International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization on TPE (IOTPE)

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

December 2011	Issue 9	Volume 3	Number 4	Pages 45-51

POWER SYSTEM STABILIZATION USING MODEL PREDICTIVE CONTROL BASED ON IMPERIALIST COMPETITIVE ALGORITHM

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Abstract- This paper presents a hybrid method based on Generalized Predictive Control (GPC) and Imperialist Competitive Algorithm (ICA) for simultaneous coordinate design of two Power System Stabilizers (PSSs) to damp the multi-machine power system low frequency oscillations. A sequential linearized model predictive controller based on the GPC is designed and an efficient ICA algorithm is proposed for optimizing the cost function of GPC. The numerical results are presented on a 2-area 4-machine power system. To show the effectiveness of the designed PSS, a line-to-ground fault and a three phase fault are applied. Also, to compare the results obtained by ICA, the Genetic Algorithm (GA) is applied, too. Furthermore, the GPC algorithm is applied for comparison. Simulation results show the superiority and capability of the proposed stabilizers to enhance the power system damping over the other methods.

Keywords: Generalized Predictive Control, Imperialist Competitive Algorithm, Low Frequency Oscillation, PSS.

I. INTRODUCTION

Power systems stability is one of the most important aspects in electric system operation. Due to increasing complexity of electric power systems, especially with the interconnection of these systems by weak tie-lines, spontaneous system oscillations present limitations on power transfer capability and affect operational system economics and security. Therefore, there is significant interest in the stabilization of such systems.

Power system stabilizer (PSS) is the most effective device to enhance the damping of electromechanical oscillations by providing supplementary stabilizing feedback signals in the excitation system. PSSs augment the power system stability limit and extend the power transfer capability by enhancing the system damping of low-frequency oscillations in range of 0.2 to 2.5 Hz [1].

Numerous works are done and published around the world on the design of PSS for mitigating the effects of low-frequency oscillation modes [2-10]. Among these, conventional PSS (CPSS) of the lead-lag compensation type is used by most utility companies because of its simple structure, flexibility and ease of physical realization. The CPSS is normally designed with a fixed gain, determined for a set of operating conditions. However, the nonlinear nature of the power system elements, wide range of operating conditions and unpredictable disturbances in the power system degrade the performance of such a fixed gains CPSS.

To overcome the shortcomings of CPSSs, many control strategies applying various techniques based on optimal control, robust control and adaptive control, have been proposed and developed by the researchers around the world over the last three decades. The works carried out in [2-10] are examples of such applied techniques.

Model Predictive Control (MPC) is one of the major control strategies that is received a great deal of attention as a powerful tool for the control of industrial process systems [11]. MPC refers to a class of computer control algorithms that utilize an explicit dynamic model of a plant to predict the effect of future actions of the manipulated variables on the output.

The basic concept of MPC is to solve an optimization problem for a finite future at current time. Once a future input trajectory has been chosen, the first optimal control input is applied as the input to the plant. This procedure for solving the optimization problem is then repeated at each subsequent instant. In other words, the purpose of the model predictive controller is to use the process model to search for the best control signals to be applied. This must be done while satisfying some constraints and optimizing some cost function [12].

There are several formulations of the MPC strategy that are different either in a way the system model is obtained or in a formulation of the objective function. However, they all explicitly use a model of the system to obtain the control signal by minimizing the objective function. Some popular MPC algorithms are Model Algorithmic Control (MAC), Dynamic Matrix Control (DMC), Generalized Predictive Control (GPC), etc. Although, the concept of MPC has been successfully applied to several power system problems in [13-15], based on the existing literature, MPC has not yet been applied to the PSS design problem.

This paper proposed an alternative method, based on GPC algorithm and Imperialist Competitive Algorithm (ICA) for simultaneous coordinate design of two PSSs to damp the multi-machine power system low frequency oscillations. ICA is a population-based optimization algorithm inspired by the socio-political process of imperialistic competition and proven its superior capabilities, such as faster convergence and better global minimum achievement [16]. The main contribution of the proposed approach is that the proposed method could be applied to higher order system and nonlinear process.

