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OPTIMAL CONTROL OF IMPACT MACHINES USING NEURAL NETWORKS

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Abstracts A newly developed discrete-time control design method for impact machines is proposed. It is composed of identification and control using neural networks, where the optimal controller with saturation and no use of velocity measurements is obtained. By computer simulation, the proposed method is demonstrated to be effective: as the training progresses, the cost function becomes smaller; the proposed control is superior to PID control tuned with Ziegler-Nichols (Z-N) parameters; robust performance with respect to uncertainty, disturbances and working time is so good.

Keywords Impact Working, Vibration, Neural Network, Digital Control, Nonlinear Control

1. INTRODUCTION

The working and assembling by vibration have been widely employed so far in many working strokes. In such working there is impact working. Impact machines have been applied to processes such as forming, punching and hammering. A harmonic driving force had been adopted as an exciting force of impact machines a few years before. Because of friction and deformation caused by collision, the motion of an impactor after an impulse is disturbed and becomes unstable. Therefore, the impact working cannot be stably continued by a predefined driving force like the harmonic one. Recently, the authors have studied impact machines[1)-3)]. K. Koizumi et al. [1), 2)] suggested energy and power minimization methods, respectively. M. Sasaki et al.[3)] presented optimal PID control with saturation using genetic algorithms, where a special controller is needed for vibration control. The working with impulses has nonlinear behavior because of collision phenomena, which bears the constraints of state variables, and has input constraints, even if the mathematical model is linear.

Neural networks have been paid much attention to as one of the most powerful nonlinear optimization methods, and employed much in the field of control engineering, so far. However, neural networks have not been adopted at all in working by impact.

In this paper, a newly developed digital control design method for impact machines is proposed. It is composed of identification and control using neural networks. The optimal controller with constraints and no use of velocity measurements is designed using an inverse dynamics of the plant and error backpropagation with a varying learning rate and momentum. Taking the repetition of the motion of a small impact machine into consideration, the control of the motion is investigated only for one working period, aiming at the high-speed, high-accuracy and stability of the small impact machine. The control objective for one working period is that at the specified start time of working, the desired impulse position and velocity of an impactor are satisfied.

2. PROBLEM STATEMENT

Consider the control problem of the impact machine given by Fig. 1. The equation of motion is governed by

$$m\ddot{y} + c\dot{y} + ky = u(t) \tag{1}$$

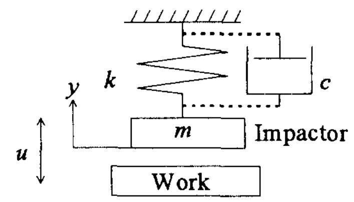


Fig. 1. Model of the impact machine.

where m denotes the mass of the impactor, c denotes a viscous damping coefficient by atmospheric air, k denotes the spring constant, $u(t)$ which is the control input represents the driving force, and $y(t)$ which is the plant output represents the displacement of the impactor. The control design is done only for one working period. Successive working is performed by the recursion of the control, taking the coefficient of rebound into consideration after impulses. The control objective for one working period is that at the specified start time of working which means the start time of an impulse, the specified impulse position and velocity of the impactor are attained. The objective is essential to high-speed and high-accurate working, and becomes an almost perfect tracking problem in finite time. Especially, it is very important to satisfy the desired velocity for good working. In this paper, it is expected that the stability after an impulse until the coming impulse is attained by the following power of the neural controller. Therefore, a special controller for vibration control after an impulse is not used. On this point, it differs from the PID control[3)]. For one working period, the reference model based on the control objective needs to be designed as

$$y_M(t) = G_M(s)r(t) \tag{2}$$

where $s = d/dt$, $y_M(t)$ denotes the reference output which is a teacher signal, $G_M(s)$ denotes the transfer function, and $r(t)$ denotes the reference input.

3. DESIGN METHOD

A newly developed discrete-time control design method for impact machines using hierarchy neural networks with supervised learning is proposed which is composed of identification and control.

3.1 Identification

To obtain good control design, the plant has to be identified quite well. The model to be identified is represented by the pulse transfer function model of Eq. (1)

$$y(k) = \frac{\beta_1 q^{-1} + \beta_2 q^{-2}}{1 + \alpha_1 q^{-1} + \alpha_2 q^{-2}} u(k) \tag{3}$$

where k represents the number of discrete time, and q^{-1} represents a unit delay operator. The cost function J to be minimized needs to be designed for a measure of identification (see the following simulation in detail). Identification is done using a linear neural network with two layers, where the weights are all updated sequentially, the activation functions of the units concerning $u(k-1)$ and $u(k-2)$ are both $f(x) = x/10$, and the others are all $f(x) = x$.

