Model Predictive Control for Power System Dynamic Security Enhancement

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***Abstract*—Voltage instability and collapse have catastrophic effect on modern life, with long outage of power and disruption of important services. For many years, research works have been directed towards finding ways to predict impending voltage collapse and to adopt appropriate control actions to avert the same. System protection schemes (SPS) have been implemented in many countries worldwide to handle voltage instability associated with power system disturbances and contingencies. The strategies are often based on reactive power compensation and load curtailments. Individual loads that are dispensable in the short-term can be curtailed with minimal consumer disruption, though at the cost of significant revenue loss for the power utility. Reactive power compensation, on the other hand requires additional capital investment and optimal sizing, location and control of these compensating devices is a challenge. The paper proposes the use of static capacitor bank and non-disruptive load control for improving voltage stability based on model predictive control (MPC). MPC uses trajectory sensitivity analysis to predict system's dynamic behaviour over a finite horizon. Control decisions are based on optimizing the size of capacitor bank and minimizing the load-disruption to stabilize the voltage. The discrete control strategy takes care of the inaccuracies in predicted voltage behaviour at the next control step. Voltage collapse prevention in heavily loaded IEEE 30 bus system has been used to illustrate the effectiveness of the control strategy.**

Keywords*—*voltage collapse; system protection; model predictive control; reactive power compensation; load curtailment

I. INTRODUCTION

Unforeseen disturbances have disrupted the operation of interconnected power systems from time to time resulting in millions of consumers losing power supply at a very expensive cost. System protection schemes and emergency control measures to counteract power system instability therefore play a very important role in power system operation. Motivated by the power industry's need to mitigate the effect of disturbances on system operation and improve power system security, the present research work has attempted to develop a novel framework for system protection scheme based on Model Predictive Control.

A system protection scheme (SPS) is meant to detect abnormal system conditions and take predetermined, corrective action (other than the isolation of faulted elements) to preserve system integrity and provide acceptable system performance [1]. System protection schemes were suggested to improve system performance in terms of stability, safety and security. The schemes gained popularity owing to their low capital investment costs as compared to the alternatives such as building new power plants and transmission lines [2]. Traditional system protection schemes were originally designed for off-line planning studies [3]. A real time SPS, on the other hand is expected to expedite control actions to mitigate the effects of potential instability or a safety/security degradation of a power system (such as a partial shutdown or a total collapse), which can be detected by an online dynamic security assessment program [3]. Based on measurements received at control centers through high-speed communication channels, a real time SPS computes the necessary control decisions such as generator tripping, capacitor/reactor bank switching, transformer tap adjustments, and load-shedding for insecure contingencies. A well thought of control strategy is therefore the heart of every SPS and in most cases discrete control is the choice [4].

In the present paper, Model Predictive Control (MPC) [5] has been proposed for designing the system protection scheme. The objective is to develop a systematic framework to determine switching control strategies to stabilize a system following a disturbance. The stability analysis or computation of the stable operating region of a power system is required for this purpose and the validity of discrete controls in transient stability design needs to be verified. A control strategy for maintaining voltage stability following the occurrence of a contingency is essential.

In this research work, a control scheme to restore the system voltage following major contingencies has been presented. Based on economic considerations and control effectiveness, an optimal control switching strategy consisting of a sequence and amount of shunt capacitors to be switched at strategic locations has been identified and optimal coordination of two or more different control strategies has been suggested to improve voltage performance and voltage restoration following large disturbances. The developed MPC algorithms has been implemented in MATLAB and tested on a heavily loaded IEEE 30-Bus system to estimate the performance of the proposed technique.

