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# LOAD FORECASTING USING DYNAMIC HIGH-ORDER NEURAL NETWORKS

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**Abstract** - A new short-term load forecasting model based on recurrent high-order neural networks (RHONNs) is presented in this paper. Short-term load forecasts are required so that the dispatch and scheduling of the generating units connected to a power system can be performed to meet the expected demand as economically and securely as possible. The proposed load forecasting model is able to provide accurate short-term load forecasts by using the minimum of input data that is, only historical load data. Due to its dynamic nature, the RHONN forecasting model is able to adapt quickly to changing load conditions like important load variations or changes of the daily load pattern (weekends, holidays etc). Simulation results over hourly load timeseries of the greek island of Crete demonstrate the efficiency of the model. The average absolute error value of the entire year hourly forecasts was 0.68 % while the average of the maximum daily errors was equal to 0.98 %.

**Keywords** : Electricity demand, power system load forecasting, recurrent high-order neural networks.

## 1 Introduction

The objective of power system load forecasting is to enable in all time an adaptation between electricity demand and generation. The requirement for an accurate and robust load forecasting model is fundamental to the secure and economic operation of a power system.

Currently, there are three possible classifications for load forecasting: short-term (from the next 1/2-hour to 24 hours ahead), medium-term (from the next day to the next year) and long-term (beyond the next year).

This paper is concerned with short-term load forecasting which plays an important role for numerous power system functions like unit commitment, economic load dispatch, hydro-thermal coordination, transaction evaluation, maintenance scheduling etc [1-6].

The most important factors, that affect the load evolution in short-term periods, are the time-of-the-day, the day-of-the-week, the various seasonal effects, the weather (dry bulb temperature, relative humidity, wind speed etc.) and so on [1-10].

Since mid-1960's an important research has been performed on load forecasting, while two main approaches to the problem have been developed: a statistical and a knowledge based one [11].

Concerning the statistical approach two types of models have been developed: the peak-load and the load-shape models. In the peak-load models the daily or the weekly peak load consists of a weather-independent base load and a weather-dependent component which is added to the base load [1-2]. Although peak-load models are structurally simple, they are of limited use because they do not contain information about the shape of the daily load curve.

Concerning the load-shape statistical approach two kind of models have been developed: static and dynamic ones [5]. In the static load-shape models, the load is considered to be a linear combination of explicit time functions (sinusoids, polynomials, etc). A special case is the spectral decomposition method in which the time functions represent the eigenfunctions corresponding to the autocorrelation function of the load time series [6]. Static load-shape models are structurally simple and provide good load forecasts for not ordinary days like weekends. However, they are of limited use because they do not represent the effects of the weather on load and they are not effective for special days like hollidays.

The most widely used methods so far are the dynamic load-shape models, like the autoregressive integrated moving average (ARIMA) and the state space models, which incorporate the cumulative effects of the recent load behaviour, of weather and of random events [5-6].

In ARIMA models the load is composed of a deterministic component which represents the periodic behavior of the load curve and a random one which represents deviations from the periodic behavior due to deviations of weather from normal and due to random correlation effects. The reported RMS error of ARIMA models ranged from 2 % to 5.3 % for one-hour ahead forecasts [5].

The main characteristic of the dynamic load-shape models is that they are effective for forecasting of ordinary days, but they are inappropriate for special days [4, 6, 8].

The knowledge based approach has been mainly developed in order to overcome the weakness of the models mentioned above to provide accurate forecasts for both ordinary and special days.

This approach has received much attention in recent years because it can combine human experts' experience with other techniques (statistical, fuzzy decision etc.) to generate load forecasts for days with unusual patterns. The reported average error for one-hour ahead forecasts varies between 1 % and 2 % while the maximum error values are in the order of 4.5 % [8-10].

Recently, a new neural network approach has been developed. In Refs [11-12], a neural network which is based on self-organizing feature maps, is used to identify the various day types from historical load data. The hourly load pattern for a specific day is obtained by averaging the load patterns of several previous days of the same type. Then, two multilayer feedforward neural networks, trained for the specific day, are used for the prediction of the peak and valley load respectively with historical weather and load data as input. The reported average and maximum error for an ordinary day is in the order of 1.25 % and 2.47 % respectively.

