PSO Based Nonlinear Predictive Control of Single Area Load Frequency Control

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Abstract: A new Model Predictive Control (MPC) algorithm is proposed which is based on Particle Swarm Optimization (PSO). The proposed method formulates the MPC as an optimization problem and PSO is used to find the solution to that optimization problem. The method is applied to the Load Frequency Control (LFC) of a single area power system to illustrate the performance of the proposed algorithm in the presence of system parameter variations as well as nonlinearities. It is seen that the variations in load frequency are handled very well and the frequency is returned to its nominal value very quickly.

Keywords: Model Predictive Control, Particle Swarm Optimization, Load Frequency Control, Nonlinear Predictive Control, Optimization Problem.

1. INTRODUCTION

The current interest of the industry in Model Predictive Control (MPC) can be traced back to a set of papers which appeared in the late 1970s. In 1978, Testud, Richalet, Rault, and Papon described successful applications of "Model Predictive Heuristic Control" as in Testud (1978) and in 1979 engineers from Shell outlined "Dynamic Matrix Control" (DMC) as discussed in Cutler & Ramaker (1980) and reported applications to a fluid catalytic cracker. "Generalized Predictive Control" was presented by Mohtadi (1987:I) and Mohtadi (1987:II). In all these techniques, an explicit dynamic model of a plant is used to predict the effect of future actions of the manipulated variables on the output, thus providing the name "Model Predictive Control".

The success of MPC can be attributed to three factors:

(1) Incorporation of an explicit process model to deal directly with all features of the plant dynamics.
(2) Consideration of the plant behavior over a future horizon in time to anticipate and remove disturbances in advance.
(3) Consideration of process input, state and output constraints directly in control calculations to avoid control violations.

The inclusion of constraints most clearly distinguishes MPC from other process control paradigms as suggested in Qin (1996). Some good reviews of model predictive control can be found in Clarke (1994), Richalet (1993), Roberts (1999), Qin (1997), Lee (1999), and Rawlings (1999). The basic structure common to all MPC algorithms is shown in Figure 1 and we can see that an explicit model is used. It also contains an optimizer which uses a cost function and process constraints to calculate the optimal inputs for the process.

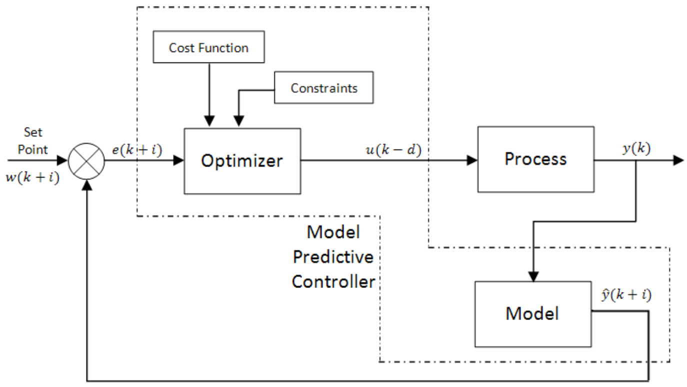

Fig. 1. Structure of MPC

Several other practical and well-researched MPC algorithms can be found in Zheng (1998), Kouvaritakis (1999), Cannon (2001), Imsland (2005).

The typical way to present MPC algorithms and applications is to apply the algorithm to a challenging problem/application and observe the results. For example, Multivariable MPC has been applied to cement mills and has shwon improved performance compared to previous LQ techniques with respect to the hardness of the raw material. This is given in Magni (1999). Load Frequency Control (LFC) itself has attracted a lot of research also. Application of Variable Structure Control using PSO to the LFC problem is illustrated by Al-Hamouz and Al-Duwaish (2000). The technique that is most closely related to the work proposed here, is the application of MPC with Genetic Algorithms to Nonlinear Models by Al-Duwaish and Naeem in the text, Al-Duwaish (2001). This was a big leap forward because it was the first time an evolutionary algorithm (EA) was applied to MPC. Also, this was the first time MPC was applied to any power system.

