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2018

Patil, B. V., Sampath, L. P. M. I., Krishnan, A., & Foo, E. Y. S. (2019). Decentralized nonlinear model predictive control of a multimachine power system. *International Journal of Electrical Power & Energy Systems*, 106, 358-372. doi:10.1016/j.ijepes.2018.10.018

<https://hdl.handle.net/10356/143556>

<https://doi.org/10.1016/j.ijepes.2018.10.018>

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Decentralized Nonlinear Model Predictive Control of a Multimachine Power System

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Abstract

This paper proposes a novel decentralized nonlinear model predictive control approach for excitation control in multimachine power systems. A key feature of the proposed approach is the reduction of the multimachine control problem to multiple single-machine control problems. These reduced size control problems only require direct measurements from individual generators, thereby making implementation simple in practice. **The effectiveness of the proposed approach is demonstrated through computer simulations on a one small-size Western System Coordinating Council (WSCC) and one large-size New England power system under a wide range of operating conditions.** The performance of the proposed approach is evaluated in terms of damping power system oscillations, critical time enhancement, and control signal energy consumption. The results are compared with those obtained using power system stabilizer and feedback linearization based control schemes and found to be impressive.

Keywords: Bernstein polynomials, Global optimization, Decentralized control, Nonlinear model predictive control, Multimachine power systems, Excitation control.

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1. Introduction

In the last two decades, modern electrical power systems have experienced great changes due to large complexities arising from increasing levels of interconnections and the introduction of new technologies such as flexible alternating current transmission systems (FACTS) [1], [2], installation of high voltage direct current (HVDC) transmission systems [3], [4], and incorporation of renewable energy sources [5], [6]. In addition, in modern power systems, the distances between the places where energy is generated and consumed are often large. As a consequence the transients occurring among energy generating units might result in blackouts (see, for instance, [7], [8]). In this environment safe, stable, and efficient operation of power systems under transients has become quite challenging and is an active area of research from the last two decades (cf. [9], [10], [11], [12], [13], [14]).

The transient stability of a power system is its ability to maintain synchronism when subject to moderate or severe transients. Under such transients, there may be large oscillations in generator rotor angles, bus voltages, and other system variables [15]. For this reason, many control strategies have been proposed to provide additional damping to enhance power system stability [15]. In current practice, the excitation control system (ECS) of each synchronous generator (SG) is supplemented by a power system stabilizer (PSS) in order to damp out transient induced power system oscillations. The design of the PSS is mainly based on a linearized power system model obtained at a specific operating point. However, in practice the operating point of a power system can shift due to several factors, such as short circuits and changes in the network topology, thereby producing stability problems which may not be satisfactorily overcome by PSS controllers. Hence, to mitigate this issue and improve system performance in the presence of severe transients, few improved PSS variants are reported in the literature. For instance, [10] have introduced a neural network based PSS, which learns online from the measurement data. Similarly, [11] proposed a linear quadratic regulator (LQR) approach to determine the optimal

gains for the PSS. [12] proposed a decentralized PSS scheme, wherein modified Heffron-Phillip's model is used to decide the structure of the PSS compensator and tune its parameters at each machine in the multi-machine environment. [13] and [14] have experimented with the genetic algorithm and neural networks to determine the optimal gains for the PSS controller.

In the power systems literature, several nonlinear controller designs have also been investigated and compared with PSS. The feedback linearization (FL) nonlinear control scheme have been extensively studied in the literature [16]. In FL the nonlinear system model is algebraically transformed to a linear representation. These control schemes have demonstrated superior performance in simulations compared with the PSS (cf. works by Mahmud et al. [17], [18], [19], [20]). However, the implementation of FL-based excitation controllers requires the exact values of power system parameters. Similarly, other nonlinear control techniques, such as sliding-mode control [21], [22], adaptive control [23], [24], H_∞ [25], and backstepping control schemes [26], [27] have also been explored in the literature. However, aforementioned control schemes are sub-optimal in terms of the power systems performance and excitation energy consumption.

In last few years, model predictive control (MPC) have been explored in the different research areas [28], [29], [30]. Similarly, MPC has also gained a wide popularity in the power system applications (see, [31], [32], [33], [34], [35]). This is due to MPC's natural ability to include the dynamic system model along with constraints on the states and control inputs directly in an online optimization problem. Further, it also has a multi-step predictive approach which reflects the future trend of system dynamics, thereby improving closed-loop control performance and robustness. Traditionally, MPC problems utilize linear models for the system description (a.k.a linear MPC schemes), for which several offline as well as online efficient solution approaches exist. In contrast to linear MPC, many applications demand model development from first-principle physical laws (for instance, power systems). These models are often nonlinear in nature and linear MPC utilizing aforementioned linear/convex optimization techniques can typically not be applied. In such situations, nonlinear model predictive control

(NMPC) are well-known tools [36], [37], [38], [39], [40], [41], [42]. It is noteworthy that NMPC has the following two challenges:

- (i) can we obtain an optimal solution for the underlying nonlinear optimization problem?
- (ii) can we achieve (i) in a restricted sampling time interval? To overcome particularly challenge (ii), researchers' in the power systems have proposed different variants of decentralized NMPC schemes (see, for instance, [43], [44], [45], [46], [47]).

The main contribution of this paper is to address the challenges (i) and (ii) in a synergistic manner. First, a novel approach is proposed to obtain a decentralized configuration of multimachine power systems. This decentralization essentially transforms the interconnected generators into individual subsystems composed as the single-machine infinite bus (SMIB). This particularly allow us to alleviate the computational burden associated with the challenge (ii). Secondly, a NMPC-based controllers are then designed for controlling these individual SMIB subsystems. It is worth noting that, a NMPC for the individual SMIB subsystems requires the solution of a *nonconvex* optimization problem at each sampling instant to obtain a control law. As such, we advocate the computationally efficient Bernstein global optimization optimization procedure to solve the online optimization problems. This aids in overcoming the challenge (i). The beauty of the proposed decentralized scheme is that it only requires local and direct measurements from the generator for its implementation. Henceforth, the aforementioned proposed approach will be referred to as the decentralized nonlinear model predictive control (DNMPC) strategy. The DNMPC strategy is applied to develop a controller for the benchmark WSCC power system (3 generators, 9 buses) [48]. Various transient simulation studies are performed and the results are compared with those obtained using well established control techniques such as PSS and FL to assess the efficacy of the DNMPC strategy. Further, scalability of the DNMPC strategy is shown by applying it to a large-size (10-machine, 39-bus) New England power system model [49].