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II. MODEL PREDICTIVE CONTROL

A. Overview

Model Predictive Control (MPC) refers to a class of algorithms that computes a sequence of control variable adjustments for optimizing the future behavior of a plant (system). Originally developed to meet the specialized control needs of petroleum refineries, MPC is now used in a wide variety of research areas including chemicals, food processing, automotive aerospace, metallurgy and power plants. Basic concepts and introduction to MPC are available in [6]. In recent years MPC has been used in power system [1]. Model predictive controllers require dynamic model of the process or the system to work upon, which is often determined by system identification technique. MPC, in principle performs optimization of the available resources at the current time slot, while at the same time, keep an eye on the predicted behaviour of the controlled variable in future time slots. Thus, optimization is carried over a longer time-horizon, but implemented only within a relatively smaller current time slot. MPC can therefore be perceived as a predictive control method, which anticipates future trends or events and takes control actions accordingly. PID and LQR controllers lack this predictive ability.

B. Model Predictive Control Methodology

The principle of MPC is depicted graphically in Fig. 1. Here the state variable that needs to be controlled to a specific range is represented by x, whereas u represents the available control is represented.

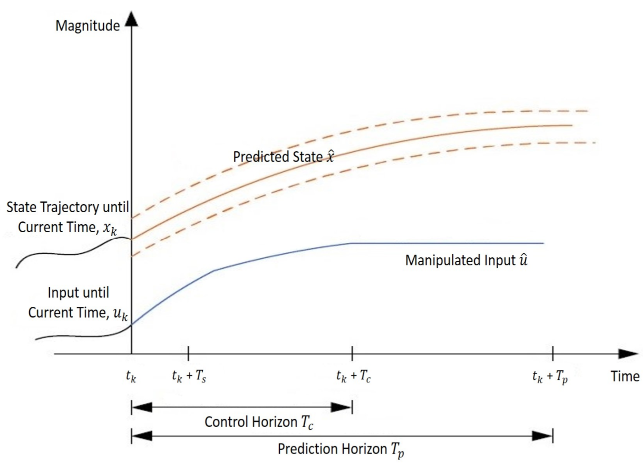

Fig. 1: The Principle of MPC

At a current timet_k, an optimization problem is solved over a finite prediction horizon $[t_k,\ t_k + T_p]$ with respect to a predetermined objective function such that the predicted state variable $\hat{x}(t_k + T_p)$stays optimally close to a reference trajectory. The control is computed over a control horizon$[t_k,\ t_k + T_c]$, which is smaller than the prediction horizon ($T_c \le T_p$). In absence of disturbances and model-plant mismatches, the prediction horizon is infinite and the control strategy found at current time $t_k$can be applied for all time instants $t \ge t_k$. However, due to the presence of disturbances, model-plant mismatch and finite prediction horizon, the true system behavior differs from the predicted behavior. In order to incorporate the feedback information about the true system state, the computed optimal control is implemented only until the next measurement instant $(t_k + T_s)$, at which point the entire computation is repeated.

In a MPC the optimization problem to be solved at time t_k can be formulated as follows:

$$min_{\hat{u}} \int_{t_k}^{t_k+T_p} F(\hat{x}(\tau), \hat{u}(\tau))\, d\tau \tag{1}$$

Subject to:

$$\dot{\hat{x}}(\tau) = f(\hat{x}(\tau), \hat{u}(\tau)),\quad \hat{x}(t_k) = x(t_k) \tag{2}$$

$$u_{min} \le \hat{u}(\tau) \le u_{max}\ ,\ \forall \tau \in [t_k, t_k + T_c] \tag{3}$$

$$\hat{u}(\tau) = \hat{u}(t_k + T_c)\ ,\ \forall \tau \in [t_k + T_c\ , t_k + T_p] \tag{4}$$

$$x_{min}(\tau) \le \hat{x}(\tau) \le x_{max}(\tau)\ ,\ \forall \tau \in [t_k, t_k + T_p] \tag{5}$$

Here, the estimated state is represented by $\hat{x}$while$\hat{u}$denotes “estimated” control. (The true state may be different, and the true control is same as the estimated control only during the first sampling period).The cost function of the MPC optimization is represented by equation (1). The dynamic system model with the initial state $x(t_k)$ is represented by equation (2). The constraints on the control input during the prediction horizon are represented by equations (3) and (4). The state operation requirement during the prediction horizon is indicated by equation (5).

