

A HYBRID APPROACH FOR VOLTAGE STABILITY OF POWER SYSTEMS

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Abstract - When interesting on voltage (in)stability, power systems can be advantageously considered as hybrid dynamical systems. In order to take into account both the non-linearity of load dynamics and the mixed nature of variables, an hybrid approach based on a symbolic linearized prediction model and predictive control is proposed. This methodology is illustrated on a nine-bus power system example.

Keywords - Power systems, Voltage stability, Hybrid systems, Predictive control

1 INTRODUCTION

Voltage control and stability problems are now of great concern for the power engineering community. Actually, in the last years, several major network collapses have occurred around the world, e.g. in North America and Europe in 2003 [1]. Voltage collapses are recognized in [2] not to be only associated with weak systems but to be also a source of concern in highly developed networks that are heavily loaded. The phenomenon of voltage instability can be briefly summarized by the following definition given in [3]: “voltage instability stems from the attempt of load dynamics to restore power consumption beyond the capability of the combined generation and transmission system”.

Dealing with electric energy transport has become a paradox. Extension of the transmission system is more and more constrained by environmental as well as economic considerations. On the contrary, populations grow and need more energy than ever before and the consequence is a constant increase of electricity consumption. Moreover the liberalization of the power market imposes new economic constraints and exchange capacities needs. Interconnection lines between countries that were originally designed to ensure the robustness of a whole interconnected electric network (e.g. in Europe) now are used, besides, to transmit power according to market laws. As a result, power systems become more stressed. They are operated closer to their stability limits that are related to maximum deliverable power [3]. Voltage collapse is characterized by the shifting of the operating point toward an unacceptable area with no equilibrium point possibly leading to dramatic blackouts.

The current protection schemes against voltage collapse are generally ruled-based and consist in load shedding and reactive power compensation. However, the

nonlinear behavior of power systems makes these rules strongly dependent on the operating conditions. Moreover, these protection schemes are most often based on the local protection equipment, which is acting locally to protect individual equipment such as transformers, generators, transmission lines, etc. but without any coordination with other protection equipment as well as with Energy Management Systems (EMS). However research has been engaged on the way of model based approaches and global control for power systems since wide-area and phasor measurements are possible and power utilities increasingly demand wide area control, protection and optimization systems [4].

Model Predictive Control (MPC) has been successfully applied on a wide range of industrial applications for a long time. MPC was first applied to voltage control problem in [5] where a coordinated system protection scheme against voltage collapse using search and predictive control is presented. To be tractable, this approach uses a single-step linearized prediction model, that is it assumes a constant control input during the entire prediction interval and moreover, it cannot handle discrete behavior. It is a small signal approach where all the control variables are discretized leading to a pure combinatorial optimization problem. As it is described later in the present paper, power systems belong to the class of hybrid systems. In [6], the Mixed Logical Dynamical (MLD) framework is used to model the hybrid behavior of power systems. This approach consists in partitioning the continuous state-input space into polytopes where, for each combination of the discrete inputs, a different affine model is used which involves a strong combinatorial complexity. Then the application of MPC to a MLD prediction model requires the solving of Mixed Integer Programming (MIP) problems.

An alternative method (not based on the MLD framework) is proposed in this paper and consists in symbolically linearizing the hybrid non-linear model of power system in order to apply a MPC based hybrid approach. This allows to be accurate around the current operating point at each sample time and to minimize the combinatorial complexity to the one induced by the possible choices for the discrete inputs only. A simple and suitable mixed optimization algorithm is presented to solve the optimization problem resulting from the proposed MPC strategy.

The paper is organized as follows. Section 2 presents the power systems modeling and symbolic linearization.

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Section 3 presents the control principle and the mixed optimization algorithm. Section 4 presents the simulation results obtained on a faulted nine-bus power system example. Finally, section 5 gives conclusions.

2 POWER SYSTEM MODELING

Voltage stability problems are commonly studied according to the framework of a quasi-static approach which is based on the following assumptions. Frequency is considered constant and fast dynamics are neglected. All the models that are used in this paper are equivalent one-line diagrams. This leads to use a polar representation (commonly named phasors) for voltage, current and state variables. The following notations are then used. Phasor magnitudes are shown as capital letters, e.g. V . Column vectors and matrices are shown as bold characters, e.g. \mathbf{x} and superscript T denotes transpose. Time derivatives appear with a dot, e.g. $\dot{\mathbf{x}}$.

