Design, Implementation and Optimal Control of a Series Robot Based on Fuzzy Logic Method

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ABSTRACT:
The series robot is a type of the mechanical arms with a function similar to human hands which is usually programmable. These robots, depending on the application, are designed in order to perform various operations such as clinch, welding, packaging, assembly and etc. One of the most important issues in the field of the series robots that has been highly regarded in the past few decades, is the path control. Various industries have urgent and serious need to know the optimal control of path. In this paper, the design and implementation of a series robot with two degrees of freedom and its fuzzy control is studied. This fuzzy controller, is an approach to optimal control of robot path. In these robots, finding the optimal path would be time consuming. This study uses fuzzy logic and the laws governing it, which will result the most efficient path in very little time. Then, how to use and implement Fuzzy toolbox in MATLAB software will be discussed. Evaluation of the results show that the proposed model has a higher rate than other existing models, in the field of the optimal control of robot path.

KEYWORDS: Fuzzy Logic, Mechanical Arm, Optimization, Series Robot

1. NTRODUCTION

Nowadays, robots are used in many aspects of extensive industrial activities. Since series robots have been introduced as one of the most versatile of industrial robots, these kind of robots are used in many activities of industry, agriculture, commercial, household, etc. for example, some series robots in automotive assembly lines, tasks such as welding, turning and conducting parts during the assembly. Development of series robotic technology as the industrial robots has made remarkable progress. Therefore, nowadays one of the most important and vital consideration in series robots is designing and developing the controllers of them which can increase the speed and meet the human demands.

As mentioned before, the most important issue in the field of robot series is controlling a path. In studies which has been done before, the Original Elasto-Geometric calibration method was proposed to improve Static Pose accuracy of industrial robots which is used in machining, forming and assembly [1]. In [1], two methods were introduced: Analytical parametric modelling and Takagi-Sugeno techniques Fuzzy Inference system. The Fuzzy Logic Model was used to increase the Static Pose accuracy. The experimental results show the usage of fuzzy logic model.

In another attempt, a new controller based on Interval-valued fuzzy model was presented to control a complex dynamic systems [2]. The fuzzy logic model was combined with a direct torque controller (DTC), in order to control a parallel robot with three degrees of freedom. The simulation results proved the superiority of the proposed controller.

Vermeiren and colleagues offered a new method that can be used to control a parallel robotic arm with two degrees of freedom [3]. They implemented the LMI Constrains Problems to extracted fuzzy rules. Results of the simulations presented the advantage of the method.

Han and Lee proposed a back stepping control system which uses the Tracking Error Constraint and Recurrent Fuzzy Neural Networks (RFNNs) [4]. They designed this controlling system in order to achieve a Prescribed Tracking Performance for a Strict-Feedback Nonlinear Dynamic system. Also, they defined a limitation variable to produce Virtual Control, which locate the tracking error to the determined boundaries. The proposed plan was validated by the control of a nonlinear system and a robotic arm.

In another work parameters of functions of a fuzzy logic controller for a wheeled mobile robot were optimized using Ant Colony Optimization (ACO) and

Particle Swarm Optimization (PSO) [5]. Simulation results were compared with the results of previous works done by the genetic algorithm and presented that the best method to optimize for this particular robotics controlling is Ant Colony Optimization and Particle Swarm Optimization.

Since the control model of self-regulation in the electro-hydraulic of excavators is nonlinear, intelligent control systems is required to overcome the Undesirable stick-slip motion, Limit cycle and oscillations. Hassan and Kothapalli in their paper discussed about fuzzy control with intelligent position control of an Electro-hydraulic Activated robotic excavator [6]. In the paper, nonlinear model for fluid flow rate of the valve, hydraulic pump and friction forces were calculated. Also, Coulomb friction forces functions, viscosity and Stribeck were modeled. The proposed models are accurate and dynamic study of operator and load are not considered in order to improve the behavior of robotic excavator.

