MODEL PREDICTIVE CONTROL FOR THE MANAGEMENT OF DC MICROGRIDS

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ABSTRACT

This paper presents a Model Predictive Control (MPC) tool for a DC microgrid that allows to perform multiple control objectives, like voltage regulation, power sharing and energy storage management, at the same time. The proposed tool is based on optimization and its performance has been tested with good results both in simulation and on a real low-voltage DC microgrid in RSE.

INTRODUCTION

Technological progress in the power conversion field is fostering the implementation of DC distribution grids. This is a growing trend, mainly due to the high penetration of distributed generation and electrical vehicle charging stations. In many applications, DC grids may offer advantages, e.g., in terms of efficiency and architectural simplicity, compared to AC grids. This is true, in particular, in the case of a microgrid characterized by a high number of distributed energy resources.

The main control objectives in DC microgrids are voltage regulation and power sharing. The first objective is required to ensure a proper operation of components, whereas power sharing prevents the overstressing of any source and permits the management of energy storage systems.

In the past, Power Flow (PF) and Optimal Power Flow (OPF) were techniques often used and well known for high voltage transmission power balance analysis. But today, these techniques are also used for distribution network. In the literature, this topic has been studied by many authors. The OPF has been used to solve various problems in different context, like the optimal management of the electrical network, or the expansion of the network and its integration with other generators, loads and storage systems [1], [2]. For gas and fuel power plants, OPF has been used in the management of the power plants for minimizing the fuel consumption (and the associated operation cost), while fulfilling the demand load [3]. Some other authors, implemented the OPF to manage and regulate the voltage nodes of the microgrid close to the common point node voltage [4]. For the dynamic control of the impedance of the line, the OPF has also been used to reduce or to increase the value of the line impedance so as to limit the current flows in the lines [5]. In [6], the authors have analyzed a distribution network of 11 kV with the aim of fulfilling two goals: reducing the voltage fluctuation at the common point, and exporting power to the grid in the case of an excess of production.

In this paper we extend the classical approach based on OPF technique so as to take into account the low level control models of the converters on a finite time horizon. We also show how to achieve different control goals by modifying accordingly the cost function of the optimization problem.

DESCRIPTION OF THE PROPOSED TOOL

This paper presents a MPC approach for the management of a DC microgrid. This allows to achieve a broad category of control objectives (e.g, voltage restoration, energy storages management, tracking of references originated from higher control levels), by simply tuning some of the cost function parameters. Our strategy relies on the solution of a Quadratic Constrained Quadratic Program (QCQP), comprising of both the classical network constraints and the low level control models of the converters. In the QCQP, the dynamics of the system is discretized with a fixed time step $\mathbf{\Delta T}$ of 10 seconds and the constraints are defined on a fixed time horizon $\mathbf{T}$ of 10 minutes. Once the optimization is completed, the first sample of the computed optimal control sequence is applied, the state is measured and the optimization is carried over again, in a Receding Horizon fashion. formulation of the optimization problem

With the fact that the secondary control work with a temporal scale of minutes, it is not important to consider the transient of electromagnetics in the network model. For this reason, in the following all the electrical quantities will be supposed constant function of time. The relation between all voltages and current injections (positive if exiting the node) at a given time $\boldsymbol{t}$ is expressed by**:**

$$I(t) = G \cdot V(t) \qquad (1)$$

where $G \in R^{n \times n}$ is called matrix of admittances, $I(t) = [I_1(t), \dots, I_n(t)]'$ is the vector containing the current injections for each node, $V = [V_1(t), \dots, V_n(t)]'$ is the vector containing the voltages of each node and n indicates the number of nodes of the network.

From equation (1), using the definition of active power we get:

$$P_k(t) = V_k(t)\left(\sum_{i=1}^{n} G_{ki}V_i(t)\right) \tag{2}$$

Equation (2) describes the relations between all the voltages and active powers in the network at a given time.

