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Power Flow Forecasts: A Status Quo Review. Part 1: RES Generation Prediction

***Abstract**. In recent years, rising electricity demand accompanied by CO_2 reduction targets has dramatically increased RES penetration into power systems, giving rise to the need to estimate power production and demand to properly manage power infrastructure. This paper is Part 1 of an extensive, two-part review of recent literature related to forecasts of RES generation, electricity demand and power flows. This Part 1 focuses on forecasts of RES generation.*

***Streszczenie.** W ostatnich latach chęć pokrycia zapotrzebowania na energię elektryczną przy jednoczesnej redukcji $CO_{2,}$ spowodowała silny wzrost mocy zainstalowanej OZE. Konsekwencją jest potrzeba szacowania generacji z OZE oraz zapotrzebowania na energię, by poprawnie zarządzać pracą systemu elektroenergetycznego. Niniejszy artykuł to 1 z 2 części szerokiej analizy najnowszej literatury dotyczącej prognoz generacji z OZE, zapotrzebowania i przepływów mocy i prezentuje pierwszy z aspektów.*
Prognozy przepływów mocy-przegląd status quo. Część 1: Predykcja generacji z OZE.

Keywords: forecasting, photovoltaics, wind turbines, review
Słowa kluczowe: prognozowanie, panele fotowoltaiczne, turbiny wiatrowe, przegląd

Introduction

Growing emphasis on environmental aspects in recent years has considerably increased hopes for RES development. The drive to reduce CO_2 emissions has been reflected in European Union legislation, among others. Regulations like EURO 2020[1] and its successor EURO 2030 [2, 3] have been followed by dynamic increase in RES share. However, the transition is not free from problems. With increased RES penetration of NPSs, the consequences inherent in them could be felt more dramatically, hindering system work planning operations or interfering with power system automatics. A rising body of legislative acts have established increasingly ambitious climate policy goals and one should expect a growing drive of the authorities to increase RES share in national energy mixes. This puts emphasis on the importance of NPSs work assistance tools, as they allow to mitigate side effects of increased RES penetration. Studies on possible tools could be found in works like [4,5,6] among others.

To make system operation more predictable and energy supply and demand balancing more flexible, RES energy generation forecasts are developed. Energy demand is forecast on the DSO and national levels. However, with sufficient data available, it would be possible to make detailed forecasts for the entire country per NPS node. Transition into nodal forecasts would make it possible to achieve the ultimate goal of nodal net energy forecasts.

A combination of both types of forecast processes into forecasts of net energy flows becomes meaningful not only in the context of system stability and detection of overloads, but also in the context of transition from the copper plate market model into the nodal pricing model. Limitations not taken into account in real time before would impact on energy prices in the nodal pricing model. Macro-scale forecasts could also become assistive tools for energy management systems of energy clusters and microgrids, increasing their sustainability.

Much research has been done in recent years on various topics associated with energy flow forecasts, from point RES generation forecasts [7], to the modeling of time-space correlations of wind farms powers in energy flows [8], to probabilistic energy flows taking PV into account [9]. This paper systematically structures the aspects discussed in the literature, identifies their common features, key differences and specifies any inconveniences associated with them. Due to significant amount of material to be presented, this paper is divided into two parts, with the first part addressing predictions of generation, while the second part discusses forecasts of demand and power flows.

Classification of topics

The aspects raised by literature can be most conveniently classified into forecasts of RES generation, power demand and power flows. There are numerous contributions discussing the two former aspects, while there are few papers which discuss the latter one. The reason can be large amount of data necessary for such research, and insufficient computational power available. Based on the example of the Polish transmission system it can be observed that if a separate forecasting model were to be used for each node of the 220/400 kV grid, 107 models [10] would be needed. The situation is getting increasingly complicated with stepping down to lower voltage levels. Consequently, for a 110 kV substation, 1,537 models would be needed, while for MV substations this number would increase to 261,169 [11].

Although each node could be modeled separately or nodes could be divided into groups, such approach would limit the potential for mapping internodal interactions. A possible trade-off would be creation of models per cluster of nodes. However, the number of currently existing clusters is not enough to make any generalizations for national power system.

The topics discussed in these two papers are addressed in their dedicated sections. For each of them, meta-analysis of component aspects is conducted to evaluate their potential usefulness for system-wide energy flow forecasts. Papers with a complete set of basic data, i.e. horizon, interval etc. were used for this review. As mentioned above, the most common shortage of explicit information was related to horizons of forecasts.