The remainder of this paper is organized as follows. The dynamic model of

the power system and formulation of an NMPC controller are reviewed in Section 2. The Bernstein global optimization algorithm to obtain an NMPC control law is presented in Section 3. The proposed DN MPC scheme is presented in Section 4. The results from various simulation studies performed on the **WSCC and New England power systems** are discussed in Section 5 wherein the performance of the proposed DN MPC strategy is compared and contrasted with the performance of the PSS and FL control schemes. The paper concludes with a summary and some future research directions in Section 6.

2. Review

2.1. Power System Modeling

The power system comprises several generators, transformers, and transmission lines forming an interconnected network spread over a wide geographical area. Let there be N SGs in the power system supplying the desired power demand. The complete excitation system model of the i^{th} generator suitable for control purposes is described as follows [15]:

$$\dot{\delta}_i = \omega_i - \omega_{0i} \quad (1)$$

$$\dot{\omega}_i = \frac{1}{2H_i} (\omega_{0i}(P_{mi} - P_{ei}) - D_i(\omega_i - \omega_{0i})) \quad (2)$$

$$\dot{e}'_{qi} = \frac{1}{T'_{d0i}} (e_{fdi} - e'_{qi} - (x_{di} - x'_{di})I_{di}) \quad (3)$$

$$\dot{e}_{fdi} = \frac{K_{Ai}}{T_{Ai}} \left(V_i^{ref} - V_{ti} - \frac{e_{fdi}}{K_{Ai}} + u_i \right) \quad (4)$$

where $i = 1, 2, \dots, N$, δ_i is the rotor angle of the i^{th} generator, ω_i is the rotor speed of the i^{th} generator, H_i is the inertia constant of the i^{th} generator, P_{mi} is the mechanical input power to the i^{th} generator which is assumed to be constant, D_i is the damping constant of the i^{th} generator, P_{ei} is the electrical power delivered by the i^{th} generator, e'_{qi} is the q -axis transient voltage of the i^{th} generator, T'_{d0i} is the excitation circuit time constant, e_{fdi} is the excitation field voltage of the i^{th} generator, x_{di} is the d -axis synchronous reactance of a

generator, x'_{di} is the d -axis transient reactance of a generator, I_{di} is the direct-axis and quadrature-axis currents of the i^{th} generator, V_i^{ref} is the reference voltage of the i^{th} generator, and u_i is the control input from the controller which modulates e_{fdi} . K_{Ai} and T_{Ai} are the exciter gain and time constant of the i^{th} generator respectively. All parameters are expressed in per unit (pu).

The algebraic equations for the electrical parameters of the i^{th} generator are given below

$$P_{ei} = e_{qi}^2 G_{ii} + e'_{qi} \sum_{j=1, j \neq i}^n e'_{qj} B_{ij} \sin(\delta_{ij}) \quad (5)$$

$$Q_{ei} = -e_{qi}^2 G_{ii} - e'_{qi} \sum_{j=1, j \neq i}^n e'_{qj} B_{ij} \cos(\delta_{ij}) \quad (6)$$

$$I_{di} = -e'_{qi} G_{ii} - \sum_{j=1, j \neq i}^n e'_{qj} B_{ij} \cos(\delta_{ij}) \quad (7)$$

$$I_{qi} = e'_{qi} G_{ii} + \sum_{j=1, j \neq i}^n e'_{qj} B_{ij} \sin(\delta_{ij}) \quad (8)$$

$$V_{ti} = \sqrt{(e'_{qi} - x'_{di} I_{di})^2 + (x'_{di} I_{qi})^2} \quad (9)$$

where x_{di} is the direct-axis synchronous reactance of the i^{th} generator, x'_{di} is the direct-axis transient reactance of the i^{th} generator, G_{ii} and B_{ii} are the self-conductance and self-susceptance of the i^{th} line respectively, G_{ij} and B_{ij} are the conductance and susceptance between the i^{th} and j^{th} lines respectively, I_{di} and I_{qi} are direct-axis and quadrature-axis currents of the i^{th} generator respectively, P_{ei} and Q_{ei} are the real and reactive powers generated by the i^{th} generator respectively, and V_{ti} is the terminal voltage of the i^{th} generator.

2.2. Nonlinear Model Predictive Control Formulation

In this section, an NMPC variant reported in the literature is presented (see, for instance, [50]). This NMPC scheme shall be employed in the proposed DNMPCC strategy reported in Section 4.

Consider a class of continuous-time systems described by the following non-

linear model:

$$\dot{x} = f(x, u), \quad x(t_0) = x_0 \quad (10)$$

where $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$ denote the vectors of states and control inputs, respectively. In practice, the continuous-time model (10) used for predictions is discretized with a sampling time Δt . One can use Runge-Kutta method (order 4/5) [51], 2-stage integration method (trapezoidal rule) [52], or Euler's method (in equation (11)). We note Euler's method provides good approximation in context of this work while keeping computational burden low. The discretized model using the Euler's method is described by the following equation:

$$x_{k+1} = x_k + \Delta t \cdot f(x_k, u_k) \quad (11)$$

where k denotes the sampling instant.

The nonlinear optimization problem in the NMPC framework is described by (12)-(16) at each sampling instant k . The control objective is to maintain the system at its equilibrium point $(\bar{x}, \bar{u})$ by minimizing the cost (12) subject to the discretized nonlinear predictive model (13) and constraints of the form (14)-(15).

$$\min_{u_k} \sum_{k=0}^{N-1} (x_k - \bar{x})^T Q (x_k - \bar{x}) + (u_k - \bar{u})^T R (u_k - \bar{u}) \quad (12)$$

$$\text{subject to} \quad x_{k+1} = x_k + \Delta t \cdot f(x_k, u_k) \quad (13)$$

$$x_k^{\min} \leq x_k \leq x_k^{\max} \quad (14)$$

$$u_k^{\min} \leq u_k \leq u_k^{\max} \quad (15)$$

$$\text{for } k = 0, 1, \dots, N-1 \quad (16)$$

where $N(\geq 1)$ denotes the prediction horizon. The cost (12) penalizes the deviations from the equilibrium point $(\bar{x}, \bar{u})$.

The aforementioned NMPC formulation requires the solution of a (usually *nonconvex*) nonlinear optimization problem at each sampling instant. NMPC is therefore mathematically challenging problem, and is dependent on the adoption

of good optimization procedures for its performance. Hence, in the present work, we employ a global optimization procedure based on the well-known Bernstein form of polynomials [53]. This procedure uses several nice geometrical properties associated with the Bernstein form. Recently, the authors of [54] reported some encouraging preliminary findings using one such Bernstein global optimization algorithm for predictive control of nonlinear hybrid systems. Based on this, the authors believe that the proposed DN MPC strategy will benefit, adopting the Bernstein global optimization algorithm in terms of systems and control performance.

