Pattern-Based Forecasting Monthly Electricity Demand Using Multilayer Perceptron

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Abstract. Medium-term electric energy demand forecasting is coming a key tool for energy management, power system operation and maintenance scheduling. This paper offers a solution to forecasting monthly electricity demand based on multilayer perceptron model which approximates a relationship between historical and future demand patterns. Energy demand time series exhibit non-stationarity, long-run trend, cycles of seasonal fluctuations and random noise. To simplify the forecasting problem the monthly demand time series is represented by patterns of yearly periods, which filter out a trend and unify data. An output variable is encoded using coding variables describing the process. The coding variables are determined on historical data or predicted using ARIMA and exponential smoothing. As an illustration, the proposed neural network model is applied to monthly energy demand forecasting for four European countries. The results confirm high accuracy of the model and its competitiveness compared to other models such as ARIMA, exponential smoothing, kernel regression and neuro-fuzzy system.

Keywords: Medium-term load forecasting · Multilayer perceptron · Pattern-based forecasting

1 Introduction

Power system load forecasting is an integral activity built into the processes of the system operation planning in a longer horizon and its current control. It is impossible to operate the system without accurate predictions. This is due to the fact that electricity cannot be stored in larger quantities and current demand has to be covered by production at any time. The accuracy of forecasts translates into production and transmission costs as well as the degree of reliability of the electricity supplies to recipients. Accurate forecasts of electricity demand are also required in competitive electricity markets. Forecasts for different time horizons and territorial areas determine the investment strategies of energy companies and allow them to optimize their market positions. This directly translates into the financial results of the competitive energy market participants.

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Time series of the monthly electricity demand, which are the subject of this work, usually express an upward trend and yearly seasonality. The trend is correlated with the level of economic development of a given country. Seasonal fluctuations reflect the annual cycle associated with climatic factors and variability of seasons. Among the factors that disrupt both the trend and seasonal variations of the series, political decisions and factors affecting economic development are mentioned.

The methods of medium-term prediction of power systems loads can be divided into two general categories [1]: autonomous modeling approach and conditional modeling approach. In the first approach primarily historical loads and information about weather conditions are applied as input variables to predict electrical power loads. This approach is more suitable for stable economies, without sudden changes affecting the electricity demand. The conditional modeling focuses on the economic analysis and long-term planning and forecasting of energy policy. The socio-economic conditions are taken into account, which influence the energy demand in a given region. Economic growth is described by economic indicators, which constitute additional inputs of the forecasting model [1,2]. The executive parts of these both approaches employ statistical models or models based on machine learning and computational intelligence. Classical statistical models include autoregressive moving average models such as ARIMA, exponential smoothing and linear regression. Limited adaptive abilities of these methods as well as problems with modeling nonlinear relationships have resulted in increased interest in artificial intelligence techniques [3]. Artificial neural networks (NNs) are the most popular representatives of this group. They offer many advantages compared to statistical models such as identifying and modeling nonlinear functions, learning appropriate relationships directly from data, ability to generalization and parallel processing. In [3] the authors applied NNs in two variants: multilayer perceptron and radial basis function network, to forecast the trend of the monthly loads time series. The seasonal component is predicted using the Fourier series. Both forecasts, trend and seasonal fluctuations are aggregated. Due to the problem decomposition, considerable simplification of neural models has been achieved. The networks contained only two hidden neurons, which translated into faster training. Both components of the monthly load time series, a trend and seasonal fluctuations, are independently predicted in [4] using NNs. To identify the trend, the authors used moving averages and cubic splines. The combined forecast turned out to be more accurate than the forecast generated by the single NN.

