Synchrophasor Based Auxiliary Controller to Enhance Power System Transient Voltage Stability in a High Penetration Renewable Energy Scenario

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Abstract — **An auxiliary coordinated control approach focusing on transient voltage stability is proposed in this paper. The concept is based on support vector machine (SVM) classifier and multiple-input and multiple-output (MIMO) model predictive control (MPC) on the high penetration renewable power system. To achieve the objective, the voltage stability condition of the power system is predicted by the SVM classifier first, using measured synchrophasor data in the power system. Next, the control strategy is triggered by the prediction results. The designed auxiliary MPC strategy will augment the existing control variables aiming to keep transient voltage stability.**

To validate the proposed approach, the Kundur two-area power system with a wind plant is built and the numerical results demonstrate the feasibility, effectiveness and accuracy of the proposed method.

Index Terms— **Support vector machine, multiple-input and multiple-output control, model predictive control, wind power plant**

I. Introduction

The voltage control of a power system with high penetration of renewable resources becomes a major concern recently. The objective of voltage control in power systems is monitoring the voltage and keeping voltage stability margin within an acceptable range in the presence of various disturbances [1]. With the development of synchrophasor measuring device (also known as phasor measurement unit - PMU), a real time data acquisition can be achieved in synchronized time frame over hundreds of buses consisting of multi-dimensional information (i.e. voltage magnitude, phase angle and frequency). Using the synchrophasor measurements, wide-area monitoring system (WAMS) based transient voltage stability prediction and control strategy with renewable energy is proposed in this paper [2].

There are two major classic methods to determine the transient stability status of a power system, one is the time-domain simulation of the system nonlinear differential equations and the other is the Lyapunov stability or energy function principle based transient-energy-function (TEF) method [3]. However, the first one requires accurate information of the network configuration and the second requires the levels of kinetic energy and potential energy, which are not easy to determine [4].

Recently, machine learning and data mining based methods are attracting more attention. These methods provide a new promising way to analyze power system stability [5-6]. The perturbation in the power system network can cause power imbalance between generation and load, and it can affect generator angles and generator speed in the power system. Meanwhile, the post-fault voltage can also be used to decipher the perturbations. Reference [7] illustrates method to predict the outcome of system stability by observing and analyzing a short-term post-fault period. In this paper, an SVM modelling method is developed to predict stability of a power system with high penetration renewable source.

The use of traditional proportional-integral derivative (PID) control strategy has limitations for MIMO or nonlinear control systems with constraints. The PID based control solution decomposes a complex system into single-input single-output loops such as cascaded systems, or linearizes the system around an operating point in a very small range [8]. On the other hand, the MPC has several advantages including robust control, easy inclusion of nonlinear systems with constraints and MIMO systems controls [9]. However, due to the high computational complexity and complicated control mechanism, this scheme is not a widely used in power system control.

In this paper, an auxiliary control strategy with low computational burden will be implemented. In order to simplify computational complexity, the proposed control strategy is only triggered after the SVM controller predicts the voltage instability after disturbance event. It is designed for power system under high penetration renewable energy. The entire system is modeled as a nonlinear MIMO dynamic system. This auxiliary controller will augment the existing control variables within the power system.

II. FORMULATION OF THE PROPOSED FAULT ANALYSIS APPROACH

As discussed in the introduction, an auxiliary coordinated control method focusing on transient voltage stability is proposed. The flowchart shown in Fig. 1 illustrates the strategies of the control system. The first part is fault disturbance prediction. This part utilizes the SVM based method to predict the transient voltage stability after disturbance.

The generator angle, generator speed, voltage, and wind speed measurements are used as the input of the SVM predictor. If the SVM predicts that the voltage will oscillate dramatically or collapse [7], the auxiliary control strategy is triggered. In this paper, the control objective is to maximize the system voltage stability margin during the transient. The observed variables used by the MPC controller are the bus voltages on the critical buses in the power system [10].

