International Journal of Control Systems and Robotics
http://www.iaras.org/iaras/journals/ijcsr

Force Analysis of a Modified Mechanism System Using Artificial Neural Networks

ŞAHİN YILDIRIM
Mechatronic Engineering Department, Faculty of Engineering,
University of Erciyes, Kayseri,
TURKEY
sahiny@erciyes.edu.tr

Abstract: -In this investigation, kinematic parameters variations of a proposed four-bar mechanism are analysed using a proposed recurrent artificial neural network predictor. The proposed neural predictor has three layers, which are input layer, output layer and hidden layer. The hidden layer consisted of recurrent structure to keep dynamic memory for later use. The mechanism is an extended version of a four-bar mechanism. Two elements, spring and viscous, are employed to overcome big force problem on the mechanism. Based on the results presented, the force analysis problem for four-bar mechanism is completely solvable by using artificial neural networks. The effectiveness of the proposed scheme is demonstrated by simulation results in high speed repetitive motion tracking and load change conditions. No prior knowledge of system dynamics is required for this scheme.

Key-Words: - Four-bar mechanism, artificial neural network, force, spring

1 Introduction

Kinematics is an important field in which mechanical engineers study motion in order to design mechanism to perform useful tasks.

Recently, an experimental investigation an active control of the elastodynamic response of a four-bar (4R) mechanism has been presented by Sannah and Smaili [1]. In their research, an experimental 4R mechanism is made such that its coupler link is flexible, its follower link is slightly less flexible and its crank is relatively rigid, two thin plate-type piezoceramic S/A pairs were bonded to the flanks of the coupler link at the high strain locations corresponding to the first and second vibration modes. The results of the experimental investigation prove that in order to prevent high mode excitations, the controller design should be based on the modes representing vibrations of all components comprising the mechanism system rather than the modes
corresponding to the link to which the S/A pairs were bonded.

A method for stability analysis of a closed-loop flexible mechanism by using modal coordinates has been investigated [2]. In their paper, mode shapes of a flexible four-bar mechanism are defined as those of individual links (single-link modes). Based on these single-link modes, the flexible four-bar mechanism has time-invariant mode shapes and its governing equations of motion become decoupled, regardless of mode-crossing. Therefore the stability of the flexible mechanism can be analysed efficiently for each mode. Floquet theory is employed to check the stability of the mechanism. The experimental study of a flexible four-bar mechanism is also presented to verify the proposed method. The experimentally determined bending strains and critical speeds are compared with numerical results obtained from the proposed method. The experimental and analytical results show a fairly good agreement.

A study has been carried out to model, simulate and control a four-bar mechanism driven by a brushless servo motor [3]. A mathematical model for the servo motor-mechanism system was developed and solved by using numerical methods. An experimental set-up based on a four-bar mechanism was built and different crank motion profiles are implemented. Simulation and experimental results were then presented, compared and discussed. An analytical formulation for computing kinematic sensitivity of the spatial four-bar mechanism has been described in [4]. An experimental code developed was used to compute an assembled configuration for the mechanism that accounts for the effect of a design variation. A mechanism was modelled using graph theory, in which a body was defined as a node and a kinematic joint is defined as an edge. The spherical joint was cut to convert the model into a tree structure by cutting an edge and introducing constraints. The effect of variation in mechanism design using concepts of virtual displacement and rotation was introduced. The variation of the spherical constraint was computed, maintaining joint-attachment vectors and orientation matrices as variables. A neural network based application has been employed to predict vertical vibration parameters of vehicles [7, 10,11,12]. The method was used to predict random vibration theory results. In their investigation, the results have demonstrated the applicability and adaptability of the neural network for analysis of the vehicles vibrations.

2 Four-Bar Mechanisms

Four-bar mechanism is a glass of mechanical linkage in which four links are pinned together to form a closed loop in order to perform some useful motion. Because the shapes of paths created by coupler are so diverse and useful. Four-bar mechanism used in industry numerous applications that require generation of simple repetitive movements.