In the context of power system voltage control, the control mechanisms can include tap changers, load-shedding and generator voltage set-points. The prediction of the output trajectory of the controlled variable (bus voltage magnitudes in this case) can be based on trajectory sensitivity. The control is exercised in form of capacitor bank switching and / or load shedding. The objective function of model predictive control is to minimize the amount of capacitance to be switched and / or load curtailment to be done to restore the voltages. The effectiveness of the control strategy on voltage restoration can be assessed through trajectory sensitivity.

C. Trajectory Sensitivity

Consider the differential algebraic equation (DAE) form of description of a system:

$$\dot{x} = f(x, y, u),\quad x(0) = x_0 \tag{6}$$

$$0 = g(x, y, u) \tag{7}$$

where x is a vector of state variables, y is a vector of algebraic variables and u is a vector of control variables. Trajectory sensitivity considers the influence of small variations in the control input u on the solution of the state equations (6) and (7). Let u_0 be a nominal value of u, and assume that the nominal system in equations (8) and (9) has a unique solution $x(t, x_0, u_0)$ over $[t_0, t_1]$. Then,

$$\dot{x} = f(x, y, u_0),\ \ x(0) = x_0 \tag{8}$$

$$0 = g(x, y, u_0) \tag{9}$$

Then the system in equations (6) and (7) has a unique solution $x(t, x_0, u)$ over $[t_0, t_1]$ that is related to $x(t, x_0, u_0)$ as:

$$x(t, x_0, u) = x(t, x_0, u_0) + x_u(t)(u - u_0) + \text{higher order terms} \quad (10)$$

$$y(t, x_0, u) = y(t, x_0, u_0) + y_u(t)(u - u_0) + \text{higher order terms} \quad (11)$$

Here $x_u(t) = \frac{\partial x(t, x_0, u)}{\partial u}$ is called the trajectory sensitivities of state variables with respect to the control variables u and $y_u(t) = \frac{\partial y(t, x_0, u)}{\partial u}$ is called the trajectory sensitivities of the algebraic variables with respect to control variables u.

The evolution of trajectory sensitivities can be obtained by differentiating equations (6) and (7) with respect to control variables u and is expressed as:

$$\dot{x_u}(t) = f_x(t)x_u(t) + f_y(t)y_u(t) + f_u(t) \quad (12)$$

$$0 = g_x(t)x_u(t) + g_y(t)y_u(t) + g_u(t) \quad (13)$$

An efficient methodology for numerical solution of the trajectory sensitivity problem is described in [7]. When time domain simulation of a system is performed using the trapezoidal numerical integration approach, the trajectory sensitivity of state variables with respect to the variations in initial state variables x and control variable u can also be computed side-by-side. The x_u and y_u in equation (12) and (13) are part of the solution matrix.

Let

$$\bar{x} = \begin{bmatrix} x \\ u \end{bmatrix}, \quad \bar{f} = \begin{bmatrix} f \\ 0 \end{bmatrix}$$

The DAE model equations (6) and (7) can be expressed as

$$\dot{\bar{x}} = \bar{f}(\bar{x}, y) \quad (14)$$

$$0 = g(\bar{x}, y) \quad (15)$$

Trapezoidal approach is used to approximate equation (14) with a set of algebraic difference equations coupled to the original algebraic equation (15). The evolution of the states $\bar{x}$ and y from time instant t_i to the next time instant t_{i+1} can be described as

$$\bar{x}^{i+1} = \bar{x}^i + \frac{\eta}{2}(\bar{f}(\bar{x}^{i+1}, y^{i+1}) + \bar{f}(\bar{x}^i, y^i)) \quad (16)$$

