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Transient Stability Enhancement using Coordinated DMPC for Power System

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Abstract— Present paper proposes a solution in the form of a Distributed Model Predictive Control (DMPC) strategy for excitation control in large scale networked applications, such as Multi-machine Power Systems (MMPS). Each MPC solves its own optimization problem using local decomposed model of the overall system, as it is more convenient to design control laws in distributed manner, based on only local measurements and reduced order dynamical model of the system. The coordination amongst these controllers is achieved through information exchange to obtain performance close to that of centralized MPC scheme. The effectiveness of the proposed DMPC is tested on a 3rd order model of 2-machine system with lossy transmission lines and loads.

Index Terms— Centralized control, Decentralized control, Distributed MPC, Excitation control, Multi-machine power system, Optimization , Transient Stability

1 INTRODUCTION

Control strategies are generally implemented depending upon dimension, complexity, and nature of the system. The centralized approach is based on the assumption that a powerful central station is available to control a group of systems and that each subsystem of the system has ability to communicate to a central location or share information via a fully connected network [1], [2]. The most natural and in some cases the only methodology for control of systems that are governed by constrained dynamics is MPC. For large systems, with a large number of inputs and outputs, synthesis and implementation of a centralized controller is not feasible in practice because the communication and computation costs increase with the size of the system. As a result, the centralized scheme does not scale well with the number of subsystems. Also real-world communication topologies are usually not fully connected. For such systems the decentralized or distributed controller strategies may be effectively used.

To match the ever increasing power demand, Multi-Machine Power Systems (MMPS) with strong interconnections among various parameters, came into existence. For such a highly complex, and nonlinear system centralized controllers were found inadequate which resulted into the need for decentralized and distributed controllers. In [1], a DMPC framework for automatic generation control is developed for large networked systems, such as power system, with strong interactions amongst the subsystems. An iterative Jacobi algorithm for solving DMPC problems with linear coupled dynamics and convex coupled constraints is addressed in [3].

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The authors have proved that the DMPC solution finally converges to the centralized one for a problem involving coupled oscillators. While applying DMPC for load-frequency control in a two-area power system, it was found that a compromise between improvement in performance and prediction errors could be achieved using DMPC rather than centralized MPC [5].

Due to the economic and infrastructure limitations, the existing power systems are stressed. Small disturbances are taken care of by the restoring torques, maintaining stability of the system. However, severe disturbances such as a 3-phase short circuit fault, may lead to cascade failure if the fault is not cleared before Critical Clearing Time (CCT). Transient stability thus being a major issue of concern, various methods are developed for its prediction, analysis and improvment. Methods such as Time Domain Simulations (TDS), Extended Equal Area Criterion (EEAC), direct methods using energy functions [6], Lyapunov methods, optimization methods are applied for transient stability analysis and improvement in MMPS. Although TDS [7] method works well irrespective of model used, it is extremely time-consuming making it unsuitable in real time. Finding Lyapunov function becomes extremely tedious when transmission line conductances are non-negligible.

In view of all this, the present paper proposes a DMPC strategy for excitation control of MMPS to improve transient stability. The distributed controller ensures fast control law generation due to the fact that each MPC needs to solve an optimization problem for a reduced order model as against a centralized controller. As a severe fault on a power system may result in complete blackout of the network in just a few milliseconds, a computation time and computation burden are most important in transient stability control and enhancement.

In a large interconnected power network, machines located at one point in a system are in unison, which can be considered as an equivalent large machine. Moreover, machines which are connected through a low reactance lines can be lumped together thereby reducing MMPS to a few machine system. Thus, the behaviour of a large power system can be thought of as extended version of a two machine system.

The paper is organized as follows: Section II describes a general MPC formulation along with different models of distributed MPC for large networked systems. An algorithm to solve optimization problem for distributed MPC is also formulated in Section II. A flux-decay model of 2-generator, 6-bus representative system is discussed in Section III, following simulation results supported by Matlab simulations in Section IV and conclusions in Section V.

2 MPC FORMULATION

A general MPC algorithm [2], [4] is described as:

1) Using the knowledge of past control inputs, past and present outputs and using the explicit model of the system, an optimization problem is solved to calculate the values of the manipulated variables, u, for the Nc sampling instants i.e. u(k), u(k + 1),…,u(k + Nc - 1), where, Nc is a control horizon. Predicted deviations from reference trajectory are computed over Np sampling instants while satisfying constraints on control variables as well as on state variables.

