Simulating Solar Forecasting for Energy Market Decision Models

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Overview

Today's energy markets are increasingly challenged by the uncertainty of supply inherently associated with weather-dependent energy resources [1]. Market participants' behaviour depends on the available forecasts. Current models of market participants' behaviour are based either on perfect foresight assumptions, or on a single forecast, usually 24 hours ahead of time. In reality, consecutive, increasingly more reliable forecasts become available closer to real time. These improvements affect consecutive decisions of market participants. For energy market modelling, usually only historical data, not the preceding forecast are available. Limited amount of work currently exists on simulating consecutive, increasingly more reliable forecasts from the available historical data. This paper details and analyses a statistical approach to solar forecasting based on historical data, for multiple forecasts, up to several days in advance.

Methods

The method proposed in this paper extends existing Gaussian noise addition methods available in literature [2]. The method relies on error addition to measured historical data. The magnitude of the error increases with increasing forecast horizon. Formally, the insolation forecast $\hat{y}_t$ for timestep *t* is calculated using the measured insolation value y_t for that timestep and a relative error ε_h with *h* the increasing forecast time horizon, i.e. the difference between the current timestep τ and the future timestep *t*. The errors are normally distributed with a mean zero and a variance σ_h^2 which increases as the forecast time horizon *h* increases:

$$\hat{y}(t,\tau) = y(t) * (1 + \varepsilon_h) \qquad \text{with } (t,\tau) \text{ such that } t - \tau = h \tag{1}$$

$$\varepsilon_h \sim N(0, \sigma_h^2) \tag{2}$$

One of the main challenges in this approach, is the estimation of time-horizon-dependent variances σ_h^2. The method proposed in this paper shows that the root mean square error (RMSE) metric, often used to assess the quality of real forecasts, can be used to estimate the σ_h^2-values. RSME-values (and derived relative RSME, or rRMSE-values) are available from literature describing meteorological forecasting models (e.g., [3]). The proposed model uses rRMSE_h for each time horizon *h*. The value of rRMSE_h is calculated based on *N* observations of measured values $y_i(t)$ for timestep *t*, and the corresponding forecasted values $\hat{y}_i(t,\tau)$ for timestep *t* made at timestep τ:

$$\text{rRMSE}_h = \sqrt{\frac{\sum_{i=1}^{N} \left(\frac{\hat{y}_i(t,\tau) - y_i(t)}{y_i(t)} \right)^2}{N}} \qquad \text{with } (t,\tau) \text{ such that } t - \tau = h \tag{3}$$

The standard deviation of a normal distribution is defined as:

$$\sigma = \sqrt{\frac{\sum_{k=1}^{M} (\hat{x}_k - \bar{x})^2}{M-1}} \tag{4}$$

Eq. 3 and 4 are equivalent if (1) the insolation predictions $\hat{y}_i(t,\tau)$ are unbiased around the real value $y_i(t)$, then $y_i(t) = \bar{\hat{y}}(t,\tau)$, and (2) with the approximation $M - 1 \approx N$. Then, $\hat{x}_k = \hat{y}_i(t,\tau)/y_i(t)$ and $\bar{x} = 1$. The rRMSE_h-value then approximates σ_h.

The resulting model is a purely statistical one, it therefore cannot entirely capture the behaviour of real meteorological forecasting methods. Two main issues need to be corrected: (1) *unrealistic values*, and (2) *independence artefacts in subsequent forecasts*.

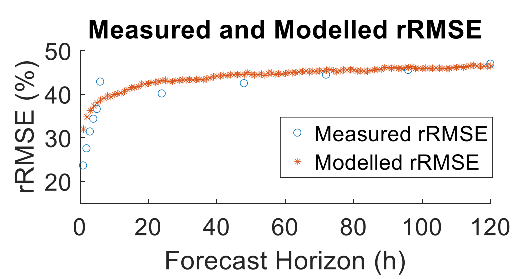

Fig. 1. Comparison of measured rRMSE (calculated from [3]) and rRMSE modelled by the method described in this paper.