NNs are often combined with other methods such as fuzzy logic and evolutionary algorithms. For example in [5] they are supported by fuzzy logic. In this work seasonal variables are defined in the form of trapezoidal indicators of the season. The authors train a collection of NNs with the same architecture but other starting weights. NNs responses are aggregated, which in effect gives more accurate forecasts. To prevent overfitting various regularization techniques are used. A weighted evolving fuzzy neural network for monthly electricity demand forecasting was proposed in [6]. Fuzzy rules implemented in neurons are introduced here additively in the training process. The novelty of this work is introducing a weighted factor to calculate the importance of each factor among the different rules. Moreover, an exponential transfer function is employed to transfer the distance of any two factors to the value of similarity among different rules. In [7] NNs trained by different heuristic algorithms, including gravitational search algorithm and cuckoo optimization algorithm, are utilized to estimate monthly electricity demands. The authors showed that the proposed approach outperforms the others and provides more accurate forecasting than traditional methods. An example of combination of NNs and genetic algorithms can be found in [8]. This work uses NNs, which architecture is developed using genetic algorithm to realize the hourly load forecasting based on the monthly total load consumption.

In this work we use multilayer perceptron for forecasting monthly electricity demand. What distinguishes the proposed model from other neural models is that it works on patterns of seasonal cycles of the time series. Patterns allows us to unify data and filter out the trend. The relationship between input and output variables in the pattern space is simpler compared to the original space. Thus, the forecasting neural model has an easier task to solve and can contain only a few neurons.

The paper is organized as follows. Section 2 presents the proposed forecasting model including time series representation using patterns. In Sect. 3 the performance of the proposed model on real-world data is evaluated. Finally, Sect. 4 is a summary of our conclusions.

2 Forecasting Model

Monthly electricity demand time series exhibit yearly cycles which we transform into input patterns. An input pattern $\mathbf{x}_i = [x_{i,1} x_{i,2} \dots x_{i,n}]^T$ of length $n = 12$ is a vector of predictors representing n timepoints preceding the forecasted point, i.e. the time series sequence covering a seasonal cycle $X_i = \{E_{i-n+1}, E_{i-n+2}, \dots, E_i\}$. The vector $\mathbf{x}_i$ is a normalized version of the demand vector $[E_{i-n+1} E_{i-n+2} \dots E_i]^T$. Its components are calculated as follows [9,10]:

$$x_{i,t} = \frac{E_{i-n+t} - \overline{E}_i}{D_i} \tag{1}$$

where $t = 1, 2, ..., n$, $\overline{E}_i$ is the mean value of the sequence X_i, and $D_i = \sqrt{\sum_{j=1}^{n}(E_{i-n+j} - \overline{E}_i)^2}$ is a measure of its dispersion.

The normalized x-vectors for different n-length demand sequences have all the unity length, mean value equal to zero and the same variance. Thus, the input data are unified. The trend is filter out and x-patterns carry information about the shapes of the yearly cycles.

The forecasted variable is $E_{i+\tau}$, i.e. electricity demand at month $i+\tau$, where $\tau \geq 1$ is a forecast horizon. This variable is also encoded to unify data filtering the trend out. The encoded demand is:

$$y_{i,\tau} = \frac{E_{i+\tau} - \overline{E}_*}{D_*} \tag{2}$$

In this equation coding variables $\overline{E}_*$ and D_* should be determined for the seasonal cycle covering the timepoint $i+\tau$. But this future cycle is unobtainable in the moment of forecasting (timepoint i). Thus, the coding variables cannot be determined from it. We use in their place coding variables determined for the known preceding seasonal cycle X_i, i.e. $\overline{E}_* = \overline{E}_i$, $D_* = D_i$. Let us mark this approach by C1.

In the second approach, C2, $\overline{E}_*$ and D_* represents mean value and dispersion of the seasonal cycle including $i+\tau$. When the forecast horizon is $\tau \in \{1, 2, ..., 12\}$, this cycle covers the future sequence $\{E_{i+1}, E_{i+2}, \ldots, E_{i+12}\}$ which is unknown. We predict the coding variables for this sequence using ARIMA and exponential smoothing (ETS).

The third approach for coding variable calculation, C3, is used only for one-step ahead forecasts. In this case $\overline{E}_*$ and D_* are determined on the basis of the sequence $\{E_{i-n+2}, E_{i-n+3}, \ldots, E_{i+1}\}$, where the last component, E_{i+1}, is unavailable. In such case, as in C2, the coding variables are forecasted using ARIMA and ETS.