2) The first control move u(k) is implemented.

3) At the next sampling instant, k + 1, control inputs are recalculated for next Nc instants i.e from (k +1) to (k + Nc-1) and first control move u(k + 1) is implemented.

4) Steps 1) and 2) are repeated for subsequent sampling instants.

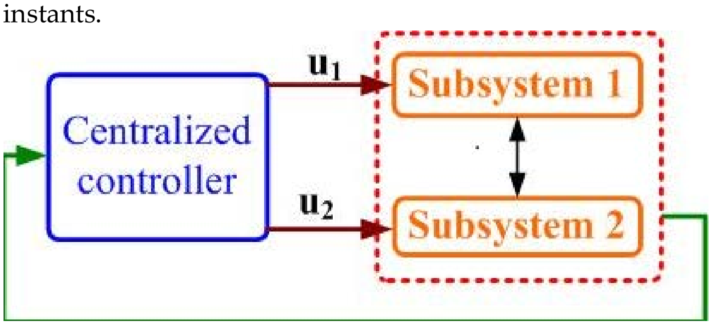

Fig 1. Centralized Controller

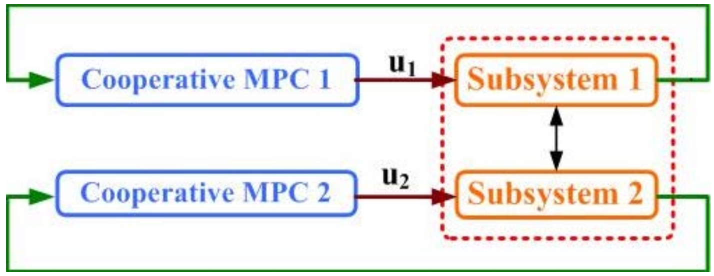

Fig. 2: Decentralized MPC

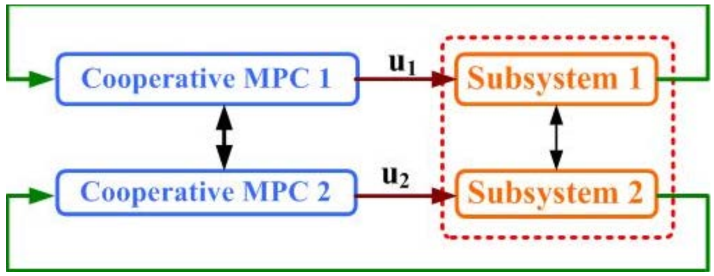

Fig. 3: Distributed MPC

In a decentralized approach, each subsystem is controlled independently and the controllers do not communicate with each other. In distributed control strategy subsystems as well as controllers communicate with each other. Distributed control designs are preferable, since they provide scalability, and reduce computational burden. They are natural realizations of the limitations in communication, networking, and sensing capabilities which are inherent in large scale systems. Different control strategies are:

2.1 Distributed MPC

Distributed MPC relies on decomposing the overall system model into appropriate subsystem models [1]. In distributed systems the resulting subsystems may have physical dependencies amongst them and therefore communication among them. One of the main problems of distributed control of large systems is to decide how those dependence relations between subsystems are preserved. The distributed approach allows for the distribution of decision making, subsystem reconfiguration with local coordination, and communications only between neighbouring agents.

2.2 Communication based MPC

Each communication based MPC utilizes the objective function for that subsystem only. For each subsystem i, at each iteration p, only the input sequence of that subsystem u_p is optimized and updated. The inputs of other subsystems remain at u_{p-1}. In the communication based MPC framework, each MPC of a subsystem has no information about the objectives of the MPCs of other interconnected subsystems.

2.3 Cooperation based MPC

To arrive at a reliable distributed MPC framework, it is required to ensure that the MPCs of subsystems cooperate, rather than compete with each other in achieving system-wide objectives. In large-scale implementations, the sampling interval may be insufficient to allow convergence of an iterative, cooperation based algorithm. In such cases, the cooperation based algorithm has to be terminated prior to convergence of exchanged trajectories. For both communication and cooperation based MPC, several subsystem optimizations and exchange of variables between subsystems are performed during a sample time. A Partitioned Model (PM) combines the effect of local subsystem variables and effect of states of the interconnected subsystems [1]. The PM is obtained by considering the relevant partition of the centralized model and can be written as [2]:

$$x_i(k+1) = x_i(k) + B_{ii}u_i(k)\sum_{j\neq i}(A_{ij}x_j(k) + B_{ij}u_j(k)) \quad (1)$$