3.2 Control

The working by impulses has nonlinear behavior due to collision phenomena and input constraints, even if the equation of motion is linear. This working problem is solved using nonlinear neural network control. From the control objective, the present and future information of impactor's position and velocity is considered to be important. Taking this and a backward difference into account, the control is derived from an inverse dynamics of state-space representation of the plant (1). Thus, only for one working period, the prototype of the proposed control with physical constraints is designed as follows:

$$u(k) = k_1 y_M(k+1) + k_2 y_M(k) + k_3 y(k) + k_4 y(k-1) \tag{4}$$

with

$$|u(k)| \le u^* \tag{5}$$

where u^* means the maximum admissible value of the input. It is noted that no velocity measurements of the impactor are used. To satisfy the tight requirement of the control objective, the control parameters have to be optimized using a cost function. This is performed using a nonlinear neural network with three layers, varying learning rate and momentum factor(see Fig. 2). The activation functions of the input and hidden units are all $f(x) = x$, while that of an output unit is the logistic sigmoid function.

$$f(x) = \frac{2u^*}{1 + \exp(-x)} - u^* \tag{6}$$

By the weight $w_{11}^{(u)}$ and Eq. (6), the sigmoid function with a temperature is obtained. In most cases, the temperature is chosen previously. In this paper, it is introduced how to estimate the temperature by a weight between a hidden and an output layers (see Fig. 2). The cost function J needs to be designed for control (see the following simulation in detail). Using error backpropagation, all the weights are batch updated as follows.

$$w_{1i}^{(l)}[N+1] = w_{1i}^{(l)}[N] + \Delta w_{1i}^{(l)}[N] + \delta w_{1i}^{(l)}[N]$$

$$w_{11}^{(u)}[N+1] = w_{11}^{(u)}[N] + \Delta w_{11}^{(u)}[N] + \delta w_{11}^{(u)}[N]$$

$$\Delta w_{1i}^{(l)}[N] = -\varepsilon[N]\frac{\partial J[N]}{\partial w_{1i}^{(l)}[N]}, \quad \Delta w_{11}^{(u)}[N] = -\varepsilon[N]\frac{\partial J[N]}{\partial w_{11}^{(u)}[N]}$$

$$\delta w_{1i}^{(l)}[N] = \alpha[N]\left\{w_{1i}^{(l)}[N] - w_{1i}^{(l)}[N-1]\right\}$$

$$\delta w_{11}^{(u)}[N] = \alpha[N]\left\{w_{11}^{(u)}[N] - w_{11}^{(u)}[N-1]\right\} \tag{7}$$

where $\Delta w_{1i}^{(l)}$ denotes a change to the weight, $\delta w_{1i}^{(l)}$ represents momentum, ε is called a learning rate, α is called a momentum factor, and N represents a training epoch.

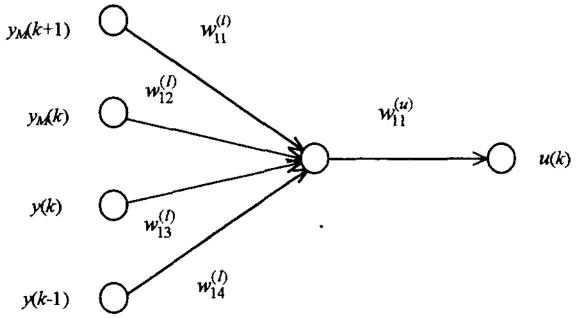


Fig. 2. Neural network for control.

4. SIMULATION

In this section, to make sure that the proposed method is effective, the computer simulation study was implemented. The parameters of the small impact machine were $m = 87.16$g, $c = 7.759 \times 10^{-2}$ Ns/m, and $k = 1.828$ N/mm.

4.1 Identification

The inputs for identification and test were chosen as rectangular waves with amplitudes 1 and 2, and periods 20ms and 10ms, respectively. The plant of Eq. (1) was calculated by the 4th-order Runge-Kutta method with the step-size 2×10^{-4} ms. The sampling period for identification was chosen as $T = 0.2$ ms. The time interval to be identified was one period of the input. The cost function was given by

$$J = \frac{1}{2}\left\{y(k) - o^2\right\}^2 \tag{8}$$

where o^2 is an output of the second layer in neural network for identification. All the initial values of weights were set to zeros. The learning rate was $\varepsilon[N] = 0.01$. The momentum factor was set to $\alpha[N] = 0.95$. The maximum number of epochs to train was 2.6×10^4. Figure 3 shows the test result of the model. From this, it is obvious that the model is in good agreement with the plant.