Having transformed input and output data the training set is composed. It includes pairs of x-patterns and corresponding encoded output variables y: $\Phi = \{(\mathbf{x}_i, y_{i,\tau}) | \mathbf{x}_i \in \mathbb{R}^n, y_{i,\tau} \in \mathbb{R}, l = 1, 2, ..., N\}$. The x-pattern size determines a number of NN inputs, 12. The number of hidden neurons is a variable, adjusted to the complexity of the target function which maps $\mathbf{x}$ onto y. When the forecast horizon is τ, the neural model has one output, y. This variant of the forecasting model is marked by A1 in the simulation study section. But other variant is also considered, marked by A2, where the network forecasts all seasonal cycle for the next year. In this case it has $n = 12$ outputs for $\tau = 1, 2, ..., 12$, and the training set is $\Psi = \{(\mathbf{x}_i, \mathbf{y}_i) | \mathbf{x}_i \in \mathbb{R}^n, \mathbf{y}_i \in \mathbb{R}^n, l = 1, 2, ..., N\}$, where $\mathbf{y}_i = [y_{i,1} y_{i,2} ... y_{i,n}]$. Variants A1 and A2 are used for twelve months ahead forecasts. In experimental part of the work we test the NNs also in one month ahead forecasting (variant B). In this case the training set is Φ, where $\tau = 1$ and x-pattern represents the sequence of twelve months directly preceding the forecasted month.

In all cases the NN has a single hidden layer with sigmoidal neurons. It learns using Levenberg–Marquardt algorithm with Bayesian regularization, which minimizes a combination of squared errors and the weights. This prevent overfitting. The model hyperparameters, i.e. the number of neurons, were selected in leave-one-out cross-validation. When the forecasts of the encoded demands are generated by the network, the forecasts of demands are calculated using transformed equation (2):

$$\widehat{E}_{i+\tau} = \widehat{y}_{i,\tau} D_* + \overline{E}_* \tag{3}$$

3 Simulation Study

In this section, the proposed neural model is evaluated on real-word data including monthly electricity demand for four European countries: Poland (PL), Germany (DE), Spain (ES) and France (FR). The data are taken from the publicly available ENTSO-E repository (www.entsoe.eu). They cover time period from 1998 to 2014 for PL, and from 1991 to 2014 for other countries. Our goal is to construct the forecasting models for 2014 using historical data.

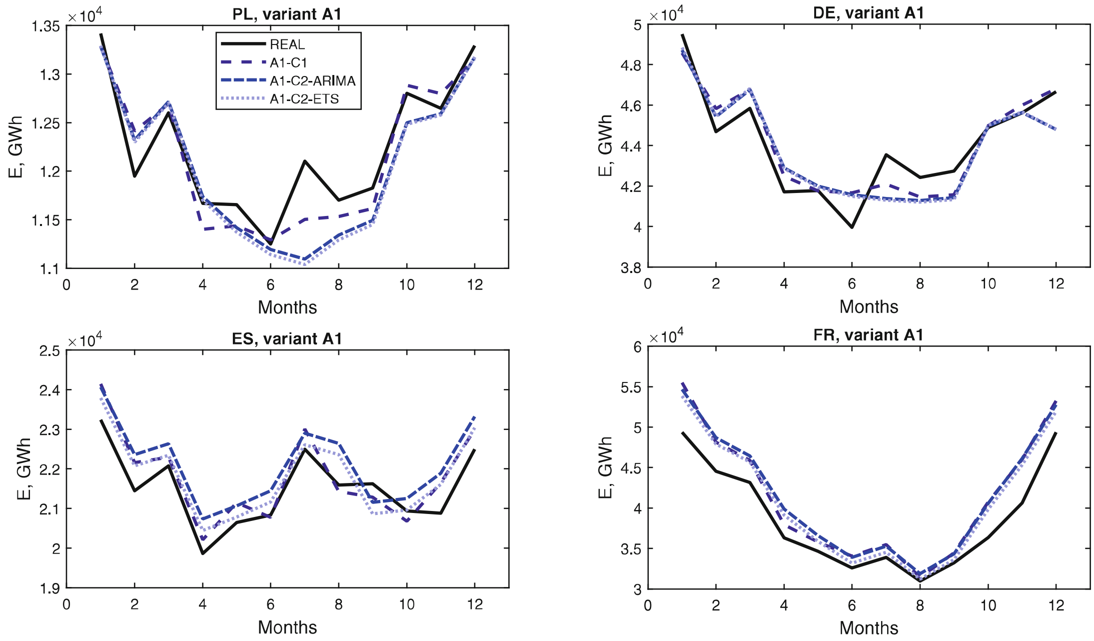

Fig. 1. Real and forecasted monthly demand for A1 variant.

