Accurate forecasts for successful renewable energy businesses – Jonathan Simon

Accurate forecasts of the expected power output in the next minutes, hours or days enable grid operators, generators, traders and other market actors to manage the resulting volatility, maximise the usage of renewable energy, and minimise balancing costs. Power forecasts have thus become a key economic factor, and their accuracy directly impacts the economic viability in an ever more competitive power market.

Several factors need to be taken into account in order to achieve consistent, high-quality forecasting results. In this article, we provide an overview of forecasting methods, including data sources used in those forecasts. We discuss which role forecast accuracy plays depending on applications and regulations.

1 Input data for forecast computation

Input data used for computing forecasts can be grouped into static data and time-variant data. Static data (also called master data) includes plant information, such as the location and physical plant characteristics. They are combined with time-variant data such as numerical weather prediction models, meter data or information about the current or future status of the plant in order to compute an accurate forecast.

1.1 Static plant data

Knowing the location of the plant is a prerequisite for setting up a forecast. This can lead to the first quality issues, as the exact geographical coordinates are not always known. And the better the forecasting system knows the physical characteristics and the environment of the plant, the more accurate forecasts it can produce. For this reason, information such as the manufacturer and model of the machine and the hub height are important data as well.

1.2 Numerical weather prediction models

Numerical weather prediction (NWP) models are the most important time-variant input for renewables forecasts. High-quality NWP models are developed and operated by meteorological services around the world to provide weather forecasts to governmental institutions, private organisations and the general public. For a grid of geographical coordinates, they compute the atmospheric conditions for the next hours and days. The NWP models are typically updated at least twice daily, sometimes even every three hours.

There are global weather models from a number of meteorological services. Some models, such as National Oceanic and Atmospheric Administration Global Forecast System (NOAA GFS), are available free of charge, but offer limited spatial and temporal resolution. High-resolution models such as European Centre for Medium-Range Weather Forecasts – High Resolution Forecast (ECMWF HRES) provide higher quality forecasts.

These global weather models are complemented by regional weather models, covering sometimes only small areas such as single countries, but with a higher spatial resolution and often better suited to depict local weather phenomena.

1.3 Live meter and availability data

Live meter data, but also live availability data, comprising updates about the plant status, maintenance and curtailments, is an important input for short-term forecasts. This data is obtained from the SCADA or monitoring system of the plants.

When live meter and availability data is systematically fed into the forecasting system and considered in the forecast calculation, this is called a real-time forecast. The maximum delay for real-time integration should be one hour, as the forecast error of real-time forecasting methods rapidly increases with increasing time distance between the last available meter data and the forecasted time interval.

2 State-of-the-art forecasting methods

The problem of forecasting the power generation of wind plants does not have a single solution. Each approach represents a different way of mapping weather parameters and other input data to generated power, effectively modelling the characteristic curve of a wind turbine, its environment and the related downstream systems.

2.1 Physical models

Physical models simulate the wind turbine characteristics using parameters from static plant information, resulting in a power curve that maps the weather data input (including wind speed) to generated power.

If all relevant parameters (including the environment of the plant) are part of the model, high forecast quality can be achieved. Physical models can even be applied without any training meter data, even though forecasts will often show a bias, so that some degree of training or calibration is still important.

However, as more and more parameters need to be considered – not only weather parameters, but also the environment of the plant and even live metering and status data – it becomes an increasingly complex task to include all of them in a physical model. In addition, there may be non-obvious obstacles, e.g. as wind turbines can run in different modes that have different power curves.

2.2 Artificial Intelligence

The dominant Artificial Intelligence technique used in power generation forecasting is Machine Learning. Historical performance data is used to train artificial neural networks (ANN) which will then predict future performance. This allows the models to learn the physical characteristics of the plant, as the same turbine type can behave very differently depending on the environment.

