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Day ahead electric power load forecasting by WT-ANN

***Abstract**. This paper presents a method for forecasting energy demand based on WT-ANN (Wavelet Transform – Artificial Neural Network). Model has been developed and assessed for system data for the period 2002-2014. As input variables following have been considered: five levels of signal decomposition (t-1, t-2), values of time series (t-1, t-2) and qualitative variables denoting day of the week.*

Streszczenie.** W artykule przedstawiono metodę prognozowania zapotrzebowania na moc elektryczną w oparciu o model hybyrdowy WT-ANN (Wavelet Transform – Artificial Neural Network). Budowę oraz ocenę jakoś prognoz modelu przeprowadzono dla danych systemowych za okres 2002-2014. Jako dane wejściowe uwzględniono: pięć poziomów dekompozycji sygnału, wartości szeregu czasowego (t-1, t-2) oraz zmienne jakościowe określające dzień tygodnia.* ***(Prognozowania obciążenia sieci elektroenergetycznej na kolejny dzień w oparciu o model WT-ANN)

Keywords: wavelet transformation, neural networks, qualitative variables, Poland.
Słowa kluczowe: transformacja falkowa, sieci neuronowe, zmienne jakościowe, Polska,

Introduction

Concept of load refers to a device or a group of devices, which due to their nature are utilizing energy from power system networks in order to perform given tasks. The pattern of electric energy demand varies with respect to time. According to [1] approximately 30% of global electricity consumption evolves from residential electricity consumption. In case of Poland, based on recent publication from GUS (Central Statistical Office) [3], households consumed 28,442 TWh which was almost 19,5% of total electrical energy consumption over the year 2013. Its nature is complex and driven by many factors, to which one may include: demographics, climate (temperature, humidity etc.), appliances, building type – however the effect of abovementioned is not completely understood [2]. According to many research papers which has been assessed by [4] the temperature which is understood usually as cooling and heating degree-days (CDD, HDD) poses a strict influence on electric energy demand in case of residential sector. However, as other studies pointed out this situation may prevail only for some sectors and even if, its range may be limited to the selected region. Authors [4] state that in case of Spain there is a total lack of industrial activities electricity demand to the temperature variation.

Literature overview

Electric energy demand patterns are complex and depend on many factors thus their prediction is not an easy task. However its importance is visible on each step of energy generation processes. Accurate demand forecast is essential for energy producers by enabling them to maximize their profits through economic operation and sustainable energy management of power plants. In literature various methods have been proposed for energy demand forecasting. Here we will briefly describe only the recent ones.

For Kuweit [5] authors proposed a methodology for electric energy demand forecasting based on time series signal decomposition and segmentation. Final predictions for seven and thirties days ahead were performed by means of ARIMA (Autoregressive Integrated Moving Average) and MA (Moving Average) models. [6] applied a hybrid dynamic and fuzzy time series model for mid-term power load forecasting using inter alia external temperature as an input variables. Different models – yielding APE <3% (absolute percentage error) have been developed for household, industrial and public service sectors. In [7] authors presented a hybrid forecasting model which consists of empirical model decomposition, seasonal adjustment, particle swarm optimization and least squares support vector machine. A new forecasting model consisting of back-propagation artificial neural network and imperialist competitive algorithm (ICA) has been proposed by [8] for Turkey and Thailand. Application of ICA enabled avoidance of weights and biases problem in training of an ANN. Other scholars [9] used artificial bee colony optimization algorithm to train ANN – conducted analysis enabled them to state that electric demand on short-term is affected by calendar inputs, weather conditions and energy price. In another paper [10] authors introduced different approach to the training process of ANN – they were taught on the basis of randomly selected samples from training subset and the results of different neural networks were averaged. Resulting models gave better results in terms of mean error and variation. In [11] researcher proposed a novel approach based on patterns which enable the elimination of trend and seasonality in case of longer periods. When it comes to the meteorological variables as an input to the forecasting models authors of [12] discussed the problem of meteorological station selection and proposed an appropriate framework.

