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Neural Networks in Electric Load Forecasting: A Comprehensive Survey

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ABSTRACT

Review and classification of electric load forecasting (LF) techniques based on artificial neural networks (ANN) is presented. A basic ANNs architectures used in LF reviewed. A wide range of ANN oriented applications for forecasting are given in the literature. These are classified into five groups: (1) ANNs in short-term LF, (2) ANNs in mid-term LF, (3) ANNs in long-term LF, (4) Hybrid ANNs in LF, (5) ANNs in Special applications of LF. The major research articles for each category are briefly described and the related literature reviewed. Conclusions are made on future research directions.

KEYWORDS: Artificial Neural Networks (ANNs), Load Forecasting(LF), Short Term LF, Mid Term LF, Long Term LF, Peak LF, Unit Commitment(UC)

1 INTRODUCTION

The forecasting of electricity demand has become one of the main research fields in electrical engineering. The basic attraction in load forecasting is normally the hourly total system load. However, load forecasting is also concerned with the estimation of hourly, daily, weekly and monthly values up to 20 years ahead of the system load, peak system load and the system energy. Srinivasan and Lee [1] categorized load forecasting in terms of the scheduling horizon's duration: up to 1 day for short-term load forecasting (STLF), 1 day to 1 year for medium-term load forecasting (MTLF), and one to ten years for long-term load forecasting (LTLF). The structure of forecasting module is based on some assumptions. The first step is finding the consumption profile. The graphs showing load demand for three types of customer are illustrated in Fig.1. They are heat sensitive, dehydrator and industrial customer. They are corresponding to STLF, MTLF and LTLF loads, respectively.

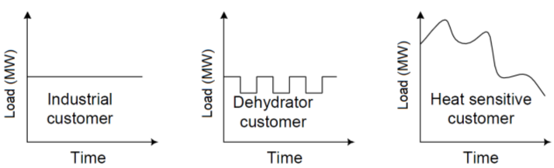

Fig. 1. Example of an ANN architecture with two neurons in the hidden layer.

Recently, much research has been conducted on the application of artificial intelligence techniques to the load forecasting problem. Expert systems such as Fuzzy inference and fuzzy-neural models have been evaluated [2-7], and compared to conventional methods [8-12]. Generally we can distinguish eleven categories of load forecasting techniques as follows:

- multiple regression;
- exponential smoothing;
- iterative reweighted least-squares;
- adaptive load forecasting;
- stochastic time series;
- ARMAX models based on genetic algorithms;
- fuzzy logic;
- neural networks;
- knowledge-based expert systems;
- Support Vector Machines(SVM); and
- Hybrid methods such as ANFIS, neuro-fuzzy and wavelet based ANNs.

However, the models that have received the largest share of attention are undoubtedly the artificial neural networks (NNs). In the past three decades, there has been an ever increasing interest in the field known as artificial neural networks (ANN). Using neural networks enhanced the forecasting accuracy associated with other prediction methods. Recently, due to the ease of use and the excellence in performance, many types of artificial neural network (ANN) have been suggested for load forecasting.

The first reports on their application to the load forecasting problem were issued in the late 1980’s and early 1990’s [13]. Since then, the number of publications has been growing gradually. Judging from the number of published papers, ANN-based forecasting systems have been well acknowledged in practice, and that they are used by many power facilities [14].

In addition to network architecture, the selection of the input vector in ANN architectures is a hot topic in the literature [37–39]. Common theories used as inputs contain past load values recognized by a necessary entropy analysis (to distinguish the number of attached data values), trend (to discriminate homologous periods, e.g. similar days of previous weeks), or exogenous factors such as macroeconomic variables, weather and seasonal variables. There are some causes for unexpected and sudden load fluctuation, as the occurrence of special days like holidays (and normal days surrounding holidays) or recording failures. These irregular load periods and the ways to minimize associated load forecast deviations, are well described in some works [38,40–42].