A Self-Organizing fuzzy controller (SOFC) under the system control has possibility of online training. However, the fuzzy rules of this controller may be change, especially when the Learning Rate and Weighting Distribution are chosen poorly. Also, while these controllers are used, the effects of Dynamic Coupling between the degrees of freedom of robotic systems is complicated.

In order to overcome this problem, a self-organizing Grey-Prediction (GP) fuzzy controller for robotic systems was designed [7]. In this method, a Grey-Prediction algorithm was added to the fuzzy rules for controlling robotic systems. In order to assess the feasibility of proposed method, this controller was implemented to a six degrees of freedom robot for determining its performance. The results show that the Grey-Prediction controller has better controlling of the robot rather than self-organizing fuzzy controller.

Mashhadany has introduced a technique which includes Inverse Kinematics solutions and Adaptive Neuro-fuzzy Inference system (ANFIS) [8]. The simulation was performed by using Simulink of the MATLAB software. The results presented that this design is suitable for reverse controlling of a robot with three degrees of freedom.

In recent years, the theories of fuzzy sets have been considered by researchers in order to develop smart systems which have high complexity and accuracy [9]. Since fuzzy logic theory has been proposed to describe complex systems, this theory became very famous and has been successfully used on several issues, especially automatic control [10].

2. THE FUZZY CONTROLLER STRUCTURE

A fuzzy controller system is based on fuzzy control algorithm. Basic structure of a fuzzy controller consists of three blocks such as defuzzification, inference device and non-defuzzification.

For practical usage, the fuzzy inference Mamdani algorithm controllers often have been used []. Equation 1 shows the interface of i^{th} algorithm:

$$if\ x_1\ is\ A_{1i}\ and\ ....\ and\ if\ x_n\ is\ A_{ni}\ then\ y\ is\ C_i \qquad (1)$$

x_1, x_2, ..., x_n are the front part of the input variables, y is the lower variable i^{th} output of A_{1i}, A_{2i}, ..., A_{ni} and C_i is fuzzy sets for the i^{th} algorithm.

The fuzzy set membership function for the i^{th} algorithm can be obtained by implementing equation 2 as follow:

$$\alpha_{C_i} . \alpha_{C_i} = min[\alpha_{A1i}(x_{1k}), \dots, \alpha_{Ani}(x_{nk})] = w_i . C_i \qquad (2)$$

$\alpha_{C_i}$is output membership functions that includes singletons of C_i^1. Also, the non-defuzzification block uses the Center of gravity (COG) method. Therefore, the final result can be determined by implementing Equation 3 as follows:

$$y = \frac{\sum_i^n w_i . C_i}{\sum_i^n w_i} \qquad (3)$$

3. OPTIMAL CONTROLLING BY USING FUZZY INFERENCE SYSTEM

In this paper, most of the previous studies in the field of fuzzy logic are investigated. Also, theoretical design, simulation and analyzing the theoretical results are presented in this study. Then the final optimization is achieved by implementing the Toolbox Fuzzy Inference System in MATLAB software and the defined inputs.

The fuzzy rules are determined by considering empirical studies and achieved results of simulations. Then with the help of fuzzy inference systems, optimal values will be achieved. For the optimal controlling of robot path two effective parameters are considered as inputs of the fuzzy system. First, work point coordinates in the transverse and longitudinal axis directions are considered as inputs of the first fuzzy system. Second, work point coordinates in the transverse and longitudinal axis directions and also the rotation angle of the first motor are considered as inputs of the second fuzzy system.

3.1. The basic model

As mentioned before, in order to create a controller model or fuzzy inference system, the fuzzy toolbox in MATLAB software is used. The fuzzy inference system is based on the understanding of motion control and how the input parameters effect on the path.

Two factors affecting engine rotation angle are considered as the transverse and longitudinal coordinates which are inputs of the fuzzy interface first system and the output is rotation angle of the

motor. Fig. 1 shows the first fuzzy inference system which is Sugeno type.
Three factors affecting the operating rotation angle of the second motor are considered as transverse and longitudinal coordinates and rotation angle of the first motor. These parameters are defined as the inputs of the second fuzzy interface system and the input is rotation angle of the second motor. The second fuzzy inference system which is based on Sugeno is shown in Fig. 2.

