Design of model predictive control for adaptive damping of power system stabilization

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Abstract: This paper proposes a robust control framework for power system stabilizer to improve system dynamic performance based on model predictive control (MPC). The effectiveness of the proposed power system stabilizer is validated by a simple power system composed of a synchronous generator connected to an infinite bus through a transmission line. A comparison between power system responses at variety of operating conditions using the proposed MPC and Linear Quadratic Regulator (LQR) control is obtained. The dynamic model of interconnected power system under study is established. To validate the effectiveness of the proposed MPC, the power system is simulated over a wide range of operating conditions. The digital simulation results prove the powerful of the proposed power system controller based on MPC theory in terms of fast power system oscillation damping under different operating conditions.

Key-Words: - Model Predictive Control, Synchronous Generator, LQR control, Power System Stabilization, Robust Systems Control,

1. Introduction

Power systems are composed of several interconnected subsystems or control areas; one area is connected to another by the tie-lines. Each area has its own generator or group of generators, and it is responsible for its own load and scheduled power interchanges with neighboring areas. Because of the differences in generation and load in a power system, systems frequency deviates from its nominal value and active power flow interchanges between areas deviate from their contracted values [1].

Power System Stabilizers (PSS) are used for many years to add damping to the electromechanical oscillations. It will act through the generator excitation system which produces a component of electrical torque (in addition to the damping torque) according to the speed deviation is generated. However it is easy to implement the PSS as its function mainly depends upon the modes of oscillation. i.e. whether it is local or inter-area mode. The highly efficient stabilizer which produces a damping torque over a wide range of frequencies whereas less efficient stabilizer for a small range of frequencies only, which makes problem when the system changes its oscillation mode also change correspondingly. Power System Stabilizer is used to provide additional modulation signal to the reference input of automatic voltage regulator. Due to this idea an electrical torque is produced in the generator proportional to the speed deviation. In earlier days PSS consists of lead block to adjust the input signal to give the correct phase [2] [3] [4].

Conventional power system damping controllers are usually based on linearization of detailed dynamic model of the system to be controlled [5]. The method may be suitable for small and moderate scale power systems, but is impractical for modern bulk power systems. Model order reduction (MOR) methods, such as dynamic equivalent [6] and model identification have been proposed to design damping controllers for large scale systems, in which transfer functions or state-space models with reduced orders are derived from system dynamic responses. However, it is difficult for the MOR-based controllers to adapt to large changes in system operating conditions because of the fixed parameters they have employed. To overcome inherent shortcomings of conventional damping controllers, robust controllers [7]and adaptive controllers [8] have been developed to enhance robustness and to adapt wide range of operating conditions of power system [9].

Model predictive control is an adaptive control strategy which has been applied in process control successfully. In MPC, the control action at each time step is obtained by solving an online optimization problem. With a linear model, polyhedral constraints, and a quadratic cost, the resulting optimization problem is a quadratic program. Solving the quadratic program using general purpose methods can be slow, and this has traditionally limited MPC to applications with slow dynamics, with sample times measured in seconds or minutes. One method for implementing fast MPC is to compute the solution of the quadratic program explicitly as a function of the initial state [10] [11].

The last two decades have seen the widespread diffusion of MPC techniques, which are now recognized as the most useful approach to deal with the control problems typical of the process industry. Indeed, with MPC it is possible to formulate the control problem as an optimization one, where many different (and possibly conflicting) goals are easily formalized and state and control constraints can be included. Also for MPC, many results are nowadays available concerning stability and robustness; see [12], so that it can now be seen as a well assessed methodology, With the on-line solution of the optimization problem, MPC presents a possibility of managing on-line the tradeoff between disturbance attenuation and control (and/or state) constraints, which appears to be an efficient strategy to control many applications in industry [13] [14] [1], a number of predictive control schemes have been presented for power system emergency control, voltage and transient stability control, as well as load frequency control [15] [16] [17] [18] [19]. These various studies illustrate that MPC can produce computationally reasonable power system control strategies. In [20] , a multivariable adaptive power system stabilizer based on a subspace model identification (SMI) method and the MPC strategy is proposed and locally implemented to damp multi-mode oscillations [9].

The present paper investigate design of power system stabilizer for improving power system dynamic performance over a wide range of operating condition with the help of MATLAB programing code, at first, Model Predictive Control is employed. Then a different approach namely linear quadratic regulator (LQR) is used. Finally, results are given to demonstrate the performance achieved when both approaches are applied to Power system stabilizer.

