How embedded micro forecasting changes the decision making for portfolio maintenance

By Dr. ir. Stijn Stevens, CTO at skytron® energy GmbH

energy empowered

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Power generation from solar energy is becoming ever more attractive: in 2018 the global installed photovoltaic capacity is expected to approach 500 GW. Favorable financing conditions and falling costs have made photovoltaics into an attractive investment. In many regions of the world the production costs (Levelized Costs of Electricity, LCOE) for utility-scale solar are now well below the LCOE of nuclear or coal-fired plants. The barrier of entry into the energy generation market has thereby become much lower today than it was only a few years ago, when the building of a conventional power plant involved huge investment costs and only a few participants dominated the market. Investment companies or family offices with an international focus are taking advantage of the new opportunities and have already assembled sizable, globally diversified portfolios. These so-called Independent Power Producers (IPP) – power producers without direct access to the grid network - are putting pressure on traditional, often regional or national utilities who, hampered by their portfolio of conventional power plant, can react much less flexibly. Utilities, for their part, are countering by investing in renewable energy for power generation, cutting their investment in conventional power plants or by splitting up. Whether IPP or utility, a global trend has become the steady growing photovoltaic portfolios, with generation capacities of more than 500 MW or even 1,000 MW, becoming the rule.

This growth in portfolio size is bringing with it an increasing demand for optimal management of the assets as a whole: minimizing investment in Operations and Maintenance (O&M) whilst maximizing the earnings/cash flow from energy production at the same time. The achievement of these goals is increasingly being assisted by data analysis, error identification and solution-oriented decision making using software solutions that are able to analyze the incoming data streams from the SCADA (supervisory control and data acquisition) systems in the individual plants and compare them with the overall portfolio performance. The human operator in the control room - the so-called Network Operations Center (NOC) - is turning into a "pilot" who has to "fly" the portfolio while managing a steadily increasing MWp volume at the same time.

Given the limited availability of resources and sustained pressure on costs, the prioritization of the necessary activities becomes crucial. One aspect that can help in this context is embedded micro-forecasting. By this, we mean the use of energy production forecasts down to device level across a regionally diversified portfolio of photovoltaic plant having heterogeneous device types (in particular inverters). These forecasts are then used to prioritize maintenance so as to minimize expected energy losses. In the event of any malfunctions, service calls are optimized according to a cost/benefit analysis.

Forecasting at a Plant Level

Meteorology has been the recipient of a wealth of innovation in recent years. The availability of powerful computer technology and high-resolution satellite data, combined with associated improvements in weather models, now provide for significantly improved forecasting quality. In addition to global models such as the American Global Forecast System (GFS), having a mesh width between individual grid points of around 28 km [1] or the German ICON model (Icosahedral, Non-hydrostatic) with a horizontal mesh width of approx. 13 km [2], there are a multitude of localized area models having a substantially finer-grained grid structure. For example, the COSMO-DE model provides a horizontal resolution down to 2.8 km for Germany, Switzerland and Austria [3]. In general, it can be said that the quality of forecast increases with reducing mesh size; however at the same time, the reliable forecasting period decreases owing to the increased complexity. On one hand, global, coarse-meshed models such as GFS can provide a forecast up to 16 days in advance [1], whilst on the other, smaller mesh models such as the COSMO-DE are often limited to about 24 hours [4]. This discrepancy between the forecast period and quality has given rise to new business models: independent providers have been able to combine widely differing models using their own computer technology, sometimes enriching the results with locally measured values or correction factors, so as to be able to offer a refined forecast for a particular location for longer time periods.

The following data channels are particularly interesting for PV plants:

Forecast-Data Channel	Forecast ability	Application
Global Horizontal Irradiation GHI (W/m²)	Challenging	Power forecast
Diffuse Horizontal Irradiance DIF (W/m²)	Challenging	Power forecast: Estimation of Plane of Array irradiation (POA)
Direct Normal Irradiance DNI (W/m²)	Challenging	Power forecast: Estimation of Plane of Array irradiation (POA)
Ambient temperature (°C)	Good	Power forecast: Dissipation of module temperature
Wind speed (m/s)	Good	Power forecast: Dissipation of module temperature; Tracker-based plants
Wind direction (°)	Good	Tracker-based plants

Figure 1: Forecast Data for PV applications

The irradiation forecast is based on satellite imagery, through which the irradiation data can be optimized using clear-sky algorithms and statistical models. As a rule of thumb, the lower the cloud-cover at any particular site over the year, the more accurate will be the irradiation forecast. At the same time, short-term forecasts of the GHI (intra-day forecasts), derived from satellite images of cloud tracks, allow much higher hourly accuracy [5].

