Importance of Numerical Weather Prediction in Variable Renewable Energy Forecast

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***Abstract*—NWP models although being an essential component of integrated VRE forecast system inflicts certain uncertainties which affect the accuracy of forecast. These uncertainties arise mainly from model assumptions of local atmospheric condition, adopted parameterization methods and post processing techniques which are not always inclusive of site specific information. In this paper, a detailed study of the NWP uncertainties, conventional biases and their possible sources are discussed. These uncertainties mainly come from model assumption of weather condition, adopted parameterization and post processing techniques. Here, various methods from published literature to remove the biases are described which will lead to a much improved energy forecast. These methods include the ensemble and nested model approach, ANN, usage of Remote Sensing data and various interpolation techniques.**

Keywords- NWP; VRE forecast; uncertainties; model bias; parameterization; post processing; ensemble; ANN; Remote Sensing

I. INTRODUCTION

A proper integration of Variable Renewable Energy (VRE) forecasts into energy and market management systems requires an improved forecast of short term weather data. Conventionally there are couples of methods of weather prediction which are practiced separately or even in combination for VRE forecast. The first is the weather prediction through Numerical Weather Prediction (NWP) which are converted into energy production and second is statistical prediction using historic and real time data. Due to its set of limitations, observed meteorological data is ideally replaced by better resolved model data obtained from NWP models which paves the way for a robust and much accurate VRE forecast system. However, NWP models with their embedded simulation algorithm are not perfect and suffer from various degrees of uncertainties which eventually influences the performance of energy forecast at a regional scale. The uncertainty does not only lie in selection of a suitable method of solution, which is site specific, but also in various steps of executing the methods. For example, the success of a NWP depends up on various factors ranging from quality of re-analysis products used as input parameters, model assumptions of both initial and boundary conditions and their suitability to local atmospheric condition. Apart from the selection of the proper data assimilation techniques, suitable interpolation methods and post processing techniques are important to remove NWP model output biases. Apart from describing the common biases of NWP in the context of VRE forecast, this paper over the following sections, also discusses various methods adopted across the community to remove these shortcomings and improve accuracy in forecast. Apart from highlighting some well practiced methods of MOS, CP and DCP, this study also describes some new parameterizations for wind and solar energy forecasts, recent development in post processing methods and suitability of ensemble model studies.

II. OBSERVED WEATHER DATA, ITS LIMITATION FOR VRE FORECAST AND BENEFIT OF NWP

Although, ideally the observed meteorological data holds an edge over model data for Variable Renewable Energy (VRE) forecasts, usually sparred populated measurement locations pose major hindrance in the forecasting process [1]. To achieve accuracy in forecast, individual sites need to have substantial past observations to build climatology, which is not always possible with observed data. For example, longer periods, say for ten years of wind data will provide more reliable results and capture long-term variability which is not possible just with one-year past observed data which however is only sufficient to determine diurnal and seasonal variations [2]. Apart from that, continuous data measurement is an expensive process which is not always compatible with forecast costs. Due to these limitations, renewable energy forecast and resource assessment application depends on data generated by Numerical Weather Prediction (NWP) models which provide simulated data of various atmospheric variables that are continuous, long in time scale and spatially well resolved.

III. NWP AND ITS BASICS PRINCIPLES

As for the basics of NWP goes, provided the initial condition of the atmosphere is known, then NWP models solve the equations of atmospheric variables, applying the physical forces that act on them over the time to obtain new values of those variables at a later time. NWP models use atmospheric reanalysis as initial and boundary conditions for the model run, which then realistically downscales to a finer physical resolution using physical equations [3].

The principal equations relative to the motion on the atmosphere are law of momentum conservation, energy conservation law of thermos dynamics, continuity equation (mass conservation) and equation of state. Ideally Weather prediction is an initial value problem; therefore, NWP model needs to know the initial state of the atmosphere to predict the future. Initial state of the atmosphere is constructed by a process called Data Assimilation using real world measurements and the previous short-range model output [4].

IV. THE ADVANTAGES OF NWP

The basic advantages of NWP model output for the renewable energy resource assessment can be attributed to its cost effectiveness, fruitful handling of Interpolation issues, handling of missing data and provision of location specific information.

To make the NWP forecast locally optimized and suitable for operation, several post processing techniques are used to refine the output of NWP models. Among the different post-processing approaches, Model Output Statistics (MOS) and spatial averaging are well known [5]. For example, spatial averaging of irradiance forecasts leads to improved solar forecast accuracy by smoothing the variations in variable sky conditions due to changing cloud cover.