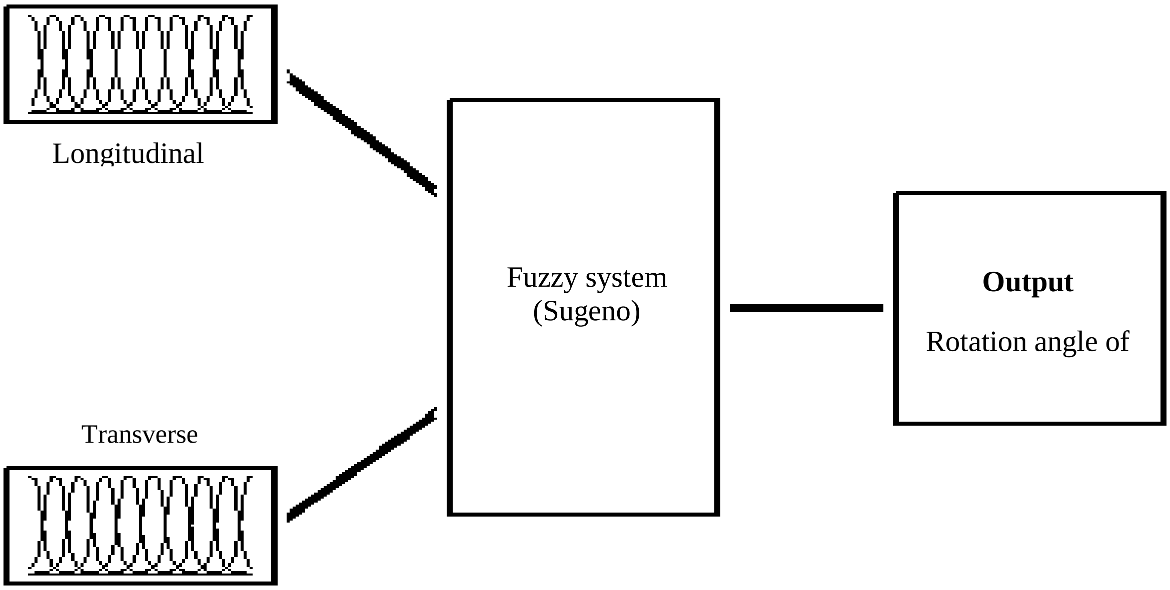


Fig. 1. The general structure of first fuzzy inference system

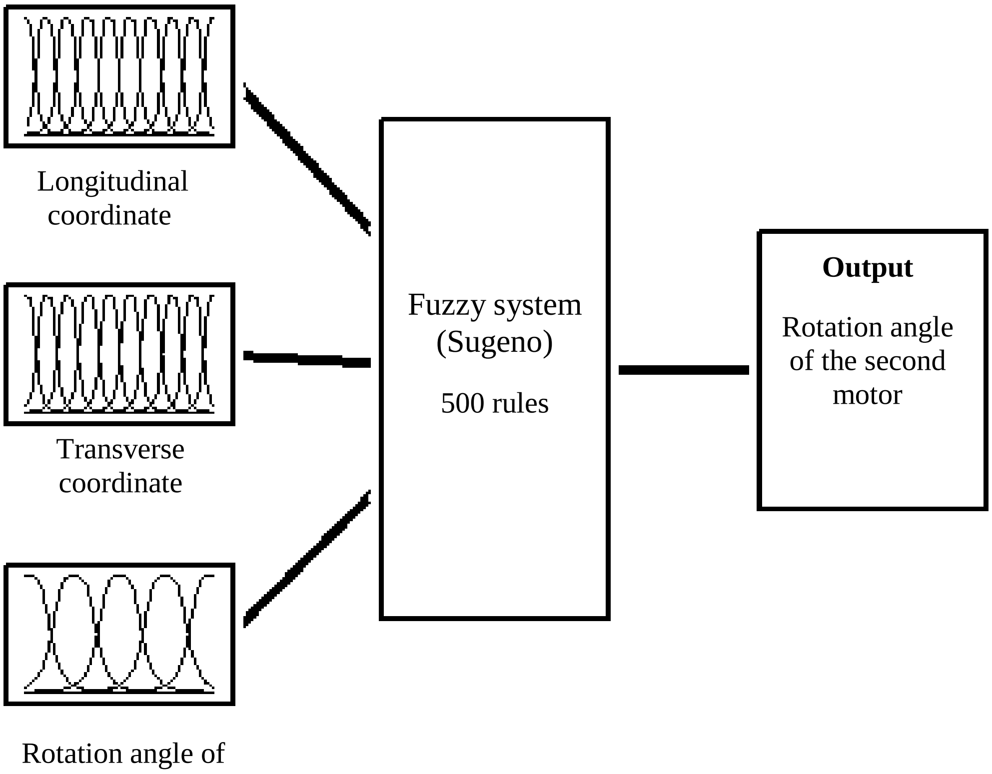


Fig. 2. The general structure of second fuzzy inference system.

In this model, for each inputs of the transverse and longitudinal coordinates, ten first working function are the representative of small amounts, and last function are representative of large quantities. First five functions are considered as inputs of rotation angle of the first motor, that each of them represents the degree of rotation of the motor. Equation 4 shows the inverted implemented functions.