Generators are modeled using the well known quasi-steady state approximation of the synchronous machine equations and associated control devices (the OverExcitation Limiter (OXL) is then modeled by a saturation). This mainly results in neglecting the (fast) electromechanical oscillations [3].

Load is a common term for aggregates of many different devices which are mainly voltage dependent. Thus load dynamics are considered from the point of view of power restoration and are described by a smooth non-linear differential equation [7]:

$$\begin{aligned} T_p \dot{x}_{lp} + x_{lp} &= P_s(V_l) + P_t(V_l) \\ P_l &= (1 - s_l k_l) (x_{lp} + P_t(V_l)) \end{aligned} \quad (1)$$

where x_{lp} is a continuous state variable, V_l the load voltage magnitude, $P_s(V_l) = P_0 V_l^{\alpha_s}$ and $P_t(V_l) = P_0 V_l^{\alpha_t}$ are the steady-state and transient voltage dependencies respectively, P_l is the actual active load power and T_p is the active power recovery time constant. A similar model is used for the reactive load power considering the following variables: x_{lq} , $Q_s(V_l) = Q_0 V_l^{\beta_s}$, $Q_t(V_l) = Q_0 V_l^{\beta_t}$, Q_l and T_q . k_l is a constant load shedding step and s_l is a discrete control variable which takes its values in a bounded discrete set. s_l and k_l are used in both active and reactive power equations. Let $x = (x_{lp}, x_{lq})$ denote the internal state of the load.

Transformers are modeled using an impedance in series with an ideal transformer whose ratio is denoted n_t . The presence of a Load Tap Changer (LTC) allows the ratio to vary tap by tap within bounds. Since the size of a tap step is quite small (usually in the range of 0.5%–1.5% of the nominal ratio), to simplify the control design, n_t is considered as a bounded continuous variable.

Two kinds of reactive power compensation devices are considered in this paper : capacitor banks and Flexible AC Transmission Systems (FACTS). The number of connected parts (denoted s_c) of a capacitor bank can only take its values in a bounded discrete set whereas a FACTS is considered as a continuously varying capacitor whose ca-

capacity value is adjusted by a variable n_c which can take its value in a bounded continuous set.

Transmission lines are modeled using impedances. If a line can be (dis)connected in order to modify the power system topology, a boolean control variable δ_L is used to represent the state of the line : connected (1) or disconnected (0).

In the framework of voltage stability, the hybrid nature of power systems is then particularly characterized by the presence of two kinds of control inputs: discrete ones arise from loads (s_l), capacitor banks (s_c) and transmission lines (δ_L) whereas continuous ones arise from transformers (n_t) and FACTS (n_c).

Power systems consist of the interconnection of several of these components then a column vector (shown as bold character) is now used to represent a set of the same kind of components. In the sequel, the discrete ones are denoted as \mathbf{u}_d then $\mathbf{u}_d^T = (s_l^T s_c^T \delta_L^T)$ and the continuous ones as \mathbf{u}_c then $\mathbf{u}_c^T = (n_t^T n_c^T)$.

A discrete disturbance is considered in this paper: a transmission line is lost, i.e. unintentionally disconnected. This discrete disturbance, the (un)saturated state of the generators and a combination of the discrete control inputs defines an operating mode denoted i in which the power system stands.

The general power system model relevant to this studies takes the differential algebraic form (in each mode i):

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}_i(\mathbf{x}, \mathbf{y}, \mathbf{u}_c) \\ \mathbf{0} &= \mathbf{g}_i(\mathbf{x}, \mathbf{y}, \mathbf{u}_c) \end{aligned} \quad (2)$$

which is a non-linear multimodel relationship where \mathbf{x} is the load state vector and the output \mathbf{y} is typically the vector of bus voltages.

Power systems are strongly non-linear and to predict the system evolution, a feasible approach is to use locally a linear or, more generally, affine model. In [5], several methods are proposed to obtain predictions of the state and output trajectories. But the reduction of equations (2) to an explicit form is done using the current values of the discrete variables and thus the linearized models obtained that way cannot handle any hybrid aspects. In [6], the continuous state-input space is gridded into polyhedral partitions. Then for each polytope and combination of the discrete inputs, the system response is approximated, in general, by a different affine model. To be accurate, the gridding needs to be tight enough and leads possibly to a great number of affine models to consider. This involves to reach a compromise between the obtained combinatorial complexity and needed accuracy.