Each ANN learns from historical meter data and historical NWP model data. When it has to determine future conditions based on future NWP model results, it recalls a similar situation. In this process, the ANN absorbs all weather-dependent effects. For example, if there is a group of obstacles, topographical effects like elevation changes, the algorithm learns that the production is different depending on the wind direction. If there is another wind turbine located to one side of the plant, wind from this side will cause the wake effect, leading to reduced production. These effects do not have to be explicitly accounted for or modelled, instead the impact on the power output is learned from the historical data fed into the training of the ANN. Additional parameters to represent season, day of week or time of day are also used to complement the weather inputs.

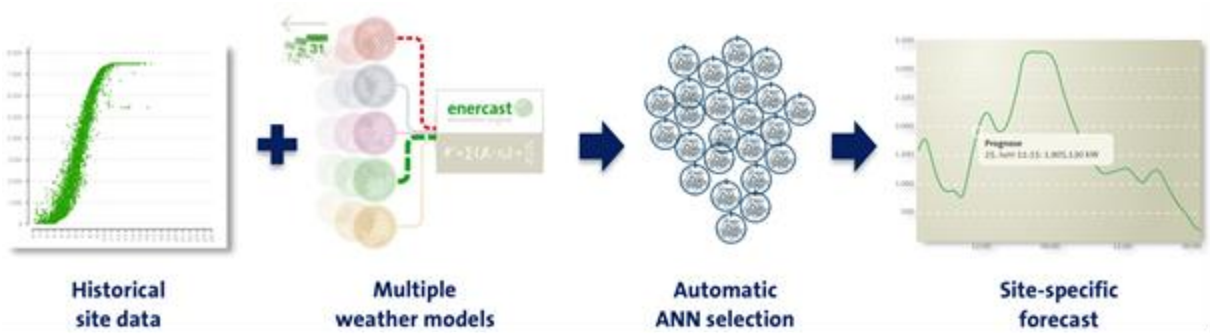

Figure 1. Forecasting process: A number of ANN models is trained using historical meter data and numerical weather prediction data. The best combination of models is then selected for the operational forecast.

The advantage of Machine Learning over physical models is that even unknown or overlooked phenomena can be learned. An additional benefit is that the training can determine how the numerous NWP model parameters, but also the other input parameters should be weighted in comparison to each other, in order to produce an optimal result for the individual asset (see Fig 1).

In order to successfully implement artificial intelligence for forecasting, the first requirement is to choose the best technology among the huge set of available methods depending on the use case. There are many types of ANN, and the structure, or topology, of the ANN determines its performance for the specific task. This includes careful selection of the right input parameters, so-called features, because providing more than the input required for the best result will make it more difficult for the machine learning algorithms to learn the link between input and output data, meaning that more training data would be required for a stable result. Designing an ANN setup that is suitable for large-scale application therefore also requires extensive experience.

2.3 Combining multiple forecast models

Each forecasting method creates one or more forecasts by using it with one or more input data source, resulting in a number of forecasts for the same plant. These forecasts can be combined to produce a forecast with even better quality than any single forecast.

What is the benefit of combining multiple forecast models? Different NWP models deliver different results for a single location, and each one has its strengths and weaknesses, depending on seasons, atmospheric conditions or other factors. For example, one model may show better results under anticyclonic atmospheric conditions, while the opposite may be the case for another model. Therefore, the most accurate result can be obtained by employing different models to create a set of forecasts, referred to as a multi-model ensemble. The forecasts created from each individual model are subsequently combined – ideally making use of each model's strengths while ignoring its weaknesses.

Combining the different NWP-based forecasts can be achieved by either first combining the NWP model data to compute a combined weather forecast which is then fed into the forecast model, or by running a given forecast model multiple times using different weather models and combining the forecasts subsequently, while real-time forecast models can be included in this case as well.

