Ahmad Ali [1,*], Mohammed Wadi[2]

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Regular paper

DETERMINATION OF THE PRIORITY OF MANAGERIAL DECISIONS USING MACHINE LEARNING

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Management considers one of the most critical factors for success, whether personally, in institutions, or even the country. The mission of management, in general, is making the best decisions within the available resources. Therefore, this matter requires qualified decision-makers with high experience, clear data, and other factors that help them make accurate decisions. The easiest and most widespread decisions are based on quantitative numerical data because of their clarity and ease of treatment, mainly when the decisions depend on calculations and results of these data. However, in most other cases, the decision-makers treat linguistic variables to make the best decisions. This paper introduces a novel idea based on machine learning in linguistic managerial decision-making. The proposed Artificial neural network approach is based on linguistic data and the priority to support decision-makers in their tasks by simulating human thinking. Three scenarios are suggested, tested, and compared to verify the applicability of the proposed approach.

Keywords: Artificial Neural Network, Artificial Intelligence, Managerial Decision, Linguistic Variables, Machine Learning.

1. Introduction

Making a decision is not a simple matter as well known. It is based on a proper reading of reality, data analysis, and a sound understanding of data. Besides, an anticipation of the consequences of matters according to the taken decisions, determining the degree of their importance, and priority for the decision-maker to make an accurate decision. This complex process requires a lot of experience, time, effort, and accuracy to reach the desired results from decision-making (DM). These decisions may be critical so that they are taken in very short times, as happens in the stock market and others. It is also worth noting the nature of the data available to decision-makers, as in many cases, digital data is not available to decision-makers, especially in administrative fields. The available data is often linguistic, and the decision-maker is forced to make a decision according to it and based on his previous experiences. From this point, if we want to make the machine perform the administrative decision-making process that simulates human thinking, it is necessary to consider the previous points with thinking about how to transfer experiences to the machine to simulate the experts in this field.

This paper proposes a machine learning (ML) model based on an artificial neural network (ANN) for the managerial DM process and prioritization. The developed ANN model is trained and tested using real collected data [1]. Three scenarios are suggested to show the network's effectiveness in making administrative decisions and setting priorities. The rest of this article will be discussed in four sections, which are as follows: a literature review of the topic, the theory of ANN, the practical model, and the results and discussion with future works.

2. Notation

The notation used throughout the paper is stated below.

* Corresponding author :Ahmad.Ali[1] Computer Engineering Department, Istanbul S. Zaim University, Istanbul, Turkey, E-mail address: ali.ahmad@std.izu.edu.tr, ORCID ID: https://orcid.org/0000-0002-5918-9528.

[2] Electrical & Electronics Engineering Department, Istanbul S. Zaim University, Istanbul, Turkey, E-mail address: mohammed.wadi@izu.edu.tr, ORCID ID: https://orcid.org/0000-0001-8928-3729.

Indexes:

ANN	Artificial Neural Network
ML	Machine Learning
FL	Fuzzy Logic
DM	Decision Making
FNN	Fuzzy Neural Network
SOI	Strength Of Interest
IOI	Inclusion Of Interest
EOI	Expectation Of Interest
FOI	Field Of Interest
DOP	Degree Of Priority

3. Literature Review

ANNs are utilized in many engineering fields, such as teaching social aspects to future business people or top managers; Sigov et al. (2017) [2] proposed criteria that considered as one of the primary criteria for innovative growth, and to implement the human ability to solve complex problems and apply them to a machine, ANNs need the ability to handle uncertainty like a human manner, so FL was added to ANNs, and the fuzzy neural method was introduced.

Corporate management is concerned with studying the interests of business owners and needs to predict their behaviour in the political, social, or economic fields to balance priorities belonging to various sectors. The fuzzy neural networks (FNNs) also provide the possibility to "manually" adjust the parameters and to correct the belonging of each unit of data. Yuan Yao et al. [3] propose an FNN system used for management DM and composed of three separate networks. This research is of great importance and relevance to its close relationship in our research, as it shows that people who make decisions use many factors influencing the decision and experience to take the appropriate decision. However, the diversity and complexity of the world always make the decision go in the wrong direction. The standard NN model ignores the ambiguity of the input vector and does not consider that one input vector can produce a variety of DM methods. In this paper, the FNN provides a method to express MF using fuzzy input vectors to resolve the problem. This approach would reduce the ambiguity of information and improve the quality of DM and network robustness.