From the above discussion it is concluded that there is a tendency to increase modelling complexity, software development and data input in order to develop models able to cover all day types.

In this paper a new load forecasting model, which is based on recurrent high-order neural networks (RHONNs), is proposed. RHONNs are proved to be able to approximate arbitrarily close any process due to their nonlinear dynamic nature. They appear exponential error convergence and they are robust in abrupt input changes and even in the case of missing data.

The implementation of RHONNs in load forecasting provides an accurate and robust load forecasting tool. The proposed neural network model is able to detect rapidly possible abrupt load variations or important changes of the load-shape curve due to special days (weekends or holidays). Then, the neural network weights are dynamically adapted according to these variations and consequently new training procedure is not necessary.

The case-study of the greek island of Crete is examined, while the simplest case where the input of the neural network is only historical load data is considered. One-hour ahead load forecasts have been compared to the actual data of one year and according to the obtained results, the method appears to be superior from other methods which use additional information like temperature etc. In addition, the method is flexible to accept additional input like timeseries of temperature values. In that case even better results should be expected.

## 2 RHONNs for System Identification

Recurrent neural network (RNN) models are characterized by a two-way connectivity between units. This distinguishes them from feedforward neural networks, where the output of one unit is connected only to units in the next layer. In the simple case, the state history of each unit or neuron is determined by a differential equation of the form

$$x_i(t+1) = a_i x_i(t) + b_i \sum_j w_{ij} y_j(t) \quad (1)$$

where  $x_i$  is the state of the  $i$ -th neuron,  $a_i$ ,  $b_i$  are constants,  $w_{ij}$  is the synaptic weight connecting the  $j$ -th input to the  $i$ -th neuron, and  $y_j$  is the  $j$ -th input to the above neuron. Each  $y_j$  is either an external input or the state of a neuron passed through a sigmoidal function, i.e.,  $y_j = S(x_j)$  where  $S(\cdot)$  is a sigmoidal nonlinearity.

In a recurrent *second-order* neural network the total input to the neuron is not only a linear combination of the components  $y_j$ , but also of their products  $y_j y_k$ . Moreover, one can pursue along this line and include higher-order interactions represented by triplets  $y_j y_k y_l$ , quadruplets, etc. This class of neural networks form a recurrent higher-order neural network (RHONN).

Consider now a RHONN consisting of  $n$  neurons and  $m$  inputs. The state of each neuron is governed by a differential equation of the form [13-15]

$$x_i(t+1) = a_i x_i(t) + b_i \left[ \sum_{k=1}^L w_{ik} \prod_{j \in I_k} y_j^{d_j(k)}(t) \right] \quad (2)$$

where  $\{I_1, I_2, \dots, I_L\}$  is a collection of  $L$  not-ordered subsets of  $\{1, 2, \dots, m+n\}$ ,  $a_i, b_i$  are real coefficients,  $w_{ik}$  are the (adjustable) synaptic weights of the neural network, and  $d_j(k)$  are non-negative integers. The state of the  $i$ -th neuron is again represented by  $x_i$ , and  $y = [y_1, y_2, \dots, y_{m+n}]^T$  is the vector consisting of inputs to each neuron, defined by

$$y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \\ y_{n+1} \\ \vdots \\ y_{m+n} \end{bmatrix} = \begin{bmatrix} S(x_1) \\ \vdots \\ S(x_n) \\ S(u_1) \\ \vdots \\ S(u_m) \end{bmatrix} \quad (3)$$

where  $u = [u_1, u_2, \dots, u_m]^T$  is the external input vector to the network. The function  $S(\cdot)$  is a monotone increasing, differentiable sigmoidal function of the form

$$S(x) = \alpha \frac{1}{1 + e^{-\beta x}} - \gamma \quad (4)$$

where  $\alpha, \beta$  are positive real numbers and  $\gamma$  is a real number. In the special case that  $\alpha = \beta = 1, \gamma = 0$ , we obtain the logistic function, and by setting  $\alpha = \beta = 2, \gamma = 1$ , we obtain the hyperbolic tangent function; these are the sigmoidal activation functions most commonly used in neural network applications.

