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Restoration of Voltage Collapse in Ethiopian Electric Power Network by Using Model Predictive Control

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Abstract:-Ethiopia power network systems have been disturbed by unanticipated disturbances from time to time when numbers of consumers lose power supply at a very expensive cost. System protection and emergency control to respond this power system instability play an important role in our country power system operation. Driven by the industry need and improper protection mechanism to alleviate the effect of disturbances on system operation and improve power system security, this paper uses a general framework for system protection scheme based on Model Predictive Control. Model Predictive Control (MPC) is implemented to apply system protection scheme. A control strategy for maintaining voltage stability following the occurrence of an outage is stated. The result of our control mechanism on voltage recovery is measured via trajectory sensitivity. Our optimization means is mixed integer quadratic programming-based algorithm is presented to study the optimal coordination of the dissimilar controls to advance voltage performance and effective use of control input following large disturbances. The developed algorithms are functional with MATLAB and Power System Analysis Toolbox (PSAT) are joined and tested on the 30-bus of the 400kV and 230kV of the modified Ethiopia power network system for preventing voltage collapse and the objective of the algorithm is to attain its voltage level [0.95, 1.05 p.u] and filter out noise within the given prediction horizon.

Key Words: - Coordinated voltage control, model predictive control, trajectory sensitivity, power system.

I. INTRODUCTION

As a result of deregulation as well as increasing demands, power systems operate close to their capacity. Although power systems are designed with proper planning and with proper stability margin, the instability can still occur under certain severe disturbances. It is imperative that schemes for power system protection be in place to mitigate their catastrophic effects such as large-scale shutdowns and collapses. The objective of SPSs is to detect a potential instability or a safety/security degradation of a power system and carry out the necessary control actions to mitigate their effects (such as a partial shutdown or a total collapse).

The traditional SPS is determined off-line and is ruling based [1]. A rule-based system protection scheme relies on voltage, or their rate of change levels, or line flow limits. For example, if the measured voltage is lower than a specific value, or the line flow exceeds the line rating limit, a predefined SPS is triggered (such as adjustment of generator outputs or

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load shedding). The limitation of the rule based SPSs lies in the use of limited local information. In contrast, a real time SPS computes and carries out control actions based on global. state information in response to an impending contingency detected by an online dynamic security assessment program. Recent advances in monitoring, communication, and computing technologies have greatly facilitated the implementation of real-time SPSs [2].

A real time system protection scheme for voltage stabilization is studied in this work. The control of voltage level is accomplished by controlling the production, absorption, and flow of reactive power at various locations in the system. With regard to a power system, sources and/or sinks of reactive power, such as shunt capacitors, shunt reactors, synchronous condensers, and static var compensators (SVCs) are used to control voltage level. In literature, many algorithms [3] have been developed to determine the amounts and locations of shunt reactive power compensation devices needed for maintaining a satisfactory voltage profile, while minimizing their cost.

Most these works however are based on *static analysis*, which means that the voltage performance criteria could be met only if the system reaches a post-contingency stable operating point. However, if the disturbances are severing, the power system may lose stability. Under this situation, the control strategy to restore the stable equilibrium point requires a *dynamic analysis*.

Model predictive control has been applied in power system voltage control based on dynamic analysis. [4] Presents a method of coordination of load shedding, capacitor switching and tap changers using model preventive control. The prediction of states is based on the numerical simulation of nonlinear differential algebraic equations (DAEs) together with Euler state prediction. A tree search method is adopted to solve the optimization. [5] Proposes a coordination of generator voltage setting points, load shedding and ULTCs using a heuristic search and the predictive control. The prediction of states is based on the linearization of nonlinear DAEs. [6] Presents an optimal coordinated voltage control using model predictive control. The controls used include: shunt capacitors, load shedding, tap changers and generator voltage setting points. The prediction of voltage trajectory is based on the Euler state prediction. The optimization problem is solved by a pseudo gradient evolutionary programming (PGEP) technique. In [7] and [8], authors present a method to compute a voltage emergency control strategy based on model predictive control. The prediction of the output trajectories is based on trajectory sensitivity. However, in these two papers, the authors employ a simplified model predictive control, which computes the control actions only at the initial time and implements it over the entire control horizon. A voltage stabilization control strategy is also