2.1 The Mechanism

The mechanism, which operates in a vertical plane, is shown schematically in Fig. 1. The system can be used as a five-bar mechanism with a rotary input at OA used an oscillatory input at CD, or, as in this case, as a four-bar linkage with the link CD fixed. The crank, OA, is driven by a variable speed motor and a spring of stiffness 671 N/m is attached to the rocker link, BC, at the point E, to provide additional loading to the mechanism. A test bearing at B has a radial clearance of 100 μm and consists of a steel pin with an oil-impregnated sintered bronze bush, of nominal diameter 25 mm and 35 mm long. Two small shock accelerometers are attached to the test bearing to record the impact accelerations at B along and perpendicular to the direction AB.

The crank speed is a periodic function of the crank angle, due to the cyclic variation of the gravitational and dynamic forces on the mechanism, and the crank motion can be expressed either as an average crank speed or as an instantaneous speed relative to a specified crank angle. All crank speeds quoted in this paper are instantaneous values at $\theta_2=90^0$ crank angle.

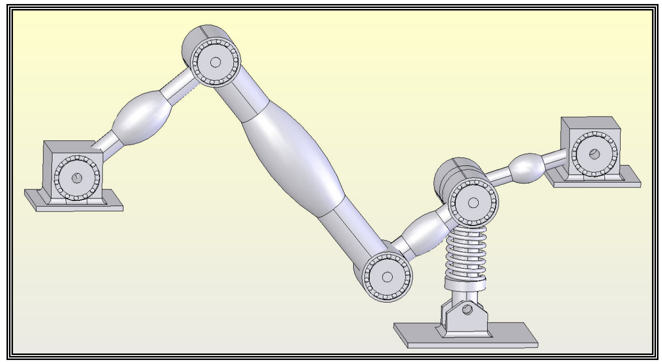

Fig.1. Representation of the modified mechanism system

The average crank speed is used in the range 200-400 r/min and the outputs from the shock accelerometers are monitored.

In the combined massless-link-spring-damper model the clearance joint , B, is presented by a masless link BC of length equal to radial clearance, r_4. BC has radial stiffness, K_c, and a radial damping μ_c.

The equation of motion for the model, are give in Appendix A. There are six kinematic equations and six dynamic equations. The equations are coupled, non-linear and, having no analytical solution, need to be integrated numerically. The numerical values for the model parameters used in the computations are given in Appendix B.

3 Neural Networks

Neural networks (NNs) are typically organised in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output. Most NNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. In a sense, NNs learn by example, as do their biological counterparts; a child learns to recognise dogs from examples of dogs. Although there are many different kinds of learning rules used by neural networks, this demonstration is concerned only with one; the delta rule. The delta rule is often utilised by the most common class of NNs called 'backpropagational neural networks' (BPNNs). BP is an abbreviation for the backwards propagation of error. With the delta rule, as with other types of BP, 'learning' is a supervised process that occurs with each cycle or 'epoch' (i.e. each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random 'guess' as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights. Backpropagation performs a gradient descent within the solution's vector space towards a 'global minimum' along the steepest vector of the error surface. The global minimum is that theoretical solution with the lowest possible error. The error surface itself is a hyperparaboloid but is seldom 'smooth' as is depicted in the graphic below. Indeed, in most problems, the solution space is quite irregular with numerous 'pits' and 'hills' which may cause the network to settle down in a 'local minimum' which is not the best overall solution. Since the nature of the error space can not be known a priori, neural network analysis often requires a large number of individual runs to determine the best solution. Most learning rules have built-in mathematical terms to assist in this process which control the 'speed' (Beta-coefficient) and the 'momentum' of the learning. The speed of learning is actually the rate of convergence between the current solution and the global minimum. Momentum helps the network to overcome obstacles (local minima) in the error surface and settle down at or near the global minimum.