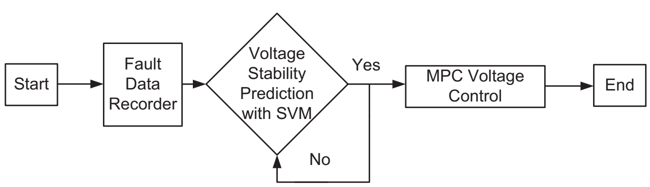


Fig.1. The data processing flowchart of the proposed method.

Considering the characteristic of the variable nature of the renewable energy generation, if the output power of wind power plant (WPP) is not sufficient to cover the loads, the voltage may decrease significantly. The proposed control strategy will be used to quickly stabilize the system voltage instantaneously.

A test system based on the Kundur-two-area system is shown in Fig. 2. A WPP consisting of six type 3 wind turbine generators (WTGs) are connected to bus 2. The WTG is a doubly fed induction generator rated at 1.5 MW each with nominal frequency of 60 Hz [11]. The 6 WTGs are divided into 3 control groups $W_1;\ W_2;\ W_3$, and each group contains 2 WTGs. The controlled vectors used for each WTG group are pitch angle $\beta_W = [\beta_1\ \beta_2\ \beta_3]^T$ and excitation voltage $\mathbf{E}_W = [E_{W_1}\ E_{W_2}\ E_{W_3}]^T$, where T is matrix transpose. Wind speeds are monitored for each group denoted as $\nu = [\nu_1\ \nu_2\ \nu_3]^T$. In addition to the WPP, there are 3 TGs, $G_1;\ G_3;\ G_4$, and each of them is 9 MW, 60 Hz. Another TG is G_5, which is a 3 MW TG, connected through a switch gear to bus 5.

The level of penetration of wind energy is above 20%. The controlled vectors of the TGs are excitation voltage $\mathbf{E}_G = [E_1\ E_3\ E_4]^T$ and mechanical power $\mathbf{M}_G = [M_1\ M_3\ M_4]^T$. There are two loads located in bus 7 and 9. They are 9.5 MW and 21 MW, respectively. In order to reduce the computational burden, voltage on bus 2, 3, 5, 10 are monitored. $\mathbf{V}_{out} = [V_2\ V_3\ V_5\ V_{10}]^T$ are selected as the observation variables [10]. The controller adjusts the multiple input variables to stabilize the voltage on bus 2, 3, 5, 10 during the transient.

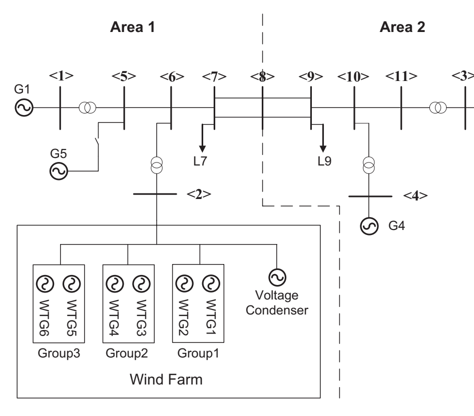


Fig. 2. The test hybrid two-area power system.

III. TRANSIENT VOLTAGE STABILITY STATUS PREDICTION

A. Basic Concept of Support Vector Machine

The SVM is a supervised learning method used for classification, regression and estimation problems. It is suitable to solve non-linear problems [7],[12]. The trajectory of the voltage stability status during transient is predicted using this SVM predictor.

B. SVM Designed for Renewable Energy Generation

In this paper, the observation inputs used by the SVM predictor includes the generator angle of the three TGs α_G = $[\alpha_{G1}\ \alpha_{G3}\ \alpha_{G4}]^T$, the generator rotor speed ω_G = $[\omega_{G1}\ \omega_{G3}\ \omega_{G4}]^T$ and the voltage of every bus $\mathbf{V}$ = $[V_1\ ...\ V_{11}]^T$ of the system. Considering that wind speed varies with time, the wind speed $\nu = [\nu_1\ \nu_2\ \nu_3]^T$ is used as the input to the SVM. So the observation vector is defined as $\mathbf{x} = [\alpha_G^T\ \omega_G^T\ \nu^T\ \mathbf{V}^T]^T$.