The proposed method formulates the GPC algorithm as an optimization problem and ICA is used for optimizing the cost function of GPC. The method is applied to a 2-area 4-machine power system. To illustrate the performance and effectiveness of the designed PSSs, the study power system is tested under two conditions: applying a line-to-ground fault at a bus and a three phase fault at a bus. Furthermore, the GPC algorithm and GPC based genetic algorithm (GPC-GA) are applied for comparison. The paper is organized as follows. The next section gives a brief summary about MPC and GPC algorithms. The basic concept of the ICA is briefly explained in Section III. A detailed description of the proposed GPC based ICA, we call GPC-ICA, design procedure is given is section IV. The study power system and simulation results are presented in section V. Finally, some concludes are drawn in Section VI.

II. MPC AND GPC METHODS

Model predictive control (MPC) which, was developed in late 1970's, is one of the design methods for process control systems that configure feedback systems by repeating online the input process of the plan.

A. MPC Strategy

The methodology of all the controllers belonging to the MPC family is characterized by the following strategy, as shown in Figure 1.

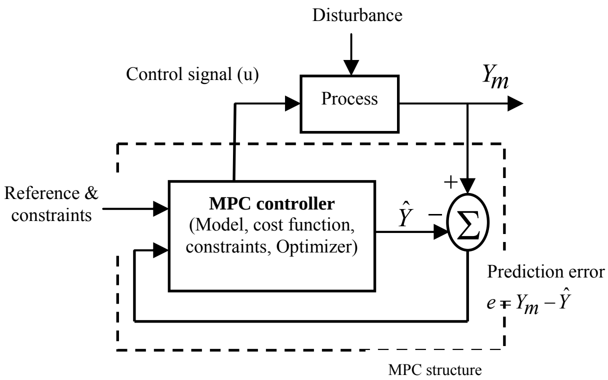

Figure 1. Structure of MPC

1. At the sampling interval k obtain the system measurements $Y_m(k)$ and calculate the prediction error, $e(k) = Y_m(k) - \hat{Y}(k)$, where $Y_m(k)$ and $\hat{Y}(k)$ are the actual measured output and prediction of the output made in the previous sample, respectively.
2. Calculate (predict) the output $\hat{Y}(k+i)$, $i = 0,...,N$ over the prediction horizon N. The prediction is obtained by using the system model, optimizing the objective function with respect to control inputs $u(k+j-1)$, $j = 1,...,M$ over the control horizon M, satisfying given constraints. The current state of the system is used as the initial state for the prediction.
3. Apply the first control signal $u(k)$ obtained from the optimization procedure until new measurements are available.
4. At the sampling interval $k+1$ go to step 1 and repeat the procedure.

B. Generalized Predictive Control (GPC) Overview

Generalized Predictive Control (GPC) is one of the most popular classes of MPC algorithms both in industry and academia. It has been successfully implemented in many industrial applications showing good performance and certain degree of robustness [17]. Actually it is a model based control strategy where an optimization procedure is performed in every sampling interval over a prediction horizon, yielding an optimal control action. The optimization criterion, or objective function, is chosen in such a way as to satisfy the controlled system dynamics and constraints, penalize system output deviation from the desired trajectory, and minimize control efforts.