In case of Poland some scholars focused on long term energy demand forecasts, which time horizon reached even the year 2040 [13]. Such predictions are of vital importance when it comes to planning of national grid development and erection of new power plants. Some authors subjected to criticism [14] governmental forecasts stating that they are highly overestimated. Also a significant amount of research has been done in case of short-term load forecasting. To some papers focusing on energy load forecasting in the context of polish energy market one may account: [15-19].

Methodology

This research focuses on an application of a hybrid forecasting model. Mentioned model is based on a wavelet transformation (WT) as a preprocessing tool for the input data to the ANN. Because the application of ANN approach [20, 21] and WT [22, 23] has been described thoroughly in many preceding papers we will not elaborate on this issue. Power demand data are usually recorded in discrete time intervals. Hence, the discrete wavelet transform (DWT) has been chosen as an adequate one. The procedure for forecasting model construction was as follows:

1) assigning of dummy variables to corresponding records (from 1 - Monday to 7 - Sunday and 8 for Public holidays);
2) five level discrete wavelet transformation of time series by means of Matlab Wavelet Toolbox (see fig. 2);

3) division of time series into a training (70%), validation (15%) and testing (15%) by means of Statistica software inbuilt method;
4) input data selection - (overall three sets have been created, in each year (2002-2014) and month (1-12) were used as qualitative exogenous variables);
5) model performance assessment based on testing set.

Data

As on 31.12.2014 Poland had installed capacity of 39,353 GW in all electric energy power sources. Nearly 20,3 GW of which was obtained from hard coal power plants and further 9,22 GW from those using lignite as a heat source. All polish power sources generated over the year 2014 164,6 TWh of electric energy and on average during 2010-2014 export exceed import by 30% [24]. As can be seen in figure 1, the demand on electric energy presents an increasing trend. A very important observation is the fact that the profile of annual energy demand has changed. The ratio of yearly minimal to maximal energy demand has slightly increased as presented by dots in figure 1. This may be attributed to a raising energy consumption in summer (air conditioning) and dwindling energy demand in winter (due to improved energy efficiency – however one should bear in mind *Jevons paradox* [25].

In this study daily mean power demand data covering period 2002-2014 [26] were used for development and testing of created models. Forecasts were made for one day ahead.

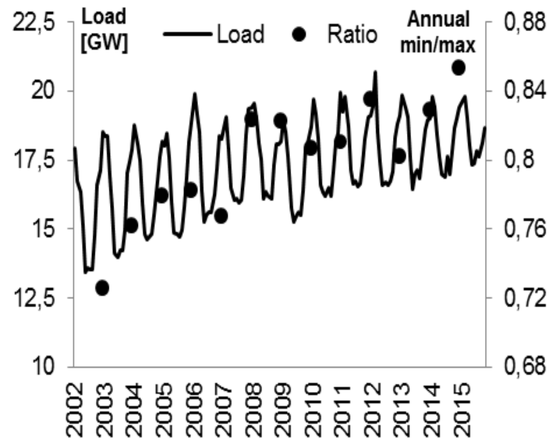

Fig. 1. Mean power load curve in Poland

Results

Application of discrete wavelet transformation at level five for signal consisting of 4748 samples was made by means of *Haar* wavelet. Figure 2 is a graphical representation of *Haar's* wavelet for years 2002-2005. Appropriately selected wavelet can accurately reflect the input signal simultaneously overlooking noise and random values.

For the most complex (WT-ANN-B) forecasting model a following subset of input variables were used: five levels of discrete wavelet transformation lagged by one and two days; values of power demand from two previous days and qualitative variables related to the calendar input. In case of the second model (ANN-B) DWT has been eliminated from input variables. The simples model (ANN) in terms of input subset was deprived of daily calendar input. Table 1 summarizes most important statistics of all models.