We consider three variants of the forecasting procedure, A1, A2 and B. In variant A1 the model generates forecast for the k-th month of 2014 on the basis of data up to December 2013. The forecast horizon changes from $\tau = 1$ for January 2014, to $\tau = 12$ for December 2014. We train twelve NNs to generate forecasts for successive months of 2014 (each month forecasted by a separate model). Inputs of the models are the same: x-pattern representing time series fragment from January to December of the previous year. The output variable is encoded using C1 or C2 approach. In the latter case coding variables $\overline{E}_*$ and D_* for 2014 are predicted using ARIMA and ETS on the basis of their historical values.

In variant A2 instead of using twelve NNs for forecasting for individual months, we use single NN with twelve outputs. Input patterns are the same as for variant A1. Output variables are encoded using C1 or C2 approach. In C2 case we use ARIMA and ETS to forecast them.

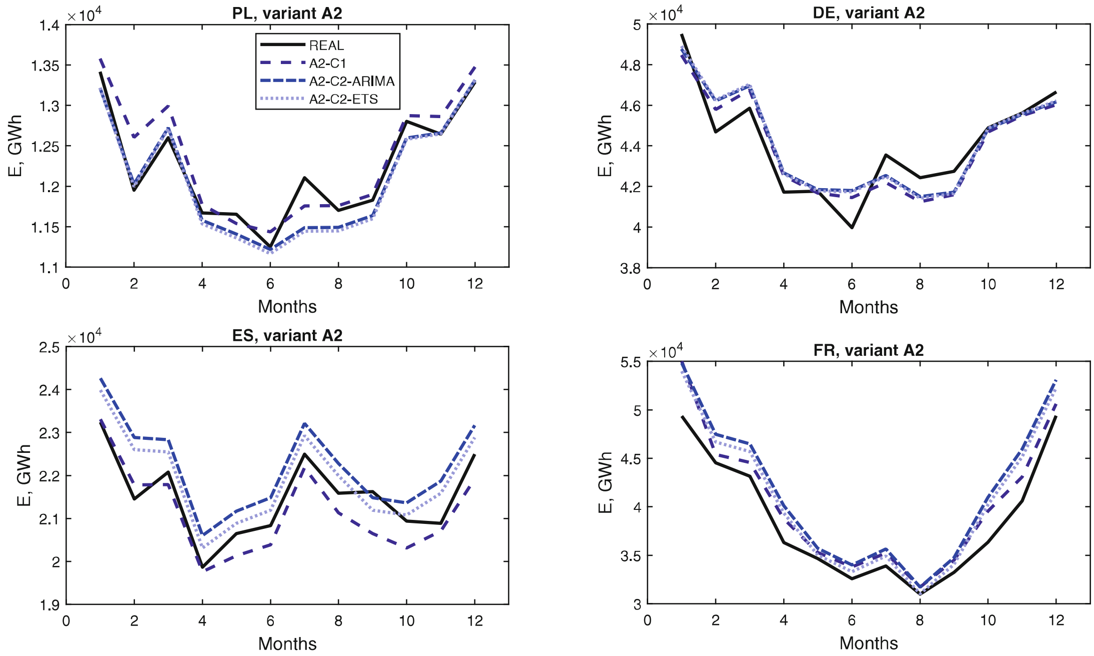

Fig. 2. Real and forecasted monthly demand for A2 variant.

In variant B the model generates forecast for the next month (from January to December 2014, $\tau = 1$) on the basis of data up to this month (e.g. the model for July 2014 gets input pattern representing time series fragment from July 2013 to June 2014). For each month we build separate NN model, which learns on the input patterns representing twelve preceding months. The output variable is encoded using C1 or C3 approach. The latter case needs the coding variables $\overline{E}_*$ and D_* to be predicted. As for the A variants we use for this ARIMA and ETS.

