

THE ARTIFICIAL INTELLIGENCE APPLICATION TO THE ANALYSIS OF THE CONSTRUCTIVE AND WORKING PARAMETERS OF PLANE MECHANISM

Denijal Sprečic, Osman Muftić, Igor Janežić and Elvedin Mujić

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1. Introduction

The task of the kinematic and dynamic analyses is to determine the basic parameters of a mechanism movement such as are: velocities v and accelerations a of the mechanism moving members, kinetic energy E_k , mechanism driving torque M_p , etc. By changing only one input value to a certain extent, the so far used methods (graphical) become unacceptable for a description, and by increasing the number of the input variables this problems becomes many times more complicated. As a logical answer the application of the computer based methods to resolve this problem is imposed. The basis of this procedure is the establishment of a functional dependence of the output values on the general input values. The group of the input values can enter some construction and working parameters of the mechanism, such as are: lengths of the members r, b, c , span between the revolving members of the mechanism $e = O_1O_2$, angle \mathbf{j} of the mechanism driving member, number of revolutions of the mechanism driving member n , technological force on the mechanism working member F_t and the specific mass of the mechanism members q .

2. Kinematic and Dynamic Analysis of the Mechanism

By using the kinematic and dynamic analyses of the mechanism we can get the functional dependence between the input values as general numbers and output values which are looked for. The method of determining the unknown kinematic values of the mechanism is based upon the conversion of conventional graphic methods into an analytical entry of general numbers which leaves the possibility of changing the input (basic) parameters of the mechanism. In the same way are determined also the dynamic values of the mechanism, such as are: kinetic energy, driving torque and the pressures in the kinematic pairs of the mechanism. Based upon the position of the firing strengths and of the geometric dependencies it is possible to get the pattern for the calculation of the driving torque M_p on the driving member r of the mechanism for any position of the mechanism. This is the moment which is necessary to overcome the inertial, weight forces and the technological forces of the mechanism.

$$M_p = \frac{r}{v_{A1}} \left[\begin{array}{l} G_1 v_{S1} \cos \mathbf{j} + G_2 v_{A1} \cos \mathbf{j} + G_3 v_{S3} \sin \mathbf{a} - G_4 \frac{v_b \sin \mathbf{a}}{2} + F_d v_d + F_d v_b + F_c v_c \sin \mathbf{g} - \\ - F_c v_b \sin(\mathbf{a} + \mathbf{g}) + F_t v_c + F_{in3}^t v_{S3} + F_{in4}^n v_c \sin \mathbf{g} + F_{in4}^t \frac{v_c^b \cos \mathbf{g}}{2} + F_{in5} v_c \end{array} \right] \quad (1)$$

In the Figure 1a. is given the graphic presentation of the change in the driving torque of the

mechanism, and in the Figure 1b. are given the gait graph and the line diagram of velocities, accelerations and the kinetic energy of the mechanism.

