The case for better PV forecasting

Grid integration | Rising levels of PV penetration mean increasingly sophisticated forecasting technologies are needed to maintain grid stability and maximise the economic value of PV systems. The Grid Integration working group of the European Technology and Innovation Platform – Photovoltaics (ETIP PV) shares the results of its ongoing research into the advantages and limitations of current forecasting technologies

Forecasting and monitoring technologies for PV are required on different spatial and temporal scales by multiple actors, from the owners of PV systems to transmission system operators. Power system operations require a real-time view of PV production for managing power reserves and networks. They also require forecasts on all timescales from the short (for dispatching purposes), where statistical models work best, to the very long (for infrastructure planning), where physics-based models are more accurate. For PV system operators, accurate forecasting is also critical to maximising the commercial value of the electricity they produce.

In its review of the challenges and opportunities associated with massive deployment of solar PV generation [1], the Grid Integration working group of the European PV Technology Platform (now ETIP PV) identified forecasting and observability as critical technologies for the planning and operations of the power system with large PV penetration. In this article we spell out in more detail what features are needed from these technologies and, after an assessment of their current status, how they need to be developed.

Some very good reviews of forecasting techniques have been published in recent years [2,3]. We have built on these by taking a step back and analysing the different use cases for forecasting in relation to PV. To estimate the economic value of further improvements in forecasting, we linked the effect of forecasting errors with the current imbalance settlement prices charged by balancing authorities in Europe.

Power system dynamics

At all times in all power systems, consumption (including charging of storage systems, and losses) and production (including

For PV to play its full part in the grid of tomorrow, further work is needed to improve forecasting techniques

discharging of storage systems) need to be equal. In a conventional power system operating in alternating current (AC), frequency is a real-time indicator of that balance. To ensure that balance is maintained any fluctuation of production

< 10 s	Inertia response
	Protection system operations
	Switching of power electronics
	Battery switching between charge and discharge
1 min	Fast start of pumped hydropower plant [4]
	Fast start of some combustion engines [5]
15 min	Gas power plant from 1/3 to full power [6]
1 h	Start-up and shutdown of most power plants
24 h	Commitment of generation units
1 year	Maintenance planning
10 years	Expanding transmission infrastructure
20+ years	Economic lifetime of PV systems
	Economic lifetime of grid assets

Table 1: Characteristic time constant of power system components

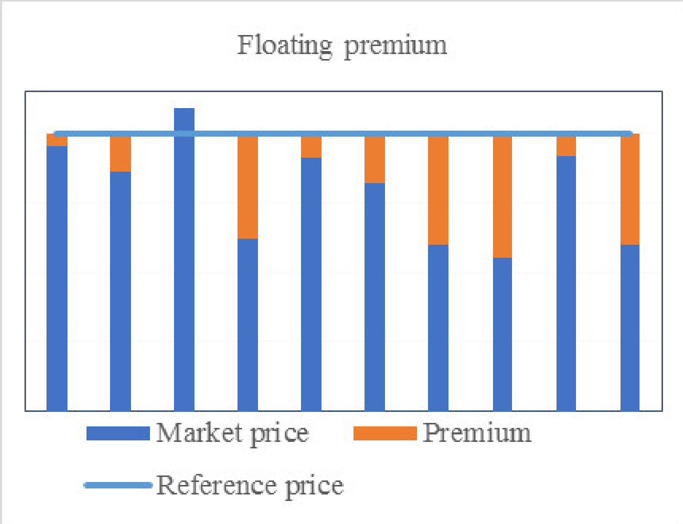
or consumption needs to be anticipated as much as possible before it translates into frequency deviations.

Indeed, any corrective action will be limited by the speed at which power system components can move to new set points. The characteristic time constants of power-system components range from less than a second to 10 years or more, as summarised in Table 1.

Prior to the introduction of variable renewable sources such as wind and PV, power consumption was the only variable component in the power system balance. The ability to forecast its variations was introduced in the 1940s. It has since been refined to take into account "seasonal" variations (day of the year, day of the week, hour of the day) and the specific characteristics of different electricity uses (heating and cooling, cooking, industrial equipment, lighting, etc.) [7]. However, the focus has always remained on regional or national aggregates.

The deployment of variable renewable generation is introducing new requirements on forecasting techniques. First of all PV and wind generators are much more sensitive to weather conditions. The main weather parameter with an influence on electricity demand – where heating or cooling is powered with electricity – is temperature. This parameter varies slowly in time and space. PV and wind on the other hand strongly depend on rapidly changing variables. As a result, the geographic distribution of the generators matter more for the aggregate variations than that of the loads.