In the following we describe the extra relations that will appear as additional constraints in our complete optimization problem for the secondary control of DC microgrids.

Voltage constraints

A typical goal in secondary control is to maintain the voltage in a desired bound, that does not violate the operative limits of the network. This requirement leads to the introduction of the following constraints on each node:

$$V_k^{min} \leq V_k(t) \leq V_k^{max} \tag{3}$$

Where the voltage limits V_k^{min} e V_k^{max} can be specified also as a function of time.

Low level control model of static generators

The aim of our proposed secondary control is to directly provide the reference signals for the low level controllers of the static generators in the network. This can be achieved by adding the following extra constraints, that, in our implemented case study, represent the droop equations of the static converters:

$$V_k(t) = V_{ref_k}(t) - D_k P_k(t) \quad k \in \mu \tag{4}$$

In Equation (4), μ represents the set of nodes of the static converters, $D_k > 0$ is the droop coefficient and V_{ref_k} is the reference signal controlled by the secondary control.

Energy storage constraints

We consider the case of storage systems connected to the network through the controlled static generators, i.e., in the model we assume that all storage systems are placed in nodes with index in μ.

In order to ensure an optimal use of these storage systems (e.g. constraining their state of energy) we consider a simple dynamical model and add it as an extra constraint to the problem. We model the batteries state of energy $E_k(t)$ as first order integrators, i.e.:

$$E_k(t + \Delta T) = E_k(t) - P_k(t) \quad k \in \mu \tag{5}$$

where the negative sign is due to the convention by which powers injections in a node are positive if generated and negative if absorbed.

For every storage system, the dynamics can be rewritten in the more compact matrix form:

$$E_k^t = \mathbf{1}E_k(t) + \boldsymbol{A}P_k^t \tag{6}$$

where $E_k^t = [E_k(\bar{t} + \Delta T), \dots, E_k(\bar{t} + T + \Delta T)]'$, $P_k^t = [P_k(t + \Delta T), \dots, P_k(t + T + \Delta T)]'$, the vector $\mathbf{1}$ is in suitable dimension and composed by only 1, and the matrix $\boldsymbol{A}$ is given by:

$$\boldsymbol{A} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ -1 & -1 & 0 & 0 \\ \vdots & \vdots & \ddots & 0 \\ -1 & -1 & \dots & -1 \end{bmatrix}$$

Having expressed the energy storage system as a function of P_k^t, it is now possible to formulate the following constraints, that, if satisfied, guarantee that the energy in the systems remains limited in the interval $[E_k^{min}, E_k^{max}]$ along the entire time horizon:

$$1E_k^{min} \leq 1E_k(t) + AP_k^t \leq 1E_k^{max} \tag{7}$$

Note that the introduction of storage systems makes the model dynamical, i.e., introduces a coupling between the electrical quantities in the network at different time steps.

Resulting optimization problem for secondary control

The constraints described so far lead to the formulation of the following complete optimization problem:

$$\begin{gathered} \min_{\substack{V_k \; k=1,\dots,n, \\ V_{ref_k} \; k\in\mu \\ P_k \; k\in\mu}} J(V, P, t) \\ P_k(t) = V_k(t)\left(\sum_{i=1}^{n} G_{ki}V_i(t)\right) \quad k = 1, \dots, N \\ V_k(t) = V_{ref_k}(t) - D_k P_k(t) \quad k \in \mu \\ V_k^{min} \leq V_k(t) \leq V_k^{max} \\ 1E_k^{min} \leq 1E_k(\bar{t}) + AP_k^t \leq 1E_k^{max} \\ \boldsymbol{t = \bar{t}, \dots, \bar{t} + T} \end{gathered} \tag{8}$$

In (8) the optimization variables are:

- Voltage module of each node: $V_k, k = 1, \dots, N$
- Reference voltage to droop controllers of static generators: $V_{ref_k}, k \in \mu$
- Active power injections in the static generators nodes: $P_k,\ k \in \mu$

All the quantities appearing in (8) - both the control variables and the power injections in non-controllable nodes - are defined on the time horizon $[\bar{t}, \dots, \bar{t} + T]$. This means that for the non-controllable variables a forecast is needed.

