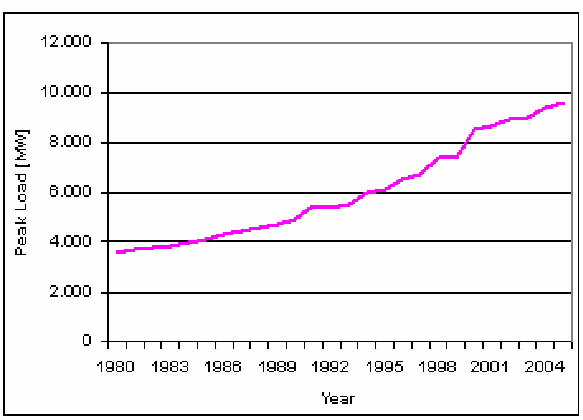

Fig. 1. Peak loads in the Greek power system, in MW

In Greece, electric power demand has steadily increased with an excessive rate, while the peak electric power demands of the total power interconnected network has been increasing at an average of 4% per year the last three decades, accounting in this process upward or downward trends [13]. Table 1 and Figure 1 reveal these interesting remarks.

Our approach examines these historical peak load data in Greece from 1980 to 2005. The applied models are described by equations (1)-(4), with or without a constant *c* that is added separately in each equation, as a possible explanation of the missing past observations before 1980. Preliminary identification techniques show that the Simple Modified Exponential model and the Gompertz model are not suitable. The selected applied models are the Logistic, the Logistic plus a constant *c* (Modified Logistic method), the GME, and the GME plus a constant *c*. The econometric software E-Views 4.0 [14] is used, in order to forecast yearly peak load in Greece for the next fifteen years (from 2006 up to 2020).

Table 2. Model estimations

	α	b	γ	ϕ	c
Logistic	24.510,73	0,059	33,4		-
-//- + c	8.972,52	0,163	20,2		3.272,16
GME	9.610,44	1,753	23,1*	39,02*	-
-//- + c	6.936,83	0,842	20,8*	9,51*	2.639,67

* N.S. = non-significant

Table 3. Model evaluations

	R-squared $-R^2$	*Sum squared resid-SSR*	*Durbin-Watson stat*	*Mean absolute error*
Logistic	0,982434	1.753,208	0,83	3,90 %
-//- + c	0,992815	717.089,6	1,91	1,88 %
GME	0,988521	1.145,683	1,24	3,01 %
-//- + c	0,994902	508.826,8	2,62	1,37 %

In order to estimate which model among these provides better results, non-linear regressions are performed separately for each one. The GME and the GME plus a constant *c* are rejected, as the model estimations gave for them ϕ > 1 and N.S. (Tables 2–3). The Modified Logistic model (the Logistic plus a constant *c* – see equation (5)) is more suitable as reveals the received results at Tables 2–3. The Modified Logistic model, with $R^2 = 0{,}992815 > 0{,}982434$, a mean absolute error of

1.88%, *SSR* = 717.089,6 > 1.753,208, and a combination of other model evaluations, proves superior to the Logistic model, which is observed to be symmetric around the point of inflection. The final results of the Modified Logistic model are better than other techniques published earlier in the long-term load forecasting literature.

4 Forecasting results

An individual forecasting with the Modified Logistic model (see equation (5)) is performed. The peak load forecasts for years 2006 to 2020 are presented in Table 4 and Fig. 2 (with ±2 S.E. - Standards Errors).

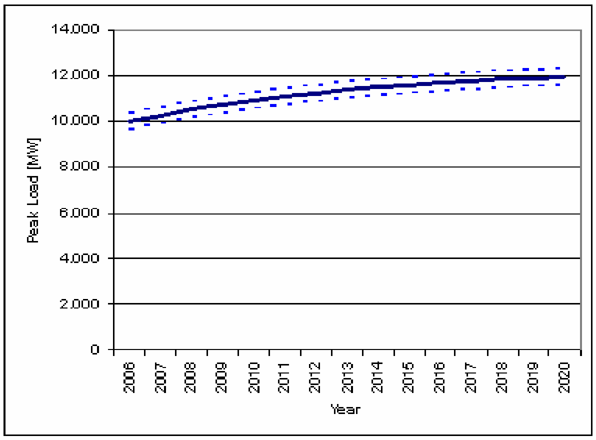

Fig. 2. Peak load forecasts, in MW

It is evident that peak load long-term forecasting will prevail in the forthcoming years, having a stable increase rate. Load forecasting for electric power will reach approximately 11.952 MW in 2020, having an increase equal to 24,73% as compared to 2005. Therefore, additional electric power production will be required in the near future to meet the excessive electric power demand.

Table 4. Peak load forecasts, in MW

Year	Peak load	Year	Peak load
2006	10.013,37	2014	11.505,14
2007	10.275,36	2015	11.608,50
2008	10.514,48	2016	11.698,38
2009	10.730,84	2017	11.776,27
2010	10.925,08	2018	11.843,58
2011	11.098,23	2019	11.901,62
2012	11.251,60	2020	11.951,54
2013	11.386,71		

5 Conclusions

Long-term peak load forecasts drives various plans and decisions on investments in modern power systems. This paper presents the results of a study on peak load forecasting in the Greek interconnected system up to 2020. The GME is applied in four different approaches. The received results from these models are evaluated and as better is concluded the Modified Logistic model. The model estimation demonstrates successful to some extent load forecast with a mean absolute error of less than 1.88%, and with a combination of other model evaluations, is proved superior to other techniques published earlier in the long-term load forecasting literature. Last, the received forecasted results shows an increase at approximately 11.952 MW in 2020 (equal to 24,73% as compared to 2005). Thus, additional electric power production will be required in the near future to meet the excessive electric power demand in the Greek power system.

Endnotes:

(i) The views expressed are those of the authors and do not necessarily represent the policies of the institutions with which they are affiliated.

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(iii) The Modified Logistic model (Logistic + *c*) is proved to be equivalent to the Bass model, as a function of time, from below [15]:

$$\begin{aligned} &\textit{Modified Logistic model} = \\ &= \frac{a}{1+\exp[-b(t-\gamma)]} + c = \\ &= \frac{(a+c)+c\exp[-b(t-\gamma)]}{1+\exp[-b(t-\gamma)]} = \\ &= \frac{a' + [c\exp(b\gamma)]\exp(-bt)}{1+\exp(b\gamma)\exp(-bt)} = \\ &= \frac{a' + b'\exp(-bt)}{1+\delta'\exp(-bt)} = \\ &= \textit{Bass model, as a function of time} \end{aligned} \tag{6}$$

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