Depending on the nature of the application and the strength of the internal data patterns you can generally expect a network to train quite well. This applies to problems where the relationships may be quite dynamic or non-linear. NNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc. Because a NN can capture many kinds of relationships it allows the user to quickly and relatively easily model phenomena which otherwise may have been very difficult or impossible to explain otherwise.

3.1 Proposed Neural Network

The neural networks employed in this work were of the recurrent type. Recurrent networks have the advantage of being able to model dynamics systems accurately and in a compact form. A recurrent network can be represented in a general diagrammatic form as illustrated in Fig. 4. This diagram depicts the hybrid hidden layer as comprising a linear part and a non-linear part and shows that, in addition to the usual feedforward connections, the networks also have feedback connections from the output layer to the hidden layer and self-feedback connections in the hidden layer. The reason for adopting a hybrid linear/non-linear structure for the hidden layer will be evident later [5-9].

At a given discrete time t, let **u**(t) be the input to a recurrent hybrid network, **y**(t), the output of the network, $\mathbf{x}_1$(t) the output of the linear part of the hidden layer and $\mathbf{x}_2$(t) the output of the non-linear part of the hidden layer.

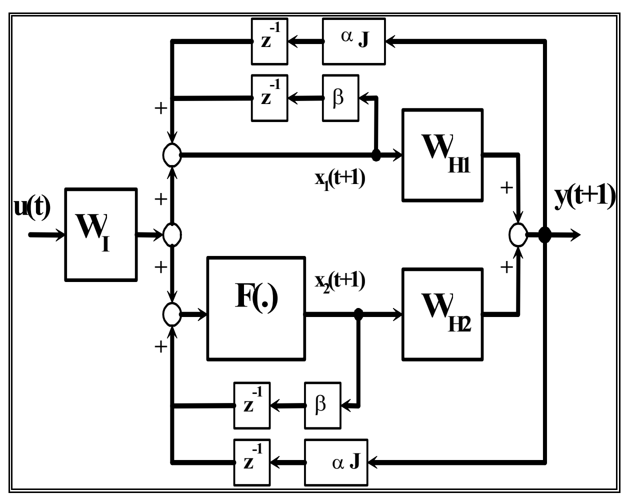

Fig.2. Block diagram of proposed recurrent hybrid network [5,6]

The operation of the network is summarised by the following equations (see also Figure 4):

$$\mathbf{x}_1(t+1)=\mathbf{W}^{I1}\,\mathbf{u}(t+1)+\beta\,\mathbf{x}_1(t)+\alpha\mathbf{J}_1\mathbf{y}(t) \quad (1)$$

$$\mathbf{x}_2(t+1)=\mathbf{F}\{\mathbf{W}^{I2}\,\mathbf{u}(t+1)+\beta\,\mathbf{x}_2(t)+\alpha\mathbf{J}_2\mathbf{y}(t)\} \quad (2)$$

$$\mathbf{y}(t+1)=\mathbf{W}^{H1}\,\mathbf{x}_1(t+1)+\mathbf{W}^{H2}\,\mathbf{x}_2(t+1) \quad (3)$$

where $\mathbf{W}^{I1}$ is the matrix of weights of connections between the input layer and the linear hidden layer, $\mathbf{W}^{I2}$ is the matrix of weights of connections between the input layer and the non-linear hidden layer, $\mathbf{W}^{H1}$ is the matrix of weights of connections between the linear hidden layer and the output layer, $\mathbf{W}^{H2}$ is the matrix of weights of connections between the non-linear hidden layer and the output layer, $\mathbf{F}\{\}$is the activation function of neurons in the non-linear hidden layer and α and β are the weights of the self-feedback and output feedback connections. $\mathbf{J}_1$ and $\mathbf{J}_2$ are respectively $n_{H1}\times n_O$ and $n_{H2}\times n_O$ matrices with all elements equal to 1, where n_{H1} and n_{H2} are the numbers of linear and non-linear hidden neurons, and n_O, the number of output neurons.