In GPC algorithm, the process to be controlled is described by the following Controlled Auto-Regressive and Integrated Moving Average (CARIMA) model, which is widely used as a mathematical model of controller design methods [17]:

$$A(z^{-1})y(t) = z^{-d}B(z^{-1})u(t-1) + C(z^{-1})\frac{e(t)}{\Delta} \quad (1)$$

where Δ is defined as $\Delta = 1 - z^{-1}$ and d is the dead time of the system. $y(t)$, $u(t)$ and $e(t)$ are output sequence of the plant, control input and a stochastic random noise sequence with a zero mean value, respectively. Also z^{-1} is the backward shift operator, e.g., $z^{-1}y(t) = y(t-1)$. The polynomials A, B and C are given as follows:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_{na} z^{-na} \quad (2)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_{nb} z^{-nb} \quad (3)$$

$$C(z^{-1}) = 1 + c_1 z^{-1} + c_2 z^{-2} + \cdots + c_{nc} z^{-nc} \quad (4)$$

where $x_1,...,x_{nx}$ are coefficients and nx, is the order of the polynomial $(x = a,b,c)$. For simplicity C in the polynomial of Equation (1) is chosen to be 1.

The optimal predicted output is derived by solving a Diophantine equation as (5), whose solution can be found by an efficient recursive algorithm.

$$1 = E_j(z^{-1})\tilde{A}(z^{-1}) + z^{-j}F_j(z^{-1}) \quad (5)$$

$$\tilde{A}(z^{-1}) = \Delta A(z^{-1}) \quad (6)$$

where $E_j(z^{-1})$ and $F_j(z^{-1})$ are polynomials satisfying Diophantine equation and defined according to the polynomials of A and prediction horizon (N). They can be obtained dividing 1 by $\tilde{A}(z^{-1})$ until the remainder can be factorized as $z^{-j}F_j(z^{-1})$. The j-step-ahead output prediction of the process is:

$$\hat{y}(t+j|t) = G_j(z^{-1})\Delta u(t+j-1) + F_j(z^{-1})y(t)$$
$$G_j(z^{-1}) = E_j(z^{-1})B(z^{-1}) \quad (7)$$

The GPC computes the vector of controls using optimization of following cost function:

$$J_{GPC} = \sum_{j=1}^{N} \delta(j)\left[\hat{y}(t+j|t) - W(t+j)\right]^2 + \sum_{j=1}^{M} \lambda(j)\left[\Delta u(t+j-1)\right]^2 \quad (8)$$

where $\delta(j)$ and $\lambda(j)$ are weighting sequences, $W(t+j)$ is the future reference trajectory or reference sequence for the output signal. $\hat{y}(t+j|t)$ is an optimum j-step-ahead prediction of the system output based on data up to time t; that is, the expected value of the output at time t, if the past input and output and the future control sequence are known. N and M are termed the prediction horizon and the control horizon, respectively. The prediction horizon represents the limit of the instant in which it is desired for the output to follow the reference sequence.

Based on the Equation (7) a set of j ahead optimal prediction can be expressed as:

$$\begin{cases} \hat{y}(t+1|t) = G_1(z^{-1})\Delta u(t) + F_1(z^{-1})y(t) \\ \hat{y}(t+2|t) = G_2(z^{-1})\Delta u(t+1) + F_2(z^{-1})y(t) \\ \vdots \\ \hat{y}(t+N|t) = G_N(z^{-1})\Delta u(t+N-1) + F_N(z^{-1})y(t) \end{cases} \quad (9)$$

Therefore, a set of N j-step-ahead output predictions can be expressed as the following equations:

$$Y = G\Delta U + F \quad (10)$$

where

$$\begin{cases} Y = \left[\hat{y}(t+1|t), \hat{y}(t+2|t), \cdots, \hat{y}(t+N|t)\right]^T \\ \Delta U = \left[\Delta u(t), \Delta u(t+1), \cdots, \Delta u(t+N-1)\right]^T \\ F = \left[f(t+1), f(t+2), \cdots, f(t+N)\right]^T \end{cases} \quad (11)$$

$$G = \begin{bmatrix} g_0 & 0 & \cdots & 0 \\ g_1 & g_0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_{j-1} & g_{j-2} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ g_{N-1} & g_{N-2} & \cdots & g_0 \end{bmatrix} \quad (12)$$