This survey intends to have a complete overview to the application of artificial neural networks (ANNs) in the field of electric load forecasting. Definitely, this is not the first paper to review the application of ANNs based systems in energy related problems with varying success. Generally, forecasting developments in the field of electrical energy may have been reviewed by some authors from several points of view. However, this study has a different focus. Due to the large number of recorded neural networks oriented forecasting systems in the literature, our paper aims to create a large knowledge base for the researcher, introducing him/her to the specific area of ANNs applications in electric load forecasting. The aim of this paper is to survey and classify ANN-based electric load forecasting techniques published in the last three decades. In comparison with those previous literature reviews, this survey not only covers newer studies, but also contains new classifications that reflect recent research trends. The authors wish to encourage the ground for further comparative discussion on these intelligent ANNs based methods. Due to dominant forecasting strategies reported in the literature, we have categorized the following sections. Section 2 reviews basic ANNs architectures commonly used in LF. In sections 3, 4 and 5, ANNs methodologies is discussed for short-term, mid-term and long-term load forecasting, respectively. Section 6 explains hybrid algorithms which is a combination of ANN with other decision support tools. Section 7 deals with peak load forecasting. Finally section 8 concludes the paper.

2. BASIC ANNS STRUCTURES IN LF

The multilayer feed-forward architecture is still the preferred model in load forecasting applications. Fig.2. gives a simple example of a neural network with two neurons in the hidden layer to relate one output (y) with respect to three independent variables (x_1,x_2 and x_3). The example of Fig.2.is illustrated to exemplify the connections (with associated weights) between the elements (inputs/neurons and neurons/output). Each connection is simply characterized by a weight, for example, the connection between input x_1 to the second neuron is defined by the weight w_{12}.

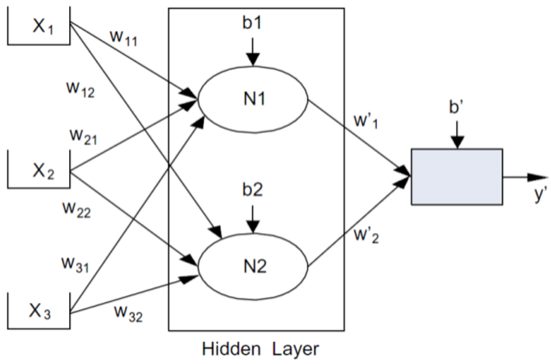

Fig. 2. Example of ANN architecture with two neurons in the hidden layer.

NARX is a non-linear model for time series prediction, resulting from Autoregressive exogenous (ARX) model. It is a recurrent dynamic network, with feedback connections enclosing several layers of the network. It can be explained by following equation and shown in Fig. 3.In this model the current value of the output y(t) is regressed upon the earlier value of the output and exogenous inputs.

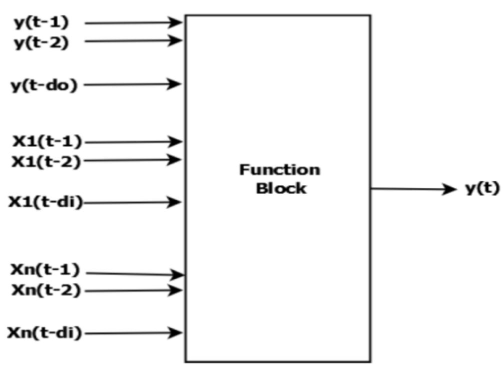

Fig. 3. NARX model.

Many applications of artificial neural network for load forecasting can be found in literature. In the work of D. Bassi et al,[43] they have presented a solution to problem of predicting monthly electric loads (medium term) based on historical load data and economic and demographic data. The neural network chosen for this work is the Time Lagged Feed forward Network (TLFN). ANN was chosen based on methodological selection of variables, a prior study of the problem, the processing that the ANN can make in temporal aspect. Fuzzy set theory based Neural Network model for short term load forecasting is reported in [44]. It uses fuzzy inference to generate rule set from historical data. Then the parameters of rule set are tuned by 3 layered feed-backward networks. This model is used to forecast daily load profile of Greek Interconnected Power System. Papalexopoulos et al, [45] has presented an ANN based STLF system for Pacific Gas and Electric company (PG&E).

