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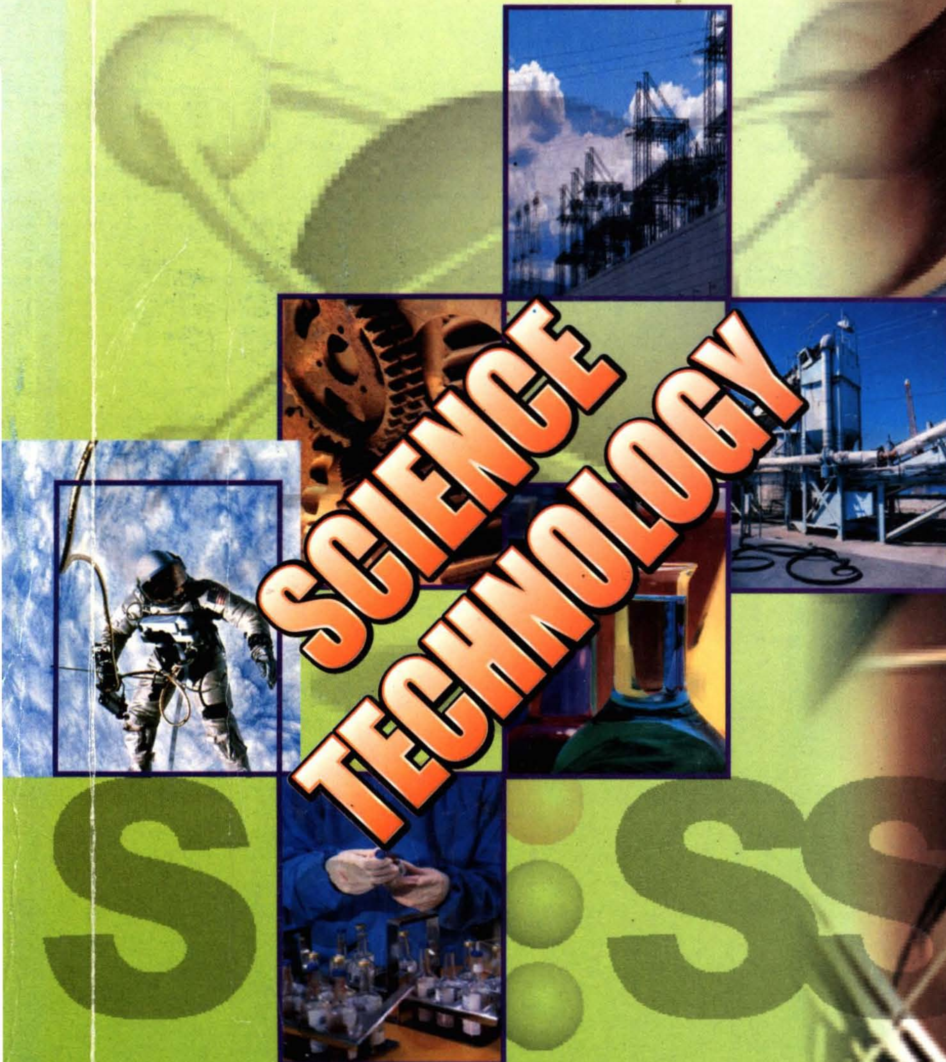

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Artificial Neural Network-Based Modeling of a Gantry Crane System

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ABSTRACT

In the process industry, the use of gantry crane systems for transporting payload is very common. However, moving the payload using the crane is not an easy task especially when strict specifications on the swing angle and on the transfer time need to be satisfied. To overcome this problem, a feedback control system is introduced. To obtain high quality control, an accurate model of the crane model is highly needed. However, the linear model is often insufficient since the crane is characterized by nonlinearity. To overcome this problem, this paper introduces an application of artificial neural network to build the crane model including its nonlinearity. A multi layer feedforward neural network trained by using backpropagation learning algorithm has been adopted to develop the crane model. Simulation studies show the effectiveness of the proposed neural network to model the gantry crane system.

