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Modeling and forecasting electric daily peak loads using abductive networks

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Abstract

Forecasting the daily peak load is important for secure and profitable operation of modern power utilities. Machine learning techniques including neural networks have been used for this purpose. This paper proposes the alternative modeling approach of abductive networks, which offers simpler and more automated model synthesis. Resulting analytical input–output models automatically select influential inputs, give better insight and explanations, and allow comparison with other empirical models. Developed using peak load and extreme temperature data for 5 years and evaluated on the sixth year, a model forecasts next-day peak loads with an overall mean absolute percentage error (MAPE) of 2.50%, outperforming neural network models and flat forecasting for the same data. Two methods are described for forecasting daily peak loads up to 1 week ahead through iterative use of the next-day model or using seven dedicated models. Effects of varying model complexity are considered, and simplified analytical expressions are derived for the peak load. Proposals are made for further improving the forecasting accuracy.

Keywords: Abductive networks; Neural networks; GMDH; Machine learning; Modeling; Forecasting; Load forecasting; Peak load; STLF; Power system planning

1. Introduction

Short-term load forecasting (STLF) [1] is important for performing many power utility functions, including generator unit commitment, hydro-thermal coordination, short-term maintenance, fuel allocation, power interchange, transaction evaluation, as well as network analysis functions, security and load flow studies, contingency planning, load shedding, and load security strategies. With ever-increasing load capacities, a given percentage forecasting error amounts to greater losses in real terms. Recent changes in the structure of the utility industry due to deregulation and increased competition also emphasize greater forecasting accuracies. STLF forecasting covers the daily peak load, total daily energy, and daily load curve as a series of 24 hourly forecasted loads. This paper is concerned with modeling and forecasting daily peak loads with lead times of 1–7 days.

Univariate time series techniques such as the Box–Jenkins integrated autoregressive moving average (ARIMA) [2] have been used for peak load forecasting. However, these techniques have limited accuracy because they ignore important weather effects, are time consuming, require extensive user intervention and may become numerically unstable [3]. Multivariate causal models use multiple regression to express the peak load as a function of exogenous inputs including weather and social variables [4]. In addition to the complexity of the modeling process, regression models are often linear devices that attempt to model distinctly nonlinear relationships [5]. Even when a nonlinear relationship is attempted, it is difficult to determine empirically the correct complex relationship that exists between the peak load and the other explanatory inputs.

The availability of large amounts of historical load and weather data at power utilities has encouraged the use of data-based machine learning modeling methods such as neural networks. With such techniques, the user does not need to explicitly specify the model relationship, which enhances automatic knowledge discovery without bias or influence by prior assumptions. Complex nonlinear input–output relationships can be modeled automatically through supervised learning using a database of solved examples. Once synthesized, the model can generalize to perform predictions of outputs corresponding to new cases. Feed-forward neural networks trained with error back-propagation have been widely used for modeling and forecasting the daily peak load, e.g. Refs. [6–13]. However, neural networks suffer from a number of limitations, including difficulty in determining optimum network topology and training parameters [14]. There are many choices to be made in determining numerous critical design parameters with little guidance available [5], and designers

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often resort to trial and error approaches [15] which can be tedious and time consuming. Such design parameters include the number and size of the hidden layers, the type of neuron transfer functions for the various layers, the training rate and momentum coefficient, and training stopping criteria to avoid over-fitting and ensure adequate generalization with new data. Recently, techniques such as genetic algorithms have been proposed for the automatic optimization of the structure and parameters of neural networks [16]. Another limitation is the black box nature of neural network models. The models give little insight into the modeled relationship and the relative significance of various inputs, thus providing poor explanation facilities [17]. The acceptability of, and confidence in, an automated load forecasting tool in an operational environment is related to its transparency and its ability to justify obtained results to human experts [18].