$$0 = g(\bar{x}^{i+1}, y^{i+1}) \quad (17)$$

where superscript i is the time instant t_i , i+1 is the time instant t_{i+1} and $\eta = t_{i+1} - t_i$ is the integration time step. Rearranging equation (16) and equation (17) as follows:

$$F = \begin{bmatrix} \frac{\eta}{2}\bar{f}(\bar{x}^{i+1}, y^{i+1}) - \bar{x}^{i+1} + \frac{\eta}{2}\bar{f}(\bar{x}^i, y^i) + \bar{x}^i \\ g(\bar{x}^{i+1}, y^{i+1}) \end{bmatrix} = 0 \quad (18)$$

Equation (18) is a set of implicit nonlinear algebraic equation. The Newton iterative technique is commonly used to solve for $\bar{x}^{i+1}$ and y^{i+1}

$$\begin{bmatrix} \bar{x}^{i+1} \\ y^{i+1} \end{bmatrix} = \begin{bmatrix} \bar{x}^i \\ y^i \end{bmatrix} - F_\chi^{-1}F \quad (19)$$

where, F_χ is the Jacobean of F with respect of $\bar{x}, y$.

$$F_\chi = \begin{bmatrix} \frac{\eta}{2}\bar{f}_{\bar{x}} - I & \frac{\eta}{2}\bar{f}_y \\ g_{\bar{x}} & g_y \end{bmatrix} \quad (20)$$

Now consider the trajectory sensitivity equation. Differentiating equations (14) and (15) with respect to the initial condition $\bar{x}_0$ results in the DAEs of trajectory sensitivities

$$\dot{\bar{x}}_{\bar{x}_0} = \bar{f}_{\bar{x}}\bar{x}_{\bar{x}_0} + \bar{f}_y y_{\bar{x}_0} \quad (21)$$

$$0 = g_{\bar{x}}\bar{x}_{\bar{x}_0} + g_y y_{\bar{x}_0} \quad (22)$$

The trajectory sensitivity can be approximated by trapezoidal integration as follows:

$$\bar{x}_{\bar{x}_0}^{i+1} = \bar{x}_{\bar{x}_0}^i + \frac{\eta}{2}(\bar{f}_{\bar{x}}^i\bar{x}_{\bar{x}_0}^i + \bar{f}_y^i y_{\bar{x}_0}^i + \bar{f}_{\bar{x}}^{i+1}\bar{x}_{\bar{x}_0}^{i+1} + \bar{f}_y^{i+1}y_{\bar{x}_0}^{i+1}) \quad (23)$$

$$0 = g_{\bar{x}}^{i+1}\bar{x}_{\bar{x}_0}^{i+1} + g_y^{i+1}y_{\bar{x}_0}^{i+1} \quad (24)$$

Rearranging the above equations results in:

$$\begin{bmatrix} \frac{\eta}{2}\bar{f}_{\bar{x}}^{i+1} - I & \frac{\eta}{2}\bar{f}_y^{i+1} \\ g_{\bar{x}}^{i+1} & g_y^{i+1} \end{bmatrix} \begin{bmatrix} \bar{x}_{\bar{x}_0}^{i+1} \\ y_{\bar{x}_0}^{i+1} \end{bmatrix} = \begin{bmatrix} \frac{\eta}{2}\left(\bar{f}_{\bar{x}}^i\bar{x}_{\bar{x}_0}^i + \bar{f}_y^i y_{\bar{x}_0}^i\right) - \bar{x}_{\bar{x}_0}^i \\ 0 \end{bmatrix} \quad (25)$$

Therefore, the sensitivity matrix in equation (26) can be obtained as a solution of a linear matrix equation. Notice that the coefficient matrix of equation (25) is exactly same as Jacobean matrix F_χ in solving for the $\bar{x}^{i+1}$ and y^{i+1}. The present work uses the Power System Analysis Toolbox [8] (a MATLAB based toolbox developed by Federico Milano) to perform the trajectory sensitivity calculation and MPC optimization.