proposed in [9] based on load shedding, where the objective function is to minimize the amount of load shedding
required to restore the voltages. It shows load shedding is an effective voltage control under emergency condition. [10] Presents a MPC based voltage control design. The controls are reference voltage of automatic voltage regulators and load shedding.
In this paper, we propose computation of the optimal strategies based on *model predictive control* (MPC). We utilize shunt capacitors for control purposes as they are effective means of voltage stabilization. The problem then becomes one of determining capacitor switching sequence and amounts given their locations and limits which are determined in a prior planning stage, together with the requirements on the magnitudes of voltages. In this work, the trajectory deviation and the cost of controls are simultaneously minimized. Here, trajectory deviation refers to the deviation of voltage trajectory from the nominal value. This is a multi-objective optimization and a positively weighted convex sum is chosen as the objective function. Trajectory sensitivities are used to estimate the effect of controls on the voltage behavior in a linear manner. Due to the use of model predictive approach, the influence of each optimization is limited to one step and the control gets recalculated and refined at each step, the overall control strategy turns out to be sound and robust.

II. BACKGROUN

A. Model predictive control

Model Predictive Control (MPC) refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimize the future behavior of a plant. An introduction to the basic concepts of MPC and a formulation can be found in [11]. The principle of MPC is graphically depicted in Fig. 1. Here x represents the state variable that needs to be controlled to a specific range. The available control is represented by variable u.

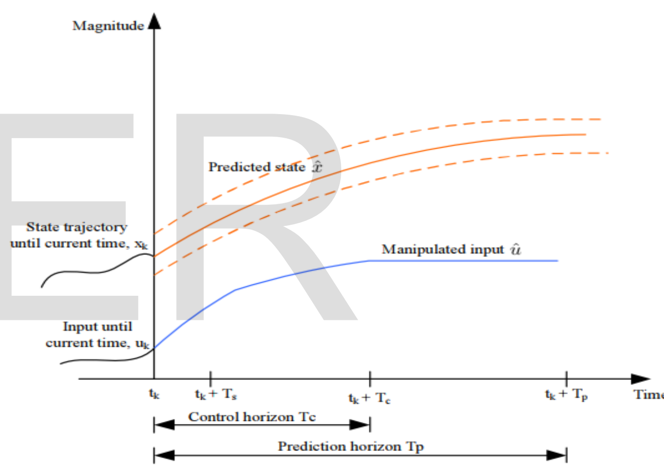

Fig. 1. Principle of MPC

At a current time t_k, the MPC solves an optimization problem over a finite prediction horizon $[t_k, t_k + T_p]$ with respect to a predetermined objective function such that the predicted state variable $x\^(tk + Tp)$ can optimally stay 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 ($T_c < T_p$). If there were no disturbances, no model plant mismatch and the prediction horizon is infinite, one could apply the control strategy found at current time *tk* for all times *t* , *tk*. However, due to the disturbances, model plant mismatch and finite prediction horizon, the true system behavior is different 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:

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

Subject to

$$\dot{\hat{x}}(\tau) = f\left(\hat{x}(\tau), \hat{u}(\tau)\right),\ \hat{x}(t_k) = x(t_k) \qquad (2)$$

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

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

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

Here, T_c and T_p are the control and prediction horizon with $T_c \le T_p$. $\hat{x}$ denotes the estimated state and $\hat{u}$ represents "estimated" control (The true state may be different and the true control matches the estimated control only during the first sampling period). Equation (1) represents the cost function of the MPC optimization. Equation (2) represents the dynamic system model with initial state x (t_k). Equations (3) and (4) represent the constraints on the control input during the prediction horizon. Equation (5) indicates the state operation requirement during the prediction horizon.