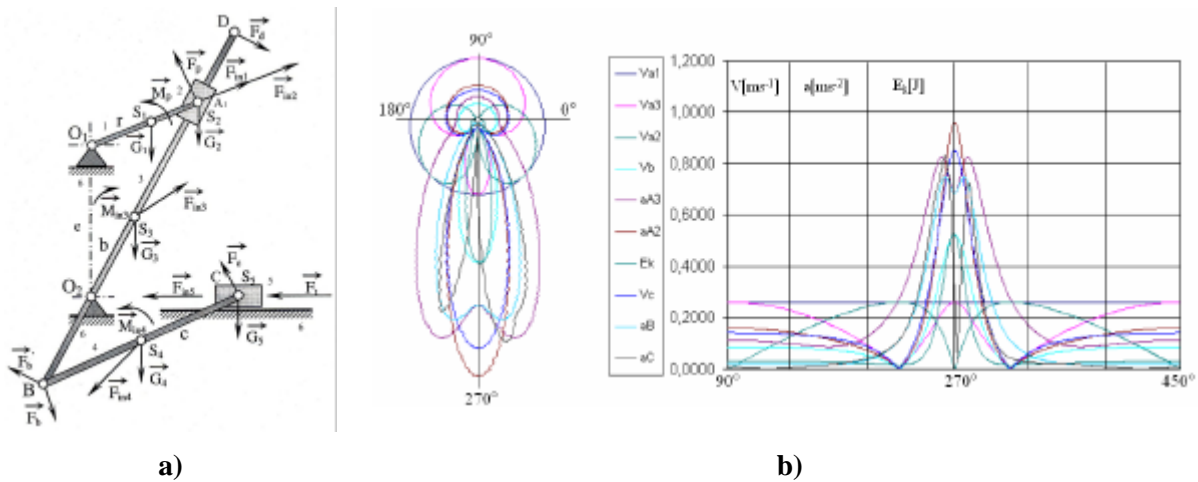


Figure 1. a) Scheme of the mechanism with the forces and moments acting upon the mechanism
 b) Gait graph and the line diagram of velocities, accelerations and the kinetic energy of the mechanism

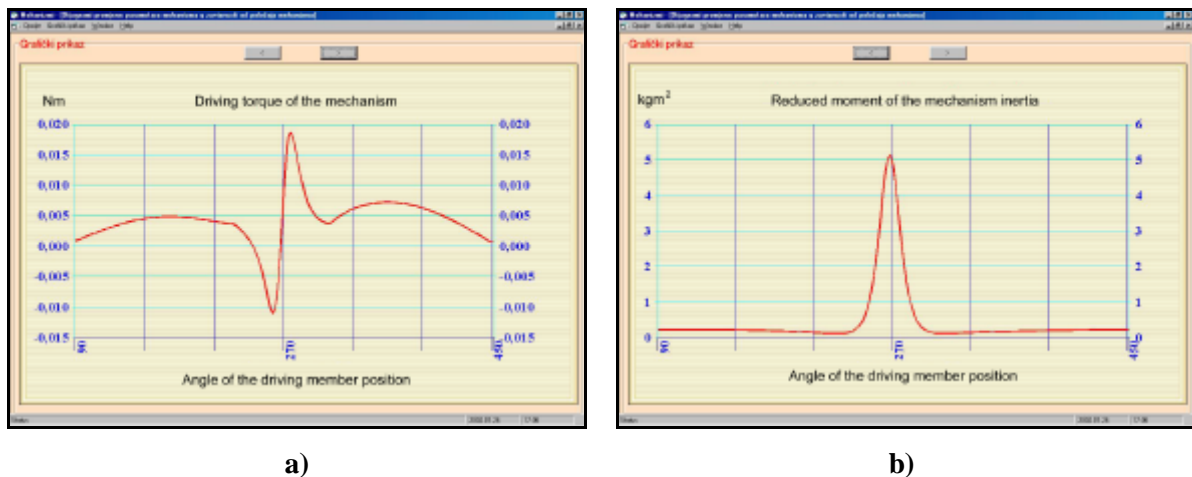


Figure 2. a) Diagram of the change in the driving torque of the mechanism
 b) Diagram of the change in the reduced mechanism inertia moment

3. Fuzzy Inference System and ANFIS Architecture

The fuzzy inference system (FIS) of the Takagi-Sugeno (TS) type has rules with fuzzy antecedents but functional consequents. In a zero-order TS FIS the consequent of each rule will be a constant real number, a weight or parameter to be estimated. In a 1st- order TS FIS, the consequent of each rule will be a linear function of inputs, with weights or parameters to be estimated. The antecedent and consequent parts of Fuzzy Rules are characterised by membership functions. The set of fuzzy rules will form a fuzzy inference engine. These influence factors must be specified a priori and can be, for example, number of revolutions of the driving member, angle of turning, technological force, length of the members, etc. A TS FIS can be organised in a neuro-fuzzy scheme, as it will be described below. Therefore, a classical way of tuning the FIS over the data (i.e., finding the best value for the weights or parameters that minimise the difference between data in a test set and the predictions by the FIS) is to use a backpropagation procedure analogue to the one used in training Artificial Neural Networks. The parameters to be found relate not only to the weights in the consequent functions, but also to the parameters of the membership functions describing the inputs. This is the basis to derive its name from

adaptive neuro-fuzzy inference system ANFIS. The basic idea behind neuro-adaptive techniques is very simple. These techniques provide a method for a TS fuzzy model to *learn* information about a data set, in order to compute the membership function parameters that allow best the fuzzy inference system to track the given input/output data relationship. This learning method works similarly to the backpropagation algorithm of neural networks. In order to present the ideas clearly, and without losing generality, we assume now that the fuzzy inference system under consideration has two inputs x and y and one output f . To fix ideas on reality, it is admitted that x measures number of revolutions of the driving member, y measures technological force and f measures the driving torque of the mechanism. A rule set with two fuzzy if-then rules for a first-order Sugeno fuzzy model may be

