ARTICLE

PREDICTING INPUT VOLTAGES TO ADJUST ANGLE AND VELOCITY OF ROBOT JOINTS USING NEURAL NETWORK, MULTI OBJECTIVE DECISION MAKING ANALYSIS AND FUZZY CLUSTERING

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ABSTRACT

As the initial contribution, by employing a neural network, this paper proposes a model to regulate the input voltages of the robot Robuarm based on the desired angle and angular velocity values of its joints. Robuarm is a robot with three degrees of freedom in which each joint has a motor. The proposed model demonstrates an accuracy of 99.5 percent. As the second contribution, based on the policies of focusing on energy consumption reduction, focusing on joints optimal angular velocities and focusing on the optimum angles in joints movements, a hybrid efficient method to select the optimized robot movements is proposed. The proposed method is based on using multi-objective decision-making analysis and fuzzy clustering and finally employing the proposed neural network model to find the optimal solution.

KEY WORDS
Robot Dynamics, Neural Network, Fuzzy Clustering, Multi Objective Decision Making Analysis.

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INTRODUCTION

Robot is an automatic device that can perform intelligent actions like human. Therefore, scientists are trying to build robots to meet human needs in different ways and ultimately, reach a robot with full functionality of human. In the dynamics calculation phase, angle and angular velocity of the robot joints are important factors which are set in terms of the input voltages. Therefore, it is necessary that this complex relationship be studied by using a complex model like the neural network (NN). Employing NNs in such problems started from the early 20th century in which Warren McCulloch and Walter Pitts applied the neural networks in the field of arithmetic and logic sciences.

By investigating the related literature of employing a neural network it can be found that they are employed in control of a mobile robot motion [1], control of industrial robots [2], design and implementation of the robot arms [3], moving audio visual robot [4], adaptive chaotic behavior of robots [5], development of compositional and contextual communicable congruence in robots [6], learning algorithms based on control systems of a robot [7], Stochastic adaptive optimal control of robots [8], learning to reinforce the visual control of robots [9].

In this paper, a neural network (NN) is designed to identify the relationship among the robot Robuarm parameters. Robuarm is a robot with 3 degrees of freedom in which each joint has a motor. The NN is designed to calculate the required voltages by identifying the angle and angular velocity of each joint. For the training purposes, this paper employs a hybrid method based on NNs, Multiple-criteria Decision Analysis and Fuzzy Clustering to show that how an optimum method could be selected among the available solutions.
The following subsections give a representation of the key points of the paper

Robuarm_s6.2 robot

As illustrated in [Fig. 1], this robot is a robot with 3 degrees of freedom (with 3 joints) that each joint has a motor. Dynamics of the robot includes dynamics of arm itself and engines used in joints, and its parameters are defined as follows:

- u1, u2, u3:input voltages to engines of each joint
- q1, q2, q3: Angles of each joint in radians
- q4, q5, q6:Angular velocity of each joint in radians per second

By changing the values input voltages, angular velocity and angles values are adjusted as a function of the voltages.

Fig. 1: The Robuarm_s6.2 robut.

Artificial neural networks

Artificial neural networks (ANN), or in simpler words neural networks, are powerful computational methods and systems for machine learning, knowledge representation and finally, applying the knowledge obtained to predict the output response of complex systems. The main idea of these networks is partly inspired by the functionality of biological nervous systems to process data and information for learning and knowledge creation. The key element of this idea is creation of new structures for data processing systems. The system consists of a large number of extra integrated processing elements called neurons which work together in harmony to solve a problem. Flexibility of neural networks to estimate non-linear functions caused them it to be used as a useful tool in data processing operations. Neural networks can solve problems which are difficult for simulation, or their rules are not known or are incomplete.

Multi-objective decision-making analysis and clustering

Multi-objective decision-making models (MODM) are used to find the optimal solutions. These models include problems in which candidate choices were not pre-determined and the decision maker should be initially focused on the design of a choice which has the highest utility considering the limited resources.
Clustering is one of the branches of non-supervised learning and it is an automatic process in which samples are divided into categories with similar members which are called clusters. Therefore, a cluster is a set of objects in which set members are similar to each other and are dissimilar with entities in other clusters. Various criteria can be considered as the similarity metric. For example, distance criterion can be used for this purpose, and objects that are closer to each other are to be considered as a single cluster. This type of clustering is also known the distance-based clustering.