$$\begin{bmatrix} \bar{x}_{\bar{x}_0}^{i+1} \\ y_{\bar{x}_0}^{i+1} \end{bmatrix} = \begin{bmatrix} x_{x_0} & x_{u_0} \\ u_{x_0} & u_{u_0} \\ y_{x_0} & y_{u_0} \end{bmatrix} \quad (26)$$

D. Model Predictive Control Algorithm

The procedure to determine the control strategy at any point of time t_k based on MPC can be described as follows:

At time t_k, an estimate of the current state $x(t_k)$ is obtained. The nominal power system evolves according to equations (6) and (7). Here, $u = \{B_c^0 + \sum_{i=0}^{k-1}\Delta B_{c1}^i\}_{c=1}^{c=C}$ is the control variable (i.e. amount of shunt capacitor currently in use). B_c^0 is the amount of shunt capacitors that exist in time 0. $\sum_{i=0}^{k-1}\Delta B_{c1}^i$ is the amount of shunt capacitors that were added over time $[0, t_k - T_s]$. Time domain simulation is used to obtain the trajectory of the nominal system equations (6) and (7), starting from the state $x(t_k)$ at time t_k to the end of prediction horizon $t_k + T_p$. At the same time, the trajectory sensitivity of the bus voltages with respect to the shunt capacitors to be added at instants $t_k + (n-1)T_s, n = 1 \ldots N - k$ is obtained and denoted as $V_{B_{cn}}^{kj}(t)$. The objective function in equation (27) is composed of two parts. The first part is the trajectory deviation, whereas the second part denotes the cost of controls. The combination of the deviation of voltages from nominal values and control cost needs to be minimized. The objective is to minimize (with respect to ΔB_{cn}^k)

$$\int_{t_k}^{t_k+T_p} \left(\hat{V}^k(t) - V_{ref}\right)' R\left(\hat{V}^k(t) - V_{ref}\right)dt$$

$$+\sum_{c=1}^{C}\sum_{n=1}^{N-k} W_{cn}\Delta B_{cn}^{k} \quad (27)$$

Subject to constraints:

$$\Delta B_c^{min} \le \Delta B_{cn}^{k} \le B_c^{max} \quad (28)$$

$$B_c^{min} \le B_c^{0} + \sum_{i=0}^{k-1}\Delta B_{c1}^{i} + \sum_{n=1}^{N}\Delta B_{cn}^{k} \le B_c^{max} \quad (29)$$

$$V_{min}^{kj}(t) \le V^{kj}(t) + \sum_{c=1}^{C}\sum_{n=1}^{N-k} V_{B_{cn}}^{kj}(t)\Delta B_{cn}^{k} \le V_{max}^{kj}(t) \quad (30)$$

$$\Delta B_{cn}^{k} \ge 0 \quad (31)$$

where, R is the weight matrix. $\hat{V}^{k}(t)$ is the predicted voltage vector at the control sampling time t_k that contains all the bus voltages in the system at time *t*. ΔB^{k} is the control matrix calculated at time t_k. W_{cn} is the weighted cost of control *c* to be added at time $t_k + (n-1)\,T_s$. C is the total number of control variables, i.e. the number of shunt capacitor locations, N is the total number of control steps. ΔB_{cn}^{k} is the entry ΔB^{k}, which is the amount of control *c* to be added at time $t_k + (n-1)\,T_s$. $\Delta B_c^{min} \in \Re$ is the minimum amount of control *c* to be added at any step, $\Delta B_c^{max} \in \Re$is the maximum amount of control *c* to be added at any step, ΔB_{c1}^{i} is the amount of control *c* implemented at control sampling point $t_i, i = 0, \dots k-1$. $B_c^{min} \in \Re$is the minimum amount of control *c* that must be used, $B_c^{max} \in \Re$is the maximum available amount of control *c*.$V^{kj}(t) \in \Re$ is the voltage of bus *j* at time $t(t_k \le t \le t_k + T_p)$, of the nominal system of time t_k.$V_{min}^{kj}(t)$is the minimum voltage at bus *j* desired at time $t_k \le t \le t_k + T_p$,$V_{max}^{kj}(t)$ is the maximum voltage at bus *j* desired at time $t_k \le t \le t_k + T_p$.$V_{B_{cn}}^{kj}$(t) is trajectory sensitivity of voltage at bus *j* at time $t_k \le t \le t_k + T_p$ with respect to control *c* added at time $t_k + (n-1)T_s$.