An alternative method is proposed here for the model to be accurate and to avoid combinatorial explosion. It consists in symbolically linearizing equations (2) with respect to continuous variables, i.e. the state x and the continuous control input u_c . The operating point denoted $(\mathbf{x}_0, \mathbf{u}_{c0})$ (which is not necessary an equilibrium) and the mode i are symbolic parameters of the linearized model. This allows to predict the evolution of the system with an accurate model around the current operating point (at each

sample time) which is assumed to be measured or estimated and to handle the hybrid aspects as well.

Nevertheless almost all power systems are large scale systems. The symbolic computation required to directly linearize equations (2) becomes too complex and then unfeasible when the size of the power system exceeds a few buses. To minimize the complexity, the elementary non-linear relations of each component are symbolically and separately linearized. It results in a set of linear relations which have to be numerically combined. The needed computational effort is then significantly reduced and allows to consider application to non-trivial systems. More details about this linearizing procedure are reported in [8] but are omitted here due to space limitations. Time is discretized with a sample period T_s and using backward-Euler method to approximate the derivative, the following discrete time affine model of power system is obtained:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}_i \mathbf{x}(k) + \mathbf{B}_i \mathbf{u}_c(k) + \mathbf{a}_i \\ \mathbf{y}(k) &= \mathbf{C}_i \mathbf{x}(k) + \mathbf{D}_i \mathbf{u}_c(k) + \mathbf{c}_i \end{aligned} \quad (3)$$

where $\mathbf{x}(k) \equiv \mathbf{x}(kT_s)$, the matrices \mathbf{A}_i , \mathbf{B}_i , \mathbf{C}_i and \mathbf{D}_i as well as the vectors \mathbf{a}_i and \mathbf{c}_i depend on the operating mode $i(k)$ and current operating point $(\mathbf{x}_0, \mathbf{u}_{c0})$. $\mathbf{u}_c(k)$ is the continuous valued control inputs vector applied to the system from instant k to instant $(k+1)$ and is assumed to be constant during the sample period. At the current operating point, the (un)saturated state of the generators is computed for each possible value of \mathbf{u}_d and is assumed to be constant until the next sample time.

3 CONTROL PRINCIPLE

The control objectives consist in designing a control law which is able, if it is possible, to restore voltage stability of the faulted power system and keep bus voltages close to nominal value. Physical constraints such as actuator limits as well as operating constraints have to be considered too. The proposed solution must then have to take account of the hybrid nature of power systems and hard and soft constraints. This has led to develop a Model Predictive Control (MPC) based approach as detailed in this section.

3.1 Model Predictive Control

MPC consists in a control algorithm based on solving an on-line optimization problem using a receding horizon approach. This is summarized in the following steps in [9]: at time k and for the current state $x(k)$, an open-loop optimal control problem over a future time interval is on-line solved taking into account the current and future constraints; the first step in the optimal control sequence so obtained is applied and then the procedure is repeated at time $(k+1)$ using the current state $x(k+1)$. The solution is converted into a closed-loop strategy by using the measured or estimated value of $x(k)$ as the current state. The stability of the resultant feedback system can be established by using the fact that the cost function acts as a Lyapunov function for the closed-loop system [10].

In [5], a MPC scheme is implemented with only one time step predictors and under the assumption of only small and quantified control variations. This leads to a pure combinatorial problem and does not allow to handle any discrete events such as a modification of the power system topology. In [6], the predictor is obtained using the MLD framework which involves the addition of a significant number of auxiliary variables and inequality constraints [11]. Then the application of MPC with a MLD model requires, at each time step of the prediction horizon, to solve a Mixed Integer Programming (MIP) problem which can be very time consuming. In this paper, an alternative approach is proposed by using a hybrid search algorithm in order to solve the optimization problem involved by the MPC strategy without addition of any auxiliary variables [12].