For the j[th] agent, information from other agents is obtained as: [2]

$$v_j(k+i|k) = [x_1^T(k+1|k-1) \ldots x_{j-1}^T(k+1|k-1) \\ x_{j+1}^T(k+1|k-1) \ldots x_M^T(k+1|k-1)]^T \quad (2)$$

The objective in the present work is to achieve coordination mong subsystems that solve MPC problems with locally relevant variables, costs, and constraints, instead of solving a centralized MPC problem. Such a coordination scheme is effective when the local optimization problem is much smaller than a centralized problem, as in network control applications where the number of local states and control variables for each subsystem and the number of variables shared with other subsystems, are a small fraction of the total number of variables in the overall system. This means that the properties of the equivalent centralized MPC problem (e.g. stability) are enjoyed by the solution obtained using the coordinated distributed MPC implementation. In order to achieve this an analytic expression of the predicted states, $x_1, x_2, \ldots x_N$ is obtained in terms of present state, x_0, control inputs $u_0, u_1, \ldots u_{N-1}$ and states of other subsystems communicated at previous sampling instant.

$$\underbrace{\begin{bmatrix} x_{i0} \\ x_{i1} \\ \vdots \\ x_{iN} \end{bmatrix}}_{X} = \underbrace{\begin{bmatrix} I \\ A_{ii} \\ \vdots \\ A_{ii}^N \end{bmatrix}}_{S_x} x_0 + \underbrace{\begin{bmatrix} 0 & \vdots & 0 \\ B & \vdots & 0 \\ \vdots & \vdots & \vdots \\ A_{ii}^{N-1}B & \vdots & B \end{bmatrix}}_{S_u} \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-1} \end{bmatrix} + \underbrace{\begin{bmatrix} 0 & \vdots & 0 \\ A_{ij} & \vdots & 0 \\ \vdots & \vdots & \vdots \\ A_{ii}^{N-1}A_{ij} & \vdots & A_{ij} \end{bmatrix}}_{S_2} \begin{bmatrix} x_{jo} \\ x_{j1} \\ \vdots \\ x_{jN} \end{bmatrix} \quad (3)$$

In a compact form (3) becomes:

$$X_i = S_x x_0 + S_u U_0 + S_2 X_i \quad (4)$$

Then the objective function for DMPC is written as:

$$J_0(x_0, U_0) = U_0^T[S_u^T Q S_u + R]U_0 + x_0^T[S_x^T Q S_x]x_0 \\ + x_j^T[S_2^T Q S_2]X_j + 2[x_0^T S_x^T + X_j^T + X_j^T S_2^T]QS_u U_0 \quad (5)$$

The stepwise procedure for DMPC is summarised as follows:
Step 1: Send previous predictions of a controller of a particular subsystem, to other controllers and also receive information from other controllers which includes predictions at the current and future instants in a prediction horizon.
Step 2: Solve the optimal control problem
subject to:

$$x_i(k+i+1) = A_{ii}x_i(k+i|k) + B_i u_i(k+i|k) \\ + K_i v_i(k+i|k) \; for \; i = 0,1,\ldots,N-1 \quad (6)$$

Step 3: Apply the first element $u(k)$ of the control vector $U(k)$. Set $k = k+1$ and repeat the algorithm at next sampling instant. Thus each MPC deals with a reduced order model with a feq variables. The control law generation becomes faster and more accurate in large networked systems.

3 Dynamic model of 2-machine system

The algorithm described in Section 2 is applied to a 2-machine, 6-bus system is shown in Fig. 4.
The system is assumed to have stable equilibrium at $[\delta_i^\star, 0, E_i^\star]$ with $E_i^* > 0$, $|\delta_i^\star - \delta_j^\star|$ is small, and transfer conductances are small.

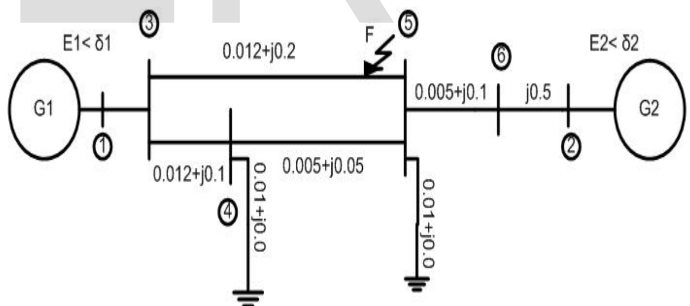

Fig. 4. 2-generator, 6-bus system

The system is represented by 3[rd] order flux decay model [6] as follows:

$$\dot{\delta}_i = \omega_i \quad (7)$$

$$\dot{\omega}_i = -D_i\omega_i + P_i - G_{ii}E_i^2 - E_i\sum_{\substack{j=1,\\ j\neq i}}^{n} Y_{ij}E_j\sin(\delta_i - \delta_j + \alpha_{ij}) \quad (8)$$

$$\dot{E}_i = -a_i E_i + b_i \sum_{\substack{j=1,\\ j\neq i}}^{n} E_j \cos(\delta_i - \delta_j + \alpha_{ij}) + E_{fi} + u_i \quad (9)$$

Where,

$$Y_{ij} \triangleq \sqrt{G_{ij}^2 + B_{ij}^2)} \quad (10)$$

$$\propto_{ij} \triangleq \tan^{-1}\frac{G_{ij}}{B_{ij}} \quad (11)$$

$$a_i \triangleq \frac{1}{T_{di}}(1 - B_{Mii}(x_{di} - x'_{di}) \quad (12)$$

$$b_i \triangleq \frac{(x_{di} - x'_{di})}{T_{di}} Y_{ij} \quad (13)$$

4 Simulation Results and Analysis

To implement the DMPC algorithm, a 2-generator, 6-bus system with lossy transmission lines represented by classical flux-decay model shown in Fig.5 is considered. The system being over stressed, is highly susceptible to a fault and its critical clearing time is almost zero. A three phase short circuit fault occurs on a power system at t =2 sec.

It is observed that DMPC designed stabilizes the system effectively. Variation of rotor angle delta and angular frequencies for the two generators are as shown in Fig. 5 and Fig. 6 respectively. The excitation voltages and corresponding control inputs are as depicted in Fig. 7 and Fig. 8 re spectively.

