Kinematic Analysis of Cranes Using Neural Networks

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Abstract

Due to load uncertainties of cranes, it is necessary to find exact kinematic parameters of crane mechanisms.

This research is concerned with application of neural network to the kinematic analysis of a crane mechanism. The type of network investigated is a Radial Basis Neural Network (RBNN). The crane mechanism is considered as a double-rocker four-bar mechanism. Desired kinematic parameteres of the crane is found by a a software dealing with simulation and analysis of mechanisms. The RBNN is employed in four parameters prediction schemes; displacement, velocity, acceleration and force. The results obtained have supported the theory that the proposed RBNN is able to predict different types of crane system.

1. Introduction

The challenges of increased production, plant extension and product quality improvements are being met in industry by the use of different crane types for carrying parts.

The types of coil handling cranes has been outlined by Bergie and Jones [1]. A criteria has been employed for selection of equipment and the solution of problems encountered during the design. An application and maintenance of controlled overhead travelling crane has been investigated by Buffington [2]. A system was selected to provide a reliable compact radio remote control system that could be interfaced into a wide range of applications. All parts of the system were designed and built for continous use in a heavy industrial service. Drive and positioning system requirements on a crane has been analysed by [3]. Various positioning schemes were examined in this research. An optimum design of box-type of crane girdes has been considered by using non-linear programming techniques [4]. The objective function for minimization was taken as the weight of the girder. The limitations on the stresses and the deflections induced in the girder in different load conditions were stated in the form of inequality constraints.

Kinematic analysis of Demag-Jig type crane is presented in this paper. The desired kinematic parameteres are found by using a software. The proposed crane is considered as a double-rocker four-bar mechanism. Neural network is employed to predict the kinemtic parameters of the crane.

2. Crane Mechanism

The proposed crane mechanism which is shown in Figure 1 is also known as Demag-Jig crane. This kind of crane is very often used at sea ports. After a load (m_L) is lifted up, in order to use minimum energy, we would like to move point D, consequently the load from one position to another position in the horizontal direction.

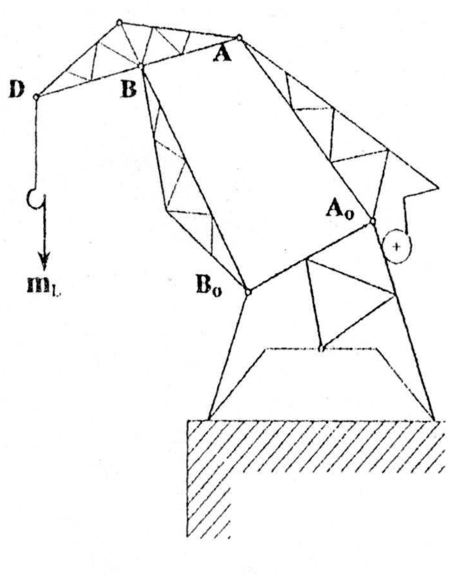

Figure 1. Schematic configuration of the crane

A double-rocker arragement as a four-bar mechanism approximetely satisfies this requirement while its load capacity is acceptable. Load capacity of this mechanism is selected between 30000 kg and 90000 kg. The kinematic parameters of the crane mechanism are given in Table 1. The schemetic representation and movement of the proposed crane mechanism are shown in Figures 2 and 3, respectively.