As a single forecast can span a time period of multiple days or weeks, it is important to consider that the different models have different horizons (e.g. NWP-based forecasts with a horizon of three days or 10 days, real-time forecast models with a horizon of only a few hours), and forecast accuracy for each model depends on the lead time. The combined forecast must therefore adjust the combination depending on the lead time while assuring a smooth transition between the different models.

enercast uses its e³ technology to combine all available forecast models, applying parametrisable optimisations and corrections in order to create the best possible forecast.

2.4 Real-time forecast models

The quality of a forecast inherently depends on the forecast lead time: Shorter lead time (e.g. intraday forecast) means smaller forecast error, larger lead-time (e.g. day-ahead or week-ahead forecast) means larger forecast error.

In order to improve intraday forecasts even further, real-time integration of live data is essential: By feeding live meter data into the forecasting system, these can be used to increase the forecast quality in the hours following the delivery using a real-time forecast model. Real-time forecast models are specific to the type of live input data used.

The biggest impact of real-time integration can be seen during the first two hours (counted from the timestamp of the live data). In markets and regulations where intraday updates of forecasts are possible, this can drastically reduce balancing costs. In addition to metered power data, algorithms can also consider maintenance and curtailment when the data is provided.

3 Consistent data and processes

The forecast quality is not only determined by the quality of the forecast model, but equally by the quality of the input data, the integration of processes and systems, and the reliability of the delivery infrastructure (see Figure 2).

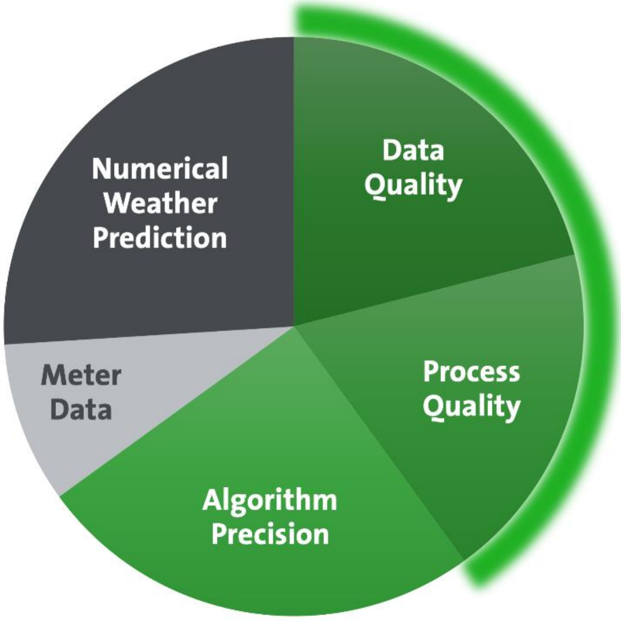

Figure 2. Not only the use of high-quality NWP models and state-of-the-art algorithms drive forecast quality, but also the quality of provided data and related processes.

3.1 Data cleansing

The forecast training and computation process inherently relies on real-world data that is provided by the user. The more accurate the input data is, the better the result. However, sometimes real-world data does not show the quality that is required to create an accurate forecast. Therefore, for both static plant data as well as meter data, data cleansing is required.

3.2 Integration of systems and processes

Integrating the forecasting system with the user's business systems ensures that forecast setup is seamless and high forecast accuracy can be achieved consistently.

Automatic synchronisation of static plant data avoids costly and error-prone manual set-up, decreasing the time until the first forecast for a new plant is delivered. Real-time transmission of metering and plant status data enables improvement of short-term forecasts. Continuous feed-in of data also provides the basis for continuously improving the forecast quality.

This integration requires open interfaces and consistent application programming interfaces (APIs) for forecasts, meter data and availabilities. In addition, transparent access to the status of the forecasting system allows users to better understand the behaviour of forecasts.

However, not only systems but also business processes need to be aligned if forecasts are to efficiently support business decisions. A thorough understanding of the effect of forecasts in the user's business is a prerequisite for creating a forecast configuration that suits the business needs. Costs associated with forecast error must be reflected by appropriate evaluation of forecasts. Therefore, state-of-the-art forecasting solutions support transparent, interactive set-up of all evaluation parameters including forecast horizons, update times and key performance indicators (KPI).