B. Trajectory sensitivity

Consider a differential algebraic equation (DAE) of a system,

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

$$0 = g(x, y, u) \qquad (7)$$

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 u (and any other variable of interest) 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 (8) and (9) has a unique solution x (t, x_0, u_0) over [t_0, t_1].

$$\dot{x} = f(x, y, \mathrm{u0}), x(0) = x_0 \qquad (8)$$

$$0 = g(x, y, \mathrm{u0}) \qquad (9)$$

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:

$$x(t, x_0, u) = x(t, x_0, u_0) + x_u(t)(u - u_0) + H.O.T \qquad (10)$$

$$y(t, x_0, u) = y(t, x_0, u_0) + y_u(t)(u - u_0) + H.O.T \qquad (11)$$

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

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

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

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

Detailed information about trajectory sensitivity theory can be found in [12]. The trajectory sensitivity can be solved numerically. [13] Provides a methodology for the computation of trajectory sensitivity. When time domain simulation of a power system is based on trapezoidal numerical integration, the calculation of trajectory sensitivity requires solving a set of linear equations, thus costing a little time. In our work, we extended the Power System Analysis Tool [14] (a MATLAB based tool) to do trajectory sensitivity calculation and the MPC optimization.

Fig. 2 illustrates the application of trajectory sensitivity in evaluating the effect of controls on system behavior. The trajectory x_k of the nominal system represents the behavior under the control u_k. When the control is increased by Δu_1^k at time t_k, the change in predicted system behavior based on sensitivity analysis at time t_l, can be approximated as $\Delta x_1^{kl} = x_{u_1^k}^l \Delta u_1^k$. Here $x_{u_1^k}^l$ is the trajectory sensitivity of the state variable at time t_l with respect to the control at time t_k. Similarly if we increase the control by Δu_n^kat time t_k + (n−1) Ts, the change in the state variable at time t_l is represented by $\Delta x_n^{kl} = x_{u_n^k}^l \Delta u_n^k$. Here, $x_{u_n^k}^l$ is the trajectory sensitivity of the state variable at time t_l with respect to the control at time t_k + (n−1) Ts.

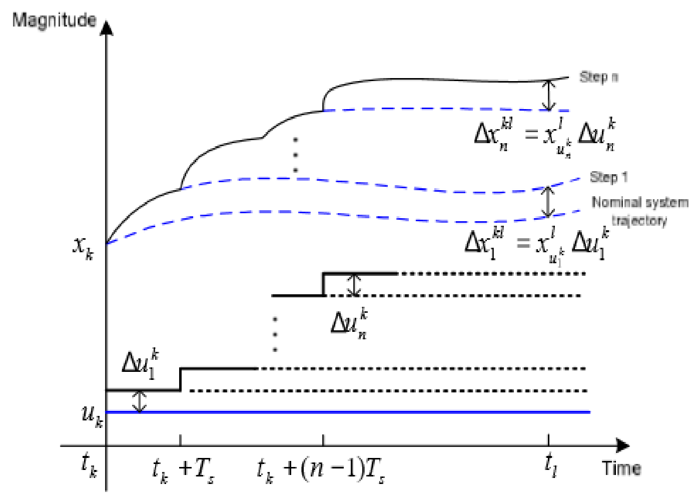

Fig. 2. Application of trajectory sensitivity in system behavior prediction

III. PROBLEM FORMULATION AND SOLUTION

The purpose of this work is to find an effective and economic control strategy for controlling the shunt capacitors so as to eliminate voltage instability following any pre-identified contingency. For analyzing voltage performance following disturbances, we model generator and automatic voltage regulator (AVR) as well as aggregated exponential dynamic load models [15], [16]. The overall power system is represented by a set of differential algebraic equations (DAE) as in Equations (6) and (7). Here x is a vector of states including state variables in generator dynamic models, AVR models and dynamic load models such as, rotor angles and angular speeds of generators, outputs of AVRs, and active power recovery and reactive power recovery of dynamic load models. y is a vector of algebraic variables such as bus voltage magnitudes and phase angles. The vector u indicates the output of shunt capacitors. The computation is iterative over a finite control horizon, where in each step a quadratic programming problem is solved to compute the amounts of shunt capacitors to be added in that step. The quadratic programming formulation is valid when the capacitor control is continuous as in SVC. Even in the case where capacitor control is discrete, we can still proceed by assuming continuous control so as to compute an optimal control by solving a quadratic programming relaxation. Then for implementation, the nearest discrete control value can be applied. Any error will get propagated to a following control step, and where it will get corrected. The control is piecewise constant, changing only at the sampling times. Let T_p be the prediction horizon, T_c be the control horizon, T_s be the control sampling interval, and $N = \frac{T_c}{T_s}$ be the total number of control steps. The procedure to determine the control strategy at time t_k based on MPC is as follows:

Step 1: At time t_k (i.e. the $(k + 1)^{th}$ sampling instant), an estimate of the current state $x(t_k)$ is obtained. The nominal power system evolves according to Equations (6) and (7). Here, $u = \left\{B_m^0 + \sum_{i=0}^{k-1} \Delta B_{m1}^i\right\}_{m=1}^{m=M}$ is the control variable (i.e. amounts of shunt capacitors currently in use). B0 m is the amounts of shunt capacitors that exist at time 0. $\sum_{i=0}^{k-1} \Delta B_{m1}^i$ is the amounts 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 (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 bus voltages with respect to the shunt capacitors to be added at instants $t_k + (n-1)$ Ts, n = *1…N−k* is obtained and denoted as $V_{mn}^{kj}(t)$ (see below for the explanation of notation).

Step 2: At time tk, solve the optimization problem over the prediction horizon $[t_k, t_k + T_p]$ and the control horizon $[t_k, t_k + T_c]$ as stated in (14)-(18). The objective function is composed of two parts. The first term is the trajectory deviation; the second term is the cost of controls. The combination of the deviation of voltages from nominal values and the control cost needs to be minimized. The number of candidate control locations and their upper limits are determined through a prior planning step. The total number of control variables in the optimization is the number of candidate control locations times the number of control steps. The optimization is solved in Matlab, and it does converge to a global minimum.

$$min_{\Delta B_{mn}^k} \int_{t_k}^{t_k+T_p} (\hat{V}^k(t) - V_{ref})' R (\hat{V}^k(t) - V_{ref}) dt + \sum_{mn} W_{mn} \Delta B_{mn}^k \quad (14)$$

Subject to

$$\Delta B_m^{min} \le \Delta B_{mn}^k \le \Delta B_m^{max} \quad (15)$$

$$B_m^{min} \le B_m^0 + \sum_{i=0}^{k-1} \Delta B_{m1}^i + \sum_{n=1}^{N} \Delta B_{mn}^k \le B_m^{max} \quad (16)$$

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$$V_{min}^{kj}(t) \leq V^{kj}(t) + \sum_{m=1}^{M}\sum_{n=1}^{\min(N,l)} V_{B_{mn}}^{kj}(t)\Delta B_{mn}^{k} \leq V_{max}^{kj}(t) \quad (17)$$

$$\Delta B_{mn}^{k} \geq 0 \quad (18)$$

- 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_{mn} is the weighted cost of control m to be added at time $t_k + (n-1)$ Ts.
- M is the total number of control variables, i.e. the number of shunt capacitor locations.
- N is the total number of control steps.
- ΔB_{mn}^{k} is the entry ΔB^k, which is the amount of control *m* to be added at time $t_k + (n-1)T_s$.
- $\Delta B_{m}^{min} \in R$ is the minimum amount of control m to be added at any step.
- $\Delta B_{m}^{max} \in R$ is the maximum amount of control m to be added at any step.
- ΔB_{m1}^{i} is the amount of control m implemented at the control sampling point t_i,i = 0,...k−1.
- $\Delta B_{m}^{min} \in R$ is the minimum amount of control m that must be used, typically 0.
- $\Delta B_{m}^{max} \in R$ is the maximum available amount of control m.
- $V^{kj}(t) \in R$ is the voltage of bus j at time t($t_k \leq t \leq t_k + T_p$), of the nominal system of time t_k.
- $V_{min}^{kj}(t)$ is the minimum voltage at bus j desired at time $t_k \leq t \leq t_k + T_p$.
- $V_{max}^{kj}(t)$ is the maximum voltage at bus j desired at time $t_k \leq t \leq t_k + T_p$.
- $V_{B_{mn}}^{kj}$ is the trajectory sensitivity of voltage at bus j at time $t_k \leq t \leq t_k + T_p$ with respect to control m added at time $t_k + (n-1)T_s$.