Keywords: *Crane, model, artificial neural network, multi layer feedforward and back propagation*

Introduction

Gantry cranes are widely used in industry for transporting heavy loads and hazardous materials in shipyards, factories, nuclear installations, and high building construction. The crane should move the load as fast as possible without causing any excessive movement at the final position. Most of the common gantry crane is open-loop system which swing motion will occur when payload is suddenly stopped after a fast motion (Abdel Rahman et. al. 2002 and Omar 2003). The swing motion can be reduced but will be time consuming i.e. reduce facility as well as productivity. Besides that open loop system is sensitive to parameter variations and disturbances (Abdel Rahman et. al. 2002 and Omar 2003).

As a result, to control the gantry crane a skilful operator is needed to control manually based on his or her experiences to stop the swing immediately at the right position. Furthermore to unload, the operator has to wait the load stop from swinging. The failure of controlling crane also might cause accident and may harm people and surrounding. To replace the skilful operators the automatic gantry crane is proposed by adopting a feedback control system. However, most of the feedback control system design process needs a model and parameters of the controlled-object (Nise 2004; Belanger 1995, Umez-Eronini 1999 and Dorsey 2002). Hence the performance of the controller for gantry crane is highly influenced by the model accuracy. Moreover, the linear model approach is insufficient since the crane system is characterized by nonlinearity.

To overcome the above-mentioned problem, in this paper, artificial neural network is introduced for developing the crane model including its nonlinearity effect. A multi layer feedforward network trained by using back propagation training algorithm is adopted for crane model development. A series of simulation study using a non-linear crane model was carried out. Then, the neural network-based crane model is trained and developed based on the pair of input-output data. Finally the neural network-based crane model of the gantry is validated and tested. The validation result shows that the obtained gantry crane model is good enough to represent the gantry crane system.

Gantry Crane System

Figure 1 show a typical planar gantry crane commonly used in the industrial applications. As shown in Figure 1, the system consists of three different parts namely mechanical sub-system, motor dynamic and torque converter. Schematically, the gantry crane is illustrated Figure 2. In the gantry crane, the payload is by a wire rope attached to a moving trolley. Since the mass of the rope is small enough as compared to the payload mass, it can be assumed as massless. There are two independent motions x and θ to describe the position and the angle of the gantry crane system respectively.