2. CONTROLLER STRUCTURE

This section gives the basic structure of the MPC-PSO controller.

2.1 Model Predictive Controller

In model predictive control, the process output is predicted by using a model of the process to be controlled. A disturbance or noise model can be added to the process model as well. In order to define how well the predicted process output tracks the reference trajectory a criterion function is used which is typically the difference between the predicted process output and the desired reference trajectory. A simple criterion function, as given in the book by Soeterboek (1992), is:

$$J = \sum_{i=1}^{H_p} [\widehat{y}(k+i) - w(k+i)]^2 \tag{1}$$

where $\widehat{y}$ is the predicted process output, w is the reference trajectory, and H_p is the predicted horizon, i.e., the time in the future up to which the output is predicted using the model.

Here the controller output sequence u_{opt} over the prediction horizon is obtained by minimization of J with respect to u. As a result the future tracking error is minimized. If there is no model mismatch i.e., the model is identical to the process and there are no disturbances and constraints, the process will track the reference trajectory exactly on the sampling instants.

Where *u(k)*, *y(k)* and $\hat{y}$*(k)* denote the controller output, the process output and the predicted process output respectively at the time instant k. w is the desired process output or the set point. Now, we define,

$$u = [u(k), u(k+1), ..., u(k+H_p-1)]^T \tag{2}$$

$$\hat{y} = [\hat{y}(k+1), \hat{y}(k+2), ..., \hat{y}(k+H_p)]^T \tag{3}$$

$$w = [w(k+1), w(k+2), ..., w(k+H_p)]^T \tag{4}$$

Using H_p, the predictive controller computes the future controller output sequence u as shown in Figure 2 such that the predicted output of the process, $\hat{y}$ is as close to the desired process output, w, as possible. This desired process is called the *reference* or the *reference trajectory.*

When the controller output sequence, *u(k)* is obtained in the above way for controlling the process in the next H_p samples, only the first element of *u(k)* is used to control the process instead of the complete controller output sequence. At the next sample, k+1, this whole process is repeated using the latest measured information. This is called the *receding horizon* principle as in the book by Maciejowski (2002). The reason for using receding horizon technique is that it allows us to compensate for future disturbances or modeling errors. The predicted process output is now

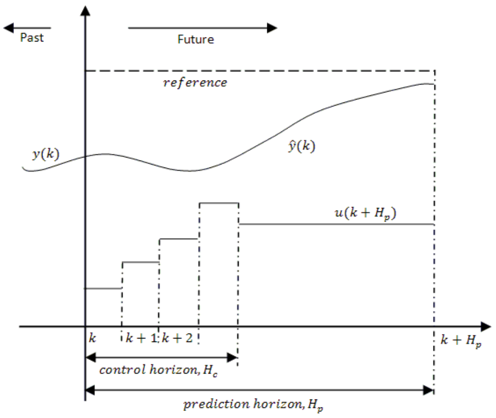

Fig. 2. Predicted output and the corresponding optimal input over a horizon H_p, where *u(k)* is the optimal input, $\widehat{y}(k)$ is the predicted output and *y(k)* is the process output.

corrected for disturbances and modeling errors activating a feedback mechanism. Resulting from the receding horizon approach, the horizon H_p shifts one sample into the future at every sample instant, predicting the process output again.

2.2 Particle Swarm Optimization

Particle swarm optimization (PSO), first introduced by James Kennedy and Russel Eberhart in 1995, is one of the modern heuristic algorithms which belongs to the category of *Swarm Intelligence* methods in Kennedy (2001). The PSO system is thought of as an intelligent system. This is because it is based upon artificial life and is a form of Evolutionary Algorithms (EA).