Step 3: At time t_k, a solution of the optimization problem (14)-(18) computes a sequence of controlsΔB_{mn}^{k}. Add only the first control ΔB_{m1}^{k} at time tk and observe or estimate the system state x (t_k+1) at time $t_k+1 = t_k + T_s$

Step 4: Increase k by k + 1 and repeat steps (1)-(3) until the k = N −1.

A. Implementation

The functional structure of a real time SPS is shown in Figure 3. Line flow, bus voltage information, switch status as well as phase measurement unit (PMU) measurements are sent to a control center through communication channels of a SCADA system. These measurements plus a network model are used by the state estimator (SE) for filtering out the noise and making best use of the measured data. The results from the state estimator are used for power flow analysis. A power flow solution is then used by an on-line dynamic security assessment program to initialize the state variables of the dynamic models. Further, it uses system models and disturbance information to perform the contingency analysis to evaluate the security margin of the power system. If a contingency is identified where the system will become unstable, the MPC based SPS computation will get triggered at the time an identified critical contingency occurs. The steps of the MPC computation in the k^{th} iteration include:

- Estimate static variables such as voltage magnitudes and angles at time t_k as well as the dynamic variables x (t_k) such as generator angles, velocities and real and reactive load recovery.

- Run time-domain simulation to compute the system trajectory given the current state. This step also requires the knowledge of a complete system model (including both dynamic and static components).
- Obtain trajectory sensitivities of voltage with respect to the control variables as a by-product of the time domain simulation performed in the previous step. This is required for the prediction of system response given a certain control strategy.

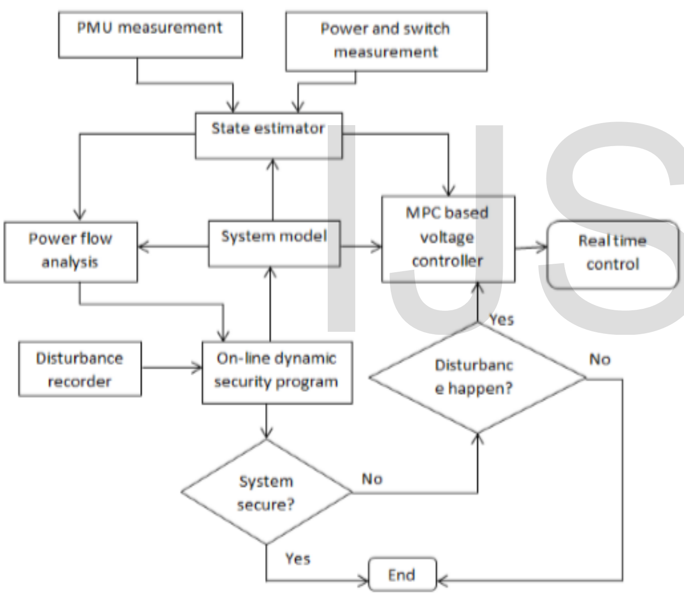

Fig. 3. Structure of a real time SPS

- Solve the quadratic programming optimization problem and implement the first step of the control.
- Repeat the above steps at each sampling point until the end of control horizon.

IV. APPLICATION TO 230 KV AND 400 KV ETHIOPIAN SYSTEMS

The suggested method is illustrated using the modified Ethiopian 400kV and 230kV 30bus system. The exponential recovery load model is used. The parameters of the load model are as following: $T_p = T_q = 30$, αs= 0, αt= 1, βs= 0, βt= 4.5. The parameters in MPC optimization are determined based on the following considerations. Any voltage instability following a contingency must be stabilized in certain time duration (typically the time in which voltage will decrease by 15%). This is the prediction horizon Tp. The control should be exercised on a time horizon Tc, which is shorter than the prediction horizon, typically the time in which voltage will decrease by 10% (if no control is applied). A discrete-time control must be applied within this duration Tc at a sample-rate high enough to adequately react to the changing voltage trajectory, as well as to allow accurate enough predictions of the voltage trajectory based on the linearization of the trajectory-sensitivity. This dictates the sampling duration Ts. The number of sampling point N is then determined as the ratio of Tc and the sampling duration Ts. The voltage control means in the test cases include SVCs, LTCs, and load shedding. To avoid over-voltage problems, the maximum amount of the controls is limited at each sampling point. For SVCs, the maximum control amount is 0.1p.u. The maximum number of load tap changer steps is 3. And the maximum load shedding at one sampling point is 10%. The step size of LTCs is 0.006p.u. The step size of load shedding is 5%.