4 Evaluating forecast accuracy

As the deviation of the forecast from the actual generation directly impacts the user's business and profitability, the common goal of the forecast provider and user is to minimise this deviation, or – in other words – to maximise forecast accuracy.

However, proper evaluation of forecast accuracy is also a critical input to the creation of the forecast model itself. During the training of ANN and the setup of the multi-model ensemble, the formula used for evaluating quality influences how and what the system learns. A forecast can only deliver satisfactory results for a business process if the accuracy evaluation during the setup phase matches the user's business need.

There is not a simple answer to the question “How good is this forecast?”, much less to the question “How good is this forecast going to be?”. As all the discussed methods use statistical approaches, going back all the way to the underlying NWP models, outcomes using the exact same algorithms can greatly vary depending on the purpose and circumstances for which the forecast has been generated.

Even if the results are the same by one accuracy measure, they may fall short of another one. Hence, it is critical to understand the various techniques of measuring accuracy and to carefully identify from the start the ones most suitable for a user's needs.

What's more, forecast accuracy is not a static value. Forecast accuracy needs to be continuously monitored and models need to be constantly updated in order to deliver the best possible outcome over the lifecycle of a forecasting service. It can also be used to identify issues with the underlying data or with the performance of the underlying asset itself.

4.1 Selecting relevant forecast quality KPIs

The difference between forecast and actual generation (typically meter data) is called forecast error. It is calculated for each relevant time interval (such as 15 or 60 minutes), and subsequently aggregated. A forecast quality KPI has to be normalised, e.g. with respect to the available capacity or the amount of energy produced, in order to be comparable across different plants.

The relevant KPI may vary from application to application and therefore needs to be clearly specified. KPIs commonly used to evaluate forecast quality are the normalised Bias (nBIAS), the normalised Mean Absolute Error (nMAE) and the normalised Root Mean Square Error (nRMSE). In the fields of meteorology and energy meteorology, nRMSE is the prevalent assessment.

4.1.1 Application-specific KPIs

Depending on the application, there may be specific KPIs representing the desired behaviour of the forecast or the cost associated with the forecast error.

Examples:

- In market-based systems, energy is traded day-ahead or intra-day at the spot market based on forecasts. The imbalance price, which is derived from the cost of control energy, is charged for any deviations. Therefore, the imbalance price could be included in the cost function.
- In regulations with fixed compensation (such as Feed-in tariffs), plant operators may be required to submit forecasts and penalised for deviations exceeding a certain threshold. In this case, the percentage of time intervals without penalty is an important KPI, and obviously also the penalty to be paid overall.
- When forecasts are applied in grid or plant operations and monitoring, forecasts are a tool to support decisions of the staff on duty. In this case, not only the numerical value of the forecast is important, but also the pattern or trend that the forecasted power generation shows. As soon as more complex forecast models are employed, these patterns do not necessarily follow physical rules. In this case, specific metrics can be used to evaluate, e.g., the physical plausibility of the forecast.
- In India, the Deviation Settlement Mechanism (DSM) imposes penalties depending on the deviation in any 15-minutes block. While the actual penalty varies from state to state, all regulations have in common that only deviations larger than 15% of the installed power are considered. For this reason, Forecast Accuracy is defined as the number of blocks where the

forecast error is greater than or equal to this threshold. Accuracy is typically expressed as percentage.

4.2 Obtaining meaningful and comparable KPIs

Forecast quality KPIs are only valid for the underlying data. However, they are used for decisions that affect the future. While this implies an unavoidable degree of uncertainty, meaningful and comparable KPIs can be obtained if some important factors are considered.

4.2.1 Evaluation period

Performance metrics cannot be transferred from one time period to another. Forecast error varies greatly from day to day, week to week and month to month, due to meteorological conditions and seasonal effects.