Table 1. Forecasting models and their specification

Network	Architecture	Teaching algorithm	Function hidden/output
WT-ANN-B	MLP 45-6-1	BFGS 113	Tanh/Linear
WT-ANN	MLP 35-5-1	BFGS 187	Tanh/Linear
ANN	MLP 27-5-1	BFGS 268	Log/Exp

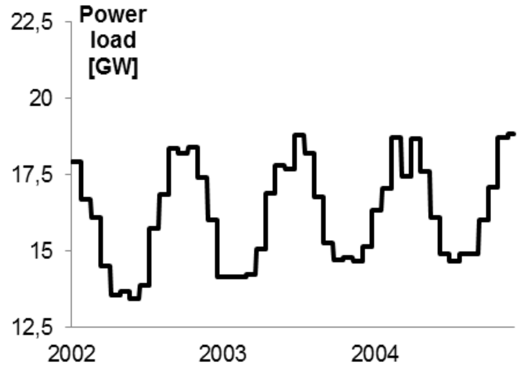

Fig. 2. Power load discrete wavelet transformation at its most crude level

Models have been compared based on the testing set. The value of MAPE (Mean Absolute Percentage Error) model performance metric for WT-ANN-B was the smallest one and equal to 1,09%. In case of model lacking discrete wavelet transformation input this value was greater and amounted to 1,25%. Worst performance was observed in case of the simplest model which MAPE was even to 4,97%. This was mainly due to the lack of qualitative input denoting week days.

The difference between models performance is clearly visible when presented on a chart. The value of mean absolute error has been calculated for each week day including public holidays. Those values are presented in figure 3. The highest errors are observed for public holidays. As further calculations have shown those values amount in worst case to 14,3% of mean public holiday power demand. In case of models with more detailed calendar input (days) those errors were reduced to less than 4%. As presented in table 2 model using DWT outperformed ANN-BIN in case of all days.

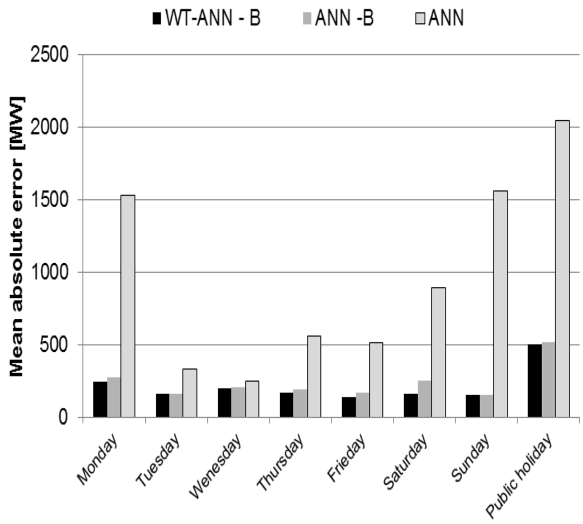

Fig. 3. Values of mean absolute error for various days

Table 2. Model performance

Day	WT-ANN-B	ANN-B	ANN
Monday	1,4%	1,6%	8,8%
Tuesday	0,9%	0,9%	1,8%
Wenesday	1,1%	1,1%	1,4%
Thursday	0,9%	1,0%	3,0%
Frieday	0,8%	0,9%	2,9%
Saturday	1,0%	1,6%	5,5%
Sunday	1,1%	1,1%	10,8%
Public holiday	3,5%	3,6%	14,3%

Conclusions

Presented research indicate that introduction of the discrete wavelet transformation as a preprocessing tool for the artificial neural networks input enables better results of forecasting models. Such procedure allowed us to decrease MAPE error by 14,4%. As has been shown the calendar input plays a vital role when it comes to deciphering of weekly patterns in energy consumption. Further research should focus on introducing additional explanatory variables such as temperature or GDP (gross domestic product). However in the case of the first one a meteorological station selection exercise should be performed in order to single out those which measurements will correlate best with power demand. Due to uneven population, industrial and commercial activities distribution more than one station may be selected.

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