Typically, meteorological departments run NWP models twice a day for forecast. For short-range forecast, three-day forecast is generated each run with hourly forecast output [6]. Wind speed and direction are typical model output parameters. Similarly, Numerical Weather Prediction (NWP) models are the basis of solar yield forecasts over a 48-hr. time horizon, as the time range being useful for grid integration and decision making in the energy market [3].

However, the basic disadvantage of NWP is the uncertainties in the assumption of initial condition of the atmosphere which is unable to replicate the real-time condition. Apart from that, the assumption itself has an obligation to generalize the state of atmosphere which often ignores the local phenomenon and weather variability.

Similarly, some discrepancies may also come in from the uncertainties of boundary conditions used from NCEP reanalysis products [7]. Apart from this, model bias can also be inflicted up on due to the simulation algorithm chosen (3d var, 4d var etc.) for that particular simulation. Forecast biases can often be location dependent and persistent in nature. To remove the bias, well-known correction MOS is conventionally applied to reduce persistent errors.

In a nutshell, i) improving the initial parameterization, ii) improving resolution and iii) applying statistical post processing are the most commonly used techniques to reduce the uncertainty in the NWP models.

V. FORECAST ERRORS

NWP output shows frequently systematic deviations depending on the meteorological situation. In these cases, a bias correction based on statistical analyses can improve the results.

Forecast accuracy was evaluated through the root mean square error (RMSE) and mean bias error (MBE). Subsequently, as discussed earlier, MOS is applied to reduce persistent errors [8]. However, MOS could not distinguish between errors in the clear sky models and errors related to cloud prediction so MOS corrections in the measured clear sky regime did not reduce in actual. In fact, many initially accurate forecasts were unnecessarily corrected by the MOS.

So, differentiating between the sources of the error is very important in understanding which forecasts need to be corrected, which was preferable to correcting all forecasts.

As mentioned earlier that resolution of the NWP models inflicts significant error. Even the 0.1° x 0.1° NAM spatial resolution is insufficient to resolve most clouds and only an average cloud cover could be forecasted. The resolution was even coarser for the GFS and ECMWF [9].

Cloud cover and cloud optical depth are the most important parameters affecting solar irradiance and needs to be resolved using NWP. This is important for predicting ramp rates and bands of variability for solar power plants.

However, it has been found that even if the spatial resolution was finer, the temporal output intervals would not permit the examination of time dependent cloud cover variability.

It is also to be noted that NWP model time-steps are on the order of minutes but radiative transfer models are run less frequently and the output was only hourly for NAM or every three hours for GFS and ECMWF. Consequently, any patterns with characteristic time scales less than an hour were unresolved [10].

Therefore, it is required to develop new capabilities and strategies to quantify and reduce the uncertainty of both the solar and wind data generated from NWP models.

VI. IMPROVEMENT OF FORECASTS

It is evident that alone NWP for VRE forecast is not sufficient in improving the accuracy since it suffers from various inherent limitations in its set up and algorithm. In view of this, some of the present studies have suggested various methods that can be used in conjunction with conventional NWP methods to minimize the bias in forecast system.

Andrade et al. [11] comes up with a forecasting framework which will explore information from a grid of numerical weather predictions. The methodology extracts the maximum information from the NWP grid and eventually combines the gradient boosting trees algorithm with feature engineering techniques. It shows significant forecast improvement compared to one NWP point for a specific location. The proposed framework in the paper extracts features from a NWP grid by using domain knowledge and prove that this information can improve the forecast skill of state of the art forecasting systems, which can be a benchmark for renewable forecast improvement. The proposed methodology constructs new variables from the raw NWP data that are used as inputs in the GBT algorithm which can be adopted both for both wind and solar energy. Similarly, some of the studies describe the devised methods that combine existing NWP outputs with real-time local data and advanced statistical analyses to produce accurate site-specific predictions [12-15].

A. Bias correction methodology

Conventionally, a bias correction methodology is applied on NWP outputs to attain an improved prediction. The bias correction methodology allows us to minimise systematic errors in future forecasts by using a knowledge of the bias in errors from past forecasts. This technique extends beyond ‘fair weather’ conditions, and is also used in predicting an extreme weather event that required shutdown of the wind farm.

Among the bias correction method, CP and DCP are well known which is shown to greatly enhance the timing and accuracy of forecasts from the NWP [16].

It is also observed that the use of actual wind farm data provides an added benefit to scaling the forecast to better represent the wind farm, which also proves that real time data from wind farm needs to be coupled with NWP models to minimize the system error which are consistent in its nature.

B. New parametrizations with a better understanding

Fitch et al. [17] describes new wind farm parameterization has been developed for the mesoscale numerical weather prediction model.

For wind energy forecast, a greater understanding of the interaction between the atmospheric boundary layer (BL) and wind turbines is necessary to ensure energy production and the lifetime of turbines are maximized.