Therefore, when assessing the general performance of a forecast model, the evaluation period should be representative for all seasons, e.g. by covering a full year.

When comparing different forecast models, in any case this must be done with exactly the same actuals (e.g. SCADA data or settlement data) and the same evaluation period.

4.2.2 Forecast horizons and update times

Typically, forecasts are delivered as time series with the maximum horizon of interest and updated frequently until the forecasted time interval has elapsed. This way, the delivered forecasts consist of a large number of overlapping time series.

For a forecast evaluation, these overlapping time series are reduced to a single time series. Typically, this is done by considering the latest forecast available at given update times and with a given lead time. The applicable update times and lead times are defined by the business-application, e.g. closure time of the energy market or submission times of forecasts to authorities.

As forecast error increases with increasing forecast horizon, forecast update times and lead times must match between different forecast models when they are compared.

4.2.3 Availability limitations

The actual performance of a wind plant does not only depend on the weather, but also on changes in the available capacity of the plant. The occurrence of temporary availability limitations of all or part of the installed capacity is strongly plant specific. As the available capacity is the basis of the forecast and is used to calculate normalised metrics, these changes directly affect the evaluation result. Availability may be limited due to reasons such as:

- Maintenance (planned or unplanned);
- Failure of technical components;
- Curtailments, e.g. due to grid congestion, regulation or in case of negative energy price;
- Limitations for environmental protection.

Most of these cannot be predicted, and the corresponding time intervals should therefore be excluded from evaluations.

5 Forecast accuracy: Who pays for deviations?

As described above, accurate forecasts allow to maintain the balance between supply and demand in energy grids and markets. In the early stage of renewable energy grid integration, the most common regulatory framework was the Feed-in Tariff, leaving the responsibility to forecast and balance the feed-in from renewable energy to the transmission system operator (TSO). However, as the share of variable renewable energy in power grids increased, new regulations have emerged, moving this responsibility to plant operators and traders.

In market-based electricity systems, which are common in Europe, the responsibility is upon the party that has traded the energy at the spot market to supply what has been traded in each block (typically 15-minutes blocks). In some cases, it is possible to control the plant so that the power output matches the traded energy. If this cannot be achieved, the deviation – or imbalance – leads to under- or oversupply. The transmission system operator (TSO), who is responsible for maintaining the balance at the grid level, will then stabilise the frequency using the operating reserve. The energy that is required to settle the imbalance is called balancing energy and is charged to the balance responsible party, while the balancing price is calculated from the actual cost of the intervention.

As the deviations resulting from renewable generation forecast error are one of the dominating factors influencing the balancing price, there is a risk that high deviation for a single site coincides with high balancing prices. To mitigate this risk, a good mix of forecast solution providers and forecasting methods should always be employed.

A phenomenon that is observed periodically in markets with high renewable energy penetration is that spot market prices for electricity can become negative during times of high renewable power generation due to the forecasted oversupply (see Figure 3). This leads traders to shut down the plants during these times, thereby reducing the imbalance.

