Robust Multi-Model Based Control

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***Abstract*-- This paper describes a novel robust control system design for nonlinear systems. The central concept is the robust identification of the plant by a time varying linear model and using it to design a robust controller stipulated by the H¥ control theory. In this approach, the nonlinear plant is replaced by a time varying linear plant, and the designed controller is also time varying. The assumption that the resulting controller will provide adequate control of the original nonlinear plant has been tested and validated on a power system model, which is a highly nonlinear and a complex dynamic system.**

***Index Terms*-- Adaptive control, Adaptive signal processing, Digital control, Discrete time systems, H-infinity control, Industrial control, Linear systems, Power system control, Power system identification, Robustness,**

I. Introduction

THE instability of power systems is an inherent problem that has challenged power system engineers for decades. The generating units in power systems were equipped with continuously-acting voltage regulators in order to boost their synchronizing power during large disturbances. As these systems became more widespread it was evident that the voltage regulators provided adequate synchronizing power and thereby improved the stability of the systems in the first swing. However, it was also observed that these fast acting controllers with high regulator gains contributed to negative dumping and consequently to undesirable sustained or growing oscillations in the range of 0.1 Hz to 2.5 Hz, when the system was recovering from the effects of a large disturbance. The need for additional supplementary stabilizing signals in the voltage regulator circuits that provide positive damping to low frequency oscillations has been firmly established in the early 1960s [1][2].

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As a result of industrial development, the transmission lines and generators are loaded to their maximum capacities. Consequently, the generators need to rely more heavily on their excitation systems to maintain synchronism, and at some point, without supplementary control, the synchronizing oscillations become unstable. The supplementary controller that has been widely used is the so-called Power System Stabilizer (PSS).

From the early days, the design of the PSS was based on the conventional control theory. The present industrial control realization is dominated by the conventional PSS1A controller, described in IEEE Standard P421.5/D15. The dominance of PSS1A can be explained by the simplicity of the lead-lag compensator implementation and maintenance, using trial and error. However, when a PSS1A is used to control a highly nonlinear process, the controller must be tuned very conservatively in order to provide stable behavior over the entire range of operating conditions. Conservative controller tuning can result in serious degradation of control system performance.

Designing a PSS that meets the ever-increasing stability requirements of the present power systems is a challenging task because of the highly nonlinear dynamics and strong performance requirements under the wide variations in plant parameters. In order to improve the power system stability, a novel robust power system stabilizer design procedure is proposed in this paper. Other methods, such as fuzzy controllers, despite their popularity over the last two decades, [3]-[5], have not gained a significant share in controller implementation. The motivation for this paper arose from recent developments in robust control theory, which include the H_∞ optimal control design and control-oriented identification.

In order to implement the H_∞ controller, it is required to obtain a linear model of the plant. Since the early 1980s, it has been gradually recognized that the real challenge of control engineering is the modeling of the plant to be controlled [6]. The main contribution of this paper is the development of a robust control-oriented modeling procedure for an unknown plant subsequently followed by a robust control design. The plant model is obtained by a control-oriented system identification procedure. This modeling process uses the observed input-output data of the system and the model is constructed by fitting a parameter model to the observed data. Although, this model will always be a simplified representation of the unknown plant, the subsequent H_∞ robust control is designed to account for the presence of the modeling error.

This process of system identification can be also seen as a search for the solution of an overdetermined system of equations. The overdetermined system is characterized by a significantly higher number of equations than variables. In system identification the observed input-output data corresponds to the equations, while the model parameters stand for the variables. An exact solution for the overdetermined system does not exist, only an approximate one. The approximate solution is based on a criterion for solution search. In the literature there are numerous criteria to fit the model parameters to the observed data. The selected criterion defines the identification method.