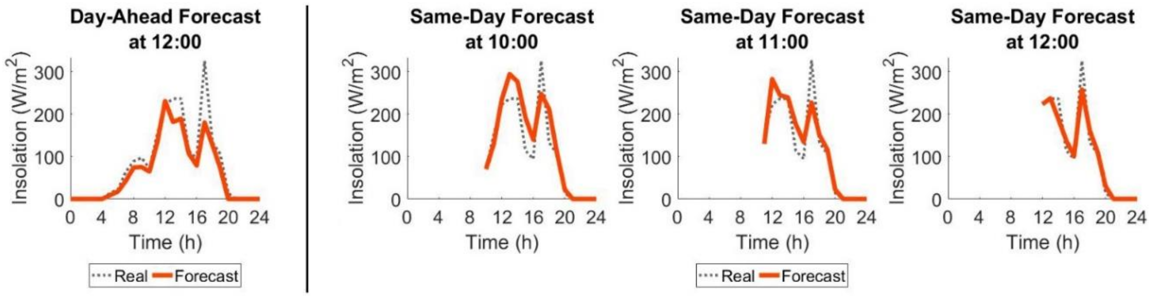

Fig. 2. Simulated consecutive day-ahead and same-day forecasts for June 3rd, 2012.

Unrealistic values, such as negative insolation and too high values for the time of the day and year, should be corrected:

- Correction rule 1: Negative insolation value == 20% of time-appropriate clear sky value (equals cloudy sky)
- Correction rule 2: Value higher than time-appropriate clear sky value == time-appropriate clear sky value

Independence artefacts in subsequent forecasts arise because forecasts made in subsequent timesteps $\tau_{j-1}$and τ_j (i.e., as the present timestep τ moves forward), are independent from each other: the errors ε_h are drawn independently at each timestep τ. This can lead to considerably different forecasts $\hat{y}(t,\tau_{\mathrm{j-1}})$ and $\hat{y}(t,\tau_{\mathrm{j}})$ for the same timestep t drawn at subsequent timesteps τ_{j-1} and τ_j. This can be corrected by making subsequent forecasts interdependent. The following empirically found correction is implemented. If two subsequent forecasts $\hat{y}(t,\tau_{\mathrm{j-1}})$ and $\hat{y}(t,\tau_{\mathrm{j}})$ differ by more than 10%, the final forecast $\hat{y}_{final}(t,\tau_j)$ is the average of the original forecast $\hat{y}_{orig}(t,\tau_j)$, a new forecast $\hat{y}_{new}(t,\tau_j)$, the forecasts of the previous timesteps τ_{j-1} and τ_{j-2}, and the real value of the previous hour $y(t-1)$:

$$\hat{y}_{final}(t,\tau_j) = \mathrm{mean}\left[\hat{y}_{orig}(t,\tau_j), \hat{y}_{new}(t,\tau_j), \hat{y}(t,\tau_{j-1}), \hat{y}(t,\tau_{j-2}), y(t-1)\right] \quad (5)$$

The parameters of this empirical correction can be adapted to the context in which this forecasting simulation is used.

The method is validated through comparison of modelled rRMSE-values with measured rRMSE-values from [3] (see Fig. 1). The modelled rRMSE values are slightly higher than measured values for small forecast horizons, yet overall, closely simulate the real rRMSE trends of meteorological forecasting models. This shows the validity of the method.

Results

The method is applied to a solar insolation dataset from the Netherlands. Fig. 2. shows an example of simulated day-ahead and same-day forecasts for June 3rd, 2012. The day-ahead forecast simulation somewhat misestimates insolation throughout the entire day (as can be expected from a real forecast). However, the model returns no unrealistic (negative or very high) values. The same-day forecast at 10:00 shows errors for the later afternoon hours, but is close to real values for the morning hours. As the day progresses, the forecasts for the later hours become closer to reality. This closely resembles the behaviour of real meteorological forecasting methods.

These forecasts can be used to realistically simulate market participant behaviour, for instance that of an aggregator with renewables in her portfolio, who bases her decisions on forecasts. This aggregator bids in the day-ahead market based on the day-ahead forecast from Fig. 1. Same-day forecasts are then used to model intraday behaviour such as intraday bidding or rescheduling of flexible loads (demand response) or dispatchable generation.

The model is implemented as a Matlab script and is available upon request from the first author.

Conclusions

The proposed method is a relatively simple, yet for many applications sufficiently powerful model, which can be incorporated in existing and future energy market models to improve insights in short-term behaviour of market participants with weather-dependent generation assets in their portfolio.

References

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