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Nuclear Power Control System Design using Genetic Algorithm

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Abstract

The genetic algorithm(GA) is applied to the design of the nuclear power control system. The reactor control system model is described in the LQR configuration. The LQR system order is increased to make the tracking system. The key parameters of the design are weighting matrices, and these are usually determined through numerous simulations in the conventional design. To determine the more objective and optimal weightings, the improved GA is applied. The results show that the weightings determined by the GA yield the better system responses than those obtained by the conventional design method.

1. Introduction

The control design techniques have been changed significantly over the last decade. Although the PID control has been used and proved to be powerful in various fields of the application, new control techniques are widespread at present with the computer aided control design. One of the control techniques which could replace the present PID is the linear quadratic regulator (LQR) method. This method is an important subset of the powerful machinery of the optimal control of Wiener-Hopf-Kalman. The plant is assumed to be a linear system in state space form and the objective function is a quadratic functional of the plant states and control inputs. In the LQR problem, the design problem boils down to the determination of the optimal weighting matrices. The usual practice is to trade off the various conflicting state variables through numerous simulations. This implies that the LQR design, although it is a synthetic machinery, is somewhat subject to the designer's experiences and in the worst case, it may be a blind search. Even after the satisfying design is obtained, the question of whether the determined weighting matrices are the 'best' ones still remains.

With this regard, an effective optimization tool, the GA, is employed to determine the weighting matrices of the LQR system. The GA emulates the biological evolutionary theories to solve the optimization problems. By using the three major operators of reproduction, crossover and mutation which are analogous to the biological processes, it searches the optimal design parameters of the given problem. Since the GA algorithm does not depend on the coupling between the parameters, it provides the more flexibility.

This paper describes how the GA is used to the design of the nuclear reactor power control system. The control scheme is fashioned into the tracking system by use of the LQR with considering the Gaussian noises. The overall scheme is described in 6 dimensional matrix equations and its corresponding weighting matrix are determined by GA. The results are then compared with those of conventional approaches.

2. System Modeling

2.1 LQR/LQG System

The plant of the nuclear power control system is modeled by employing the one delayed neutron group point kinetics equation. Also the singly lumped energy balance equations are used to reflect the temperature feedback effects in the plant itself. This system is MIMO (multi-input, multi-output) and has five state variables. By assuming that the coolant inlet temperature and the coolant flow rate are constant, and by controlling the output matrix, the system becomes SISO (single-input, single-output), and has the form of

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}u, \quad y = \mathbf{C}\mathbf{x}$$

where $\mathbf{x}$ is the state variable vector, $\mathbf{A}$ and $\mathbf{B}$ are system matrices, and u is the system input.

The system matrices are functions of the nuclear properties as well as of the thermal hydraulic properties of the system, hence depends on the reactor power. The input, u, is the scalar and stands for the control rod velocity. It can be shown that the eigenvalues of $\mathbf{A}$ vary with the reactor power. As the power becomes low, the most sensitive eigenvalue approaches to the $j\omega$ axis, which indicates the fact that the system is harder to control at low powers. The system described above is the continuous system and it is digitalized with the sampling period of 0.05 sec. For this digitalized plant, the LQR design is made. The cost function of the LQR is

$$J = \frac{1}{2}\Sigma\left(\mathbf{x}(k)^T \mathbf{Q}\,\mathbf{x}(k) + u(k)^T R\, u(k)\right)$$

where $\mathbf{Q}$ is the state weighting matrix of 5 by 5, and R is the input weighting scalar. And it should be noted that the system performance depends on the relative values of $\mathbf{Q}$ and R, rather than their absolute values, R is fixed as 1.0, and the design problem is to determine the $\mathbf{Q}$.

The basic premise of the LQR is that all states be available for the feedback. In practice, not all the state variables are available for the direct measurement, and it is necessary to estimate the unmeasured state variables. With the augmentation of the estimated variables, the system is described as

$$\dot{\xi}(k) = \Psi\xi(k) + \Lambda v, \quad y(k) = \Gamma\xi(k)$$

where $\xi(k)$ is $[\ \mathbf{x}\ \ \hat{\mathbf{x}}\ ]^T$, Ψ and Λ are functions of the LQR feedback gain and the observer gain.