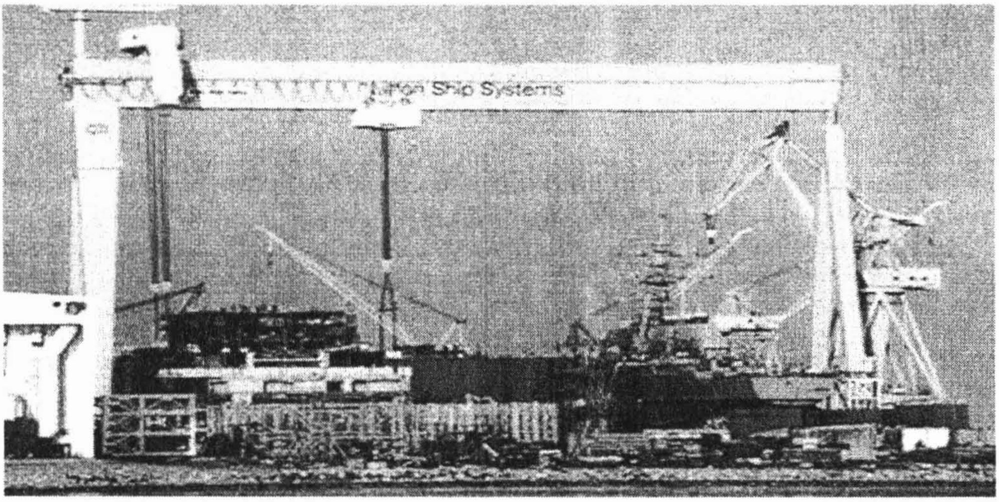


Fig. 1: Typical Gantry Crane System

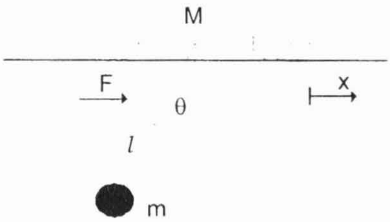


Fig. 2: Schematic Diagram of the Gantry Crane

By applying the Lagrange method (Wahyudi et. al. 2005), the equation of motions related to the trolley motion x and payload swing angle θ are as follows:

$$(M+m)\ddot{x}+ml\ddot{\theta}\cos\theta-ml\dot{\theta}^2\sin\theta=F \tag{1}$$

$$ml^2\ddot{\theta}+ml\ddot{x}\cos\theta+mgl\sin\theta=0 \tag{2}$$

where M, m, l and F represent trolley mass, payload mass, length of the rope and driven force respectively. Furthermore, by assuming that the crane is driven by a DC motor, the following DC motor dynamics are also included in the crane model:

$$V=Ri+L\frac{di}{dt}+K_e\dot{\theta}_m \tag{3}$$

$$K_t i-b\dot{\theta}_m-F.r=J\,\ddot{\theta}_m \tag{4}$$

$$T=K_t i \tag{5}$$

$$\dot{\theta}_m\, r=\dot{x} \tag{6}$$

where V, R, i, L, K_e, θ_m, K_t, b, r, J and T are motor input voltage, motor resistance, motor current, inductance, back-emf constant, motor displacement, motor constant, viscous damping coefficient, radius of the trolley wheel, motor inertia and motor torque respectively. Detail discussion on the derivation of this model can be found in Wahyudi et. al. 2005.

Artificial Neural Network

Artificial neural network, which is one of the approaches in artificial intelligence (AI), can be regarded as functional imitation of the human brain function (Haykin, 1999). The main feature of the ANN is the ability to learn effectively from the available data. In general, an ANN is characterized by its architecture, learning algorithm and activations function. The architecture describes the connections between the neurons. It consists of, generally, an input layer, an output layer and adequate number of hidden layers in between.

Multilayer feedforward network (MFN) trained with back propagation algorithm has been widely used in system identification and control since due to its capability as general approximator. As shown in Figure 3, MFN generally consists of three main parts. The first part is the input layer which distributes the input data to the processing elements in the next layer. The second part made up of hidden layers where the nonlinear behavior comes from. The third part is the output layer which produces the neural network outputs. Input and output layers are directly accessible while the hidden layers are not. Each layer contains several processing which are generally called neurons. The MFN structure shown in Fig. 3 has inputs x_1, x_2, x_n and output y. The connections between the neurons of the different layers are called weight and bias.

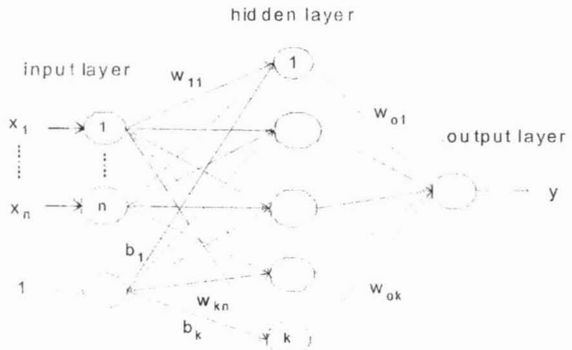


Fig. 3: A Typical Feedforward Neural Network.