By considering $\lambda(j) = \lambda$ and $\delta(j) = 1$, the cost function defined in (8) can be written as:

$$J = (Y-W)^T (Y-W) + \lambda \Delta U^T \Delta U \quad (13)$$

The objective function of Equation (11) can be solved by making the gradient of J equal to zero which leads to:

$$\Delta U = \left(G^T G + \lambda I\right)^{-1} G^T (W-F) \quad (14)$$

The control signal that is actually sent to the process is the first element of vector ΔU, which is given by:

$$\Delta u(t) = K(W-F) \quad (15)$$

where K is the first row of matrix $\left(G^T G + \lambda I\right)^{-1} G^T$. In this study, the future control input sequence $\Delta U = \left[\Delta u(t), \Delta u(t+1), \cdots, \Delta u(t+N-1)\right]^T$ is obtained by minimising cost function (13), via an ICA algorithm. General principles of ICA are described in next section.

III. ICA OVERVIEW

Imperialist competitive algorithm (ICA) is a new evolutionary optimization algorithm inspired by the socio-political process of imperialistic competition. Compared with the conventional evolutionary optimization algorithms, ICA has proven its superior capabilities, such as faster convergence and better global minimum achievement [16]. Flowchart of the ICA is illustrated in Figure 2.

Similar to other evolutionary algorithms, this algorithm begins with an initial population. Each individual of the population is called a *country*. Some of the best countries (countries with the best fitness value) are selected to be the *imperialist states* and the rest form the *colonies* of these imperialists. Based on the imperialists' power, each country is distributed to their states. The power of an empire is proportional to its fitness value.

After creating initial empires, their colonies begin moving toward the relevant imperialist country. This movement is a simple model of assimilation policy that was pursued by some imperialist states [18]. Figure 3, shows the movement of a colony towards the imperialist.

In this movement, θ and x are random numbers with uniform distribution as shown in (16), (17) and d is the distance between colony and the imperialist.

$$x \sim U(0, \lambda \times d) \quad (16)$$

$$\theta \sim U(-\gamma, \gamma) \quad (17)$$

where λ and γ are arbitrary numbers that modify the area that colonies randomly search around the imperialist.

The power of an imperialist country and its colonies represents the total power of an empire. In this algorithm, the total power of an empire is calculated by the power of imperialist state plus a percentage of the mean power of its colonies. In imperialistic competition, every empire tries to take possession of colonies of other empires and control them. As a result, a gradually decrease in the power of weaker empires and therefore increase in the power of more powerful ones will happen.

This competition is done by picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess them (that) colonies. In this competition, each of empires will have a likelihood of taking possession of the mentioned colonies, based on their total power. The more powerful an empire, the more likely it will possess these colonies. In other words, the possession probability of the colonies depends on the power of the empires trying to possess them. Any empire that is not able to succeed in imperialist competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated.

