THE IMPACT OF SOLAR POWER FORECAST ERRORS ON VOLTAGE CONTROL IN SMART DISTRIBUTION GRIDS

André MADUREIRA
INESC TEC – Portugal
andre.g.madureira@inesctec.pt

Ricardo BESSA
INESC TEC – Portugal
ricardo.j.bessa@inesctec.pt

José MEIRINHOS
INESC TEC – Portugal
jose.l.meirinhos@inesctec.pt

Dewan FAYZUR
INESC TEC – Portugal
dewan.f.rahman@inesctec.pt

Jorge FILIPE
INESC TEC – Portugal
jorge.m.filipe@inesctec.pt

António A. MESSIAS
EDP Distribuição – Portugal
Aires.messias@edp.pt

Diogo A. LOPES
EDP Distribuição – Portugal
Diogo.alveslopes@edp.pt

Pedro G. MATOS
EDP Distribuição – Portugal
Pedro.godinhomatos@edp.pt

ABSTRACT

The high penetration of renewable generation in distribution grids requires preventive control actions based on load and generation forecasts. This paper describes a multi-temporal voltage control functionality that results from the combination of a solar power forecast method and an Optimal Power Flow (OPF) algorithm. The impact of solar power forecast errors is evaluated for a real Portuguese MV network and the main objective is twofold: minimise renewable generation curtailment and number of control actions.

INTRODUCTION

The solar power penetration is reaching non-marginal levels in numerous power systems. In terms of cost, photovoltaic (PV) generation is reaching grid parity in many countries, meaning a levelized cost less than or equal to the electricity retailing tariff.

The massive deployment of PV generation in Medium Voltage (MV) and Low Voltage (LV) grids will create under and over-voltage problems in the distribution grid, which can be mitigated by using advanced management functions that are being developed in the framework of the FP7 European project SuSTAINABLE for a Smart Grid architecture, i.e. MV control tool fed by a solar power forecasting tool. These tools are described in this paper with the main focus being the assessment of the impact of forecast errors on the voltage control function.

The proposed voltage control tool approach of a multi-temporal OPF that produces a set of control actions (e.g., set-points for Distributed Energy resources – DER, On-Load Tap Changer – OLTC – transformers, capacitor banks) for the next day by MV network node with the objective of maximizing Renewable Energy Sources (RES) integration subject to a set of technical and operational constraints.

The proposed forecasting tool comprises different statistical algorithms and aims to explore information from the smart grid infrastructure. It combines vector auto-regressive (VAR) that takes as inputs distributed (or spatial-temporal) time series information and a local quantile regression that uses information from a Numerical Weather Prediction (NWP) model. The output is a 48 hours-ahead (but can go up to 72 hours) solar power probabilistic forecast for each secondary substation.

A large-scale demonstration pilot in the city of Évora, Portugal, named InovCity, is the demonstration site of the EU Project SuSTAINABLE. The architecture described in [1] is adopted in this paper and consists of three main components: Smart Meter (EB), Distribution Transformer Controller (DTC) and Smart Substation Controller (SSC).

The EB is a smart meter with load and generation management functions, located at each delivery point. The DTC is located at the secondary substation level, comprising modules for measurement, remote control and communication actions. It collects data from the EB and the secondary substation. Each EB has a bi-directional communication with the corresponding DTC. At the primary substation level, an SSC is installed. The SSC is responsible for aggregating and managing the operational data from EB and DTC, and for applying demand-side and generation management, as well as self-healing. The MV grid is managed by the SSC.

In this paper a distribution network feeder with PV generation will be used to evaluate the solar power forecast errors in the voltage control function. Three situations will be compared: (a) observed solar power; (b) naïve forecast; (c) advanced forecast. The comparison is performed in terms of severity of the technical problems created by the uncertainty caused by PV generation and/or number of control actions associated to each forecast type.

This paper is organized as follows: firstly, the solar power forecasting tools is described; then, details about the MV control algorithm are presented; both algorithms are used in a case-study with real data to evaluate the impact of solar power forecast errors; in the end, the main conclusions are drawn.

SOLAR POWER FORECASTING TOOL

The time-horizon of interest for power system operations can be divided into two classes: (a) very short-term (up to six- hours-ahead); (b) short-term (up to three days ahead).

As mentioned in the SuSTAINABLE architecture [1], the forecasting system is installed at the SSC level and explores distributed time series information from DTC and EB. The outputs are 48 hours-ahead forecasts for each DTC (groups of consumers with PV generation). The EB measurements can be used as distributed sensors to capture the spatial-temporal effect of clouds in solar generation and consequently improve the forecast skill.