Topics of RES generation forecasts

The subjects appearing in present-day literature related to RES generation predictions could be divided into four categories:

a) Forecasts of meteorological parameters
b) Transformation of meteorological forecasts from climate models into energy generation
c) Point forecasts of RES generation
d) Area forecasts of RES generation

Each category is described in a dedicated section.

Forecasts of meteorological parameters

The accuracy of forecasting largely depends on the quality of meteorological variables as input data for energy forecasts. The quality of such variables, depending on the model, affect forecast models in linear or non-linear fashion. Hence, the drive to improve accuracy of meteo variables seems natural. Zhao, Liu, Yu &Chang [12] make one such attempt. With the use of NARX network and autocorrelation analysis of wind speed prediction errors for wind farm they developed an error correction model. Then, with the KDE they calculated the probability density of improved forecasts and errors. A different approach is proposed by Liu, Jiang, Zhang & Niu [13]. First, wind speed is decomposed into IMFs. Then, after discarding signals interpreted as noise and reconstructing the signals, 5 forecasting models were developed, namely ARIMA, BPNN, ENN, ELM and GRNN. Linear combination of model outputs was optimized by modified MODA algorithm.

Each of the above-mentioned approaches was used for wind speed predictions, which is highly popular subject of publications, including due to the magnitude of power generated from wind farms and as a consequence greater potential business value achieved from smaller prediction errors. The mentioned research studies addressed short-term forecasts. Their relevance to power system operations planning would be therefore limited to short-term activities.

Transformation of meteorological forecasts from climate models into power generation

This subtype of research attempts to transform climate wind data into generated power. Papers by Lledó,Torralba, Soret, Ramon, Doblas-Reyes [14] and MacLeod, Torralba, Davis, Doblas-Reyes [15] could be examples of such research. The former use wind power curves and averaging of seasonal forecasts to create seasonal forecasts of correction degree for power generation from wind turbines of different classes. In the latter work, forecasts with 6h/1day/1 month resolution were averaged to monthly values and compared with monthly generation measures. In this case, the goal was to find which time resolution is best for climate prediction data to be used for seasonal forecasting.

Both studies have to deal with problems typical for climate prediction models, i.e. low time resolution and forecasts existing as an ensemble. It is impossible to state the superiority of one component of the bundle over any other due to the fact that each component represents different starting conditions, such as the state of the atmosphere at the respective point or period of time. Bundle components complement each other, due to which they cannot be separated, and only the outcomes of the most extreme ones can be discarded. Another important problem is incomplete data, due to additional differences in models, e.g., horizon. Although no studies on solar climate forecasts were found, in such case the time resolution problem would become evident. The primary challenge would be to translate sun position in the sky depending on date and time and PV location into average solar irradiance over a period. Further studies concerning both wind and solar conditions seem indispensable in the expected realities of RES increasing penetration into power systems.

Point forecasts of RES generation

Point forecasts remain the most popular subject concerning RES generation. Current trend is development of increasingly refined hybrid models and preprocessing. For reasons similar to point weather forecast, wind farms generation predictions [16-20] belong to more popular topic, while PV forecasts [21-22] are relatively rare. Due to their generalization capabilities, ANN remain popular, although rather as a component of more complex models [16-19]. Meanwhile, statistical models are used usually in their improved versions, often with the mentioned networks [20]. A distinct group of methods is classification-based models, e.g. Random Forests [21].

The goal of hybrid models is to increase the final accuracy of predictions by using the advantages of each component model/method, or in worst case compensation of negative features of one model by another. And so, Wang, Zhang &Ma [16] make a model based on SSA used for preprocessing and Laguerre polynomial and ANN used for wind farm generation prediction. Decomposition is used by authors to extract the trend, harmonics and noise from data. The applied STA algorithm is improved by adding an anti-local optimum module. It seems that good convergence is the only advantage of the method, as results speak against the superiority of such solution.

The approach in Çevik, Çunkaş & Polat [7] is to use decomposition as preprocessing as well. This time it is achieved by EMD and SWD. The authors tested the effectiveness of ANN, ANFIS and SVR with and without decomposition. These models were combined to make up a cascade model. First-stage models were based on historical generation and meteo data. The middle stage integrated the output of the models into a new model input. On the last stage, prediction errors were corrected by linear function and models were combined with weighted average. Such solution, however, was a trade-off between less error and simpler procedures.