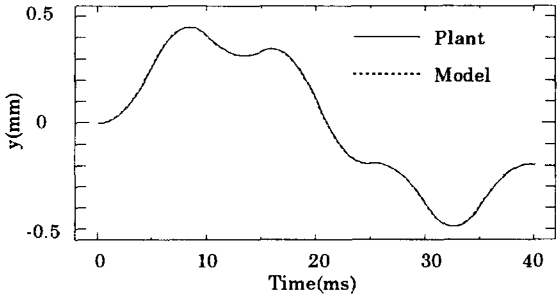


Fig. 3. Test result of the model.

4.2 Control

In this simulation, one working period was 30.2ms and the control objective was as follows: the start time of the period was $t = 0$ ms; the start time of an impulse was $t = 30$ ms; the impulse position was $y(30) = -0.05$ mm; the velocity of the impactor was $v(30) = -0.05$ m/s, where $v(t) = \dot{y}(t)$. The limitation of input was set as $u^* = 1$. For simplicity, it was assumed that the final time of working was 30.2ms, which means that impact (i.e., working) time is 0.2ms, and that the coefficient of rebound was 0.6 for successive working. Taking these into consideration, the reference model for one working period was designed as follows:

$$y_M(t) = \begin{cases} \dfrac{0.01}{(s+0.1)(s+0.15)} r_1(t) & (0 \le t \le 15) \\ \dfrac{0.01}{(s+0.1)(s+0.15)} r_2(t) & (15 < t \le 30) \\ -0.05 & (30 < t \le 30.2) \end{cases} \quad (9)$$

where $y_M(0) = v_M(0) = 0$, $r_1(t) = 1.546$ N, and $r_2(t) = -1.085$ N. The cost function for control design was as follows.

$$J = \frac{1}{2}\sum_{k=1}^{150}\left(\frac{k}{50}\right)^2 \left\{ (y_M(k) - y(k))^2 + \left(\frac{y_M(k) - y_M(k-1)}{T} - \frac{y(k) - y(k-1)}{T} \right)^2 \right\} \quad (10)$$

where time means discrete-time. All the initial values of weights were generated by uniform random numbers with [-0.5,0.5]. The maximum number of epochs to train was 3×10^5. Especially in the following results, taking practical applications into consideration, the plant was computed using the 4th-order Runge-Kutta method with the step-size 2×10^{-4}ms. The absolute values (percentage) of the relative errors of the working start time and velocity of the impactor at the target, $y = -0.05$ mm are denoted by t^* and v^*, respectively.

1) Working for one period: The three cases were considered (see Fig. 4): a) the learning rate is invariant and the moment factor is zero ($\varepsilon[N] = 0.3$, $\alpha[N] = 0$); b) the learning rate and the momentum factor are both invariant ($\varepsilon[N] = 0.3$, $\alpha[N] = 0.6$); c) the proposed method, i.e., both the learning rate and the momentum factor are both variant ($\varepsilon[N]$ ($\alpha[N]$) = 0.3 (0.6) for $0 \le N < 3\times10^3$, 1 (0.2) for $3\times10^3 \le N < 8\times10^4$, and 2 (0.7) for $8\times10^4 \le N \le 3\times10^5$). From these, it is clear that the proposed method is best. The results by the proposed method are shown in Fig. 5, which shows the evolution of dynamic behavior and control parameters concerning epochs, and each gain and the relative errors

$$k_1 = -28.47,\ k_2 = 21.94,\ k_3 = 35.90,\ k_4 = -29.39$$

$$w_{11}^{(u)} = -56.12;\ t^* \le 0.06\%,\ v^* \le 1.1\% \quad (11)$$

were obtained in a final epoch, respectively. The results are acceptable.

2) Successive working: Simulation for successive working, which means the repetition of one working period, was implemented. For comparison, the simulation result by PID control tuned with Z-N parameters[4] is shown in Fig. 6, where there are a lot of irregular impulses, so control performance is very bad. The result of the proposed method is shown in Fig. 7. From this, it is obvious that the proposed method yields a high-accurate and stable control result, where the t^* and v^* both lay within the range of 1.1 percent in each working period. From these results, it is clear that the proposed control is extremely superior to the PID control tuned with Z-N parameters. Especially, it is remarkable that the proposed method has no particular vibration control to remove undesirable vibration after impact, while the PID control method[3] using genetic algorithms needs special vibration control.