A solution of problem is the optimal sequence of reference voltages $V_{ref_k}^{opt}$ of the low level controller of the static generators, the corresponding optimal values of powers P_k^{opt} and the optimal voltages of each node V_k^{opt} that minimize the cost function J. All these quantities are defined as a function of time on the horizon $[\bar{t}, \dots, \bar{t} + T]$.

Note that, in order to solve problem, a measure of the state of energy at the first time instant $E_k(\bar{t}), k \in \mu$, is needed.

Lastly, the cost function J of problem can be tuned so as to satisfy different control objectives, as explained in the following paragraph.

Elements of the cost function

The cost function in (8) has been defined as the sum of different terms. For this purpose for each node, it has been defined a desired voltage and active power profile. In the cost function, it has been inserted the quadratic sum deviation from desired profile weighted with time variant coefficient:

$$\begin{aligned} J_V &= \sum_{k}\sum_{t} c_{V_k}(t)\big(V_k(t) - V_k^*(t)\big)^2 \\ J_P &= \sum_{k\in\mu}\sum_{t} c_{P_k}(t)(P_k(t) - P_k^*(t))^2 \end{aligned} \qquad (9)$$

For the nodes connected to the storage system, it has been included a desired stored energy profile $E_k^*(t)$ and its corresponding terms in the cost function has the form:

$$J_E = \sum_{k\in\mu}\sum_{t} c_{E_k}(t)(E_k(t) - E_k^*(t))^2 \qquad (10)$$

A further term J_{loss} can be introduced in the cost function for losses minimization:

$$J_{loss} = c_{loss}\sum_{k\in\mu}\sum_{t} P_k(t) \qquad (11)$$

This term favors the minimization of powers generated from controllable converters. This term could be settled to an ideal minimum value (in case of zero losses) equal to the total sum of the generated power into the network minus the absorbed one.

The complete cost function is given by the sum of terms discussed so far:

$$J = J_V + J_P + J_Q + J_E + J_{loss} \qquad (12)$$

and the optimal solution will be the one that determines the best *trade-off* between the different elements contained in J. From this point of view, the weighted coefficients of each element play an important role: in fact, they can be used for favoring the minimization of one of the elements of the cost function with respect to the others.

In the light of what have been exposed in the previous paragraphs, it is possible to formulate the complete optimization problem to be solved in order to find the optimal sequence of control variables in the horizon $[\bar{t} \;\; \bar{t} + T]$.

$$\min_{\substack{V_i\; i=1,\dots,n \\ V_{ref_i}\; i\in\mu \\ P_i\; i\in\mu}} J_V + J_P + J_Q + J_E + J_{loss}$$

The solution of this problem is the optimal sequence of reference voltage ${V_{ref}}_k^{opt}(t)$ to be send to static converters, and consequently the optimal sequences of all the unknown electrical quantities in the network.

It has to be noted that the optimal control sequence returned by problem (8) is actually computed in open loop, based on the available forecasts on the horizon $[\bar{t}, \dots, \bar{t} + T]$. In order to avoid the propagation of errors derived by not accurate enough forecasts or errors in the model, the control scheme is implemented in a Receding Horizon fashion. This means that, at each time step t, the optimization on the entire horizon $[t, t + \Delta T, \dots, t + T]$ is carried out, but of the resulting optimal sequence ${V_{ref}}_k^{opt}(t), \dots, {V_{ref}}_k^{opt}(t + T)$ only the first control action ${V_{ref}}_k^{opt}(t)$ is applied. Then, once that a ΔT period is passed, the state of the system (i.e., the values $E_k(t + \Delta T), k \in \mu$) is measured, a new optimization is carried out on the shifted horizon $[t + \Delta T, \dots, t + \Delta T + T]$, and the procedure repeats. The resulting control scheme is also referred to as Model Predictive Control (MPC) scheme and guarantees greater robustness thanks to the feedback implementation.