Both normal operations and different types of disturbances are simulated for numerical experiments during the training sessions. For the transmission line faults, single-line to ground, line-to-line, and line-to-line to ground as well as three-phase-to ground faults are simulated for all transmission lines at different locations (at 5%, 10%, 25%, 50%, 60% and 80% of the length). The fault durations as 5, 10, 15, 20, 25 cycles as well as permanent faults with different starting times are simulated. Load increasing and decreasing at 1%, 2%, 3%, 5%, 10%, 15%, 17.5% and 20% are simulated on the two loads. The WPP is simulated at different wind turbulence levels.

Both the opening and closing of the switch are also simulated. According to the rule presented in reference [7], the generated training data are labeled into classes, one is the stable system transient voltage and labeled as “1”; the other is unstable and labeled as “-1”. The K-fold [13] cross-validation is used to separate the generated data into the training set and testing set. In this paper, 10 fold cross validation are selected; i.e., 90% of the generated data are used as the training data and 10% are used as the testing data.

To maintain the transient voltage stability, the controller is required to make a quick corrective action, to predict the status, and to deliver the control decisions [7]. The overall control process is usually expected to take less than 1 second. In the proposed method, the observation time is set to 100 ms. The prediction algorithm is executed in a computer with Intel i7 3.0 GHz CPU and 12 GB RAM, and the resulting average computation time for prediction is only 14.93 ms.

C. SVM Prediction Results

1) Transient Voltage Stability with PMUs Fully Placed:

Assuming that every bus in the system is equipped with a PMU, Table I illustrates that the prediction rate with such configuration is 100%, which demonstrates that the proposed method has higher successful prediction rates than the method in reference [7] whose results are shown in Table II. The performance improvement is due to the higher dimensional input vectors and longer observation time in the proposed approach, thus, allowing more information used in training of the SVM algorithm in the nonlinear system.

TABLE I. CLASSIFICATION CONFUSION MATRIX BETWEEN TRANSIENT VOLTAGE FOR STABLE AND UNSTABLE STATUS

	STABLE	UNSTABLE
STABLE	**1(125/125)**	0(0/125)
UNSTABLE	0(0/55)	**1(55/55)**

TABLE II. CLASSIFICATION CONFUSION MATRIX BETWEEN TRANSIENT VOLTAGE FORSTABLE AND UNSTABLE STATUS FORM REFERENCE [7]

	STABLE	UNSTABLE
STABLE	**0.984(123/125)**	0.016(2/125)
UNSTABLE	0.055(3/55)	**0.945(52/55)**

2) Transient Voltage Stability with PMU Optimally Placed on Selected Buses:

In real-world applications, the number of PMU is limited due to its cost. It is imperative to optimally place PMUs in the power system. If PMUs are placed on buses 2, 3, 5, 7, 10, the installation percentage is 45% of the total buses. The system is observable and the voltage on every bus of the system can be calculated [14-16]. The prediction result shown in Table III is very good as well. Thus, the level of accuracy is not compromised. This provides a way to predict the transient voltage stability with reduced number of but optimally placed PMUs.

TABLE III. CLASSIFICATION CONFUSION MATRIX BETWEEN TRANSIENT VOLTAGE FORSTABLE AND UNSTABLE STATUS

	STABLE	UNSTABLE
STABLE	**1(125/125)**	0(0/125)
UNSTABLE	0(0/55)	**1(55/55)**

IV. AUXILIARY CONTROL STRATEGY BASED ON MODEL PREDICTIVE CONTROL

MPC has been successfully used in many industrial applications due to its ability to handle the nonlinear MIMO control problems with constraints on the system variables. The principles of MPC is illustrated in Fig. 3 [17],[18].