At time t_k, a solution of the optimization problem in equations (27) to (31) computes a sequence of ΔB_{mn}^{k}. Only the first control ΔB_{c1}^{k} is added at time t_k and the system state $x(t_k + 1)$ at time $t_{k+1} = t_k + T_s$is estimated.

k is increased to$k+1$ and the entire procedure is repeated until $k = N - 1$.

III. Case Study of IEEE-30 Bus System

A. System Description

The single line diagram of the IEEE 30-bus system is presented in Fig. 2.The IEEE 30-bus system comprise of 6 generators equipped with automatic voltage regulators (AVR).The simulation considers the system to be heavily loaded (approximately 1.8 times the standard conditions) with total generation of 567.96 MW and total load demand is 563.99 MW.

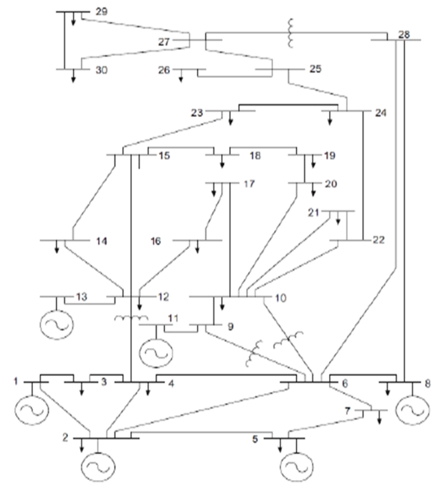

Fig. 2: Single Line Diagram of IEEE-30 Bus System

B. Developed Simulink Model of the System\

The IEEE 30-bus system described earlier was simulated in MATLAB simulink as shown in Fig. 3 under fault scenario for PSAT based time domain analysis and dynamic security assessment.

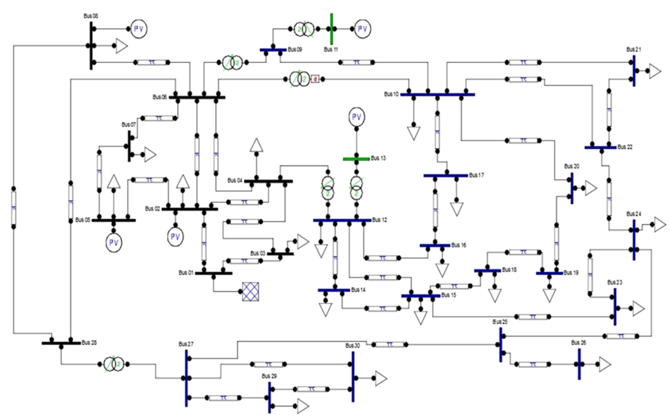

Fig. 3: Developed Simulink Model of the System

C. Voltage Scenario without Contingency

The voltage scenario without contingency is depicted in Fig.4. It is observed that not all the bus voltages are within acceptable range of 0.95 p.u. – 1.05 p.u. particularly bus no. 26.