Generally, the criterion for solution search is based on minimizing a particular norm of the error between the output from the estimated model and the observations. There are three dominant norms in the literature. The first norm criterion, l_1, is when the criterion is selected to minimize the average absolute value of the difference between the model and the observations. The second norm criterion, l_2, is applied when the parameters for the model are selected in a way to minimize the average squares of the differences between the model and the observations. The third or infinity norm criterion, l_∞, is implemented when the objective is to minimize the single largest difference between the model and the observations. These three types of identification methods are the basis for the different types of algorithms.

A countless number of implementation methods for the identification algorithms can be found in the research literature. It is impossible to define the best identification method due to the fact that for the different implementations the criterion for the "best" changes with the particular requirements. A system identification that uses many different models simultaneously dismisses the task of evaluating the best identification method for a particular implementation. Instead, an expert system is designed which, in real-time, selects the best identification method from a pool of methods running in parallel. This real-time multi model system identification is possible due to the advances in computation power.

The research in this paper describes a robust PSS implementation, where the system model is obtained in real-time by system identification processes, and it is used to determine the discrete-time H_∞ (sub)optimal controller, also in real-time. Each time when an updated system model is available, an optimal control problem with an H_∞ control objective is solved. The resulting H_∞ controller is utilized until a new update on the system model becomes available, thereby providing an update to the H_∞ controller.

The effectiveness of the proposed robust PSS is demonstrated by simulation and experimental tests. Through the implementation process, the robust PSS is examined in order to determine how well it handles model uncertainty, disturbances and measurement noise. The results are compared to that of a Conventional Power System Stabilizer (PSSA1) on the same benchmark power system model realized in software and on a scaled physical model using the micro-synchronous generator at the University of Calgary.

II. Robust System Identification

The generic problem formulation for system identification using the black-box model can be described as an observation of the unknown system, $G(t)$, based on the collected N discrete data points, $Z^N = [\{u_n\},\{y_n\}]$, that consist of the applied input signal, $\{u_n\}$, and the observation of the (possibly) disturbed output signal, $\{y_n\}$, as presented in Fig. 1. [7]. The additive disturbance, v^x_n, acting on the output of the system is used to model the effects on the observation that cannot be described by the input, applied to the system [8].

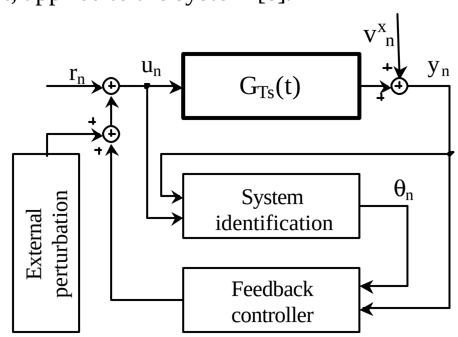

Fig. 1. Closed-loop system identification

Identification in closed-loop [9], as presented in Fig. 1., leads to a control oriented identification, which is a better predictor of the closed-loop dynamics, resulting in a more accurate estimation of the system model, $G(?)$, at the control relevant frequencies

A. *System identification*

System identification of general nonlinear structures is quite demanding in the estimation mathematical procedures as well as in the observed data quality and quantity. The well practiced solution for this problem is the linearization of the nonlinear system around a certain trajectory, using the fact that the controller in closed-loop system identification can linearize the nonlinear system behavior at a relevant operating point. This trajectory will be a time varying function of the nonlinear system's operating point, with a linear model

$$G(q_n, Ts) = f_n^T \cdot q_n \tag{1}$$

using a time varying parameter vector q_n and measurement vector f_n. The estimated parameter vector is

$$q_n = [d_{md}, a_1 \ldots a_{ma}, b_1 \ldots b_{mb}, c_1 \ldots c_{mc}]^T \tag{2}$$

where m_d, m_a, m_b and m_c are the dimensions of the appropriate measurements and parameters, which are selected as zero if the corresponding parameter is not included in the model. The measurement vector is defined as

$$f_n = [1, y_{n-1} \dots y_{n-ma}, u_{n-1} \dots u_{n-mb}, v_{n-1} \dots v_{n-mc}]^T . \quad (3)$$

There are many means available to provide an estimate for using q_n observation of input-output data sequence, Z^N. The strategy for identification, $\mathrm{T_i}$, can be defined as

$$q_n = \mathrm{T_i}(\{u_n\}, \{y_n\}) \quad (4)$$

where $\mathrm{T_i}$ represents the selected strategy for identification.