2.2 Tracking System

The LQR/LQG system is a regulating system. But the actual system should be a tracking system in which the output of the system follows the input command system. Two schemes could be considered. One is the unity feedback system as described in Fig. 1. This system is made by locating the LQR/LQG controller on the inner feedback loop, and the output is feedbacked to generate the error signal. An integrator and power-to-rod velocity gain are also incorporated. This system is simple, but the number of design parameters increases because of the feedforward gain. Further it is found that there is a limitation on the feedforward gain for the system stability, and the system response is very sensitive to the gain value. This indicates the system is susceptible to the setting point drift and is not desirable with respect to the robustness.

Another system configuration is the order increased regulating system (OIRS), which is described in Fig. 2. The error between the command input and the system output is integrated and is augmented to the estimated state variables out of the observer. Then the LQR gained signal is feedbacked to sum with the input command signal. The number of state variables increases by one because of the error signal, and the order of LQR weighting matrix increases from 5 to 6. This configuration seems to be complex, since the system order is increased and the feedforward gain is included. However, simple math shows that the feedforward gain has the effect only on the system zeros, and could be dropped off from the system.

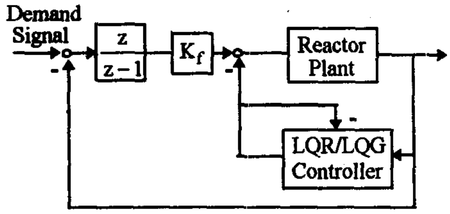

Figure 1. Configuration of Unity Feedback System

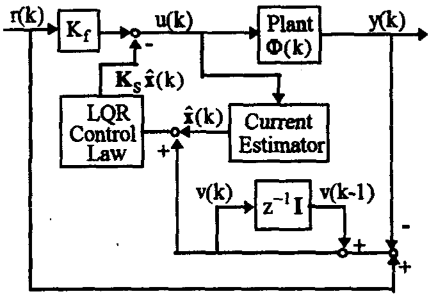

Figure 2. Configuration of Order Increased Regulating System

Then the number of parameters to be determined is the same as that of the unity feedback configuration. Since the overall system is described in the LQR, the system has a sufficient margins, which is an intrinsic advantage of the LQR. The cost function of the of the OIRS is

$$J_S = \frac{1}{2}\Sigma\left(x_S(k)^T Q_S\, x_S(k) + u(k)^T R_S\, u(k)\right), \text{ where } x_S(k) = \left(\hat{x}(k)\ \ v(k)\right)$$

The optimal feedback gain vector of the OIRS is $K_S = \left(K\ K_V\right)$, where K is feedback gain corresponding to the LQR system, and K_V is the gain which is applied to the error signal. With the input weighting R_S be equal to 1, the design of the power tracking system boils down to the determination of the state weighting matrix, Q_S.

3. Application of Genetic Algorithm to the Determination of Weighting Matrix

In the conventional design, Q_S is determined along with the design procedure. With the assumption that Q_S has the form of $Q_S = \begin{pmatrix} Q & 0 \\ 0 & q_S \end{pmatrix}$, Q is first determined in the process of LQR/LQG design. Then q_S, which reflects the error integration effects, is found during the OIRS design. This implies the limitation that the two design steps of the LQR and the OIRS has no coupling, which is not always true. The system matrices of the OIRS are function of the original LQR system matrices, feedback and observer gains, as well as of the feedforward gain. If the feedforward gain is employed to control the locations of zeros, the LQR and the OIRS are coupled each other, hence the determination of Q_S is somewhat involved. Further, even there be no coupling, the elements of Q and q_S are determined through various simulations and the final proper values are selected by exercising designer's discretion. And, even the system works well, the question whether that design is the best one still remains.

