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Technical losses computation for short-term predictive management enhancement of grid-connected distributed generations

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ABSTRACT

the integration of distributed generations in medium voltage feeders is conditioned by multiple rules, especially, by those related to power flow management through the network and the efficient handling of renewable energies intermittency. For that purpose, we proposed in this work an active management algorithm to predict the need in terms of the power to be injected by a High Voltage/Medium Voltage substation for every single feeder issued from this substation. We apply it on a medium voltage feeder, considering that this feeder contains a photovoltaic installation and a storage system. The developed algorithm will allow us to underpin the forecast accuracy results through the adoption of many approaches. Those approaches aim to adjust the load demand forecast, ensure a reliable photovoltaic power production prediction, estimate the technical losses of the system and manage economically and optimally the energy flow in the battery storage bank. The present study will permit, from the one hand, to minimize energy losses in a grid connected distributed generations. The latter can be realized by managing in advance the energy flow between the different medium voltage feeders and substations for each region. Then, predict the whole energy production from conventional sources at the National Dispatching level. From the other hand, it will allow us satisfy load demand while avoiding peaks and rising the electrical devices lifetime by optimizing the number of operations on the network and forecasting the different suitable regulations. To succeed those objectives, we tried to find the best way to minimize the prediction error of our model. We exclusively adopt a particular approach to define each key performance indicator. We cite mainly the estimation of the technical losses in distribution and production segments, separately, the forecast of the load demand by considering the impact of weather conditions, the evaluation of the impact of cloud motion on PV panels and finally integrating those parameters into a MPC to enhance the accuracy of the transformer output prediction.

1. Introduction

The high penetration of Photovoltaic Power Stations (PVPSs) in Medium Voltage Distribution Systems (MVDSs) can cause sudden fluctuations in power flow that need to be dealt with in order to maintain and control grid reliability. This is due do the fact that the PV generation and load demand fluctuate continuously under changeable weather conditions and along the day. Hence, the power flow through MVDSs have to be managed in advance, especially with the massive presence of PVPSs, in order to ensure peak shaving feed-in, self-sufficiency optimization as well as frequency and voltage adjustment. This should be done in parallel with the rationalized use of the energy delivered by the High Voltage /Medium Voltage (HV/MV) transformer substations.

Accordingly, power flow prediction in grid-connected PV plants is an important measure to face the electrical grid management constraints. Likewise, coupling those PVPSs to Battery Energy Storage Systems (BESSs) may make the task easier. In fact, those two measures can allow regional grid operators to ensure an optimal power flow, an economic dispatch and an appropriate electrical device regulation. This must be prominent in cases of PVPSs overproduction or unexpected imbalances in the system. Therefore, accurate power flow prediction can enhance voltage stability and lead to more profitable operating decisions for the power system. Moreover, power prediction is important for National Dispatching operators to schedule different types of conventional generation plants or stations, determine reserve levels, and provide information for electricity market trading.

In the present paper a Model Predictive Control (MPC) strategy is adopted, that will put together the prediction results of its input variables, namely, the PV power production, the load demand and the technical losses of the system, to underpin the forecast accuracy of the active energy flow through distribution substations. A significant

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number of studies based their predictive control strategies on MPC; for instance, Wei Qi et al. have designed a supervisory control system via MPC to optimize the operation and management of an integrated wind-solar energy generation and reverse-osmosis water desalination system combined to a battery bank [1,2]. The same authors have developed another supervisory MPC for hybrid standalone wind-solar generation systems management [3]. An approach has been proposed in [4] to elaborate a new MPC-based dynamic Voltage and VAR Control scheme for a microgrid connected renewable and conventional DGs. It uses a simplified voltage prediction model to predict the voltage behavior of the system for a time horizon ahead. Xiangkun Li, et al. have used MPC to take into account uncertainties associated to weather forecast [5]. The control strategy of MPC has been also used in [6] to account for the battery charge redistribution effect on the operation of MV feeders and energy dispatching. As we can notice, every author has used MPC in its control strategy depending on the control variables and the system state that he wants to forecast. In our paper, we developed a Multi Inputs-Single Output (MISO) system based on the enhancement of the short-term forecast of the energy debited by a HV/MV substation for a time interval of 10 min [7]. This was done respecting a number of defined equations and techniques for input variables specification before their implementation in the MPC.

There are a plenty of works regarding the PV generation and load demand forecast as input variables of our system. Concerning the load demand prediction, a lot of studies have been reported in the relevant literature proposing Fuzzy Subtractive Clustering Method (FSCM) based on Adaptive Neuro Fuzzy inference system (ANFIS) to forecast energy demand [8]. In another work two approaches to model uncertainty in customer load demand were highlighted [9]. The first approach was based on a first order non-stationary Markov chain. A maximum likelihood estimator (MLE) was derived to estimate the time variant transition matrix of the Markov chain. The second approach was based on time series analysis techniques. For the PV power production prediction, a survey on the existing approaches to forecast solar irradiance have been proposed in [10], others specific methods have been enlightened in [11–13].