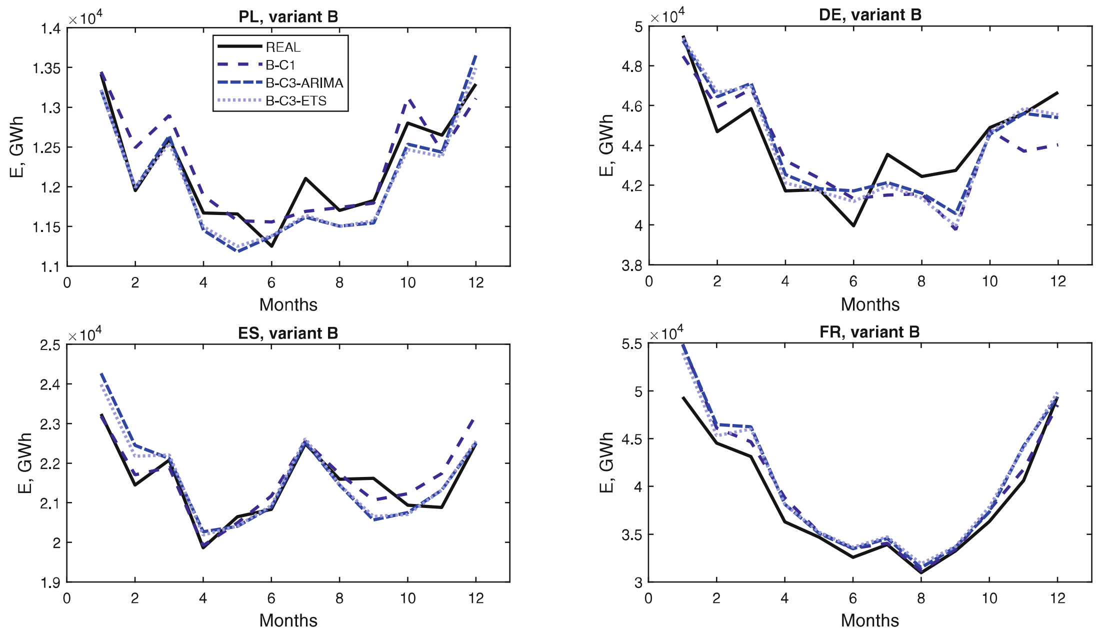

Fig. 3. Real and forecasted monthly demand for B variant.

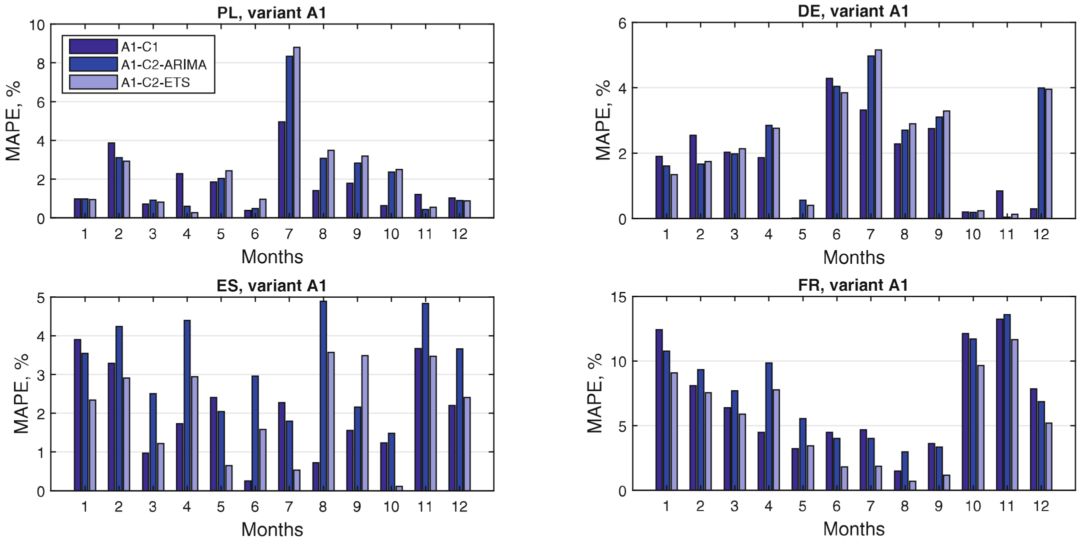

Fig. 4. Errors for A1 variant.