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A. Modified Ethiopian 6-Generator 30-Bus Test System

1) *System description*: The proposed method is illustrated using a modified Ethiopian 30-bus system as shown in Fig.4. There are totally 32 buses and 6 generators. Two transformer banks with load tap changers are added between bus 8 and bus 31, bus 4 and bus 32. A fourth-order generator model is used. The exception is that a third-order model is used for the generator at bus 30 that does not include the d-axis transient voltage as part of the state space. In addition, all generators excluding those at bus 27 have automatic voltage regulators (AVRs), which are represented by fourth-order models. There are around 14 loads are consider which are represented by the exponential recovery dynamic models with two dimension. The total dimension of the state space is 72.The parameters of the load model are $T_p = T_q = 30$; $\alpha s= 0$; $\alpha t= 1$; $\beta s= 0$; $\beta t= 4.5$. The control variables are as follows:

- SVCs at buses 2, 6, 17, and 19;
- Load tap changers at the transformer banks between bus 8 and bus 31, bus 4 and bus 32;
- Load shedding at bus 15 and bus 16.

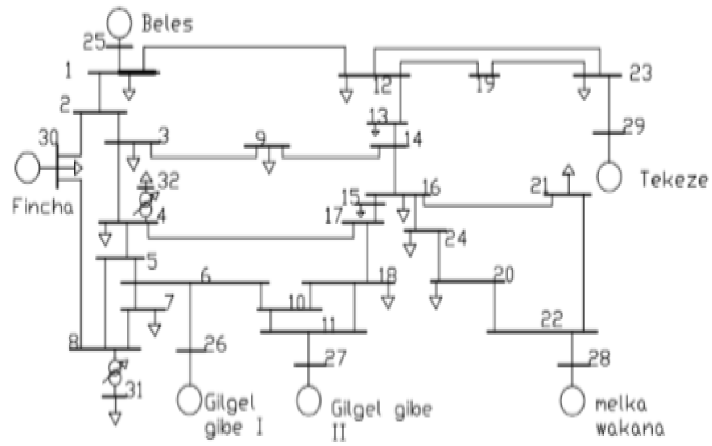

Fig.4. Modified Ethiopian 230 kV and 400kV 30-bus network system

Load shedding is an emergency voltage control action. A higher cost weight should be used to make sure that load shedding is trigged only when other control actions are not sufficient. To avoid over-voltage problems, the maximum amount of the controls is limited at each sampling point. For SVCs, the maximum control amount is 0.1p.u. The maximum number of load tap changer steps is 3 and the maximum load shedding at one sampling point is 10%. The step size of LTCs is 0.006p.u. The step size of load shedding is 5%.

2) *Fault scenario*: As we have mentioned in the above sub section we have many fault scenarios in power system but we obligate to consider only one type of fault because the process become very complex and difficult to handle. Therefore, the contingency considered here is a three-phase-to-ground fault at bus 21 at t = 1.0 second, which is cleared at t = 1.2 seconds by the tripping of the transmission line between bus 21

and bus 22. Voltage behavior of the modified Ethiopian system is shown in Fig. 5. From t = 0 second to t = 1.0 second, voltages are constant representing that they are in steady state. At time t = 1.0 second, voltages drop dramatically when the fault occurs. After the fault is cleared at 1.2 seconds, the voltages recover greatly whereas some oscillations follow but this oscillation is very dangerous for the material involved in the system. After seconds later, the oscillations are damped out, but the voltages start to decline slowly because of the exponential recovery of the loads. Around 1 minutes later, the voltages collapse.