RESULTS AND OBSERVATIONS

The proposed control scheme has been validated through experimental tests carried out resorting to the DC microgrid test facility of RSE [7]. This LVDC network is unipolar with a nominal voltage level of 380 V and present two ac/dc converters, of about 100 kVA and 30 kVA, that allow the exchange of power with the AC grid. The network is also equipped with different ESS units to ensure stabilization of the dc voltage during transient and at a steady state for different loads, both in ac grid-tie condition and in dc island operation. The ESSs are two high-temperature NaNiCl batteries, each with a rated power of 32 kW and a capacity of 18 kWh, along with two supercapacitor (SC) banks, each with a rated power of 30 kW for 10 s. Each battery and supercapacitor bank are coupled to the dc grid through a 35 kW dc/dc bidirectional converter to allow charge and discharge. Finally, one programmable purely resistive load-bank with a maximum power of 30 kW, one constant power load of 30 kW and a PV emulator of 30 kW are installed in the dc microgrid. The layout of the grid is reported in Figure 1.

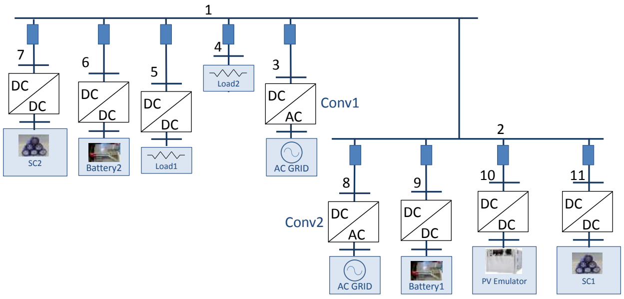

Figure 1. Layout of the RSE's DC Microgrid

To evaluate the behavior of the proposed control scheme two tests are performed through the DC microgrid. The goal of these tests is to demonstrate that the MPC is able to provide the best trade-off among the control objectives (voltage, power and energy regulation), that can be done by simply tune the cost function, in presence of disturbances.

The different rate parameters of the impedances of the lines have been used to define the admittance matrix of the DC grid configuration used for the tests.

The control objectives are: maintaining the voltage at the PCC at the desired value of 380 V, following the active power profile for the converter1 and the state of charge profile for the batteries (highlighted in yellow in Figure 3 and Figure 5), considering bound voltages of 5%.

During the tests, starting from a steady state condition, the power profile of the PV generator, the load and the converter 2 are modified as shown in Figure 2.

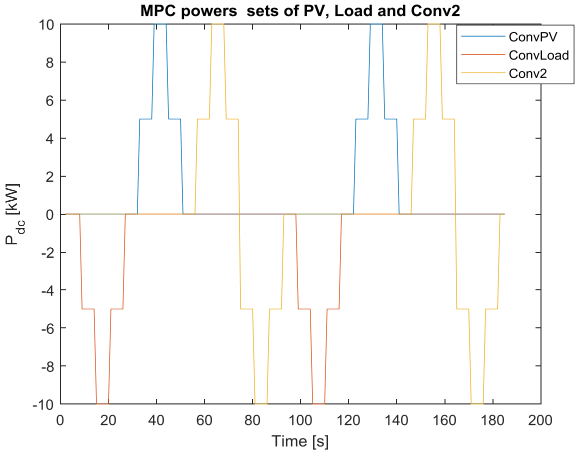

Figure 2. Power profile for the PV, Load and converter2 during the tests

Test1

In the first test, the weights used in the cost functions are the following: cE=1e-7, cP=1 and cV=100. The trend of power and state of energy of the batteries during the test are shown in Figure 3.

With these cost values, the MPC fosters the power regulation of the converter1, while the voltage and energy regulation are weak.