Consider now that there is a dynamical process, whose input/output relation is given by a general difference equation

$$\chi(t+1) = F(\chi(t), \dots, \chi(t-n_\chi), \dots, z(t), \dots, z(t-n_z)) \quad (5)$$

where  $\chi$  is the scalar process output,  $z$  is scalar the process input,  $n_\chi, n_z$  denote the maximum delays of output and input, respectively, and  $F(\cdot)$  is an unknown function.

By setting  $u(t) = [\chi(t), \dots, \chi(t-n_\chi), \dots, z(t), \dots, u(t-n_z)]$  relation (5) is rewritten as

$$\chi(t+1) = F(u(t)) \quad (6)$$

In [13-15] it has been shown that if (i) the function  $f(\cdot)$  satisfies some very mild continuity assumptions, (ii) the vector  $u(t)$  is available for measurable, (iii) the number  $L$  of high-order connections is sufficiently large, and (iv) an appropriate adaptive (learning) algorithm for adjusting the weights of the RHONN, then the RHONN can predict with any degree of accuracy the process (6) output. Moreover, since the process is single-input single-output we can use the following simplified *single-neuron* RHONN model

$$x(t+1) = ax(t) + \left[ \sum_{k=1}^L w_k \prod_{j \in I_k} y_j^{d_j(k)}(t) \right] \quad (7)$$

where all the entities are defined as previously, with the difference that the subscript  $i$  has been omitted since the RHONN consists of one and only one neuron. Moreover, in order to simplify further our model, the vector  $y$  is set equal to  $[S(u_1), \dots, S(u_m)]$ .

The weights  $w_k$  of the RHONN (7) are adjusted using the learning algorithm proposed in [13-15]

$$w_k(t+1) = w_k(t) + \eta \left[ \prod_{j \in I_k} y_j^{d_j^{(k)}}(t) \right] c(t) \quad (8)$$

where  $c(t) = x(t) - \chi(t)$  denotes the prediction error and  $\eta$  is a small positive parameter denoting the learning rate.

## 2.1 RHONNs for Forecasting the Load of Power Systems

We now turn our attention to the problem of forecasting the load of power systems. Our approach is to model the process of the load as a dynamical process of the form (6) where  $\chi(t)$  denotes the load at the time-instant  $t$ . The main problem is that the complete vector of inputs  $u := [u_1, \dots, u_m]$  is not completely available for measurement. Such a situation causes two problems: the first is that the inputs that are not available for measurement may affect considerably the model behavior, and the second problem is that we may consider inputs that do not affect the model behavior at all. The last problem may cause problems to the whole prediction process due to the additional complexity that is required.

In our approach the input vector  $u(t)$  consists of:

- (i) the history of the load of the past 24 hours, i.e. the first 24 components of the vector  $u(t)$  consist of the subvector  $[\chi(t), \dots, \chi(t-23)]$ , where the temporal variable  $t$  is assumed to be updated every one hour,
- (ii) some selected values of the load of the previous days and
- (iii) the error history of the past 24 hours.

The selected values of the load of the previous days are usually selected to be the values  $\chi(t-23 \cdot 2), \chi(t-23 \cdot 3), \chi(t-23 \cdot 4)$ , etc. In other words, if we wish to predict the load at the 10-th hour of May, 23, we include in the input vector the load at the 10-th hour of May, 22, the 10-th hour of May, 21, etc. In our model only selected inputs of the previous two days are used.

## 3 Case Study: Forecasting the Load of the Power System of Crete

In this paper, it is examined the case of the largest greek island of Crete, where the installed generating capacity is 546 MW, while the annual load peak is in the order of 300 MW.

Hourly load timeseries of the year 1987 have been used. The minimum and maximum load in that year was 39.4 MW and 173.4 MW respectively. The daily load curves present generally two peaks; one between 11:00 and 12:00 o'clock and another one between 18:00 and 20:00 o'clock. The minimum load values appear generally between 06:00 and 08:00 o'clock and between 15:00 and 17:00 o'clock. From the graphic representation of the annual timeseries, it is easy to remark the weekly and seasonal periodicities, the dominating weather effects and finally the important effects of special days.

The RHONN that was used was of the form (7), (8); the high-order connections that were used was up to fourth order, i.e. all the terms of the form  $S(u_i), S(u_i)S(u_j), S(u_i)S(u_j)S(u_k), S(u_i)S(u_j)S(u_k)S(u_\ell)$  for all  $i, j, k, \ell$  were included in the RHONN model. The input vector was as described in subsection 2.1.