Similar to a proposed model for the same work but using a fuzzy logic (FL) system. We find that the fuzzy logic system can be used in different fields as well [4][5][6][7]. One of this, they have divided the outputs into five categories as fuzzy sets. These five categories represent the system's outputs, which is called the degree of priority. The five ranks are, respectively: lowest priority, low priority, medium priority, high priority, and the highest priority. After that, they created the membership functions of all inputs and output, then the system's rules were created using the If-Then statement. Finally, they have suggested three scenarios to compare the results. [8].

The problem of uncertainty in management is another issue. The causes of uncertainty generally arise due to three aspects. The first is that the information used in DM is not integrated. The second is that DM is a function of decision variables and contains subjective factors. Third, the identification process is often unclear. Therefore, simply using quantitative management methods to solve complex management DM problems in a environment is challenging.

An approach to DM using self-organizing multi-layered ANNs is presented [9]. The model helps in deciding on the construction of an industrial processing plant which is a significant problem in construction management due to its economic impact. Both the expert system approach and the ANN have been shown and can be helpful in DM problems, although the ANN approach is superior to the expert system approach in some cases. A developed model identifies an ANN as an enabling tool for assessing credit applications to support loan decisions in Jordanian commercial banks [10]. A proposed model uses a multilayer ANN with a backpropagation learning algorithm. Noppakorn Klintong et al. [11] introduced an ANN-based model to develop a decision support system to benefit from it in selecting which projects are most appropriate for product development and innovation that maintain the company's strength and competition.

The decisions were divided into three sections in terms of organization, which are as follows: structured, unstructured, and semi-structured. This matter depends on the degree of certainty in representing the problem and its solution. A structured decision can be defined as inevitable with a known solution, while an unstructured decision can be defined as a decision dependent on a specific decision-maker, and that decision-maker has little or no knowledge of the solution. While structured decisions do not require any judgment for any part of the decision-maker, we find that unstructured decisions depend mainly on the experiences or suggestions of the decision-maker. Between these two divisions of decisions, there is a wide range of problems called semi-structured decisions. So, that semi-structured decisions depend on analytical models or data, so these decisions receive the most attention from technical assistance.

In another research a set of AI tools have been reviewed and included in Intelligent Decision Support Systems (IDSS) decision-making processes. Some of them have been applied to healthcare and clinical DM. The AI tools reviewed are ANNs, FL, evolutionary computing, and intelligent agents. [12][13]. The digital outputs are computed using size-based noise cancellation for specific digital blur inputs. A supervised learning procedure based on gradient descent is used to train the network. The model was tested on two different approximation problems: Approximate the sine and cosine function and the Narazaki-Ralescu function and show their natural ability to infer, approximate the function, and classify [14].

Table 1. List of Decision-Making review with ML systems

No	Review Area	Major Contribution	Reference	Year of Publication
1.	The concept of the fuzzy neural method to implement the human ability to solve complex problems and apply them to a machine	proposed criteria that considered as one of the primary criteria for innovative growth: social institutions and social risks; socially intertwined or delusional goods; and new business modeling that incorporates human creativity, to implement the human ability to solve complex problems and apply them to a machine, ANNs need the ability to handle uncertainty in a human-like manner, so FL was added to ANNs, and the concept of the fuzzy neural method was introduced.	[2]	2017
2.	An FNN system used for management DM composed of three separate networks.	It shows many factors influencing the decision and experience to take the appropriate decision. The causes of uncertainty: 1. The information used in DM is not integrated. 2. The DM is a function of decision variables and contains subjective factors. 3. The identification process is often unclear.	[3]	2010
3.	Using a fuzzy logic (FL) system.	The FNN provides a method to express MF using fuzzy input vectors to resolve the problem. This approach would reduce the ambiguity of information and improve the quality of DM and network robustness.	[4][5][6][7]	2018, 2018, 2022, 2021
4.	The system's rules were created using the If-Then statement.	The five ranks are, respectively: lowest priority, low priority, medium priority, high priority, and the highest priority. After that, they created the membership functions of all inputs and output, then the system's rules were created using the If-Then	[8]	2021