$$f(x;a,b,c,d) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \qquad (4)$$

where a, b, c and d are the hallmarks of membership functions that will be modified during learning [11]. Fig. 3 presents longitudinal coordinate of the membership functions which are inverted inputs.
Fig. 4 shows transverse coordinate of the membership functions which are inverted inputs.

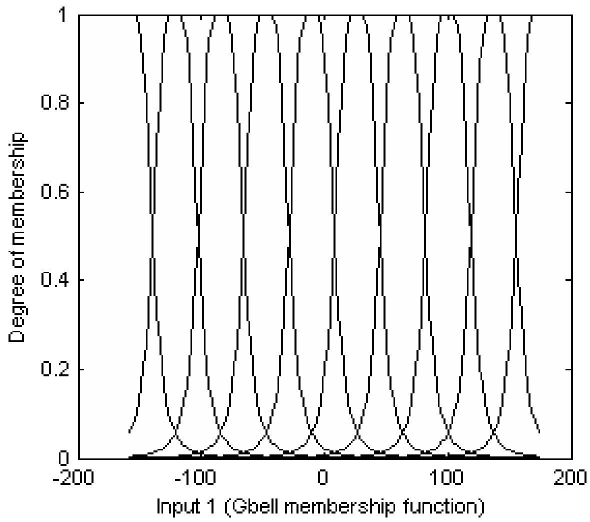


Fig. 3. Longitudinal coordinate of the membership functions

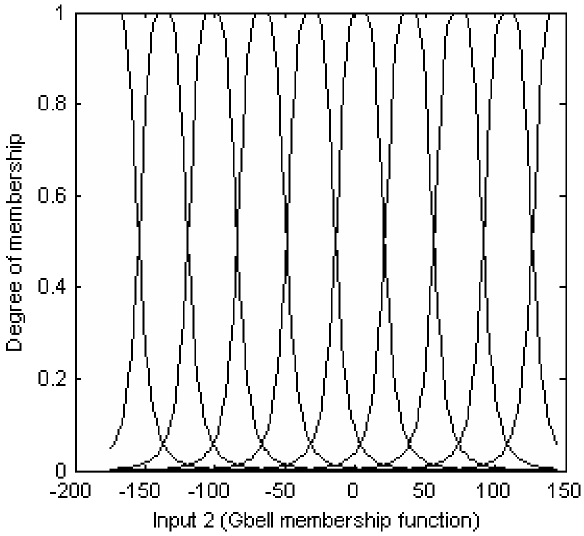


Fig. 4. Transverse coordinate of the membership functions.