To reach the control objectives, the cost function typically includes a term based on the deviations of the chosen outputs from their reference trajectories and a term based on the control inputs. Other terms can be added to the cost function, e.g. to take into account the violation of outputs constraints. Let

$$\mathbf{u}_N = \{\mathbf{u}(k), \mathbf{u}(k+1), \dots, \mathbf{u}(k+N-1)\} \quad (4)$$

be the control sequence over the prediction horizon of length N with $\mathbf{u}^T(l) = (\mathbf{u}_c^T(l) \mathbf{u}_d^T(l))$. Consider the following cost function:

$$J_N(\mathbf{x}(k), \mathbf{u}_N) = \sum_{l=k}^{k+N-1} L(\mathbf{x}(l), \mathbf{u}(l)) \quad (5)$$

with

$$\begin{aligned} L(\mathbf{x}(l), \mathbf{u}(l)) &= \\ &\|\mathbf{y}(l) - \mathbf{y}^{ref}(l)\|_{\mathbf{Q}_y} + \|\mathbf{u}(l)\|_{\mathbf{Q}_u} \end{aligned} \quad (6)$$

where \mathbf{y}^{ref} is the output reference trajectory. 2-Norm is used to obtain a quadratic cost function, i.e. $\|\mathbf{v}\|_{\mathbf{Q}} = \sqrt{\mathbf{v}^T \mathbf{Q} \mathbf{v}}$. \mathbf{Q}_y and \mathbf{Q}_u are weighing matrices such that $\mathbf{Q}_y \geq 0$ and $\mathbf{Q}_u > 0$ and will allow to tune the controller.

The MPC algorithm needs to solve the optimization problem:

$$J_N^o(\mathbf{x}(k)) = \min_{\mathbf{u}_N} J_N(\mathbf{x}(k), \mathbf{u}_N) \quad (7)$$

subject to model constraints (3). Additional constraints allow to take into account some knowledge about the system which is not captured by the model. Input constraints take account of actuators limits over the prediction horizon and thus are considered as hard constraints. On the contrary, outputs ones are not generally considered as hard constraints. The optimization problem (7) could be infeasible due to the impossibility for the outputs to fulfill the constraints. These hard constraints can be softened by adding slack variables representing the amount of constraints violation. It requires to modify the outputs constraints by including the slack variables $\mathbf{s}(l)$:

$$\mathbf{y}_{inf} - \mathbf{s}(l) \leq \mathbf{y}(l) \leq \mathbf{y}_{sup} + \mathbf{s}(l) \quad (8)$$

and adding the penalty term $\|s(l)\|_{Q_s}$ to (6). Thus an optimal solution of the MPC optimization problem can be found while minimizing the constraints violation.

3.2 Mixed Optimization

A particular feature of the optimization problem previously formulated is that it has a mixed nature. The presence of continuous (\mathbf{u}_c) and discrete (\mathbf{u}_d) valued control inputs leads to consider the searched optimal control sequence as a sequence of continuous (\mathbf{u}_{cN}) as well as discrete (\mathbf{u}_{dN}) valued control inputs over the prediction horizon. Then the optimization problem (7) can be written as follows:

$$J_N^o(\mathbf{x}(k)) = \min_{\mathbf{u}_{dN}} \left(\min_{\mathbf{u}_{cN}} J_N(\mathbf{x}(k), (\mathbf{u}_{cN}, \mathbf{u}_{dN})) \right) \quad (9)$$

Given a discrete valued control sequence \mathbf{u}_{dN} then

$$J_N^*(\mathbf{x}(k), \mathbf{u}_{dN}) = \min_{\mathbf{u}_{cN}} J_N(\mathbf{x}(k), (\mathbf{u}_{cN}, \mathbf{u}_{dN})) \quad (10)$$

is the optimal cost found by solving the corresponding Quadratic Programming (QP) subproblem. The associated continuous valued control sequence denoted as \mathbf{u}_{cN}^* is optimal regarding to \mathbf{u}_{dN} .

To reach the solution of the mixed optimization problem (9), the purpose of the algorithm proposed in [12] is to minimize the number and the size of QP subproblems to solve. Consider all the possibilities for the discrete controls at each time step of the prediction horizon. A brute force strategy consists in completely covering the decision tree so obtained, which is a NP-hard problem. The basic idea of the proposed algorithm is to prune the tree by cutting the branches that are not able to lead to the optimum.