Rest of the paper is organized as follows: Section 2 describes the NN model for prediction of the input voltages. It also discusses the performance evaluation of the model. The hybrid efficient method to select the optimized robot movements is proposed and discussed in section 3. Finally, section 4 concludes the paper.

PREDICTION OF THE INPUT VOLTAGES USING NN

To determine the amount of input voltages based on the angle and angular velocity of joints, we define independent variables as angle and angular velocity of joints and dependent variables as input voltages. Therefore, we define six independent variables that have an influence on the three dependent variables. To find a relation between dependent variables and the independent ones there is a need for training data for various input voltages, angles, and angular velocities of the respective joints. Therefore, data obtained from the evaluation of 2397 experimental data was collected and saved in the data matrix. Then the neural network, its inputs (q1,q2,q3,q4,q5,q6) and its outputs (u1,u2,u3) were defined in the MATLAB software based on the following piece of code:

```
transpose=data';
input=transpose(1:6,:);
output=transpose(7:9,:);
net = newff(input, output, [10 10], {}, 'traingdm', 'learngdm');
net.trainparam.epochs = 1000;
net.trainparam.lr = 0.05;
net.trainparam.mc = 0.9;
net = train(net,input,output);
actual = sim(net,test);
```

[Fig. 2] shows the performance of the model. It can be seen that after its training, the model error is just 0.5 percent which is an acceptable and eligible value.

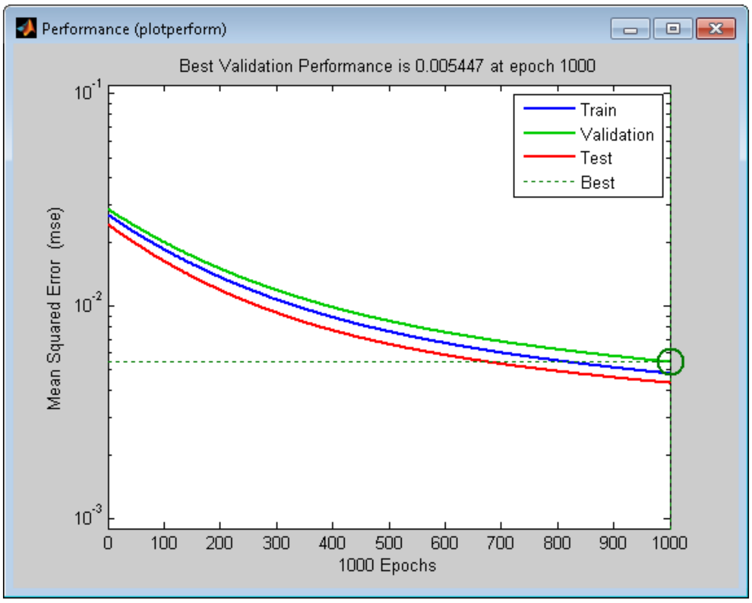


Fig. 2. The Network performance.

Performance evaluation of the network

To evaluate the performance of the NN, in the next phase, it was fed by 5 different input group values of q1,q2,q3,q4,q5,q6 and the output was compared with the empirical expected values. The data of this experiment is shown in [Table 1].

Table 1: Results of evaluating the network performance

Input Data						empirical expected values			Network output		
q1	q2	q3	q4	q5	q6	u1	u2	u3	u1	u2	u3
2.094	1.920	1.484	0.186	-0.208	0.471	2.212	17.700	11.261	2.212	17.695	11.250
2.094	1.920	1.484	0.153	-0.213	0.551	1.944	17.668	9.094	1.943	17.653	9.085
2.094	1.920	1.484	0.150	-0.216	0.631	3.058	18.811	8.636	3.058	18.802	8.630
2.094	1.920	1.484	0.170	-0.220	0.708	5.086	20.412	9.350	5.085	20.407	9.342
2.094	1.920	1.484	0.186	-0.224	0.778	6.469	21.506	9.570	6.464	21.487	9.568

As it can be seen the input voltages of the robot and the output of the NN have a low difference which approves the performance of the NN. Therefore, this NN can be employed in tuning the input voltages of the robot.