The availability of local weather measurement data is fundamental when deriving key performance indicators (KPI) for assessing the performance of a PV system. Without this data, especially irradiation and temperature, the energy production of a PV power plant cannot be assessed. Innovations and cost reduction by the producers of meteorological sensors has led to the situation where today almost every plant with > 1 MWp rated output is equipped with its own measuring technology. The recommended sensor scope and sampling rates are specified in IEC 61724-1:2017 "Photovoltaic System Performance -Part 1: Monitoring". Pyranometers are widely used for measuring global irradiance and temperature sensors are usually in place for recording the module temperature. Digital weather stations provide measurements of data such as air pressure, ambient temperature, humidity, precipitation, type of precipitation (rain, snow), wind speed and direction. As a result, every large PV system usually has extensive, site-related weather data available across the whole of the system's life.

	Pyranometer Secondary standard (ISO 9060)	**Temperature Sensor**
Used to measure:	Radiation [W/m²]	Temperature (module & ambient air temperature)
Typical measurement range:	100 W/m² to 1500 W/m²	-40 °C to +80 °C
Accuracy:	Uncertainty ≤ 3%	Uncertainty ≤ 2°C (module level), Uncertainty ≤ 1°C (ambient air level) Commonly used are[1]: Class A ± 0.15° + 0.002 [t] or Class B ± 0.3° + 0.005 [t]
Maximum sampling-interval[2]	3 s	3 s
Maximum recording interval[2]	1 minute	1 minute

Digital Weather Station						
Relative Humidity	**Air pressure**	**Wind speed**	**Wind direction**	**Precipitation quantity**	**Relative Humidity**	
Typical measurement range:	0 % to 100 %	400 to 1100 hPa	0 to 70 m/s	0° to 360°	-	
Accuracy:	± 3 %	± 0.5 hPa	≤ 0.5 m/s (wind speed ≤ 0.5 m/s) ≤ 10 % (wind speed > 5 m/s)	± 5°	± 5 % to ± 10 %	
Maximum sampling-interval:[2]	1 minute	not specified	3 s, suggestion: track maximum values to determine gusts	3 s	1 minute	
Maximum recording interval:[2]	1 minute	1 minute	1 minute	1 minute	1 minute	

Notes:

1) *According to IEC 60751*
2) *IEC 61724-1:2017, Class A - high accuracy*

Table 1: Characteristics of widely used sensor types in PV plants

Forecast providers often offer predictions for energy yield based on an irradiation prediction combined with a simple system model: tilted surfaces, system capacity and an assumption about performance ratio. This is inadequate for maintenance scheduling, especially in areas with volatile weather conditions.

The first key element in obtaining a reliable basis for O&M decisions is to combine these forecasts with data from local weather sensors. This increases the accuracy of the plant forecast and, indirectly, allows the local geographic physiology to be learned over time. The second element is to get the component models to match the reality. Both objectives are obtainable by moving to machine learning of a different kind.

To increase forecasting accuracy a neural network approach is suitable, although not always needed. Picking the correct number of nodes, both for the inputs as well as for the hidden layers, is far from trivial and if not done well can lead to neural network models that are computationally very expensive. Here, it is essential to tailor the model to the plant. If this is setup correctly, the neural network will be able to learn the geographical characteristics of the plant and its evolution over time, based on the constant plant feedback.