In addition, PV generation is highly distributed in terms of locations and ownership. It is therefore often necessary to forecast generation with a higher spatial resolution than demand. Indeed single



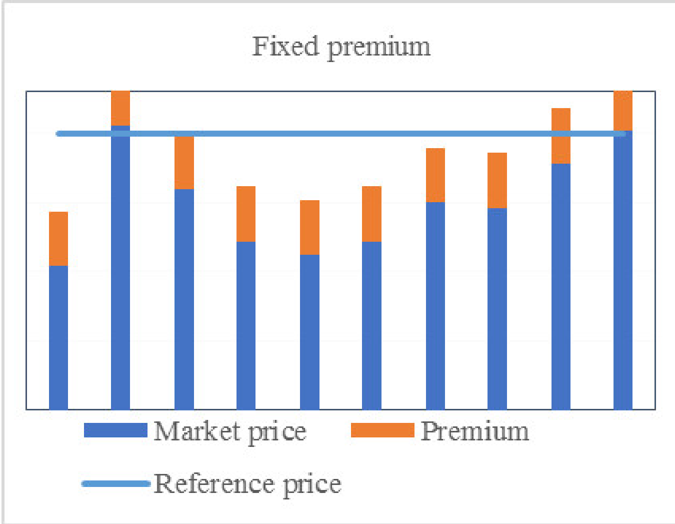


Figure 1: Working principle of market premiums; adapted from [15]

MW-scale plants may be exposed to market trades, and microgrid operations with self-consumed PV electricity require forecasts at the building or district levels. Such granularity increases the forecasting difficulty: the standard deviation of PV power production is reduced as $1/\sqrt{S}$ and $1/\sqrt{N}$, where S is the surface area of a PV power plant and N is the number of aggregated plants [9,10].

Drivers for PV forecasting

An important concept when dealing with forecasting in the power system is the balance group. Balance groups can include generation units, consumption units, or be 'virtual' when operated by financial actors who only trade. Forming a balance group is a requirement to participate in wholesale electricity markets. All balance groups report to a balancing authority, which in Europe is generally the transmission system operator (TSO). This authority ensures that trades on the electricity market are balanced i.e., that contracted generation matches forecast consumption. Balancing group managers are responsible for ensuring that at each time-step of market operations their contracted production and/or consumption matches the realised values. In case of mismatch between prediction and realisation, balance group managers are penalised based on intraday market prices; if the imbalance is in the same direction as the whole system (e.g., a producer under-delivering when there is a shortage in production), the penalty will be above the intraday market price and if the imbalance is in the opposite direction the penalty will be below.

PV generators were until recently shielded from this balancing responsibility. In Germany for example, TSOs carry the responsibility and operate a balance group for PV systems which are connected under the Renewable Energy Sources Act (EEG) in their area [11]. Regulators are now pushing to increase exposure of PV generators to market conditions and increase their responsibility in the balancing mechanisms. A 2014 ruling by the Italian regulator introduced imbalance charges for renewable power generators of more than 1MW in capacity; the mechanism is similar to that applied to conventional balance groups but the fees are modulated to take into account the inherent volatility of the different sources [12]. The resulting cost for PV generators is estimated around €5/MWh, which is still significantly lower than imbalance prices applied to regular balance groups in Europe [13,14].

In addition, support mechanisms for large PV generators are evolving from feed-in tariffs to market premiums in France, Germany and the UK [15] under which these generators receive a regulated payment on top of market prices. As illustrated in Figure 1, these premiums can be fixed, or floating, i.e. cover the difference between the average market price over a certain period of time – generally one month – and a reference price set by the regulators. In both cases generators have a direct interest in maximising the value on the market of the electricity they produce and the volumes they can effectively sell. Since a generator can only commit on the market power it is confident it can produce, accurate forecasts are essential to maximising these sold volumes.

Finally, the development of micro-grids and of combined PV-plus-storage systems requires local energy management, which, for optimal operations, relies on predictive control. Single-system or neighbourhood-level power forecasts on timescales from a few minutes to 24 hours are therefore necessary.

These drivers and the dynamics of power system components described earlier together create a range of use cases for forecasts on time horizons ranging from 15 minutes or less to decades, and on geographical scales ranging from the single site to an entire region or country. These use cases are summarised in Table 2, which shows in particular the central role of day-ahead forecasting.