3.3 Branch cutting

The following notations are used. \mathbf{u}_{dP}^N is the discrete valued control subsequence of length $P \leq N$ extracted from the discrete valued control sequence \mathbf{u}_{dN} . The superscript * denotes optimality regarding to a given discrete control sequence. Given a discrete valued control sequence \mathbf{u}_{dN} . For any $P \leq N$,

$$J_N^*(\mathbf{x}(k), \mathbf{u}_{dN}) \geq J_P^*(\mathbf{x}(k), \mathbf{u}_{dP}^N) \quad (11)$$

This proposition has been proved in [12] and leads to a suitable optimization algorithm. The method consists in:

- going toward a leaf and obtain a first suboptimum of (5);
- looking over the decision tree and eliminate the nodes (and following branches) for which the optimal cost is greater than the known suboptimum.

The following descent strategy is proposed. Consider a node at a depth P in the decision tree. The optimal costs $J_{P+1}^*(\mathbf{x}(k), \{\mathbf{u}_{dP}^N, \mathbf{u}_d(k+P)\})$ are computed for all the possible decisions $\mathbf{u}_d(k+P)$. The branch which gives the minimal cost is chosen to continue the exploration. This is illustrated on figure 1.

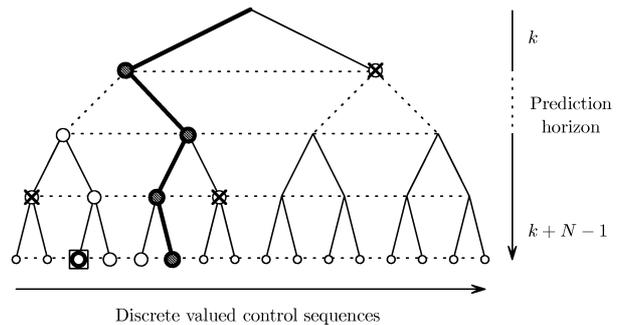


Figure 1: Pruning strategy for mixed optimization

At bottom, the leaves (symbolized by small circles) are the set of QP sub-problems to solve in order to find the optimum by complete enumeration.

The path leading to the first suboptimum is marked out with bold lines and shaded bold circles. The nodes for which the optimal cost is lower than the cost of the known suboptimum are marked out by an empty circle. On the contrary, the nodes for which the optimal cost is greater than the cost of the known suboptimum are marked out by a crossed circle. All the branches following these nodes are cut. A better suboptimum is marked out by an empty bold circle and the last suboptimum which is the searched optimum is marked out by a square.

Note that only the QP subproblems associated to the nodes marked out by a circle have been required to be solved.

4 POWER SYSTEM EXAMPLE

We shall now deal with the application of the proposed methodology to a nine-bus power system example. To simulate the power system, a full non-linear model has been used. After a brief description of the example, simulation results are given and discussed. All the numerical values are given using the per unit (p.u.) system.

4.1 Nine-Bus Power System

Consider the power system shown on figure 2 which is a case study that allows to reproduce most of the phenomena of interest such as loss of stability and voltage collapse. G_∞ is a generator modeling the surrounding network which is assumed to be strong. G_1 and G_2 are generators equipped with a voltage regulator and an OXL, L_1-L_9 are transmission lines, C_1 is a FACTS, C_2 is a capacitor bank, Tr_1 and Tr_2 are transformers with fixed ratio, Tr_3 is a transformer equipped with a LTC and Ld_1 , Ld_2 and Ld_3 are dynamic loads modeling sets of consumers.

The control inputs are the following ones: $(\delta_{L7}, \delta_{L8}, \delta_{L9}) \in \{0, 1\}^3$ allow to connect (1) or disconnect (0) lines L_7 , L_8 and L_9 respectively, $n_{C1} \in [0, 2]$ is the control input of C_1 (reactive power injection up to 0.1 p.u.), $s_{C2} \in \{0, 1, 2, 3\}$ is the capacitor bank C_2 control input (3 parts of 0.05 p.u.), $V_9^{ref} \in [0.8, 1.2]$ is the voltage reference of the LTC of Tr_3 and $(s_{l1}, s_{l2}, s_{l3}) \in \{0, 1, 2\}^3$ are load shedding inputs (0, 5 or 10 % of load).