Neural network trained with exogenous and endogenous variables is reported in [46] and termed as multi context artificial neural network (MCANN). It is modified form of multi context ANN as it has divided the hidden layer into two parts to speed up network training. Clustering based forecasting method has been reported in [47]. Radial Basis Functions (RBF) has been used to train ANN model. Based on similarity, data is first divided into different clusters and then delivered to two layered RBF-NN for estimation of future demand. Industrial load forecasting has been discussed in [48], in which authors has presented a composite model of fuzzy based neural network to predict long term industrial load. First fuzzy inference is used to estimate yearly maximum and minimum load values, further these results are combined with ANN to predict the annual peak loads. Fuzzy inference and neural model were developed on 10 year data of the industrial city of Ramadan in Egypt. Problem of short term load forecasting for Spanish industrial customers is discussed in [49]. They presented neuro-fuzzy system with back propogation (BP) learning algorithm as well as Autoregressive Integrated Moving Average (ARIMA) process. Industrial customers are classified into different sets based upon their time of use, and then these sets are passed to ANN models. Final results are obtained by averaging results of these models.

In [50], a general methodology based on approximate gradient descent based back-propagation neural network and its variant is used for Spiking Neural Networks (SNN) modeling [14, 15] which is applied for load forecasting. The SNN are the third generation artificial neural networks which are more detailed models and use the neural code of precisely timed spikes. The input and the output of a spiking neuron are described by a series of firing times known as the spike train.

General regression neural network (GRNN) is a precise, reliable, and short-time processing technique in which data is trained in just one presentation of the training patterns and is capable of providing fast and accurate results [54].The GRNN has a structure, arranged in four layers: one input,two intermediate, and one output, as shown in Fig.4.

The paper [51] proposes two methodologies based on a conventional GRNN (C-GRNN) for STMLF. It illustrates the architecture and describes the algorithm of the conventional GRNN. It also describes the studies realized to determine the inputs of the ANNs. The paper [52] proposes a filter based on a GRNN and a moving average filter (MAF) for preprocessing half-hourly load data for STMLF. The paper [53] proposes a modified GRNN (M-GRNN) for quicker forecasting and a procedure to automatically reduce the number of inputs of the ANNs (MRGRNN) for STMLF.

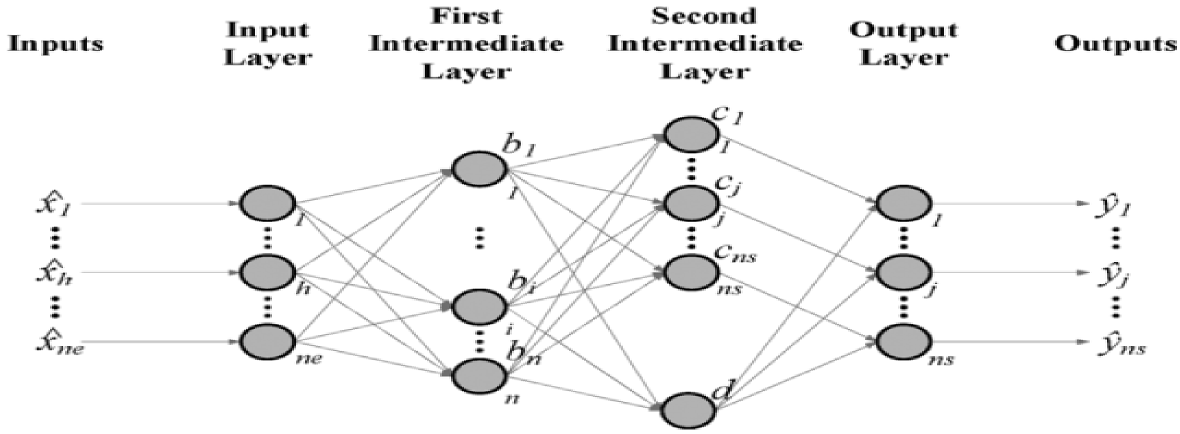

Fig. 4. Architecture of the GRNN.

The SOM acronym stands for self-organizing maps and it was first introduced by T. Kohonen [55]. SOM are a popular neural network based on unsupervised learning. Forecasting is not an intuitive application of self-organizing maps such as the aforementioned clustering or classifying. However, SOM networks' ability to associate new data with similar previously learnt data can be applied to forecasting applications. Fig.5. shows an example of forecasting the second half of a sinusoidal function. In the top left corner of Fig. 5 visualization of a SOM is provided showing its topology and the content of its cells. In this case, each neuron contains both the relevant information known at the forecasting time (the first half of the function) and the actual data to be forecasted (the second half). The paper [56] uses SOM for STLF.