The research literature on closed-loop identification is very extensive, suggesting that in the closed-loop environment, the prediction error method is one of the best approaches to be applied [9], which minimizes the p norm of the prediction error

$$T_i: \ q_n = \underset{q}{\arg\min} \left\| y_n - f_n^T q_n \right\|_p . \quad (5)$$

Selection of different norms renders different solution strategies, T_i. For example, if $p = 1$ it is the "Worst-Case Estimation" algorithm; if $p = 2$ it is the "Least Squares" algorithm; and if $p = \infty$ it is the "Least Mean Squares" algorithm. This can be interpreted as a problem of an overdetermined system [10], where there are more equations than unknowns.

The use of a $p = 1$ norm criterion is appropriate when it is suspected that a small portion of the data being analyzed is unreliable (i.e., contains data outliers). The $p = 1$ norm criterion has the capability of effectively ignoring a few bad data points while emphasizing the majority of data points which more properly reflects the true nature of the data [11].

The use of a $p = 2$ norm criterion makes no assumption other than the measurement errors of the data being analyzed have a normal distribution about the mean (i.e., broadband measurement noise).

The use of a $p = \infty$ norm criterion is appropriate when it is desired to find an approximate solution to an inconsistent system of linear equations in which the largest error magnitude is to be minimized [11].

B. Expert System Definition

Many different parameter estimation techniques, which differ in the necessary a priori information, convergence speed, required calculation-power, variances in estimated parameters, and robustness to external disturbances, are described in the literature. Different situations make all techniques equally attractive. In order to select the right approach in every particular implementation, it would require the execution of countless tests with all available algorithms. To eliminate the long procedure of selection or the compromise between the techniques, an intelligent supervisor is proposed which in real-time continuously performs the evaluation of the implemented algorithms, and selects the identified parameters from the concurrently running algorithms. This approach not only simplifies the required research prior to the implementation, but also increases the robustness of the parameter identification without compromising the parameter identification convergence, speed, and robustness. This research focuses only on a few algorithms that were selected with the aim to achieve good performance in terms of applicability, stability, accuracy, etc.

In the multiple model estimation procedure, the implemented r algorithms calculate the model parameters for the selected model structure M^*. Although each algorithm results in an optimally estimated parameter vector, q_n^k, these vectors differ from each other because of the different optimization criteria used to develop the particular algorithms. These estimated parameter vectors assemble the model set, M, at time $t = n \cdot T_s$, with r particular system models

$$M = \{q_n^1, q_n^2 \dots q_n^r\} . \quad (6)$$

The task for the model selection is to identify one parameter set, which will have the best chance to be the stable one in a sense of functions in the next $T_d = N \cdot T_s$ interval, where T_d is the time between two selections. Practically, the model selection process assumes the hypothesis that the selected model will meet the performance specifications in the next T_d time period based on the past observations. The ultimate objective of this selection process is to choose a model from the model set, M, and use that model to construct a model-based robust controller that best controls the plant. The selection can be performed using the optimization equation

$$J_n^*(q_n) = \min_{q_n^k \in M} \{L(q_n^k, f_n)\} \rightarrow q_n^S \quad (7)$$

where the optimal decision at time n is the q_n^k that achieves this minimum. $L(q_n^k, f_n)$ is the selected performance index.