2. Power System Mathematical Model

Figure 1 shows the Block diagram of the power system model which consists mainly of a synchronous machine connected to an infinite bus through transmission line. The linear differential equations of the power system under study described as follow [21]:

$$\Delta\dot{\delta} = \omega_0 \Delta\omega \qquad \text{Eq. 1}$$

$$\Delta\dot{\omega} = -\left(\frac{K_1}{M}\right)\Delta\delta - \left(\frac{D}{M}\right)\Delta\omega - \left(\frac{K_2}{M}\right)\Delta E'_q + \left(\frac{1}{M}\right)\Delta T_m - \left(\frac{1}{M}\right)\Delta P_d \qquad \text{Eq. 2}$$

$$\Delta\dot{E}_q = -\left(\frac{K_4}{T'_{d0}}\right)\Delta\delta - \left(\frac{1}{K_3 T'_{d0}}\right)\Delta E'_q + \left(\frac{1}{T'_{d0}}\right)\Delta E_{fd} \qquad \text{Eq. 3}$$

$$\Delta\dot{T}_m = -\left(\frac{1}{T_t}\right)\Delta T_m + \left(\frac{1}{T_t}\right)\Delta P_g \qquad \text{Eq. 4}$$

$$\Delta\dot{P}_g = -\left(\frac{1}{RT_g}\right)\Delta\omega - \left(\frac{1}{T_g}\right)\Delta P_g + \left(\frac{1}{T_g}\right)U_2 \qquad \text{Eq. 5}$$

$$\Delta\dot{E}_{fd} = -\left(\frac{1}{T_A}\right)\Delta E_{fd} - \left(\frac{K_A K_5}{T_A}\right)\Delta\delta - \left(\frac{K_A K_6}{T_A}\right)\Delta E_q' + \left(\frac{K_A}{T_A}\right)\Delta U_1 \qquad \text{Eq. 6}$$

Where, K1 to K6 are the coefficient of synchronous machine

The state space forms of the above equations are:

$$\dot{X} = AX + BU \qquad \text{Eq. 7}$$

Where A: System matrix, X: State vector, B: input matrix, are as follow:

$$A = \begin{bmatrix} 0 & \omega_0 & 0 & 0 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & \frac{1}{M} & 0 & 0 \\ -\frac{K_4}{T'_{d0}} & 0 & \frac{-1}{(K_3 T'_{d0})} & 0 & 0 & \frac{1}{T'_{d0}} \\ 0 & 0 & 0 & \frac{-1}{Tt} & \frac{1}{Tt} & 0 \\ 0 & -\frac{1}{(RT_g)} & 0 & 0 & \frac{-1}{T_g} & 0 \\ -\left(\frac{K_4 K_5}{T_A}\right) & 0 & -\left(\frac{K_A K_6}{T_A}\right) & 0 & 0 & \frac{-1}{T_A} \end{bmatrix} \qquad \text{Eq. 8}$$