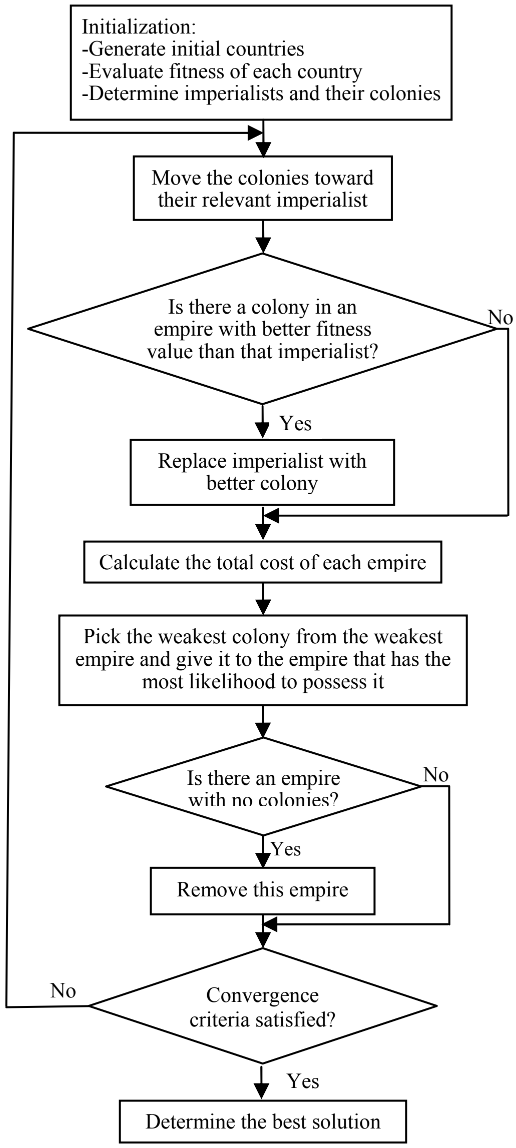

Figure 2. General principle of the ICA

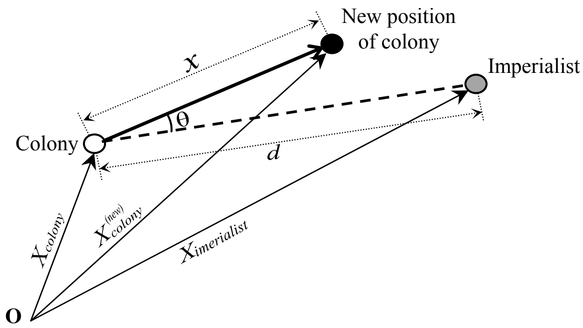

Figure 3. Motion of colonies toward their relevant imperialist

The imperialistic competition will gradually result in an increase in the power of great empires and a decrease in the power of weaker ones. The power of weak empires will gradually loose and ultimately they will collapse. The above procedures cause that all the countries converge to a state in which there exist just one empire in the world and all the other countries are its colonies. More details can be found in [18, 19].

IV. GPC BASED ICA CONTROLLER (GPC-ICA)

The GPC-ICA uses the process model to search for the best control signals to be applied, which satisfying the process constraints and optimizing a cost function. The following steps describe the operation of GPC-ICA algorithm [20]. At time step k:

1. Evaluate process outputs using the process model.
2. Use ICA to find the optimal control moves which optimize the cost function and satisfy process constraints.
3. Generate a set of random possible control moves (countries) for the process and apply to the model. A country such as Figure 4 which is a candidate solution of the optimization problem is represented by, whose elements consist of present and future control inputs and has the following structure, where t indicates the current time.

$$Country = [c_1,\ c_2\ ,\ ...,\ c_N\ ]$$

$$\Delta U = [\Delta u(t),\ \Delta u(t+1),\ ...,\ \Delta u(t+N-1)]$$

Figure 4. Countries structure

4. Find the corresponding process outputs for all possible control moves using the process model.
5. Evaluate cost function based on the model outputs of each solution using the cost function and the process constraints. The used fitness function is given by (18).

$$fitness = \frac{1}{J_{GPC}} \tag{18}$$

6. Find optimal input sequence consisting of physical control moves using ICA. Repeat a certain number of times and thus the optimal control moves are determined.
7. Apply the first optimal control moves generated in step 6 to the process.
8. Repeat steps 1 to 7 for time step k+1.

Summarized the whole proposed approach for is illustrated in Figure 5.

V. STUDY SYSTEM AND SIMULATION RESULT

In this study, a 2-area-4-machine system, shown in Figure 6 is considered for simulation studies. The sub-transient model for the generators, and the IEEE-type DC1 and DC2 excitation systems are used for machines 1 and 4, respectively. Moreover, the IEEE-type ST3 compound source rectifier exciter model is used for machine 2 and the first-order simplified model for the excitation systems is used for machine 3. Two PSSs are going to be designed simultaneously for the study system and placed on machines 2 and 3. Details of system data and concept of small-signal stability are given in [21].

