Forecasting the hourly power output of wind farms for day-ahead and intraday markets

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***Abstract*— The penetration of large-scale wind farms causes a number of challenges. The market participants have to deal the wind power output for different market time horizon in order to minimize the deviations of their trading schedules. In order to control the balance between production and consumption, transmission system operators need information in advance, concerning wind generation, to prepare necessary types of reserves and to activate them in real time. The wind power forecasting is frequently identified as an important tool to address the variability and uncertainty of the wind power and to more efficiently operate the power systems with large wind power penetrations. In this report is presented the experience of the implementation of a forecasting model suitable for day-ahead and intraday markets.**

Keywords— electricity, forecasting, markets, modeling, wind

I. Introduction

In parallel with increasing penetration of the wind farms, the forecasting of their hourly production became important topic for the power industry. The transmission system operators (TSOs), wind farms' producers and regulation authorities support the efforts for developing better, reliable and precise forecasting models. The wind power output forecasting is necessary for large range of purposes [1] as: electricity trading; network planning; procurement of operational reserves; economic dispatching and accumulation facilities portfolio optimization. In this report is presented the functionality of developed and used since 2013 forecasting model used in national dispatching center of Bulgaria. The forecasting error is analyzed for different time horizons and further proposals for improvement are marked.

II. Forecasting Model Functionality

The basic functionality of the presented forecasting model is presented at (Fig. 1). It is completely physical approach and some statistical technics are used for improvement of the forecast [2]. As inputs it uses:

- Real time SCADA data concerning wind speed on turbine level, provided from big wind farm's producers and several TSO's anemometer stations;
- Numerical weather forecast (NWF) up to 72 hours ahead, concerning wind speed and temperature for different wind farm locations and turbine levels, provided from National institute of meteorology and hydrology in Bulgaria and updated twice per day at 9:00 and 21:00 o'clock;
- Wind turbine technical characteristic (power curve) available from manufacturers;
- Information concerning available number of turbines provided from wind farm's operators.

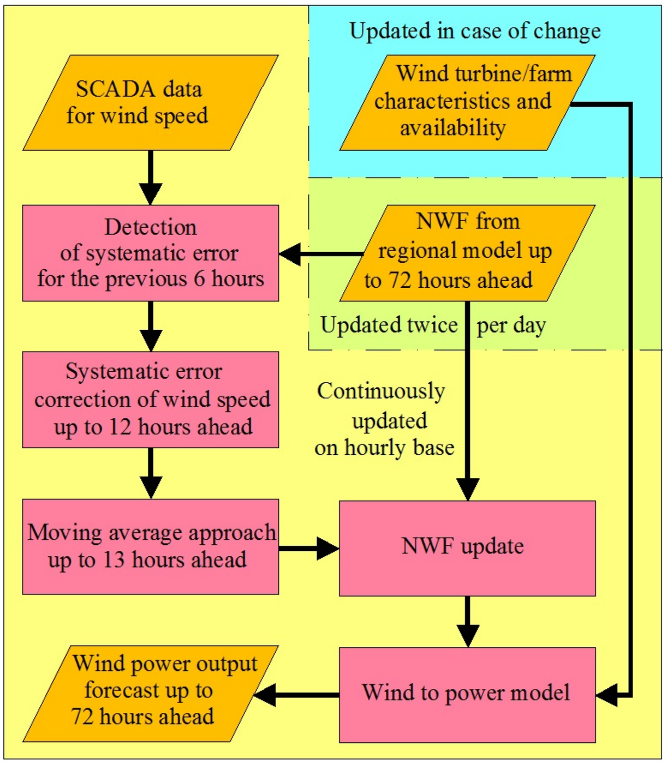

Fig. 1. Basic functionality of the forecasting model.

A. Wind speed systematic error correction

Due to the fact that NWF is not continuously updated and provided on hourly granularity, its accuracy decreases after the first hour till the next NWP receiving. The availability of real time SCADA data is suitable for applying systematic error correction of wind speed continuously for each hour. Based on historical data statistical analyzes, the improvement of NWF accuracy through systematic error correction for the next 13 hours is settled. It is obviously that with increasing

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of the forecast horizon the effect of correction of the systematic error decreases based on previous hour's performance. Therefore weighting coefficients are applied with decreasing rounded values from 1 for the first hour to 0 for the last forecasted hour.