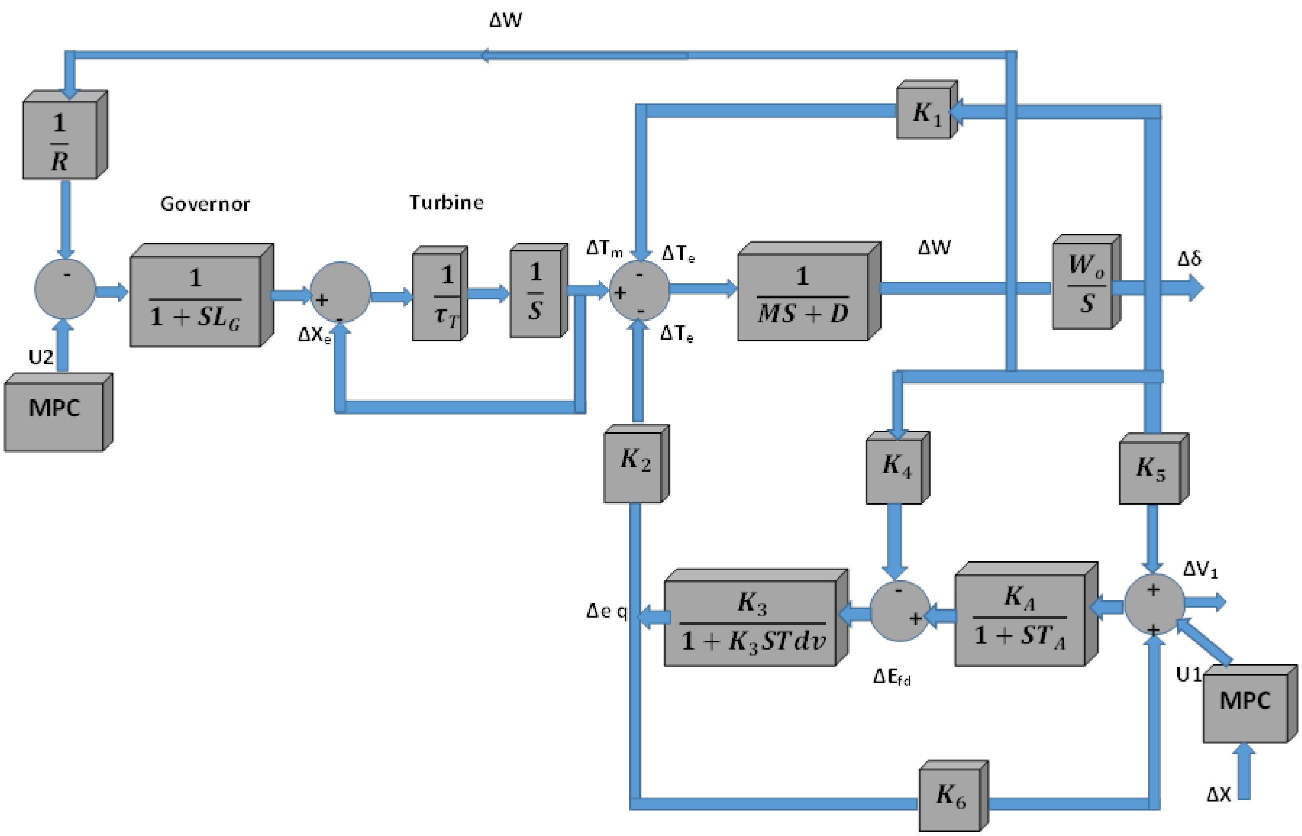

Figure 1: Block diagram of the power system model

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1/Tg \\ \dfrac{K_A}{T_A} & 0 \end{bmatrix} \qquad \text{Eq. 9}$$

$$X = \begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \Delta\dot{E}'_q \\ \Delta\dot{T}_m \\ \Delta\dot{P}_g \\ \Delta\dot{E}_{fd} \end{bmatrix} \qquad \text{Eq. 10}$$

3. Overview of Model Predictive Control

Model predictive control is a control strategy that offers attractive solutions for the regulation of constrained linear, nonlinear or hybrid systems. Within a relatively short time, MPC has reached a certain maturity due to the continuously increasing interest shown for this distinctive part of control theory. This is illustrated by its successful implementation in industry and by many excellent articles and books as well.

One of the reasons for the fruitful achievements of MPC algorithms consists in the intuitive way of addressing the control problem. In comparison with conventional control, which often uses a pre-computed state or output feedback control law, predictive control uses a discrete-time model of the system to obtain a prediction of its future behavior. This is done by applying a set of input sequences to a model, with the measured state/output as initial condition, while taking into account constraints. An optimization problem built around a performance oriented cost function is then solved to choose an optimal sequence of controls from all feasible sequences.

The feedback control law is then obtained in a receding horizon manner by applying to the system only the first element of the computed sequence of optimal controls, and repeating the whole procedure at the next discrete-time step.

MPC is built around the following key principles:
- The explicit use of a process model for calculating predictions of the future plant behavior;
- The optimization of an objective function subject to constraints, which yields an optimal sequence of controls;
- The receding horizon strategy, according to which only the first element of the optimal sequence of controls is applied on-line.

The MPC methodology involves solving on-line an open-loop finite horizon optimal control problem subject to input, state and/or output constraints. A graphical illustration of this concept is depicted in Figure 2.