A different methodology is employed by Afshari-Igder, Niknam & Khooban [17]. Preprocessing by wavelet transform is followed by prediction of wind farm generation with ELM and IKHOA algorithms. Bootstrap technique is used by researchers to compute margins of confidence of forecasts. Such method yielded upper and lower bounds relating to estimates of possible forecast deviations from reality. This procedure could be useful in the power market, where predictions are to be presented in intervals.

López, Valle, Allende, Gil & Madsen [18] propose a combined model with capabilities similar to CNN. Authors model a ESN network by LSTM blocks as hidden units, obtaining a feature extraction tool similar to autoencoder. Network output weights are optimized by quantile regression. The proposed approach seems to be an interesting alternative, however, a less forgiving benchmark than the persistence method could be used to prove the superiority of the tool.

Just like Afshari et al. [14], Kushwaha & Pindoriya [19] use wavelet transform for preprocessing. However, to overcome high-frequency changes of PV power during rainy or cloudy days, a modification of method was used –

MODWT. To extract seasonal dependencies, Kushwaha & Pindoriya use the SARIMA model, which is further combined with RVFL model. An advantage of this approach is less likelihood of getting stuck in local optima and decoupling of the solution quality from the learning coefficient.

Among recent studies, works of Lahouar & Slama [20] and Shang & Wei [21] could be perceived as research pertaining to point forecast of PV generation. Lahouar & Slama use random forests method to predict generation 1h ahead. Such method is based on decision trees and bagging algorithm and its key features are fast speed attributed to no need for optimization and balanced sensitivity to changes in input data.

Shang & Wei modify EMD to get rid of the mixing mode caused by asymmetric distribution. As prediction model, the authors propose modified SVR optimized by PSO with the addition of chaos operator [21] and fuzzy logic.

<u>Area forecasts of RES generation</u>

Data availability is a limiting factor for research. Nonetheless, in recent years, papers were published pertaining to predictions of aggregated wind farms [22,23] and PVs [24] power. Studies like these could become a significant step towards sustainability on the area scale. Authors of [22] developed a model for 10 wind farms using mapping interdependences between farms based on R-Vine Copula and marginal distributions described by KDE. Further predictions were generated by a probabilistic model consisting of, *inter alia*, MDM. Felder et al. [23] propose an interesting alternative. After discretizing time series to 20 bins they used DNN to recognize patterns existing in bins. Based on the results, probability of pattern appearance was calculated for the given input pattern which rendered interval forecasts. Approach like this allows us to tap the DNN potential, reduce the size of the dataset, and increase prediction stability. Unfortunately, the results proved to have certain dispersion for shown examples.

Paper by Umizaki, Uno & Oozeki [24], in turn, addresses PV predictions. The goal of the study was to find out how effectively various quantities of PVs in the area can be upscaled to the aggregated power for the entire region. A sample of 2219 PVs used for studies deserves special attention. The authors compared the outcome of calculations for predictions with 1 h, 3h, intraday and 1 day ahead. The method used here was compared to GPV-SVM forecasts model and persistence model. An observation was made that increased number of PVs results in less error, but this effect was relatively soft for the combined model. The upscaling model yielded better result for such case, which could be attributed to a large number of PVs with different properties, which in turn resulted in averaging of results by the combined model.

<u>Features of RES generation prediction studies</u>

Out of all mentioned papers related to weather and RES generation predictions, the following common features could be extracted:

a) The horizon spanned from 10 min to 24 h for almost all cases.
b) Time resolution of forecast was usually 1h. Resolutions ranging from 10 min to 24 h were rare.
c) Medium-term forecasts were rare and their resolution was brought to 1 h.
d) Medium-term predictions were burdened with the existence of weather forecasts bundles, averages over periods instead of momentary values and low time resolution.
e) Emphasis was put on advanced preprocessing, where EMD and wavelet transform were particularly popular.
f) Non-hybrid/non-combined methods were almost non-existent.
g) ANN were the most popular base of forecasting engines, probability methods were less successful
h) Weather-based predictions remained a popular topic, although rather in the context of point forecasts.
i) Climate data and aggregated power-based predictions remained almost unexplored.