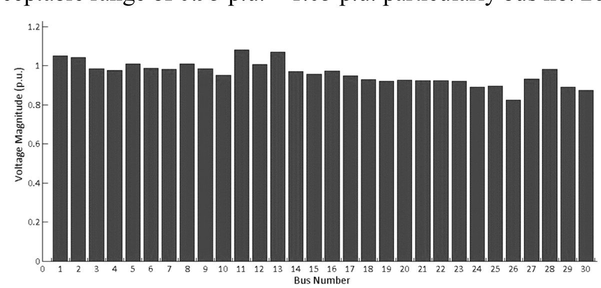

Fig. 4: Bus Voltage Profile without Contingency

D. *Time Domain Simulation Result under Contingency*

A credible set of contingencies were considered to analyze system's dynamic performance under variable operating conditions including contingencies. A three-phase fault at bus 28 is assumed to have occurred at t = 1.0 second, which is cleared at t = 1.1 seconds by the tripping of the line between bus 6 and bus 28. Based on the time domain simulation, the voltages at buses 25, 26, 29 and 30 are plotted in Fig.5 and are observed to be not satisfactory. At t = 1.0 second, the voltages drop drastically due to the three phase to ground fault. At t = 1.1 seconds, the voltages start to recover since the fault gets cleared and due to the control action of the AVRs, though the voltages become oscillatory. After 15 seconds the voltages begin to decline gradually. The dynamic load models considered in the simulation, result in slight recovery of the load consumption post fault-clearing, which further deteriorates the voltage condition. These three bus voltages fall out of the lower limit 0.95 p.u. eventually and after 55 seconds there is a complete voltage collapse. Therefore, more effective control actions are required.

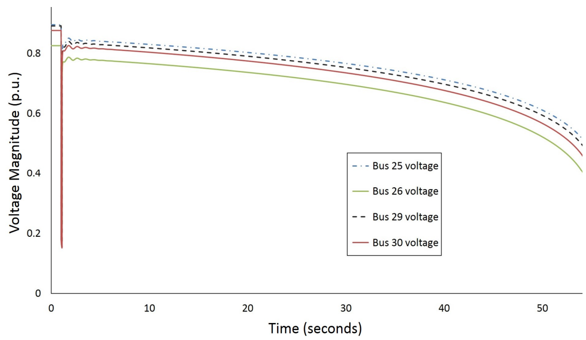

Fig. 5: Bus Voltage Profile under Fault Scenario

E. *Application of MPC for Improvement of Voltage Profile*

In the first phase strategic capacitor switching has been implemented. The maximum capacitance to be added at any step ΔB_m^{max} was set to be 0.1 p.u. This is because if large amounts of capacitors are added at one time, an over-voltage may occur. During the optimization, the lower bound of all load bus voltages is set to 0.95 p.u. and upper bound of load bus voltages to 1.05 p.u. For other buses, such as a generator bus, the maximum voltage magnitude has been set to 1.08 p.u., a bit higher than a load bus. Fig. 6 shows the bus voltages after MPC based control was implemented starting at time t = 1.1 seconds and all the bus voltages were restored to above 0.95 p.u within 30 seconds.

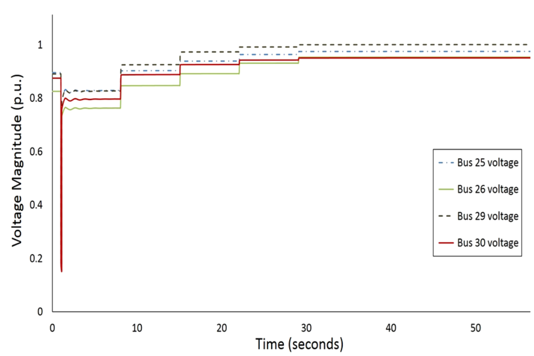

Fig. 6: Bus Voltage Profile under Fault Scenario with MPC

The control strategy is shown in Table 1. The control action starts right after the fault is cleared. The first control action happens at t = 1.1 seconds, when 0.1 p.u. capacitors at each bus were added. The sample duration is 7 seconds. So, the second control action happens at t = 8.1 seconds. The third, fourth and fifth control steps happen at 15.1 seconds, 22.1 seconds and 29.1 seconds respectively.