3) Robustness: Robustness with respect to uncertainty, disturbances and working time using the result of the proposed method was considered. The simulation results are shown in Fig. 8: +20% and +50% changes of parameters m and k, respectively; a periodic disturbance with a period: $d(t) = 1$ for $0 \le t \le 15$ and 0 for $15 < t \le 30.2$; working time with 0.1ms and 0.4ms. The cases of working time, 0.1ms and 0.4ms were both similar to that of working time, 0.2ms, respectively. From these, it is obvious that robust performance is so good.

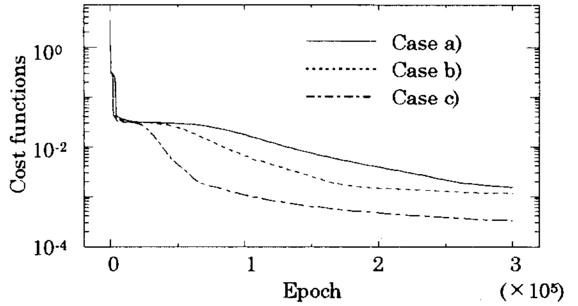
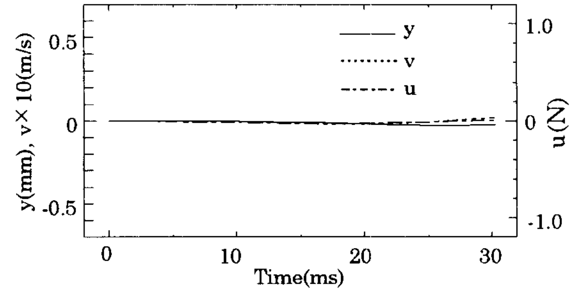
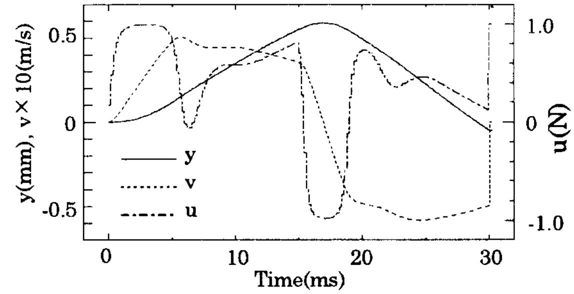


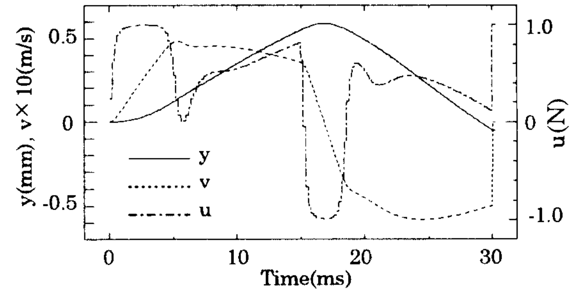
Fig. 4. Comparison among three cases.



a) Initial epoch.

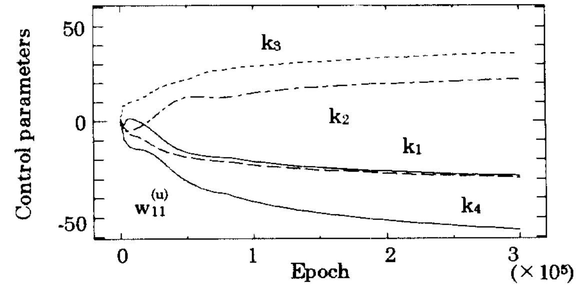


b) 1.5×10^5th epoch.



c) Final epoch.

1) Dynamic behavior.



2) Evolution of control parameters.

Fig. 5. Simulation results for one working period.

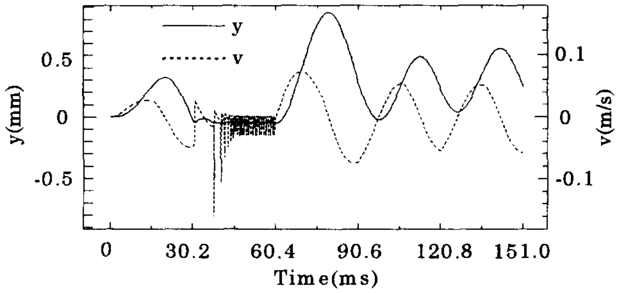
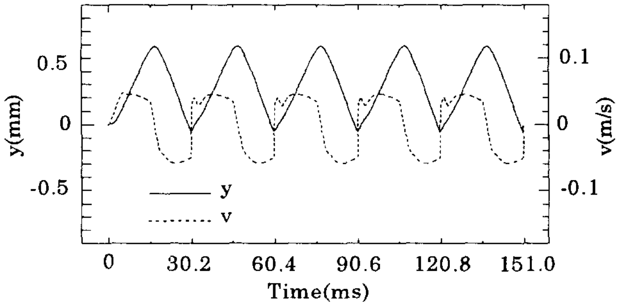
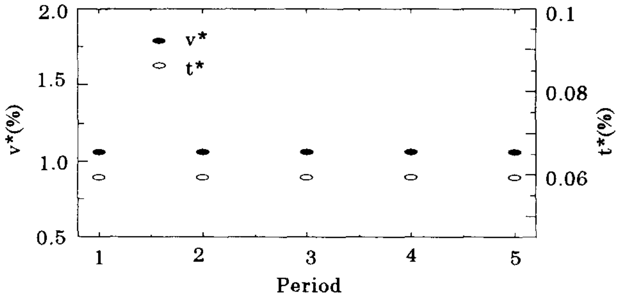


