# Vibration Control of Load for Rotary Crane System Using Neural Network with GA-based Training

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## Abstract

A neuro-controller for vibration control of load in a rotary crane system involving rotation about the vertical axis only is proposed. As in a nonholonomic system, the vibration control method using a static continuous state feedback cannot stabilize the load swing. It is necessary to design a time-varying feedback controller or a non continuous feedback controller. We propose a simple three-layered neural network as a controller genetic algorithm-based training in order to control load swing suppression for the rotary crane system. The controller is trained by a real coded genetic algorithm, substantially simplifying the design of the controller. It is demonstrated that a control scheme with performance comparable to conventional methods can be obtained by a relatively simple approach.

## 1 Introduction

A rotary crane system is used to transport a load mass to a desired position through rotation of the boom and raising and lowering of the boom. This motion is accompanied by oscillation of the load, or load swing. In order to suppress such load swing, rotary crane systems are commonly operated using both the rotation angle and the lean angle. Operation of the rotary crane system solely by rotation around the vertical axis results in a nonholonomic system for which the control problem is complex and necessary to design a time-varying feedback controller or a non continuous feedback controller [1]. It is proposed in this paper that such control can be achieved relatively simply by applying a neuro-controller (NC) [2] trained by a genetic algorithm (GA) [3, 4, 5, 6, 7].

Many vibration control methods of load swing in a rotary crane system have been proposed[8, 9, 10, 11, 12]. An example is a control method in which the control law follows the most suitable trajectory along which the load swing will be smallest[8]. The theory of the optimal regulator for linear systems fuzzy reasoning, and the feedback law for nonlinear systems are examples of such control methods. These control methods can fundamentally stabilize the load swing in the circumferential direction, but cannot suppress swing in the radial direction. Some vibration control methods for the crane system with only controllable rotation operation have been reported [10, 11, 12]. Anti-sway control method of the crane system based on a skillful operator's knowledge has been reported [10]. Load swing suppression based on a linear feedback law by switching the two modes in the radial and circumferential directions has been reported [11, 12]. However, all of these control methods require knowledge of difficult control theories. In contrast, a neuro-controller trained by an evolutionary computation technique such as a genetic algorithm is substantially simpler to realize than conventional control systems.

In this paper, a simple three-layered neural network is applied as a controller with GA-based training, and the performance of the resulting controller is compared with that of conventional controllers using computer simulations. The training algorithm of the neural network uses a real coded GA. It is considered that a real coded GA is faster than a bit-spring GA.

## 2 Model of rotary crane system

Figure 1 shows the schematic diagram of the rotary crane system. Rotation around the $z$ axis is the only controllable movement of the crane. Here, $x$, $y$, $z$ are

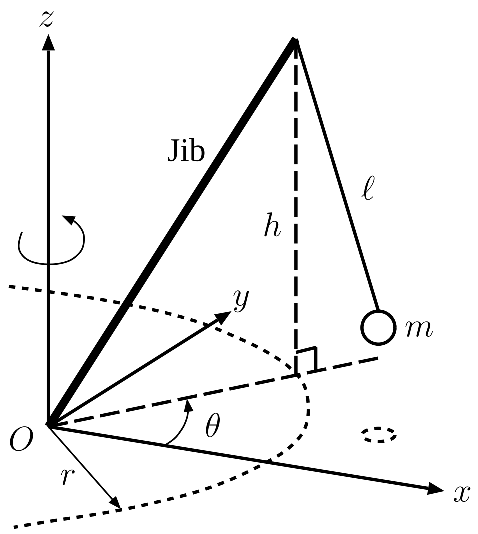



Fig. 1 Schematic diagram of rotary crane system

the coordinates of the load mass position, $\theta$ is the rotation angle (control input), $r$ is the radius of rotation, $h$ is the height from the tip of the boom, $m$ is the mass of the load, and $\ell$ is the length of wire which is not elastic or slack. The aim of control purpose is to suppress load swing from the arbitrary position to the reference position by control of crane rotation alone.

Using a Lagrange equation for the constraint system, the dynamic model of the rotary crane system can approximately be described in terms of the following equations:

$$\left\{ \begin{array}{lcl} \ddot{x}(t) + \omega^2 x(t) & = & \omega^2 r \cos\theta(t) \\ \ddot{y}(t) + \omega^2 y(t) & = & \omega^2 r \sin\theta(t) \end{array} \right. \tag{1}$$

where $\omega = \sqrt{g/\ell}$ is natural frequency. Because if the vibration of the load swing is sufficiently small, only the $x$–$y$ plane needs to be considered.