		statement.		
5.	DM using self-organizing multi-layered ANNs	The model helps in deciding on the construction of an industrial processing plant which is a significant problem in construction management due to its economic impact. Both the expert system approach and the ANN have been shown and can be helpful in DM problems.	[9]	1994
6.	ANN as an enabling tool for assessing credit applications	A developed model identifies an ANN as an enabling tool for assessing credit applications to support loan decisions in Jordanian commercial banks. A proposed model uses a multilayer ANN.	[10]	2010
7.	ANN-based model to develop a decision support system	Introduced an ANN-based model to develop a decision support system to benefit from it in selecting which projects are most appropriate. The decisions were divided into three sections in terms of organization, which are as follows: structured, unstructured, and semi-structured.	[11]	2012
8.	Intelligent Decision Support Systems (IDSS) decision-making processes	A set of AI tools like ANNs, FL, evolutionary computing, and intelligent agents have been reviewed and included in Intelligent Decision Support Systems (IDSS) decision-making processes. Some of them have been applied to healthcare and clinical DM.	[12][13]	2019, 2012
9.	Different approximation problems are used for testing models.	The digital outputs are computed using size-based noise cancellation for specific digital blur inputs. A supervised learning procedure based on gradient descent is used to train the network. The model was tested on two different approximation problems: Approximate the sine and cosine function and the Narazaki-Ralescu function and show their natural ability to infer, approximate the function, and classify.	[14]	2010

4. Artificial Neural Network

a) Fundamentals of ANN

ANNs are one of the methods used in deep ML. ANNs learn in a way that simulates human learning in real life, meaning that every piece of information and situation they gain experience helps to make the right decisions later. [15]

b) Basic Elements of ANN

An ANN comprises three essential components - weights, thresholds, and an activation function. Figure 1 shows the basic elements of the ANN model. [16]

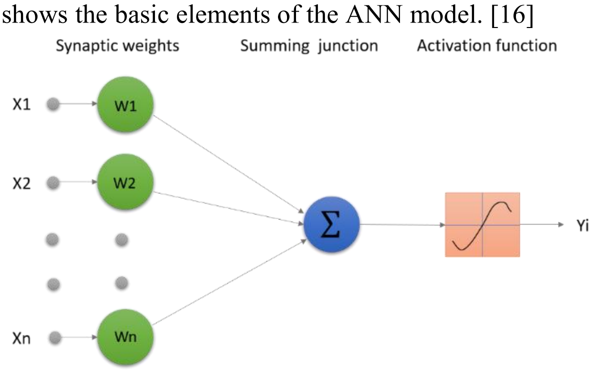


Figure 1. Basic Elements of ANN

The artificial neuron consists of five main parts:

• **Input**: information received from the ANN by the user or from another cell.

• **Weights**: the parameters that determine the value of the information received into the cell and the level of activity on the cell. Weights values can be zero, positive, or negative. The high weight value of the relevant input means that it is strongly associated with the artificial neuron. A smaller weight value of the related inputs means a weaker correlation. When the weight value is zero, the cell has no activity.

• **Summation function**: multiplies the entry in the cell by the relevant weights and adds up. This calculates the net income of the cell. Different grouping activations are used depending on the problem.

• **Activation function**: It provides the determination of the cell's output by subjecting the net input to a mathematical treatment. These functions are usually nonlinear.

• **Output**: These are the output values obtained after processing by activation functions. Depending on the problem, the output can be sent to users, cells of different layers, or as input for itself.

c) Working Principle of Artificial Neural Networks

The way ANNs work is as follows: initially, input vectors are received in the input layer, then each neuron in the hidden layer takes all the values in the input layer using weights. Besides, selecting the bias (threshold) depends on the function chosen as the neuron which performs the calculation and produces output results. Activation functions play a vital role in the performance of ANNs. The next layer takes the output results of the previous layer as the input value, performs the calculation according to the activation function, and produces the output results. Depending on the number of hidden layers, this situation continues until the output layer and the result from the output layer come out to the outside world. This means that information is constantly fed forward and never fed back. Therefore, such architectures are called feedforward neural networks. [17].

d) Training Artificial Neural Networks

The learning process starts by taking inputs from the external environment to the input layer of ANN. Initially, the weights are randomly determined. After the received inputs are subjected to mathematical processing in the activation function, outputs are obtained in the output layer. In the next step, the result obtained from the system is compared with the expected result, and the error rate is found by using the loss function or cost function. After the residual error rate is determined, it appears as an optimization problem, and it is aimed to minimize the error rate with the feedback method by using various optimization algorithms. The most widely used algorithm in the training of ANN is the feedback algorithm. In feedback ANNs, the output of a cell can be fed as input to any cell in the previous or same layer. The feedback method consists of three main functions; feedforward to calculate the result, gradient taking to backward the error rate, and updating the weights with any optimization algorithm.