The difference between PSO and other EAs lies in how we change the population/swarm from one iteration to the next. In EAs, genetic operators like *selection*, *mutation* and *crossover* are used whereas in PSO, the particles are modified according to two formulas after each iteration. Conceptually, in PSO, the particles stay *alive* and inhibit the search space during the whole run, whereas in EA, the individuals are replaced in each generation. PSO is a more robust and fast algorithm compared to other EAs and it can solve nonlinear, non-differentiable, and multimodal problems, generating a high-quality solution within shorter calculation time and more stable convergence characteristic than other stochastic methods. Due to this ability, it is effective in solving problems in a wide variety of scientific fields as in Parsopoulos (2004).

As in other EAs, a population of individuals exist in PSO. These individuals "evolve" by cooperation and competition among themselves through generations. Each "particle" adjusts its "flying" according to its own experience as well as its companions' experience. Each particle in fact, represents a potential solution to the problem.

Each particle is treated as a point in D-dimensional space. The ith particle is represented as

$$X_i = (x_{i1}, x_{i2}, ..., x_{iD}) \tag{5}$$

The best previous position (the position giving the best fitness value) of any particle is recorded and represented as

$$P_i = (p_{i1}, p_{i2}, ..., p_{iD}) \tag{6}$$

Similarly, the position change (velocity) of each particle is

$$V_i = (v_{i1}, v_{i2}, ..., v_{iD}) \tag{7}$$

The particles are manipulated according to the following equations:

$$V_i^{n+1} = w * V_i^n + c_1 * r_{i1}^n * (P_i^n - X_i^n) + c_2 * r_{i2}^n * (P_g^n - X_i^n) \tag{8}$$

$$X_i^{n+1} = X_i^n + x * V_i^{n+1} \tag{9}$$

2.3 State Space Model

The model of the process is the heart of the Model Predictive Controller concept. All MPCs explicitly use a model of the plant to be controlled. State space model is used in this paper to model the example. It is of the form:

$$\dot{x}(t) = \mathbf{A}x(t) + \mathbf{B}u(t) \tag{10}$$

$$y(t) = \mathbf{C}x(t) + \mathbf{D}u(t) \tag{11}$$

where, x are the states, $\dot{x}$ represents the derivative of the states, u is the input and y is the output of the process. The nonlinearity is added on the states separately.

2.4 Plant Constraints

Most practical control problems are dominated by process constraints and nonlinearities. Usually, constraints are on the manipulated and/or state variables and they can make even a linear system nonlinear. The most common constraints used are equality & nonequality, as given below:

$$k(x(t), u(t), t) = 0 \tag{12}$$

$$k(x(t), u(t), t) \geq 0 \tag{13}$$

$$k(x(t), u(t), t) \leq 0 \tag{14}$$

2.5 Cost Function

The cost function (also called performance index) is evaluated as the weighted sum of square of errors between actual and predicted outputs over a finite prediction horizon. Incorporated into the performance index is the weighted sum of the square of the change in inputs over the control horizon, H_c, and the weighted sum of the square of the input moves over the prediction horizon. This can be explained more easily in the form of equation below:

$$J = \sum_{i=1}^{H_p} e(k+i)^T Q e(k+i) + \sum_{i=1}^{H_c} \Delta u(k+i)^T R \Delta u(k+i) + \sum_{i=1}^{H_p} u(k+i)^T S u(k+i) \tag{15}$$

Subjected to the following constraints:

$$u_{min} \leq u(k+i) \leq u_{max} \tag{16}$$

$$\Delta u_{min} \leq \Delta u(k+i) \leq \Delta u_{max} \tag{17}$$

$$y_{min} \leq y(k+i) \leq y_{max} \tag{18}$$

In Equation 15 Q, R and S are the weights on the prediction error, *e(k)*, change in the input, Δu, and magnitude of the input, u, respectively. The prediction error is defined as, e = *w(k)* - $\hat{y}$*(k)*, where *w(k)* is the desired set point.

