SWARM INTELLIGENCE APPROACH FOR DAMPING OSCILLATIONS IN INVERTER FED INDUCTION MOTOR DRIVES

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ABSTRACT

In this paper, selection of the state feedback gains by Particle Swarm Optimization (PSO) technique is presented contrary to the selection of the feedback gains reported in literature. The proposed design has been applied to the inverter fed induction motor drive system. The system performance has been simulated and compared with some previous methods such as Variable Structure Controller (VSC) method, and Genetic Algorithm (GA) approach. Simulation results show that the dynamic system performance has been improved much with PSO compared to other two methods such as VSC and GA . The results show the effectiveness of the proposed technique.

Keywords: Induction Motor Drives, Particle Swarm Optimization, Variable Structure Controller, Genetic Algorithm

1. INTRODUCTION

Optimal control deals with the problem of finding a control law for a given system such that a certain optimality criterion is achieved. A control problem includes a cost functional that is a function of state and control variables. An optimal control is a set of differential equations describing the paths of the control variables that minimize the cost functional. Application of the variable structure controllers to different engineering problems including power systems [l-4], aerospace [5], robotics [6], and many others had been increasing in the last two decades. Very recently, the problem of VSC feedback gains selection has been considered by [3]. Their approach essentially was to try all allowable values of the feedback gains and evaluate a performance index for each set of feedback gains. The optimal feedback gains selected are those which minimize the performance index. This approach is numerically intensive especially for large numbers of feedback gains.

Particle Swarm Optimization is a new evolutionary computation technique which has been applied recently to some practical problems [7]. In the present work, a new approach based on PSO is proposed for the selection of the state feedback gains. This is accomplished by formulating the state feedback gains selection as an optimization problem and PSO is used in the optimization process. The proposed method provides an optimal and systematic way of state feedback gains selection.

In order to test the effectiveness of the proposed new method of selecting the state feedback gains, it has been applied to the inverter fed induction motor drive oscillations damping problem.

2. OVERVIEW OF VSC THEORY

The fundamental theory of variable structure systems may be found in [8].A block diagram of the VSC is shown in Figure 1, where the control law is a linear state feedback whose coefficients are piecewise constant functions. Consider the linear time-invariant controllable system given by

$$\dot{X} = Ax+Bu \tag{1}$$

where X is n-dimensional state vector, u is m-dimensional control force vector, A is a n x n system matrix, and B is n x m input matrix. The VSC control laws for the system of Equation (2) are given by

u_i =-$\psi^T{}_i$ X=-$\sum_{j=1}^{n}\psi_{ij}x_j$:i=1,2,………m (2)

Where the feedback gains are given as

ψ_{ij} ={ α_{ij} , if $x_i\sigma_j \rangle$ 0 ;i=1, 2,……,m;

{-α_{ij} , if $x_i\sigma_j \langle$ 0;j=1,2,…… ,n;

and

σ_i (x) = C_i^T X=0, i=1, 2,………., m; (3)

where C_i are the switching vectors which are determined usually via pole placement technique.

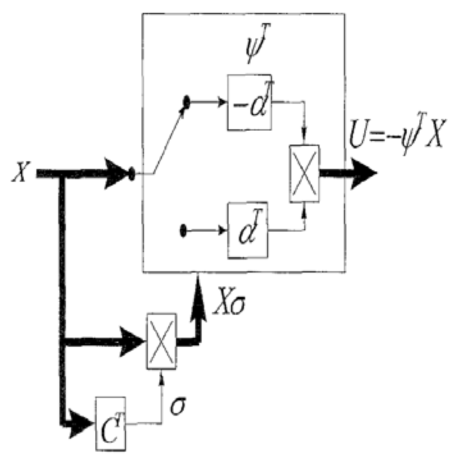

Figure 2 Block diagram of VSC

The design procedure for selecting the constant switching vector C_i is described below [2].

Step l: Define the coordinate transformation

Y=MX (4)

such that

$$MB=\begin{bmatrix}0\\ B_2\end{bmatrix} \quad (5)$$

where M is a non-singular n x n matrix and B_2 is a non- singular m x m matrix.

From (2), (4) and (5)

$$\dot{Y} = M\dot{X} = MAM^{-1}Y + MBU \quad (6)$$

where Y is an n-dimensional vector.

Equation (6) can be written in the form

$$\begin{bmatrix}\dot{Y}_1\\ \dot{Y}_2\end{bmatrix} = \begin{bmatrix}A_{11} & A_{12}\\ A_{21} & A_{22}\end{bmatrix}\begin{bmatrix}Y_1\\ Y_2\end{bmatrix} + \begin{bmatrix}0\\ B_2\end{bmatrix} \quad (7)$$

where $A_{11}, A_{12}, A_{21}, A_{22}$ are respectively (n-m) x (n-m), (n-m) x m, m x (n-m) and (m x m) submatrices. Y_1 *and* Y_2 are respectively (n-m) and m-dimensional vectors

The first equation of (7) together with equation (2) specifies the motion of the system in the sliding mode that is

$$\dot{Y}_1 = A_{11}Y_1 + A_{12}Y_2 \quad (8)$$

$$\sum(Y) = C_{11}Y_1 + C_{12}Y_2 \quad (9)$$

where C_{11} and C_{12} are m x (n-m) and (m x m) matrices, respectively satisfying the relation

$$[C_{11} \quad C_{12}] = C^T M^{-1} \quad (10)$$

Equations (9) and (10) uniquely determine the dynamics in the sliding mode over the intersection of the switching hyper planes

σ_i (x) = C_i^T X=0, i=1, 2,……….,m;

The subsystem described by equations (9) may be regarded as an open loop control system with state vector Y_1 and Y_2 control vector being determined by equation (10), that is

$$Y_2 = -C_{12}^{-1}C_{11}Y_1 \quad (11)$$

Consequently, the problem of designing a system with desirable properties in the sliding mode can be regarded as linear feedback design problem. Therefore, it can be assumed, without loss of generality, that C_{12}= identity matrix of proper dimension.

Step 2: Equations (8) and (11) can be combined to obtain

$$\dot{Y}_1 = [A_{11} - A_{12}C_{11}]\ Y_1$$

Utkin and Yang [9] have shown that if the pair (A, B) is controllable, then the pair (A_{11}, A_{12}) is also controllable. If the pair (A_{11}, A_{12}) is controllable, then the eigenvalues of the matrix [$A_{11} - A_{12}C_{11}$] in the sliding mode can be placed arbitrarily by suitable choice of C_{11} .

The switching vector C_{11} can be determined by pole placement or optimal placement of the eigenvalues to achieve a specific response [2].The feedback gains α_{ij} are usually determined by simulating the control system and trying different values until satisfactory performance is obtained.

3. OVERVIEW OF GENETIC ALGORITHM

Genetic algorithms are directed random search techniques which can find the global optimal solution in complex multidimensional search spaces. GA was first proposed by Holland [10] and has been applied successfully to many engineering and optimization problems [11-19]. GA employs different genetic operators to manipulate individuals in a population of solutions over several generations to improve their fitness gradually. Normally, the parameters to be optimized are represented in a binary string .To start the optimization, GA use randomly produced initial solutions created by random number generator. This method is preferred when a priori knowledge about the problem is not available.

There are basically three genetic operators used to generate and explore the neighborhood of a population and select a new generation. These operators are selection, crossover, and mutation. After randomly generating the initial population of say N solutions, the GAs use the three genetic operators to yield N new solutions at each iteration. In the selection operation, each solution of the current population is evaluated by its fitness normally represented by the value of some objective function, and individuals with higher fitness value are selected. Different selection methods such as stochastic selection or ranking-based selection can be used.

The crossover operator works on pairs of selected solutions with certain crossover rate. The crossover rate is defined as the probability of applying crossover to a pair of selected solutions. There are many ways of defining this operator. The most common way is called the one-point crossover which can be described as follows. Given two binary coded solutions of certain bit length, a point is determined randomly in the two strings and corresponding bits are swapped to generate two new solutions.

Mutation is a random alteration with small probability of the binary value of a string position. This operation will prevent GA from being trapped in a local minimum. The fitness evaluation unit in the flow chart acts as an interface between the GA and the optimization problem. Information generated by this unit about the quality of different solutions is used by the selection operation in the GA. The algorithm is repeated until a predefined number of generations have been produced. More details about GAs can be found in [12, 10, 20].

3.1 SELECTION OF STATE FEEDBACK GAINS USING GA

The feedback gains of the variable structure controller are usually determined by trial and error. In this section, the proposed GA approach for the selection of the state feedback gains is explained. To start the proposed GA method, a performance index must be defined. The selection of the performance index depends on the objective of the control problem. The following step by step procedure describes the use of GA in determining the state feedback gains optimally for the system described in section 6:

- Generate randomly a set of possible feedback gains.
- Evaluate the following performance index to keep the change in (Δx_1) as close to zero as possible regardless of the control effort (u) for all possible state feedback gains generated in step 1.

$$j = \int_0^\infty \Delta x_1^2(t)\ dt \qquad (12)$$

- Use genetic operators (selection, crossover, mutation) to produce new generation of feedback gains.
- Evaluate the performance index in step 2 for the new generation of state feedback gains. Stop if there is no more improvement in the value of the performance index or if certain predetermined number of generations has been used, otherwise go to step 3.

4. OVERVIEW OF SWARM INTELLIGENCE

Particle Swarm Optimization (PSO) is an evolutionary computation technique developed by Eberhart and Kennedy [21] inspired by social behavior and bird flocking or fish schooling[22]. The PSO algorithm applied in this study can be described briefly as follows.

- Initialize a population (array) of particles with random positions and velocities v on d dimension in the problem space. The particles are generated by randomly selecting a value with uniform probability over the optimized search space [$x_d^{\min}, x_d^{\max}$]. Set the time counter t = 0.
- For each particle x, evaluate the desired optimization fitness function, J, in d variables.
- Compare particles fitness evaluation with x_{pbest}, which is the particle with best local fitness value. If the current value is better than that of x_{pbest} , then set x_{pbest} equal to the current value and x_{pbest} locations equal to the that is current locations in d-dimensional space.
- Compare fitness evaluation with population overall previous best. If current value is better than gbest, the global best fitness value, then reset x_{gbest} to the current particle's array index and value.
- Update the time counter t, Inertia weight w, velocity v, and position of x according to the following equations

  t = t+1

$$w(t) = w_{\min} + (w_{\max} - w_{\min}\left(\frac{m-t}{m-1}\right)) \tag{13}$$

$$v_{id}(t) = w(t)v_{id}(t-1) + 2\alpha(x_{idpbest}(t-1)$$
$$-x_{id}(t-1)) + 2\alpha(x_{idgbest}(t-1) - x_{id}(t-1))$$
$$x_{id}(t) = v_{id}(t) + x_{id}(t-1) \tag{14}$$

where $w_{\min}$ and $w_{\max}$ are the maximum and minimum values of the inertia weight w ,m is the maximum number of iterations, i is the number of the particles that goes from 1 to n, d is the dimension of the variables, and α is a uniformly distributed random number in (0,l).

The particle velocity in the d^{th} dimension is limited by some maximum value $v_d^{\max}$.This limit improves the exploration of the problem space. In this study, $v_d^{\max}$ is proposed as

$$v_d^{\max} = kx_d^{\max} \tag{15}$$

Where k is a small constant value chosen by the user, usually between 0.1-0.2 of $x_d^{\max}$ [11].

- Loop to 2, until a criterion is met, usually a good fitness value or a maximum number of Iterations (generations) m is reached.

4.1 SELECTION OF STATE FEEDBACK GAINS USING SWARM INTELLIGENCE

The following step by step procedure describes the use of PSO in determining the feedback gains optimally for the system described in section 1.

- Generate randomly a set of possible feedback gains (particles).
- Evaluate some performance index for all feedback gains generated in step 1. In the present work, the following performance function was used. The function minimizes the system variable variation (Δx_1), i.e.

$$j = \int_0^\infty \Delta x_1^2(t)\, dt \tag{16}$$

- Use PSO (number of particles, dimension and maximum number of iterations), as described in section 4, to generate new state feedback gains.
- Evaluate the performance index in step 2 for the new state feedback gains. Stop if there is no more improvement in the value of the performance index or if the maximum number of iterations has been used, otherwise go to step 3.

5. OBJECTIVE FUNCTION

The minimization problem will be more easily solved if we can express performance index in terms of transform domain quantities. For quadratic performance index this can be done by using the parseval's theorem which allows us to write

$$\int_0^\infty x^2(t)dt = \frac{1}{2\pi j}\int_{-j\infty} X(s)X(-s)ds \tag{17}$$

In which X(s)=Laplace transform of x(t),where x(t) is defined for t≥ 0 and x(t) is zero for t <0.

The value of right hand integral in eqn.(1) can easily be found from tables, provides that X(s) can be written in the form B(s)/A(s);

$$B(s) = b_0 + b_1 s + ... + b_{n-1} s^{n-1}$$
$$A(s) = a_0 + a_1 s + ... + a_n s^n \qquad (18)$$

$$J_n = \frac{1}{2\pi j} \int_{-j\infty}^{j\infty} \frac{B(s)B(-s)}{A(s)A(-s)} \qquad (19)$$

$$B(s) = \sum_{i=0}^{n-1} b_i s^i$$

$$A(s) = \sum_{i=0}^{n} a_i s^i$$

$$J_1 = \frac{b_0^2}{2a_0 a_1}$$

$$J_2 = \frac{b_1^2 a_0 + b_0^2 a_2}{2a_0 a_1 a_2}$$

$$J_3 = \frac{b_2^2 a_0 a_1 + (b_1^2 - 2b_0 b_2) a_0 a_3 + b_0^2 a_2 a_3}{2a_0 a_3 (-a_0 a_3 + a_1 a_2)}$$

$$J_4 = \frac{b_3^2(-a_0^2 a_3 + a_0 a_1 a_2) + (b_2^2 - 2b_1 b_2) a_0 a_1 a_4 + (b_1^2 - 2b_0 b_2) a_0 a_3 a + b_0^2 (-a_1 a_4^2 + a_2 a_3 a_4)}{2a_0 a_4 (-a_0 a_3^2 - a_1^2 a_4 + a_1 a_2 a_3)}$$

$$J_5 = (b_4^2 m_0 + (b_3^2 - b_2 b_4) m_1 + (b_2^2 - 2b_1 b_3) m_2 + (b_1^2 - 2b_0 b_2) m_3 + b_0^2 m_4) / (2a_5)$$

$$m_1 = (-a_0 a_3 + a_1 a_2)$$
$$m_2 = (-a_0 a_5 + a_1 a_4)$$
$$m_3 = (a_2 m_2 - a_4 m_1) / a_0$$
$$m_4 = (a_2 m_3 - a_4 m_2) / a_0$$
$$m_0 = (a_3 m_1 - a_1 m_2) / a_5$$
$$Y_5 = a_0 (a_1 m_4 - a_5 m_3 + a_5 m_2)$$

For generalized

$$J_n = \frac{P_{n-1}}{2a_n} \qquad (20)$$

Where P_{n-1} is the solution of the n equations for P_i, i=0, 1, 2……….n-1

$$\sum_{i=0}^{m} a_{m-i} (-1)^i P_i = d_m \quad for\ 0 \le 2m \le n-1$$

$$\sum_{i=m-n}^{m} a_{m-i} (-1)^i P_i = d_m \quad for\ 0 \le 2m \le 2n-1$$

And the $d_m, m = 0,1,2,..........., n-1$ are given by

$$d_m = \begin{cases} \sum_{i=0}^{m} (-1)^i b_i b_{m-i} & for 0 \le 2m \le n-1 \\ \sum_{i=m-n+1}^{m} (-1)^i b_i b_{m-i} & for n \le 2m \le 2n-2 \end{cases} \qquad (21)$$

This expression can be written more compactly as

$$d_m = \sum_{i,j=0}^{n-1} (-1)^i b_i b_j \,, \quad \text{where } i+j=2m \qquad (22)$$

If we let d=col $(d_0, d_1, ...d_{n-1})$

$$P_{n-1} = \frac{|\Omega_1|}{|\Omega|} \qquad (23)$$

Where Ω_1 is the matrix formed Ω by replacing its last column by vector d. so,

$$J_n = \frac{(-1)^{n-1}}{2a_n} \frac{|\Omega_1|}{|\Omega|} \qquad (24)$$

Where

$$|\Omega| = \begin{vmatrix} a_{n-1} & a_{n-3} & a_{n-5} \cdots\cdots & 0 & 0 \\ a_n & a_{n-2} & a_{n-4} & & . & . \\ 0 & a_{n-1} & a_{n-3} & a_{n-5} & . & . \\ 0 & a_n & a_{n-2} & a_{n-4} & . & . \\ 0 & 0 & a_{n-1} & a_{n-3} & 0 & 0. \\ . & & & . & a_1 & 0 \\ 0 & 0 & 0 & . \ ... & a_2 & a_0 \end{vmatrix}$$

6. DYNAMIC MODEL OF INVERTER FED INDUCTION MOTOR DRIVE

Recently considerable interest has been shown in the control of Induction motor drives by the researchers [23-29]. The dynamic behavior of an induction machine can be described by three vector differential equations in a reference frame attached to the stator [25]:

$$\frac{d\overline{\psi}_s}{dt} = \overline{u}_s - \overline{i}_s R_s \tag{25}$$

$$\frac{d\overline{\psi}_r}{dt} = jw\overline{u}_r - \overline{i}_r R_r \tag{26}$$

$$j\frac{dw}{dt} = \mathrm{Im}(\overline{\psi}_s * \overline{i}_s) - T_M \tag{27}$$

With the algebraic conditions

$$\overline{\psi}_s = \overline{i}_s(L_{sl} + L_m) + \overline{i}_r L_m = \overline{i}_s L_s + \overline{i}_r L_m$$
$$\overline{\psi}_r = \overline{i}_s L_m + \overline{i}_r(L_{rl} + L_m) = \overline{i}_s L_m + \overline{i}_r L_r \tag{28}$$

The equations are in *per unit* (p.u.) notation. The stator current vector and stator voltage vector are

$$\overline{i}_s = \frac{2}{3}(i_a + \overline{a} i_b + \overline{a}^2 i_c)$$
$$\overline{u}_s = \frac{2}{3}(u_a + \overline{a} u_b + \overline{a}^2 u_c) \tag{29}$$

where

$$\overline{a} = e^{j2\pi/3}$$

u_a, u_b and u_c are instantaneous values of phase-to-neutral voltages, i_a, i_b and i_c are instantaneous values of line currents.

The system of equations is non-linear and it is difficult to see the reasons for the oscillations in the equations. If the equations were linear, the eigenvalues could be calculated, but they wouldn't give any clue to why the oscillations occur.

However, a mechanical equivalent of the mathematical model can be used to gain a better intuitive understanding of the induction machine. In this paper apparent mechanical equivalent model representations that give physical explanations for the oscillations is considered for the studies.

Resonance frequencies of linear systems can be found by computing the eigenvalues of the system matrix. The induction machine is non-linear, and this method can not be used directly. However, the equations describing the machine can be linearized, and the eigenvalues of the linear system can be computed.

To facilitate the linearization, the following time constants are defined

$$\tau_{ls} = L_L / R_s$$
$$\tau_{lr} = L_L / R_R \tag{30}$$

$$\tau_{ms} = \frac{\dfrac{L_M L_L}{L_M + L_L}}{R_s} = \frac{1}{R_s(1/L_M + 1/L_L)} \tag{31}$$

$$\tau_{mech} = JL_L \tag{32}$$

The dynamic equations are rewritten so that the deviation from an operating point, $\psi_{so}, \psi_{Ro}, \omega_o$, is investigated,

$$\overline{\psi}_s = \overline{\psi}_{so} + \Delta\overline{\psi}_s$$
$$\overline{\psi}_R = \overline{\psi}_{Ro} + \Delta\overline{\psi}_R \quad , \omega = \omega_o + \Delta\omega , \tag{33}$$
$$\overline{u}_s = \overline{u}_o + \Delta\overline{u}$$

At steady state, the stator and rotor fluxes are equal,

$$\overline{\psi}_{so} = \overline{\psi}_{Ro} = \overline{\psi}_o \tag{34}$$

The voltage needed at steady state for the flux ψ_o is

$$\overline{u}_o = \frac{R_s}{L_M}\overline{\psi}_o \tag{35}$$

With the above equations inserted, the following equations for the fluxes are obtained,

$$\frac{d\Delta\overline{\psi}_s}{dt} = \Delta\overline{u} - \frac{1}{\tau_{ms}}\Delta\overline{\psi}_s + \frac{1}{\tau_{ls}}\Delta\overline{\psi}_R \tag{36}$$

$$\frac{d\Delta\overline{\psi}_R}{dt} = \frac{1}{\tau_{lr}}\Delta\overline{\psi}_s - \frac{1}{\tau_{lr}}\Delta\overline{\psi}_R + j\Delta\omega\Delta\overline{\psi}_R + j\Delta\omega\Delta\overline{\psi}_o \tag{37}$$

The value of ψ_o and ω_o in the tests of section is

$$\psi_{ox} = 0 \quad \text{and} \quad \psi_{oy} = -1, \ \omega_o = 0 \tag{38}$$

The flux equations split into real (x) and imaginary (y) parts become

$$\frac{d\Delta\psi_{sx}}{dt} = \Delta u_x - \frac{1}{\tau_{ms}}\Delta\psi_{sx} + \frac{1}{\tau_{ls}}\Delta\psi_{Rx} \tag{39}$$

$$\frac{d\Delta\psi_{sy}}{dt} = \Delta u_y - \frac{1}{\tau_{ms}}\Delta\psi_{sy} + \frac{1}{\tau_{ls}}\Delta\psi_{Ry} \quad (40)$$

$$\frac{d\Delta\psi_{Rx}}{dt} = \frac{1}{\tau_{lr}}\Delta\psi_{sx} - \frac{1}{\tau_{lr}}\Delta\psi_{Rx} - \Delta\omega\Delta\psi_{Ry} + \Delta\omega \quad (41)$$

$$\frac{d\Delta\psi_{Ry}}{dt} = \frac{1}{\tau_{lr}}\Delta\psi_{sy} - \frac{1}{\tau_{lr}}\Delta\psi_{Ry} - \Delta\omega\Delta\psi_{Rx} \quad (42)$$

and the mechanical equation can be written

$$\frac{d\Delta\omega}{dt} = \frac{1}{\tau_{mech}}\Delta\psi_{sx} - \frac{1}{\tau_{mech}}\Delta\psi_{rx} - \frac{1}{\tau_{mech}}T_M \quad (43)$$

If the non-linear terms, underlined above, are neglected, equations can be replaced by the matrix equation

$\dot{x} = Ax + Bu$ or

$$\dot{x} = \begin{bmatrix} \frac{-1}{\tau_{ms}} & 0 & \frac{1}{\tau_{ls}} & 0 & 0 \\ 0 & \frac{-1}{\tau_{ms}} & 0 & \frac{1}{\tau_{ls}} & 0 \\ \frac{1}{\tau_{lr}} & 0 & \frac{-1}{\tau_{lr}} & 0 & 1 \\ 0 & \frac{1}{\tau_{lr}} & 0 & \frac{-1}{\tau_{lr}} & 0 \\ \frac{1}{\tau_{mech}} & 0 & \frac{-1}{\tau_{mech}} & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{-1}{\tau_{mech}} \end{bmatrix} u \quad (44)$$

Where

$$x = \begin{bmatrix} \Delta\psi_{sx} \\ \Delta\psi_{sy} \\ \Delta\psi_{Rx} \\ \Delta\psi_{Ry} \\ \Delta\omega \end{bmatrix} = \begin{bmatrix} X1 \\ X2 \\ X3 \\ X4 \\ X5 \end{bmatrix}, u = \begin{bmatrix} u_{sx} \\ u_{sy} \\ T_M \end{bmatrix}$$

7. SIMULATION RESULTS

The inverter fed induction motor oscillations problem described in the above section has been used as a case study. The following are the system parameters:

$\tau_{ls} = L_L / R_s$ =0.138/0.07 = 1.97

$\tau_{lr} = L_L / R_R$ = 0.138/0.076 = 1.82

$$\tau_{ms} = \frac{1}{R_s(1/L_M + 1/L_L)} = \frac{1}{0.07(1/1.66 + 1/0.138)}$$

$=1.82$

$\tau_{mech} = JL_L = 13.5 * 13.8 = 1.86$

which gives the matrix A and B ,

$$A = \begin{bmatrix} -0.55 & 0 & 0.51 & 0 & 0 \\ 0 & -0.55 & 0 & 0.51 & 0 \\ 0.55 & 0 & -.55 & 0 & 1 \\ 0 & 0.55 & 0 & -0.55 & 0 \\ 0.54 & 0 & -0.54 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -0.54 \end{bmatrix}$$

Using the design procedures in section 4, and 5, the state feedback matrix was obtained for the above system of controllable pair (A, B). The proposed PSO algorithm described in section 4 has been applied to minimize the performance index in equation (16) for optimal selection of the state feedback gains. The PSO parameters used are the number of particles n = 15, maximum number of iterations m =100, w_{max} =0.9, w_{min} = 0.4, and the maximum velocity constant factor k= 0.1. The algorithm is terminated when there is no significant improvement in the value of the performance index. The eigen values of the system matrix with and without feedback are given in Table 1.

Table 1
Eigen values of the system

Without feedback	With GA	With PSO
-0.0417	-0.7904	-3.4976
-..5291+0.4877i	-.0570+.6402i	-.0582+0.5512i
-.5291- 4877i	-.0570-.6402i	-0.0582-.5512i
-1.0796	-.7379+.4821i	-0.7250+ .3590i
-0.0204	-.7379-.4821i	-0.7250-0.3590i

The variation of the performance index is shown in Figure 2. Figures 3 to 7 shows the simulation of the state variables for the present PSO method and previous designs using VSC and GA. It can be observed from the figures 3 to 7 that the PSO method gives best oscillations damping compared with other methods.

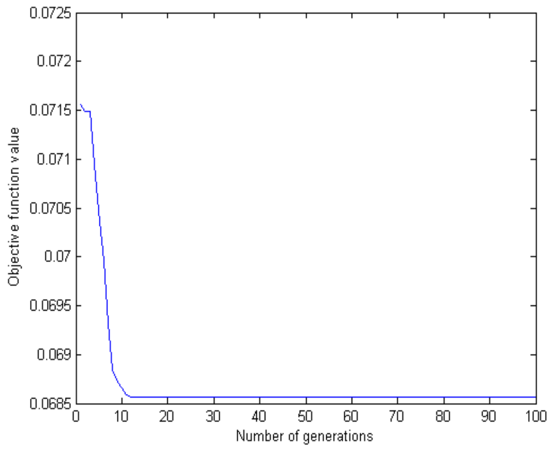

Figure 2: Performance index

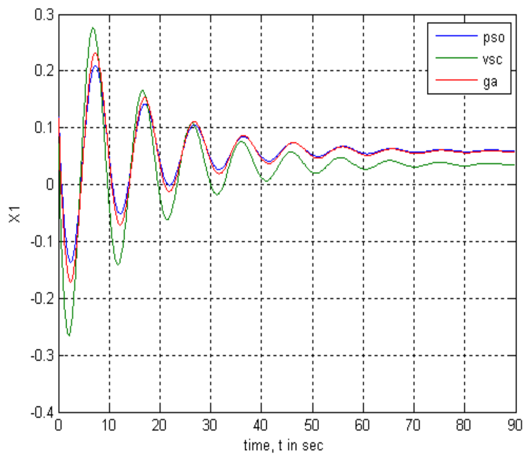

Figure 3: Variation of state variable X1

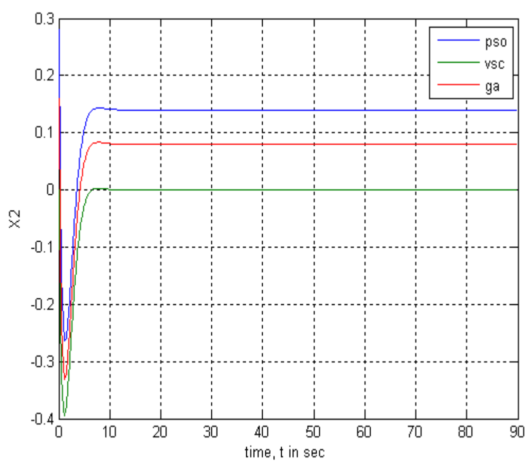

Figure 4: Variation of state variable X2

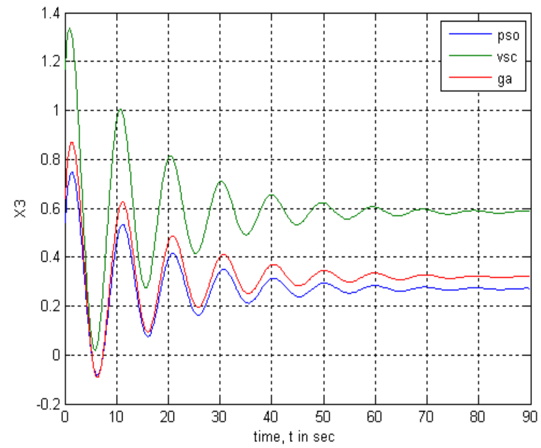

Figure 5: Variation of state variable X3

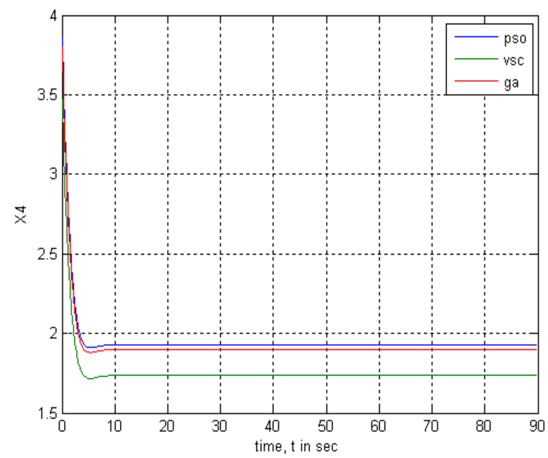

Figure 6: Variation of state variable X4

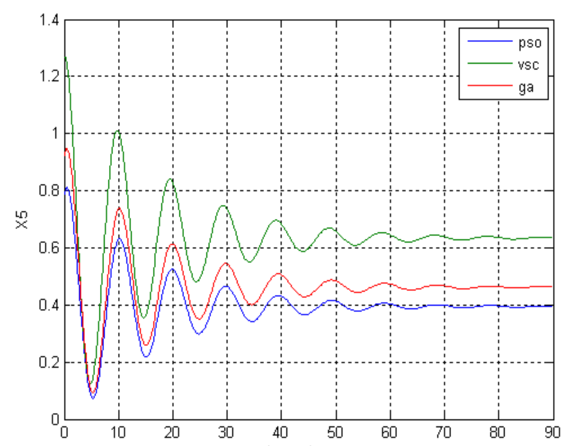

Figure 7: Variation of state variable X5

8. CONCLUSIOS

A new method of selecting the state feedback gains is presented in this paper. This is accomplished by formulating the state feedback gains selection as an optimization problem and PSO is used in the optimization process. The proposed method provides an optimal and systematic way of feedback gains selection compared to methods reported in the literature such as VSC and GA. The application of the proposed method to improve the oscillations in the inverter fed induction motor drive problem reveals an improvement in the system performance.

REFRENCES

[l] AI-Hamouz and Y. Abdel-Magid, "Variable Structure load Frequency controllers for multiarea power systems," *Znt. J. Elect. Power and Energy Syst.,*, vol. 15, no. 5,pp. 293-300, 1993.

[2] Sivarmakrishnan, M. A. Hariharan and M. C. Srisailam,"Design of Variable structure load frequency controller using pole assignment technique," *Int. J. Control*, vol. 40, no. 3, pp.487-498, 1984.

[3] Bhattacharya, M. Kothari, and J. Nanda, "Design of discrete mode variable structure power system stabilizers," *Znt. J.Elect. Power and Energy Syst.*, vol. 17, no. 6, pp. 399-406, 1995.

[4] AI-Hamouz Z. and AI-Duwaish H., "A new Load Frequency variable structure controller using Genetic Algorithms," *Electric Power Systems Research*, vol. 55, pp. 1- 6, 2000.

[5] X-Y Lu, S. Spurgeon and I. Postlethwaite, "Robust variable structure control of a PVTOL aircraft," Znt. J. System Science, vol. 28, no. 6, pp. 547-558, 1997.

[6] Zribi, L. Huang and S. Chan, "Variable structure control of two manpulators handling a constrained object," *Cybernetics and systems*, vol. 28, No. 4, pp. 263-286, 1997.

[7] Sen sarma P. S., Rahmani M., Carvalho A., "A comperehensive method for Optimal Expansion Using Particle Swarm Optmization," *ZEEE Power Engineering Society Winter Meeting2002*, vol. 2, pp. 1317-1322, 2002.

[8] Itkis, Control systems of variable structure, *Keter Publishing House*, Jerusalem, 1976.

[9] Utkin and K. Yang, "Methods for constructing discontinuity planes in multidimensional variable structure systems", *Autom. and Remote Control*, vol. 39, pp. 1466-1470, 1978.

[10] Holland, J. H. Adaptation in Natural and Artificial Systems, Ann Arbor, MI: University of Michigan Press, 1975.

[11] R. Caponetto, L. Fortuna, S. Graziani, and M. Xibilia, "Genetic Algorithms and Applications in System Engineering: a Survey", Trans. Inst. Meas. Control, 1993, Vol. 15, pp. 143-156.

[12]D. Goldberg, Genetic Algorithms in Search Optimization, and Machine Learning, Addison-Wesley, 1989.

[13] H. N. Al-Duwaish, M. Bettayeb, "Control of Nonlinear Dynamical Systems Using Genetic Algorithms", Proceedings of the 12th IEEE International Symposium on Intelligent Control, pp. 421-424, 16-18 July 1997, Istanbul, Turkey.