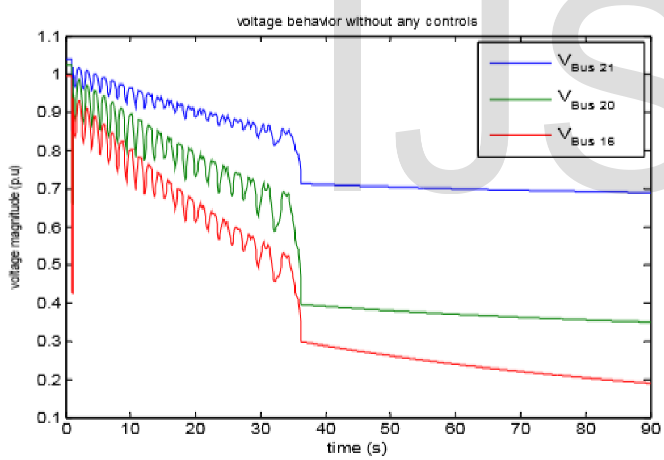

Fig.5. Voltage behavior of the 6-generator 32-bus test system without any control

3) *Simulation result with coordinate control*: In this test case too, there are three types of voltage control options. They are LTCs, SVCs and load shedding. This subsection studies the effect of coordinate control on the restoration of the voltage behavior. There are mentioned on Table 1, which locate in the network. The upper limit of these SVCs, LTCs and load shedding is 0.3p.u, 3p.u, 10p.u respectively. The control strategy is to switch all the available coordinate controls of SVCs at 20 seconds. The voltage behavior is presented in Fig.6. From this figure, we find that though all the coordinate controls are put into use, the voltage cannot be stabilized following the contingency as well as at the initial there is an overshot and also it is dangerous for the system and instrument that involve in electric power system. Therefore, we need a special control mechanism to solve the drawback of coordinate control voltage stabilization that mentioned in the above. So the model predictive control can solve the weakness of the coordinate control mechanism.

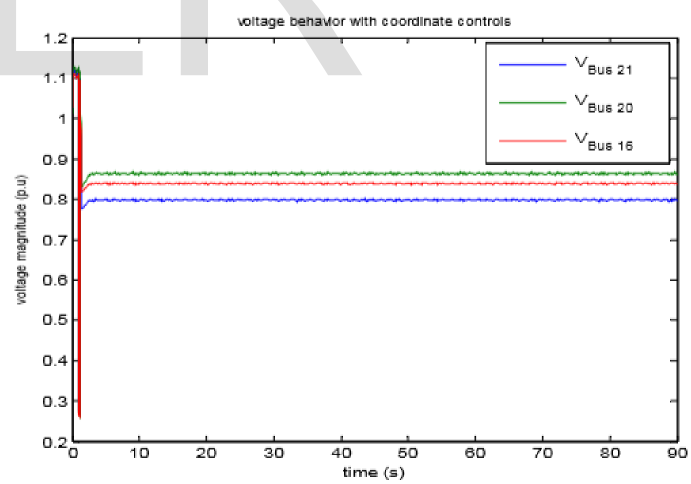

Fig.6. Voltage behavior of the modified Ethiopian system with coordinate control

Table 1 the control strategy for the 6-generator 32-bus test system

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Time(second)	20	35	50	65	75
SVC at bus 2 (p.u.)	0	0	0	0	0
SVC at bus 6 (p.u.)	0	0.0215	0	0	0
SVC at bus 17 (p.u.)	0.0065	0.1	0.1	0.094	0
SVC at bus 19 (p.u.)	0	0	0.013	0.093	0
LTC between buses 8 and 31 (steps)	3	3	3	3	0
LTC between buses 4 and bus 32 (steps)	3	3	3	3	0
Load shedding at bus 15 (%)	10	10	10	5	5
Load shedding at bus 16 (%)	10	10	0	0	0