It is difficult for a designer to control the rotation angle of the rotary crane system by conventional methods because the dynamic model is a type of nonholonomic system. As in a nonholonomic system, the vibration control method using a static continuous state feedback cannot stabilize the load swing. It is necessary to design a time-varying feedback controller or a non continuous feedback controller. The controller is instead designed using a neural network with GA-based training in this paper.

## 3 Structure of control system

Figure 2 shows the control system using a neural network with GA-based training. The algorithm uses a real coded GA. The NC receives the position error and the velocity of the load mass as inputs, and outputs the rotation angle of the boom.

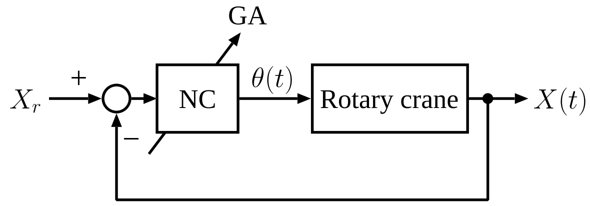



Fig. 2 Control scheme for rotary crane system

The NC is composed of three hierarchical layers, with 4 input neurons, 5 hidden neurons, and 1 output neuron. A linear threshold function is used at the input and output layers, and a hyperbolic tangent function is used at the hidden layer. The control method purposes to suppress the load swing accompanying movement from an arbitrary initial position $(x_0, y_0)$ to the reference position $(x_r, y_r)$ by rotation control.

The NC is trained using the real coded GA in an off-line process. The algorithm of evolution process for the NC is as follows:

STEP 1. Create initial NCs randomly. The initial connecting weights $w_{ij}$ and $w_{jk}$ are set in the range of $[-0.3, 0.3]$.

STEP 2. Calculate an error function $E$ while demonstrating control simulation for all NCs.

STEP 3. Select the parent NCs by roulette wheel parent selection.

STEP 4. Perform a crossover operation of $BLX_\alpha$ method to produce new NCs.

STEP 5. Alternate the NCs including the new NCs to the next generation. Iterate from step 2 until the evolution process reaches generation 5000.

Further information regarding the parameters of the GA is provided in Table 2.

An error function $E$ is used to evaluate the performance of each NC during the GA-based training process. The error function $E$ is described by

$$E = \sum_{t=T_s}^{T_e} \{(x_r - x(t))^2 + (y_r - y(t))^2\} \tag{2}$$

where $x_r$ and $y_r$ are the desired positions on the $x$ and $y$ axes, respectively. The error function is defined so as to settle the load at the desired position between $T_s$ (s) and $T_e$ (s). The fitness of the NC is expressed in terms of the inverse of the error function $E$. In the GA evolution, the connecting weights of the NC are modified in order to maximize the fitness function determined by the error function in Eq. (2).

## 4 Simulation results

The validity of the proposed NC was verified through computer simulations using Runge-Kutta method. Sampling time is 10 (ms). The parameters of the rotary crane system and the initial conditions are listed in Table 1.

In the GA simulation, the real coded GA parameters were set as shown in Table 2.

Table 1 Parameters of rotary crane system and initial conditions

| | |
|---|---|
| Load mass $m$ | 1.0 (kg) |
| Rotation radius $r$ | 1.0 (m) |
| Length of wire $\ell$ | 5.0 (m) |
| Acceleration of gravity $g$ | 9.8 (m/s$^2$) |
| Initial rotation angle $\theta_0$ | $\pi$ (rad) |
| Reference position $(x_r, y_r)$ | $(1, 0)$ (m) |
| Evaluation start time $T_s$ | 5.0 (s) |
| Evaluation end time $T_e$ | 6.0 (s) |

Table 2 GA parameters

| | |
|---|---|
| No. initial NCs | 100 individuals |
| No. children | 100 individuals |
| Selection | Roulette wheel |
| Crossover | BLX$_\alpha$ |
| $\alpha$ | 1.0 |
| Final generation | 5000 |

The goal of the evolution progressed by the GA is to obtain an NC that suppress the load swing of the rotary crane system upon movement from the initial position $(x_0, y_0)$ to the reference position $(x_r, y_r)$.