The output of neuron j in the hidden layer is given by

$$h_j = f\left(\sum_{i=1}^{m} w_{ji} x_i + b_j\right) \tag{7}$$

where w_{ij} and b_j are the hidden layer neuron weights and bias. Furthermore, f(.) is the activation function which may be threshold, tansig, or other functions. On the other hand, the output of the network by is as follows

$$y = f\left(\sum_{i=1}^{k} w_{oi} h_i + b_o\right) \tag{8}$$

where f(.), w_{oi} and b_o are the output layer neuron activation function, weights and bias respectively. The learning process of MFN is carried out using input-output data to update the weights and biases. The output training data d is referred to as the target output of the neural network. The goal is to train the network until the output of neural network is suitable closely to the target output. Backpropagation algorithm is the most popular learning algorithm for the MFN. The backpropagation algorithm basically is an iterative learning algorithm used to minimize the following mean square error based on the a set of N given patterns:

$$E = \frac{1}{2}\sum_{n=1}^{N}(d_i - y_i)^2 \tag{9}$$

The weights of the MFN are iteratively and continuously updated until the mean square error (MSE) between the network output and the desired output is as small as acceptable for the desired case (Haykin, S. 1999). The weights are updated to get a minimum E with the use of the gradient descent method. The weight update equation is given by (Haykin 1999)

$$w_{ij}(t+1) = w_{ij}(t) + \eta\left(\frac{\partial E}{\partial w_{ij}}\right) \tag{10}$$

where η represents the learning rate constant, $w_{ij}(t)$ is the old weight and $w_{ij}(t+1)$ represent the new updated weight. The weights are updated through iterations called epochs. The epochs are continued until the error between the desired and actual outputs as small as desired.

In summary, the steps of building model based on the MFN are as follows:

- Input collection and preprocessing of the input data (if necessary). This includes the number of sampled data and normalization.
- Determining the structure of the ANN, including number of inputs, neurons, hidden layers and activation functions.
- Training the ANN, using the input pattern and desired output.
- Validation of the trained ANN.

ANN-Based Modeling and Identification

In order to model the crane system by using ANN, the ANN network must be designed its structure and then trained to emulate the plant dynamic. Here, the parallel-series NARX model identification (Ham 2001) shown in Figure 4 was used. The plant consists of two outputs namely trolley position x and load swing angle θ while the plant input is only the input voltage V. The proposed NN outputs are as follows:

$$\hat{\theta}(t) = f(x(t) \quad (11)$$

$$\hat{x}(t) = f(x(t) \quad (12)$$

where x(t) is the input vector of the ANN-based crane model. The input vector of the model is not only the plant input V(t) but also one time lags of plant input, trolley position and swing angle respectively. That is

$$x(t) = [u(t) \quad u(t-1) \quad x(t) \quad x(t-1) \quad \theta(t) \quad \theta(t-1)] \quad (13)$$

Furthermore, the residual or error vector, **e**(t), used for updating the ANN weights during training process is given by

$$e(t) = \begin{bmatrix} e_x(t) \\ e_\theta(t) \end{bmatrix} = \begin{bmatrix} x(t) - \hat{x}(t) \\ \theta(t) - \theta(t) \end{bmatrix} \quad (14)$$