The training of the RHONN was as follows: initially a large learning rate  $\eta$  was selected (in particular  $\eta = 2.0$ ) and the RHONN was trained using all the available load data. Then, we decreased a little bit the learning rate and we retrained the RHONN; the initial values of the weights  $w_k$  that were used in the second training phase, was that of the end of the first training phase. After the end of the second training phase we used the resulted weights and retrained the RHONN with a lower learning rate. This procedure lasted five training phases. After the fifth training phase, a sixth phase was initiated; the learning rate in this phase was very small ( $\eta = 0.0001$ ). This was done in order to investigate the learning capabilities of the RHONN model; a small learning rate means that the weights are not rapidly changed, and therefore, the previous training is not "forgotten".

The average prediction error that was observed during the 6th phase was 0.68 %, while the average of the daily maximum prediction error was equal to 0.98 %.

Results from testing the forecasting model for seven days (1st to 7th January 1987) are presented in Figure 1. It is remarked that the load patterns of these seven days are different since two holidays (Thursday 1st is New Year's Day and Tuesday 6th is a religious holiday) and one weekend (3rd-4th of January) are included among them.

Detailed results for the 24 one-hour ahead forecasts of the 1st of January as well as the actual load data of this day and the corresponding percentage forecast error are presented in Table 1.

Hour	Actual load (MW)	Forecasted load (MW)	Error (%)
1	95.4	95.5	-0.162
2	81.9	82.0	-0.182
3	71.7	71.8	-0.198
4	59.8	59.9	-0.193
5	54.9	55.0	-0.232
6	51.2	51.3	-0.205
7	51.5	51.6	-0.264
8	50.7	50.8	-0.217
9	54.1	54.2	-0.294
10	65.3	65.4	0.229
11	91.9	92.2	-0.322
12	109.4	109.6	0.241
13	109.9	110.3	-0.348
14	88.9	89.1	0.253
15	73.6	73.9	-0.372
16	70.5	70.7	-0.266
17	72.1	72.4	-0.393
18	89.1	89.3	0.278
19	101.8	102.2	-0.412
20	102.1	102.4	-0.291
21	98.3	98.7	-0.430
22	93.2	93.5	-0.304
23	89.2	89.6	-0.444
24	84.1	84.4	-0.317

Table 1: One-hour ahead load forecasting results for 1st January 1987.

In Figure 2 we present the results of forecasting two consecutive days - 13th and 14th of January 1987 - with different load patterns. The 13th of January has an ordinary day load pattern, while the 14th can be characterized as a special day since

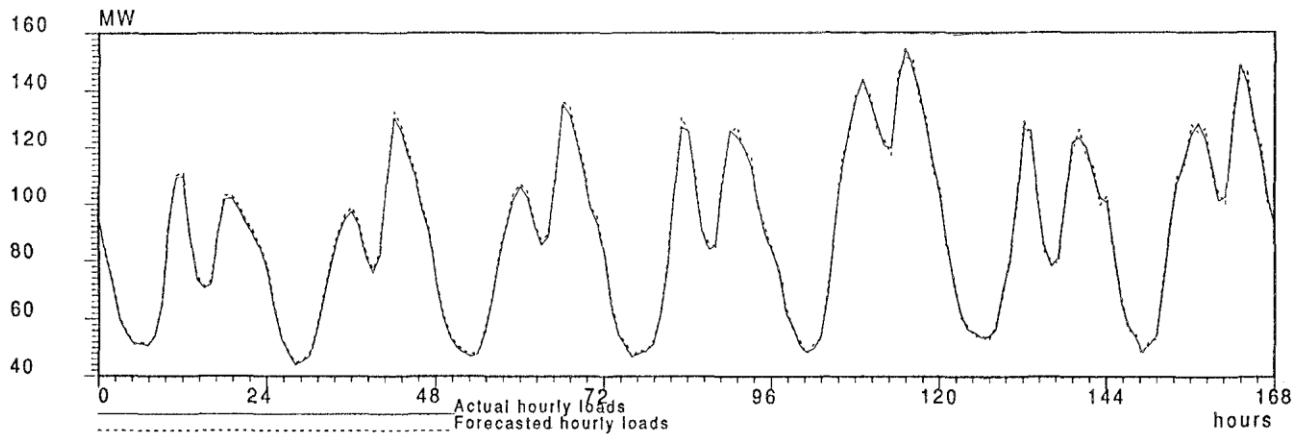


Figure 1: Comparison of actual and one-hour ahead forecasted loads for 1st to 7th January 1987.

