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Methods of weather variables introduction into short-term electric load forecasting models - a review

***Abstract**. Short-term load forecasting (STLF) is a problem of noticeable significance for operation of power systems. Wide range of methodologies for STLF is given in the literature – univariate models as well as multivariate ones (mostly extended with weather variables). This paper is an attempt to categorize various approaches of introducing exogenous variables into models. Different classifications of this aspect are created and described in an effort to demonstrate the problem from various perspectives. Finally, the advantages and disadvantages of reviewed solutions are discussed.*

***Streszczenie.** Krótkoterminowe prognozowanie obciążeń jest istotnym elementem działania systemów elektroenergetycznych. W literaturze opisane zostało szerokie spektrum metod – modele zarówno jedno- jak i wielowymiarowe (najczęściej używające zmiennych pogodowych). W pracy podjęto próbę przeglądu metod prognozowania pod kątem sposobu w jaki korzystają one ze zmiennych egzogenicznych. Przedstawiono klasyfikacje dla tych metod opisujące problem z różnych perspektyw. **(Przegląd metod uwzględniania zmiennych pogodowych w modelach prognozowania krótkoterminowego)**.*

Keywords: short-term load forecasting, exogenous variables, weather factors, temperature.
Słowa kluczowe: krótkoterminowe prognozowanie obciążeń, zmienne egzogeniczne, czynniki pogodowe, temperatura.

Introduction

Short-term load forecasting (STLF) is an forecasting horizon defined as a range from one hour to one week ahead [1, 2]. Accessibility of quality forecasts of relatively short time horizon is important point of interest for several parties participating in deregulated energy markets. STLF is considered meaningful in spinning reserve allocation, unit commitment and generation dispatch. In addition, it is used by managers for forecasting and planning financial and economic aspects of operation [2, 3].

A large number of methods have been proposed for STLF problem. One of the most commonly proposed classifications is to assign STLF methods into conventional (statistical) and computational intelligence (soft-computing) groups [2, 3, 4]:

- Conventional – based on statistical analysis of time series. Most popular techniques [4]: exponential smoothing (Holt-Winters models), multiple regression (different variants of ARIMA).
- Computational intelligence – based on artificial intelligence methods such as Artificial Neural Networks [5], Neuro-Fuzzy and Expert systems, Support Vector Machines.

Electrical demand is influenced by many interdependent factors, including economic situation, calendar (weekly and annual periodicities) and weather variables [1, 4]. Influence of economic factors such like demographics of region or industrial structure is stronger in long time perspective and is usually not explicitly considered by STLF [1]. Weather data is not unanimously used in STLF models, however a lot of proposed methods includes it as an influential factor. These models are investigated in the next chapters.

Weather factors influencing electrical demand

It is well-recognized that weather conditions affect significantly the electrical demand [1, 4]. However, the impact of weather factors on power system could vary depending on its geographical location, climate and industrial structure of the region. Influence of following weather variables is mostly considered [1]: temperature, humidity, wind velocity, precipitation (rainfall), cloud cover, sun radiation.

Temperature is considered to have most influence on electrical demand of all weather-related factors [1, 6]. In general, there is a non-linear relationship between temperature and demand as there is a visible increase of electricity consumption associated with both decrease of temperature value below some point and also its increase above some threshold [7, 8]. Usage of HVAC (heating, ventilation, and air conditioning) equipment with proportions of heating and cooling depending on temperature profile is commonly attributed to be the reason of this effect [6, 7]. Detailed analysis of this nonlinearity is presented in a paper [7]. The authors proposed to classify regions (European countries) into three groups of cold, intermediate and hot, depending on their average monthly temperature. As a result, a regularity between being a part of specified group and form of temperature-demand scatter plots became visible. “Cold” countries demonstrated almost linear relationship with only heating component clearly visible. For “intermediate” countries, cooling component became visible, though dominated by heating part. “Warm” countries presented highly non-linear relationship with cooling component of similar scale as heating.

Presence of wind speed above some value could cause bigger electricity usage for heating in the winter as it increases feeling of coldness when temperatures are low [9]. The effect of cooling exterior walls of buildings by wind is intensified if they are wet [10]. For summer, correlation between wind speed and electrical demand is not clearly visible [9].