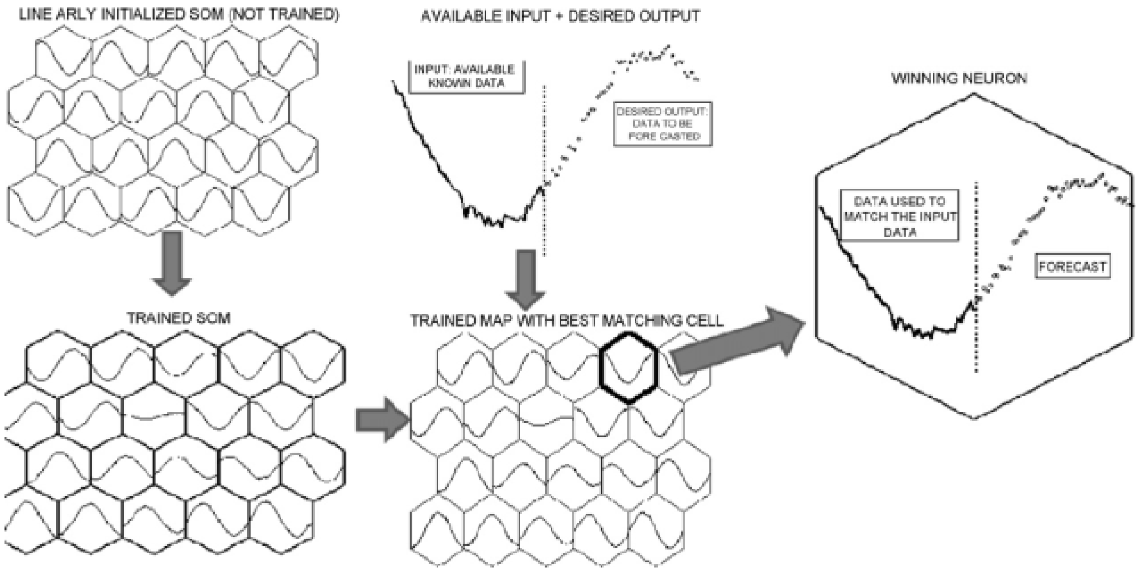

Fig. 5. The application of SOM to forecasting can be described in three steps: (1) Training. (2) Association. (3) Forecasting.

3. ANN-BASED STLF

Estimation of the system load over an interval usually from one hour to one week is known as short-term load forecasting (STLF), an main process in real-time energy supervision. Neural networks demonstrated their ability to extract and learn the relationships between observed variables, leading to excellent results also in STLF [15]. Here we review STLF literatures based on ANNs.

Kazeminejad et al. [16] presented a NN-based short term load forecasting (STLF) method for Iran national power system (INPS) and its regions. The architecture of the proposed network is a three-layer feed forward neural network. Instead of seasonal training, an input as a month indicator is added to the input vectors. The forecasting simulator achieved satisfactory results for one hour up to a week prediction of INPS loads.

Topalli et al.[17], proposed a method to forecast entire electric load one day ahead by neural networks. The learning scheme combined off-line learning with real-time forecasting. They applied Elman's recurrent neural networks for adapting the weights and further adjusting connections according to variable conditions. By separating special days from the normal training sets and a solution is provided for all load types, including working days, weekends and special holidays. Proposed method gave lower percent errors all the time, especially for holidays.

Lauret et al. [18] used Bayesian techniques to optimize neural network based model for electric load forecasting. By this way, significant advantages over classical neural network (NN) learning methods were achieved. This model is capable of citing automatic tuning of regularization coefficients, selection of the most important input variables, derivation of an uncertainty interval on the output.

Xiao et al. [19], introduced a back propagation neural network with rough set (RSBP) for complicated STLF with dynamic and non-linear factors to develop the accuracy of predictions. Using rough set, they avoided the influence of noise data and weak interdependency data to BP and also they decreased the training time.