For the very-short term horizon, a new forecasting method, constructed on the top of a Smart Grid infrastructure, is proposed to combine VAR, recursive least-squares and gradient boosting frameworks to explore information from the distributed PV panels.

The very short-term forecasting module is solely based on time series data collected with, at least, a 60-minute update frequency. The mathematical formulation for two solar installations with power $p_{t,1}$ and $p_{t,2}$ at time t and two lagged terms is as follows:

$$\hat{\mathbf{p}}_{t+k|t} = \boldsymbol{\nu} + A_1\mathbf{p}_t + A_2\mathbf{p}_{t-1} + \mathbf{E}_{t+k|t} \qquad (1)$$

where $\mathbf{p}_t = (p_{t,1}, p_{t,2})^T$ and $\hat{\mathbf{p}}_{t+k|t}$ is the prediction of $\mathbf{p}_{t+k}$ made at time t. More details can be found in [2].

For time horizons greater than 4 hours-ahead, the NWP based power forecasts outperform models purely based on past time series observations. For this short-term horizon, solar power forecasts are generated from NWP through Local Quantile Regression (LQR), where the median gives the point forecast.

The LQR is a non-parametric approach. Considering the air temperature (temp) and the global horizontal irradiance (GHI) as inputs, the model is defined as follows:

$$\hat{q}^{\tau}_{t+k|t} = \theta\left(temp_{t+k|t}, GHI_{t+k|t}\right) + e_{t+k|t} \qquad (2)$$

where θ(.) is a vector of coefficient functions to be estimated, temp and GHI are NWP. The θ(.) functions are estimated at a number of distinct reference points by approximating the functions using the kernel-local polynomial smoothing method [3].

This model is also used to generate probabilistic forecasts of solar power, represented by a set of quantile forecasts ranging between 5% and 95%.

Figure 1 shows the layout of the solar power forecast tool developed in the SuSTAINABLE project and that will be demonstrated in the Smart Grid test pilot of Évora, Portugal. The inputs are observations collected by a subset of reference EBs (or sensors) with real-time communication and NWP. The output is a probabilistic forecast of solar power up to a 72 lead-times for each secondary substation.

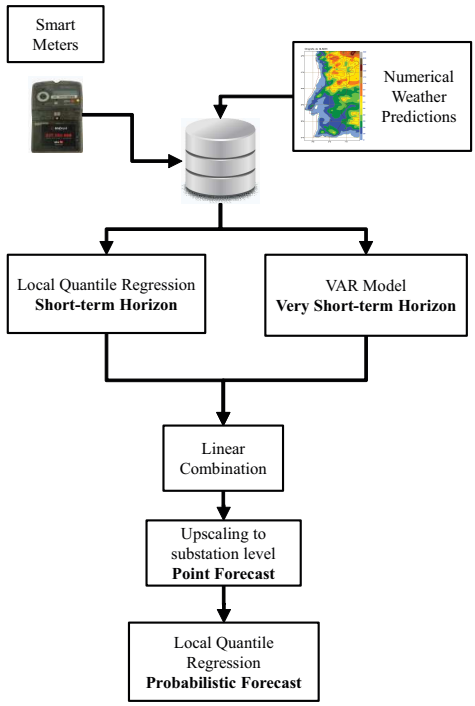

Figure 1 – Autocorrelation plot of the AR model's residuals.

The VAR framework is used to produce solar power forecasts for the next 10 hours, and two different models are considered, i.e. one fitted with recursive least squares and another with gradient boosting [2].

The LQR is used to produce point and probabilistic forecasts for the next 48 hours, based on NWP. The NWP data was generated by a service provider (Prewind, www.prewind.eu) with the Weather Research & Forecasting Model parameterized for Portugal and covering a spatial grid of 4x4 km.

Since the forecasts from the VAR and LQR models overlap for the first 10 hours, a linear model is used to combine both forecasts, and produce a single point forecast. This combined forecast is upscaled to the DTC (or secondary substation) level using a linear regression framework if historical offline observations are available from the other EBs. If these measurements are not

available, a proportion related to the rated power is used due to the spatial proximity between solar sites.

VOLTAGE CONTROL FOR MV GRIDS

Under a smart grid paradigm, advanced voltage control in distribution grids involves a coordinated management of the several DER connected at the MV level in order to ensure a smooth and efficient operation of the distribution system as a whole [4].

As previously mentioned, a voltage control scheme was developed that is able to control voltage throughout the MV network by exploiting all regulation capability of the available DER.