Value of humidity is reported to matter only if coincides with specified value of other variable. Feeling of hotness accompanying temperature above certain value is intensified by high humidity, what can increase energy used for air conditioning [11]. For regions with certain climate, usage of humidity is then reasonable as shown in [12] for Hong Kong.

Other weather conditions like cloud cover or occurrence of rainfall seem to only marginally affect electrical demand. The measurement of such variables is not always clear, e.g. as mentioned in [11], cloud cover is usually expressed as a fraction of sky covered with clouds and thus refers to very large area. Rainfall affect electrical demand rather indirectly by affecting other weather variables. When it appears on a hot day it can decrease temperature [11]. It also affects humidity what matters for some systems (like already mentioned Hong Kong [12]). Exact time and value of precipitation are also difficult to predict.

Types of variables representation

Weather variables could be introduced into the forecasting model in a plain (primitive) form or in a complex (derived) form created by transforming one or few of them [13]. The primitive variables are just records of data as obtained from weather stations. In following classification, we assume that after linear transformation of only one variable (e.g. average of n past values) it is still considered primitive type. Derived variables are intended to catch complex relationships between factors. They are effect of multivariate calculation or nonlinear transformation of one variable. Both approaches are represented in a literature.

Primitive variables are the same as appropriate factors influencing electrical demand, although they could use different units or variants:

Temperature – in general it is most commonly used exogenous variable among models [4]. Many traditional models which often uses only one exogenous variable uses temperature in its plain form [14, 15]. For conventional regression-based models plain value of temperature seems to share popularity with its derivative form, but for soft-computing models plain values are even more popular. Hippert et al. have analyzed 22 models based on Neural Networks [5]. Only three of them do not use temperature. All of the rest use plain value of temperature. Two of them in addition uses derived temperature variable. Sometimes averaged past values of temperature are included to take into account a tendency of heat accumulation in buildings [11]. An example of such approach could be also *effective temperature*, exponentially smoothed form of average calculated as the mean of the spot temperature measured for each four previous hours [16].

Humidity – included in some models, but always as an addition to temperature. Only in one paper it was used with conventional model [17], but in analysis of Neural Network models by Hippert et al. [5] it appears in 6 of 23 models. Almost universally used in form of a *relative humidity* [12, 17, 18], although it is also rarely used in form of *wet-bulb* or *dew point temperature* [9, 11]. In one of analyzed papers, Friedrich and Ashkari [19] use *specific humidity* what could be considered atypical.

Wind speed – sporadically used by some of soft-computing models [5], rather used for calculation of derived variables.

Derived variables are more popular among conventional models, especially temperature derivatives [17, 20]. Derivatives created by mixing different variables (temperature and humidity, temperature and wind speed) are as well popular among computational-intelligence based approaches. Types of complex variables worth to be noted:

Heating degree-days (HDD) and **Cooling degree-days** (CDD) have been introduced by Quayle and Diaz [21] as a deviations of mean daily temperature from a base “comfortable” temperature (balance point). The HDD of a day are the number of degrees that the mean daily temperature falls below this threshold (for CDD it is a number of degrees above mean value). In original work, 65 °F (18.3 °C) was selected as a balance point temperature, although various other values have been used in literature depending on characteristics of power system. In some works two points marking comfort zone instead of one point are proposed [20]. This derivative of temperature was used in numerous conventional models [10, 20, 22, 23] and sporadically in soft-computing solutions [24].

Heat Index (HI) is weather parameter introduced by USA National Weather Service [25]. It tries to represent perception of temperature by a human depending on relative humidity and is defined for temperatures in range of 27 °C to 43 °C and relative humidity of 40-95%. HI is sometimes labeled as *human-perceived equivalent temperature* [26] or *humidex*. The latter expression is also used in literature for another, different index based on same variables (*Canadian humidex*). This other index is covered later in this paper and they must not be confused. Because of limited range of weather conditions in which Heat Index is defined, it is applied rarely and its usage is limited to regions with hot and humid climate. HI was used for multi-region STLF by ANN model developed for Taiwan [26]. The authors tested three variants of the model using: only temperature, temperature plus humidity and Heat Index. Variant with HI performed better for summer months and although variant with temperature was better for more separate months, the overall result averaged over whole year was better for model using HI.