The corrected wind speed V^c for the first hour ($i=1$) is calculates as follow:

$$V^c_{i=1} = V^f_{i=1} * \left(C_1 * \left(\frac{V^r_{i-1}}{V^f_{i-1}} - 1 \right) + 1 \right) \quad (1)$$

where V^f is forecasted (NWF) wind speed and V^r is realized wind speed for the respective hour. C_1 is weighted coefficient for the first hour settled to be 1, respectively the highest influence of the previous hour systematic error on the next forecasted hour.

The correction of the second hour ($h=2$) wind speed V^c depends from the previous three hours systematic error and the weighting coefficient C_2=0.75.

$$V^c_{i=2} = V^f_{i=2} * \left(C_2 * \left(\frac{V^c_{i-1} + V^r_{i-2} + V^r_{i-3}}{V^f_{i-1} + V^f_{i-2} + V^f_{i-3}} - 1 \right) + 1 \right) \quad (2)$$

Concerning the third hour, the number of the impacting wind speed values for the previous hours increase to 4 and weighting coefficient decreases to 0.5.

$$V^c_{i=3} = V^f_{i=3} * \left(C_3 * \left(\frac{V^c_{i-2} + 0.75 * V^f_{i-1} \frac{V^c_{i-2} + V^r_{i-3} + V^r_{i-4}}{V^f_{i-2} + V^f_{i-3} + V^f_{i-4}} + V^r_{i-3}}{V^f_{i-1} + V^f_{i-2} + V^f_{i-3}} - 1 \right) + 1 \right) \quad (3)$$

The correction of the wind speed forecast systematic error from the forth till twelfth hour is based on the equations, where the previous sixth hours are taken into account with weighting coefficients decreasing from 0.9 till 0.1 with step 0.1 from the forth hour till twelfth hour.

$$S_{i=4 \div 12} = \frac{V^c_{i-3} + 0.75 * V^f_{i-2} \frac{V^c_{i-3} + V^r_{i-4} + V^r_{i-5}}{V^f_{i-3} + V^f_{i-4} + V^f_{i-5}} + V^r_{i-4} + V^r_{i-5} + V^r_{i-6}}{V^f_{i-2} + V^f_{i-3} + V^f_{i-4} + V^f_{i-5} + V^f_{i-6}} \quad (4)$$

$$V^c{}_{i=4 \div 12} = V^c_i * [C_i * (S_i - 1) + 1], \quad (5)$$

Concerning the wind speed for the thirteenth hour a linear interpolation between V^c_{12} and V^f_{14} is applied.

B. Moving average technic application

In order to smooth out short-term fluctuations and highlight middle-term trends, the simple moving average technic is applied as type of convulsion [3].

The value of wind speed based on moving average V^{MA} for the first hour ($i=1$) is calculated as follow:

$$V^{MA}{}_{i=1} = (V^r{}_{i-2} + V^r{}_{i-1} + V^c{}_{i=1})/3, \quad (6)$$

By analogy is calculated the wind speed for the second hour ($i=2$):

$$V^{MA}{}_{i=2} = (V^r{}_{i-2} + V^c{}_{i=2} + V^c{}_{i=1})/3, \quad (7)$$

For the next hours till thirteenth hour is applied the following equation:

$$V^{MA}{}_{i=3 \div 13} = (V^c{}_i + V^c{}_{i-1} + V^c{}_{i-2})/3, \quad (8)$$

C. Wind to power calculation

After applying systematic error correction and moving average technic for the next thirteen hours concerning wind speed forecast, the calculated values are coupled with the rest hours till 72nd hour, as input data (V_i) for wind turbine output (P_i) forecasting. The power curves provided by wind turbine manufacturers are used in order to transform wind speed to power (wind to power model). The power curve is divided in six sections (Fig. 2):

- From wind speed 0 m/s to the value, where the wind turbine starts to generate;
- The second, third and fourth sections represent different concave/convex curve parts values between P_{min}=0 and P_{max}. Each point of these parts is calculated through quadratic function – $P(V)=a*V^2+b*V+c$;
- The fifth part represents the maximal power output of the respective wind turbine for different wind speed;
- The last section is for the higher values of wind speed that are dangerous for wind turbine and it stop to produce electricity.