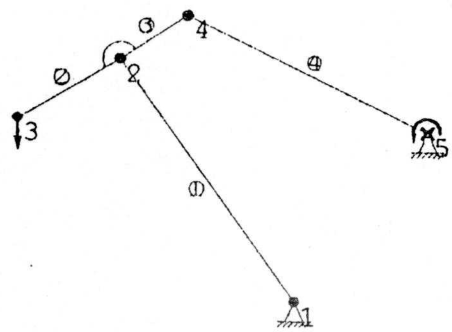

Figure 2. Kinematic representation of the model crane

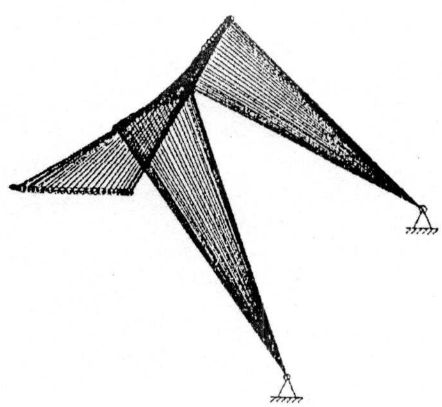

Figure 3. Movement of mechanism

Table 1. Kinematic parameters of the crane

Link lengths	[cm]	Link mass	[kg]
A_oA	617	m_{AoA}	6800
AB	185	m_{AB}	2000
B_oB	692	m_{BoB}	8000
A_oB_o	578	m_{AoBo}	-----
BD	270	m_{DB}	1850

3. Radial Basis Neural Network

The basic concept underlying the RBNN is that of a fixed non-linear mapping of the input space to a higher dimensional space followed by a linear, adjustable output mapping. The structure of the RBNN is shown in Figure 4 which is a model of three-layer feedforward network. The hidden layer consists of a set of basis function units each of which has associated with its a parametric vector known as its receptive field. These units compute the distance between the centre of the field and the input vector. The output of the units is then a function of the distance measure.

The RBNN is expressed by

$$f(x) = \sum_{j=1}^{N} w_j y_j (x - c_j) \tag{1}$$

where x is an n-dimensional input vector. N is the number of hidden units and $c_j = (\xi_j, \sigma_j)$ is the receptive field. The basis function is such that y_j has a significant result only in the neighbourhood of c_j.

There are several possibilities for the choice of basis functions. However, Gaussian-type functions offer desirable properties making the hidden units responsive to locally tuned regions. The typical examples of basis function include [5]

a) thin-plate spine

$$y_j(x) = (x - \xi_j)^2 \times \log(x - \xi_j) \tag{2}$$

b) Gaussian

$$y_j(x) = \exp\left[-\frac{(x - \xi_j)^2}{(\sigma_j)^2} \right] \tag{3}$$

c) Multiquadratic

$$y_j(x) = \sqrt{((x - \xi_j)^2 + \sigma^2)} \tag{4}$$

d) inverse multiquadratic

$$y_j(x) = \frac{1}{\sqrt{((x - \xi_j)^2 + \sigma^2)}} \tag{5}$$

The chosen basis function influences both the learning and modelling abilities of the network, and will also influence the choice of learning rule used to train the network. Radial basis Gaussian function and backpropagation learning algorithm are employed to train the proposed RBNN.

4. Results

The crane mechanism and neural predictor were implemented in simulation using program written in the C languange running on PC 586 100 MHz computer. The desired kinematic parameters of the crane were found by using software. These parameters were displacement, velocity, acceleration and force of the end-effector of the crane. A RBNN was designed to predict kinematic parameters of the crane. The network was fistly trained for 250000 iteration to 72 randomly located points in the X-Y plane. The structural and training parameters are given in Table 2. After training, kinematic parameters were employed as testing data for the network.

The result of displacement of the end-effector is plotted in Figure 5. The veleocity traced by end-effector is shown in Figure 6. Figure 7 indicates acceleretion of the end-effector. Force of the end-effector is also analysed for different loads. Figures 8(a), 8(b) and 8(c) show the results of neural approach.