Figures 1, 2 and 3 show the real and forecasted monthly demand and Figs. 4, 5 and 6 show the errors (mean absolute percent errors MAPE) for each forecasted month. The forecast errors are shown in Tables 1 and 2. For comparison errors for other forecasting models are also presented: ARIMA, ETS, Nadaraya-Watson estimator NW-E [10] and neuro-fuzzy system N-FS [9]. The last two models work on patterns defined in the same way as in this work. Best results for each data are underlined. When comparing errors of all models, it should be noted that both NW-E and N-FS overcame other models in three out of eight cases each. As we can see from Tables 1 and 2, the proposed method is competitive to other ones but it is hard to indicate its best variant. However, C1 variant is usually better than C2 and C3 ones. It means that the coding variables do not have to be predicted. We can calculate them from the known preceding seasonal cycle. This simplifies the forecasting procedure.

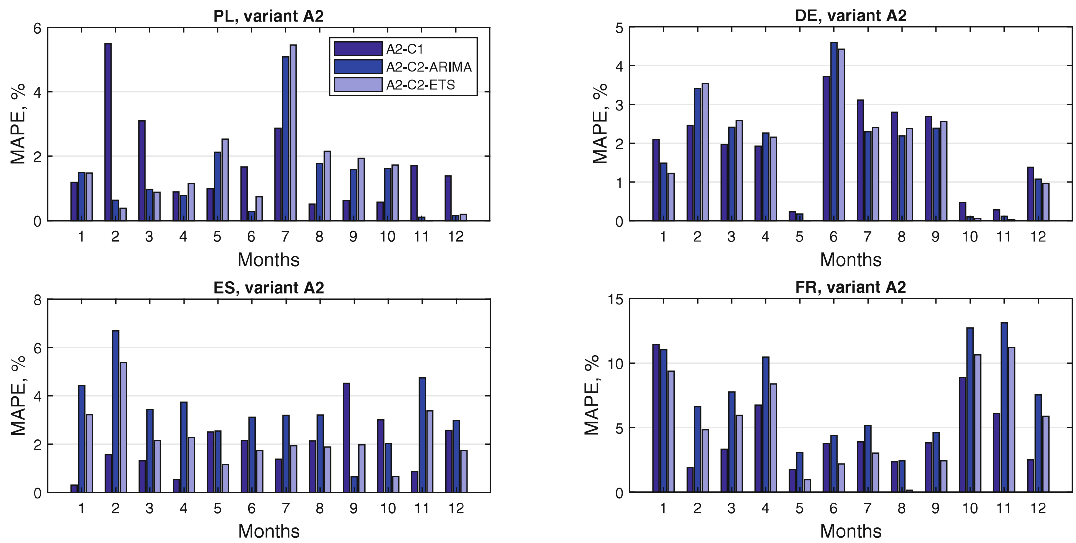

Fig. 5. Errors for A2 variant.

