Optimization of Double Loop Control Parameters for a Variable Displacement Hydraulic Motor by Genetic Algorithms

Kyoungkwan AHN* and JangHwan HYUN**

The optimization of control gains for hydraulic servo systems is very difficult because of the high nonlinearities and uncertainties in the systems. In this paper, genetic algorithm is adopted to optimize the feedback gains for an over-centered variable displacement hydraulic motor (VDHM). The reciprocal of the ITAE criterion is proposed as the fitness function that evaluates the control performance. The appropriate specification of the genetic algorithms and the search range of each control gain for the speed control system are presented. It is found that the near-optimal values of the feedback gains can be obtained within 10 generations, which corresponds to about 100 experiments. The optimal gains are also obtained when the inertia or the supply pressure is varied. Optimized feedback gains are confirmed by plotting the fitness function in a given gain space and it was verified that the genetic algorithm is an efficient scheme in optimizing feedback gains for hydraulic servo systems.

Key Words: Fluid Power System, Variable Displacement Hydraulic Motor, Optimization, Genetic Algorithm, Double Loop Control

1. Introduction

In recent years, much attention has been paid to the optimization of control gains for hydraulic servo systems to improve the control performance. The feedback gains have usually been tuned manually since it is almost impossible to determine them theoretically because of high nonlinearity of the systems and the uncertainty in system modeling(1),(2). Several control strategies including fuzzy-PI, self tuning and model reference adaptive control have been developed for the control of variable displacement hydraulic motor systems(3)–(5). However, fuzzy-PI control algorithm has the difficulty in the optimal gain tuning of design parameters of fuzzy rules and adaptive control scheme together with parameter identification using recursive least-square method don’t generally work well for systems with abrupt parameter changes, and often requires a large amount of real time computation. Jeon has recently shown that genetic algorithms (GA) can be applied to optimize the feedback gains of the three loop controller of a pneumatic cylinder drive(6). Genetic algorithms are general-purpose search procedures, optimization methods, or learning mechanisms based on the Darwinian principle of biological evolution; that is, reproduction and “the survival of the fittest” along with genetic recombination. When provided with a suitable fitness function that evaluates the performance of control systems, feedback gains may readily be optimized by GA(7)–(11).

In this paper, GA is adopted to optimize the feedback gains for an over-centered variable displacement hydraulic motor (VDHM) which is noted for its small energy loss and high system efficiency(12)–(14). The system is connected to a constant pressure supply, and output torque is adjusted through motor displacement control. For speed control of an over-centered VDHM, a double-loop control, called cascade control, is often used to improve the response characteristics of a single loop control which consists of an inner loop for the angular position control of swash plate and an outer loop for motor-speed control. A PID and a PD controller may be used for the inner and outer loop, respectively, so that a total of five feedback gains are involved in this speed control system. Manual tuning of five feedback gains is an extremely time-consuming task.

In this study, it is also demonstrated that the optimal or near-optimal values of five feedback gains for the speed control system can experimentally be determined by using GA with minimum information specific to the system such
as the search range of each feedback gain.

2. Rotational Speed Control of a VDHM

The schematic diagram of the speed control system with a VDHM at a constant supply pressure is shown in Fig. 1.

For motor displacement control the swash plate angle is controlled by a double rod cylinder stroked by an electrically activated servo valve. The signal for the servo valve is provided by a controller using the deviation of rotational speed and an auxiliary stroke feedback. At a constant speed, the torque of the motor corresponds to the load. By increasing the load, the actual rotational speed will drop. As the result, the valve opens and the actuating cylinder corrects the displacement to adjust the torque to the load. The displacement changes until the nominal rotational speed is reached. Since the damping of the controlled system driven in an open loop is very low, a suitable controller is necessary for establishing the closed loop. Figure 2 shows a block diagram for such double control loops with a PID- and a PD- controller.

In Fig. 2, $\omega$ is the rotational speed, $X_p$ the position of the cylinder-rod, and $\omega_d$ and $X_{pd}$ are the reference speed and reference position, respectively. Gains of the PID controller for rotational speed control are $K_{pw}$, $K_{iw}$ and $K_{dw}$, and those of the PD controller are $K_{pp}$ and $K_{dp}$, respectively.

The control law of this system can be expressed by the following equation.

$$X_{pd} = K_{pw} \cdot (\omega_d - \omega) + K_{iw} \cdot (\dot{\omega}_d - \dot{\omega}) + K_{iw} \cdot \int (\omega_d - \omega) dt$$

$$U = K_{pp} \cdot (X_{pd} - X_p) + K_{dp} \cdot (\dot{X}_{pd} - \dot{X}_p)$$

where $U$ denotes the inner loop controller output voltage.

3. Application of Genetic Algorithm to Hydraulic Servo Systems

A genetic algorithm (GA) is a population-based global search procedure inspired by the laws of natural selection and genetics. The GA evolves a collection element called population of individuals. Each individual of population represents a trial solution to the problem of maximizing a given fitness function. The standard simple genetic algorithm (SGA) works as follows(7):

Step 1. : Randomly generate an initial population.
Step 2. : Compute the fitness function of each individual of current population.
Step 3. : Generate the next population by applying three genetic operators; reproduction, crossover and mutation.