If only linear activation is adopted for the hidden neurons, the above equations simplify to:

$$\mathbf{y}(t+1)=\mathbf{W}^{H1}\,\mathbf{x}(t+1) \quad (4)$$

$$\mathbf{x}(t+1)=\mathbf{W}^{I1}\,\mathbf{u}(t+1)+\beta\mathbf{x}(t)+\alpha\mathbf{J}_1\,\mathbf{y}(t) \quad (5)$$

Replacing $\mathbf{y}(t)$ by $\mathbf{W}^{H1}\,\mathbf{x}(t)$ in equation (5) gives

$$\mathbf{x}(t+1)=(\beta\,\mathbf{I}+\alpha\,\mathbf{J}_1\,\mathbf{W}^{H1})\mathbf{x}(t)+\mathbf{W}^{I1}\,\mathbf{u}(t+1) \quad (6)$$

where $\mathbf{I}$ is a $n_{H1}\times n_{H1}$ identity matrix

Equation (6) is of the form

$$\mathbf{x}(t+1)=\mathbf{A}\,\mathbf{x}(t)+\mathbf{B}\,\mathbf{u}(t+1) \quad (7)$$

where $\mathbf{A}=\beta\mathbf{I}+\alpha\mathbf{J}\mathbf{W}^{H1}$ and $\mathbf{B}=\mathbf{W}^{I1}$ Equation (7) represents the state equation of a linear system of which $\mathbf{x}$ is the state vector. The elements of $\mathbf{A}$ and $\mathbf{B}$ can be adjusted through training so that any arbitrary linear system of order n_{H1} can be modelled by the given network. When non-linear neurons are adopted, this gives the network the ability to perform non-linear dynamics mapping and thus model non-linear dynamic systems. The existence in the recurrent network of a hidden layer with both linear and non-linear neurons facilitates the modelling of practical non-linear systems comprising linear and non-linear parts.

4 Simulation Results

In this section, simulations of the modified four-bar mechanism for force analysis using the proposed neural network predictor are performed for finding . The training parameters of the network are given in Table 1. Firstly, the network was randomly trained between the force values of the mechanism's joints. Training numbers of the network are also given in Table 1. Performances of the proposed method are executed.

The performance of the proposed neural predictor was tested on the system for different forces of the joints such as joints 5, 6 and 7. The actual forces of the system's joint 4 superimposed on the specified forces are plotted in Fig. 5. Neural predictor possesses a much faster response characteristic and therefore has better performance.

In Fig. 6, the neural network predictor exactly follows the desired results of the system for joint 4.