Fig. 6. Successive working of PID control tuned with Z-N parameters.

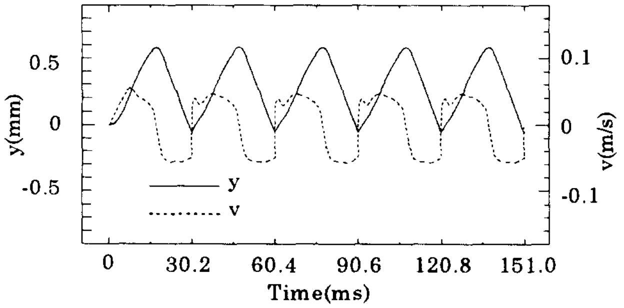


1) Dynamic behavior.

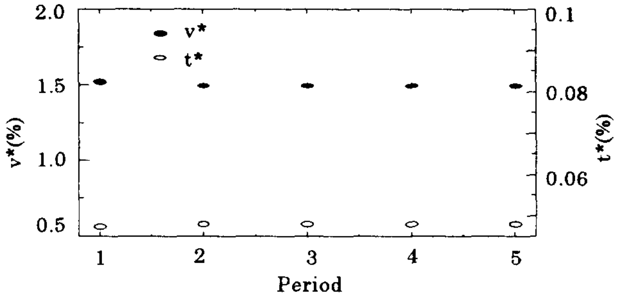


2) Control performance.

Fig. 7 Successive working of the proposed control.

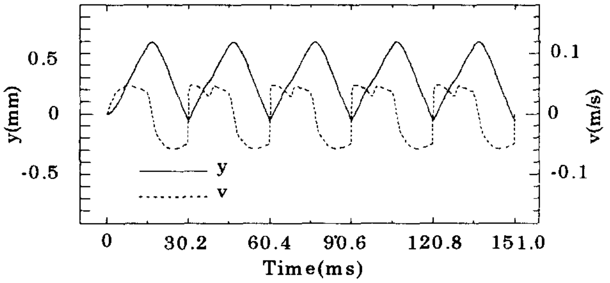


a) Dynamic behavior.

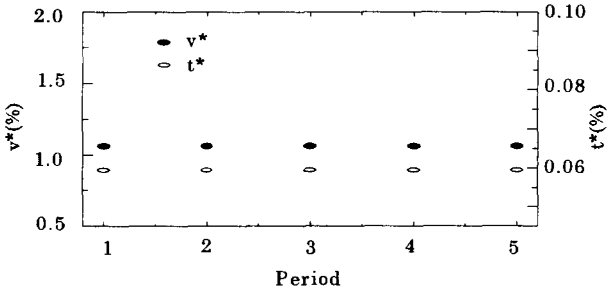


b) Control performance.

1) Uncertainty.



a) Dynamic behavior.



b) Control performance.

2) Disturbance.

Fig. 8. Successive working: robustness of the proposed control.

5. CONCLUSIONS

A newly developed discrete-time control design method for impact machines has been proposed. The optimal control problem with constraints of both the input and state variables has been successfully solved using an inverse dynamics of the plant and neural networks with varying learning rate and momentum factor. The main characteristics are as follows:

1) The proposed method is composed of identification and control using neural networks; the temperature of the sigmoid is estimated; the optimal nonlinear controller with constraints and no use of velocity measurements is obtained;

2) The high-speed and high-accurate control is realized; no particular vibration control after impact is needed;

3) By computer simulation, it has been demonstrated that the proposed method is effective: the plant is identified very well; the more the training advances, the smaller the cost function becomes; the proposed control method is superior to the PID control method tuned with Z-N parameters; good successive working is obtained by repeating the proposed control; the proposed method is robust with respect to uncertainty, disturbances and working time.

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