3. PROBLEM FORMULATION

The problem of MPC-PSO controller is formulated as follows:

Given a linear or nonlinear plant, construct the PSO based predictive controller such that:

- Search the best control signals to be applied so that the plant is operated at desired setpoints
- Minimize the error between the reference and setpoint in the form of a cost function
- Do this in the presence of disturbances and constraints, in minimum time using minimum effort

4. PSO BASED PREDICTIVE CONTROL ALGORITHM

The proposed controller is shown in Figure 3. The purpose of the controller is to use the process model to search for the best control signals to be applied. However, this must be done while satisfying some constraints and optimizing some cost function.

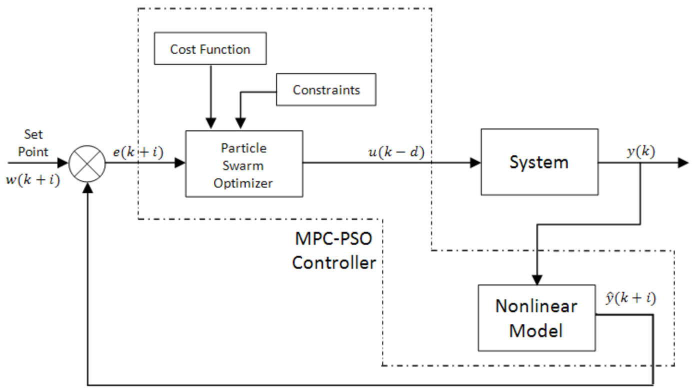

Fig. 3. Structure of Proposed MPC-PSO Controller

The algorithm is as follows:

- Initialize particles at the start by assigning them random values
- Generate set of inputs for the process and apply to the model
- Evaluate cost function based on the model outputs
- Evaluate fitness function,

$$fitness = \frac{1}{|J|} \tag{19}$$

  where J is the cost function or the performance index.
- Find optimal input sequence consisting of physical control moves or signals using PSO

- Update particles with these values and apply them to the model again, repeating a certain number of times
- Apply the first optimal control signal and repeat for the next sample

The number of particles represent the prediction horizon. If the system is MIMO, the number of particles is increased proportionally. So for a two input system, the number of particles is doubled.

5. MPC-PSO FOR LOAD FREQUENCY CONTROL

This section studies the application of our proposed MPC-PSO to the LFC problem for single area.

5.1 Load Frequency Control

LFC has been one of the most important subjects for power systems engineers for decades. It is also known as Automatic Generation Control (AGC) as in Chan and Hsu (1981). Loading in power systems is never constant, and changes in load induce changes in system frequency. This is because imbalance between the real power generated and loading causes the generator shaft to either speed up or slow down, resulting in the variation of system frequency.

Hence, to maintain the quality of the power supply, an LFC is needed to keep the frequency of the output electrical power at the nominal value. The input mechanical power to the generators is used to control the load frequency. This regulates the generator shaft speed, hence the frequency. The main quality risk involved is that control area frequencies can undergo prolonged fluctuations due to a sudden change of loading in an interconnected power system. This is described in detail in Chan and Hsu (1981). These prolonged fluctuations are mainly the result of system nonlinearities. One of the main type of nonlinearities is the Generation Rate Constraint (GRC).

5.2 Model of an LFC System

The block diagram is given in Figure 4.

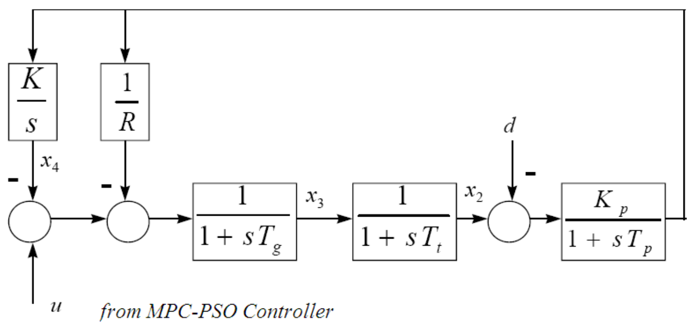

Fig. 4. Block diagram of single area LFC

The dynamic model for an n-area interconnected system is given here as in Zribi (2005):