When the initial rotation angle $\theta_0$ is $\pi$ and the initial positions $(x_0, y_0)$ are set four patterns $(x_0, y_0) = (\cos\theta_0 - 0.05, \sin\theta_0)$, $(\cos\theta_0, \sin\theta_0 - 0.05)$, $(\cos\theta_0 + 0.05, \sin\theta_0)$, $(\cos\theta_0, \sin\theta_0 + 0.05)$, the evolution process affording the best NC with GA-based training is shown in Fig. 3. The training involved 5,000 iterations. The figure shows the evolution in the range $[0, 2000]$. The result demonstrates the GA evolution process of NCs is successful. The error values of the GA initially decrease gradually, then decreases rapidly after 150 generations until the evolution stagnates near generation 1000. When the evaluation start time of the error function $E$ set to $T_s = 0$, the evolution process stagnated immediately.

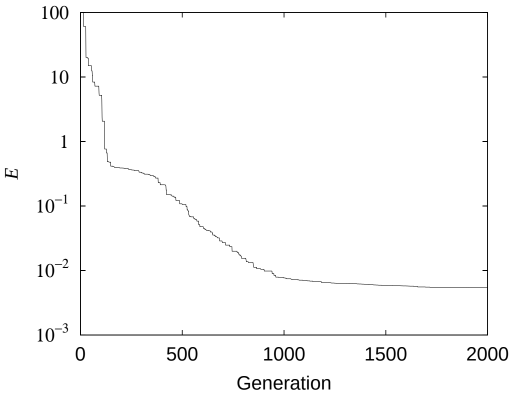


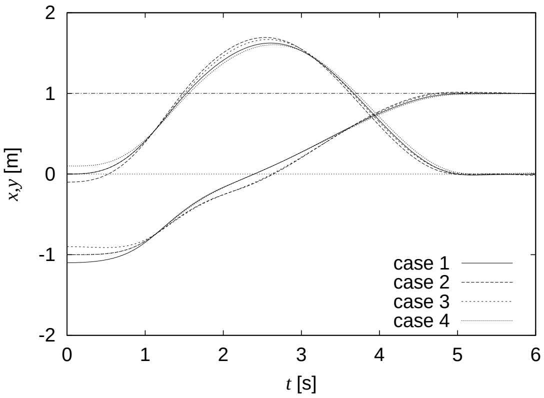

Fig. 3 Evolution process

The simulation results for control using the trained NC are shown in Fig. 4. Control by the trained NC converges to the reference position on the $x$ and $y$ axes in approximately 0 (s). The training is therefore effective for achieving good load swing suppression.

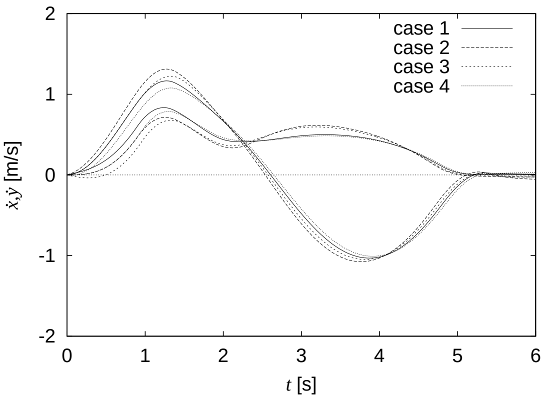
Figure 5 shows the trajectory of the load mass in the $x$–$y$ plane using the trained NC. The load is transferred along the control trajectory with very little swing oscillation.

## 5 Conclusion

A simple GA-based approach was applied to realize a neuro-controller for load swing suppression in rotary crane systems involving only rotation about the vertical axis. Simulations confirmed that the real coded GA training scheme is effective for generating a reliable neuro-controller for the rotary crane system, with performance comparable to conventional control schemes.




(a) position




(b) velocity

Fig. 4 Control results

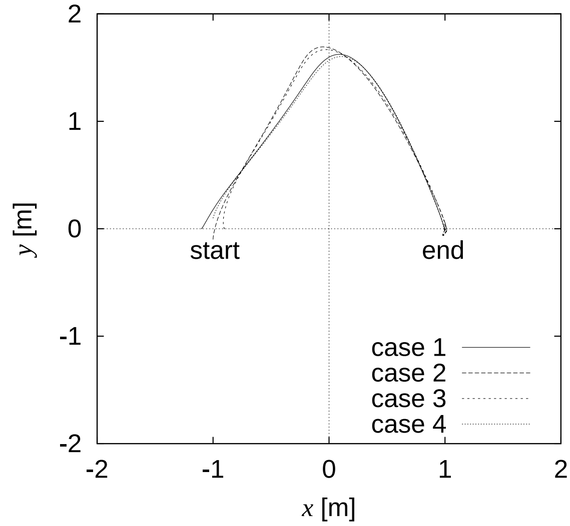



Fig. 5 Trajectory on $x$–$y$ plane

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