Hour	Actual load (MW)	Forecasted load (MW)	Error (%)
1	80.0	79.9	0.091
2	65.0	65.7	-1.093
3	56.0	55.9	0.087
4	52.0	52.5	-1.055
5	49.0	48.9	0.083
6	52.0	52.5	-1.016
7	60.0	59.9	0.080
8	80.0	80.8	-1.055
9	98.0	97.9	0.076
10	104.0	105.1	-1.011
11	107.0	106.9	0.073
12	107.0	108.0	-0.965
13	107.0	106.9	0.069
14	102.0	102.9	-0.919
15	95.0	94.9	0.066
16	90.0	90.8	-0.872
17	92.0	91.9	0.063
18	104.0	104.9	-0.825
19	107.0	106.9	0.06
20	107.0	108.1	-1.065
21	107.0	106.9	0.056
22	107.0	108.1	-1.001
23	102.0	101.9	0.053
24	90.0	90.8	-0.936

Table 2: One-hour ahead load forecasting results for 14th January 1987.

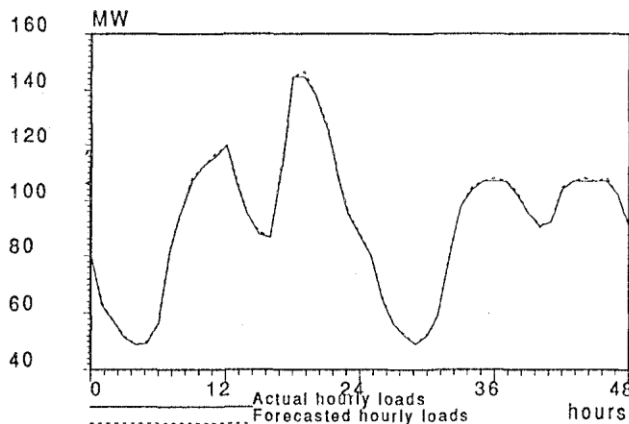


Figure 2: Comparison of actual and one-hour ahead forecasted loads for 13th and 14th January 1987.

an important change from the ordinary load pattern appears. The analytical one-hour ahead forecasting results for the 14th of January are provided in Table 2.

Finally, the values of the average and the maximum absolute percentage errors for each one of the first 15 days of 1987 are given in Table 3. The average values range from 0.285 % to 0.761 %, while the maximum error values range from 0.444 % to 1.242 % respectively.

Day	Mean absolute error (%)	Maximum abs. error (%)
1	0.285	0.444
2	0.438	0.486
3	0.443	0.671
4	0.456	0.888
5	0.601	0.983
6	0.679	0.733
7	0.761	0.923
8	0.707	0.983
9	0.684	1.081
10	0.662	1.097
11	0.674	1.242
12	0.649	1.142
13	0.611	1.228
14	0.528	1.093
15	0.403	0.948

Table 3: One-hour ahead load forecasting results for 1st to 15th January 1987.

## 4 Conclusions

In this paper, a new model for short-term load forecasting is presented and tested with electric utility historical load data. The proposed model is based on recurrent high-order neural networks (RHONN) which, due to their dynamic and nonlinear nature, are able to approximate accurately dynamical processes like the power system load evolution.

The RHONN forecasting model is robust, adaptive to changing load conditions, while its data and computational requirements are minimal.

The case study of the power system of the island of Crete has been examined. Initially, timeseries of actual load data have been utilised for the neural network training. Then, one-hour ahead

forecasts have been performed and compared with the actual hourly load data of one year. The average error of the entire year hourly forecasts was 0.68 %, while the average of the maximum daily errors was equal to 0.98 %.

These results as well as the good performance of the model in forecasting both the load of ordinary and special days prove that recurrent high-order neural networks can be a very efficient tool for power system load forecasting.

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