LITERATURE SURVEY

[1] Milligan, et., al., used the Elfin model to assess the financial benefits of good forecasting, taking into account the load time series, a wind time series, the distribution of power plants for different utilities, and the forced outage probabilities of the normal plant mix. Even though his method of simulating the forecast error was not very close to reality, some general conclusions could be drawn. When varying the simulated forecast error for three different utilities, zero forecast error always came out advantageously. The relative merit of over- respectively underpredicting varied between the two utilities analysed in detail: while underpredicting was cheaper for one utility, the opposite held true for the other. The cost penalty in dependency of the forecast error was dependent very much on the structure of the plant mix and the power exchange contracts. Generally speaking, a utility with a relatively large percentage of slow- start units is expected to benefit more from accuracy gains.

[2] Lionel, et., al., compare various algorithms for wind power forecasting and show that random forests with and without random input selection yield a prediction performance similar to SVR, but recommend to prefer a linear model when the computation time grows too large.

[3] Kanna, et., al., proposed an" adaptive wavelet neural net- work for mapping the NWP's wind speed and wind direction forecasts to wind power forecasts. Wind direction inherently being a circular variable, for better training and function approximation, a transformed version of wind direction variables are used as inputs. Further, the closest set of patterns based on Euclidean distance are chosen for training patterns and block- wise training and forecast strategy is employed for carrying wind power forecast. The results show that the significant improvement over the persistence method is achieved.

[4] Guo, et., al., performed the multi-step forecasting of wind speed using an ensemble or combination of two models EMD and FFNN. For each of these techniques, the nonlinear wind speed is decomposed into small chunks. The continuing the counterpart EMD enhanced insights on the data structures involving monthly mean wind speed data over three years. The performances of these models is evaluate using mean absolute error, mean square error and some trials independently.

[5] Landberg, et., al., used a poor man's ensemble to estimate the error of the forecast for one wind farm. A poor man's ensemble is formed using the overlapping runs of the forecasting model from different starting times for a given point in time. In his case, HIRLAM comes every 6 hours with a model horizon of 48 hours, leading to an ensemble size of up to 8 members for the same time. The assumption is that when the forecasts change from one NWP run to the next, then the weather is hard to forecast and the error is large. However, no conclusive proof for this intuitive assumption could be found.

[6] Kariniotakis and Miranda propose a methodology to assess the benefits from the use of advanced wind power and load forecasting techniques for the scheduling of a medium or large size autonomous power system. The case study of the Greek island of Crete is examined. The impact of forecasting accuracy on the various power system management functions is analysed. According to the calculations in the accuracy of the prognostic tools should be improved to more than 90% to reduce the costs for regulating power to an acceptable level.

[7] Ensslin talks about the value of a forecasting tool in the framework of an "Internet-based information system for integration of Renewable Energy Sources and Distributed Generation in Europe". While not directly connected to wind power forecasts.

[8] Lin, et., al., implemented isolation forest (IF) along with deep learning neural network to detect outliers for more accurate wind power forecasting. Wind speed, wind direction, air temperature, etc., were extracted from a supervisory control and data acquisition (SCADA) dataset of an offshore wind turbine to be used as inputs while employing wind power as the output in the predictive model. Comparison results showed that IF is a more effective way of providing accurate forecasting, especially when the investigated data do not follow the normal distribution. In another paper, the authors critically evaluated eleven features from a 7 MW wind turbine in Scotland, including four wind speeds at different heights, average blade pitch angle, three measured pitch angles for three blades, ambient temperature, yaw error and nacelle orientation. The results revealed that the blade pitch angle had the greatest effect on the performance of the prediction model, even more than wind speed and wind shear.

[9] Marcos, et., al., used a mixture of a physical and a statistical model. The input data were atmospheric global-scale forecasts, which were provided by the global forecasting system (GFS). A Brazilian NWP model (BRAMS) was also used to refine the atmospheric global-scale forecasts by using physical considerations about the terrain, such as vegetation cover, soil texture, etc. After that, a systematic error correction filter with the capability of learning the dynamic behaviour of wind data was used to reduce the biases of the forecasted wind. After elimination of the biases, two main methods were used for wind power forecasting, manufacture's power curve and regression equations, which were derived from wind measurements and generated power data from SCADA systems. For generating polynomial regressions, observed one-year data of wind and power were considered using four equations: linear, quadratic, quadratic with considering previous power outputs and cubic. Comparing these four equations with statistical indexes like RMSE showed that cubic regression provides the best results. As other factors can also influence the power output, such as air density, wake effect, orography, etc., the Kalman filter was used again to eliminate systematic errors from the conversion model. Finally, it was concluded using the Kalman filter decreased the value of RMSE and increased the values of anomaly correlation coefficient (ACC) and Nash–Sutcliffe coefficient (NSC), all representing better forecasting.

[10] Liu, at., al., combined three different prediction models including BPNN, RBFNN and least square support vector machine (LSSVM) by an adaptive neuro-fuzzy inference system (ANFIS) for 48-h-ahead wind power forecasting. As the first step, a Pearson correlation coefficient (PCC) based method was used to eliminate outliers. Sixty-day datasets of a wind farm in China, containing wind speed, wind direction, temperature and generated power, were used as inputs and an output to train the three methods. The evaluation of the proposed hybrid model showed that it outperformed the three individual forecasting models and can predict with remarkable accuracy progress. Zhao et al. [41] used a Kalman filter to decrease the systematic errors of wind speed.