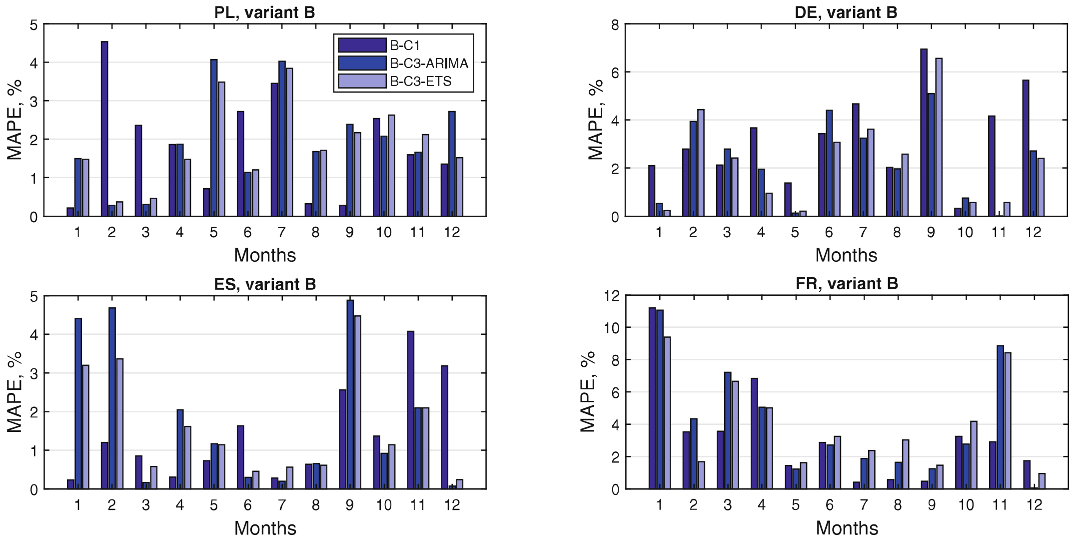

Fig. 6. Errors for B variant.

In Table 3 the number of neurons are shown selected in leave-one-out procedure. Surprisingly, NN in variant A2 having the most difficult task to forecast twelve monthly demands at once needs the least hidden neurons: in most cases only one. Single-output NNs need more neurons to approximate the target function: from 2.58 up to 5.92.

Table 1. MAPE for optimal number of neurons, A1 and A2 variants.

Model	PL	DE	ES	FR
A1-C1	1.76	1.86	2.02	6.84
A1-C2-ARIMA	2.17	2.31	3.21	7.47
A1-C2-ETS	2.31	2.32	2.10	5.48
A2-C1	1.75	1.93	1.90	4.71
A2-C2-ARIMA	1.38	1.88	3.39	7.41
A2-C2-ETS	1.55	1.86	2.28	5.42
ARIMA	3.25	4.36	1.93	10.76
ETS	6.42	2.82	2.36	6.77
N-WE	1.53	1.80	1.49	4.71
N-FS	1.57	4.94	1.67	3.34

Table 2. MAPE for optimal number of neurons, B variant.

Model	PL	DE	ES	FR
B-C1	1.83	3.27	1.42	3.23
B-C3-ARIMA	1.97	2.29	1.80	4.00
B-C3-ETS	1.87	2.30	1.62	4.00
ARIMA	1.75	2.33	1.43	4.10
ETS	2.28	2.64	2.85	3.66
N-WE	1.30	2.47	1.16	2.83
N-FS	1.06	2.87	0.95	5.85

Table 3. Optimal number of neurons.

Model	PL	DE	ES	FR
A1-C1	5.25	4.17	3.33	4.58
A1-C2-ARIMA/ETS	2.92	4.17	5.92	4.00
A2-C1	4	1	2	2
A2-C2-ARIMA/ETS	1	1	1	1
B-C1	4.42	4.50	3.42	4.33
B-C3-ARIMA/ETS	3.00	2.58	4.17	3.17

4 Conclusion

In this work we examine the neural network model for pattern-based forecasting monthly electricity demand. The model works on patterns representing normalized yearly seasonal cycles of the demand time series. Input patterns express shapes of the yearly cycles after filtering out a trend and unifying a variance. Also the output data are unified using coding variables which are calculated based on the historical data or they are predicted. The pattern approach simplify the forecasting problem so the forecasting model does not have to capture the complex nature of the process. This leads to model simplification and faster learning.

Multilayer perceptron provides a flexible model which can forecast both individual monthly demand and the whole yearly cycle. The proposed neural model is competitive with other state-of-the-art models such as neuro-fuzzy system and Nadaraya-Watson estimator as well as the classical statistical models including ARIMA and exponential smoothing. However, it is difficult to indicate the best variant of the model. It should be selected depending on the data, because each monthly demand time series is characterized by its own features such as the trend, variance, seasonal variations and the level of random noise.

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