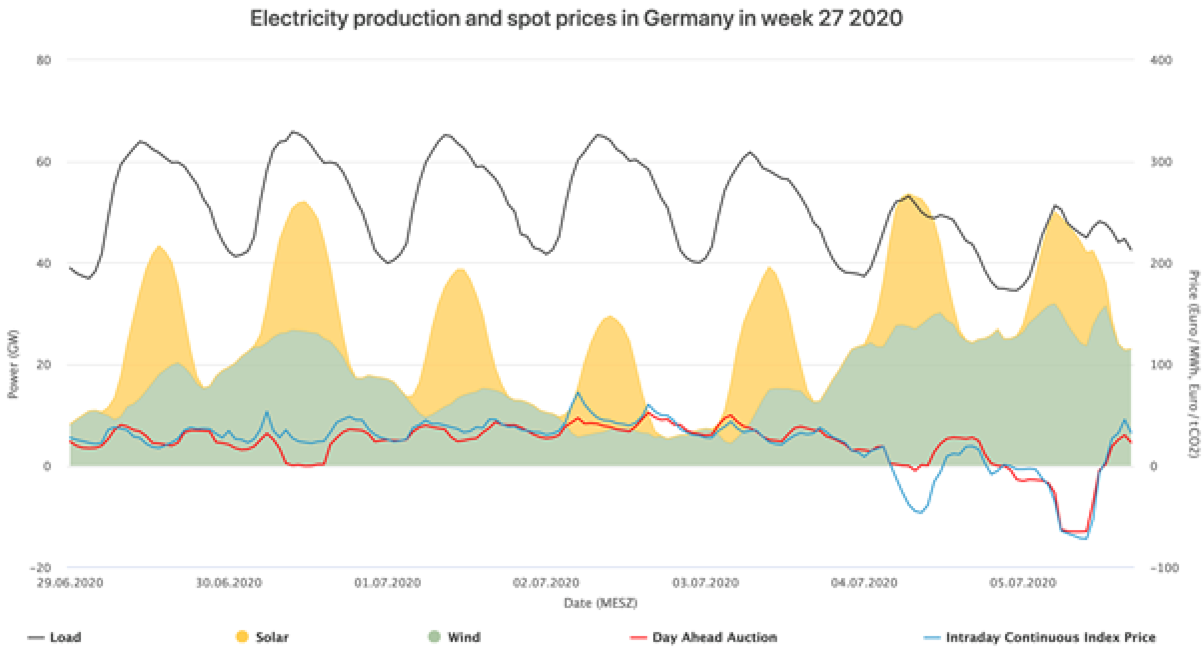

Figure 3. Negative spot market prices for electricity can be observed during times of high renewable energy generation in Germany. Source: Fraunhofer ISE / energy-charts.de

As forecast accuracy improves through aggregation of multiple sites in clusters, this also reduces the balancing costs. Therefore, the typical approach is to combine multiple plants within one bidding zone in a virtual power plant. Bidding zones are typically aligned with country borders, however there are exceptions where bidding zones cover multiple countries, or where countries are split into multiple bidding zones. As this may lead to grid congestion in cases where there is high renewable energy generation in regions with low demand, regulations need to foresee tools to manage these congestions. However, the responsibility for congestion management and related costs lies with the grid operator.

However, not all deviations are weather-related and therefore forecastable: Outages of plants or grid connections can reduce the available generation capacity and thus the generated power. For this reason, it is important that the availability of plants is always considered in forecast evaluations.

6 enercast in India

enercast is a leading technology provider for applied artificial intelligence and the digital transformation of renewable energy. Its self-learning software-as-a-service products deliver accurate power forecasts for wind power and solar plants, thus enabling the integration of renewable energy into power grids and energy markets worldwide. Its integration platform for the industrial application of artificial intelligence and big data supports its customers' decision-making processes, fulfilling enercast's promise: "Weather insights that put you in control". Founded in 2011, enercast is headquartered in Kassel, Germany and delivers 100 million forecast data points to 20 countries around the globe, covering 160 GW of installed capacity.

enercast has been delivering forecasts for renewable energy assets in India since 2014 and holds contracts with several major IPPs. enercast has also been awarded a 4-year contract to deliver state-wide power forecasts for the Renewable Energy Management Centres (REMC) in the northern and western Indian regions. REMCs were created under the Green Energy Corridor Initiative and are overseen by the Power Generation Company of India, Ltd. Using aggregated regional feed-in from wind and solar power, they ensure grid stability while maximising the usage of green electricity. Today, enercast forecasts cover more than 38 GW of installed capacity in India.

Jonathan Simon is product manager at enercast GmbH in Kassel, Germany. A software engineer with an M.Sc. degree from RWTH Aachen University, he has worked at Fraunhofer Institute for Applied Information Technology in smart energy research projects before joining enercast in 2014. He can be contacted at j.simon@enercast.de