Table 1: Strategic optimal capacitor switching scheme

Time (seconds)	1.1	8.1	15.1	22.1	29.1
Capacitor at Bus 25 (p.u.)	0.1	0.1	0.092	0.1	0.084
Capacitor at Bus 26 (p.u.)	0.1	0.1	0.1	0.1	0.1
Capacitor at Bus 29 (p.u.)	0.1	0.1	0	0.067	0
Capacitor at Bus 30 (p.u.)	0.1	0.1	0.083	0	0

F. *Application of MPC based on Coordinated Reactive Power Compensation and Load Curtailment Approach for Improvement of Voltage Profile*

In the second phase, an optimal coordinated control strategy consisting of static capacitor bank switching and load curtailment is formulated to improve voltage performance and prevent voltage instability when a contingency is detected. The voltage control measures applied here include the followings:

a. Static capacitor bank switching at buses 25, 26, 29 and 30.

b. Load curtailment at buses 24, 26, 29 and 30

To prevent any problems due to over-voltage, the maximum amounts of controls is limited at each sampling instant. For static capacitor banks the maximum control amount at a sampling instant is set at 0.1 p.u. And the maximum load curtailment at one sampling instant is 6% with a step size of 2%. Fig. 7 shows the bus voltages after MPC based control was implemented starting at time t = 1.1 seconds and all the bus voltages were restored to above 0.95 p.u within 30 seconds, but using less capacitance value as compared to the earlier case where capacitance switching was the sole control mechanism. The complete control strategy is shown in Table 2.

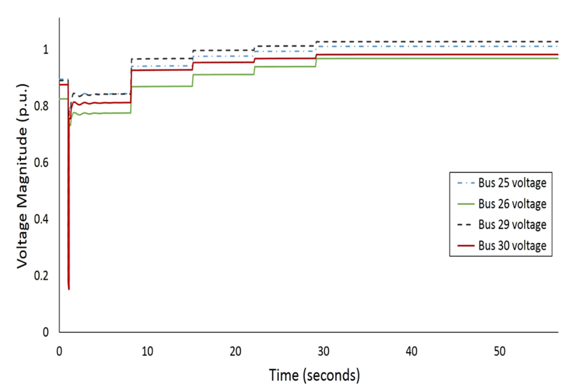

Fig. 7: Bus Voltage Profile under Fault Scenario with Coordinated Control

Table 2: Combined optimal capacitor switching and load curtailment scheme

Time (seconds)	1.1	8.1	15.1	22.1	29.1
Capacitor at Bus 25 (p.u.)	0.1	0.1	0.082	0.068	0.05
Capacitor at Bus 26 (p.u.)	0.1	0.1	0.1	0.1	0.1
Capacitor at Bus 29 (p.u.)	0.1	0.077	0	0	0
Capacitor at Bus 30 (p.u.)	0.1	0.089	0.054	0	0
Load Curtailment at Bus 24 (%)	2	4	4	2	0
Load Curtailment at Bus 26 (%)	2	4	4	4	2
Load Curtailment at Bus 29 (%)	2	4	0	0	0

IV. CONCLUSION

Model predictive control was proposed and implemented in this paper on IEEE 30-bus system with good results. In the test system, major contingencies were simulated. Dynamic voltage stability analysis revealed voltage collapse is probable in the test system under major contingencies. A case depicting dynamic voltage collapse was presented in the study. The next challenge was to prevent such collapse and to maintain all the load bus voltages within acceptable range. The simulation studies revealed that the proposed MPC based technique is capable of fulfilling the objective of restoring bus voltages to acceptable range within a reasonable time frame.Two separate as well as coordinated approaches were presented such as reactive power injection in specific buses in the form of capacitor bank switching, and load curtailment in a strategic manner. The results indicate that both the approaches were successful in preventing dynamic voltage collapse and maintaining acceptable voltage magnitudes in all the system buses even under heavily loaded conditions and during contingencies.

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