Fig. 5 shows the input functions of rotation angle of the first motor. As can be seen, these functions are also inverted type.

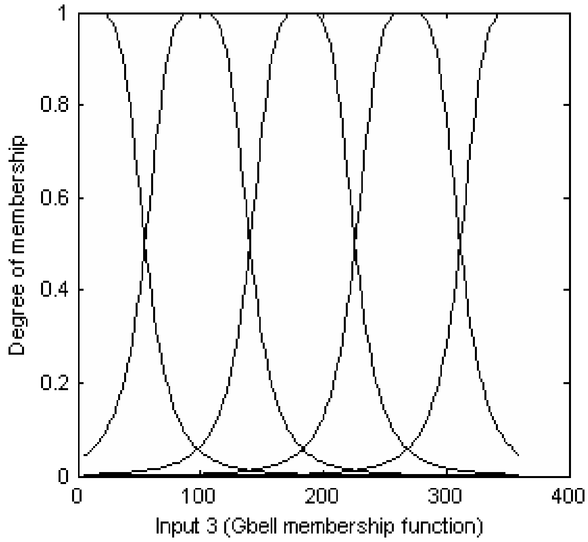


Fig. 5. The inverted input membership functions of rotation angle of the first motor.

For each rule in the fuzzy inference there is an output function which can be fixed or linear [12]. In this system, the linear membership functions are implemented in order to achieve uniform results.
Fuzzy rules in the system, are based on the initial assumption that whenever the transverse and longitudinal coordinates of the working point are changed, the rotation angle of the first and second motor will change. For example, a rule is considered as equation 5.

$$if\,(x\ is\ low)\,and\,(y\ is\ high)\,and\,(S_1 is\ medium)\,then\,(S_2 is\ high) \qquad (5)$$

Where x is longitudinal coordinate of working point, y is transverse coordinate of working point, S_1 is rotation angle of the first motor and the second motor rotation angle is S_2. In total there are 500 states that for every case will be a rule and a membership function output.

3.2. Range and number of input variables

According to table 1, range and levels of input variables are selected. The range determines the fuzzy inference system operation limit and membership functions represent the number of possible combinations of input factors.

3.3. Network testing

In order to measure the ability of the simulation of the path of the robot control system, some number of test data are used. Test data are presented in Table 2.

Table 1. The range and number of input variables

Input variables	Range (mm)	No. membership functions

Longitudinalcoordinate	-174 –158	10
Transversecoordinate	-144 –174	10
Rotation angle of the first motor	5˚– 359 ˚	5

Table 2. Fuzzy inference system test data

No.	Longitudinal coordinate (mm)	Transverse coordinate(mm)	Rotation angle of the first motor (degree)	Rotation angle of the second motor(degree)
1	-9	-24	240	177
2	49	2	316	152
3	120	-88	297	64
4	18	-33	259	161
5	174	-1	354	13
6	-42	60	77	133
7	68	51	350	124
8	141	-93	313	32
9	-102	-142	233	3

4. ANALYSIS OF RESULT EM

4.1. Experimental Setup

Before taking into account results, the experimental setup is introduced. The experimental setup is shown in Fig. 6. This setup is a 2DOF robot manipulated by 2 servo motor in order to capture position and velocity signals. To capture data, a data acquisition and controller board was utilized. Malab/Simulink was applied to implement the control scheme. For controller implementation and communication channel sampling, the time interval was set at 0.001 second. It is noticeable that this 2 DOF robot has been designed and fabricated at Majlesi University.