APPLICATION OF THE MULTI-OBJECTIVE DECISION MAKING AND FUZZY CLUSTERING TO SELECT THE OPTIMAL MOVEMENT SCENARIO

We define 3 requirements that we prefer to meet them for a better performance of robots. These requirements can be defined based on the following policies:
1- First policy, entitled "approach with focusing on reducing energy" pays more attention to the issue of reducing input voltages.
2- Second policy, entitled "approach with focusing on optimal speed of joints movement" pays more attention to movement velocity of the joints.
3- Third policy, entitled "approach with focusing on optimum angle in joint movement" pays more attention to the issue of movement angle of joints.
To select the optimal movement scenario which meets most of our requirements, an innovative method is proposed which is more fully described in the following. In this method, a combination of multi-objective decision making analysis and fuzzy clustering is provided and eventually, an NN, to select the best scenario, is applied. The purpose of multi-objective decision-making model is to optimize the overall utility function for the decision maker.

Considering all the applicable movement scenarios in Robuarm, one should be chosen to have the most effectiveness on the performance of the robot. To accomplish this, at first, different scenarios should be applied to the model and their results on the robot be observed. Therefore, 100000 random data, each consisting of six angles and angular velocity of joints (q1,q2,q3,q4,q5,q6) are given to robot to sort their effectiveness value by employing them. In the next step, the input voltages can be chosen by one of the forecasting methods via using those sorted effectiveness values. Through considering the following restrictions, the best policy can be selected:

- The input voltages should not be more than the amount of defined voltages.
- Velocity of joint movements should be defined in the movement velocity range.
- Angle of joint movements should be within the defined movement angles.

To create 100000 data points, it is initially necessary that the range of values q1,q2,q3,q4,q5,q6 be determined. Therefore, we design the optimization matrix. Ideal solutions are obtained for each q^*_j[1] by solving following problems (we run the model every time for optimizing each qj).

$$\max : q_j \quad j = 1,2,\dots,k$$
$$\text{limitations} : ax <= b$$
$$x>=0 \qquad (1)$$

To optimize the above model, we form the following matrix in such a way that it optimizes each j-th row. Any$\mathbf{q}_{ij}$ represents the value of i-th objective, when the j-th objective comes to its ideal (q*j).

Table 2: The optimization matrix

	q_1	q_2	q_3	q_4	q_5	q_6
q_1	q^*_{11}	q_{12}	q_{13}	q_{14}	q_{15}	q_{16}
q_2	q_{21}	q^*_{22}	q_{23}	q_{24}	q_{25}	q_{26}
q_3	q_{31}	q_{32}	q^*_{33}	q_{34}	q_{35}	q_{36}
q_4	q_{41}	q_{42}	q_{43}	q^*_{44}	q_{45}	q_{46}
q_5	q_{51}	q_{52}	q_{53}	q_{54}	q^*_{55}	q^*_{56}
q_6	q_{61}	q_{62}	q_{63}	q_{64}	q^*_{65}	q^*_{66}

The considered ranges are shown in [Table 3].

Table 3: The range of the qi values

	q_1	q_2	q_3	q_4	q_5	q_6
min	2.094	1.920	1.484	0.245	0.239	0.779
max	2.006	1.571	1.484	0.225	0.237	0.710

An important issue raised is that sorting the 100000 data points based on their value for the decision maker is very difficult, because it should perform n*(n-1)/2=4999950000 comparisons for sorting data. To solve this problem, we will make the performance of the robot simpler by employing an innovative method. Our proposed method is as follows.

At first, we divide the data into several groups using the clustering method. In this grouping, the distance measurement is used to compare any two points. An important issue raised was to determine the number of clusters which is the most important issue in clustering. Given that some points may be placed between clusters, any data point often cannot be precisely assigned to a cluster. In these cases, fuzzy clustering method is a more suitable method for displaying the crisp structure of this type of data. Many studies relating to the fuzzy clustering have been conducted, but here we use the following criterion for this purpose:

$$s(c)=\sum\sum(\mu_{ik})m(||x_k-v_i||^2-||v_i-x_{bar}||^2) \qquad (2)$$

n : number of data items that should be clustered
c : number of clusters (c>=2)
x_k : the k-th data point which is shown using the vector $x_k=(x_{k1},x_{k2}, \dots ,x_{km})$
x_{bar} : average of the values $x_1,x_2,\dots,x_n$
v_i :a vector that shows the center of the i-th cluster
||.|| : norm
μ_{ik} : membership degree of the k-th data item in the i-th cluster
m : an adjustable weight (generally 1.5<= m<=3)