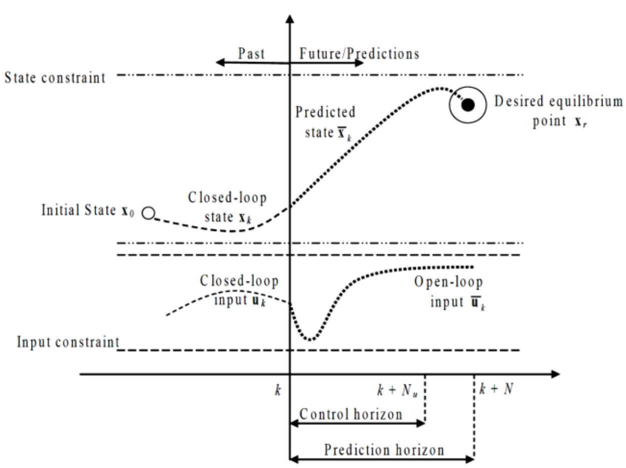

Figure 2, A graphical illustration of model predictive control [22]

At each discrete-time instant k, the measured variables and the process model (linear, nonlinear or hybrid) are used to (predict) calculate the future behavior of the controlled plant over a specified time horizon, which is usually called the prediction horizon and is denoted by N. This is achieved by considering a future control scenario as the input sequence applied to the process model, which must be calculated such that certain desired constraints and objectives are fulfilled.

To do that, a cost function is minimized subject to constraints, yielding an optimal sequence of controls over a specified time horizon, which is usually called control horizon and is denoted by Nu. According to the receding horizon control strategy, only the first element of the computed optimal sequence of controls is then applied to the plant and this sequence of steps is repeated at the next discrete-time instant, for the updated state [22].

MPC is an effective and acceptable control strategy to stabilize dynamical systems in the presence of nonlinearities uncertainties, constraints and delays, especially in process industries. A general MPC scheme is shown in Figure 3.

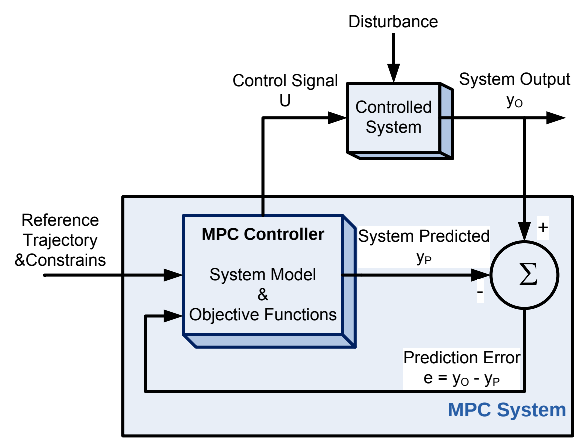

Figure 3, A general scheme of MPC Controller [23]..

The MPC controller consists of two units i.e., prediction and controller unit.
- The prediction unit includes system and disturbance model which estimates future behavior of system based on its current output, measured disturbance, unmeasured disturbance and control signal over a finite prediction horizon. The predicted output is fed to control unit as known parameters to minimize an objective function in presence of system constraints in an optimization problem. The first element of the sequence is injected into the plant and the whole procedure is repeated in the next sampling interval with the prediction horizon moved one sampling interval forward.
- The control horizon is then the number of samples that the optimal input is calculated for.

With a shorter control horizon than prediction horizon the complexity of the problem can be reduced. From the calculated input signal only the first element is applied to the system. This is done at every time step. The idea is thus to go one step at a time and check further and further ahead. The method can be described as "repeated open-loop optimal control in feedback fashion" [23].

4. Model Prediction formulation

The formulation of an optimal control problem involves a specification of performance measure, a statement of physical constraints, and a mathematical model of the system to be controlled A nonlinear time-varying system can usually be represented by a set of nonlinear differential equations Eq. 11 is the typical form for this set of differential equations

$$\dot{x} = f\left(x(t), u(t), v(t), t\right) \qquad \text{Eq. 11}$$

Arguments of the function f include a state vector x(t), a control input u(t), and a disturbance input v(t). The set of physical quantities that can be measured in a system is the output. Eq.12 expresses the fact that the output of the system y(t) is a function of the same arguments.

$$y(t) = g(x(t), u(t), v(t), t) \qquad \text{Eq. 12}$$

A scalar cost function J is chosen to quantitatively evaluate the performance of the system over an interval of time. The form J usually takes can be found in Eq.13, where h is strictly a terminal cost.

$$J = \int_{t_o}^{t_f} j(x(t), u(t), v(t), t)dt + h\left(x\left(t_f\right), t_f\right) \qquad \text{Eq. 13}$$

The limits on the integral, to and tf, are the initial and final time, respectively. An estimate of the disturbance input for the interval [to, tf] is needed before J can be minimized. The sequence of disturbances in this interval is called the disturbance history v. Similarly, the sequence of control input values in the interval [to, tf] is called the control history u. Starting from an initial state x(to) and applying the control and disturbance histories causes the system to follow a particular output trajectory y.