5. Practical Model

a) Managerial dataset

Table 2 shows a numerical scale from one to 120 [19], representing the degree of priority in DM. The value 120 is equivalent to the highest priority, whereas the value one refers to the lowest priority case. There are four main variables in Table 2: (Strength of Interest (SOI), Inclusion of Interest (IOI), Expectation of Interest (EOI), and Field of Interest (FOI). In the case of the highest priority, the case of 120, which corresponds to: (SOI: essential, IOI: general, EOI: current, and FOI: religion).

Table 2. The used dataset

Power of Interest	Inclusion of Interest	Anticipating Interest	Fields of Interest				
			Religion	Soul	Brain	Race	Money
Essential	General	Current	120	119	118	117	116
Essential	General	Expected	115	114	113	112	111

Essential	Partially General	Current	110	109	108	107	106
Essential	Private Transitive	Current	105	104	103	102	101
Requirement	General	Current	100	99	98	97	96
Essential	Private minor	Current	95	94	93	92	91
Essential	Partially General	Expected	90	89	88	87	86
Requirement	General	Expected	85	84	83	82	81
Essential	Private Transitive	Expected	80	79	78	77	76
Essential	Private minor	Expected	75	74	73	72	71
Requirement	Partially General	Current	70	69	68	67	66
Requirement	Private Transitive	Current	65	64	63	62	61
Requirement	Private minor	Current	60	59	58	57	56
Requirement	Partially General	Expected	55	54	53	52	51
Improvement	General	Current	50	49	48	47	46
Improvement	General	Expected	45	44	43	42	41
Requirement	Private Transitive	Expected	40	39	38	37	36
Requirement	Private minor	Expected	35	34	33	32	31
Improvement	Partially General	Current	30	29	28	27	26
Improvement	Partially General	Expected	25	24	23	22	21
Improvement	Private Transitive	Current	20	19	18	17	16
Improvement	Private minor	Current	15	14	13	12	11
Improvement	Private Transitive	Expected	10	9	8	7	6
Improvement	Private minor	Expected	5	4	3	2	1

The obtained real data are divided into five outputs categories. These five categories represent the system's outputs, which are called the Degree of Priority (DOP). The five ranks: lowest priority, low priority, medium priority, high priority, and the highest priority, as illustrated in Table 3.

Table 3. The Degree of Priority for the entered variables

Strength of Interest		Inclusion of Interest		Expectation Of Interest		Fields of Interest		Degree of Priority		Degree of Priority
Essential	3	General	4	Current	2	Religion	5	120	5	highest priority
Essential	3	General	4	Current	2	Soul	4	119	5	
Essential	3	General	4	Current	2	Brain	3	118	5	
Essential	3	General	4	Current	2	Race	2	117	5	
Essential	3	General	4	Current	2	Money	1	116	5	
Essential	3	General	4	Expected	1	Religion	5	115	5	
…	...	…	…	…	…	…	…	…	...	
Essential	3	Partially General	3	Current	2	Money	1	106	5	
Essential	3	Private Transitive	2	Current	2	Religion	5	105	5	

…	...	…	…	…	…	…	…	…	...	
Essential	3	Private minor	1	Current	2	Religion	5	95	4	high priority
…	...	…	…	…	…	…	…	…	...	…
Requirement	2	Partially General	3	Expected	1	Religion	5	55	3	medium priority
…	...	…	…	…	…	…	…	…	...	…
Improvement	1	General	4	Current	2	Race	2	47	2	low priority
…	...	…	…	…	…	…	…	…	...	…
Improvement	1	Private minor	1	Expected	1	Money	1	1	1	lowest priority

Table 3 shows the factors affecting DM. To shape the given dataset to suit the ANN, the four main factors, SOI, IOI, EOI, and FOI, are ranked between one and five. For example, the first factor, SOI, contains three classifications, namely Essential, Requirement and Improvement. Each classification has a weighting of its own according to its importance. The essential has a value of three, the requirement two, and the improvement one. For FOI, religion is given a value of five, soul a value of four, brain a value of three, race a value of two, and money a value of one. Likewise, the output results were divided into classes, so the Highest Priority took a value of five, High Priority a value of four, Medium Priority a value of three, Low Priority a value of two, and Lowest Priority a value of one.

b) Proposed ANN architecture

As in the proposed study, there are four inputs. Therefore, we need at least four neurons in the input layer, each node representing one of the inputs. As for the outputs, one output is sufficient because there is only one value that the system must give us, which is the DOP. Moreover, one hidden layer with three neurons is designed since the classification of analyzed data is not linear, as shown in Figure 2. [20]