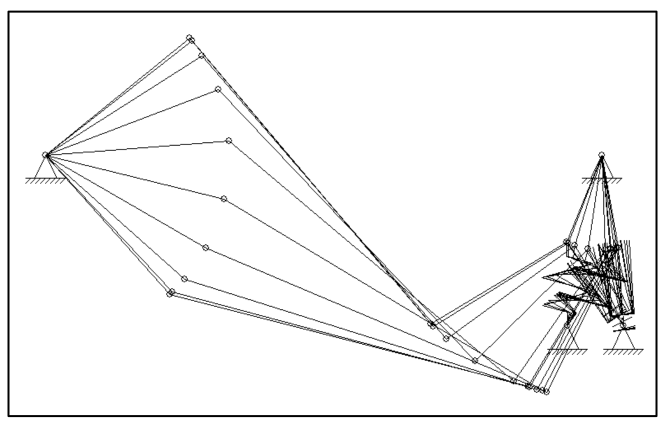

Fig. 3. Schematic representation of the extended mechanism

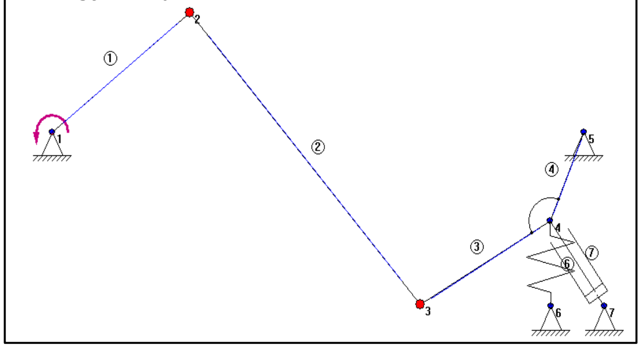

Fig.4. Representation of the proposed mechanism during working

There is also another analysis for joint 5 as depicted in Fig. 7. There is good stability between two approaches.

From the results obtained, it can be seen that the proposed neural predictor produced the best performance. The advantages of the proposed predictor is faster learning and small tracking errors. A reason for the strong performance of the proposed network was the inclusion of both linear and non-linear neurons in the network.

Appendix:

Equation of motion for the model mechanism

Kinematic Equations

$$-r_1 + r_2 Cos\theta_2 + r_3 Cos\theta_3 + r_4 Cos\theta_4 + r_5 Cos\theta_5 + r_c Cos\theta_c = 0 \quad (8)$$

$$r_2 Sin\theta_2 + r_3 Sin\theta_3 + r_4 Sin\theta_4 + r_5 Sin\theta_5 + r_c Sin\theta_c = 0 \quad (9)$$

$$r_2 \dot{\theta}_2 Sin\theta_2 + r_3 \dot{\theta}_3 Sin\theta_3 + r_4 \dot{\theta}_4 Sin\theta_4 + r_c \dot{\theta}_c Sin\theta_c - \dot{r}_c Cos\theta_c = 0 \quad (10)$$

$$r_2 \dot{\theta}_2 Cos\theta_2 + r_3 \dot{\theta}_3 Cos\theta_3 + r_4 \dot{\theta}_4 Cos\theta_4 + r_c \dot{\theta}_c Cos\theta_c + \dot{r}_c Sin\theta_c = 0 \quad (11)$$

$$r_2 \ddot{\theta}_2 Sin\theta_2 + r_3 \ddot{\theta}_3 Sin\theta_3 + r_4 \ddot{\theta}_4 Sin\theta_4 + r_c \ddot{\theta}_c Sin\theta_c - \ddot{r}_c Cos\theta_c + r_2 \dot{\theta}_2^2 Cos\theta_2 + r_3 \dot{\theta}_3^2 Cos\theta_3 + r_4 \dot{\theta}_4^2 Cos\theta_4 + r_c \dot{\theta}_c^2 Cos\theta_c + 2\dot{r}_c \dot{\theta}_c Sin\theta_c = 0 \quad (12)$$

$$r_2 \ddot{\theta}_2 Cos\theta_2 + r_3 \ddot{\theta}_3 Cos\theta_3 + r_4 \ddot{\theta}_4 Cos\theta_4 + r_c \ddot{\theta}_c Cos\theta_c + \ddot{r}_c Sin\theta_c - r_2 \dot{\theta}_2^2 Sin\theta_2 - r_3 \dot{\theta}_3^2 Sin\theta_3 - r_4 \dot{\theta}_4^2 Sin\theta_4 - r_c \dot{\theta}_c^2 Sin\theta_c + 2\dot{r}_c \dot{\theta}_c Cos\theta_c = 0 \quad (13)$$

Dynamic Equations

For link 2:

$$X_{32} r_2 Sin\theta_2 - Y_{32} r_2 Cos\theta_2 + m_2 g s_2 Cos\theta_2 = -(I_2 + m_2 s_2^2)\ddot{\theta}_2 \quad (14)$$

$$X_{32} - X_{43} = m_3 r_2 \ddot{\theta}_2 Sin\theta_2 + m_3 s_3 \ddot{\theta}_3 Sin\theta_3 + m_3 r_2 \dot{\theta}_2^2 Cos\theta_2 + m_3 s_3 \dot{\theta}_3^2 Cos\theta_3 \quad (15)$$

$$X_{32} s_3 Sin\theta_3 - Y_{32} s_3 Cos\theta_3 + X_{43}(r_3 - s_3) Sin\theta_3 - Y_{43}(r_3 - s_3) Cos\theta_3 = -I_3 \ddot{\theta}_3 \quad (16)$$