The power output PWF_i^j of the wind farm j for each hour i is calculated as follow:

$$PWF_i^j = T_i^j * N^j * P_i^j(V_i), \quad (9)$$

where N_i^j is the number of available wind turbine (due to outage and/or maintenance), $P_i^j(V_i)$ is the wind turbine power corresponded to the forecasted wind speed for the hour i, T_i^j is temperature Boolean variable indicator with value 0 when the ambient temperature is below the level when the turbine stops to produce (manufacturer requirements) or 1 when the temperature is above this level.

III. Testing Results

Based on described methodology and functionality, forecasting software was developed and put in operation starting from January 2013. Due to reaching thermal limits on overhead lines connected wind farms concentrated in

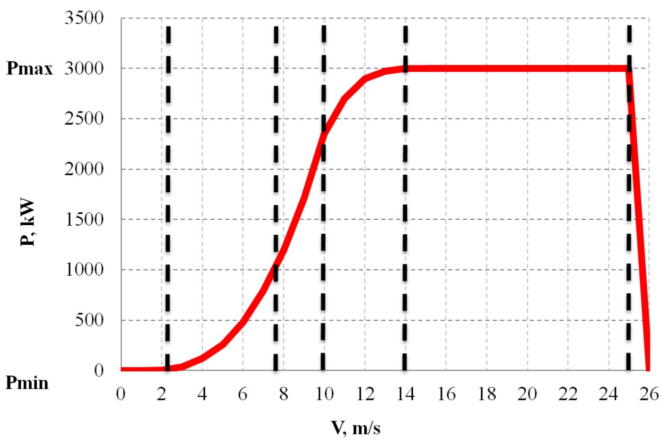

Fig. 2. Power curve.

northwest Bulgaria, curtailment of production was applied by TSO and DSO during 2013 and 2014 in some hours. In these cases implemented forecasting software was very useful for short-term estimations of network power flows and respective dispatchers' orders for power output curtailment. The network bottleneck concerning wind farm power output transmission was solved at the end of 2014. Therefore, estimation of the accuracy of the presented forecasting model is applied from January 2015 till December 2017.

For estimation the quality of forecasting model, the observed forecast error e^i_{i+t} for time period $i+t$ concerning the forecast output in hour i, is defined as difference between the values of average realized power P^r_{i+t} of the wind farm and forecasted in hour i power output P^f_{i+t}.

$$e^i_{i+t} = P^r_{i+t} - P^f_{i+t}, \tag{10}$$

The most popular measure for quantifying the forecasting model error that take into account the contribution of negative and positive errors [4, 5] is NRMSE (Normalized Root Mean Square Error):

$$NRMSE_t = \frac{1}{P_{inst}} * \sqrt{\frac{\sum_{i=1}^{N} \left| e^i_{i+t} * e^i_{i+t} \right|}{N}} \tag{11}$$

where N is the number of observed values and P_{inst} is installed capacity of wind farms.

On Fig. 3 is presented continuously update based on wind speed systematic error of the forecasting model that can be used for operating purposes and intraday market optimization of traded electricity production. It is obvious that with increasing of the forecasting horizon the NRMSE increase, but the forecast error is in very satisfied range for the first hour (less than 0.65%), where dispatchers have to take some decisions, concerning network operation or power system balancing. In the next two hours the forecast error is three times less than the error observed in day ahead performance (Fig.4) and serves to the market participants good perspectives for intraday optimization of their portfolio. Due to the fact that the wind speed profile,

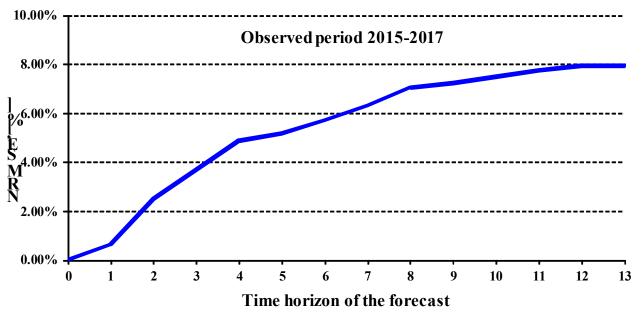

Fig. 3. NRMSE for thirteen hours ahead.