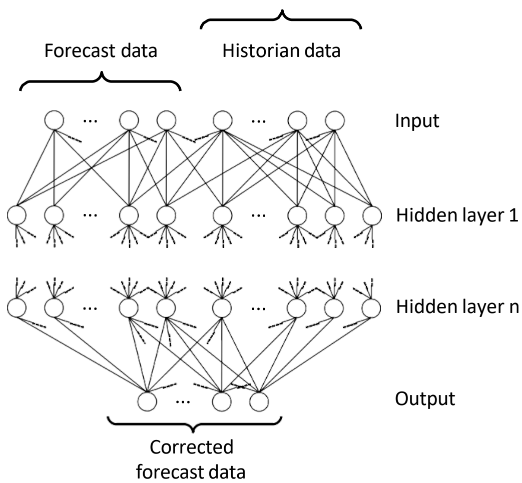

Figure 2: Neural network to tailor the model

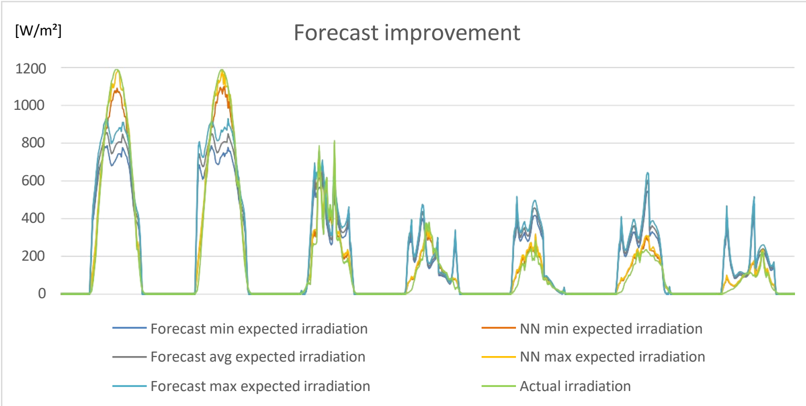

Figure 3: Irradiation forecast improvement through neural network (NN) model

The irradiation forecast is then used to predict the plant's energy yield by using a plant model consisting of a series of component/loss models: surfaces, soiling, shading, modules, DC cabling, inverter, AC cabling and a transformer model. The parameters of some of these models are fixed, such as the surface model which incorporates the module orientation and occasionally tracking. Other models require data from datasheets or other parameters that are estimated from the plant's historically measured data. Simple quality factors or machine learning can be applied in both cases, either to determine or to verify and correct these parameters, so that a best fit can be obtained between measured data and models.

As an example, a generic Sandia inverter model [7] can be inversely modelled, so that the parameters of the model (the manufacturer datasheets) become the variables of the equations. By using the actual inverter and measurement data, a best fit for these variables are looked for. Using linearization and assuming that the parameter variables have a Gaussian distribution, a Kalman filter structure can deliver a best guess for the parameters. The power generation predictions will become more accurate against the fitted data, and in addition, this allows unexpected changes in parameters to be used for predictive maintenance.

Micro-Forecasting at a Device Level

A significantly improved picture about the expected yield can be gained by compiling a forecast at an inverter level. In this, the expected yield in the future is based on the forecast weather data for each individual inverter across the entire portfolio. Individual correction factors for the weather data can be included separately for each inverter in the calculation.

If the monetary worth of the individual kWh output is included to enrich this data, one can quickly put together a prediction of the total revenue for each individual inverter. The illustration below shows an example of a financial ranking for three PV systems which use central inverters but have different remuneration schemes. The ranking is based on an energy forecast at device level.

				Energy Yield						
PV Plant	**Inverter**	**Inverter DC-Power**	**Current day**	**Forecast current day**	**Forecast +1 Day**	**Forecast +2 Days**	**Forecast +3 Days**	**∑ Forecast 3 Days**	**$/kWh**	**∑ Forecast 3 Days / $**
2	Central Typ B / No.2	2.850 kWp	6.200 kWh	9.600 kWh	9.380 kWh	10.750 kWh	4.980 kWh	25.110 kWh	0,06	$1.507
3	Central Typ C / No. 7	860 kWp	1.600 kWh	2.850 kWh	3.810 kWh	2.150 kWh	4.530 kWh	10.490 kWh	0,14	$1.469
3	Central Typ C / No. 1	840 kWp	1.560 kWh	2.810 kWh	3.760 kWh	2.130 kWh	4.595 kWh	10.485 kWh	0,14	$1.468
3	Central Typ C / No. 8	855 kWp	1.595 kWh	2.845 kWh	3.790 kWh	2.140 kWh	4.520 kWh	10.450 kWh	0,14	$1.463
3	Central Typ C / No. 9	860 kWp	1.580 kWh	2.830 kWh	3.800 kWh	2.150 kWh	4.500 kWh	10.450 kWh	0,14	$1.463
3	Central Typ C / No. 5	840 kWp	1.550 kWh	2.800 kWh	3.770 kWh	2.130 kWh	4.510 kWh	10.410 kWh	0,14	$1.457
3	Central Typ C / No. 2	840 kWp	1.540 kWh	2.790 kWh	3.760 kWh	2.120 kWh	4.500 kWh	10.380 kWh	0,14	$1.453
3	Central Typ C / No. 6	835 kWp	1.540 kWh	2.790 kWh	3.760 kWh	2.120 kWh	4.500 kWh	10.380 kWh	0,14	$1.453
3	Central Typ C / No. 3	840 kWp	1.550 kWh	2.800 kWh	3.770 kWh	2.100 kWh	4.500 kWh	10.370 kWh	0,14	$1.452
3	Central Typ C / No. 4	840 kWp	1.560 kWh	2.810 kWh	3.730 kWh	2.100 kWh	4.490 kWh	10.320 kWh	0,14	$1.445
3	Central Typ C / No. 10	860 kWp	1.570 kWh	2.820 kWh	3.730 kWh	2.130 kWh	4.460 kWh	10.320 kWh	0,14	$1.445
2	Central Typ B / No.1	2.750 kWp	6.090 kWh	9.490 kWh	9.110 kWh	9.860 kWh	4.910 kWh	23.880 kWh	0,06	$1.433
2	Central Typ B / No.5	2.650 kWp	5.460 kWh	8.860 kWh	8.700 kWh	10.290 kWh	4.560 kWh	23.550 kWh	0,06	$1.413
2	Central Typ B / No.3	2.850 kWp	5.450 kWh	8.850 kWh	8.500 kWh	9.480 kWh	4.400 kWh	22.380 kWh	0,06	$1.343
2	Central Typ B / No.4	2.630 kWp	5.540 kWh	8.940 kWh	8.650 kWh	9.070 kWh	4.550 kWh	22.270 kWh	0,06	$1.336
1	Central Typ A / No.4	1.060 kWp	2.355 kWh	6.855 kWh	2.620 kWh	2.900 kWh	6.280 kWh	11.800 kWh	0,10	$1.180
1	Central Typ A / No.1	1.060 kWp	2.300 kWh	6.800 kWh	2.600 kWh	2.920 kWh	6.225 kWh	11.745 kWh	0,10	$1.175
1	Central Typ A / No.3	1.060 kWp	2.270 kWh	6.770 kWh	2.610 kWh	2.920 kWh	6.195 kWh	11.725 kWh	0,10	$1.173
1	Central Typ A / No.2	1.060 kWp	2.250 kWh	6.750 kWh	2.620 kWh	2.900 kWh	6.175 kWh	11.695 kWh	0,10	$1.170
2	Central Typ B / No.2	2.850 kWp	6.200 kWh	9.600 kWh	9.380 kWh	10.750 kWh	4.980 kWh	25.110 kWh	0,06	$1.507