For clearance link:

$$X_{43} r_c Sin\theta_c - Y_{43} r_c Cos\theta_c = 0 \quad (17)$$

$$X_{43} Cos\theta_c + Y_{43} Sin\theta_c = K_c (r_c - r_{c0}) + \mu_c \dot{r}_c \quad (18)$$

For link 4:

$$Y_{43} r_4 Cos\theta_4 - X_{43} r_4 Sin\theta_4 - m_4 g (g(r_4 - s_4) Cos\theta_4 = -[I_4 + m_4 (r_4 - s_4)^2]\ddot{\theta}_4 \quad (19)$$

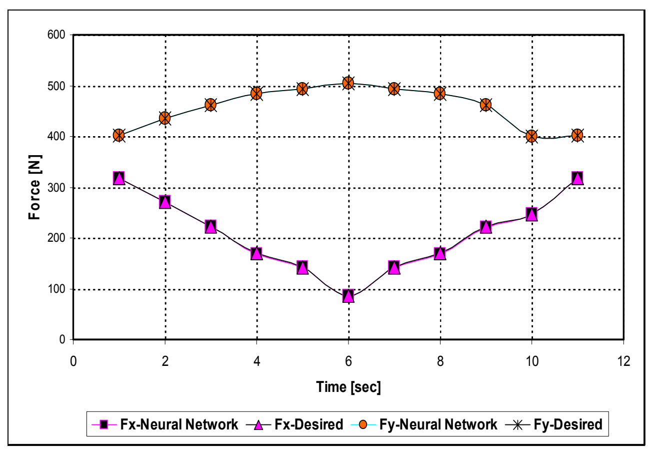

Fig. 5. Force variations of Joint 3 for both approach on the X and Y directions

Table 1. Kinamatic Parameters of the mechanism

Parameters	Values
I_2	0.2188 kg m^2
I_4	0.2094 kg m^2
m2	12.9 kg
m_3	2.41 kg
m_4	5.04 kg
r_1	800 mm
r_2	100 mm
r_3	390 mm
r_4	580 mm
r_5	100 mm
r_c	100 μm
s_2	17.4 mm
s_3	195 mm
s_4	329 mm
θ_5	70^o