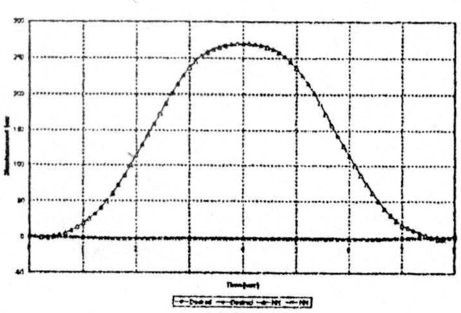

Figure 5. Displacement of the end-effector

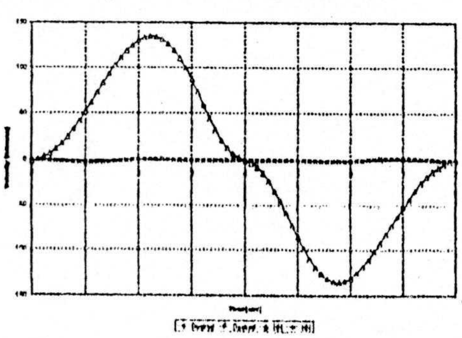

Figure 6. Velocity of the end-effector

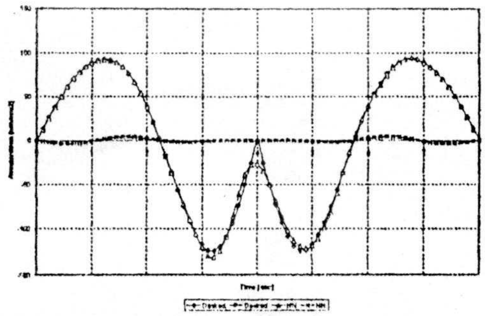

Figure 7. Acceleration of the end-effector

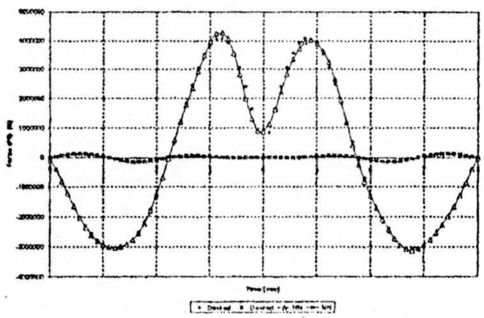

Figure 8(a). Force of the end-effector (m_L=30000 kg)

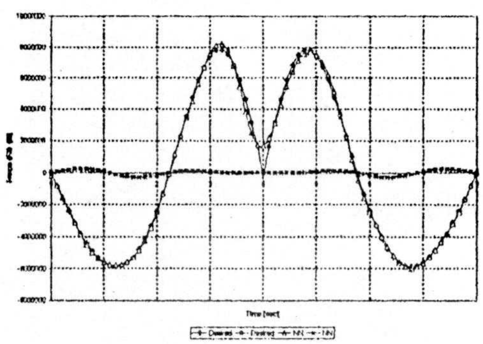

Figure 8(b). Force of the end-effector (m_L=60000 kg)

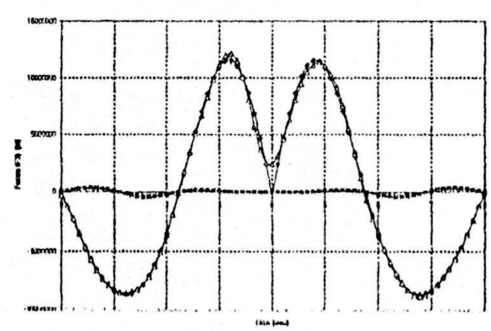

Figure 8(c). Force of the end-effector (m_L=90000 kg)

Table 2 reinforces this observation by showing numerical values of the root mean squared (RMS) deviations from the ideal kinematic parameters for the neural predictor. As can be seen from figures, due to horizontal movement of the en-effector of the crane, the displacement, velocity, acceleration and force are zero in the vertical direction.

Table 2 Performance errors

Parameters	RMSE
x	0.0029
v	0.0026
a	0.0028
F (F1) m_L=30000 kg	0.0065
F (F2) m_L=60000 kg	0.0087
F (F3) m_L=90000 kg	0.0094

x : displacement
v : velocity
a : acceleration
F : force
m_L : mass of load

5. Conclusion

This paper has presented a neural network predictor employing a radial basis neural network for analysing the kinematic parameters of a crane. Using the neural network to predict the kinematic parameters of the carane, the scheme does not require a priori knowledge about its kinematics. The results of computer simulations have shown that advantages of the proposed neural predictor include fast convergence of the tracking error. The ability of the neural predictor to reject large disturbances has also been demonstrated in simulation.

6. References

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