3. Bernstein global optimization algorithm

We first introduce necessary notions and properties about the Bernstein form of the polynomials. This Bernstein form is embed in a suitable branch-and-bound framework for globally optimizing the nonlinear optimization problems encountered in an DN MPC strategy (of Section 4).

Assume $l \in \mathbb{N}$ be the number of variables and $x = (x_1, x_2, \dots, x_l) \in \mathbb{R}^l$. Then we define the following quantities.

- A multi-index, $I = (i_1, i_2, \dots, i_l) \in \mathbb{N}^l$, and $N = (n_1, n_2, \dots, n_l) \in \mathbb{N}^l$.
- For two multi-indices $I, N \in \mathbb{N}^l$, inequalities $I \leq N$ as $0 \leq i_1 \leq n_1, \dots, 0 \leq i_l \leq n_l$.
- Binomial coefficient, $\binom{N}{I}$ for $\binom{n_1}{i_1} \cdots \binom{n_l}{i_l}$, if $N \geq I$.
- Division, (N/I) for $(n_1/i_1, \dots, n_l/i_l)$ provided that $0 < i_k, k = 1, 2, \dots, l$.
- The multi-power, $x^I = (x_1^{i_1}, x_2^{i_2}, \dots, x_l^{i_l})$.
- An interval $\mathbf{x}$ as a closed connected subset of $\mathbb{R}$ with lower and upper bounds $\underline{x}, \bar{x} \in \mathbb{R}$. We write $\mathbf{x} = [\underline{x}, \bar{x}] = \{x \in \mathbb{R} : \underline{x} \leq x \leq \bar{x}\}$.
- An l -dimensional interval vector or box $\mathbf{x}$ as a vector of l intervals $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_l)$. The width of this box as maximum of its component-wise widths, $w(\mathbf{x}) := \max(w(\mathbf{x}_1), w(\mathbf{x}_2), \dots, w(\mathbf{x}_l))$.

Now we can write an l -variate polynomial p with real coefficients as

$$p_f(x) = \sum_{I \leq N} a_I x^I, \quad x \in \mathbb{R}^l, \quad (17)$$

with N being the degree of p . We transform (17) into the following Bernstein form to obtain bounds for its range over an l -dimensional box $\mathbf{x}$

$$p_b(x) = \sum_{I \leq N} b_I(\mathbf{x}) B_I^N(x), \quad (18)$$

where $B_I^N(x)$ is the I^{th} Bernstein basis polynomial of degree N defined as

$$B_I^N(x) = B_{i_1}^{n_1}(x_1) \cdots B_{i_l}^{n_l}(x_l), \quad x \in \mathbb{R}^l, \quad (19)$$

for $i_j = 0, 1, \dots, n_j$, $j = 1, 2, \dots, l$,

$$B_{i_j}^{n_j}(x_j) = \binom{n_j}{i_j} \frac{(x_j - \underline{x}_j)^{i_j} (\bar{x}_j - x_j)^{n_j - i_j}}{(\bar{x}_j - \underline{x}_j)^{n_j}}, \quad (20)$$

and $b_I(\mathbf{x})$ are the Bernstein coefficients computed as a weighted sum of coefficients a_I in (17) over the box $\mathbf{x}$ as

$$b_I(\mathbf{x}) = \sum_{J \leq I} \frac{\binom{I}{J}}{\binom{N}{J}} w(\mathbf{x})^J \sum_{K \leq J} \binom{K}{J} (\inf \mathbf{x})^{K-J} a_K, \quad I \leq N. \quad (21)$$

Note all the Bernstein coefficients $b_I(\mathbf{x})_{I \in S}$ form an array, where $S = \{I : I \leq N\}$. Further, we denote S_0 as a special set comprising only vertex indices from S , that is

$$S_0 = \{(0, 0, \dots, 0), (n_1, 0, \dots, 0), (0, n_2, 0, \dots, 0), \dots, (n_1, n_2, \dots, n_l)\}.$$

Properties:

For a polynomial p_f in (17), let its range be $\text{Range}(p_f(x)) = [a, b]$. Then following properties hold [53]:

(P1) Range enclosure

$$\text{Range}(p_f(x)) \subseteq [\min b_I(\mathbf{x})_{I \in S}, \max b_I(\mathbf{x})_{I \in S}].$$

The above property says that the minimum and maximum Bernstein coefficients from the array $b_I(\mathbf{x})_{I \in S}$ provide lower and upper bounds for the range of the polynomial $p_f(x)$.

(P2) Convex hull

$$\text{Conv}(p_f(x)) \subseteq (I/N, b_I(\mathbf{x})_{I \in S}).$$

The above property says that the range of the polynomial $p_f(x)$ is contained in the convex hull generated using the points $(I/N, b_I(\mathbf{x})_{I \in S})$.

(P3) Vertex

$$\begin{aligned} a &= \min_{0 \leq I \leq N} b_I(\mathbf{x}) \text{ if and only if } \min_{0 \leq I \leq N} b_I(\mathbf{x}) = \min_{I \in S_0} b_I(\mathbf{x}) \\ b &= \max_{0 \leq I \leq N} b_I(\mathbf{x}) \text{ if and only if } \max_{0 \leq I \leq N} b_I(\mathbf{x}) = \max_{I \in S_0} b_I(\mathbf{x}) \end{aligned}$$

The above property says that the range of a polynomial $p_f(x)$ is exact, if and only if $\min b_I(\mathbf{x})_{I \in S}$ (respectively $\max b_I(\mathbf{x})_{I \in S}$) is attained at the Bernstein coefficients from an array $(b_I(\mathbf{x}))$ with $I \in S_0$. In practice, satisfaction of vertex property within user-specified accuracy (ϵ_f) is adequate. As such, following form of the vertex property is used

$$b_I(\mathbf{x})_{I \in S_0} - \min_{I \in S} b_I(\mathbf{x}) \leq \epsilon_f. \quad (22)$$

Remark 2: Define $B_f(\mathbf{x}) := [\min b_I(\mathbf{x})_{I \in S}, \max b_I(\mathbf{x})_{I \in S}]$ be the Bernstein range enclosure for a polynomial $p_f(x)$ on a given box $\mathbf{x}$. Then, the following mathematical identities hold

- $B_f(\mathbf{x}) \leq 0 \Rightarrow p_f(x) \leq 0$ for all $x \in \mathbf{x}$.
- $B_f(\mathbf{x}) > 0 \Rightarrow p_f(x) > 0$ for all $x \in \mathbf{x}$.
- $0 \notin B_f(\mathbf{x}) \Rightarrow p_f(x) \neq 0$ for all $x \in \mathbf{x}$.
- $B_f(\mathbf{x}) \subseteq [-\epsilon_h, \epsilon_h] \Rightarrow p_f(x) \in [-\epsilon_h, \epsilon_h]$ for all $x \in \mathbf{x}$, where $\epsilon_h > 0$.