Figure 3 shows the flowchart of the parameter optimizing procedure using GA. For details of genetic operators and each block in the flowchart, one may consult literature(7).

Because GA needs only objective functions to be opti-
timized and no limitations are placed on the search spaces, they can be applied to optimize the feedback gains of fluid power system controllers such as control gains for PID of three loop controllers. Selection of a reasonable population size, crossover rate, mutation rate, and string length is critical for good performance of GA (9). In the design of genetic algorithms, every possible point in the search space should be reachable from the initial population by crossover only. This requirement can only be satisfied if there is at least one instance of every allele at each locus in the whole population of strings. From a Ref. (9), the probability $P^*$, where at least one allele exists at each locus in the initial population, can be given as follows:

$$P^* = (1 - (1/2)^M)^{L}$$  \hspace{1cm} (2)

where $L$ is the length of strings and $M$ is the number of population. In the design of genetic algorithms, the length of string and the probability $P^*$ are set to be 25 and 95%, respectively. From the above equation, the population size is determined to be 10. Table 1 shows the specification of the GA used in this study.

In optimizing feedback gains using GA, a criterion that evaluates the fitness representing the possibility of survival in the next generation is needed. A well designed fitness function gives fitness values that agree with human intuition for good control performance and that are sensitive to small variations in the system response. In this paper, the reciprocal of the well-known ITAE (integration of time multiplied by absolute error) criterion that minimizes the transient variations about the steady-state value is used as the fitness function.

$$Fitness\ function = 1/\int_{0}^{\infty} t|e(t)|dt$$  \hspace{1cm} (3)

4. Experiments

4.1 Experimental apparatus

Figure 4 is a schematic diagram illustrating the experimental setup. This consists of three parts: a motor system, a load generating system and a data-acquisition and control system. The motor system comprises a VDHM (Rexroth, A4VSO-40), an encoder (Sansei, OES-10-2M), a LVDT and a servo valve (Moog/73-102, Step response: 32 ms). The load generating system includes a load pump, a proportional pressure control valve, an inertia wheel, a clutch, a torque transducer, a servo valve controller and a personal computer. Some of the technical specifications of the experimental setup are as follows: the nominal supply pressure is 15 MPa, the rated current of servovalve is 60 mA and the rated flow 30 L/min at a pressure drop of 7 MPa, maximum displacement volume of the VDHM is 40 cc/rev, the encoder resolutions and the A/D, D/A converter are 1000 pulse/rev and 12 bits, respectively.

4.2 Experimental results

The initial and final search ranges for feedback gains used in this study and the corresponding resolution and the number of bits are given in Table 2. The initial search range of each feedback gain should be selected by considering the system stability. If, in an experiment, a feedback gain is found to converge near the boundary of the given search range, then the search range must be adjusted. The five feedback gains, which are called a gain set, for the speed control of an over-centered VDHM are optimized by experiment using the test rig discussed in Fig. 4. The genetic algorithms can be continuously run on the control computer according to the flowchart shown in Fig. 3 with specifications given in Tables 1 and 2 to obtain optimal feedback gains. The number of gain sets in one generation equals the population size in Table 1. An experiment is made with each gain set, and the resultant motor speed is stored at each sampling time (0.005 second). The

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
Population size & 10 \\
\hline
Crossover rate & 0.7 \\
\hline
Mutation rate & 0.02 \\
\hline
String length & 25 \\
\hline
\end{tabular}
\caption{Specification of the GA}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Gain & Initial & Final & Resolution \\
\hline
$K_p$ & 0.0 - 1.0 & 5 & 0.000125 & 0.0 - 25 & 5 & 0.625 \\
\hline
$K_i$ & 0.0 - 0.01 & 5 & 0.0000125 & 0.0 - 0.024 & 5 & 0.09575 \\
\hline
$K_d$ & 0.0 - 1.0 & 5 & 0.000125 & 0.0 - 1.8 & 5 & 0.046875 \\
\hline
$K_{sv}$ & 0.0 - 0.01 & 5 & 0.0000125 & 0.0 - 0.024 & 5 & 0.00075 \\
\hline
\end{tabular}
\caption{The initial and final search ranges for feedback gains, number of bits and resolution}
\end{table}
Fig. 5 Speed response with optimized gains obtained using GA

Optimized Gains

\[ K_{pw} : 13.1875 \]
\[ K_{iw} : 6.06250 \]
\[ K_{dw} : 0.00720 \]
\[ K_{pw} : 0.98750 \]
\[ K_{dp} : 0.00880 \]