According to Figure 5, the first step to implement the GPC-ICA is generating the initial control inputs (n countries) where n is considered to be 50. The numbers of *imperialist states* is set to be 10 and thus, 40 *colonies* will be existed. Based on the author's previous experience λ and γ are set to 2 and 0.5 (radian), respectively. Also, the prediction horizon and control horizon in the GPC algorithm are set to 5 and 3, respectively.

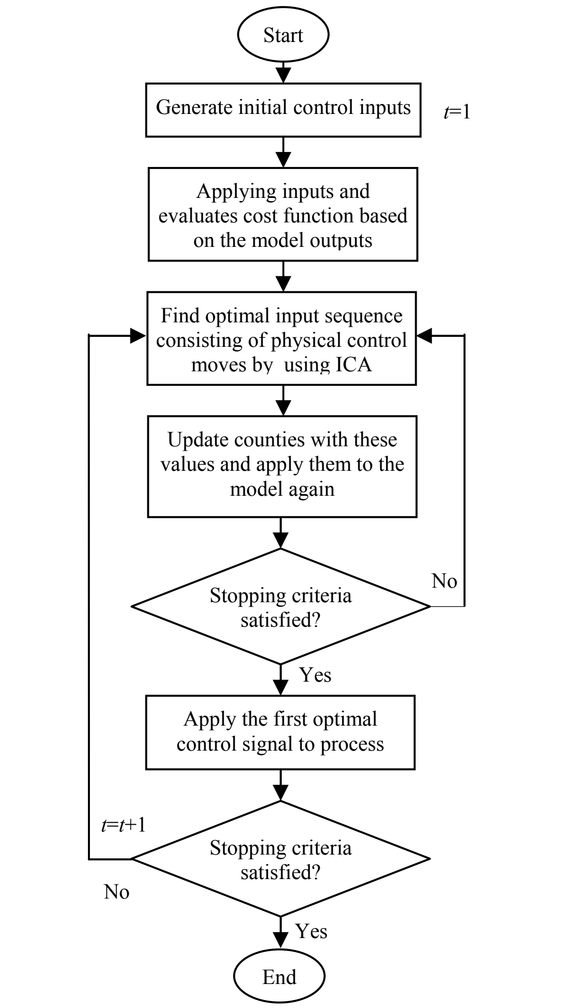

Figure 5. General principles of GPC-ICA

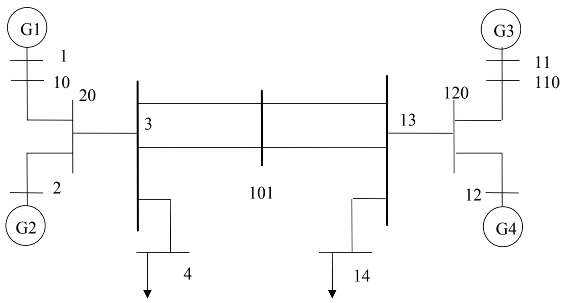

Figure 6. A 2-area study system

Then the solution vector is obtained by ICA by minimizing the fitness function defined in (18) which gives the optimal control inputs. The number of iteration is set to be 100. By using the obtained optimal control inputs, the first optimal control signal applied to the process followed by calculating the new output.

To validate the obtained result by GPC-ICA, a GPC based genetic algorithm (GPC-GA) is applied. Details of GA can be found in [22, 23].The number of chromosomes in the population is set to be 50. One point crossover is applied with the crossover probability $p_c = 0.9$ and the mutation probability is selected to be $p_m = 0.01$. Also, the number of iterations is considered to be 100, which is the stopping criteria used in ICA. The designed GPC-ICA controllers as two PSSs and those obtained by GPC and GPC-GA are placed in the study system (Figure 6). To indicate the effectiveness of the proposed GPC based ICA stabilizers for improving the stability of the study system, a time-domain analysis is performed and its performance is investigated.