We now give the pseudo-code for the main Bernstein global optimization algorithm BBB.

Algorithm Bernstein branch-and-bound $[f^*, \mathbf{x}^*] = \text{BBB}(f, g_i, h_j, \mathbf{x}, \epsilon_f, \epsilon_{zero})$

Inputs: The cost function (12) as f , equality constraints (13) as h_j , and inequality constraints (14)-(15) as g_i , the initial search box for x_k and u_k as $\mathbf{x} = [x_k \ u_k]^T$, the tolerance parameter ϵ_f on the global minimum, and the tolerance parameter ϵ_{zero} to which the equality constraints are to be satisfied.

Outputs: The global minimum f^* and global minimizer $\mathbf{x}^*$.

BEGIN Algorithm

Initialization step

- Compute the Bernstein range enclosures (as per **Remark 2**) for f , g_i , and h_j , respectively as B_f, B_{g_i} , and B_{h_j} over $\mathbf{x}$. Set $\hat{f}$ to the minimum Bernstein coefficient of B_f and $\tilde{f} = \hat{f}$ ($\tilde{f}$ is the best minimum estimate).
- Construct $\mathcal{L} \leftarrow \{(\hat{f}, B_f, B_{g_i}, B_{h_j}, \mathbf{x})\}$, $\mathcal{L}^{sol} \leftarrow \{\}$.

Sorting step

- If $\mathcal{L}$ is empty, then go to termination step. Else sort item(s)² in $\mathcal{L}$ in ascending order of $\hat{f}$.
- Pick the first item from $\mathcal{L}$ removing its entry. Denote this item of the form² as $\mathcal{I}$ and proceed to the feasibility-bounding step.

Feasibility-Bounding step

- For an item $\mathcal{I}$, check the constraint feasibility (cf. **Remark 2**). If the constraint is not strictly feasible, then go to the branching step.

²Each item in the list $\mathcal{L}$ is of the form: $(\hat{f}, B_f, B_{g_i}, B_{h_j}, \mathbf{x})$.

- Check the vertex condition for an item $\mathcal{I}$ (cf. property (P3)). If ‘true’, then update $\tilde{f} = \min(B_f)$ and add that item to $\mathcal{L}^{sol}$. Go to sorting step.

Branching step

- For an item $\mathcal{I}$, partition the (feasible) search space $\mathbf{x}$ into two subregions as $\mathbf{x} = \mathbf{x}_1 \cup \mathbf{x}_2$.
- Compute the Bernstein range enclosures for f , g_i , and h_j over $\mathbf{x}_1$ and $\mathbf{x}_2$ as done in the initialization step.
- Discard $\mathbf{x}_k$, $k = 1, 2$ for which $\min(B_{f,k}) > \tilde{f}$. Enter $(\hat{f}_k, B_{f,k}, B_{g_{i,k}}, B_{h_{j,k}}, \mathbf{x}_k)$ into the list $\mathcal{L}$ ($\hat{f}_k := \min(B_{f,k})$).

Termination step

- Find that item in $\mathcal{L}^{sol}$ for which the first entry is equal to $\tilde{f}$. Denote that item by $\mathcal{T}_f$.
- $\mathcal{T}_f$: the first entry is a global minimum f^* , last entry is the global minimizer $\mathbf{x}^*$.
- Return the global solution $(f^*, \mathbf{x}^*)$.

END Algorithm

4. Proposed Decentralized Strategy

In this section, the proposed DN MPC strategy is presented. Specifically, a multimachine power system consisting of N interconnected generators as given by (1)-(4) is considered. The main essence of the DN MPC strategy lies in transforming these interconnected generators into N subsystems composed as the single-machine infinite bus (SMIB) [15]. This allow us to alleviate the computational burden associated with the centralized NMPC of (1)-(4) (cf. Fig. 6). NMPC-based controllers are then designed for controlling these individual subsystems. The WSCC system shown in Fig. 1 is used as an exemplar system

Step 2: Obtain SMIB representation for generators.

The SMIB subsystems (M) is obtained at the generator buses (*i.e.*, 4, 7, and 9). In this case, we obtain $M = 3$ models of the form (23)-(26), wherein (v_r) is the reference bus voltage at each bus obtained in *Step 1*. For simplicity, the subscript i ($i = 1, 2, \dots, M$) is omitted from the subsystem models of the form given in (23)-(26). Fig. 2 shows an example of the SMIB subsystem being applied for the second generator.

$$\dot{\delta} = \omega - \omega_r \quad (23)$$

$$\dot{\omega} = \frac{1}{2H} (P_m - P_e - D(\omega - \omega_r)) \quad (24)$$

$$\dot{e}'_q = \frac{1}{T'_{d0}} \left(-\frac{x_{dr}e'_q}{x'_{dr}} + \frac{(x_{dr} - x'_{dr})}{x'_{dr}} \nu_r \cos(\delta) + e_{fd} \right) \quad (25)$$

$$\dot{e}_{fd} = -\frac{1}{T_A} e_{fd} + \frac{K_A}{T_A} (V^{\text{ref}} - V_t) + \frac{K_A}{T_A} u \quad (26)$$

where

$$P_e = \frac{e'_q \nu_r \sin(\delta)}{x_{dr}} + \frac{(x_{dr} - x_{qr})}{x_{dr} x_{qr}} \nu_r^2 \cos(\delta) \sin(\delta). \quad (27)$$

$$Q_e = \frac{\nu_r}{x_{dr}} (e'_q \cos(\delta) - \nu_r) - \nu_r^2 \frac{(x'_{dr} - x_{qr})}{x_{dr} x_{qr}} \sin^2(\delta). \quad (28)$$

$$V_t = \sqrt{(e'_q - x'_d I_d)^2 + (x'_q I_q)^2}. \quad (29)$$

$$x_{dr} = x_d + x_r, \quad x_{qr} = x_q + x_r, \quad x'_{dr} = x'_d + x_r. \quad (30)$$

Note that the aforementioned symbols have their usual meanings in the context of SMIB systems as reported in the literature [15].