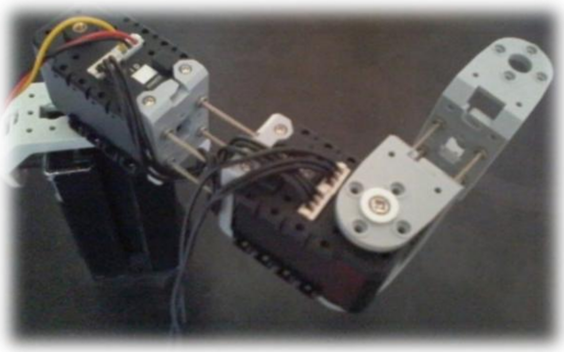


Fig. 6. Experimental setup

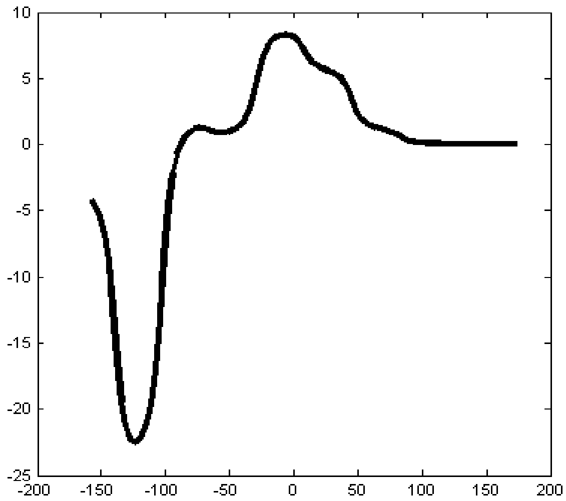
4.2. System Performance Analysis

Based on the results presented in table 2, impact of the transverse and longitudinal coordinates of the working point and rotation angle of the first motor are investigated. According to the curve value changes depending on the rotation angle of the second motor and longitudinal coordinates, Fig. 7 shows that, while longitudinal coordinate changes, the rotation angle of the second motor will change.

The curve changes depending on the values of the rotation angle of the second motor and transverse coordinates are shown in Fig. 8. According to the graph, it can be seen that, while longitudinal coordinates changes, the rotation angle of the second motor will change.

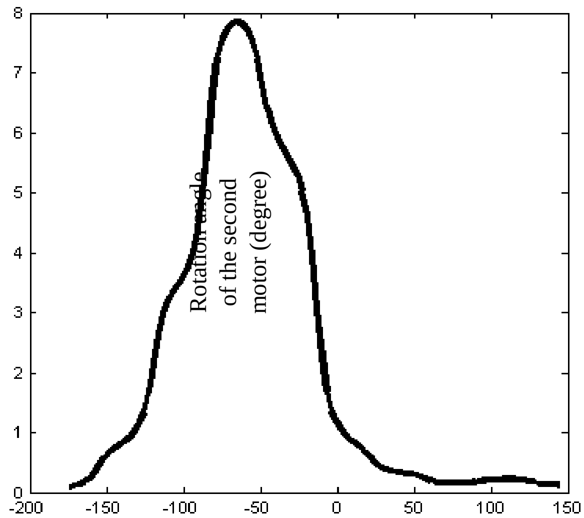
Consider to the curve value changes depending on the rotation angle of the second motor versus the rotation angle of the first motor, Fig. 9 presents that, while rotation angle of the first motor increases the rotation angle of the second motor decreases.

Fig. 9 shows the 3-D curve of the rotation angle of the second motor versus changes of the transverse and longitudinal coordinates.



Longitudinal coordinate (mm)

Fig. 7. The Rotation angle of the second motor versus longitudinal coordinate.



Transverse coordinate (mm)

Fig.8. The Rotation angle of the second motor versus transverse coordinate.