This suggested optimization equation could be effectively implemented using the exponentially weighted moving average (EWMA) function, which is calculated for every decision period, T_d, for every concurrently running algorithm

$$J_n^k = l \cdot J_{n-N}^k + (1-l) \cdot v_{qma}^k \cdot v_{mer}^k \qquad (8)$$

where J_{n-N}^k is the last calculated performance index at time $t=(n-N)T_s$, l is the reminiscence factor, v_{qma}^k and v_{mer}^k are the quadratic moving average of the prediction error and the maximum prediction error for the T_d period, respectively. The reminiscence factor shall be selected from the interval $0 \le l \le 1$. If $l=1$ the decision will be based on the latest residual analysis only and the decision will ignore any past experience. If $l \to 1$ the decision is more reliant on the past behavior of the residuals. In this research, $l=1/3$ was selected as a compromise solution, since it results in a less frequent switching between the parameters. However, it allows the selection of new parameters when the system changes.

III. H∞ OPTIMAL CONTROLLER DESIGN

The selected robust controller, Σ_K, for the system Σ, is based on the H8 (sub)optimal control design theory. This controller is formulated using the game theoretic approach [12], where the external disturbances, w_n, are seen as the opponent to the controller, u_n. While the external disturbances act in a way to inflict maximal damage to the system output z_n, the controller aims to minimize the worst case energy gain from the disturbances to the system output z_n, as presented in Fig. 2.

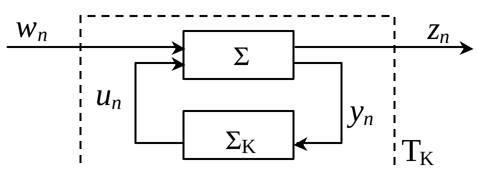

Fig. 2. Control System

The linear discrete-time finite-dimensional system S, presented in the state-space realization form, can be written as [12]

$$\Sigma: \quad \begin{aligned} x_{n+1} &= Ax + Bu_n + Dw_n \\ y_n &= Cx_n + Ew_n \\ z_n &= Hx_n + Gu_n \end{aligned} \qquad (9)$$

where for all $n \in \Re$, $x_n \in \Re^m$ is the state, $u_n \in \Re^r$ is the control input, $y_n \in \Re^q$ is the measurement, $w_n \in \Re^l$ is the unknown disturbance and $z_n \in \Re^p$ is the output to be controlled. The matrices $A \in \Re^{m \times m}$, $B \in \Re^{m \times r}$ and $C \in \Re^{q \times m}$ represent the dynamic system behavior. They are formulated based on the identified model parameters q_n^s, while the matrices $D \in \Re^{m \times l}$, $E \in \Re^{q \times l}$, $H \in \Re^{p \times m}$ and $G \in \Re^{p \times r}$, are selected to express robustness and performance requirements for the control system.

The objective is to design a controller such that the resulting closed-loop system minimizes the l_2-induced operator norm of $w_n \to z_n$, for the closed-loop system T_K that internally stabilizes the plant

$$\|T_K\|_\infty = \sup_{w \in l_2, w \ne 0} \frac{\|z\|_2}{\|w\|_2}. \qquad (10)$$

The resulting H8 control system design leads to a dynamic feedback law in state-space form [12]

$$\Sigma_K: \quad \begin{aligned} \hat{x}_{n+1} &= F^x \hat{x}_n + F^u u_n + F^y y_n \\ u_n &= K^x \hat{x}_n \end{aligned} \qquad (11)$$

where F^x, F^u, F^y, and K^x are matrices with appropriate dimensions, calculated from S by the H8 design algorithm. When it is implemented in real-time with the system identification, it takes the form of a Model Predictive Controller (MPC). The step-by-step implementation of the algorithm for calculating these matrices is detailed in [13] and in the literature referenced there.

IV. SIMULATION STUDIES

In order to investigate the performance of the proposed MPC as Power System Stabilizer (PSS), a number of simulation studies were performed. In the studies described below, the model of the power system is identified by a fifth order ARMAX model with time-varying coefficients. The rotational speed deviation of the generator, Δw, as the output of the system, is sampled in $T_S = 0.025s$ intervals both for system identification and control action calculation.

To demonstrate the proposed robust system identification, seven concurrently running algorithms were implemented [13]:

PRO – Proposed model algorithm, where the parameters are estimated parameters, selected at the last decision. These fixed parameters are used by the controller.