Rule 1: If x is A_1 and y is B_1 , then

$$f_1 = p_1x + q_1y + r_1, \quad (2)$$

Rule 2: If x is A_2 and y is B_2 , then

$$f_2 = p_2x + q_2y + r_2. \quad (3)$$

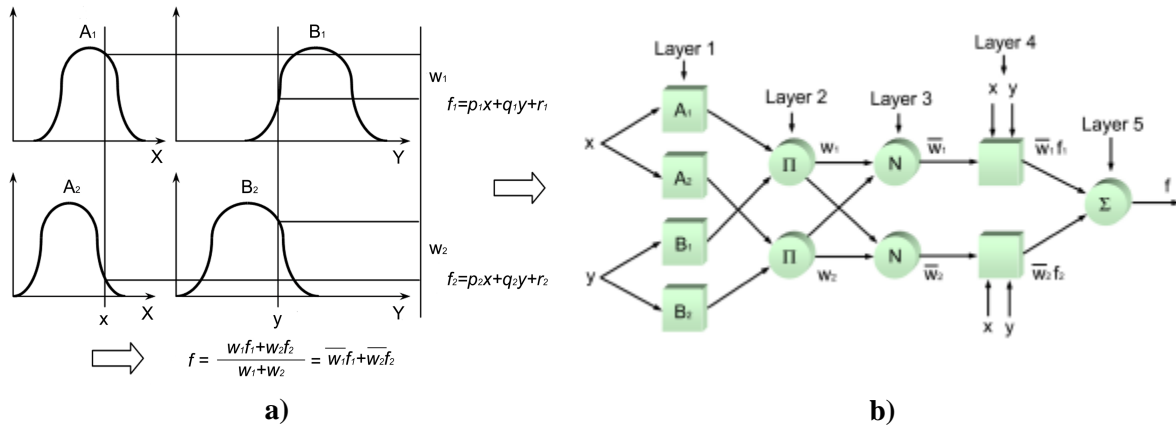


Figure 3. a) A two-input first-order Sugeno fuzzy model with two rules b) Equivalent ANFIS architecture for a two-input first-order Sugeno fuzzy model with two rules

Layer1; Each node i in this layer is an adaptive node with function:

$$O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1, 2; \quad O_{1,i} = \mu_{B_{i-2}}(y), \text{ for } i = 3, 4 \quad (4)$$

where x or y is the input to node i and A_i or B_{i-2} is a linguistic label (such as “small” or “large”) associated with this node. In other words, $O_{1,i}$ is the membership grade of fuzzy set A ($= A_1, A_2, B_1$ or B_2) and it specifies the degree to which the given input x or y satisfies the quantifier. The membership function for A can be any appropriate parameterized membership function such as the Gaussian function:

$$\mu_A(x) = e^{-\frac{(x-c_i)^2}{2\sigma_i^2}} \quad (5)$$

where c_i and σ_i belong to the parameter set. Parameters in this layer are called premise parameters.

Layer2; Each node i in this layer is a fixed node labelled Π , whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \text{ for } i = 1, 2. \quad (6)$$

This can be interpreted as the adoption of the T-norm “product” for the conjunction or intersection of fuzzy sets. Each output node represents the firing strength of a rule.

Layer 3; Each node i in this layer is a fixed node labelled N . The i^{th} node calculates the ratio of the i^{th} rule’s firing strength to the sum of all rule’s firing strengths:

$$O_{3,i} = \bar{w}_i = \frac{w_1}{w_1 + w_2}, \text{ for } i = 1, 2. \quad (7)$$

These outputs are called normalized firing strengths.

Layer 4; Each node i in this layer is an adaptive node with function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i), \text{ for } i=1, 2. \quad (8)$$

where \bar{w}_i is a normalized firing strength from layer 3 and p_i , q_i and r_i represent the parameter set of this node. Parameters of this layer are consequent firing parameters.