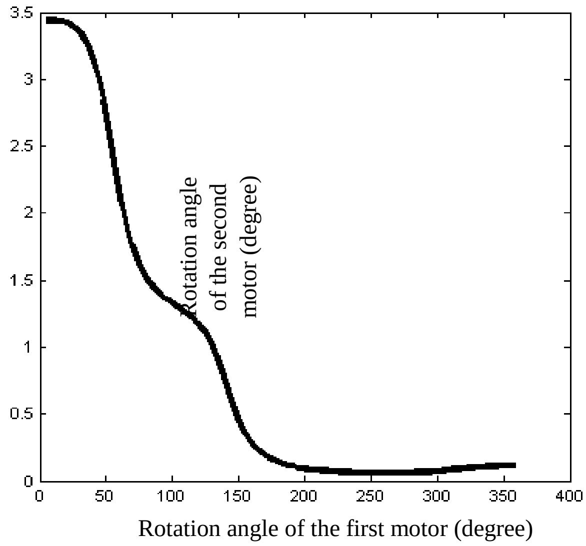


Fig. 9. The Rotation angle of the second motor versus Rotation angle of the first motor.

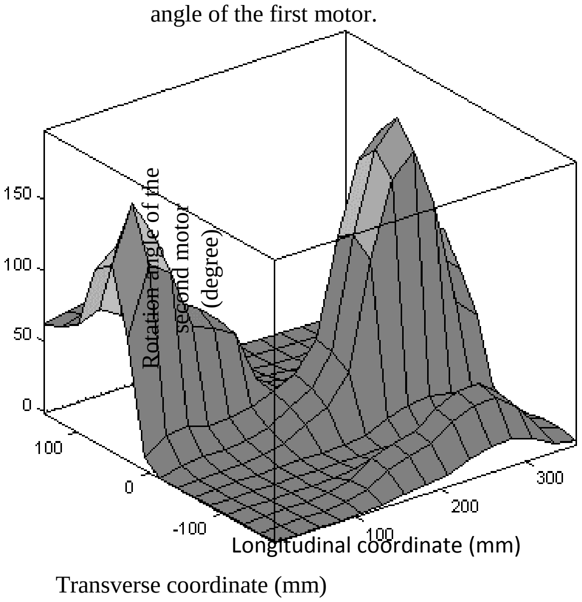


Fig. 10. The rotation angle of the second motor versus transverse and longitudinal coordinates of working point.

5. CONCLUSION

Fig. 11 shows the achieved results of fuzzy interface system compared with obtained experimental. As can be seen in this figure, the error of these two results is negligible. Considering the rotation angle of the second motor based on the changes of the transverse and longitudinal coordinates and rotation angle of the first motor (Fig. 7 – 9), these inputs effects are observable on rotation angle of the second motor.

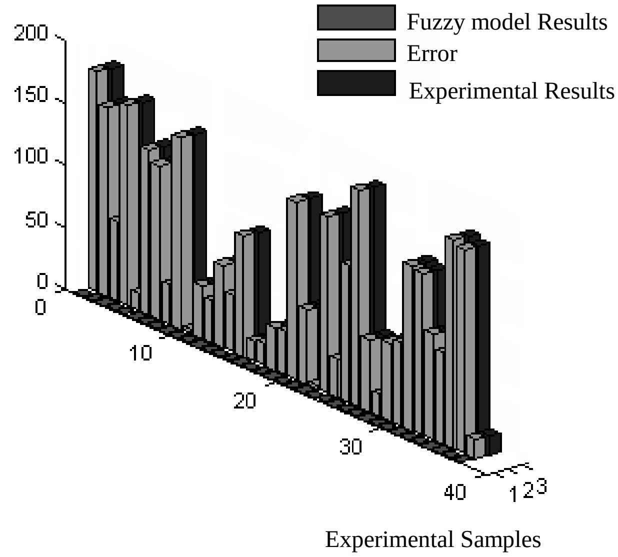


Fig. 11. Comparison the results of fuzzy inference system model with experimental results.

List of Symbols

A	The first character of membership
α_{Ci}	Output of membership function
$A_{1i}, A_{2i}, \dots, A_{ni}$	Fuzzy sets for the i^{th}rule
b	The second characteristic
c	The third characteristic
C_i	Fuzzy set for the i^{th}rule
D	The fourth characteristic
high	Large amounts
Low	Low amounts
Medium	Average values
$x_1, x_2, \dots, x_n$	The initial parts of the input variables
y	The output of i^{th} variable

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