$$\dot{X}_i(t) = A_i x_i(t) + B_i u_i(t) + \sum_{j=1,\, j\neq i}^{n} E_{ij} x_j(t) + F_i d_i(t)$$

$$y_i(t) = C_i(t) x_i(t)$$

Where,

$$\dot{X} = \left[\, \Delta\dot{f}_i(t)\ \Delta\dot{P}_{g_i}(t)\ \Delta\dot{X}_{g_i}(t)\ \Delta\dot{P}_{c_i}(t)\ \Delta\dot{P}_{t_i}(t) \,\right]^T$$

$$A_i = \begin{bmatrix} -\dfrac{1}{T_{p_i}} & \dfrac{K_{p_i}}{T_{p_i}} & 0 & 0 & -\dfrac{K_{p_i}}{T_{p_i}} \\ 0 & \dfrac{-1}{T_{t_i}} & \dfrac{1}{T_{t_i}} & 0 & 0 \\ -\dfrac{1}{R_i T_{G_i}} & 0 & -\dfrac{1}{T_{G_i}} & \dfrac{-1}{T_{G_i}} & 0 \\ K_{E_i} & 0 & 0 & 0 & K_{E_i} \\ \sum_j T_{ij} & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B_i = [\,0\ 0\ 1/T_{G_i}\ 0\ 0\,]^T$$

$$E_{ij} = \begin{bmatrix} 0 & 0\,0\,0\,0 \\ 0 & 0\,0\,0\,0 \\ 0 & 0\,0\,0\,0 \\ 0 & 0\,0\,0\,0 \\ -T_{ij} & 0\,0\,0\,0 \end{bmatrix}$$

$$F_i = [\,-K_{p_i}/T_{p_i}\ 0\ 0\ 0\ 0\,]^T$$

$$d_i(t) = P_{d_i}(t)$$

In the model, $\Delta f_i(t)$ is the incremental change in frequency for i^{th} area subsystem (Hz), ω is the rotor angular velocity in rad^{-1} w.r.t. synchronous speed, H is the inertia constant (s), D is the damping coefficient in (s^{-1}), P_m is p. u. mechanical power, P_{ac} is p. u. AC power, P_{dc} is p. u. power stored in the converter, $\omega_B = 377$ rad/s & $K = 1$.

The control objective of LFC is to keep the change in frequency, $\Delta\dot{f}_i(t) = x_1(t)$ as close to 0 as possible in the presence of load disturbance, $d_i(t)$ by the manipulation of the input, $u_i(t)$.

5.3 Simulation Results

Taking the case of a single area LFC for this paper, E_{ij} is ignored. The PSO parameters are $c_1 = c_2 = 2.04$, and a time varying weight is used. The population is 20 and the prediction horizon, $H_p = 7$.

The constraint on the control signal is:

$$-0.5 \leq u \leq 0.5 \qquad (20)$$

The system is simulated first for the linear case and then for nonlinear case with parameter variations. Initially, all states are at zero.

LFC Excluding Nonlinearity In the cost function, Equation 15, the value of Q = 1, R = 10 & S = 0. Using the following values:

$T_s = 20$s, $K_p = 120$ Hz p.u. MW^{-1}, $T_t = 0.3$s, $K = 0.6$ p.u. MW^{-1} rad^{-1}, $T_g = 0.08$s, $R = 2.4$ Hz p.u. MW^{-1}

The corresponding values of A, B & F are:

$$A = \begin{bmatrix} -0.05 & 6 & 0 & 0 \\ 0 & -3.33 & 3.33 & 0 \\ -5.208 & 0 & -12.5 & -12.5 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}$$

$$B = [\,0\ 0\ 12.5\ 0\,]^T$$

$$F = [\,-6 \;\; 0 \;\; 0 \;\; 0\,]^T$$

Figures 5 and 6 give the results. The disturbance is given in the form of 0.03 p.u. (3%) and 0.05 p.u. (5%) step changes on the load. Frequency deviation is seen at the start of the steps, however, MPC-PSO quickly controls it and bring it back to zero. The frequency deviation is apparent at the load only for a few instants and then remains at zero even in the presence of up to 5% disturbance.

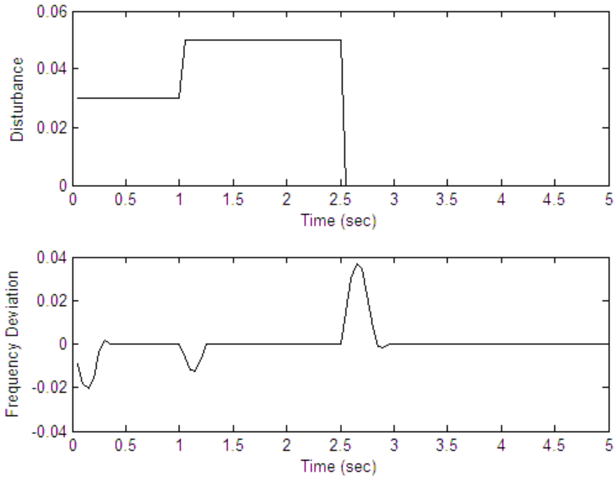

Fig. 5. Frequency Deviation in Single Area

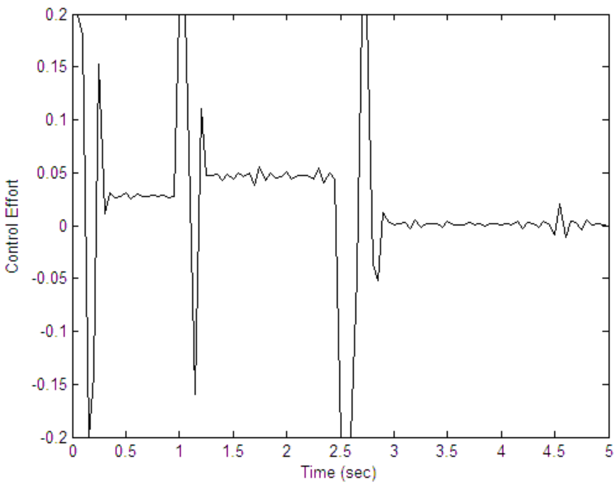

Fig. 6. Control Effort

LFC Including Nonlinearity and Parameter Variations
Here we consider a challenging case involving two parts:

- 25% parameter variations in the system due to severe disturbances or modeling errors
- GRC nonlinearity applied on two states, x_2 and x_4

The corresponding values of A, B & F are:

$$A = \begin{bmatrix} -0.0665 & 8 & 0 & 0 \\ 0 & -3.663 & 3.663 & 0 \\ -6.86 & 0 & -13.736 & -13.736 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}$$

$$B = [\,0 \;\; 0 \;\; 13.736 \;\; 0\,]^T$$
$$F = [\,-8 \;\; 0 \;\; 0 \;\; 0\,]^T$$

The nonlinearities are in the form of saturation of states and can be illustrated by the block diagram in Figure 7.

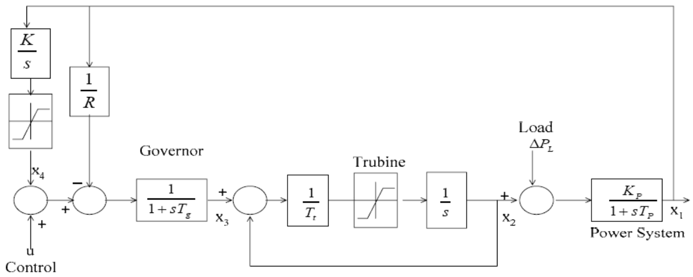

Fig. 7. Block diagram of single area LFC with GRC nonlinearities

A GRC value of 0.1 p.u. $MW\ min^{-1}$ = 0.017 p.u. $MW\ sec^{-1}$ is taken from Al-Musabi (2003). The results are illustrated in Figures 8 and 9. It is seen that the frequency deviation, again is minimal. As soon as there is a disturbance of 0.1 p.u. in the system, the frequency deviates by up to 0.008 p.u. and is controlled back to being 0 p.u. in under half a second by the MPC-PSO controller. Figure 10 shows the value of fitness function for the solution given by PSO.

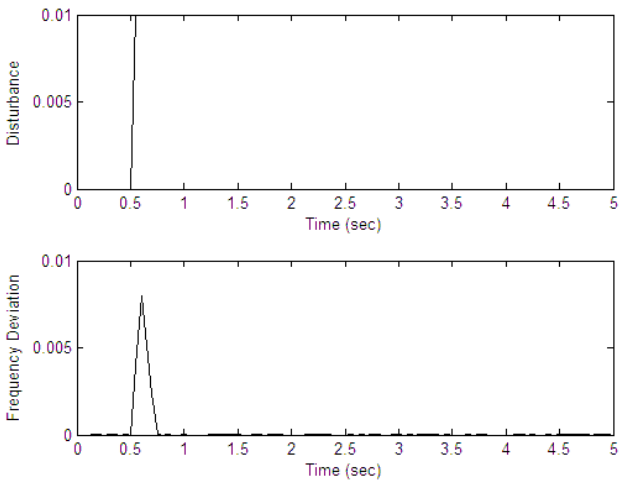

Fig. 8. Frequency Deviation in Single Area with GRC & parameter variation

6. CONCLUSION

A new model predictive algorithm based on PSO is presented. It is applied successfully to the load frequency control of a single area power system while input of the system is constrained. It is found that the frequency deviation is kept at zero in the presence of disturbances, even in the presence of nonlinearities and parameters variations. The reason for obtaining good results is the combination of efficient predictive control theory with the robust PSO

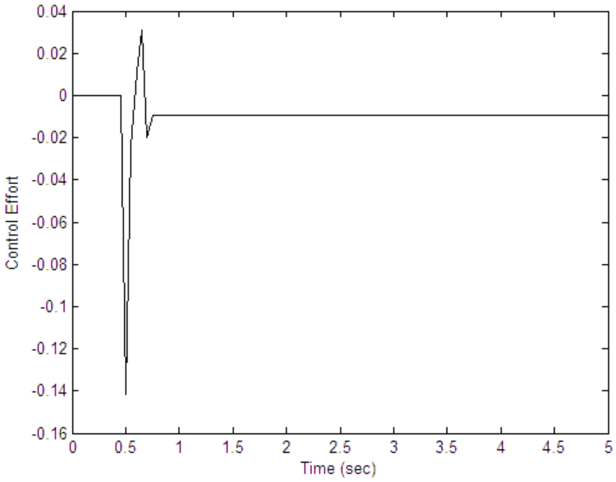

Fig. 9. Control Effort

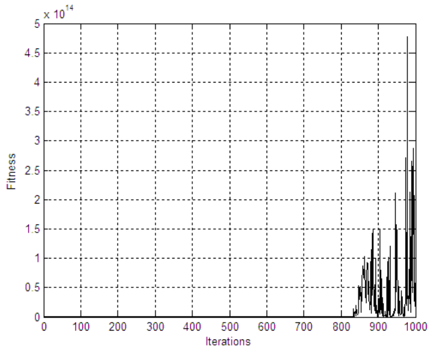

Fig. 10. Fitness Function

technique. Similar results are hoped from future work on multiarea nonlinear load frequency control.

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