The output trajectory and control history are typically subject to constraints for the entire interval. One simple type of constraint is given by Eq.14 and Eq.15, where t ϵ [to, tf]. Control histories and output trajectories that satisfy these constraints are called admissible

$$u(t)_{\min} \le u(t) \le u(t)_{\max} \qquad \text{Eq. 14}$$

$$y(t)_{\min} \le y(t) \le y(t)_{\max} \qquad \text{Eq. 15}$$

The optimal control problem is to then find an admissible control history u*, which causes the system in .Eq.11 and Eq12 to follow an admissible output trajectory that minimizes the cost function in Equation 13, u* is the optimal control for the interval [to, tf].

5. Linear Model Predictive Control

Linear MPC solves a special case of the general optimal control problem. The functions defining x. and y are assumed to be linear and time-invariant. Approximations for the differential equations are also made, using Euler's method in Eq.16 or any other form of numerical integration.

$$\dot{x} \approx \frac{x(k+1) - x(k)}{T_S} \qquad \text{Eq. 16}$$

The letter k is used in place of t to distinguish between a, discrete and continuous variable Values x(k) occur repeatedly at instants of time TS, seconds apart. This small interval of time is called a time step. The dynamic model of the system is rewritten in Eq.17 and Eq.18 using these assumptions and approximations

$$x(k+1) = Ax(k) + Bu(k) + B_d v(k) \qquad \text{Eq. 17}$$

$$y(k) = Cx(k) + Du(k) + D_d v(k) \qquad \text{Eq.18}$$

The cost function is also specialized. The scalar function j is assumed to have a quadratic form, such as the one given by Equation 2.9, and the integral is replaced with a summation since the model has been discretized. The cost function in Eq.19 penalizes the control and deviations from a reference trajectory at each time step in the problem interval. Any terminal costs are added to J by increasing the weighting matrices Q(k) and R(k) for the final time step.

$$J = \sum_k \{[y(k) - y'(k)]^T Q(k)[y)k) - y'(k))] + u(k)^T R(Ku(k)\} \qquad \text{Eq.19}$$

Control and output constraints are still considered in their inequality form. The only change is that the constraints are enforced at each discretized point in the control history and output trajectory rather than continuously throughout the problem interval as shown in Eq.20 and Eq. 21

$$u(k)_{\min} \le u(k) \le u(k)_{\max} \qquad \text{Eq.20}$$
$$y(k)_{\min} \le y(k) \le y(k)_{\max} \qquad \text{Eq.21}$$

The MPC problem in this setting is to minimize J by choosing u, subject to the constraints in Eq.20 and Eq.21 and the dynamics of Eq.17 and Eq.18.

6. Nonlinear MPC

Nonlinear MPC is used for models that have the form found in Eq.11 and Eq.12 The only necessary change is that the differential equations are approximated. The system model is rewritten below in Eq.22 and Eq. 23 using Euler's method.

$$x(k+1) = x(k) + T_S\, f(x(k), u(k), v(k), k) \qquad \text{Eq.22}$$

$$y(k) = g(x(k), u(k), v(k), k) \qquad \text{Eq.23}$$

Eq.19, 20 and 21 also apply to nonlinear MPC since the form of the cost function and constraints are identical to Linear MPC.

7. Linear Quadratic Regulator

The feedback gain of the closed loop system design by the design of the power system stabilizer based on linear-quadratic regulator LQR control for continuous-time systems as follow:

$$[K, S, E] = lqr(A, B, Q, R, N) \qquad \text{Eq. 24}$$

Calculates the optimal gain matrix K such that the state-feedback law u=-Kx minimizes the cost function

$$J = Integral(X'QX + u'Ru + 2X'Nu)dt \qquad \text{Eq. 25}$$

Subject to the state dynamics (in Eq. 7)

$$X = AX + Bu$$

The matrix N is set to zero when omitted. Also returned are the Riccati equation solution S and the closed-loop eigenvalues E:

$$SA + A'S - (SB + N)R^{-1}(BS + N) + Q = 0 \qquad \text{Eq. 26}$$

$$E = EIG(A - B * K) \qquad \text{Eq. 27}$$

8. Results and Discussion

The single line diagram of power system based on MPC and LQR are indicated in Figure 4