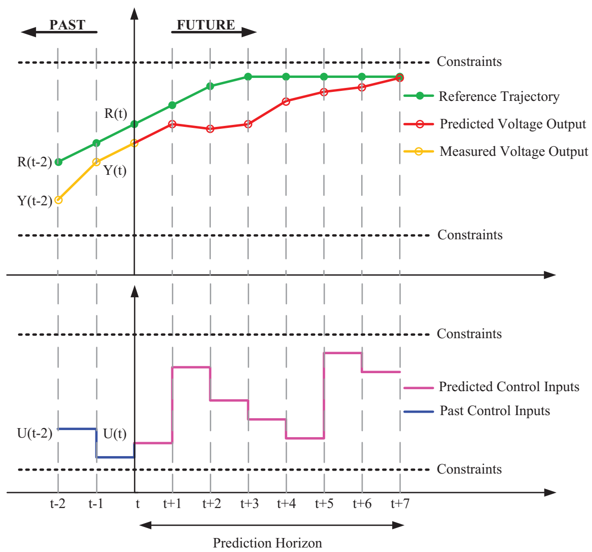


Fig. 3. Model Predictive Control Concept**.**

In this paper, we consider different types of fault in the power system with renewable energy generation, a flexible control strategy based on MPC is proposed.

A. General Control System Formulation

It is assumed that the discrete time state space model of the MPC is given by

$$X(t+1) = A(t)X(t) + B(t)U(t) + D_1(t)d_1(t) \quad (1)$$

$$Y(t) = C(t)X(t) + D_2(t)d_2(t) \quad (2)$$

where $X(t) \in \mathbf{R}^n$ is the system states at time t. $A(t) \in \mathbf{R}^{n \times n}$, $B(t) \in \mathbf{R}^{n \times m}$ and $C(t) \in \mathbf{R}^{l \times n}$ are the system control coefficient matrices, $U(t) \in \mathbf{R}^m$ is the control vector of the system; $Y(t) \in \mathbf{R}^l$ is the output vector of the system; $d_1(t)$ and $d_2(t)$ are the system state uncertainty and measurement noise, respectively, and their coefficient matrices are $D_1(t)$ and $D_2(t)$.

B. Auxiliary Control for Traditional Generator and Wind Turbine Generator

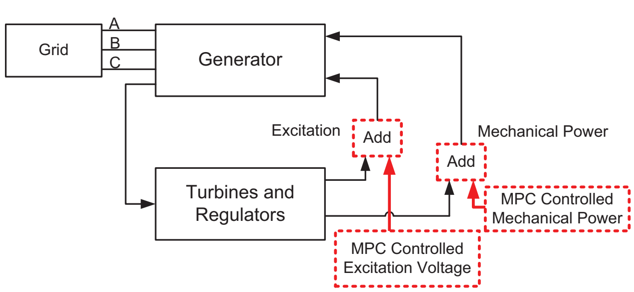


Fig. 4. Designed Model Predictive Control on Traditional Generator.

Different from traditional MPC strategies [9], [19], the proposed control strategy operates as an auxiliary controller and revises the control vector along the way.

As Fig. 4 illustrates, the control loop in black is the existing control loop for the TG, which controls excitation voltage and mechanical power. The proposed control strategy uses the two adder blocks in red, the MPC controlled excitation voltage and MPC controlled mechanical power are two auxiliary control variables that revise the excitation voltage and mechanical power of the existing control loop. As shown in Fig. 5, the WTG controller controls the pitch angles of the wind turbine and excitation voltage variables. Auxiliary MPC blocks revise the pitch angle and excitation voltage variables in the existing control loops.