RLS - Recursive Least Squares algorithm with $l=0.985$

LMS - Least Mean Squares algorithm with $m=0.7$

WCE - Worst-Case Estimation algorithm, based on the linear programming method $d=100$

KF - Kalman Filter based system identification $R=0.1$, $Q=0.1I$

FQR - a mathematically more stable Recursive Fast QR RLS algorithm $l=0.999$

IQR - another version of a mathematically more stable Inverse QR RLS algorithm $l=0.985$

The performance of these algorithms is evaluated in every $T_d = 4.575s$ intervals by (8). The estimated parameters with the smallest performance index (8) are selected for H_∞ controller formulation at the same intervals, see [13]. The resulting robust-adaptive controller is the MPC. For comparison, in a separate test, an optimally tuned PSS1A as conventional power system stabilizer (CPSS), with the parameter set defined in [13] was used to validate the proposed MPC.

The performance of the proposed robust controller was examined in a complex test environment. Specifically, the implementation of the proposed robust controller in a multi-machine power system was investigated. The interconnection scheme of a multi-machine power system model is shown in Fig. 3. This model consists of five generating units. Generators G_1, G_2 and G_4 have much larger capacities than G_3 and G_5. All five generators are equipped with governors, exciters and automatic voltage regulators. In the selected model, generators G_2, G_3 and G_5 form one area, while generators G_1 and G_4 form a second area. These two areas are linked through a tie line, connecting busses #6 and #7. Normally, each area serves its own load and it is almost fully loaded with a small load flow over the tie line [14]. Generator G_3 is connected to bus #6 through a double transmission line, which enables different fault tests on the second line. In Fig. 3. a square indicates the second line, where the fault test takes place.

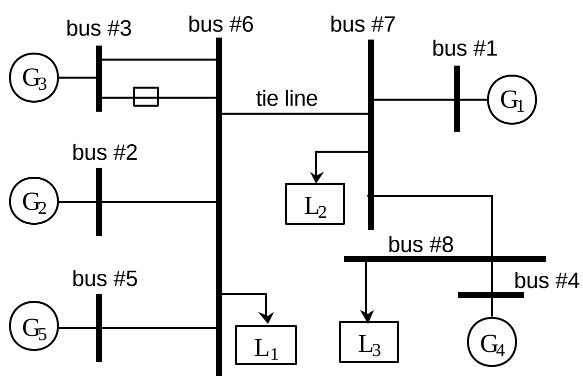

Fig. 3. Five-machine power system model

A. Mechanical torque reference step change tests (MTRT)

When the system operates under normal operating conditions, as specified in the Appendix [13], a 0.1 pu step decrease in the mechanical torque reference of G_3 occurs at 1s. After 4s the system returns to its original operating condition. When the system is disturbed, see Fig. 4., multi-mode oscillations arise because of the different size generators and network configurations. The rotational speed difference between G_3 and G_2 exhibits mainly local mode oscillations, while the speed difference between G_2 and G_1 shows the inter-area mode oscillations. Both local and inter-area oscillations exist in the rotational speed difference between G_1 and G_3 [15].

1) PSS on G_3

The system response for MTRT is shown in Fig. 5. The MPC installed on G_3 effectively damps the local mode oscillations, which arise as a rotational speed difference between the generators G_2 and G_3. However, as expected, it has little influence on the inter-area mode oscillations, which arise as a rotational speed difference between the generators G_1 and G_3. This is because the rated power of G_3 is much less than G_1 and G_2; and G_3 does not have enough power to control the inter-area mode oscillations.