Step 3: Derivation of control law for the decentralized system.

At the outset, the nonlinear dynamic model in (23)-(26) is discretized using Euler's method to obtain a model of the form (11). Then, based on the NMPC scheme reported in Section 2.2, the control signal is obtained at every sampling instant k . The optimization problem is nonconvex due to the nonlinearities involved in individual decentralized subsystems of the form (23)-(26). As already mentioned, we solve these optimization problems using the Bernstein global optimization algorithm reported in the Section 3. Fig. 3 shows the complete

(a)

(b)

Figure 2: Example of decentralization of the WSCC system shown in Fig. 1. (a) Decoupling of the generator connected to bus 2. v_r is the reference voltage at bus 7 obtained from the power flow solution. (b) Equivalent circuit used to model the synchronous generator as an SMIB subsystem.

DNMPC strategy along with the excitation control system (ECS).

Remark 1: The ECS for the decentralized system shown in Fig. 3(b) requires the generator states δ , ω , and e'_q to be known. The rotor speed ω of SG is directly measured while e'_q can be determined from the internal voltage drop of the SG ($e'_q - V_t$) as shown below [15].

$$e'_q - V_t = \frac{P_e r_s + Q_e x_d}{V_t} \quad (31)$$

where r_s is the generator's stator winding resistance. Assuming this resistance is very small, the following equation can be written [15]:

$$e'_q = \frac{Q_e x_d}{V_t} + V_t \quad (32)$$

(a)

(b)

Figure 3: (a) DNMPC strategy for the WSCC system shown in Fig. 1. (b) Excitation control system (ECS) for i^{th} subsystem (shown by red dotted blocks in Fig. 3(a).)

where active and reactive powers, respectively P_e and Q_e , the terminal voltage V_t are measured while parameter x_d is known. Further, we can obtain δ by substituting Q_e and e_q' in (28).

5. Simulation Results

In this section, the dynamic performances of various control schemes for the WSCC system shown in Fig. 1 are evaluated first. Later, we study scalability aspect of the proposed DNMPC strategy over a large New England power sys-

tem. For all simulations, the dynamic performance is evaluated through various time domain studies in MATLAB environment [56] running on a desktop PC with Intel®Core i7-5500U CPU processor at 2.40 GHz with a 8 GB RAM. Note that for the DN MPC strategy, the power system model and NMPC controller is implemented as two separate m-functions in a working MATLAB directory. The main MATLAB file sequentially calls each of this sub-functions during execution phase. The main MATLAB script also executes pre-defined faults in a sequential manner so that system dynamics is evaluated as per the call for power system model and control law is computed as per a NMPC controller evaluation.

The performances of linear and nonlinear MPC schemes for the centralized power system described in (1)-(4) are evaluated first. The findings of this study provide further motivation for adopting the DN MPC strategy. Subsequently, the DN MPC strategy is evaluated on the basis of the following: i) additional damping provided during the post-fault period; ii) the transient stability enhancement ability; and iii) control signal energy consumption. The DN MPC strategy is compared with two well established control schemes for the excitation control problem, namely PSS [15], and partial feedback linearization (PFL) [19].

To demonstrate the efficacy of the DN MPC strategy, two simple performance metrics given by (33)-(34) were calculated.

$$DM = \mathcal{W}_{os} \times (OS)^2 + \mathcal{W}_{us} \times (US)^2 + (ST)^2. \quad (33)$$

DM indicates a damping measure for the generator rotor angle obtained by summing peak positive deviation from equilibrium point (OS), peak negative deviation from equilibrium point (US), and the settling time (ST) as time taken by the response to reach and steady within 2% of its equilibrium point. $\mathcal{W}_{os}$ and $\mathcal{W}_{us}$ are the weights on OS and US respectively. Both these values are chosen to be 100. DM reflects the ability of the controller to damp out power system oscillations in the post-fault state. As such, better damping capabilities lead to better OS, US, and ST. Hence, a lower value for this index indicates

better controller performance in terms of the additional damping required by the power system during the post-fault state.

$$EM = T \times \sum_{i=0}^{N_s-1} u_i^2. \quad (34)$$

EM is a measure of energy which indicates the total energy utilized by the control signal (u_i) in bringing the system back to its equilibrium state. T is the sampling-time, u_i is the control signal to the i^{th} generator, and N_s the number of samples. EM reflects the controller's ability to optimally use the control signal to bring the system back to the equilibrium state. In other words, a lower EM value indicates a better energy utilization capability of the controller.

For all simulation scenarios (I, II, III), an NMPC scheme to maintain the decentralized WSCC system (Fig. 3) at its equilibrium point is implemented. The nonlinear model for each decentralized subsystem (23)-(26) is discretized using Euler's method for purpose of the simulation studies. The NMPC control law is derived by solving a nonlinear programming problem of the form (12)-(16) using the Bernstein global optimization algorithm BBB (see Section 3). The states are updated based on the set of given initial conditions and the first optimal control input computed by the NMPC controller. The following parameter values were used for simulating the DN MPC strategy:

- sampling time of 30 ms
- prediction horizon, $N = 3$
- $Q = I_{12 \times 12}$ and $R = I_{3 \times 3}$ as weighting matrices
- equilibrium point, $\bar{u} = [3.5899 \quad 4.5098 \quad 4.9531]$ and

$$\bar{x} = [0.0396 \quad 1 \quad 1.0565 \quad 1.0321 \quad 0.3443 \quad 1 \quad 1.0502 \quad \dots \\ 0.7766 \quad 0.2299 \quad 1 \quad 1.0169 \quad 0.9967]^T$$

- constraints on the control input, $-5 \leq u_i \leq 5$ ($i = 1, 2, 3$)
- tolerances, $\epsilon_p = \epsilon_{zero} = 0.001$ in the algorithm BBB on the global minimum and equality constraint satisfaction.

Based on our experience with the simulation experiments reported in this work, the prediction horizon (N) of 3 is sufficient to stabilize the system. This also facilitates practical feasibility of the DN MPC strategy for a sampling time of 30 ms.

Centralized model predictive control of the power system

In this study, the control performance and feasibility of implementing MPC schemes for the centralized power system model (1)-(4) are assessed. Specifically, the performance of the linear MPC (LMPC) and nonlinear MPC (NMPC) schemes are compared for the centralized power system model with a sampling time of 30 ms. The findings of this study further motivate the need to explore the DN MPC strategy. The simulation study is carried out as described below.