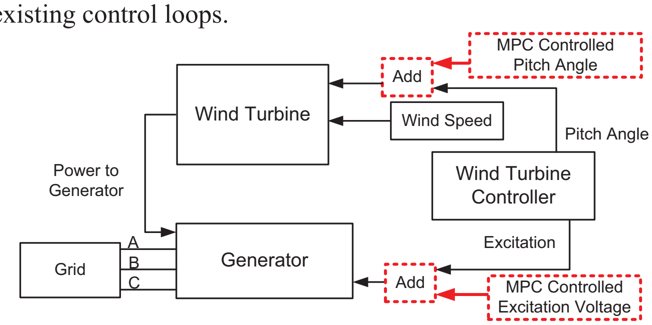


Fig. 5. Designed Model Predictive Control on Traditional Generator**.**

C. Optimization Problem

To achieve the objective of transient voltage stability control, the control strategy considers the active power control and reactive power control. In this paper, the auxiliary MPC controlled variables contain excitation $\mathbf{E}_{AG}$ = $[E_{AG1}\ E_{AG3}\ E_{AG4}]^T$ and mechanical power $\mathbf{M}_{AG}$ = $[M_{A1}\ M_{A3}\ M_{A4}]^T$ for the TGs; excitation voltage $\mathbf{E}_{AW}$ = $[E_{AW1}\ E_{AW2}\ E_{AW3}]^T$ and pitch angle β_{AW} = $[\beta_{AW1}\ \beta_{AW2}\ \beta_{AW3}]^T$ for the WTGs.

The control vector U is the combination of the auxiliary MPC control vector U_{MPC} = $[\mathbf{E}_{AG}^T\ \mathbf{M}_{AG}^T\ \mathbf{E}_{AW}^T\ \beta_{AW}^T]^T$ and existing control vector U_{EX} = $[\mathbf{E}_G^T\ \mathbf{M}_G^T\ \mathbf{E}_W^T\ \beta_W^T]^T$. So U is given by

$$U = U_{MPC} + U_{EX}. \quad (3)$$

The observation vector is the voltage measurements on bus 2, 3, 5, 10 denoted as $\mathbf{V}_{obs} = [V_2\ V_3\ V_5\ V_{10}]^T$. According to the discussion above, based on the state space model, the optimization function can be defined as

$$\min\{\sum_{j=N_1}^{N_1+T_p} \left\| \hat{Y}(t+j\,|\,t) - R(t+j) \right\|_O^2 + \sum_{j=1}^{1+T_c} \left\| \Delta U(t+j-1) \right\|_Q^2\} \quad (4)$$

and considering the realistic application, the constraints are

$$\underline{y}_i \le y_i \le \overline{y}_i, i = 1,2,3... \tag{5}$$
$$\underline{u}_i \le u_i \le \overline{u}_i, i = 1,2,3...$$

where N_1 is the lower value of prediction horizon; $N_1 + T_p$ is the higher value of prediction horizon; $1+T_c$ is the upper value of the control horizon. $Y(t)$ is the observation vector of the power system with WPP at time t; $\hat{Y}(t+j\,|\,t)$ is the expected observation vector of $Y(t+j)$ with available information at instant t, $R(t)$ is the reference observation vector. Δ is defined as $1-z^{-1}$, where z^{-1} is the backward shift operator. O is the weighting matrix for predicted errors and Q is the weighting matrix for control moves. y_i and u_i are the elements of the vector Y and U, respectively. $\underline{y}_i$ and $\overline{y}_i$ are the lower and upper limits of y_i; $\underline{u}_i$ and $\overline{u}_i$ is the lower and upper limits of u_i.

V. Numerical Simulation and Results

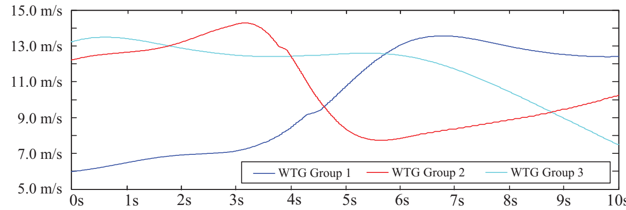
The constraints of the parameters are shown in Table IV.