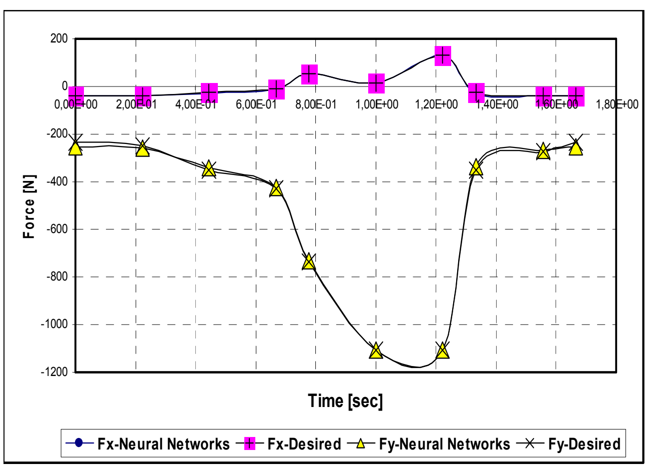

Fig. 6. Force variations of Joint 4 for both approach on the X and Y directions

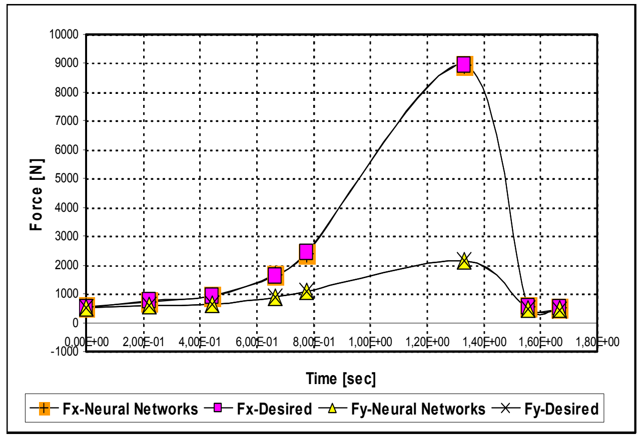

Fig. 7. Force variations of Joint 5 for both approach on the X and Y directions

5 Conclusion

This paper has presented a neural network predictor for analysing forces of joints of a modified four-bar mechanism. In this new approach, a well-trained network supplies good prediction on kinematic parameters of the mechanism. The results presented were given superior performance to predict kinematic parameters of the proposed mechanism. Finally, it can be said that the neural networks would be useful algorithm for analysing such as mechanisms in experimental works.

References

[1] M. Sannah, and A. Smaili, Active Control of Elastodynamic Vibrations of a Four-bar Mechanism System with a Smart Coupler link Using Optimal Multivariable Control: Experimental Implementation, *Journal of Mechanical Design,* Vol 120, No. 2, 1998, pp. 316-326.

[2] K.H. Yang, and Y.S. Park, Dynamic Stability Analysis of a Flexible Four-bar Mechanism and Its Experimental Investigation, *Mechanism and Machine Theory,* Vol 33, No. 3, 1998, pp. 307-320.

[3] L.C.T. Dulger, and S. Uyan, Modelling, Simulation and Control of a Four-bar

Mechanism with a Brushless Servo Motor, *Mechatronics*, Vol 7,No. 4, 1997, pp 369-383

[4] Z.H.L. Zou, K.A. AbdelMalek, and J.Y. Wang, A Variational Approach for the Design of Spatial Four-bar Mechanism. *Mechanics of Structures and Machines*, Vol 25, No. 1, 1997, pp 41-59.

[5] Ş. Yıldırım, Robot Trajectory Control Using Neural Networks. *IEE Electronics Letters,* Vol. 38, Iss. 19,2002, pp. 1111-113.

[6] Ş. Yıldırım, Neural Network Controller for cooperating robots. *IEE Electronics Letters*, Vol. 37, 2001, No. 22, pp. 1351-1352.

[7] Ş.Yıldırım, and İ, Uzmay, Neural Network Applications to Vehicle's Vibration Analysis. Mechanism and Machine Theory 2003, Vol. 38, pp. 27-41.

[8] Ş. Yıldırım, and İ. Eski, Noise Analysis Of Robot Manipulator Using Neural Networks, *Robotics and Computer-Integrated Manufacturing*, Vol.26, 2010, pp.282-290.

[9] Ş. Yıldırım, Vibration Control of Suspensions Using a Proposed Neural Network, Journal of Sound and Vibration, Vol. 27, 2004, pp. 1059-1069.

[10] J.Moon, and B. Lee, B., Modelling and sensitivity anaysis of a pneumatic vibration isolation system with two air chambers, *Mechanism and Machine Theory*, Vol. 45, 2010, pp. 1828-1850.

[11] H. Pu, X. Luo, X. Chen, Modelling and analysis of dual-chamber pneumatic spring with adjustible damping for precision vibration isolation. *Journal of Sound and Vibration*, Vol.330, 2011, pp. 3578-3590.

[12] M. Karpenko, and N. Sepehri, 2002. Neural network classifiers applied to condition monitoring of a pneumatic process valve actuator, *Engineering Applications of artificial Intelligence*, Vol.15, 2002, pp.273-283.