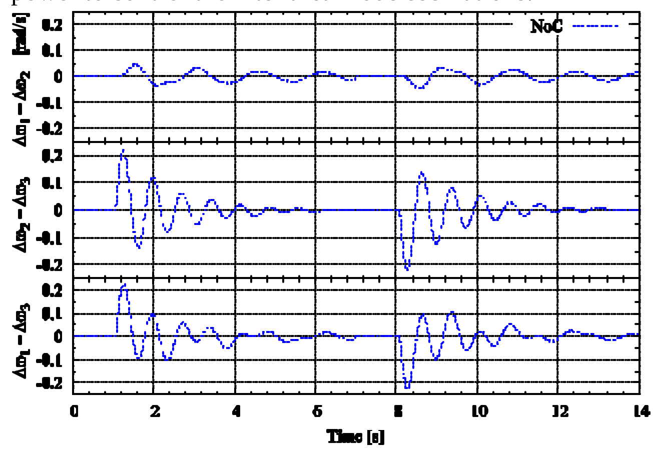

Fig. 4. Multi-mode oscillations in the power system

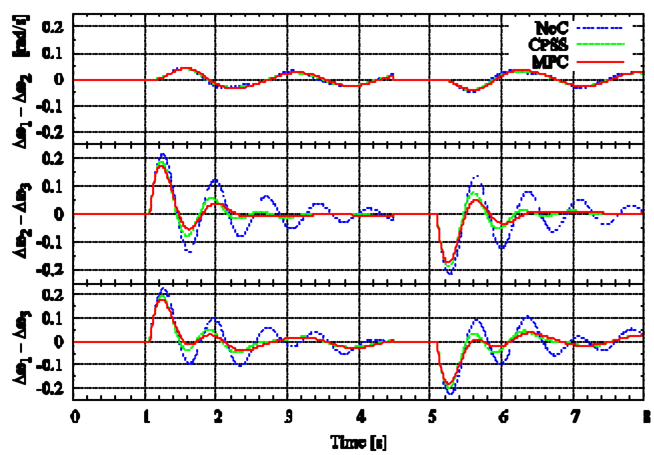

Fig. 5. PSS installed on G_3

2) PSS on G_1, G_2 and G_3

In order to damp both local and inter-area mode oscillations, it is required that the PSS be installed on two additional generators, G_1 and G_2. The power system response for an MTRT is shown in

Fig. 6., which demonstrates that both modes of oscillations are damped effectively by the MPC and the CPSS.

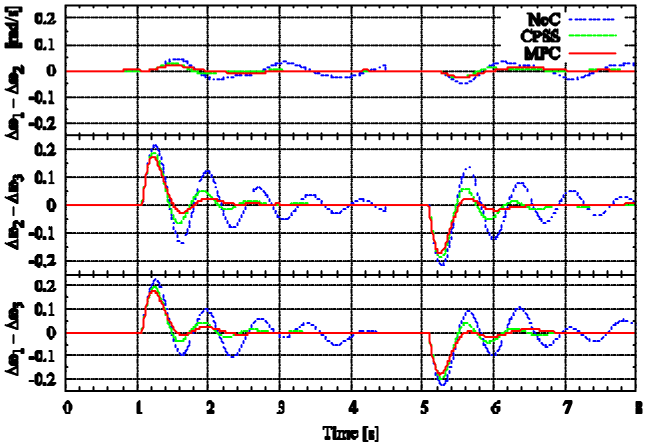

Fig. 6. PSS installed on G_1, G_2 and G_3

3) PSS on all generators

The MTRT is repeated when all the generators are equipped with PSSs. The power system oscillations, presented in Fig. 7., are very similar to that presented in

Fig. 6. due to the fact that the oscillations in this power system model can be well contained by the PSSs on G_1, G_2 and G_3.