Khosravi et al. [20] constructed prediction intervals using delta techniques and applied them for outcomes of neural network models. Also, simulated annealing is used for minimization of cost function and adjustment of neural network parameters. The generated prediction intervals out performs the traditional ones by delta techniques. The advantages of the proposed method are that its computation mass after completion of optimization stage is nothing. This makes its application for real time planning possible.

Deihimi and Showkati [21] introduced ESN as the state-of-the-art recurrent neural network (RNN) to do both 1-h and 24-h ahead predictions while using the least number of inputs: current-hour load, predicted target-hour temperature, and only for 24-h ahead forecasting, day type index. In addition, they studied the effect of temperature prediction errors on ESN network by sensitivity analysis and applying noisy temperature series. Furthermore, the trend of effects of temperature errors on the ESN-based load forecasts indicates more sensitivity to positive deviations than to negative ones.

Wang et al.[22] employed improved variable learning rate back propagation (IVL-BP) neural networks. IVL-BP introduced two threshold parameters for the amount of the mean square increasing and decreasing in which the learning algorithm is sensitive to the error and convergence speed. They conducted BP algorithm with the optimized weights to achieve short-term load forecasting and illustrated that the proposed load forecasting system has higher accuracy and real-time.

Lópeza et al. [23] presented a forecasting model based on the use of Kohonen's self-organizing maps (SOM) which remained yet mostly unexplored. The scope of this study was not only to prove that SOM neural networks can be effectively used in load forecasting but to offer a detailed analysis of the prediction and a real-world application. The data used to evaluate the validity of the model relates to real consumption data. Also weather-related data was used.

BP algorithm by itself has slow convergence, and easily falls into local minimum limitations. Though the reason for introducing hybrid algorithms is to optimize the network weights though the improved expert tools such as genetic algorithm, fuzzy inference, ANN structure with internal memory or feedback, and wavelet features.

4. ANN-BASED MTLF

This type of load forecast has many uses such as maintenance programing, mid-term hydro thermal management, adequacy assessment, management of restricted energy units, intervention of forward agreements, and expansion of cost effective fuel purchasing schemes. It also provides valuable information for power system development and operations, and offers important benefits for firms working in a regulated or deregulated energy industry.

Chandrashekaraa et al. [24] offered a neuro-expert system for medium term load forecasting and development planning of power distribution systems. The planning module used optimization technique, with heuristic procedures to minimize the entire loss and annual cost. The trained network is applied to forecast the yearly peak loads for a period of ten years. The back propagation algorithm is used to train the artificial neural network and somewhat modified to reduce the training time and memory needs.

Ghiassi et al. [25] introduced a dynamic artificial neural network model (DAN2) for accurate medium term electrical load forecasting (MTLF).They developed seasonal model as an alternative to seasonal weather forecasts which provided excellent fit without reliance upon weather variables. They compared results with those of multiple linear regressions (MLR), ARIMA and a traditional neural network model.

Bunnoona et al. [26] proposed the level appropriately of a wavelet transform and a neural network method that are very significant technique for a load forecasting.

The feature correlating with approximate and detail of each level of wavelet is selected by using the correlated value between factors and components. All of wavelet features are applied to the neural network for training and forecasting.

5. ANN-BASED LTLF

Long term electric load forecasting is very essential for scheduling and development electric supply. This helps in infrastructure development, distribution management and continuous supply, specifically to industrial sector.

Ghanbari et al.[27] used Adaptive Neuro-Fuzzy Inference System (ANFIS) and regression (Linear and Log-Linear) approaches for forecasting annual electricity load. They employed feature selection technique for choosing most important features out of twenty socio-economic and energy-economic factors, and presented a model that was affected by four economical parameters which are Nonoil Real-GDP, Population, Wholesale Price Index and Energy Intensity. Statistical evaluations of the root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) on ANFIS results illustrated higher performance of the proposed method .

Awan et al. [28], introduced long term industrial load forecasting (LTLF) using Nonlinear Autoregressive Exogenous model (NARX) based Feed-Forward Neural Network (FFNN) method, Support Vector Regression (SVR) and Neural Network models. Comparison of results indicated a high acceptable accuracy on monthly and yearly demand estimation for industrial sector.