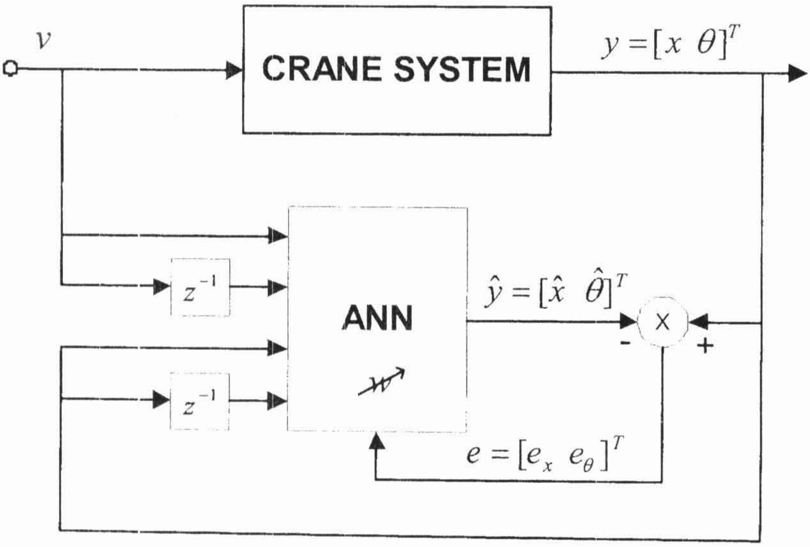


Fig. 4: Schematic Diagram of the Gantry Crane

Results and Discussion

System Description

In order to evaluate the effectiveness of the ANN-based crane model, a simulation study is carried out in the MATLAB/Simulink environment. A simulink model was built based on the nonlinear crane model described using Equations [1]-[6]. In addition crane parameters shown in Table 1 are used in the simulation.

Table 1: The Gantry Crane Parameters

Symbol	Description	Value
M	Cart mass	3 kg
m	Load mass	2.5 kg
l	Cable length	0.5 m
g	Gravitational acceleration	9.81 m/s^2
R	Resistance of armature	2 Ohm
L	Inductance of armature	10^{-3} H
K_e	Electric constant	0.1 Nm/Amp
K_t	Torque constant	0.1 Nm/Amp
r	Radius of gyration	0.04 m
J	Moment of inertia of the rotor	10^{-4} kgm^2
b	Viscous damping coefficient	10^{-7} Nms

Training ANN-Based Crane Model

The proposed ANN-based crane model is trained based on the dynamic model of the crane. A chirp signal of 1-60 Hz as shown in Figure 5 is applied to drive the crane. The response is then recorded. After that, this pair of input output data is used to train the ANN-based soft sensor. The data is normalized to interval between -1 and 1 to improve generalization capability of the ANN-based crane model.

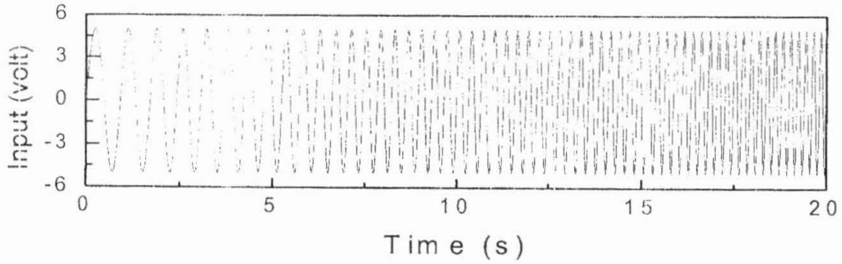
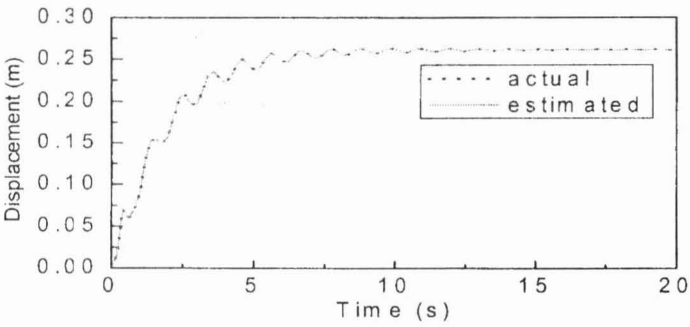
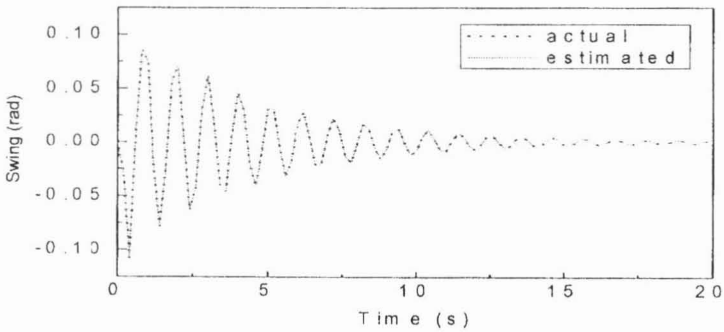