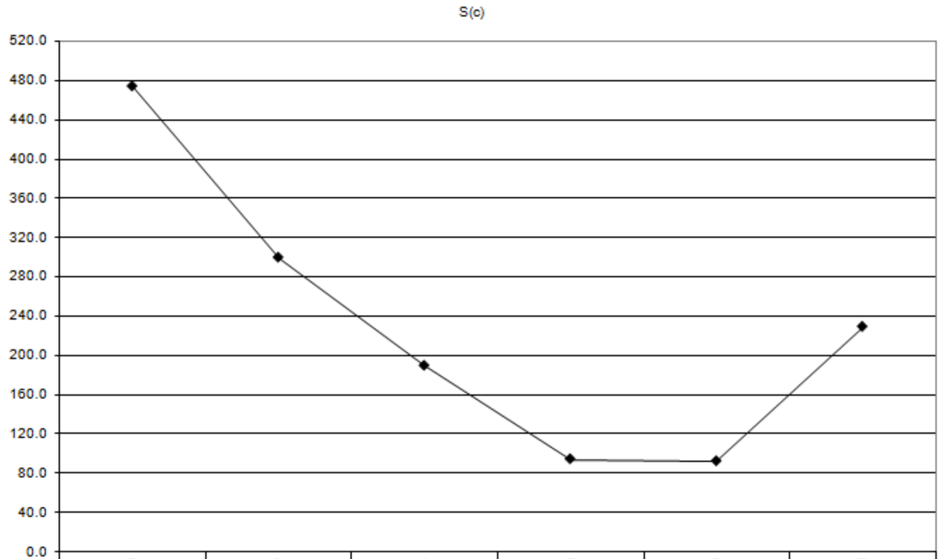
The optimal number of clusters c is equal to integer that value of s(c) comes to its minimum value. As always, it is assumed that this minimum point is a local minimum .As seen in the above equation, the first sentence on the right is variance of the data within a cluster, and the second sentence is variance among the clusters themselves. Therefore, the optimal number of clusters is determined by minimizing variance among data within each cluster and maximizing variance among clusters themselves. The above formula

[1] q^*_j is the ideal value of q_j

will be employed for different values of c. When an extremum point on the curve of s(c) is tracked, that value is selected for c.
MATLAB software was used to calculate the values of above parameters in which parameters of the equation s(c) have been obtained by using equation (3).

$$[v,u,obj]=fcm(x,c) \tag{3}$$

Using the above equation, we obtain values of v (which are v_i s in equation (2)) and also u (which are μ_{ik} s in equation (2)), for different values of c. In our case study, values of s(c) are achieved in accordance with [Fig. 3].



	2	3	4	5	6	7
S(c)	473.7	299.6	189.7	94.7	92.6	229.3

Fig. 3: s(c) and number of clusters.

The above graph shows the changes of s(c) in the fuzzy modeling of our case study based on the above equation. In this case, the optimal number of fuzzy clusters was 6. Therefore, we assign these 100000 data points to 6 clusters according to their highest degree of membership to those clusters.

After the placement of data points in clusters, we select the best cluster and evaluate only the data of it in order to determine the optimal data points and put the rest of data aside. To select the best cluster, we compare $\mathbf{v_i}$ of the categories (center of clusters) together. Here, cluster no 2 was selected as the best one. Finally, to select the best data points, it is necessary that input voltages values for the angle and angular velocity of the selected points be estimated. This can be achieved using the designed NN in section 2. Therefore, the optimum data items based on the overall gain were selected.

CONCLUSION

Robuarm is a robot with three degrees of freedom (with three joints) that each joint has a motor. For the accurate operation of Robuarm, it is necessary to select the input voltage of each joint based on its desired angle and angular velocity. Since a known relation is not found between these parameters, a neural network was designed for modeling the relation. Using the 2397 training samples, we trained it and showed that it can predict the input voltages with an accuracy of 99.5 percent.

It was shown that three policies which are focusing on energy consumption reduction, focusing on joints optimal angular velocities and focusing on the optimum angles in joints movements can be considered before implementation of a robot. As the second contribution, this paper employed a hybrid method based on neural networks, Multi-objective decision-making analysis and fuzzy clustering to optimize the utility function and showed that how an optimum method could be selected among the available solutions. To achieve this 10000 points in the parameters space of the joints were selected and we sorted them based on their efficiency value. The sorting operation was optimized using a fuzzy clustering method. Then, using the multi-objective decision-making analysis and by employing the designed NN; optimum data items based on their overall gain were selected.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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