The GA which was first proposed by J. Holland in 1975 and revived by D. E. Goldberg in mid 1980 has proven to be a useful tool in a variety of search and optimization problems over the last years[1-3]. GA is based on the survival-of-the-fittest principle in nature. GA maps a problem onto a set of binary string to represent a candidate solution called an individual. Each solution is associated with a *fitness* value to measure how good it is. GA then manipulates the most promising strings to search the improved solutions. Ultimately, GA differs from traditional searching techniques in several aspects as follows;

- GA is the direct searching method independent of the coupling of design parameters and does not need the intensive system information such as the derivatives of the system.
- GA makes use of the probabilistic search and not the deterministic one. Owing to this feature, it can escape from the local traps, but may tend to wander around the true solution.
- GA operates on several solutions simultaneously (concurrent multi-point search), gathering information from current search points to direct subsequent search.

To apply the GA to the determination of the weighting matrices of the LQR system, the problem is formulated as follows ;

Find	$X = [x1,x2,x3,x4,x5,qs]$
to maximize	$fitness(X) = 1/cost(X)$
subject to	$cost(X) = \int \lvert y_0 - y(t) \rvert dt + \int \lvert u(t) \rvert dt$
	$1.*10^{-6} < x_i < 1.*10^{-2}, i = 1, 2, ..., 5$
	$1.*10^{-6} < q_s < 1.*10^{-2}$

where,

X : an individual or a candidate solution

x_i : diagonal elements of the assumed weighting matrix **Q**

q_s: assumed value for error integration effect

cost(X) : cost function for the individual X

fitness(X) : fitness of the individual X

y_0 : target value

y(t) : system output

u(t) : control input

Through out the repeated generation changes in GA, the average fitness of the candidate solutions in the population gradually increases. That is, the quality of the solutions are improved toward an unknown optimal one. The major improvements made on the simple GA are : 1) the adoption of variable crossover site, 2) the usage of an 'interpolation scheme' instead of the bit-wise crossover to avoid the hamming-cliff effects, 3) the adoption of the fitness scaling and the roulette-wheel selection scheme based upon the scaled-fitness, 4) the re-initialization of the population per every 5 generation changes with the best POP_SIZE solutions which have been already found and stored, and 5) in addition to the elite-policy, the introduction of a new GA operator named 'exchange' to avoid pre-maturing to a local optima.

4. Application Example

Figures 3 and 4 show the responses of the OIRS for the case of conventional design. Figure 3 describes the reactor output, when the power is step increased by 10 % from the initial state of 90% power. The peak value of the output is sufficiently low than the 103%, which is set forth by the FSAR[4]. The transient of the control effort, that is the relative control rod velocity, is shown in Fig. 4. This transient is much milder than that of the unity feedback system. The elements of **Q** and the integrator weight q_s are determined as $3.\times 10^{-6} \cdot \mathbf{I}(5)$ and 0.003 , respectively, where **I** indicates the identity matrix. All these results are obtained through numerous simulations, and it can not be affirmed this design is uniquely the best.

On the other hand, Figs. 5 and 6 show the results of the GA design. The overall responses are quite similar to those of Figs. 3 and 4. But the weighting values are different from those values obtained by the conventional approach. Figure 7 shows how the weighting values are updated and converged as the generation proceeds. After about the 35-th generation, there are no significant changes in the weighting values. The effectiveness of the GA can be found in Fig.8. The 'improvement' in the figure indicates the relative values of the fitness of GA to the 'best' result obtained by conventional approach. Although the GA gives the poor relative fitness value of approx. 0.85 at the initial stages , it soon exceeds the fitness of conventional design. After the 20-th generation, 21% of improvement is achieved although the results of each approach seems to be similar as shown in Figs. 3 - 6.

5. Conclusion

The GA is applied to the nuclear power control system. The control model is set up in the machinery of the LQR. To make the system output to follow the input command signal, the model order is increased by one. The weighting values, which are the key parameters of the design, are determined by the GA. The result of the GA approach shows that it can replace the conventional method which requires the designer's experiences and also is time consuming. Further the GA gives the better results, once the cost function is determined and various forms of cost function can be easily implemented.