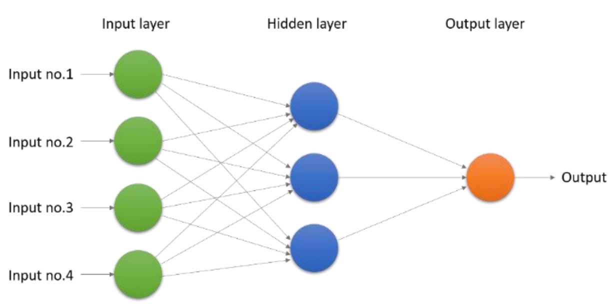


Figure 2. Architecture for given data

c) Weights of inputs data

The weights can be imposed by starting, and after the work of the system, it will modify the values of the weights based on the operations that the system will use to reach the desired results, as depicted in Figure 3. In our case, the Mean Squared Error (MSE) measure is utilized to determine weights and modify them.[21].

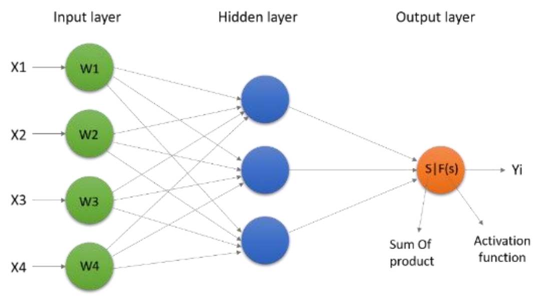


Figure 3. Representation of weights

$$S = SOP\ (X_i, W_i) \tag{1}$$

$$S = \sum_1^m X_i\, W_i \tag{2}$$

Where X_i represents inputs and W_i represents weights of inputs, bias can be added to equation 2.

d) Artificial neural network training steps

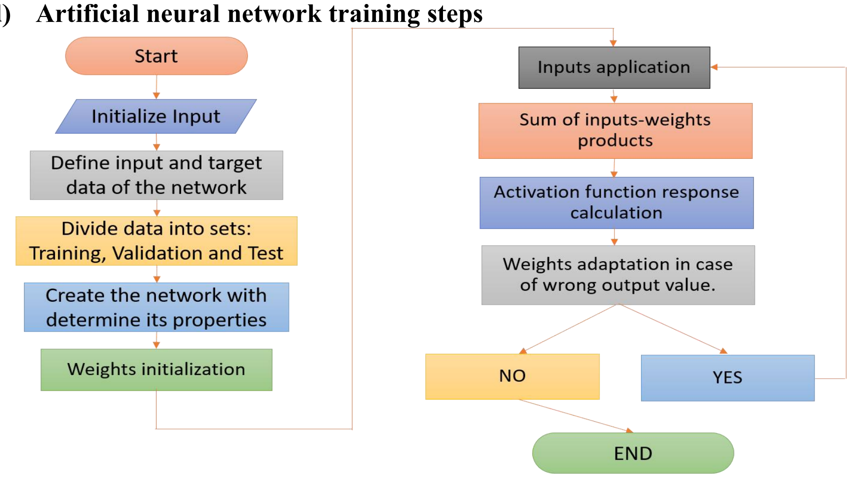


Figure 4. Representation of training steps

If the predicted output is not the same as the desired output, then the weights are to be adapted according to the following equation:

$$W(n+1) = W(n) + \eta\left[y_d\,(n) - y_p\,(n)\right] X(n) \tag{3}$$

where $W(n+1)$ is the new weight to be calculated, $W(n)$ is the current weight that did not pass the classification process, η: is the learning rate, $y_d\,(n)$ is the desired output, $y_p\,(n)$ is the predicted output, and $X(n)$ is the input value.

6. Results

a) Application on the MATLAB Program

The Prototype of the implemented NN based on feedforward propagation, Levenberg-Marquardt (TRAINLM) as the training algorithm, the adaption learning function as LEARNGDM [22], the performance function as MSE [23-25], the number of layers two, the number of neurons for hidden layer 10, and the transmission function is TANSIG [26]-[31].

b) First scenario

In this scenario, data was divided into three sections: a training 70%, a 15% validation, and a testing 15%. The proposed input nodes are 4, the proposed output node is one, and the proposed hidden layers are 10. Table 4 and Table 5 illustrate the obtained results in the first scenario. We can note that the result of the first scenario is excellent because the performance represented by MSE is deficient, and we can see the simulation time is very low too. Additionally, the gradient is also a very small value which gives an indicator that our scenario is treated ideally with these data with a low cost too because the gradient measures how much the output of a function changes if you change the inputs a little bit by finding a local minimum of a differentiable function that minimizes a cost function as far as possible. Moreover, we can see the learning rate is between 0 and 1, as it must be.