TABLE IV. CONSTRAINTS OF THE MODEL PREDICTIVE CONTROL VARIABLES

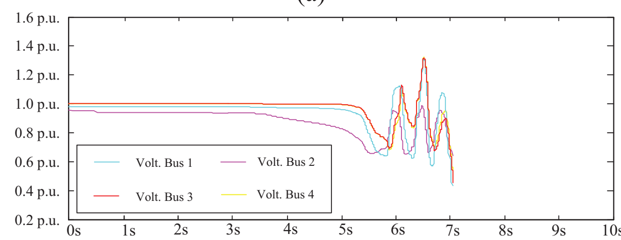
Lower Limits	Variables	Upper Limits
0.0 P.U.	$E_{AG1}, E_{AG3}, E_{AG4}$	2.0 P.U.
0.0 P.U.	M_{A1}, M_{A3}, M_{A4}	1.2 P.U.
0.0 P.U.	$E_{AW1}, E_{AW2}, E_{AW3}$	1.2 P.U.
0°	$\beta_{AW1}, \beta_{AW2}, \beta_{AW3}$	30°
0.0 P.U.	V_2, V_3, V_5, V_{10}	1.5 P.U.

All simulations are executed using a computer with an Intel i7 3.0 GHz CPU and 12 GB RAM, and the simulation software for the proposed approach is Matlab Simulink. The data length for the SVM to classify normal and abnormal conditions is 100 ms; the computation time for SVM is 20 ms; the computation time for MPC auxiliary control variables is 35 ms; and 10 ms is for extra consumption such as system delay. The resulting total consumption time is 165 ms.

In this study case, the switch to bus 5 is open, and the 3 MW TG does not connect to the hybrid power system. As Fig. 6(a) illustrates, it is assumed that there are three different profiles of wind speed for the three groups of WTGs, respectively. In order to create power margins for voltage regulation, deloaded WPP operate at about 80% maximum available power. At the beginning of the simulation, since the wind speed for WTG group 1 is very low, the output power of the wind farm is insufficient. As Fig. 6(b) illustrates, there are the voltage curves on selected buses without the proposed auxiliary MPC approach. The purple curve illustrates the voltage of bus 2, which is connected to the WPP, is lower than voltages on other buses.



(a)

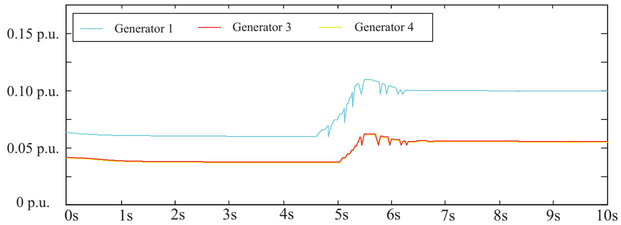


(b)

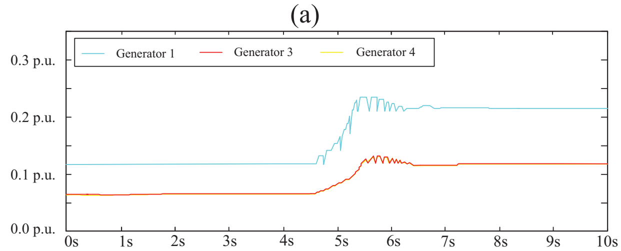
Fig. 6. Voltage oscillation caused by low wind power output: (a) wind speed, (b) voltage on bus 2, 3, 5, 10.

Then, during time period 4 s to 6 s, the wind power is further decreased. As a result, in Fig. 6(b), the decrease in output power of the WPP causes the voltage oscillation of the power system. And at 7 s, the voltage is below 0.5 p.u., thus indicating the failure of the power system.