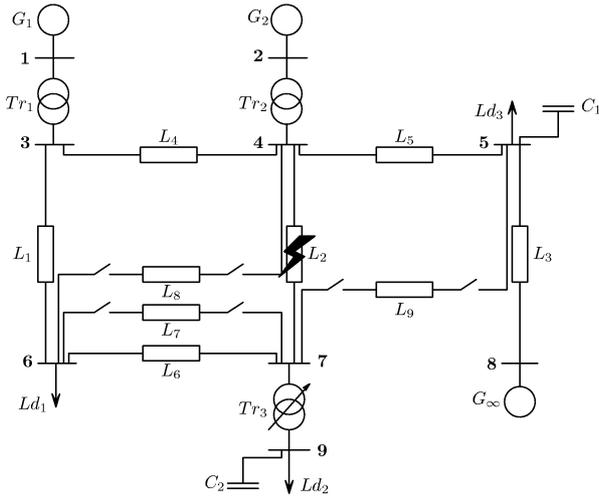


Figure 2: Nine-bus power system

Then s_{C2} , s_{L1} , s_{L2} , s_{L3} , δ_{L7} , δ_{L8} and δ_{L9} are discrete valued control inputs whereas V_9^{ref} and n_{C1} are continuous ones. V_i with $i = \{1, \dots, 9\}$ are the voltage magnitude of corresponding buses and are considered as the outputs of the power system.

Now consider a fault on line L_2 at time $t = 150$ s which corresponds to the disconnection of both extremities of the transmission line. As illustrated by figure 3, at time $t = 200$ s which is only 50 s later, an example of manual control consisting in load shedding of 10 % for all the loads as well as maximum reactive power compensation is not sufficient to prevent voltage collapse. As it is shown by power responses of Ld_2 , voltages start to collapse when the load power consumption reach the maximum transfer capability of the system ($t \approx 300$ s).

4.2 MPC Simulation Results

The MPC based method detailed in this paper has been applied to this case study. The control objectives are to keep the voltages close to the nominal value with acceptable levels, i.e. within an interval of $\pm 10\%$ centered around 1 p.u..

For the control design, the following choices have been made: the time scale of phenomena such as voltage collapse is typically about several minutes also the sample period T_s has been chosen equal to 30 s; the length N of the prediction horizon has been chosen equal to 3 to exceed the time constants of the load dynamics ($T_p = T_q = 60$ s).

In the power system modeling section, the ratio n_t has been assumed to be controllable. In this nine-bus example, the LTC of Tr_3 controls the transformer ratio n_t with $n_t \in [0.8, 1.2]$ in order to keep the secondary voltage (bus voltage magnitude V_9) close to the reference voltage denoted V_9^{ref} .

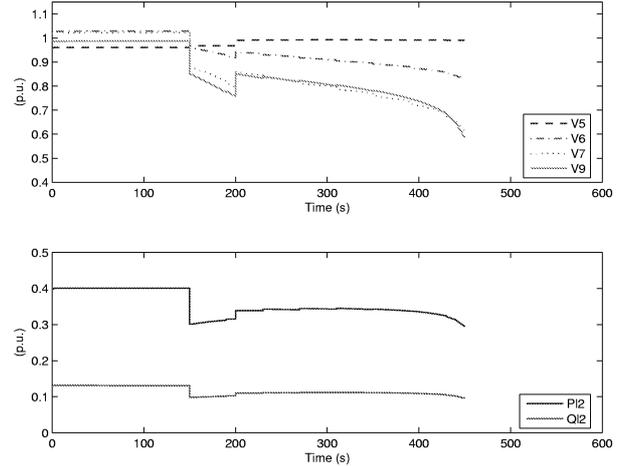


Figure 3: Responses to the fault with an example of manual control

The value of V_9^{ref} to apply to the LTC at each step time is computed from the optimal value of n_t given by the MPC algorithm. For instance, when the optimal control is to stay at the current tap (typically when voltages collapse, a well known emergency action is to lock the LTCs), the reference voltage that is set to the LTC is the secondary voltage prediction that is computed by the predictor.