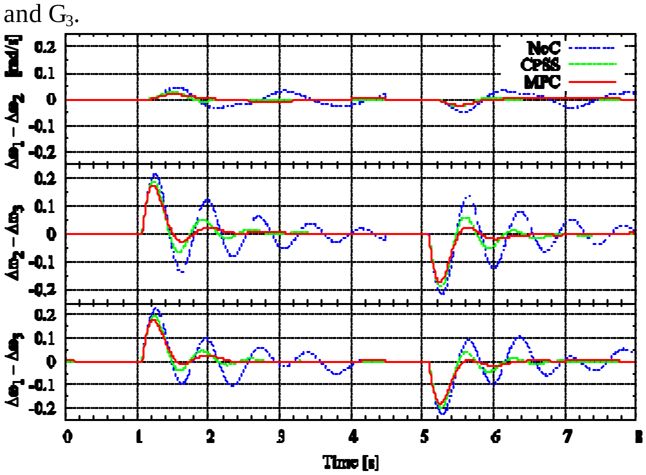

Fig. 7. PSS on all generators

4) System response with a mixed CPSS and MPC

Since the power industry is widely using the CPSSs, any new PSS introduced to the system must be able to work together with the already installed stabilizers. MPCs are installed on G_1 and G_3, while CPSSs are installed on G_2, G_4 and G_5. The results for MTRT, in Fig. 8, confirm that the two types of PSSs can work co-operatively.

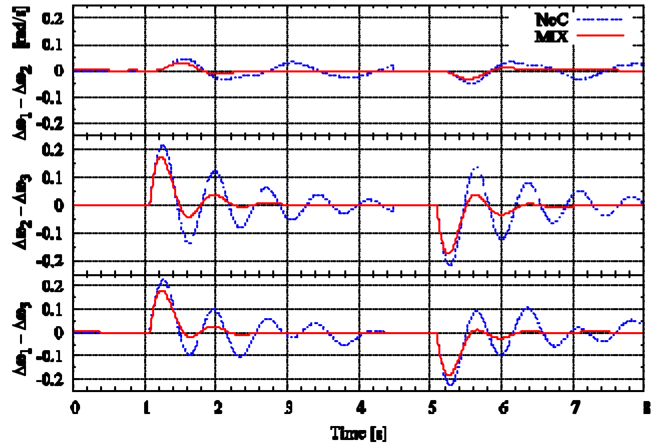

Fig. 8. System response with a mixed CPSS and MPC

B. Three phase to ground fault test (TPGT)

With the power system operating under normal operating conditions, as defined in [13], a three phase to ground fault is applied at the middle of the transmission line between buses #3 and #6 at 1s. The fault is cleared 100ms later, when the faulty line is removed.

1) PSS on G1, G2 and G3

Fig. 9. shows the system response for TPGT with no PSS, with the proposed MPC, and with the CPSSs installed on G_1, G_2 and G_3. The results show that the MPC minimizes the deviation of the rotational speed after the fault.

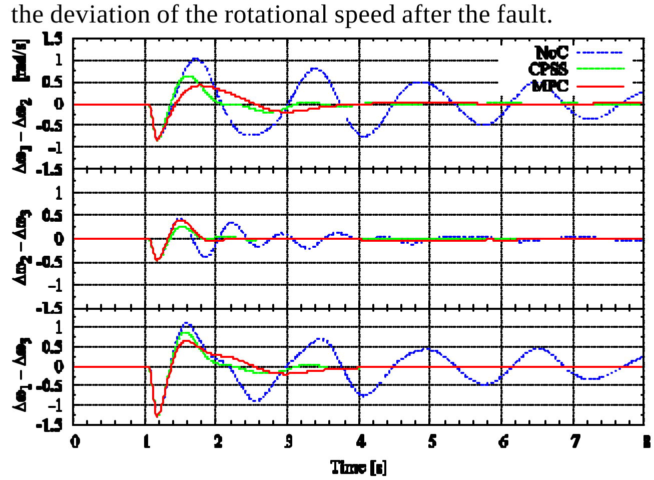

Fig. 9. Three phase to ground fault with 3 PSS

2) PSS on all generators

The TPGT is repeated when all the generators are equipped with PSSs. The power system oscillations for this test are presented in Fig. 10. The results show that the PSSs greatly reduce the speed deviations both for MPC and CPSS.