The simulation is carried out by applying a symmetrical three-phase to ground short-circuit fault in the middle of the transmission line connecting buses 5 and 7 (Fig. 1). The fault duration is 120 ms and it is applied and cleared as follows:

- The fault occurs at $t = 0.15$ seconds.
- The fault is cleared at $t = 0.27$ seconds.

Fig. 4 shows the rotor angle deviations of the generators G1, G2, and G3. The solid red lines represent the rotor angle response obtained with the centralized NMPC scheme which provides better damping when compared with the centralized LMPC (dotted blue lines) scheme. It is observed that the NMPC scheme offers better control overall especially for G2 and G3 with a notable 15% decrease in overshoot.

Fig. 5 shows the change in the control signals applied to the generators. It is observed that both LMPC and NMPC schemes have smooth variation in control signals which are well within the saturation limits (± 5). It is observed that the NMPC scheme resulted in stronger control signals in terms of magnitude. This accounts for the improved response seen in Fig. 4). Fig. 6 assesses the practical applicability of the LMPC and NMPC strategies wherein the computational

Figure 4: Rotor angle deviations from the equilibrium point ($\bar{x}$) of G1, G2, and G3 obtained using centralized linear MPC (LMPC) and nonlinear MPC (NMPC) schemes for Scenario I.

Figure 5: Control signal deviations from the equilibrium point ($\bar{u}$) of G1, G2 and G3 obtained using centralized linear MPC (LMPC) and nonlinear MPC (NMPC) schemes for Scenario I.

times taken by both MPC schemes to compute the control law at each sampling instant are compared. It is observed that LMPC and NMPC take an average of 11 ms and 60 ms respectively to compute the control law. Subsequently, it is observed that the DN MPC strategy takes an average of 22 ms to compute the control law. More details on this are provided in later sections.

The following paragraphs present results from various simulation studies

Figure 6: Comparison of the computation times needed to compute the control law using centralized LMPC, centralized NMPC and decentralized NMPC schemes at each sampling instant for Scenario I. Sampling time is 30 ms.

conducted with the DN MPC strategy presented in Section 4.

Example 1: 9-bus WSCC system

Scenario I: Outage of one transmission line connecting buses 5 and 7.

In this study, the simulation is carried out under the same short-circuit fault scenario described earlier in centralized MPC of the power system. Fig. 9(a) shows the rotor angle deviations of generators G1 and G2. The solid red line represents the rotor angle response obtained with the DN MPC strategy which provides much better damping when compared with the PSS (dotted black line). Further, based on the rotor angles response of G2, it is observed that DN MPC offers slightly better damping when compared with the PFL scheme. This is

evident from Table 1 which reports DM (see Eq. 33) of G2 for the Scenario I. We observed around the improvement of 32% in the rotor angle damping of G2 when compared with the PFL scheme. Fig. 9(b) shows the rotor speed deviations of G1 and G2. It is observed that the DN MPC strategy provides better control overall, especially for G2 for which an 85% decrease in overshoot and faster settling time are observed. The corresponding terminal voltage responses of G1 and G2 are shown in Fig. 10. It is observed that both PFL and DN MPC achieve transient stability quickly in the post-fault scenario when compared with PSS.

Fig. 11 shows the change in the control inputs applied to the generators. It is seen that both PSS and PFL switch back and forth between ± 5 pu at high frequency before settling. In practice, such control signal oscillations may shorten the working life of power electronic devices in the system. On the other hand, control inputs generated by the DN MPC controller have smaller oscillations and are well within the saturation limits (± 5). This is further verified from Table 1 which reports the EM (see equation (34)) of G2 for Scenario I. The DN MPC strategy results in an 86% reduction in control signal energy consumption when compared with the PFL scheme. Further, similar findings were observed for G3 for the same simulation scenario. These results have been omitted for the sake of brevity.

Scenario II: Three phase to ground short-circuit fault at the terminal of G3.

In this study, the simulation is carried out by applying a symmetrical three-phase to ground fault at bus 9. The consequences of this fault include disconnection of G3 and transmission lines connecting bus 9 to bus 6 and bus 9 to bus 8. Further, the system may become unstable during the post-fault period due to insufficient damping. A fault duration of 120 ms is considered to assess the performance of the DN MPC strategy. The performance of the DN MPC strategy is again compared with the PSS and PFL control schemes.

The system is simulated by assuming constant input mechanical power ($P_m = 0.8504$ pu) to G3. Fig. 12(a) shows the corresponding rotor angle deviations.

It is observed that the DN MPC strategy results in less overshoot with a faster settling time when compared with the PSS and PFL schemes. This is further evident from Table 1 which reports the DM (see equation (33)) of G3 for Scenario II. With the DN MPC strategy, an improvement of 43% in the rotor angle damping of G3 was observed when compared with the PFL scheme.

Fig. 12(b) shows the speed deviation responses of G3 obtained with DN MPC (solid red line), PFL (solid blue line), and PSS (dotted black line) schemes from which zero speed deviation is obtained during the post-fault period. The proposed DN MPC ensures very good transient stability when compared with PSS and slightly better settling time when compared with the PFL scheme.

Further, when the terminal of G3 is faulted, the post-fault generator electrical power and terminal voltage have to be controlled to their equilibrium operating points. The stability of these parameters is mainly influenced by the rotor angle and speed deviation responses. As the DN MPC and PFL ensure good transient stability of rotor angle and speed deviation, the electrical power and terminal voltage which are close to zero, shift to their pre-fault levels. Fig. 12(c) illustrates the electrical power responses. It is observed that the DN MPC strategy results in very good control of electrical power when compared with PSS (approximately 15% less overshoot) and slightly less overshoot when compared with the PFL scheme. Similarly, Fig. 12(d) shows the terminal voltage responses. It is observed that the DN MPC strategy quickly brings the terminal voltage to its equilibrium value during the post-fault period when compared with the PSS and PFL control schemes.

Fig. 8 shows the change in the control inputs applied to the generator. It is seen that both PSS and PFL schemes have large oscillations in control inputs before settling. On the other hand, the control input obtained with the DN MPC strategy has smaller oscillations and is well within the saturation limits (± 5). This is further verified from Table 1 which reports the EM (see Eq. 34) of G3 for Scenario II. The DN MPC strategy results in a 64% reduction in control signal energy consumption when compared with PFL.

Scenario III: 5% and 10% step changes in P_m to G2.