[14]A. Varsek, T. Urbancic, and B. Filipic, "Genetic Algorithms in Controller Design and Tuning", IEEE transactions on Systems, Man, and Cybernetics, Vol. 23, no. 5, 1993.

[15]B. Porter, and A. Jones, "Genetic Tuning of Digital PID Controllers", Electron. Lett., 1992, Vol. 28, pp. 843-844.

[16]Lansbeny, L. Wozniak, and D. Goldberg, "Optimal Hydro generator Govemer Tuning with A Genetic Algorithm", IEEE Trans., 1992, Vol. 7, pp. 623- 630.

[17]K. Krishnakumar, and D. E. Goldberg, "Control System Optimization Using Genetic Algorithms", Journal of Guidance, Control and Dynamics, Vol.15, no. 3, pp. 735-740, 1992.

[18]B. Porter, and S. S. Mohamed, "Genetic Design of Multivariable Flight Control System Using Eigenstructure Assignment", Proc. IEEE Con$ Aerospace Control Systems, 1993.

[19]U. Itkis, Control systems of variable structure, Keter Publishing House, Jerusalem ,1976.

[20]L. Davis, The Handbook of Genetic Algorithms, Van Nostrand Reinhold, NY, 1991.

[21] Kennedy J. and Eberhart R., "Particle Swarm Optimization," *IEEE International Conference on Neural Network*, vol. 4, pp. 1942 -1948, 1995.

[22]Eberhat and Yuhui Shi, "Particle Swarm Optimization: developments, applications, and resources," *Proceedings of the 2001 Congress*

on Evolutionary Computation, vol. 1, pp. 81-86, 2001.

[23]Alexandrovitz, A. (1987), Determination of Instability Range of a Frequency Controlled Three-Phase Induction Motor Fed Through Series Capacitors, *ETZ Arch*.(Germany), vol. 9, no. 7, July 1987, 235-9.

[24]Fitzgerald, A. E., Charles Kingsley, Jr., Stephen D. Umans (1985). *Electric Machinery*, McGraw-Hill, New York.

[25] Kov.cs, P. K. (1984) *Transient phenomena in electrical machines*, Elsevier, Amsterdam.

[26]Leonhard, W. (1985). *Control of electrical drives*, Springer, Berlin.

[27] Mutoh, N., A. Ueda, K. Sakai, M. Hattori and K. Nandoh (1990). Stabilizing Control Method for Suppressing Oscillations of Induction Motors Driven by PWM Inverters, *IEEE Transactions on Industrial Electronics*, vol. 37, no 1, 48-56

[28] Palit, B. B. (1978), Eigenvalue Investigations of a 3-phase Asynchronous Machine with Self-Excited Hunting, *Bull. Assoc. Suisse Electr*. (in German), vol .69, no. 8, 29 April 1978, 371-6.

[29] Slemon, G. and A. Straughen (1980). *Electric Machines*, Addison-Wesley, Reading, Mass..

APPENDIX

A. LIST OF SYMBOLS

Amplitude factor : K
Angular velocity : ω
Capacitance : C
Current : i
Rotor current : i_r, i_R
Stator current : i_s
Line current : i_a, i_b, i_c
Frequency : f
Stator frequency : f_s, ω_s
Inductance : L
Mutual inductance : L_m, L_M
Rotor leakage inductance : L_{rl}
Stator leakage inductance : L_{sl}
Laplace operator : s
Linked flux : ψ
Rotor flux : ψ_r, ψ_R
Stator flux : ψ_s
Moment of inertia : J
Natural frequency : Ω
Power factor : $\cos\varphi$
Relative damping : ζ
Resistance : R
Rotor resistance : R_r, R_R
Stator resistance : R_s
Slip : s
Pull-out slip : s_p
Time constant : τ
Time : t
Torque : T
Load torque : T_m
Pull-out torque : T_p
Voltage : u
Stator voltage : u_s
Phase-to-neutral voltage : u_a, u_b, u_c

B. PER UNIT NOTATION

Rated phase voltage : U_n (peak value)
Rated phase current : I_n (peak value)
Rated electrical angular velocity : ω_1
Rated mechanical angular velocity: $\omega_n = \omega_1 / z_p$
The number of pole pairs : z_p
Rated phase flux : $\psi_n = Un / \omega_1$
Rated apparent power : $P_n = \frac{3}{2} U_n I_n$
Rated torque : $T_n = P_n / \omega_n$
Base impedance : $z_n = U_n / I_n$
Rated start time : $H = J\omega^2{}_n / P_n$
Voltage (pu) : u / Un
Current : i / I_n
Resistance : R / Z_n
Inductance : $\omega_1 L / Z_n$
Capacitance : $\omega_1 C Z_n$
Flux : ψ / ψ_n
Moment of inertia : $\omega_1 H$
Torque : T / T_n
Time : $\omega_1 t$
Electrical angular velocity : ω_{el} / ω_1
Mechanical angular velocity : ω_{mech} / ω_n