6. HYBRID METHODS

Since, conventional artificial neural network (ANN) based short-term load forecasting techniques have limitations in their use on holidays, Kim et al. [29] proposed a new short-term load forecasting method for special days in irregular load conditions. These days contain public holidays, repeated holidays, and days proceeding and following holidays. The proposed method uses a hybrid approach of ANN based technique and fuzzy inference method to forecast the hourly loads of special days. In this scheme, special days are ordered into five different day-types. Five ANN models for each day-type are employed to forecast the scaled load curves of special days, and two fuzzy inference models are used to forecast the maximum and the minimum loads of special days. Finally, the results of the ANN and the fuzzy inference models are joined to forecast the 24 hourly loads of special days. They observed that load pattern changes in special days follow the load levels of the same special days in the previous years. Therefore, in order to effectively predict the maximum and the minimum loads of a special day, fuzzy inference model was added to capture the relationship among the above mentioned terms.

Kodogiannis et al. [30] introduced an improved neural networks based short-term electric load forecasting model for the power system of the Greek Island of Crete. Their novel approach was based on neural-fuzzy and performances are evaluated and compared to the conventional back-propagation network forecasting models.

Amjady and Keynia [31] proposed a new methodology to solve the problem of mid-term load forecasting (MTLF). They composed an efficient data model, pre-forecast mechanism and combination of neural network and evolutionary algorithm as the hybrid forecast technique.

7. SPECIAL APPLICATIONS

In this section we review two important applications of load forecasting solved by neural networks. They are unit commitment (UC) and daily peak load. Unit commitment is a tool for the utility company to define an economic schedule of producing units subjected to several unit and system limitations. Daily peak load is a nonlinear, volatile, and non-stationary signal and its precise prediction is very difficult. In the following each case is explained separately:

- Saksornchai et al. [32] used precise hour-ahead and day-ahead demand forecasting for proper unit commitment scheduling. Results from the newly developed neural network based STLF program improved the unit commitment scheduling and minimized the total production costs over a period of time [33-35] which consists of :1)unit generation cost;2) startup and shutdown costs;3)operating and maintenance costs.

The most commonly used constraints in the UC problem are as follows:

1) load demand constraint;

2) system reserve requirement;

3) minimum up/down time of generating units;

4) units' maximum/minimum output power;

5) units' ramp rate limits;

6) crew constraints.

Their proposed new ANN STLF program was able to track a sudden change of load characteristics during the change of seasons. By integrating ANN STLF into the UC scheduling potential cost savings was investigated.

- In case of peak load forecasting (PLF), Amin-Naseri and Soroush [36], presented a hybrid neural network model for daily electrical PLF. Several factors in peak load, e.g. weather temperature, relative humidity, wind speed and cloud cover, were introduced into the model in order to enhance forecast quality. In this study a novel approach for clustering data applied using a self-organizing map. A feed forward neural network (FFNN) has been developed for each cluster to provide the PLF. Eight training algorithms have also been used in order to train the proposed FFNNs. Applying principal component analysis (PCA) decreased the dimensions of the network's inputs and led to simpler architecture. To evaluate the effectiveness of the proposed hybrid model (PHM), forecasting has been performed by developing a FFNN that uses the un-clustered data. The results proved the superiority and effectiveness of the PHM. the results indicated better performance of the PHM than those of Linear Regression (LR) models.

8 Conclusions

Various artificial neural networks (ANN) techniques which have been applied to load forecasting(LF), surveyed in this study. Numerous structures of ANNs commonly used in LF reviewed. Different application of ANN in LF categorized and reviewed in this paper: 1)ANNs in STLF; 2) ANNs in MTLF; 3) ANNs in LTLF; 4) Hybrid ANNs in LF; 5) Special applications of ANNs in LF. After surveying all these approaches, we can observe a clear trend toward new and hybrid ANN forecasting techniques. It seems a lot of current research effort is focused on ANN based STLF systems and particularly combined with other expert methods. There is also a clear move towards hybrid methods. Over the years, the direction of research has shifted, replacing old approaches with newer and more efficient ones.

Over the last few years, the most active research area has been new application dependent structures of neural networks used for load forecasting. Four structures of ANN reviewed in this paper are recurrent neural networks, ANFIS, Self Organizing Maps(SOM) and neuro-fuzzy structures.

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