Time horizon	Single site (10 m – 100 m) **PV plant owners** **PV plant operators**	MV distribution grid (1 km – 10 km) **DSOs** **Microgrid operators**	Transmission system (100 km – 1000 km) **TSOs** **Market operators**
15 min	Management of storage system	Management of active/reactive power	Activation of reserves
1 h	Management of storage system Intra-day trades	Storage and load management	Intra-day trades
24 h	Management of storage system Compliance with regulations Day-ahead trades	Storage and load planning	Booking of reserves Transmission scheduling Day-ahead trades
1 year	O&M contract	Planning of maintenance operations	Long-term trades
20+ years	Investment case	Infrastructure planning	Infrastructure planning

Table 2: Summary of use cases for PV power forecasting

Metric	**Formula**	**Application**
Mean bias error	$MBE = \frac{1}{N}\sum_{i=1}^{N}(Y_{forecast} - Y_{realised})$	Investment decision
Mean absolute error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert Y_{forecast} - Y_{realised}\rvert$	Balance group management
Root-mean-square error	$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(Y_{forecast} - Y_{realised})^2}$	Optimisation of generation reserves

Table 3: Main performance metrics used to assess forecasting methods

Forecasting approaches and performance

Performance criteria

Because the use cases are so diverse, there is no single metric to characterise an absolutely "good" forecast. Instead, any of the three most commonly used metrics, which are listed in Table 3, can be preferred depending on the target application. These metrics are generally reported in a normalised way; particular attention must be paid to the normalisation factor and to the integration period. It is good practice to integrate the error only over daytime hours, since PV production is sure to be zero in the night. And while errors in irradiance forecasts are generally normalised by the average measured irradiance, those on power forecasts are often normalised by the nominal peak power of the system. This difference mechanically results in reported errors which are about three times lower for power generation than for irradiance.

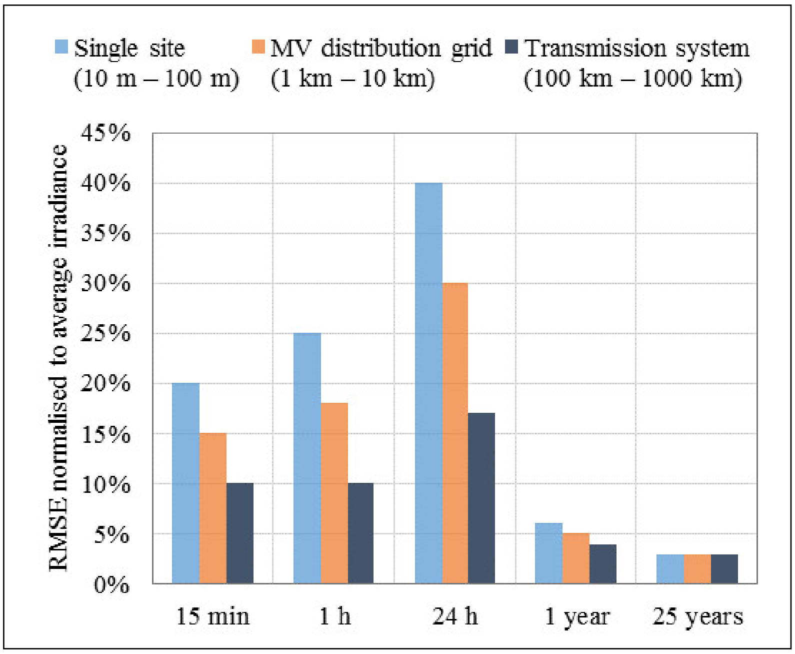


Figure 2: Error obtained with state-of-the-art physical forecasting methods for irradiance.

Current forecasting techniques

The first approach in PV power forecasting relies first on the prediction of relevant weather parameters (at least temperature and irradiance), followed by a calculation of the corresponding power output. This approach can build on existing weather forecasting tools. The most appropriate tool to predict irradiance depends on the desired time horizon.

For resource assessment – i.e. to predict patterns of energy generation over the lifetime of the system – statistically representative time series of weather parameters are generated based on interpolation of ground-level measurements (weather stations) or satellite images to produce "typical meteorological years".

For time horizons between six hours and three days, numerical weather prediction (NWP) is preferred. NWP data are generated by global or mesoscale simulation models which provide the numerical integration of the coupled differential equations describing the dynamics of the atmosphere and radiation transport mechanisms [16]. The initial conditions are given by satellite, radar, radiosonde and ground station measurements. NWP data are often corrected by post-processing algorithms called Model Output Statistics (MOS) which use historical ground measurements to partially remove systematic errors [17].