C. Persistent approach to improve accuracy

Apart from the conventional NWP modeling method, Zhang et al [18] suggests a persistent approach which corresponds to using the persistence of the recent observations. This study shows superior skill in the shorter forecasting periods and when atmospheric variability is smaller (e.g., dry climates, few clouds). Specifically, the persistence forecasts show better skill than the model forecasts in the short term, whereas the model forecasts show better skill (than the persistence) after a few hours in the forecasting period.

D. Improved post-processing: Adequate interpolation technique

A common post-processing task is the temporal interpolation of global model forecast output, which typically is provided with a temporal resolution of 3 hours. Solar power forecasting with one-hour time resolution therefore needs an adequate interpolation technique.

Another technique for improving forecast quality is spatial averaging. In variable cloud situations, this reduces fluctuations in the irradiance forecast values, but in homogeneous (clear-sky or overcast) situations it does not harm the forecast quality. For example, ECMWF irradiance forecasts show best results when averaging over 4×4 grid points, corresponding to a region of 100km×100km, is applied [19].

E. Usage of remote sensing for a better prediction:

For physically-based forecasting, cloud cover and cloud optical depth are the most important parameters affecting solar irradiance. Through processing of satellite or ground imagery, clouds can be detected, characterized, and adverted to predict GHI accurately up to 6 h in advance [20].

Hammer et al. [21] demonstrated 17% rRMSE in satellite imagery for 30 min cloud index forecasts and 30% rRMSE at 2 h forecast horizons. For intra-day forecasts, a reduction in rRMSE by 7–10% compared to persistence forecasts was found.

Other than NWPs, sky camera and geostationary satellite image analyses are also employed for short term forecasting [22-26].

F. Ensamble and nested approach

The output of the ensemble members is used to derive the ensemble mean for different atmospheric variables including wind, temperature and pressure. This regional scale ensemble forecast is then used for preliminary wind resource assessment after validation with the available measurements.

Ensemble approach is also used to reduce the systematic biases in regional climate modeling. WRF model was forced by reanalysis of NCEP-R2, ERA-40 and IRA-25 datasets [27]. The ensemble system showed considerable bias reduction compared to each individual model.

The differences in wind, temperature, and pressure data between the ensemble members give the sense of the assessment uncertainty. This is an advantage over the classical approach by depending on single model data.

Through averaging, the less predictable features are smoothed out while the predictable features in the forecast remain intact. As a result, ensemble mean values are smoother than values for the individual ensemble members. Because of smoothing, the ensemble mean forecast performs better on average [28] than the higher resolution NWP model on which it is based.

Apart from this, Nesting approach also ensures that the local scale model resolution is fed by the information from both coarser scales.

G. ANN and post processing

Artificial neural networks (ANNs) as a post-processing technique, in order to improve mesoscale WRF solar radiation outputs have been widely used. ANNs are data driven approaches capable of recognizing patterns in data. Data of key parameters depending up on the type of weather forecast, obtained from ground stations are often used and trained to construct the ANN model in order to reduce the bias of the WRF forecasts.

For example, the NWP models (especially GFS and NAM) are biased towards forecasting clear conditions resulting in large, positive biases which can be removed using ANN method [29].

It is to be noted that ANN network has been successfully applied to solar forecasting. Using training data, typically years of measured ground data [30], ANNs have been developed to reduce relative RMSE (rRMSE) of daily average GHI by as much as 15% when compared to 12–18 h ahead NWP forecasts [30].

In a similar study, Voyant et al. [31] describes a method, where they have used an optimized multi-layer perceptron (MLP) with endogenous input and exogenous inputs (meteorological data) which forecast the global solar radiation time series with acceptable errors.

VII. Conclusion

It is evident from the study, that although NWP models are indispensable for VRE forecasts, it has its set of limitations coming both from its intrinsic structure as well as the input products derived from external sources. This study, if on one hand, tries to highlight the necessity of NWPs as an integral component of energy prediction, on the other, emphasizes the scope of their improvements in various capacities to further improve the accuracy of VRE forecasts.

In order to achieve its objective, this paper assembles and describes various methods and techniques used across the community to remove the errors and biases for both the wind and solar forecasts which needs to be analyzed thoroughly. This is very important in view of exploring possibilities for the betterment of Indian renewable energy forecast scenario which faces many difficulties. It is subjected to further research and discourse if any of the methods, or combination of many as described in this paper can be adopted to Indian Energy market. Nevertheless, the present study, through a detailed literature survey, attempts to highlight various uncertainties related to conventional NWP models, their nature and sources and at the same time provides insight on possible solutions, practiced both on regional and global scale.

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