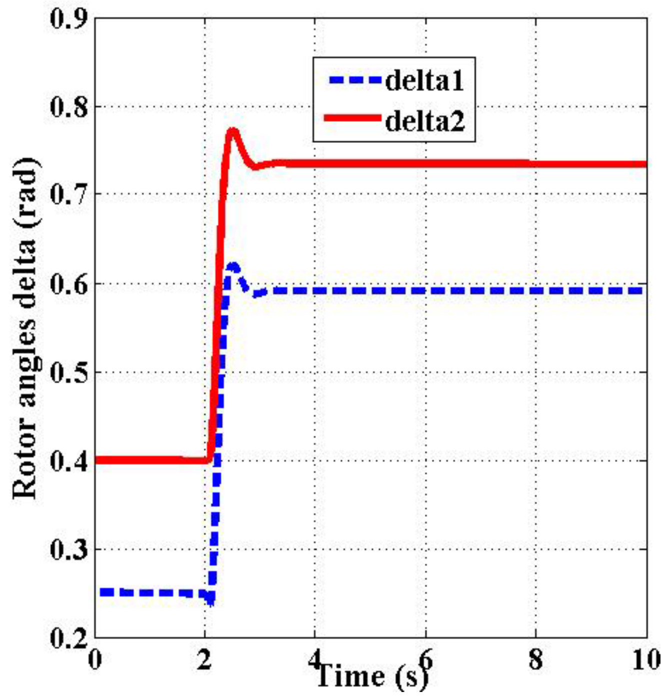

Fig. 5. Variation of rotor angle delta using DMPC

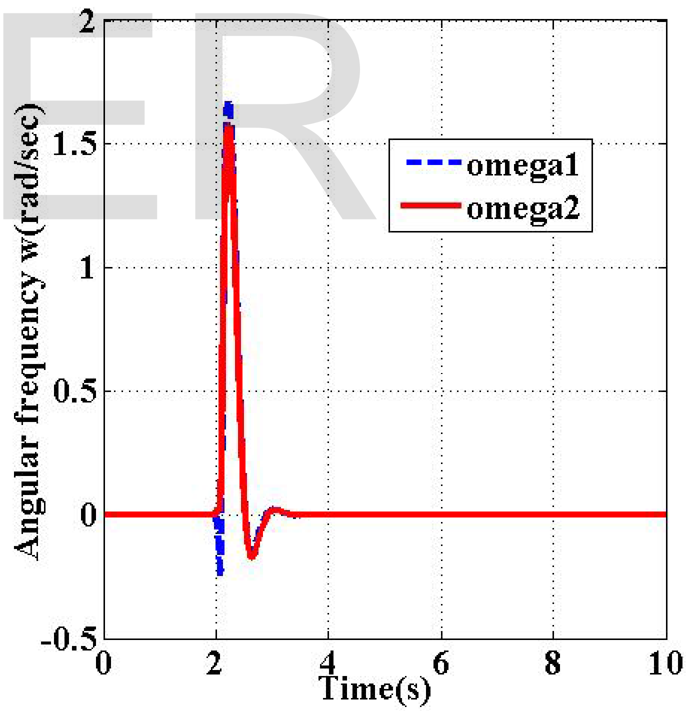

Fig. 6. Angular grequencies in 2-generator system

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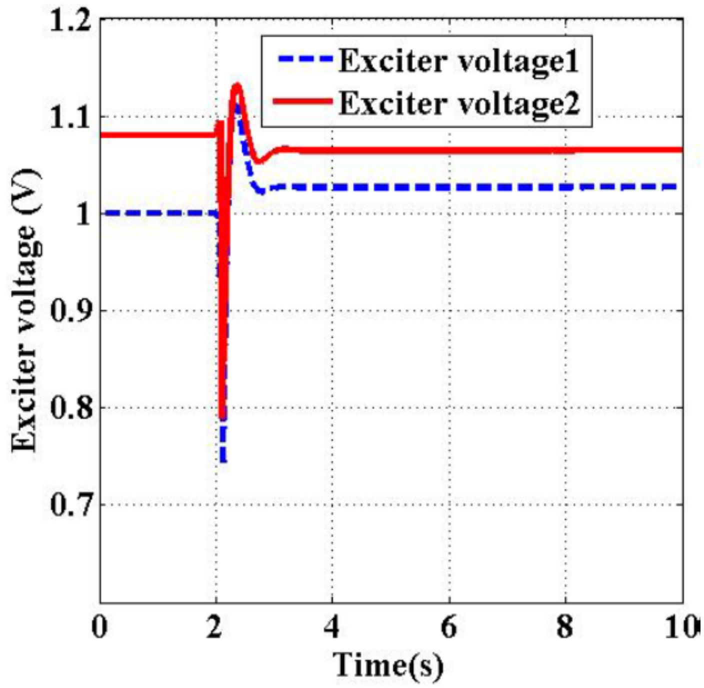

Fig, 7. Exciter voltages

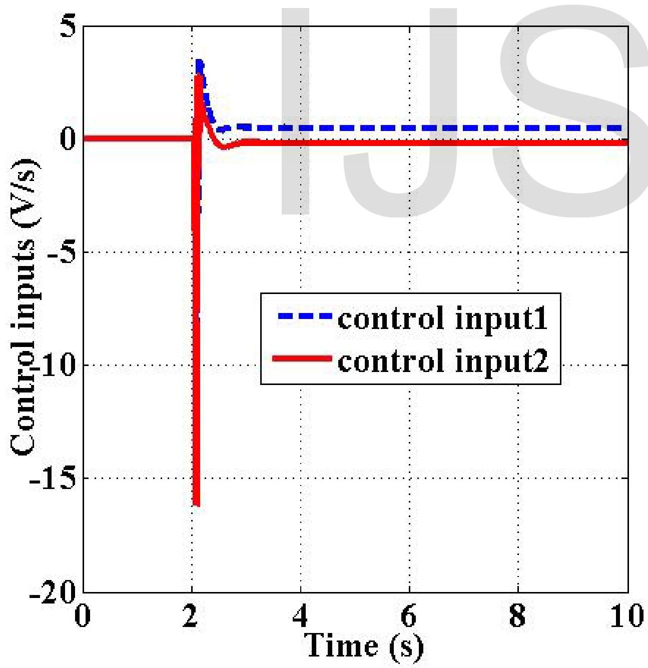

Fig. 8. Control inputs

5 Conclusions

The major limitation of centralized MPC application in large power system network is because of complexity and computation burden, which increases with the sizeof system and lengths of prediction and control horizon, Np and Nc respectively. The computation burden may result in large computation time making it unsuitable for real-time application. This limitation of centralized MPC is overcome with the help of DMPC, in which the complete network is controlled in the form of controllers taking care of their local subsystems. The controllers may exchange and communicate system as well as control information to remain in synchronism with eachother which is one of the essential criteria of power system stability. The 2-machine case study has been carried out to verify the proposed DMPC which has confirmed the effective use of DMPC for a large system

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