For time horizons between two hours and six hours, visible and/or infrared images are acquired by satellite-based sensors. A cloud index is computed based on reflectance measurements and is typically used to derive ground-level global and direct irradiances [18]. As compared to NWP, only a few relatively simple modelling assumptions have to be applied to derive the solar resource. Persistence of cloud speed and direction (as derived from the last two images) is generally assumed. The dynamic nature of clouds challenges cloud-motion vector approaches as cloud distribution can change substantially within the typical 30-minute interval between two images. It is indeed challenging to account for cloud convection, formation, dissipation and deformation. However, since large-scale cloud systems (such as those associated with a cold front) are more persistent, satellite-based forecasts typically perform more accurately than NWP-based forecasting models up to six hours ahead, mostly because of ingestion, data assimilation and latency of calculations required to "spin up" NWP-based forecasts.

For time horizons below 30 minutes, total sky imaging is the preferred method. It consists of four steps:

1. Acquisition of the sky image from a ground-based, wide-angle camera;
2. Analysis of the sky image to identify clouds;
3. Estimation of cloud motion vectors;
4. Prediction of future cloud cover and ground irradiance.

The maximum accuracy with this method is generally obtained between five and 20 minutes; with low and fast-moving clouds it can be reduced to three minutes and for high and slow-moving clouds it can be extended to 30 minutes. The state-of-the-art accuracy for all these physical forecasting methods is summarised in Figure 2.

Models for computing PV power from irradiance and environmental parameters also carry their own uncertainty, which compounds the error on forecasted irradiance. In a review of major modelling tools, the hourly root-mean-square error (RMSE) on AC power output was found to be below 7% in all situations [19].

To avoid this amplification of errors and to deal with time horizons between 30 minutes and two hours where there is no satisfactory physical forecasting technique for irradiance, stochastic learning techniques are used. These methods can be separated between:

Univariate methods i.e. methods where only time series of the target variable (here, PV power) are fed into the model. These include:

- Persistence: P(t+1)=P(t);
- STL: seasonal decomposition of time series by Loess;
- Holt-Winters seasonal method;
- TSLM: linear model fit with time series components;
- ARIMA: autoregressive integrated moving average;
- BATS: exponential smoothing state-space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components;
- Nnetar: Feed-forward neural networks with a single hidden layer and lagged inputs for forecasting univariate time series.

Multivariate methods i.e. methods where exogenous variables such as measurements of ground irradiance, temperature or humidity levels are fed into the model in addition to the target variable. These include:

- MLR: Multi-Linear Regression Model;
- SVM: Support Vector Machine;
- ANN: Artificial Neural Network;
- Regression Tree.

Value of forecasting

To estimate the value of forecasting, and of improvement in forecasting techniques, the best analogy is the operations of balance groups, since for them forecasting errors have a well-defined cost. Indeed, European TSOs currently charge a typical imbalance price of €20/MWh.

If a 1MWp plant in the North of Italy were a balance group on its own it would then be charged this price. The mean absolute error over four years for such a plant is 11.6% of nominal power with clear-sky persistence, and 7.1% with an advanced forecasting technique (numerical weather forecast plus support vector machine) [20]. Since only daytime is taken into account (12 average), these errors translate into an annual imbalance of 0.50 MWh/kWp and 0.31 MWh/kWp, respectively. So the annual imbalance cost would be €10,000 and €6,200 respectively. As a comparison, with power purchase agreements at €80/MWh as are now contracted in Germany, annual income for this plant would be €80,000. So two conclusions can be drawn:

- Forecasting errors can reduce the value of PV electricity by more than 12%
- Advanced forecasting techniques can generate a value of almost €4,000 per year for a 1MWp plant.

Conclusion

Accurate forecasting of PV power production has many use cases in both current power system operations and foreseen evolutions towards a more PV-centric system. Many of these cases require day-ahead forecasting, which is also the time horizon among those considered for which forecast errors are the largest. Research and development efforts should therefore focus on this horizon.

Other promising developments for using forecasts in power system operations include the communication of confidence intervals in addition to forecast values [21], and regional clustering to improve the accuracy of estimates of current power production and of forecasts.

Both physical and stochastic learning techniques are available to forecast PV power. Their choice mainly depends on the target time horizon and on the availability of sensors.

In a simple case, the lost value of PV electricity due to forecast errors can be estimated at more than 12% of annual revenues. Using advanced forecasting techniques can significantly reduce this loss and generate a value of almost €4,000 per year for a 1MWp plant based on power system balancing only. In smaller, weaker power systems than those considered here this value would be even higher. ■

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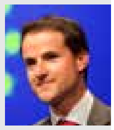

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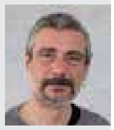

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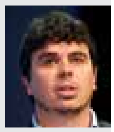

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