In order to remedy the situation presented in Fig. 6(b), the proposed approach is employed. Since at the beginning, the low wind speed causes the voltage at bus 2 lower than others, the auxiliary MPC is triggered immediately to compensate for voltage reduction caused by the decreasing wind speed. The TG mechanical power increases to compensate the lack of generation as demonstrated in Fig.7(a). Similarly the excitation voltage increases to provide reactive power support during the under voltage condition as shown in Fig. 7(b). Since TG 1 is located the closest to the WPP, it has the largest impact to compensate for the WPP output power drop. So the additional output of the TG 1 shows the largest increase in mechanical and excitation voltage control variables. From t = 4.5 s to t = 6.3 s, there is an increase in the mechanical power and excitation to compensate for the power loss of the WPP.



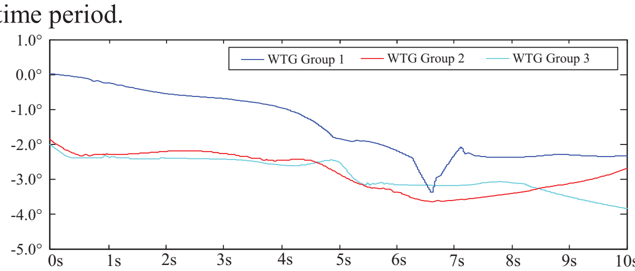
(a)



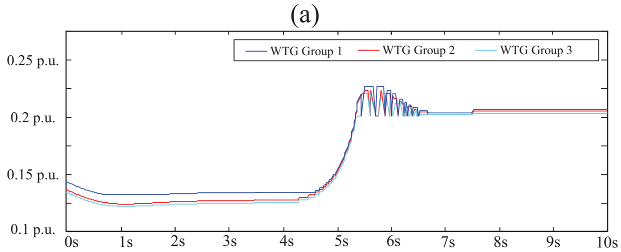
(b)

Fig. 7. Proposed method for TGs: (a) auxiliary mechanical power variables, (b) auxiliary excitation voltage variables.

TG 3 and TG 4 are in the same area, because they are both located in area two and close to each other. They have similar mechanical and excitation voltage control and they also have a smaller crest than the ones for the TG 1 in this time period.



(a)



(b)

Fig. 8. Proposed method for WTGs: (a) auxiliary pitch angle variables, (b) auxiliary excitation voltage variables.

Fig. 8 illustrates the auxiliary MPC controlled pitch angle and excitation voltage variables for the WTGs. In Fig. 8(a), the pitch angle curves of the three WTG groups change to increase the output active power. From t = 4 s, the MPC controlled pitch angles of the three WTG groups decreases dramatically to generate more active power when the wind speed decreases at the same time. In Fig. 8(b), there is a crest in control variables from t = 4.5 s to t = 6.3 s, the MPC controlled excitation voltage variables also increases to generate more reactive power and compensate for the voltage drop.

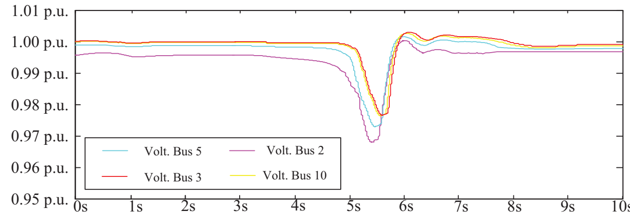


Fig. 9. Voltage controlled by the proposed method for wind power loss.

After the proposed method is employed, the improvement to bus voltages are shown in Fig. 9, and the voltage collapse is avoided. The voltage curves of the four selected buses are more consistent with respect to each others, and the amplitude of the transient voltage dips are less than 4%.

VI. Conclusions

A novel auxiliary coordinated voltage control approach is proposed in this paper. In our proposed approach, the SVM classifier provides prediction of transient voltage stability. From our investigation, the impact of reduced number of installed PMUs does not cause reduced accuracy and effectiveness of our proposed prediction approach. Compared with traditional control strategies, this proposed approach provides an effective way on transient voltage control for the power system with high wind energy penetration.

In real-world applications, the power system is much more complicated than the test system and contains a variety of renewable energy sources such as photovoltaic, geothermal, etc. Therefore, we expect that our proposed approach to be a cornerstone for other application scenarios that includes large scale renewable power system integration.

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