4) *Simulation result with model predictive control*: In this example, we have chosen prediction horizon T_p to be 90 seconds (the time in which voltage drops by nearly 12% at bus 21). T_c has been chosen to be 75 seconds. We found that sample duration of T_s = 15 seconds works well for this example, and so we have the number of control steps: $N = \frac{T_c}{T_s} = \frac{75}{15} = 5$. The control action determined by the MPC based algorithm starts around 20 seconds to recover voltage. The system response with MPC in place is shown in Fig.7. With the MPC implemented, the voltages are stabilized at a value between [0.95, 1.05] p.u and it is stable in the system and also we have guaranteed to the safety of electric equipment from damage at the instant of the fault occurred. The corresponding control strategy is shown in Table1. It can be famous in the table that the load tap changers are applied to the maximum allowed at each sampling point. Load shedding is also used to stabilize the system. The table shows a coordinated control strategy among load tap changers, static var compensators and load shedding is utilized for voltage stabilization with a certain stability margin. As shown in simulations, MPC is applied after a fault has occurred, and it is not required that MPC be used before the occurrence of a fault. Also since MPC is applied after a fault, the initial condition is arbitrary in all our simulations, i.e., the MPC-based control is successful autonomously of the initial conditions.

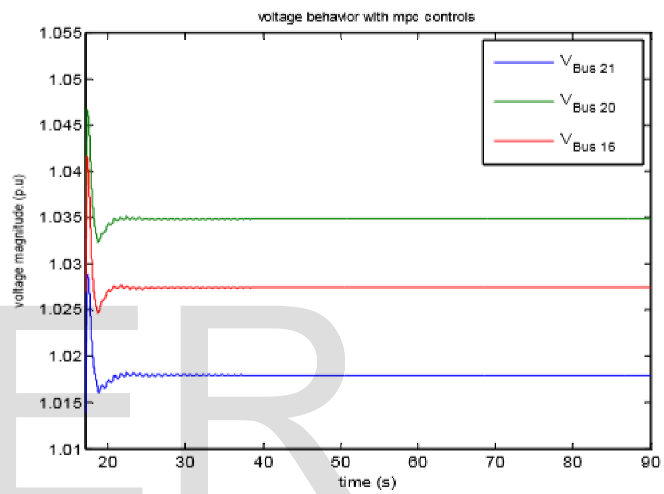

Fig.7. Voltage behavior of the modified Ethiopian system with MPC-based coordinated voltage control

V. CONCLUSION AND DISCUSSION

This paper states a coordinated voltage control strategy for voltage stability following disturbances in Ethiopia high voltage power network system. The design is based on system protection scheme on MPC method with a decreasing control horizon. Trajectory sensitivity technic is used to measure the effect of controls on the voltage improvement. The iterative optimization procedure of MPC helps confirm that errors introduced due to trajectory sensitivity linearization and any model inaccuracies are minimized. The coordination of static var compensators, under load tap changers and load shedding is attained by solving a quadratic mixed integer optimization formulation. The 30-bus Ethiopian system test case shows that the proposed MPC-based coordinated control strategy can effectively attain the desired system performance. The model prediction control based coordinated control for voltage stabilization and security proposed in this thesis is anticipated to be applicable for industrial-size systems. The control computation at each control step in trajectory sensitivity needs (i) estimation of static and dynamic variables, (ii) time-domain simulation to predict system trajectory starting from lately estimated state under the controls applied in the past steps, (iii) trajectory-sensitivity computation, (iv) quadratic mixed-integer programming solution. The most time-consuming component, dominating the other components, is time-domain simulation. Currently there already exist on a traditional system protection scheme and propose online real time system protection scheme based on model predictive control. It runs stability study for single contingencies for a 30 bus system based on a time domain simulation and we can get what we propose (i.e. between 0.95 and 1.05 p.u). We believe therefore that it should be possible to design controls based on the proposed method for on-line real-time system protection against a single contingency.

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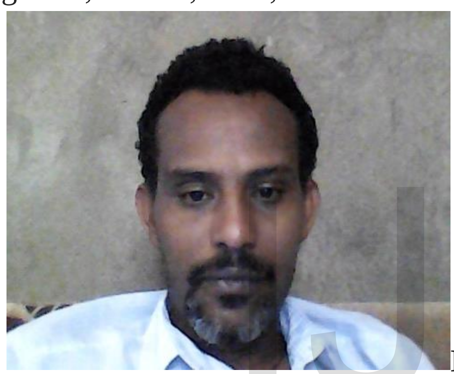

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