Apparent temperature was developed by Steadman [27] as a generalization of the Heat Index (what originally covers only temperatures above 27 °C). Like an original HI, it attempts to evaluate the human-perceived equivalent temperature with use of the air temperature and the relative humidity, but for extended range of temperatures (-40 °C to +50 °C). It was used in paper [6] to estimate weather-related component of electrical demand what was one of steps in a forecasting procedure.

Humidex is a parameter proposed by Canadian meteorologists Masterton and Richardson in 1979 [28] and because of this, it is sometimes labeled *Canadian humidex* to distinguish it from Heat Index (sometimes imprecisely described as *humidex* too). Humidex is another parameter calculated using temperature and humidity. It was one of the derived variables used for forecasting of tomorrow load by similar day-based wavelet neural network [29]. As an inputs of NN both primitive weather variables (wind speed, precipitation, cloud cover) and derived ones (wind-chill index, humidex) are used. Authors of this work [29] also evaluated variants of model where air temperature was used instead of wind-chill index and primitive humidity (dew point temperature) instead of humidex. Models using derived variables performed better than ones using primitives.

Temperature-humidity index (THI, discomfort index) – another parameter formulated to include combined effect of temperature and humidity in creation of summer heat stress and discomfort [9]. One has to be aware that this index is different than previously mentioned Heat Index despite both using the same primitive variables. THI was utilized in forecasting demand by rule-based expert system proposed in [9] and by generalized knowledge-based system described in [11]. Both models makes also use of primitive weather variables like temperature or wind speed.

Real sense of temperature – weather parameter combining together temperature, relative humidity and wind speed in an attempt to capture coupling effect of these factors on human perception [30]. Parameter was used as one of inputs in model forecasting electrical load with use of backpropagation NN [30]. The Authors tested variants using regular temperature and real sense temperature obtaining better results with the latter solution. However, limited number of applications using this derived variable was found suggests that we should wait with making statements about its usefulness.

Enthalpy latent days (ELD) – parameter accounting for the influence of humidity on summer demand for cooling and air-conditioning [31]. It can be interpreted as an amount of energy necessary to lowering indoor humidity to an acceptable level without reducing the indoor temperature. ELD is defined in a way that it is non-zero only if the temperature is above 78 °F (25.6 °C). Possible utility of an ELD as an exogenous variable in demand forecasting has been considered in paper [10]. The authors proposed a multiple regression model that uses derived variables (HDD, CDD and ELD), as well as primitive ones (relative humidity, wind speed, sunshine hours, rainfall). Depending on a variant of the model, different variables were included. Variants including ELD or relative humidity performed much better on summer days than variants lacking them. However, the authors are not sure whether usage of ELD or relative humidity is better. One of the reasons is characteristics of investigated region (England and Wales) where CDD and ELD components of the demand are not very meaningful [10].

Wind-chill index (WCI) is a parameter aiming to capture cooling effect of the wind blowing while temperature is below threshold of 50 °F (10 °C) [32]. WCI was first defined on a base of empirical observations and several equations trying to fit obtained data has been proposed [32]. Hence, it is possible to spot different papers describing application of WCI using in fact different equations [9, 29, 33]. Chen et al. [29] have used WCI as an input to wavelet neural network working as a correction for similar-day forecasting model. They noticed an improvement of the results while using WCI over regular air temperature. Ruzic et al. [33] have proposed a model where WCI is used as a base for a number of calculations leading to obtain limits of two temperature sensitivity zones created by heating and air conditioning.

Cooling power of the wind (CP) was proposed by Taylor and Buizza [16]. It is a nonlinear function of wind speed and average temperature trying to capture chill induced by gusts of wind. Assumption is that such coolness is sensed only when temperature is below 65 °F (18.3 °C) and then it is proportional to square root of wind speed and difference between threshold and temperature. The authors of paper [16] uses CP, effective temperature and cloud cover to create *weather ensemble predictions* – scenarios of weather behavior what are then used for creation of scenarios for weather-related component of electrical load.