Layer 5; The single node in this layer is a fixed node labelled Σ , which computes the overall output as the summation of all incoming signals:

$$\text{overall output} = O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \quad (9)$$

Thus an adaptive network that is functionally equivalent to a Sugeno fuzzy model, was constructed.

4. Hybrid Learning Algorithm

For parameter tuning in an adaptive network one can apply a backpropagation algorithm, which is well known and is based on the steepest descent principle. This simple optimisation method, although enhanced by a number of algorithmic improvements, usually takes a long time before it converges. However, it may be observed that the adaptive network’s output is linear in some parameters; therefore, these linear parameters can be tuned using an analytical Least-Squares method. This Least-Squares approach, by the way, may be directly used in tuning TS FIS output parameters, when the parameters in the input membership functions remain constant. From the ANFIS architecture shown in figure 3b., it is observed that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters. The output f in figure 3b. can be rewritten as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2, \quad (10)$$

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2), \quad (11)$$

$$f = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2 \quad (12)$$

which is linear in consequent parameters p_1 , q_1 , r_1 , p_2 , q_2 and r_2 . From this observation, there is a set of total number of parameters, a set of premise (non-linear) parameters and a set of consequent (linear) parameters. The hybrid learning algorithm is composed of a succession of iterations of a forward pass and a backward pass. In the forward pass, the input parameters remain fixed, node outputs are propagated forward until layer 4 and the consequent parameters are identified by the Least-Squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by a gradient descent procedure, analogue to the backpropagation in neural networks. Table 1. summarises the characteristics of each pass.

Table 1. Two Passes in the Hybrid Learning Procedure for ANFIS

	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least-square estimator	Fixed
Signals	Node outputs	Error signals

These data have been divided into a training set and a test set of equal size (360 points each), and the convergence of the training processes in the usual way has been controlled, avoiding phenomena of over-fitting, while minimising the mean square error between actual data and predictions. First, five different membership functions (gaussian, triangular, trapeze, dsigmoid and psigmoid) have been tested and compared in the same zero-order Sugeno model. Then, the procedure was repeated with same five different membership functions in the first-order Sugeno model.

5. Verification of the ANFIS models and of the Results Obtained

Based upon the expression (1) for the driving torque of the observed mechanism the values for this torque for certain input parameters that figure in the equation (1) were obtained. In addition, the data base consisting of the results obtained by calculating the kinematic and dynamic values using the software for kinetic and dynamic analyses of the observed mechanism, was used as a basis for the establishment of the dependency of the driving torque M_p of the mechanism on the set input variables such as are: the angle of the working member \mathbf{j} , number of revolution of the driving member n , specific mass of the members q and the technological force F_t . In the paper the adaptive neuro-fuzzy inference module which is presented by means of a simplified structure, is used (Figure 4).

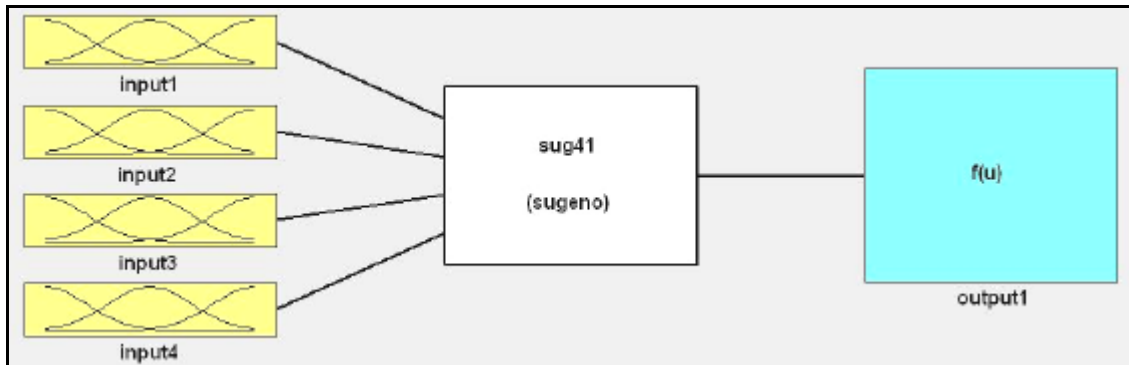


Figure 4. Simplified structure of the ANFIS model

In the set model the functional dependence is given:

$$M_p = M_p(\mathbf{j}, n, q, F_t) \quad (13)$$

where it is:

- angle of the driving member position f [°] – input1,
- number of revolutions of the driving member n [°/min] – input2,
- specific mass of the members q [kg/m³] – input3,
- technological force F_t [N] – input4 and
- driving torque of the mechanism M_p [N] – output1.