In this study, the power system is first simulated with G2 operating with a nominal $P_m = 0.8504$. Subsequently, P_m is initially reduced by 5% from its nominal value (*i.e.* from 0.8504 pu to 0.8079 pu) at 1s and again increased by 10% (*i.e.* from 0.8079 to 0.8887) at 4s. For the first change in P_m (reduction by 5% from its nominal value), the difference between the electrical power generated and the desired load is reflected in a reduction in the rotor speed. Consequently, the rotor angle settles down to a lower equilibrium point value. This phenomenon is reversed when P_m is increased by 10%.

The rotor angle and speed deviation responses are shown in Figs. 13(a) and (b) respectively. The dotted black line indicates the response obtained with PSS; solid blue line indicates the response obtained with the PFL scheme; whereas the solid red line shows the response obtained with the DN MPC strategy. It is observed that the performance of the DN MPC strategy is far superior to the PSS and slightly better than the PFL in terms of the damping provided and settling time.

Fig. 13(d) shows the terminal voltage response to the changes in P_m to G2. It can be seen that the voltage responses obtained using both the DN MPC strategy and PFL scheme experience brief periods of transients but finally settle close to the original equilibrium point (*i.e.* equal to V^{ref}). Small offsets are evident in the voltage response obtained with the PFL scheme. In addition, notable transients are observed in the voltage response obtained with PSS.

Finally, the practical applicability of the DN MPC strategy for a sampling time of 30 ms is assessed. The computational times required to compute the control law at each sampling instant for simulation scenarios I, II, and III are evaluated and compared. Fig. 14 shows the computation time cluster of the DN MPC strategy for Scenarios I, II, and III. Table 2 reports the computation times taken to compute the control moves at each sampling instant (*i.e.* to solve an NLP of the form (12)-(16)) by the algorithm BBB (see Section 3). It is clear that the time taken to compute control inputs is well within the sampling period of 30 ms (average of 20-22 ms for all scenarios).

Scenario IV: Model mismatch simulation under Scenario I.

In this study, the simulation is carried out under the same short-circuit fault described earlier in Scenario I. However, the simulations has been carried out in two different ways. The results with the solid blue line represents DN MPC strategy without any mismatch between NMPC prediction model and the actual power systems model. On the other hand, the results with the solid red line represents DN MPC strategy with mismatch in the NMPC prediction model and the actual power systems model. To obtain the mismatch in the models, the inertia constant (H) in the actual power systems is reduced by 20% from its value used in the NMPC prediction model.

Figs. 7(a)-(b) shows the rotor angle deviations of generators G1 and G2. The solid blue line (no model mismatch) with the DN MPC strategy clearly provides slightly better damping in terms of the overshoot and undershoot when compared with the solid red line. Similar findings were observed in case of the terminal voltages of generators G1 and G2 in Figs. 7(c)-(d). It is worth noting that, despite of the model mismatch, the solid red and blue lines has a same settling time. This clearly demonstrates the robustness property of the DN MPC strategy under the model mismatch.

Figure 7: Performance of DNMPC strategy for Scenario I under model mismatch. (a) Rotor angle deviation from the equilibrium point $(\bar{x})$ of G1. (b) Rotor angle deviation from the equilibrium point $(\bar{x})$ of G2. (c) Terminal voltage of G1. (d) Terminal voltage of G2.

Table 1: Comparison of performance metrics for PFL and DN MPC strategies.

Performance metrics	Scenario I (Generator 2)		Scenario II (Generator 3)	
	PFL	DN MPC	PFL	DN MPC
DM	8.9792	6.1392	9.8070	5.5821
Improvment in DM using DN MPC	...	31.63 %	...	43.08 %
EM	6.5016	0.9252	5.6542	2.0348
Reduction in EM using DN MPC	...	85.77 %	...	64.01 %

Table 2: Comparison of average computational times for the DN MPC strategy (sampling time 30 ms).

DN MPC	Scenario I	Scenario II	Scenario III
At Gen. 1	0.0203	0.020	0.0212
At Gen. 2	0.0206	0.0211	0.0222
At Gen. 3	0.0209	0.0211	0.0223

Figure 8: PSS, PFL, and DN MPC control signal deviations from the equilibrium point ($\bar{u}$) of G3 in case of three phase fault at the terminal of G3 (Scenario II).

(a)

(b)

Figure 9: Performance of PSS, PFL, and DN MPC schemes for Scenario I. (a) Rotor angle deviations from the equilibrium point ($\bar{x}$) of G1 and G2. (b) Speed deviations of G1 and G2.

(a)

(b)

Figure 10: Performance of PSS, PFL, and DN MPC schemes for Scenario I. (a) Terminal voltage of G1. (b) Terminal voltage of G2.

(a)

(b)

Figure 11: Control signal deviations from the equilibrium point ($\bar{u}$) of G1 and G2 obtained using PSS, PFL, and DN MPC schemes for Scenario I.

Figure 12: Performance of PSS, PFL, and DNMPC schemes for Scenario II. (a) Rotor angle deviation from the equilibrium point ($\bar{x}$) of G3. (b) Speed deviation of G3 (c) Electrical power of G3. (d) Terminal voltage of G3.

Figure 13: Performance of PSS, PFL, and DNMP schemes for Scenario III. (a) Rotor angle deviation from the equilibrium point ($\bar{x}$) of G2. (b) Speed deviation of G2 (c) Electrical power of G2. (d) Terminal voltage of G2.

Figure 14: Comparison of the computation times needed to compute the control law for generators G1 ($\circ$), G2 ($*$), G3 ($\star$) using the DN MPC scheme at each sampling instant for Scenarios I, II, and III. Sampling time is 30 ms.

Example 2: 39-bus New England power system

In contrast to the above simulations on the WSCC three-machine power system, this section presents the simulation on the 10-machine, 39-bus New England power system. This way we further observe the effectiveness of the DN MPC scheme for a large power system. The New England system is shown in Fig. 15. In this system, bus bar 39 is an infinite bus. For space restrictions, rest of the system data is not presented. Remaining details of the system data used in the analysis for generator, transformer, network and load flow can be obtained from the reference [49].

Figure 15: New England 10-machine, 39-bus power system.

Note that due to more generators and buses for New England system, the interaction in the system dynamics will be more and may pose problems in the control parameter adjustment. However, under the DN MPC scheme, each generator is modeled as an independent SMIB subsystem and nonlinear interactions between generators are considered through a explicit power flow solutions and control law of each generator is derived separately. From the forthcoming system responses and computational time results, it is worth noting that DN MPC

scales very well with the size of the power system, and each individual DN MPC controller in turn contributes positively to the overall system performance.