Table 2: Example of an energy yield prediction at inverter level

This type of micro-forecast at device level is especially well suited to decision making for large portfolios incorporating many plants, including perhaps with extremely large numbers of inverters. Especially when combined with a Computerized Maintenance Management System (CMMS), the information provided, including estimates of the financial impact of faults across several inverters, can be used to prioritize repair work. Sensible decisions can then be made about when to send technicians to which sites, so that the repair can work be optimized from a cost-benefit perspective. If internal resources are overstretched, it can make a clear case for calling in external technicians – or not. In this way, micro-forecasting allows transparent decision making whether such a strategy would pay off economically or whether repairs should be delayed because the expected yield would not justify the higher cost. For plants that use string inverters, where an outage of an individual inverter might not have a huge financial impact, it allows the development of a sensible agglomeration strategy.

In the other direction, long-term planned maintenance intervals for inverters can also be included in the forecast. Here, the maintenance planning in a CMMS would be directly linked with the production of the yield forecast for the power plant. If maintenance is planned, the generation capacity available is suitably reduced and the yield forecast at a power plant level adjusted to match. In this way a refined overall plant forecast can be assembled, which includes factors that are independent of the weather.

Conclusion

Forecasting will continue to gain in importance in the future. Large, centralized power generation plants burning fossil fuels will increasingly be replaced by decentralized plants based on renewable energies. This will place high demands on availability planning if a stable and reliable grid is to be guaranteed into the future. It will also increase the attraction of battery storage systems or other innovative conversion technologies such as power to gas, which allow surplus power to be converted and stored during periods of high yield and retrieved during periods of low yield. Managing this increased complexity in the electricity market will require reliable estimation of energy production, which in-turn will require high accuracy production forecasts.

The incorporation of plant-related weather forecasts is therefore a significant way of improving the plant-by-plant yield forecasts of an operational fleet. As a further step, forecasts can be compared with historic data under similar weather conditions, making use of pattern recognition algorithms. Such innovations have the potential to reduce the uncertainty and increase the quality of the local irradiance forecast by several factors, thereby optimizing the yield forecasts for individual plants. In this process, the differing quality of the recorded data, which is subject to factors such as contamination, shading, and the state of sensor calibration, will have to be taken into account in order to minimize negative influences. This can only succeed if the data is viewed holistically and data from the SCADA system can be amalgamated with information from the CMMS.

For operators of large portfolios, the integrative use of SCADA and CMMS will not only improve the yield forecast at plant level, but also offer a great opportunity to optimize cross-portfolio maintenance work from a cost/benefit perspective, for example at inverter level. The developments in this area are still young; the potential is very promising.

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