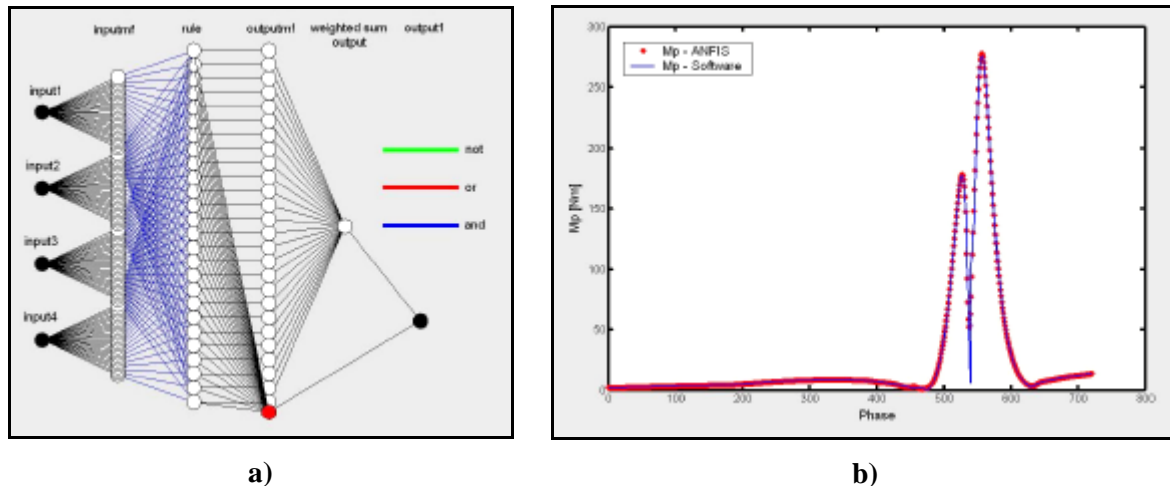


Figure 5. a) ANFIS model structure b) Diagram of the values for the driving torque obtained by means of the software computing and ANFIS model

The results for the driving torque, obtained based upon the classical graphic and analytical methods in accordance with the Figure 5b. for the same values of the input parameters, show a high level of tuning with the values for the driving torque which were obtained by means of the ANFIS model for the same values of the input variables.

Acknowledgement

In order to perform the analysis of a mechanism and to provide relevant indices of the effect of the input parameters upon the individual outputs, it is necessary to have a model which will make the calculation of the required values in a quick and exact way possible. The data basis consisting of the results obtained by calculating the kinematic and dynamic values using the software for kinetic and dynamic analyses of the observed mechanism, was used as a basis for a more comprehensive analysis of the dependency of the driving torque on the set input variables such as are: the angle of the working member \mathbf{j} , number of revolutions of the driving member n , specific mass of the members q and the technological force F_t . In the paper the adaptive neuro-fuzzy inference module was used for this purpose, which is actually the application of the artificial intelligence to resolve the problems of analysing the plane mechanism. The values obtained for the driving torque based upon the ANFIS model fully correspond to the changes in the stated input variables as can be seen based upon the Figure 5b. By means of the set model it is possible to determine approximately which of the input variable effects most the change in the driving torque of the mechanism as an output value. Therefore, this is a supplement to the classical methods of performing kinematic and dynamic analyses of plane mechanisms in terms of improvement of their working performances.

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Prof. Dr. Denijal Sprecic
 University of Tuzla
 Faculty of Mechanical Engineering
 Univerzitetska 8, 75000 Tuzla, Bosnia & Herzegovina
 Tel./Fax: +387 35 283 304
 E-mail: espreic@bih.net.ba