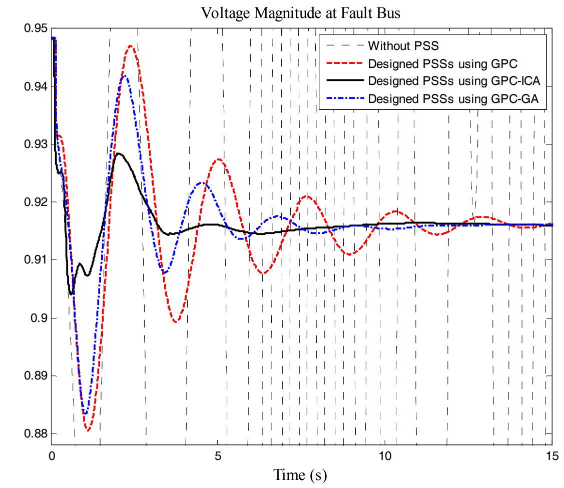

Figure 7. The voltage response of the system to a line-to-ground fault at bus 3

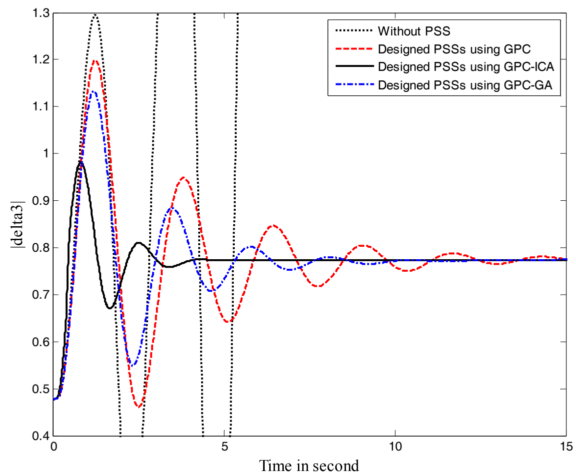

Figure 8. The response of generator 3 to a line-to-ground fault

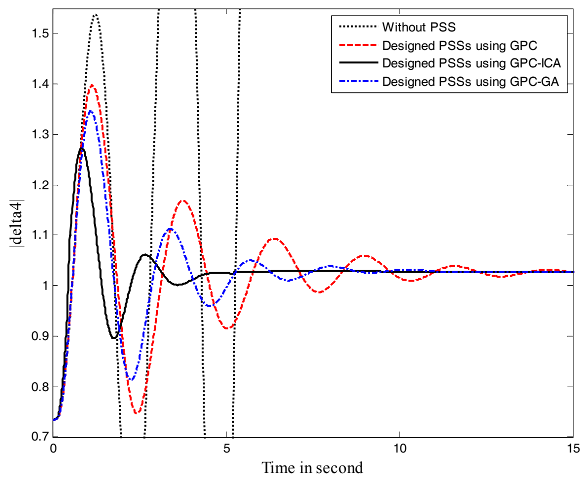

Figure 9. The response of generator 3 to a line-to-ground fault

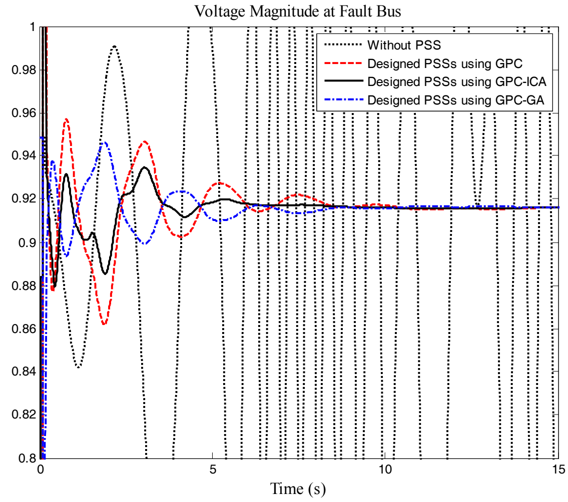

Figure 10. The voltage response of the system to a 3-phase fault at bus 3

A line-to-ground fault is applied in one of the tie lines at bus 3. The fault persisted for 70.0 msec. The behavior of the system was evaluated for 15 s. Figure 7 shows the voltage magnitude at the faulted bus. The machine angles, δ with respect to a particular machine (machine 1), were calculated over the simulation period time and illustrated in Figures 8 and 9. These figures show that all methods provide a good damping for the study system, but the controllers designed by GPC-ICA method improves the transient response characteristics and has a better performance in terms of overshoot, settling time and rise time compared to PSSs designed by GPC and GPC-GA method.