References

1. Goldberg, D. E., *Genetic Algorithm in search, optimization & machine learning*, Addison-Wesley Publishing Co., NY, 1989
2. Koza, J. R., *Genetic Programming on the programming of computers by means of natural selection*, MIT Press, 1992
3. Srinivas, M. and L. M. Patnaik, "Genetic Algorithms : A Survey," *Computer*, **Vol. 27, No. 6**, pp. 17-26, 1994
4. *Final Safety Analysis Report of Kori Unit* 2, 2nd Ed.., KEPCO, 1989

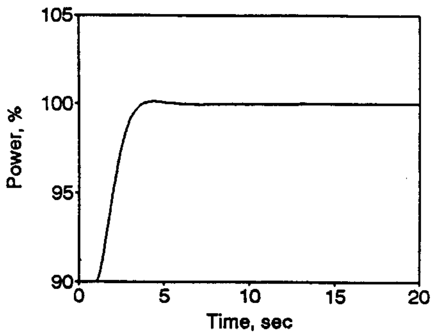

Figure 3. Power Responses of the Conventional Design

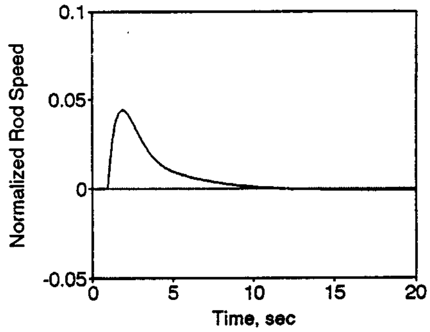

Figure 4. Control Input Responses of the Conventional Design

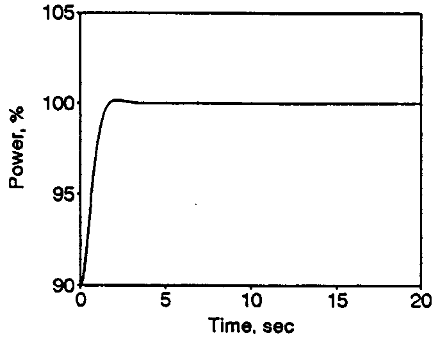

Figure 5. Power Responses of the GA Approach

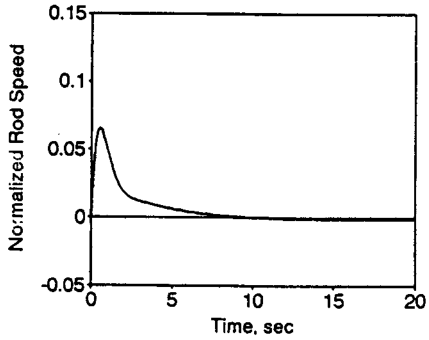

Figure 6. Control Input Responses of the GA Approach

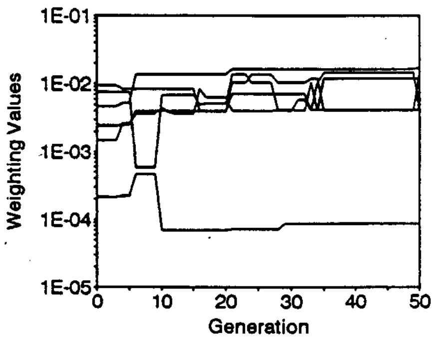

Figure 7. Evolution of Weighting Values

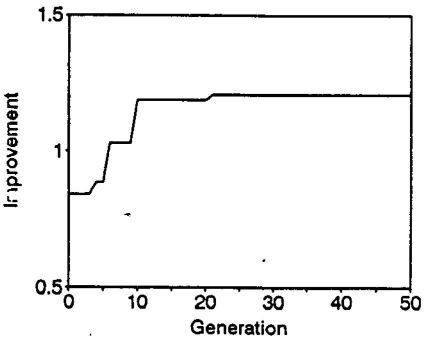

Figure 8. Fitness Improvements of GA