Table 1 Aspects of RES generation forecasts in literature

Aspect	No.	Method	Place	Interval	Horizon	Description /Novelty
Wind speed prediction	12	NARX network with mixture KDE	1 WF	15 min	1 d	Inherent errors of NWP are included in probabilistic forecast
	13	Optimized combination of models	4 adjacent WF	10 min	1/2/3 steps	Linearly weighted combination of ARIMA/BPNN/ENN/ELM/GRNN optimized by modified MODA
Climate NWPs to WFs yield transforma -tion	14	Probabilistic method based on ensemble forecasts	Multiple points, Europe	1 month	7/13 or 1 month	Analyses of transformation of seasonal NWPs to WTs generation
	15	Based on WFs efficiency and elements of statistics	Multiple points, UK	1 month	n\a	Analyses of transforming climate NWPs to WTs seasonal generation
Point generation forecasts of FW [13-15,17] and PV [16,18]	7	(ANFIS) vs (ANN) vs SVR and their ensemble with EMD and SWD as preprocessing	1 WF	1 h	1 step	Ensemble method with decomposition
	16	SSA, OTSTA, Laguerre polynomial and ANN	1 WF	15 min	1/2/3/6 steps	New hybrid prediction method with feature extraction and converse wind power series
	17	ELM, IKHOA, WTr, and bootstrap techniques	1 WF	1 h	1 week	New Hybrid Method with preprocessing
	18	ESN and LSTM	1 WF	1 h	48 h	New Hybrid method based on ANNs
	19	SARIMA-RVFL	One solar site	20 min	1/2/3/6 steps	New Hybrid model with wavelet decomposition as preprocessing
	20	Random Forests	1 WF	1 h	1h	Speed, limited sensitivity to irrelevant data
	21	SVR with optimization algorithm	4 solar sites	1 h	1 d	Hybrid method with improved EMD,SVR and PSO
Regional generation from WFs [19,20] and PVs [21]	22	Method Based on Regular Vine Copulas	10 WF	1h	1 d	Probabilistic forecast for multiple wind farms
	23	DNN	Germany	1 h	n\a	DNN with discrete classes
	24	Upscaling of chosen PV plants	Kyushu, Japan	0.5 h	1h/3h/ intraday/ day	Upscaling and error analysis made on large data set (2219 PV plants)

Summary

For both parts of this paper, more than 90 articles published in 2017-2020 were analyzed. Unfortunately, many of them were largely incomplete in terms of basic characteristic information on forecasts. Therefore, they were discarded from further analyses.

Among the papers concerning generation prediction, most of the studies pertained to point or region-aggregated prediction of RES generation. This shows that interest in such subjects is not fading. Far from it – it becomes increasingly more refined.

Forecasts of scale different than above were relatively less popular. Multinodal predictions are still a niche, possibly waiting for more easily accessible and bigger computational power, and simplification of data acquisition procedures.

To test flexibility of methods, some researchers have adapted methods primarily used for different purposes, such as image recognition. The results achieved by them allow us to expect that creative use of tools from other fields could offer great development opportunities.

Abbreviations:

Abbreviation	Meaning
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BPNN	Back Propagation neural network
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DSO	Distribution System Operator
DWT	Discrete Wavelet Transform
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
ENN	Elman Neural Network
ESN	Echo State Network
GPV	NWP model name
GRNN	General Regression Neural Network
IKHOA	Improved Krill Herd Optimization Algorithm
IMF	Intrinsic mode function
KDE	Kernel Density Estimation
LSTM	Long Short-Term Memory
MDM	Multivariate Distribution Model
MODA	Multi-Objective dragonfly optimization algorithm
MODWT	Maximum Overlap Discrete Wavelet Transform
MV	medium voltage
NARX	Nonlinear Autoregressive Exogenous Model
NPS	National Power System
NWP	Numerical Weather Prediction
OTSTA	Opposition Transition State Transition Algorithm
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Sources
RVFL	Random Vector Functional Link
SARIMA	Seasonal Autoregressive Integrated Moving Average
SSA	Singular Spectrum Analysis
STA	State transition algorithm
SVM	Support Vector Machine
SVR	Support Vector Regression
SWD	Stationary Wavelet Decomposition
UK	United Kingdom
WF	Wind Farm
WTr	Wavelet Transform

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