The simulation is carried out by applying a symmetrical three-phase to ground short-circuit fault in the middle of the transmission line connecting buses 26-29. The fault duration is 120 ms which occurs at 0.15 seconds and is cleared at 0.27 seconds. NMPC prediction horizon (N) is chosen to be 3 and suffices to give good system responses. The weighting matrices in the individual NMPC controllers are chosen as $Q = I_{40 \times 40}$ and $R = I_{10 \times 10}$. Considering the typical nature of results as obtained for the WSCC system and space limitations, results are presented only for the generators in the vicinity of the fault. Fig. 16 shows the rotor angle deviations of the generators G8 and G9, and terminal voltages of G8 and G9. Similarly, Fig. 17 shows electrical power variations of G8 and G9 under three-phase fault. It also shows the respective computational time in milli-seconds at each sampling instant for the individual NMPC controllers for G8 and G9 in the DN MPC scheme. It can be seen from the results, that all states and parameters of New England system safely restore to the stable values in the post-fault under the DN MPC control scheme. Moreover, control inputs generated in the DN MPC strategy are quite smooth in nature and well within the saturation limits (± 5).

Finally, we observe the consistency in terms of the computational time results for a sampling time of 30 ms. The computational times required to compute the control law at each sampling instant for generators G1-G10 are evaluated and compared. Fig. 18(b) shows the computation time cluster of the DN MPC strategy for the individual NMPC controllers at a each generator. It is clear that the time taken to compute control inputs is well within the sampling period of 30 ms. Moreover, we note on an average individual NMPC controllers took same 20-22 ms as obtained for WSCC system. This clearly demonstrates the scalable nature of the DN MPC scheme.

(a)

(b)

Figure 16: Performance of DNMPCC scheme for New England system. (a) Rotor angle deviations from the equilibrium point ($\bar{x}$) of the generators G8 and G9. (b) Terminal voltages of G8 and G9.

(a)

(b)

Figure 17: Performance of DNMPD scheme for New England system. (a) Electrical power of the generators G8 and G9. (b) Comparison of the computation times needed to compute the control law for G8 ($\circ$) and G9 ($*$) using the DNMPD scheme at each sampling instant. Sampling time is 30 ms.

(a)

(b)

Figure 18: Performance of DNMPCC scheme for New England system. (a) Control signal deviations from the equilibrium point ($\bar{u}$) of the generators G8 and G9. (b) Comparison of the computation times needed to compute the control law for generators G1-G7 and G10 using the DNMPCC scheme at each sampling instant. Sampling time is 30 ms.

Acknowledgment

This research is supported by the National Research Foundation, Prime Ministers Office, Singapore under its CREATE programme.

6. Conclusions

This paper presented a new decentralized strategy for excitation control of interconnected multimachine power systems. In this decentralized strategy, each machine was modeled using a single-machine infinite bus, wherein the reference voltage for the infinite bus was obtained from the power flow solution of the network. Further, the derivation of the excitation control law was formulated as an optimization problem in the nonlinear model predictive control framework. The resulting optimization problem was solved using the Bernstein global optimization algorithm. The overall applicability of the DN MPC strategy was demonstrated on the 3-machine, 9-bus WSCC power system under a wide variety of fault scenarios. Simulation results clearly demonstrated the superior performance of the DN MPC strategy. The DN MPC strategy achieved the post-fault steady-state operating condition with better oscillation damping and settling time when compared with the PSS and PFL control schemes. Further, scalability of the DN MPC strategy is shown by applying it to a large-size (10-machine, 39-bus) New England power system model.

The DN MPC strategy is expected to be of practical benefit for power systems due to its efficient constraint handling capability. Further, the authors believe that the DN MPC strategy benefits from the adoption of the Bernstein global optimization algorithm due to its ability to accurately locate the globally optimal solution thereby making it a good candidate for solving online nonlinear optimization problems. Put together, these factors lead to improved control performance, as demonstrated on the WSCC and New England power system models studied in this work.

The work reported in this paper can be extended in the following directions:

- In future the implementation of the DNMPCC strategy on more efficient platforms, such as FPGA can be considered so as to study realistic scenarios at faster time-scales (≈ 10 ms).
- Future work can consider the design of DNMPCC strategy by considering an extensive model of multimachine power systems, e.g., the inclusion of steam-valving systems.

Appendix I (WSCC power system data)

The data for all the generators in the WSCC system (shown in Fig. 1) apart from parameter values for the exciter (shown in the Fig. 3(b)) and PSS used in our simulation studies are listed below. The conventional PSS structure shown in Fig. 19 was adopted for all the simulation studies in this paper.

Table 3: Generator Data For The WSCC System [48].

Parameter	Generator 1	Generator 2	Generator 3
D	0.31	0.5350	0.6
H (sec)	23.64	6.4	3.01
x_d	0.1460	0.8958	1.3125
x'_d	0.0608	0.1198	0.1813
x_q	0.0969	0.8645	1.2578
x'_q	0.0969	0.1969	0.25
T'_{d0} (sec)	8.96	6	5.89
V^{ref} (pu)	1.04	1.04	1.02

Figure 19: Conventional power system stabilizer (PSS) controller structure.

The conductance matrix (G_{ij}) and the the susceptance matrix (B_{ij}) in Eqs. (5)-(8) are as follows:

$$G_{ij} = \begin{pmatrix} 0.8453 & 0.2870 & 0.2095 \\ 0.2870 & 0.4199 & 0.2132 \\ 0.2095 & 0.2132 & 0.2770 \end{pmatrix}$$

$$B_{ij} = \begin{pmatrix} -2.9882 & 1.5130 & 1.2256 \\ 1.5130 & -2.7238 & 1.0879 \\ 1.2256 & 1.0879 & -2.3681 \end{pmatrix}$$

Table 4: Exciter Parameters [15]

Description	Parameter	Value
Exciter gain	K_A	200
Exciter time constant (sec)	T'_{d0}	0.001
Minimum excitation voltage (pu)	$e_{fd}^{\min}$	-5
Maximum excitation voltage (pu)	$e_{fd}^{\max}$	5

Table 5: PSS Parameters [14]

Parameter	Value		
	Generator 1	Generator 2	Generator 3
Gain (K_p)	31.6110	27.0077	33.3345
Washout filter (T_w in sec)	1.4120	1.4120	1.4120
Phase compensation (T_1, T_2) in sec	(0.0562, 0.0173)	(0.0202, 0.0155)	(0.0560, 0.0104)
Phase compensation (T_3, T_4) in sec	(0.0576, 0.0172)	(0.0674, 0.0185)	(0.0781, 0.0115)

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