In addition to those input variables we have the technical losses through the system to which we gave a particular attention in the present work as they were underestimated in many papers treating the DGs penetration in the networks [14,15]. Those papers focus essentially on energy losses minimization by acting on DGs location and size. Nevertheless, some authors treated the technical losses partially; some talked about, others tried to calculate only the technical losses in distribution segments [16],inverters [17], PV cells [18] or Battery circuits [19] without doing neither a global calculation of the technical losses in a grid-connected DGs nor the prediction of the technical losses of any element of this system. Furthermore, the impact of the technical losses on the forecast accuracy has never been evaluated as well as their part from the consumption of this type of systems.

In this context, the present study presents a new methodology based on forecasting the whole parameters that can influence the save behavior of the grid to avoid ulterior fluctuations and keep the balance between demand and generation. The forecast of these parameters will be given by a future distribution network manager based on a MPC that can actualize data on time, basing its operations on algorithms which manage historical data, weather forecast and energy distribution. The system under study represents a grid-connected PVPS with a BESS as illustrated in Fig. 1 with its principal components.

This paper is organized as follows:

Primarily, the formulation of the problem beside its different inputs and output identification is done. Secondarily, the methods for the accuracy amelioration of the model by quantifying and eliminating the disturbances are presented. Finally, the explanation of the distribution network management system algorithm and its component functioning is fulfilled.

2. Problem formulation

The control objective of our problem is to keep the grid balanced while introducing PVPS, which means, satisfying load demand and keeping indicators on standard levels and values namely, the voltage magnitudes and angles of the feeder buses. This must be ensured by minimizing the energy debited from the transformer and maximizing the one from PVPS and BESS.

Consider that our explicit discrete time invariant system is modeled by the following equation [20]:

$$X_{t+1} = AX_{t+1} + BU_t + CV_t + ED_t \tag{1}$$

with system state $X_t = [x_{t,(1)}]$, where $x_{t,(1)}$ denotes the active power generated by the transformer. There is a prediction for the external input defined as a measured disturbance $V_t = \begin{bmatrix} v_{t,(1)} \\ v_{t,(2)} \end{bmatrix}$, where $v_{t,(1)}$ denotes the energy produced by the PVPS and $v_{t,(2)}$ denotes the distribution system technical losses including the distribution and the production segments that will me described later. We add to these terms another one relative to the unmeasured disturbance, denoted by $D_t = [d_{t,(1)}]$. The available control input or manipulated variable is $U_t = [\Phi.\ u_{t,(1)}]$, where $u_{t,(1)}$ denotes the energy contents of the BESS and Φ the rate defined by the manufacturer in W/Wh unit per module. This input is constrained to $U_{SOC\ \min} \le u_1 \le U_{SOC\ \max}$(State Of Charge minimal and maximal). The different variables U_t, V_t and D_t are predicted at the instant t for the instant t+1 and their prediction will rely on the equations defined in the following section. Thus, the Eq. (1) becomes:

$$X_{t+1,(1)} = AX_{t,(1)} + B\Phi u_{t,(1)} + C\begin{pmatrix} v_{t,(1)} \\ v_{t,(2)} \end{pmatrix} + Ed_{t,(1)} \tag{2}$$

We add a second equation representing the output of the system Y_t or the controlled variable, which is the active power generated by the whole system:

$$Y_t = FX_t + GV_t + HD_t \tag{3}$$

where the matrices A, B, C, E, F, G and H represent the State Space Models (SSMs).

The main objective is to hold the output Y_t, at a reference value or set point r_t that represents the total load demand of our system by adjusting the manipulated variable. In Fig. 2, the block labeled MPC represents the controller designed to achieve the control objective.

3. System identification for the MPC functionning

The optimal functioning of the MPC depends on the quality and accuracy of the inputs identified. Furthermore, basing our definition on mathematical models and equations will help us add ameliorations for the aim of approximating the forecasted values to the real ones. This must be a valuable approach for any similar system to Fig. 1.

3.1. Load demand forecast

Many short term forecasting techniques have been developed, ranging from very simple extrapolation methods to more complex time-series techniques, or even hybrid models that use a combination of these for purposes of prediction [21]. The methods of load demand prediction vary depending on the need and the purpose behind the use of these predictive data.

In our case, we will adapt the load demand forecast formulation to our studied system that aims to predict the whole values in a very short time interval. For that purpose, we formulated two empirical equations able to update and ameliorate the load demand forecast every ten minutes [7].

Case No. 1. we consider that the instant*t* belongs to a Normal Day of the year ℓ (normal means that this instant did not belong to a day of legal and religious holidays, week-end or other special national events). The load demand at this instant is expressed as follows: