ELSEVIER

Electric Power Systems Research 55 (2000) 1–6

ELECTRIC POWER SYSTEMS RESEARCH

www.elsevier.com/locate/epsr

A new load frequency variable structure controller using genetic algorithms

Z.M. Al-Hamouz *, H.N. Al-Duwaish

Department of Electrical Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

Received 6 July 1998; received in revised form 1 January 1999; accepted 26 February 1999

Abstract

In this paper, selection of the variable structure controller (VSC) feedback gains by genetic algorithms (GA) is presented contrary to the trial and error selection of the variable structure feedback gains reported in the literature. This is considered as one of the main underlying problems associated with VSC. The proposed method provides an optimal and systematic way of feedback gains selection in the VSC. To test the effectiveness of the new selection method, the proposed design has been applied to the load frequency problem of a single area power system. The system performance against step load variations has been simulated and compared to some previous methods, Simulation results show that not only the dynamic system performance has been improved, but also the control effort is dramatically reduced.

Keywords: Load frequency control; Variable structure; Genetic algorithms; Simulation

1. Introduction

Application of the variable structure controllers (VSC) to different engineering problems including power systems [1–9], aerospace [10–12], robotics [13,14], and many others has been increasing in the last two decades. One of the main underlying problems associated with VSC design is the selection of the feedback gains. Generally, the gains are chosen by trial and error such that they will satisfy certain system performance requirements. 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 possible 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.

Genetic algorithms (GA) are robust search and optimization techniques which have been applied to many practical problem [15,16]. The use of GA in control application is increasing considerably [17–22]. In the present work, a new approach based on GA is proposed for the selection of the VSC feedback gains. This is accomplished by formulating the VSC feedback gains selection as an optimization problem and GA are used in the optimization process. The proposed method provides an optimal and systematic way of feed back gains selection in the VSC.

In order to test the effectiveness of the proposed new method of selecting the VSC gains, it has been applied to the load frequency control (LFC) problem of a power system. Fig. 1 shows the transfer function model of the LFC for a single area power system [2]. The dynamic model in state-variable form can be obtained from the transfer function model and is given as

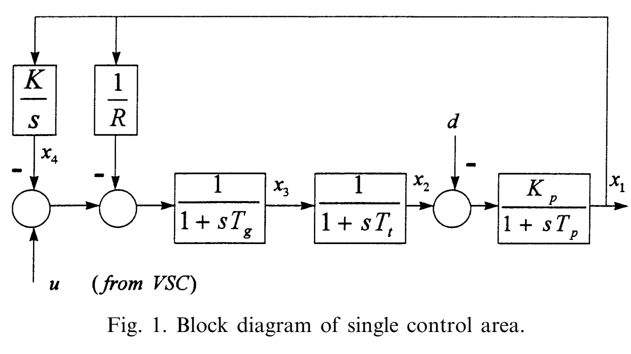

Fig. 1. Block diagram of single control area.

* Corresponding author.
E-mail address: zhamouz@kfupm.edu.sa (Z.M. Al-Hamouz)

0378-7796/00/$ - see front matter
PII: S0378-7796(99)00095-4

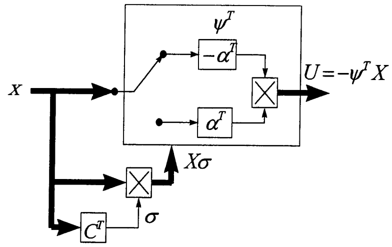

Fig. 2. Block diagram of VSC.

$$\dot{X}(t) = \boldsymbol{A}\boldsymbol{X}(t) + \boldsymbol{B}\boldsymbol{u}(t) + \boldsymbol{F}\boldsymbol{d}(t) \tag{1}$$

where $\boldsymbol{X}$ is four-dimensional state vector, $\boldsymbol{u}$ one-dimensional control force vector, $\boldsymbol{d}$ one-dimensional disturbance vector, $\boldsymbol{A}$ 4×4 system matrix, $\boldsymbol{B}$ 4×1 input matrix, and $\boldsymbol{F}$ is the 4×1 disturbance matrix.

$$\boldsymbol{A} = \begin{bmatrix} -1/T_p & K_p/T_p & 0 & 0 \\ 0 & -1/T_t & 1/T_t & 0 \\ -1/RT_g & 0 & -1/T_g & -1/T_g \\ K & 0 & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{B}^T = [0 \quad 0 \quad 1/T_g \quad 0]$$

$$\boldsymbol{F}^T = [K_p/T_p \quad 0 \quad 0 \quad 0]$$

The control objective in the LFC problem is to keep the change in frequency ($\Delta\omega = x_1$) as close to 0 as possible when the system is subjected to a load disturbance (d) by manipulating the input (u).

2. Theory of VSC

The fundamental theory of variable structure systems may be found in [23]. A block diagram of the VSC is shown in Fig. 2, where the control law is a linear state feedback whose coefficients are piecewise constant functions. Consider the linear time-invariant controllable system given by

$$\dot{X} = \boldsymbol{A}\boldsymbol{X} + \boldsymbol{B}\boldsymbol{U} \tag{2}$$

where $\boldsymbol{X}$ is the n-dimensional state vector, $\boldsymbol{U}$ the m-dimensional control force vector, $\boldsymbol{A}$ the $n \times n$ system matrix, and $\boldsymbol{B}$ the $n \times m$ input matrix.The VSC control laws for the system of Eq. (2) are given by

$$\boldsymbol{u}_i = -\boldsymbol{\psi}_i^T \boldsymbol{X} = -\sum_{j=1}^{n} \boldsymbol{\psi}_{ij} x_j; \quad i = 1, 2, \ldots m \tag{3}$$

where the feedback gains as

$$\boldsymbol{\psi}_{ij} = \begin{cases} \alpha_{ij}, & \text{if } x_i\sigma_j > 0; \quad i = 1, \ldots, m \\ -\alpha_{ij}, & \text{if } x_j\sigma_i < 0; \quad j = 1, \ldots, n \end{cases}$$

and

$$\sigma_i(\boldsymbol{X}) = \boldsymbol{C}_i^T \boldsymbol{X} = 0, \quad i = 1, \ldots, m$$

where $\boldsymbol{C}_i$ are the switching vectors which are determined usually via a pole placement technique.

The design procedure for selecting the constant switching vectors $\boldsymbol{C}_i$ is described below [2].

2.1. Step 1

Define the coordinate transformation

$$\boldsymbol{Y} = \boldsymbol{M}\boldsymbol{X} \tag{4}$$

such that

$$\boldsymbol{M}\boldsymbol{B} = \begin{bmatrix} 0 \\ \cdots \\ \boldsymbol{B}_2 \end{bmatrix} \tag{5}$$

where $\boldsymbol{M}$ is nonsingular $n \times n$ matrix and $\boldsymbol{B}_2$ is a nonsingular $m \times m$ matrix. From Eqs. (2), (4) and (5)

$$\dot{Y} = \boldsymbol{M}\dot{X} = \boldsymbol{M}\boldsymbol{A}\boldsymbol{M}^{-1}\boldsymbol{Y} + \boldsymbol{M}\boldsymbol{B}\boldsymbol{U} \tag{6}$$

Eq. (6) can be written in the form

$$\begin{bmatrix} \dot{Y}_1 \\ \dot{Y}_2 \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} \end{bmatrix} \begin{bmatrix} \boldsymbol{Y}_1 \\ \boldsymbol{Y}_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \boldsymbol{B}_2 \end{bmatrix} \boldsymbol{U} \tag{7}$$

where $\boldsymbol{A}_{11}$, $\boldsymbol{A}_{12}$, $\boldsymbol{A}_{21}$, $\boldsymbol{A}_{22}$ are, respectively $(n-m) \times (n-m)$, $(n-m) \times m$, $m \times (n-m)$ and $(m \times m)$ submatrices.

The first Eq. (7) together with Eq. (2) specifies the motion of the system in the sliding mode i.e.

$$\dot{Y}_1 = \boldsymbol{A}_{11}\boldsymbol{Y}_1 + \boldsymbol{A}_{12}\boldsymbol{Y}_2 \tag{8}$$

$$\sum(\boldsymbol{Y}) = \boldsymbol{C}_{11}\boldsymbol{Y}_1 + \boldsymbol{C}_{12}\boldsymbol{Y}_2 \tag{9}$$

where $\boldsymbol{C}_{11}$ and $\boldsymbol{C}_{12}$ are $m \times (n-m)$ and $(m \times m)$ matrices, respectively, satisfying the relation

$$[\boldsymbol{C}_{11} \quad \boldsymbol{C}_{12}] = \boldsymbol{C}^T\boldsymbol{M}^{-1} \tag{10}$$

Eqs. (9) and (10) uniquely determine the dynamics in the sliding mode over the intersection of the switching hyperplanes

$$\sigma_i(\boldsymbol{X}) = \boldsymbol{C}_i^T \boldsymbol{X} = 0, \quad i = 1, \ldots, m$$

The subsystem described by Eq. (9) may be regarded as an open loop control system with state vector $\boldsymbol{Y}_1$ and control vector $\boldsymbol{Y}_2$ being determined by Eq. (10), i.e.

$$\boldsymbol{Y}_2 = -\boldsymbol{C}_{12}^{-1}\boldsymbol{C}_{11}\boldsymbol{Y}_1 \tag{11}$$

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

2.2. Step 2

Eqs. (8) and (11) can be combined to obtain

$$\dot{Y}_1 = (\boldsymbol{A}_{11} - \boldsymbol{A}_{12}\boldsymbol{C}_{11})\boldsymbol{Y}_1$$

Utkin and Yang [24] have shown that if the pair ($\boldsymbol{A}$, $\boldsymbol{B}$) is controllable, then the pair ($\boldsymbol{A}_{11}$, $\boldsymbol{A}_{12}$) is also controllable. If the pair ($\boldsymbol{A}_{11}$, $\boldsymbol{A}_{12}$) is controllable, then the eigenvalues of the matrix ($\boldsymbol{A}_{11} - \boldsymbol{A}_{12}\boldsymbol{C}_{11}$) in the sliding mode can be placed arbitrarily by suitable choice of $\boldsymbol{C}_{11}$. The switching vector $\boldsymbol{C}_{11}$ 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. Genetic algorithms

GA are directed random search techniques which can find the global optimal solution in complex multidimensional search spaces. GA was first proposed by Holland [25] and have been applied successfully to many engineering and optimization problems [16]. GA employ 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.

The flow chart of a simple GA is shown in Fig. 3. 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 GA 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.

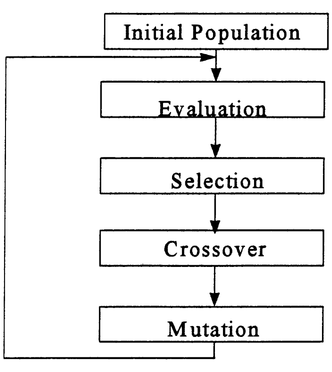

Fig. 3. Flow chart for a simple GA.

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 are used by the selection operation in the GA. The algorithm is repeated until a predefined number of generations have been produced. More details about GA can be found in [16,25,26].

4. Selection of the VSC feedback gains using GA

The feedback gains of the VSC are usually determined by trial and error. In this section, the proposed GA approach for the selection of the 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 feedback gains optimally for the system described in Section 1.

1. Generate randomly a set of possible feedback gains.
2. Evaluate some performance index for all feedback gains generated in step 1. In the present work, the following two indices were selected. The first minimizes the system frequency variation ($\Delta\omega$) regardless of the control effort (u), i.e.

$$J_1 = \int_{\infty} 0\Delta\omega^2(t)\mathrm{d}t \tag{12}$$

while the other performance index minimizes both the frequency variation and the control effort, i.e.

$$J_2 = \int_{\infty} 0q_1\Delta\omega^2(t) + q_2\Delta u^2(t)\mathrm{d}t \tag{13}$$

where q_1 and q_2 are weighting coefficients.

Minimizing these indexes will keep the frequency variation and/or the control effort as close to 0 as possible when the system is subject to a step load change.

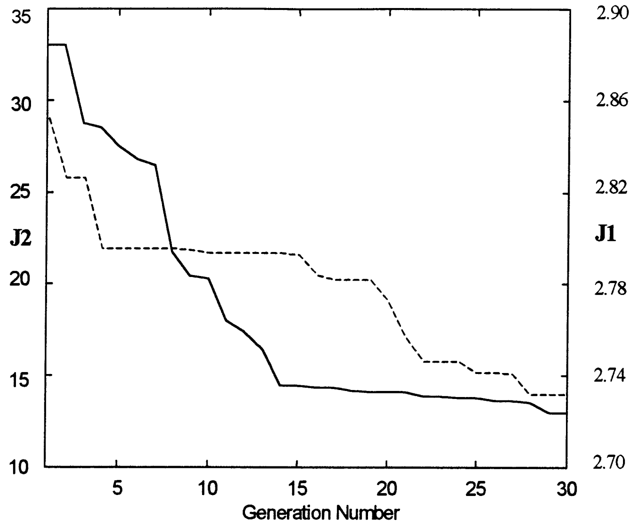

Fig. 4. Performance indices J_1(- - -), and J_2(—).

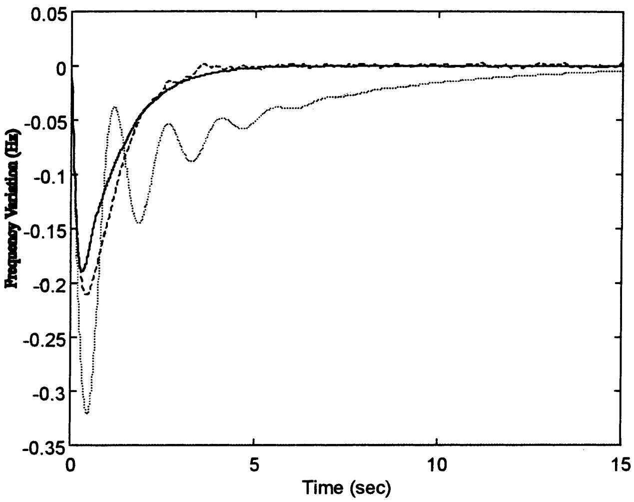

Fig. 5. Frequency variation ($\Delta\omega$), proposed, minimizing J_1 (- - -); minimizing J_2 (....); method of [2] (—).

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

5. Simulation results

Consider the LFC problem described in Section 1 with the following system parameters [2],

$T_s = 20$ 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}.

Therefore, the corresponding numeric values of $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{F}$ are

$$\boldsymbol{A} = \begin{bmatrix} -0.05 & 6 & 0 & 0 \\ 0 & -3.33 & 3.33 & 0 \\ -5.208 & 0 & -12.5 & -12 \\ 0.6 & 0 & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{B}^{\mathrm{T}} = [0 \quad 0 \quad 12.5 \quad 0]$$

$$\boldsymbol{F}^{\mathrm{T}} = [-6 \quad 0 \quad 0 \quad 0]$$

A VSC for this system was designed in [2]. The matrix $\boldsymbol{M}$ was taken as

$$\boldsymbol{M} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

and the poles of the matrix $(\boldsymbol{A}_{11} - \boldsymbol{A}_{12}\boldsymbol{C})$ were arbitrarily chosen at -4, -6 and -8. Therefore, the switching vector obtained by applying the procedure of Section 2 is

$$\boldsymbol{C} = [5.155 \quad 4.385 \quad 1 \quad 16]^{\mathrm{T}}$$

and the feedback gains were selected by trial and error as

$$\alpha_1 = 6 \quad , \alpha_2 = 6 \quad , \alpha_3 = 2 \quad , \alpha_4 = 0.$$

To start the proposed algorithm, a decision has to be made about the GA parameters which include population size, crossover probability, mutation probability, and number of generations. The proper choice of these parameters will ensure sufficient diversity in the population, which prevents the GA from being trapped in a local minimum. Moreover, random initial population will prevent premature convergence, and does not bias the performance of the GA. General guidelines available in the literature can be used in the selection process of the GA parameters [16,26]. After so many trials, a

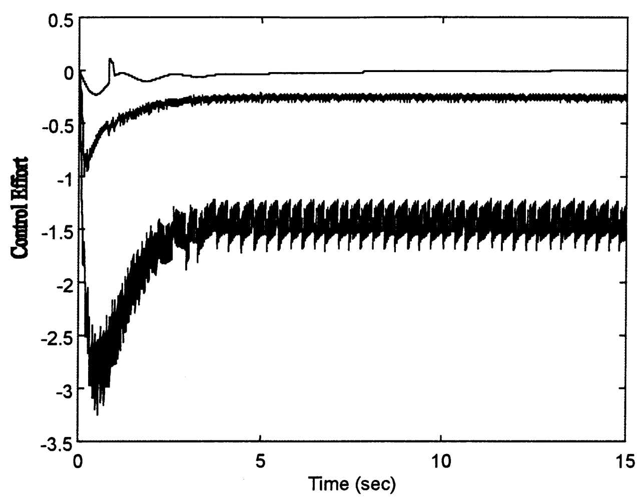

Fig. 6. Control effort (u), upper, minimizing J_2; middle, minimizing J_1; lower, method of [2].

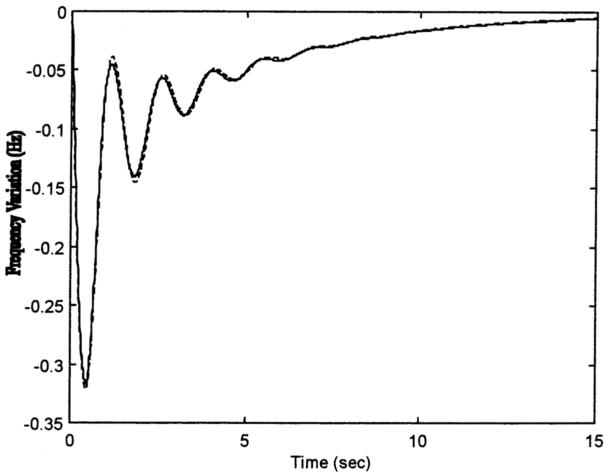

Fig. 7. Frequency variation ($\Delta\omega$), $\alpha_2 = 0.0019$; $\alpha_3 = 0.0022$ (—); $\alpha_2 = 0$; $\alpha_3 = 0$ (- - -).

population size of 30, a crossover probability of 0.7, and a mutation probability of 0.001 are used. However, it has been observed that the algorithm is robust for small variations in the values of these parameters. The search space for the feedback gains α_1, α_2, α_3, and α_4 is determined based on the knowledge that these parameters are positive quantities. A random initial population with size of 120 is generated uniformly in the search space. The algorithm is terminated when there is no significant improvement in the value of the performance index.

Using the GA design procedure described in Section 4, the optimal feedback gains that minimizes the performance indices J_1 and J_2 (where $q_1$and q_2 were both selected = 1) when the system is subjected to a step load change of 0.03 (3%) are, respectively given by:

$$\alpha_1 = 2.0844 \quad, \alpha_2 = 0.0249 \quad, \alpha_3 = 1.4022 \quad, \alpha_4 = 0$$

and

$$\alpha_1 = 0.7551 \quad, \alpha_2 = 0.0019 \quad, \alpha_3 = 0.0022 \quad, \alpha_4 = 0$$

The behavior of the performance indices J_1 and J_2 are shown in Fig. 4.

Fig. 5 shows the simulation results of the change in frequency ($\Delta\omega$) for the present and previous [2] designs when the system is subjected to a step load change of 0.03 p.u. Although not much improvements is obtained in the behavior of $\Delta\omega$ for the proposed two designs as compared to the previous one [2], the feedback gains obtained through the proposed GA approach are much smaller than those of [2]. As a result, a dramatic decrease in the magnitude of the control efforts (u) is observed as shown in Fig. 6. This can be considered as one advantage of the GA selection of the feedback gains. In addition, it is worth mentioning that since the values of α_2, and α_3 are very close to 0 (in the case of minimizing J_2), the controller complexity can be reduced by setting these gains to 0. The implication of this setting on the controller performance is shown in Fig. 7. It is quite clear that the controller performance is almost the same. It is very interesting to notice that when minimizing J_2, the controller effort is much better than that when minimizing J_1, Fig. 6. This is of course on the expense of more frequency variation as shown in Fig. 5. Therefore, it can be concluded that by proper choice of q_1 and q_2 in Eq. (13), the designer can achieve a trade off between the frequency deviation and the control effort.

6. Conclusions

A new method of selecting the variable structure feedback gains is presented in this paper. This is accomplished by formulating the VSC feedback gains selection as an optimization problem and GA are used in the optimization process. The proposed method provides an optimal and systematic way of feedback gains selection in the VSC compared to trial and error methods reported in the literature. The application of the proposed method to the LFC problem reveals that not only the system performance is highly improved but also the control effort is dramatically reduced as compared to previous methods. Using GA and by proper choice of the performance index to be evaluated, the designer can achieve a trade off between the frequency deviation and the control effort.

Acknowledgements

The authors would like to acknowledge King Fahd University of Petroleum and Minerals for the support they received during the progress of this work.

References

[1] Z. Al-Hamouz, Y. Abdel-Magid, Variable structure load frequency controllers for multiarea power systems, Int. J. Elect. Power Energy Syst. 15 (5) (1993) 293–300.

[2] A. Sivarmakrishnan, M.A. Hariharan, M.C. Srisailam, Design of variable structure load frequency controller using pole assignment technique, Int. J. Control 40 (3) (1984) 487–498.