Fig. 6 Fitness values with respect to the number of generations

Table 3 Optimal gains with respect to the inertia variation

<table>
<thead>
<tr>
<th>( J )</th>
<th>( K_{pw} )</th>
<th>( K_{iw} )</th>
<th>( K_{dw} )</th>
<th>( K_{pw} )</th>
<th>( K_{dp} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.005 kg·m²</td>
<td>1.19647</td>
<td>9.25500</td>
<td>0.01624</td>
<td>0.93125</td>
<td>0.04127</td>
</tr>
<tr>
<td>0.04 kg·m²</td>
<td>13.18750</td>
<td>6.66250</td>
<td>0.07290</td>
<td>0.98750</td>
<td>0.08888</td>
</tr>
<tr>
<td>0.2 kg·m²</td>
<td>14.87500</td>
<td>1.00000</td>
<td>0.00162</td>
<td>1.09075</td>
<td>0.06126</td>
</tr>
</tbody>
</table>

Fig. 7 Optimized speed response showing the effects of inertia variation \( (\omega_d = 1000 \text{ rpm and } P_s = 15 \text{ MPa}) \)

Table 4 Optimal gains with respect to the supply pressure variation

<table>
<thead>
<tr>
<th>( P_s )</th>
<th>( K_{pw} )</th>
<th>( K_{iw} )</th>
<th>( K_{dw} )</th>
<th>( K_{pw} )</th>
<th>( K_{dp} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>10MPa</td>
<td>15.10500</td>
<td>6.56250</td>
<td>0.00100</td>
<td>1.19075</td>
<td>0.00900</td>
</tr>
<tr>
<td>15MPa</td>
<td>13.18750</td>
<td>6.06250</td>
<td>0.07290</td>
<td>0.98750</td>
<td>0.08888</td>
</tr>
<tr>
<td>20MPa</td>
<td>11.50000</td>
<td>7.00000</td>
<td>0.08889</td>
<td>0.94875</td>
<td>0.01126</td>
</tr>
</tbody>
</table>

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fitting function given by Eq. (3) is then computed with the stored data for each gain set. Once the tests for all the gain sets in the current generation are completed, the next population is generated through GA operations (reproduction, crossover, and mutation) by utilizing the evaluated fitness of each gain set. A test is again run with each gain set in the new generation. This process is repeated until the feedback gain sets converge to the optimal values.

Figure 5 shows the speed response obtained by using the optimal feedback gains by GA. The optimal gains of PID-PD controller are selected to maximize the fitness function. Therefore some oscillations in the transient response may be shown in the selected optimal PID-PD parameters. In order to reduce steady state error and oscillations in the transient response, the fitness function must be modified in order to include the steady state error and the oscillations in the transient response. At the same time, the nonlinear characteristics of the regulator of variable displacement motor and the fluctuation of supply pressure in the hydraulic pump are also the reasons of steady state error and oscillations in the transient response.

Figure 6 plots the corresponding fitness value with respect to the number of generations. Figure 6 shows both the generation best represented by the fitness value of best chromosome and the generation average which is the average fitness value of the chromosomes of each generation. We can see in Fig. 6 that near-optimal values of feedback gains can be obtained within 10 generations, which corresponds to about 100 experiments. More than this number of experiments would be needed for manual tuning by an experienced technician.

If the inertia or the supply pressure changes, then changes in dynamics of hydraulic servo systems would occur, so that re-tuning of feedback gains must be carried out to obtain the desired control performance. Optimal values are determined by GA when the inertia and the supply pressure are varied. The results are tabulated in Tables 3 and 4.

Figure 7 shows the speed responses with the optimal parameters given in Table 3 when the inertia is varied, and Fig. 8 the speed responses with the optimal parameters in Table 4 when the supply pressure is varied.

It is shown from Tables 3 and 4 that, as the inertia decreases or as the supply pressure increases, the proportional gains of both internal and external loop \( (K_{pw} \text{ and } K_{pw}) \) tend to decrease while the other gains \( (K_{iw}, K_{dw} \text{ and } K_{dp}) \) increase. The fitness distribution is computed by Eq. (3) and the plots in the \( K_{iw} \) and \( K_{iw} \) space, the \( K_{pw} \) and \( K_{pw} \) space, and the \( K_{pw} \) and \( K_{pw} \) space are shown in Figs. 9–11, respectively. In each figure, the remaining
feedback gains (for instance, $K_{pw}$, $K_{dw}$ and $K_{dp}$ in Fig. 9) are fixed at the optimal values. Here, $K_{pw}$, $K_{iw}$ and $K_{pp}$ are dominant control gains and the other gains are not dominant control parameters from the experimental results. From the fitness distribution plot, the optimal values of feedback gains are clearly defined in a given gain space. These figures also indicate that it would be very hard to determine optimal gains by manual tuning, because the optimal gains are represented by the maximum point in a gain space.

5. Conclusions

This paper presents a new optimization method of 5 control parameters for the speed control of over-centered VDHM by GA with minimum information specific to the system such as search range of each feedback gain. The reciprocal of ITAE criterion is found to be an appropriate fitness function for GA to evaluate the control performance of the given feedback gains and the optimal feedback gains are clearly defined as the maximum point of the fitness distribution in a given gain space. When the system parameters such as the inertia or the supply pressure are changed, the optimal gains can readily be obtained by GA. It was also found that both proportional gains in the outer and inner loop tend to increase while the other three gains decrease as the inertia increases or as the supply pressure decreases.

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References