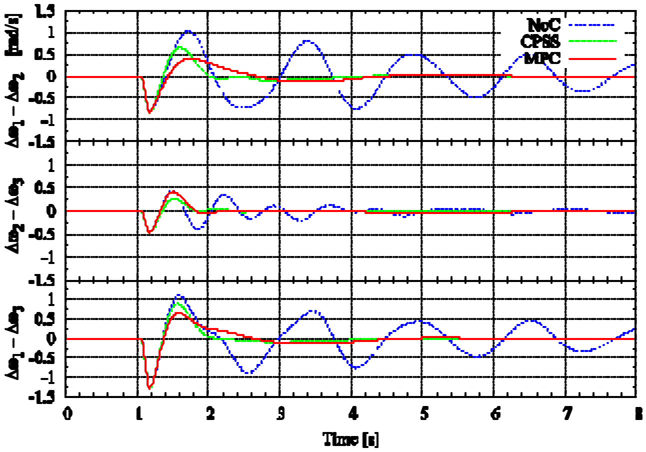

Fig. 10. Ground fault test with PSS on all generators

V. Conclusion

The simulation results indicate that the proposed MPC not only performs well in damping multi-mode oscillations in the system but it also exhibits good adaptation and stable operation in all tested environments. When compared to the well tuned CPSS, the MPC outperforms the CPSS in the reduction of high speed deviations.

VI. Appendix

A. Generator model

The generating unit is modeled by five first order differential equations. These equations are presented below.

$$\dot{d} = w_0 w \tag{12}$$

$$\dot{w} = (T_m + g + K_d w - T_e)/2H \tag{13}$$

$$T'_{d0}\dot{e}'_q = e_f - (x_d - x'_d)i_d - e'_q \tag{14}$$

$$T''_{d0}\dot{e}''_q = [e'_q - (x'_d - x''_d)i_d - e''_q] + T''_{d0}\dot{e}'_q \tag{15}$$

$$T''_{qo}\dot{e}''_d = (x_q - x''_q)i_q - e''_d \tag{16}$$

Table 1 Generator parameters

	G_1	G_2	G_3	G_4	G_5
x_d	0.1026	0.1026	1.0260	0.1026	1.0260
x_q	0.0658	0.06580	0.6580	0.0658	0.6580
x'_d	0.0339	0.0339	0.3390	0.0339	0.3390
x''_d	0.0269	0.0269	0.2690	0.0269	0.2690
x''_q	0.0335	0.0335	0.3350	0.0335	0.3350
T'_{d0}	5.6700	5.6700	5.6700	5.6700	5.6700
T''_{d0}	0.6140	0.6140	0.6140	0.6140	0.6140
T''_{q0}	0.7230	0.7230	0.7230	0.7230	0.7230
H	80.000	80.000	10.000	80.000	10.000

All resistances and reactances are expressed in PER UNIT and the time constants are shown in seconds.

Table 2 Transmission line parameters

Bus #	R_t	X_t	$B_t/2$
1--7	0.00435	0.01067	0.01536
2--6	0.00213	0.00468	0.00404
3--6	0.01002	0.03122	0.03204
3--6	0.01002	0.03122	0.03204
4--8	0.00524	0.01184	0.01765
5--6	0.00711	0.02331	0.02732
6--7	0.04032	0.12785	0.15858
7--8	0.01724	0.04153	0.06014

All resistances and reactances are shown in PER UNIT.

Table 3 Power flow parameters

	G_1	G_2	G_3	G_4	G_5
P	5.1076	8.5835	0.8055	8.5670	0.8501
Q	6.8019	4.3836	0.4353	4.6686	0.2264
V	1.0750	1.0500	1.0250	1.0750	1.0250
δ	0.0000	0.3167	0.2975	0.1174	0.3051

Table 4 Load parameters

L1	L2	L3
7.5 - j5.0	8.5 - j5.0	7.0 - j4.5

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VIII. Biographies

Antal Soós (M93) received his Dipl.Ing. degree from the University of Neoplantensis in former Yugoslavia in 1986, and the M.Sc. and Ph.D. degrees in electrical engineering in 1997 and 2005 at the University of Calgary, Canada,. His consulting work is linked to his primary interest in digital signal processing.

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