[3] K. Bhattacharya, M. Kothari, J. Nanda, Design of discrete mode variable structure power system stabilizers, Int. J. Elect. Power Energy Syst. 17 (6) (1995) 399–406.

[4] A. Kumar, O.P. Malik, G.S. Hope, Discrete variable structure for load frequency control of multiarea interconnected power systems, IEE Proc. Gener. Transm. Distrib. 134 (2) (1987) 116–122.

[5] Y. Abdel-Magid, Z. Al-Hamouz, J. Bakhashwain, A variable-structure stabilizer for wind turbine generators, Elect. Power Syst. Res. 33 (1995) 41–48.
[6] V. Samarasinghe, N. Pahalawatha, Damping of multimodal oscillations in power systems using variable structure control technique, IEE Proc. Gener. Transm. Distrib. 144 (3) (1997) 323–331.
[7] T.-L. Chern, J. Chang, G.-K. Chang, DSP-based integral variable structure model following control for brushless dc motor drivers, IEEE Trans. Power Elect. 12 (1) (1997) 53–63.
[8] T.-L. Chern, C.-S. Liu, C.-F. Jong, G.-M. Yan, Discrete integral variable structure model following control for induction motor drivers, IEE. Proc. Elect. Power Applic. 143 (6) (1996) 467–474.
[9] A. Murty, S. Parameswaran, K. Ramar, Design of decentralized variable structure stabilizers for multimachine power systems, Int. J. Elect. Power Energy Syst. 18 (8) (1996) 535–546.
[10] X.-Y. Lu, S. Spurgeon, I. Postlethwaite, Robust variable structure control of a PVTOL aircraft, Int. J. Syst. Sci. 28 (6) (1997) 547–558.
[11] M. Innocenti, A. Thukral, Robustness of a variable structure control system for maneuverable flight vehicles, J. Guidance Control Dynamics 20 (2) (1997) 377–383.
[12] S. Singh, M. Steinberg, R. DiGirolamo, Variable structure robust flight control system for the F-14, IEEE Trans. Aerospace Electron. Syst. 33 (1) (1997) 77–84.
[13] M. Zribi, L. Huang, S. Chan, Variable structure control of two manipulators handling a constrained object, Cybernetics Syst. 28 (4) (1997) 263–286.
[14] K. Lee, S. Coates, V. Coverstone-Carroll, Variable structure control applied to underactuated robots, Robotica 15 (3) (1997) 313–318.
[15] R. Caponetto, L. Fortuna, S. Graziani, M. Xibilia, Genetic algorithms and applications in system engineering: a survey, Trans. Inst. Meas. Control 15 (1993) 143–156.
[16] D. Goldberg, Genetic Algorithms in Search Optimization and Machine Learning, Addison-Wesley, Reading, MA, 1989.
[17] H.N. Al-Duwaish, M. Bettayeb, Control of nonlinear dynamical systems using genetic algorithms, in: Proceedings of the 12th IEEE International Symposium Intelligent Control, 16–18 July 1997, Istanbul, Turkey, pp. 421–424.
[18] A. Varsek, T. Urbancic, B. Filipic, Genetic algorithms in controller design and tuning, IEEE Trans. Syst. Man Cybernetics 23 (5) (1993).
[19] B. Porter, A. Jones, Genetic tuning of digital PID controllers, Electron. Lett. 28 (1992) 843–844.
[20] J. Lansberry, L. Wozniak, D. Goldberg, Optimal hydrogenerator governer tuning with a genetic algorithm, IEEE Trans. 7 (1992) 623–630.
[21] K. Krishnakumar, D.E. Goldberg, Control system optimization using genetic algorithms, J. Guidance Control Dynamics 15 (3) (1992) 735–740.
[22] B. Porter, S.S. Mohamed, Genetic design of multivariable flight control system using eigenstructure assignment, in: Proc. IEEE Conf. Aerospace Control Systems, 1993.
[23] U. Itkis, Control Systems of Variable Structure, Keter, Jerusalem, 1976.
[24] V. Utkin, K. Yang, Methods for constructing discontinuity planes in multidimensional variable structure systems, Autom. Remote Control 39 (1978) 1466–1470.
[25] J.H. Holland, Adapation in Natural and Artificial Systems, University of Michigan Press, Ann Arbor, MI, 1975.
[26] L. Davis, The Handbook of Genetic Algorithms, Van Nostrand Reinhold, New York, 1991.