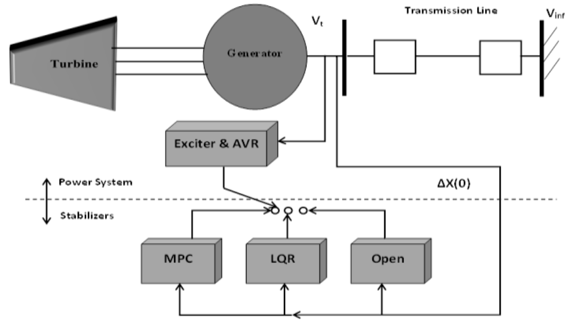

Figure 4, Single line Diagram of PSS

The following mathematical linearized state space model represents a power system which consists of synchronous machine connected to infinite bus through transmission line. The block diagram is shown in Figure 1. Choosing the machine parameters and nominal operating point as [24];

$$X_d = 1.6; X_q = 1.55;$$
$$X'_d = 0.32; X_e = 0.4\, p.u$$
$$\omega_0 = 377; M = 10; T_{d0} = 6;$$
$$D = 0; T_A = 0.06;$$
$$K_A = 25(P = 1; Q = 0.25);$$
$$T_t = 0.08; R = 1.82; re = 0$$

Figure 5 – A through Figure 5 – D shows the rotor speed deviation response due to 0.1 pu load disturbance with and without controllers at different load condition as follow:

A:	p=1 pu,	Q= 0.25 pu
B:	p=1 pu,	Q=-0.25 pu
C:	p=1.2 pu,	Q= 0.8 pu
D:	p= 0.2 pu,	Q= 0 pu

Figure 6– A through Figure 6 – D shows the rotor angle in pu response due to 0.1 pu load disturbance with and without controllers at the same load condition used in speed deviation response.

It is clear from the two figures that the system performance with the proposed MPC is much better than that of LQR and the oscillations are damped out much faster in all operation condition. This illustrates the potential and superiority of the proposed design approach to obtain an optimal set of PSS parameters.

A summary for the settling time with and without control at different operation condition are indicated in Table 1.