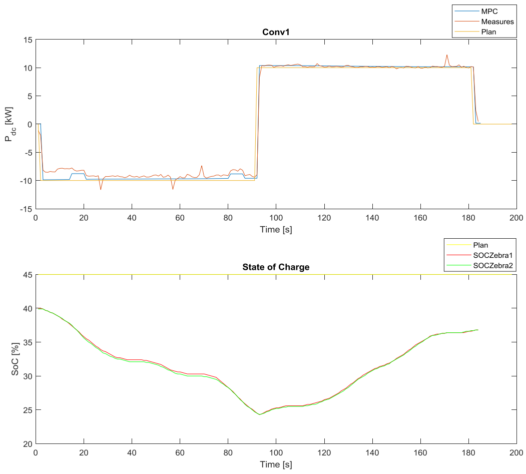

Figure 3. Secondary control performance of the power of the converter 1 and the state of charge of the batteries during the test1

In Figure 4, the voltage of each node of the DC grid is shown. In particular, the real measurements are highlighted in red, the magnitudes generated by the second level control in blue (MPC). It's worth noting that the voltage generated by the MPC are very closed to the real measurement. This is a good result, considering that the model of the DC grid is realized starting from the nominal line parameters.

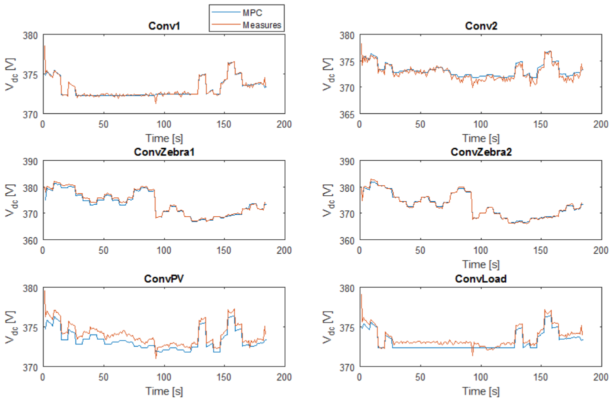

Figure 4. Secondary control performance of voltage in the network nodes during the test1

Test2

In the second test, the weights used in the cost function are the following: cE=1e-5, cP=0.1 and cV=10000. The trend of power and state of energy of the batteries during the test are shown in Figure 5. With these cost values, the MPC fosters the regulation of the voltage at the PCC, while the power and energy regulation are weak.

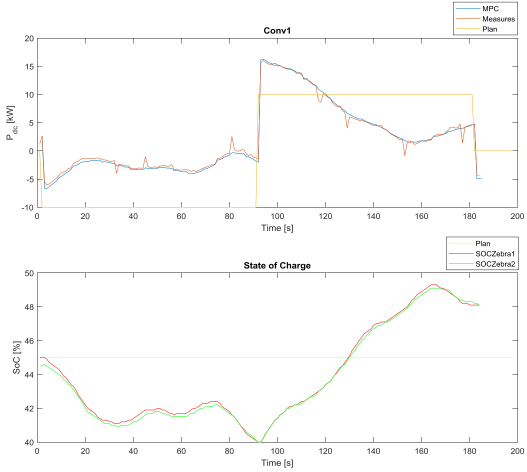

Figure 5. Secondary control performance of the power of the converter 1 and the state of charge of the batteries during the test2

In Figure 6, the voltages of the each node are shown. It's possible to note that, during this test, the voltages of the

PCC and of each node are always near 380 V.