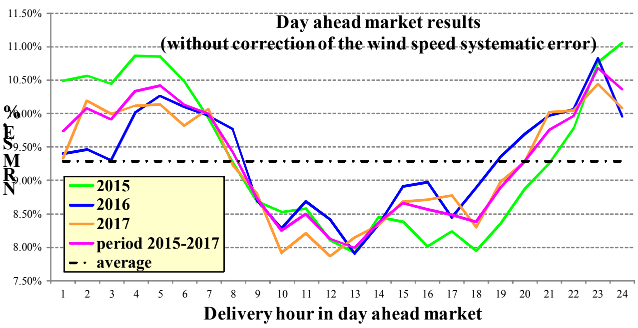

Fig. 4. NRMSE for day ahead market.

respectively power output, is with lower values during the noon than after midnight, NRMSE follow this profile, because P_{inst} is constant for all hours. However, the absolute forecast deviation always increases with enlargement of the time horizon.

Day ahead performance of the presented model is always in good correlation (error level and error phase) with realized trends of wind farms power output (Fig. 5). This predictability gives to TSO and market participants enough qualitative information in order to take appropriate measures to optimize power system performance and financial profit.

IV. Conclusions

The quality of the forecasting models depends on several factors as:

- Precisely determination of the terrain through ruggedness index (RIX);
- Wind turbine number, characteristics and their disposition;
- Geographical location - offshore or onshore;
- Data quality of NWF and SCADA;
- Type of NWF – global, regional and spatial;
- Type of the model – statistical, physical or combined;
- Specific weather condition of the location.

Concerning the presented forecasting model further

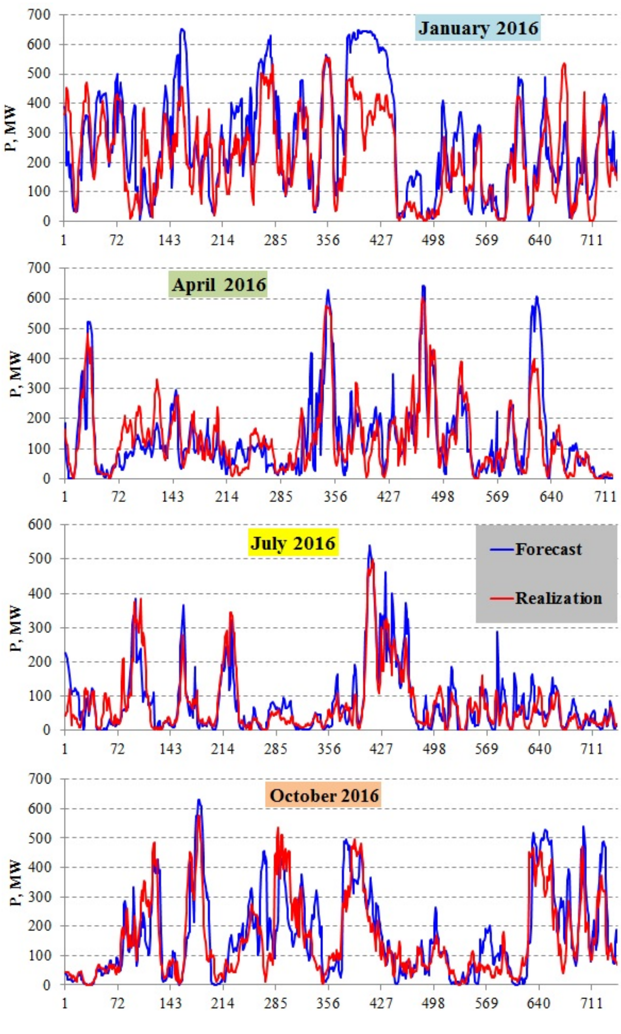

Fig. 5. Day ahead performance of the forecasting model.

improvements can be realized in several directions:

- Spatial modeling (wind rose) of power curves based on statistical analyzes of the historical data;
- Applying statistical forecasting models for very short time horizon;
- Applying ensemble of different forecasting approaches.

The proposed forecast model presents NRMSE close to world achievements in this field [6, 7, 8, 9]. In addition to the advantage for power system operation, the presented forecast model provides to TSO input data for calculating the electricity that is needed (TSO has to buy) in order to supply transmission losses [10, 11].

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