To overcome such limitations, we propose using the alternative machine learning technique of abductive networks [19] for daily peak load forecasting. We have previously used this approach to model and forecast next day's hourly load profile [20], monthly domestic electric energy consumption [21], and the minimum and maximum daily temperatures [22,23]. The approach is based on the self-organizing group method of data handling (GMDH) [24]. The potential for GMDH in load forecasting has been realized about three decades ago [25]. However, the technique was somewhat neglected in the literature due to its heuristic nature and limited set of elementary functions [26], as well as the multiple-input–single-output nature of the resulting models and the difficulty of fine-tuning them. Compared to neural networks, however, the method offers the advantages of faster model development requiring little or no user intervention, faster convergence during model synthesis without the problems of getting stuck in local minima, and automatic configuration of the model structure [14]. While relevant input variables are selected automatically during abductive network training, with neural networks this requires additional and separate preprocessing in the form of feature extraction using techniques such as principal components analysis (PCA) [27]. With the abductive model represented as a hierarchy of polynomial expressions, resulting analytical model relationships can provide greater insight into the modeled phenomena, highlight contributions of various inputs, and allow comparison with previously used empirical or statistical models. Information on the significance of the various inputs to the neural network output requires additional effort, e.g. in the form of sensitivity analysis [28]. While many conventional neural network paradigms use a separate validation data set to guard against overfitting, thus reducing the amount of data available for actual training, the method proposed here uses an automatic stopping criterion that penalizes model complexity and operates on the full training set. Analytical model relationships are also easier to export to other software applications compared to neural network models.

This paper uses modern GMDH approaches to model and forecast daily peak loads up to 1 week ahead, illustrating modeling simplicity and adequate forecasting accuracy, and highlighting unique explanation capabilities not provided by neural networks. Following a brief description of GMDH and the abductive network modeling tool in Section 2, the load and temperature data set used is described in Section 3. Next-day peak load forecasters are described in Section 4 and their performance compared with neural networks and flat forecasting methods. In Section 5, two different abductive modeling approaches are presented for forecasting the daily peak load up to 7 days ahead, and the influence of temperature forecasting errors is considered.

2. GMDH and AIM abductive networks

Abductory inductive mechanism (AIM) [29] is a supervised inductive machine-learning tool for automatically synthesizing abductive network models from a database of inputs and outputs representing a training set of solved examples. As a GMDH algorithm, the tool can automatically synthesize adequate models that embody the inherent structure of complex and highly nonlinear systems. The automation of model synthesis not only lessens the burden on the analyst but also safeguards the model generated from being influenced by human biases and misjudgements. The GMDH approach is a formalized paradigm for iterated (multi-phase) polynomial regression capable of producing a high-degree polynomial model in effective predictors. The process is 'evolutionary' in nature, using initially simple (myopic) regression relationships to derive more accurate representations in the next iteration. To prevent exponential growth and limit model complexity, the algorithm selects only relationships having good predicting powers within each phase. Iteration is stopped when the new generation regression equations start to have poorer prediction performance than those of the previous generation, at which point the model starts to become overspecialized and therefore unlikely to perform well with new data. The algorithm has three main elements: representation, selection, and stopping. It applies abduction heuristics for making decisions concerning some or all of these three aspects.

To illustrate these steps for the classical GMDH approach, consider an estimation database of n_e observations (rows) and $m+1$ columns for m independent variables ($x_1, x_2, \ldots, x_m$) and one dependent variable y. In the first iteration we assume that our predictors are the actual input variables. The initial rough prediction equations are derived by taking each pair of input variables ($x_i, x_j; i,j=1,2,\ldots,m$) together with the output y and computing the quadratic regression polynomial [24]

$$y = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_ix_j \quad (1)$$

Each of the resulting $m(m-1)/2$ polynomials is evaluated using data for the pair of x variables used to generate it, thus producing new estimation variables ($z_1, z_2, \ldots, z_{m(m-1)/2}$) which would be expected to describe y better than the original variables. The resulting z variables are screened according to some selection criterion and only those having good predicting power are kept. The original GMDH algorithm employs an additional and independent selection set of n_s observations for