Fig. 5: Chirp Signal of the NN Input

Furthermore, the sampling data is taken at interval of 20ms. The initial weights and biases are randomly selected. The error goal of mean square error (MSE) is specified at first namely 10^{-6}. The activation functions used are hyperbolic tangent sigmoid and pure linear in hidden layers and output layer respectively. The number of neurons and hidden layers used are examined in several tryouts. The ANN is trained using back propagation learning algorithm with learning constant of 0.1. The ANN which consists of a hidden layer with 10 neurons gives the best result. The result of the training is shown in Figure 6. By referring to Figure 6, it is clear that the estimated response is close to the actual response.



(a) Crane displacement



(b) Crane swing angle
Fig. 6: Response Comparison with Training Data

Model Validation

In order too validate the obtained ANN-based crane model, different type of input signal shown in Figure 7 is applied. Figure 8 shows the testing result with another input signal as shown in Figure 8 which is not used in the training. It can be seen that although the input signal is different, the soft sensor is still able to estimate the unmeasured state well as those in training. Therefore, it can be concluded that the proposed soft sensor is good enough to estimate the plant output.

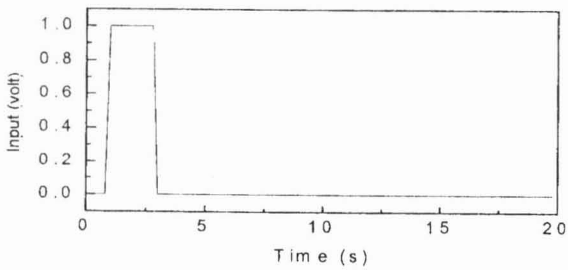
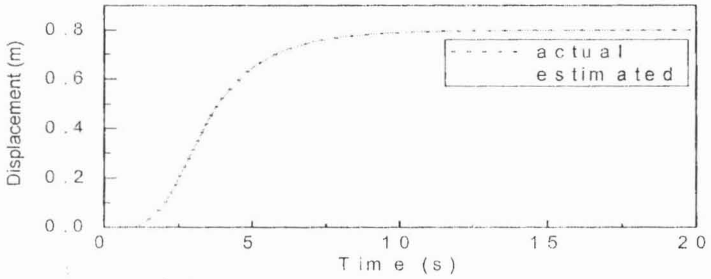
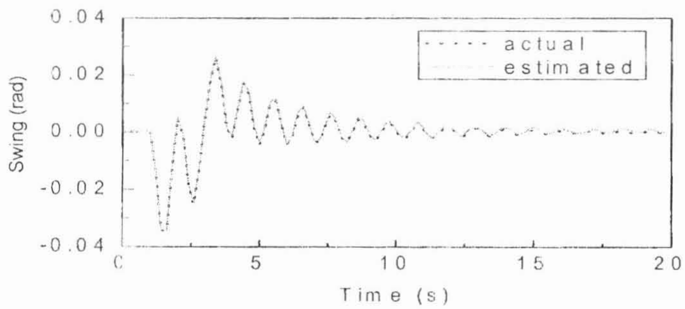


Fig. 7: Input Signal for Model Validation



(a) Crane Displacement



(b) Crane Swing Angle

Fig. 8: Response Comparison with Testing Data

Conclusion

An artificial neural network (ANN) based model has been developed for gantry crane system. The multilayer feedforward ANN trained with back propagation learning algorithm was adopted. The effectiveness of the proposed ANN-based crane model was evaluated through simulation and compared with the non-linear mathematical model of the crane system. It was shown through a series of simulation study that the proposed ANN-based crane model if effective as non-linear model of the gantry crane.

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