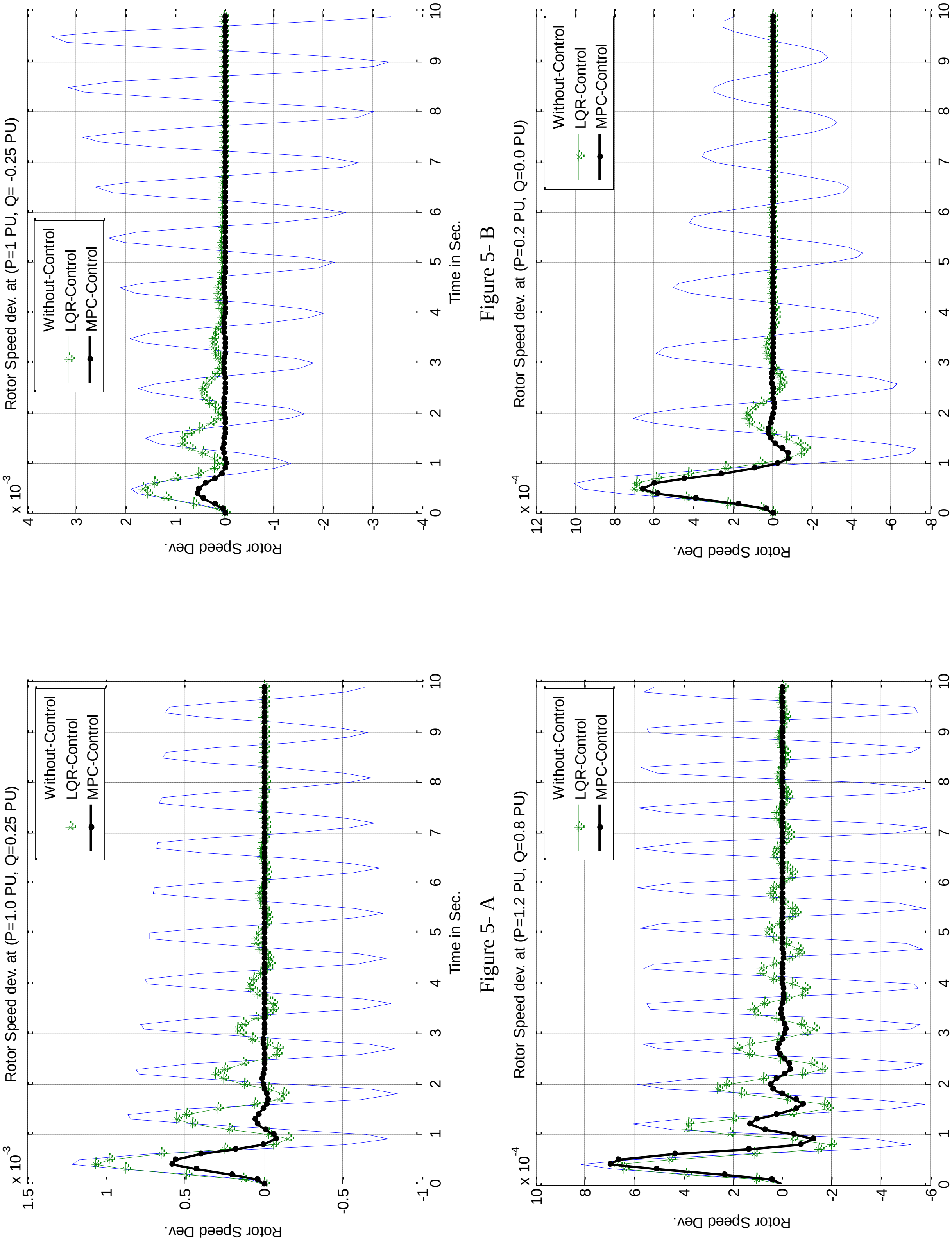

Figure 5- A

Figure 5- B

Figure 5- C

Figure 5- D

Figure 5: Rotor speed dev. Response due to 0.1 pu load disturbance with and without controllers, at different load condition