Function of weather variables within model

Weather variables could play different role in a STLF models. Depending on their significance for the solution, we classify forecasting models with weather variables as:

- Integrated models – use weather data as an integral part of forecasting process.
- Switching models – certain weather variable has ability to change ("switch") behavior of a model between predefined discrete states. Into this group we also include models containing internally few sub-models and selecting which one to use depending on value of weather variable(s).
- Correction models – use weather variables only to correct and improve already built forecast. These models would work without it, but their accuracy would be worse.

The first group, using weather variables as an integral part of a solution is the most populous. It is common approach among neural network approach an many of such solutions have been mentioned in [5]. Most of them use weather data as another input, next to past demand data and calendar variables [12, 18, 24, 30] or calendar variables only [34]. Primitive variables are more popular for this group. Among conventional, statistics-based models integrated approach is also noticeably represented. A number of models estimates one set of parameters for all data with weather variables as another factor in equations [13, 16, 22]. It has to be noted, that conventional models utilize derived variables rather than primitive ones.

Several models using weather variables to change their behavior have been proposed in the literature. As an interesting example, we can quote model described in [35]. The authors proposed model built of many separated regression-based components. It depends on expected weather conditions which component is used. As an example application, models is tested on Texas winter data, where three types of weather are recognized: normal days, type I cold front days and type II cold front days [35]. Model was compared with auto-regressive model with exogenous variables (ARX) using one set of parameters for whole days. Proposed model preformed better and improvement was significant for front days with rapid change of weather conditions. Another examples of conventional, auto-regressive models using weather data (mostly temperature) to create many separated sub-models could be work of Amjady [36] (Iranian power system, two models, threshold is 23 °C) or models presented in paper [23] (*switching regression* and *threshold regression*). Soft-computing models also could have their behavior controlled by switching variable. In paper [37] an adaptive two-stage hybrid network containing self-organizing map (SOM) and support vector machine (SVM) is proposed. SOM is applied to cluster the input data and then the group of 24 SVMs creates forecast of load for every hour of next day. The authors investigated the load-temperature relationship and observed that its behavior changes rapidly at around 55 °F (12.8 °C). To account this fact into the model, discrete variable of value depending on temperature relation with this threshold was added as an input to SOM. Model itself also uses other weather data like temperature, humidity and wind speed.

Correction models are the least popular type, although some examples has been also described. One could be already mentioned model by Chen et al. [29] building a forecast by similar-day approach. Already decent performance of the model was improved with use of a correction based on wavelet transform and ANN. Wavelet transformation separates low and high frequency components of the electrical demand time series, then two NNs (one for every component) create correction using past load data and weather variables. The authors examined variants using various primitive and derived variables obtaining better results with the latter type. Another example was described by Senjyu et al. [38]. The proposed model also uses similar-day approach as first forecasting step and then correction is applied. The value of correction is estimated by a three-layer feedforward ANN on a basis of demand forecasted at first step and deviations between temperature of similar days and temperature expected on forecasted day. With the correction the authors reported to achieve slight improvement of forecasting for Okinawa Electric Power Company. Similar model with correction component improved by fuzzy estimator using precipitation and discomfort index was proposed in [39].

Conclusion

In this paper we analyzed various aspects of exogenous variables introduction into STLF models. Different forms of weather variables representation described in the literature have been discussed. Finally, the role of these variables in various forecasting procedures has been presented.

Weather variables are utilized in numerous STLF models up to the point that this kind of solutions outnumbers univariate models. From the analysis of several papers it appears, that both primitive and derived weather variables are commonly used. However primitive ones are more frequently used by soft-computing models, while derived ones gathers more popularity among conventional models. The reason seems to arise from the fact, that conventional approaches try to model explicitly relationships between variables. Derived variables are already effect of some processing trying to capture more complex behavior of the load-weather relationship. Moving some part of processing outside of the model (by using derived variables) makes it simpler. On the opposite, soft-computing methods are expected to implicitly recognize complex relationships on a basis of provided data. Hence, for most cases there is no need to do redundant, parallel processing and resolving existing interrelations of the system is left for the model.

Some of the investigated works have reported that in some cases different sets of primitive and derived variables were examined and results were not globally conclusive. This effect has to be attributed to different characteristics of the power system and region climate. Thus, for successful introduction of weather variables into model, any assumptions regarding weather influence on demand has to be considered on a local basis.

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