The controller is tuned by using the weighing matrices. \mathbf{Q}_u is chosen to penalize the resort to control actions. Then the resort to reactive power compensation devices and transformer is slightly penalized. On the contrary, the resort to line reconfiguration is more penalized than the previous ones and obviously, the most penalized is load shedding : $\mathbf{Q}_u = \text{diag}(0 \ 0 \ 1 \ 1 \ 1 \ 0 \ 0.5 \ 0.5 \ 0.5)$. Note that \mathbf{Q}_u doesn't need to be strictly positive defined since the control inputs are bounded. \mathbf{Q}_y is chosen to penalize the voltage deviations. According to the viewpoint of an electric energy provider, voltages at buses 5, 6 and 9 are of particular interest because of their connections to consumers and are the most penalized in the cost function : $\mathbf{Q}_y = \text{diag}(0.1 \ 0.1 \ 0.1 \ 1 \ 5 \ 6 \ 0 \ 0 \ 8)$

From time $t = 30$ s, the controller is engaged and optimal controls are applied to the system. At time $t = 150$ s, the fault occurs and voltages start to collapse. From time $t = 180$ s, i.e. 30 s after the fault occurrence, voltage stability is recovered and all the voltages still remain above 0.9 p.u. There has been no need to have resort to load shedding. The solution given by the controller consists in injecting all the remaining reserve of reactive power (C_1 and C_2) and to connect the transmission line L_9 at time $t = 180$ s. The controller computes the value of V_9^{ref} to apply to the LTC of Tr_3 in order to control the level of tension V_9 . Looking at power and state responses of the load Ld_2 which is connected to bus 9 shows that power consumptions have been restored to their level before the fault on line L_2 and that a new equilibrium point has been reached.

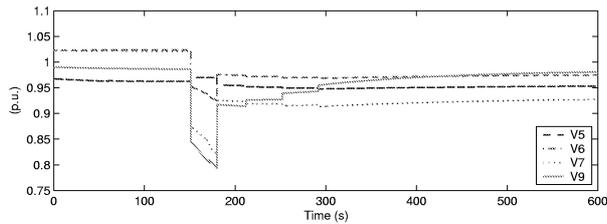


Figure 4: Bus Voltage Magnitude with MPC

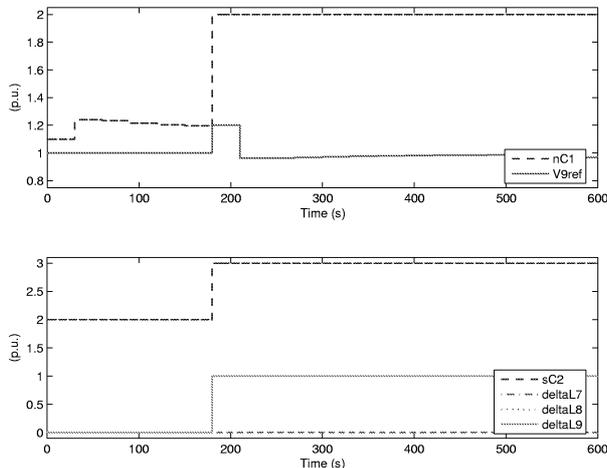


Figure 5: Continuous and discrete control inputs

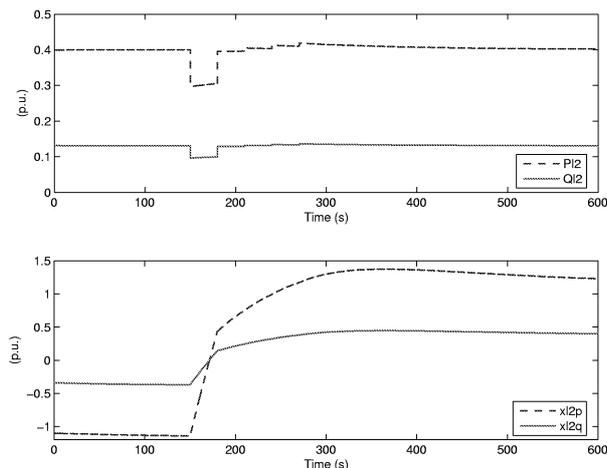


Figure 6: Load Ld_2 (bus 9) power consumption and internal state

5 CONCLUSIONS

The methodology presented in this paper allows to take account of the hybrid nature of power systems according to the framework of voltage stability. The proposed control strategy requires a symbolically linearized prediction model and a mixed optimization algorithm. In [12], the first developments of the proposed approach have been tested on the four-bus power system example used in [6]. In the present paper, simulation results have illustrated the implementation of this approach on a nine-bus power example.

The methodology presented here is a model based approach, including the load dynamics. Reliable models and parameters are available for all power system components except for loads whose models are generally unknown. For the proposed approach to be efficient, the structure and

parameters of the aggregate load model should be on-line estimated.

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