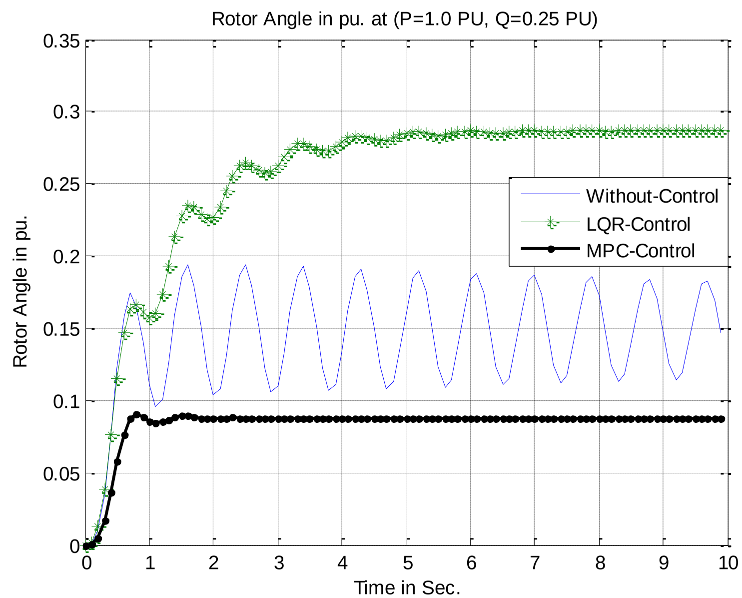

Figure 6- A

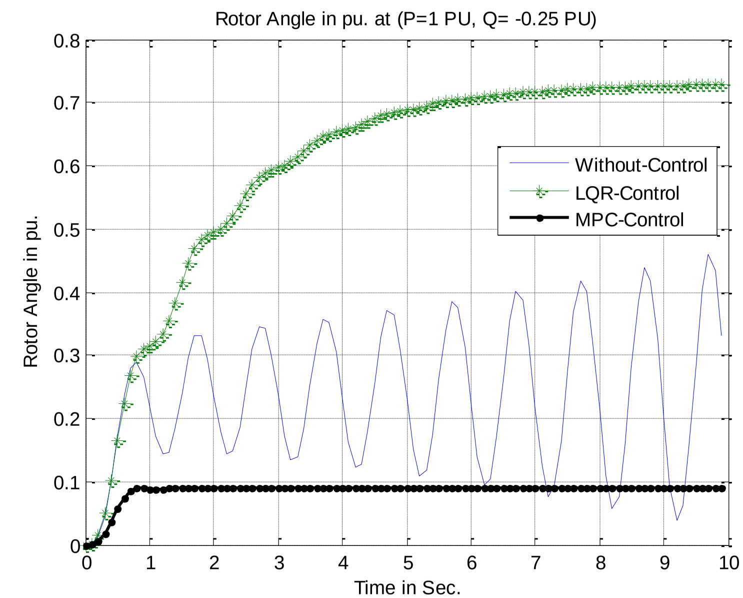

Figure 6- B

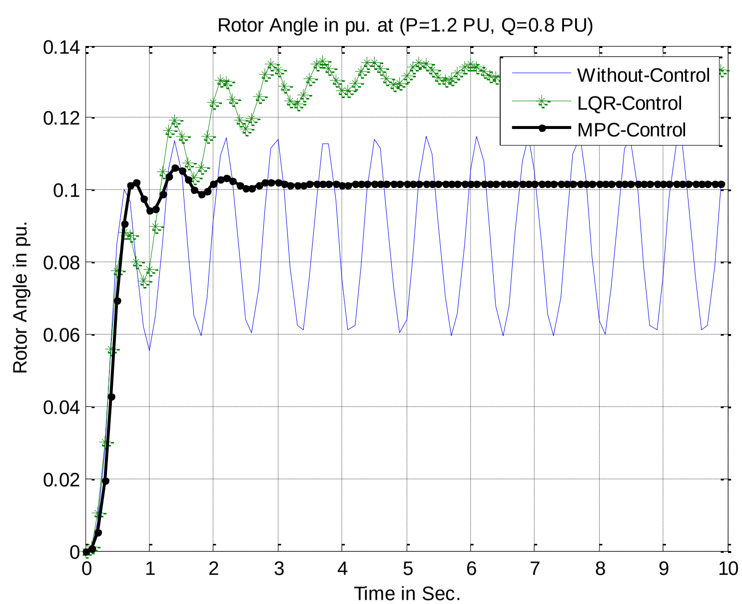

Figure 6- C

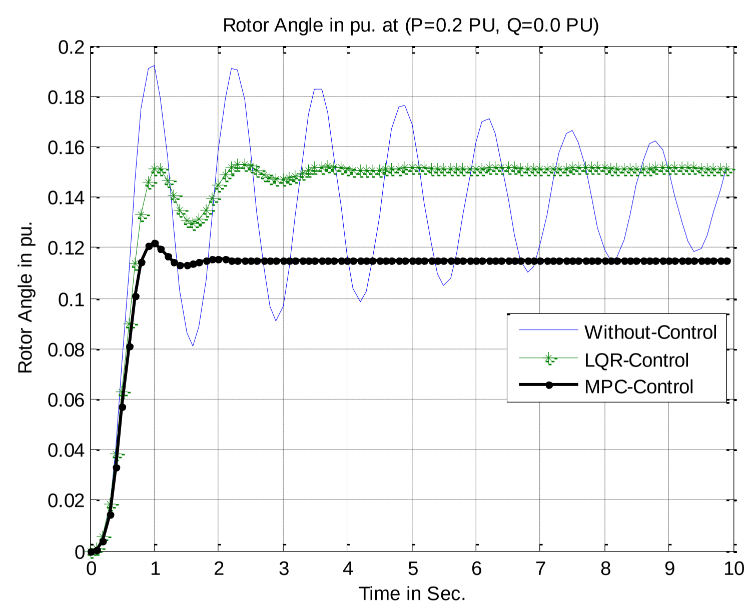

Figure 6- D

Figure 6: Rotor angle dev. response due to 0.1 pu load disturbance with and without controllers at different load condition

Table 1: Settling time with and without controllers

Operating point	Without control	LQR control	MPC control
A: P=1, Q=0.25 pu.	➢10 Sec.	6.5 Sec.	2 Sec.
B: P=1, Q= -0.25 pu.	∞	9 Sec.	3 Sec.
C: P=1.2, Q=0.8 pu	➢10 Sec.	4 Sec.	2 Sec.
D: P=0.2, Q=0.0 pu.	∞	7 Sec.	1.2 Sec.

9. Conclusion

In this paper, the design of power system stabilizer for improving power system dynamic performance over a wide range of operating conditions based on MPC was investigated and compared with LQR controller. In summary, we have shown that the oscillations are damped out with the two PSS controller at different load conditions, but with MPC the oscillations are damped out much faster.

The MPC has been developed to be included in power system in order to improve the dynamic response and gives the optimal performance at any loading condition. The MPC is better than LQR controller in terms of small settling time and less overshoot and under shoot. The simulation results show that the proposed PSS based upon the MPC can achieve good performance over a wide range of operating conditions.

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