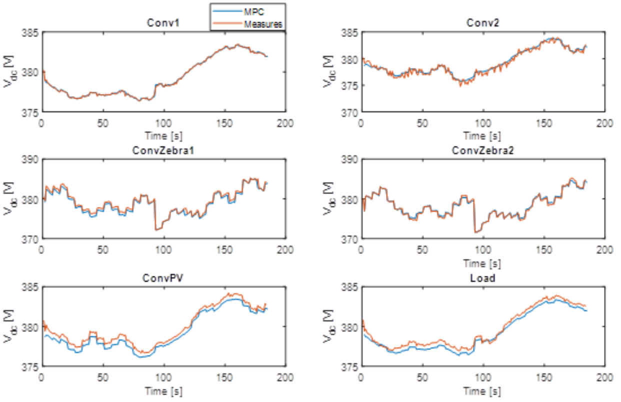

Figure 6. Secondary control performance of voltage in the network nodes during the test2

The two different tests have been carried out in two different ways: the first way is to give a strong weight on the power of the converter1 and weakly the weight on voltage and energy storage of the batteries and the second way is to weakly the weight on power of the converter1 and the energy storage of the batteries, when strong the weight of voltage regulation. We observe that, the power of the converter1 in the first test follow very well the plan, while the state of charge of the battery works under the planned state of charge. On the second test, we observe that the power of the converter1 is not following very well the plan, the batteries state of charge go over the planned and the voltage profile of the MPC at each node is quite similar to the measurement. These tests carried out by varying costs parameters, permit to verify the performance, the robustness and the feasibility of the proposed developed tool. The means voltage deviation from test1 to test2 are respectively 0,3V to 0,25V.

CONCLUSION

In this paper, we test the propose MPC tool on the RSE DC grid with the aim of regulating the PCC voltage to a desired value while keeping the energy stored in the batteries in a desired band. The outputs of the tool are the optimal voltage references for the low level controllers (droop) of the two static converters connected with storages (node 2 and node 7 in Fig.1). The results obtained in simulation agree with the experiments tests carried on the real test facility, and demonstrate the validity of the approach.

The results of the study show that the implemented tool fulfills very well the goal of optimal operation of a DC microgrid, achieving voltage and energy storage regulation. In particular, the tool presents key features and advantages that are typical of model based optimization approaches:

- *optimality*: the scheme always provides the best tradeoff among all the user defined - and sometimes even conflicting - control objectives.
- *flexibility*: by simply tuning the cost function, the user can induce many different behaviors in the network, from voltage restoration to energy management in island mode, power sharing etc.
- *robustness*: the scheme is robust with respect to errors in the model thanks to the feedback provided by its receding horizon implementation.

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REFERENCES

[1] R. A. F. Currie, M. J. Dolan, G. W. Ault, J. R. McDonald, “Assessing the Impact of Active Power Flow Management on SCADA Alarm Volume”, 19th International Conference on Electricity Distribution (CIRED 2007), Vienna, 2007.

[2] G. P. Harrison, A. Piccolo, P. Siano, A. R. Wallace, “Multi-Objective Optimal Power Flow To Evaluate the Tensions Involved in Connecting Distributed Generation,” 19th International Conference on Electricity Distribution (CIRED 2007), Vienna, 2007.

[3] J. F. Manwell et al., “Hybrid2: A Hybrid System Simulation Model: Theory Manual,” no. XI, p. 267, 2006.

[4] A. Berger, M. Hennig and C. Körner, "Voltage control in smart distribution grids — Overview and practical experience of available solutions," 22nd International Conference and Exhibition on Electricity Distribution (CIRED 2013), Stockholm, 2013, pp. 1-4.

[5] M. Khederzadeh, “Application of voltage source converters to manage power flow and enhance operational performance of a Microgrid,” 21st International Conference and Exhibition on Electricity Distribution (CIRED 2011), Frankfurt, 2011, pp. 1-4.

[6] N. Wade, P. Taylor, P. Lang and J. Svensson, "Energy storage for power flow management and voltage control on an 11kV UK distribution network," CIRED 2009 - 20th International Conference and Exhibition on Electricity Distribution - Part 1, Prague, Czech Republic, 2009, pp. 1-4.

[7] D. Ronchegalli and R. Lazzari, “Development of the control strategy for a direct current microgrid: A case study,” in 2016 AEIT International Annual Conference (AEIT), Capri, Italy, Oct. 2016.