The proposed approach relies on a multi-temporal OPF at the functional level of the HV/MV primary substation SSC to coordinate the several MV voltage control resources (including Distributed Generation – DG, storage devices, controllable loads, O LTC transformers, capacitor banks, etc.) in order to avoid technical problems, namely voltage violations. This functionality is fed with results from the RES forecasting system presented in the previous section. An overview of the voltage control scheme developed is shown in Figure 2.

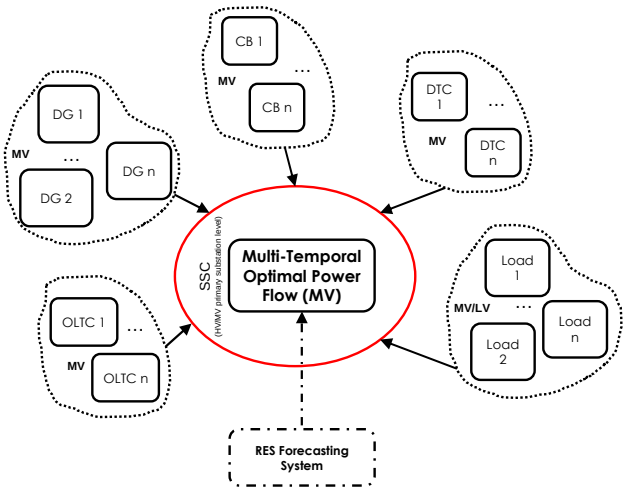

Figure 2 – Framework of the voltage control system for the MV grid.

The multi-temporal OPF performs an analysis for the day-ahead (D-1 analysis), taking as inputs load and generation bids from the market agents as well as the results from the RES forecasting to produce a set of control actions for the next day by MV network node (i.e. by DTC). In this approach, it is assumed that all the DER available at the MV level will be utilized, including not only the resources owned by the Distribution System Operator (DSO) but also resources from customers providing ancillary services to the distribution system. The resulting actions will allow defining the operation plan for the next day and close both the energy and ancillary services market.

Therefore, the main control variables considered here are the following:

- Reactive power from DG units
- Active power curtailment from DG units
- Active power injection/absorption from dispersed storage devices
- Power consumption from controllable loads
- Tap positions of OLTC transformers
- Tap positions of capacitor banks.

In this work, advanced voltage control was formulated as an optimization problem aiming at minimizing a given objective function, subject to a set of technical and operational constraints.

The problem was formulated as follows:

$$\min F(x) = \min \left(\omega_1 \cdot f_1\ (x) + \omega_2 \cdot f_2\ (x)\right) \quad (3)$$

Subject to:

$$g(x) \leq 0 \quad (4)$$

$$h(x) = 0 \quad (5)$$

Where f_1^h corresponds to the DG curtailment, f_2^h corresponds to the shedding of controllable loads, ω_1 and ω_2 are the weights associated to functions $f_1(x)$ and $f_2(x)$, respectively, $g(x)$ are the inequality constraints and $h(x)$ are the equality constraints.

The main constraints considered for this multi-temporal OPF are:

- Load flow equations
- Voltage limits
- Thermal limit of lines/cables/transformers
- OLTC transformers / capacitor banks tap limits
- DG operating limits (active power, reactive power, power factor…)
- Capacity and state-of-charge limits of storage devices

This optimization problem is solved using a new meta-heuristic approach that is a variant of Evolutionary Particle Swarm Optimization borrowing concepts from Differential Evolution – DEEPSO.

The proposed control functionality is intended to aid the DSO in real-time to optimize the operation of the distribution system in terms of voltage control based on data from generation scheduling and RES forecasting for the next operation period, in a sort of predictive mode. In this work, it was considered that hourly intervals for the day-ahead analysis.

It is assumed that this algorithm will be implemented at the level of the HV/MV primary substation (i.e. SSC).

RESULTS FROM THE CASE STUDY

The proposed approach was validated through simulation using a real Portuguese MV network. A future scenario was created by adding several DER, namely PV-based DG and dispersed storage systems. Perfect forecasts were assumed for the load and wind power. For solar power, day-ahead forecasts from the solar power forecasting tool were used with hourly time resolution. Figure 3 depicts the normalized Root Mean Square Error (RMSE) as a function of the lead-time obtained with the model described in the previous section ("VAR+LQR") and also with a benchmark model ("AR+LQR", i.e. univariate model without spatial-temporal information). These results show that spatial-temporal information can improve the forecast skill during the first ten hours of the time horizon.

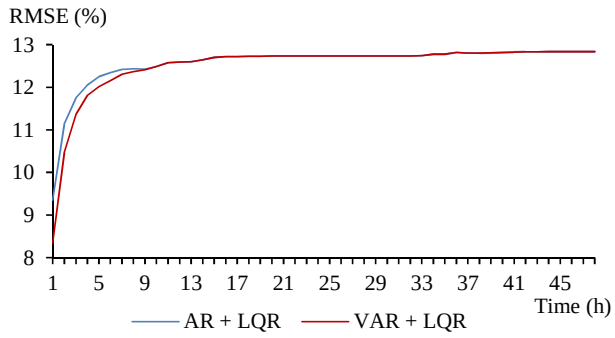

Figure 3 – Normalized root mean square error (RMSE) of the forecast system for each lead-time.

Scenario 1 – Forecast with Acceptable Accuracy

Figure 4 depicts the load and generation profiles used in the simulation for scenario 1. Note that for solar power three profiles are considered in the simulations: (red) solar generation under clear-sky conditions (naïve model); (green) solar power forecast from the developed tool; (blue) observed solar power. Note that scenario 1 is basically characterized by a small forecast error under overcast conditions.

The clear sky generation (naïve forecast) leads to a significant overestimation of the solar power generation for the next-day, which results in overvoltage problems (yellow bars in Figure 5 – initial conditions). Based on these forecasts, the multi-temporal OPF defines a set of preventive measures that consist of RES curtailment (shown in Table 1 – absolute and relative values) and changes in the HV/MV OLTC transformer position (Figure 6). For the case with advanced forecast, only a slight change in the tap positions was needed since the cloud effect in solar generation was foreseen with acceptable accuracy.

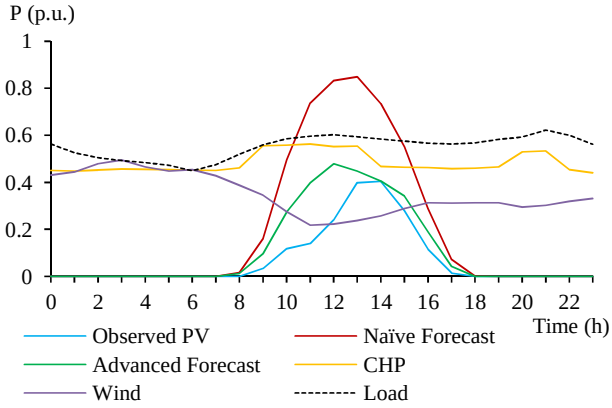

Figure 4 – Load and generation profiles of scenario 1.

Table 1 – Curtailed RES in scenario 1.

	Curtailed Power (MW)	Curtailed Power (% of Total DG Power)
Naïve Forecast	3.10	4.63
Advanced Forecast	0	0.00

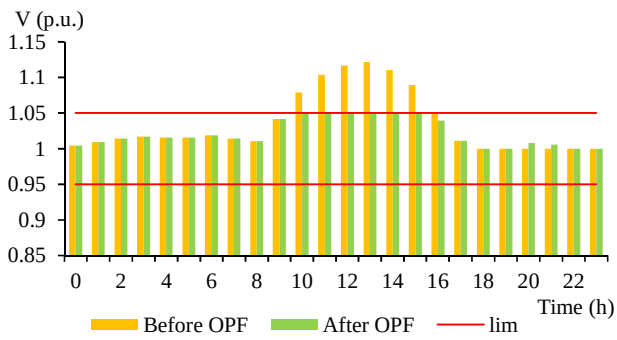

Figure 5 – Maximum voltages limits, before and after OPF for naïve forecast.

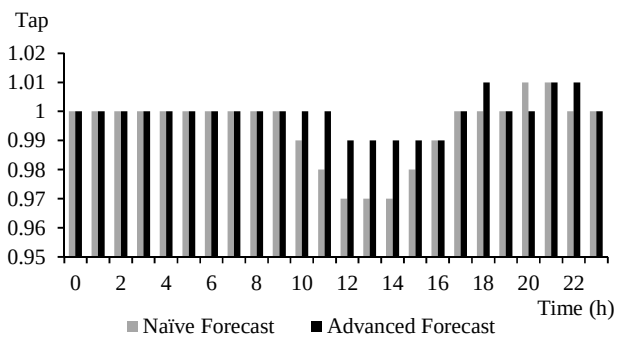

Figure 6 – Comparision of OLTC tap positions.

Figure 5 shows that the voltage problems are solved by the OPF tool. If a perfect forecast was available, the expected result would be a voltage value equal to the upper limit meaning that no RES was curtailed unnecessarily. Table 2 shows the voltage difference between the multi-temporal OPF solution and the load-flow solution obtained with perfect forecast (or observed solar power) using the control actions defined by the OPF. For the naïve forecast, the maximum values of

voltage in hours with voltage problems is, on average, 0.050 below the maximum voltage obtained (1.05). This means the control actions based on the naïve forecast are exaggerated compared to the ones obtained with a perfect forecast. For the advanced forecast, the average voltage difference is only 0.024.

This result shows that an advanced solar power forecast tool, combined with a multi-temporal OPF, can lead to a reduction of curtailed RES at the distribution system level.

Table 2 – Voltage difference from the perfect forecast based load-flow in scenario 1.

Hour	10	11	12	13	14	15
Naïve Forecast	0.050	0.050	0.050	0.050	0.047	0.050
Advanced Forecast	0.033	0.033	0.031	0.009	0.009	0.029

Scenario 2 – Forecast with High Error

In contrast to scenario 1, this scenario is characterized by a high solar power forecast error. As shown in Figure 7, the solar generation is underestimated by the advanced tool and overestimated by the naïve model.

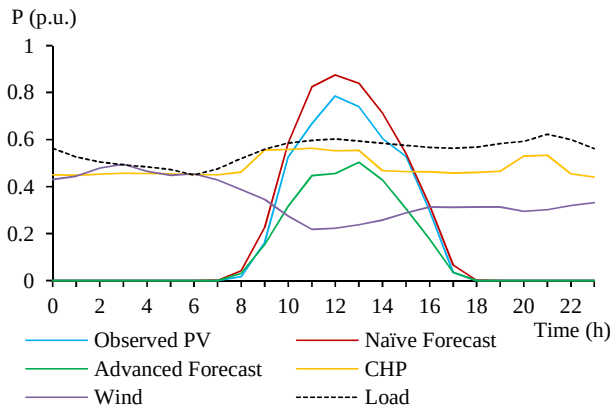

Figure 7 – Load and generation profiles of scenario 2

As can be seen in Table 3, for the naïve forecast, the maximum values of voltage in hours with over-voltage problems is, on average, 0.016 below the maximum voltage obtained (1.05). This information combined with Table 4 means that the naïve forecast leads to an excessive curtailment of RES.

Table 3 – Voltage difference from the perfect forecast based load-flow in scenario 2 (negative means over-voltage problem).

Hour	10	11	12	13	14	15
Naïve Forecast	0.005	0.031	0.018	0.020	0.018	0.001
Advanced Forecast	-0.027	-0.027	-0.042	-0.027	-0.024	-0.020

Conversely, for the advanced forecast, the average voltage difference is 0.028 higher (i.e., negative difference). This suggests that a wrong forecast of a cloud effect in solar generation can result in voltage violations that have not been predicted.

Table 4 – Curtailed RES in scenario 2.

	Curtailed Power (MW)	Curtailed Power (% of Total DG Power)
Naïve Forecast	3.25	4.67
Advanced Forecast	0	0.00

CONCLUSIONS

This paper described a solar power forecast function that provides an input for a multi-temporal OPF developed in the SuSTAINABLE project for MV grid control. The proposed methodology is expected to be operationalized as a centralized management system to be used by the DSO for managing DER and it was demonstrated through simulation using real-world data.

The results show that one of the main challenges for PV integration are overvoltages during daytime. A naïve forecast model may lead to excessive RES curtailment in comparison to an advanced forecast. Nevertheless, weather predictions may also predict clouds when they do not occur, which can lead to overlooked voltage problems. It was showed that an OPF fed by forecasts with high accuracy can solve voltage problems, while minimizing RES curtailment and control actions.

Acknowledgments

This work was developed within the framework of the SuSTAINABLE project (contract no. 308755), co-financed by European funds through the 7th RTD Framework Programme (FP7).

REFERENCES

[1] A. Madureira, R. Bessa, L. Seca, J. Pereira, A.A. Messias, D.A. Lopes, P.G. Matos, 2015, "Advanced system architecture and algorithms for smart distribution grids: The SuSTAINABLE approach", *CIRED 2015*. Lyon, France.

[2] R.J. Bessa, A. Trindade, V. Miranda, 2015, "Spatial–temporal solar power forecasting for Smart Grids", *IEEE TIE*. In Press.

[3] J.B. Bremnes, 2014 "Probabilistic wind power forecasts using local quantile regression", *Wind Energy*, vol. 7, 47-54.

[4] A.G. Madureira, J.P. Lopes, 2009, "Coordinated voltage support in distribution networks with distributed generation and microgrids", IET RPG, vol. 3, 439-454.