Once again to show the robustness of the designed controllers, a three-phase fault is applied at bus 3. The dynamic behavior of the system was evaluated for 15 s. The voltage magnitude at the faulted bus and machine angles, δ, were computed over the simulation period and shown in Figures 10-12. Again, these responses are similar to the responses in Figures 7-9 for a line-to-ground fault, showing the robustness of the designed controllers. These figures show that all methods provide a good damping for the study system, but the controllers designed by GPC-ICA method improves the transient response characteristics and has a better performance in terms of overshoot, settling time and rise time compared to PSSs designed by GPC and GPC-GA method.

VI. CONCLUSIONS

A new hybrid method based on Generalized Predictive Control (GPC) and Imperialist Competitive Algorithm (ICA) is presented. The proposed method formulates the GPC algorithm as an optimization problem and ICA is used for optimizing the cost function of GPC. It is applied successfully to simultaneous coordinate design of two Power System Stabilizers (PSSs) to damp the multi-machine power system low frequency oscillations. The performance of designed PSSs is tested on a 2-area-4-machine system.

The robustness and effectiveness of the proposed GPC-ICA based PSSs is verified under different disturbances. Furthermore, the GPC method and GPC based GA method (GPC-GA) are applied for comparison. Simulation results show the superiority and capability of the proposed stabilizers in comparison with the designed PSSs by GPC and GPC-GA approaches in improving the stability of the system.

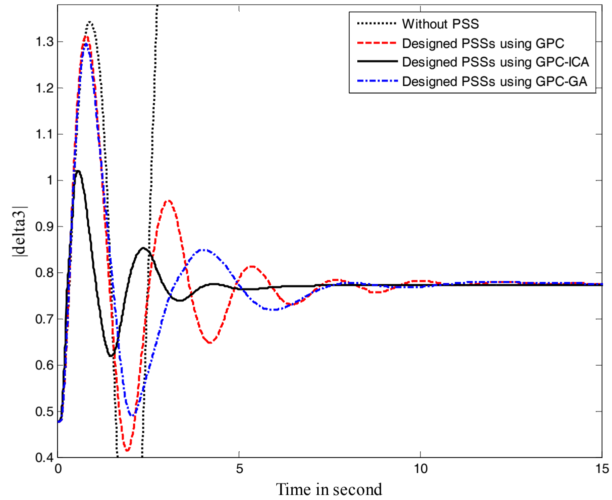

Figure 11. The response of generator 3 to a 3-phase fault

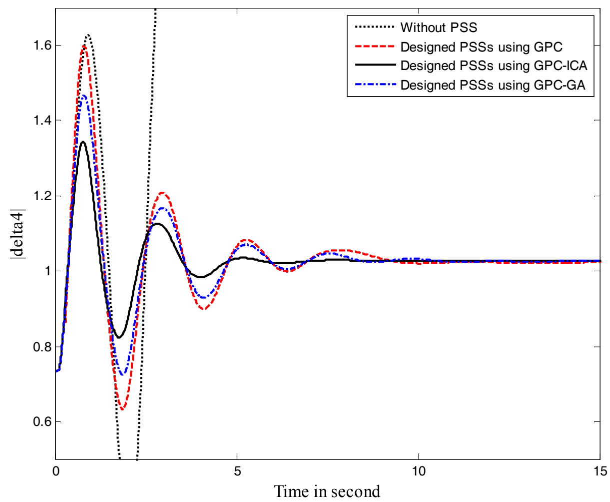

Figure 12. The response of generator 3 to a 3-phase fault

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