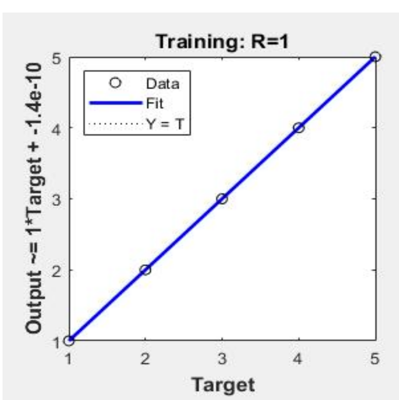
Table 4. The results of MSE and Regression for all samples (base scenario)

	Samples	MSE	R
Training	84	3.0687E-19	1
Validation	18	7.8462E-19	1
Testing	18	1.42968E-18	1

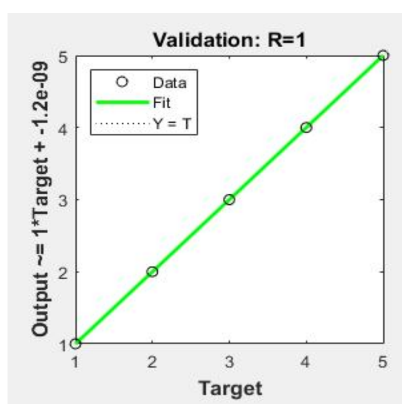
Table 5. The results for the training of the ANN (base scenario)

Scenario no.	Base
Epoch	19
Time	3 sec.
Performance	$3.07E^{-19}$
Gradient	$9.64E^{-10}$
μ	$1.00E^{-08}$
Validation Checks	0
no. of neurons in the hidden layer	10

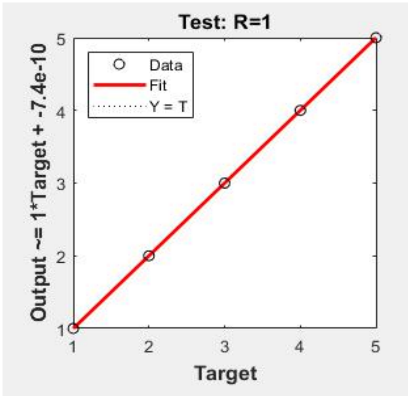
Figure 4a to Figure 4c shows that the error between the obtained outputs and the desired outputs in the case of training, validation, and test is tiny.

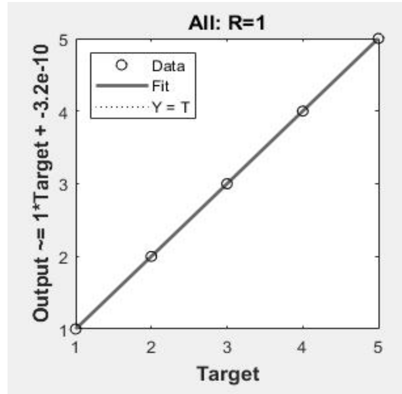


(a)



(b)





(c) (d)

Figure 4. The results of 1st scenario: (a) Training (70%), (b) validation (15%), (c) Testing (15%), and (d) All results

c) The Second Scenario

In this scenario, the number of neurons in the hidden layer is changed to notice the improvement of the DM model. The data proportions are kept as in the first scenario. Tables 6 and 7 show the results of the second scenario.

Table 6. MSE and Regression results for all samples (2nd scenario)

	Samples	MSE	R
Training	84	1.12E-01	9.68E-01
Validation	18	1.42E-01	9.70E-01
Testing	18	6.84E-02	9.88E-01

Table 7. The results for the training of the ANN (2nd scenario)

Scenario no.	Second
Epoch	11
Time	2 sec
Performance	1.00E-01
Gradient	2.48E-06
μ	1.00E-11
Validation Checks	6
no. of neurons in the hidden layer	1

Examining Tables 6 and 7, it can be noticed that there is a considerable difference between the obtained results and the desired results. Figure 5 clearly illustrates this difference. From this scenario, the simulation time is very short, but the performance compared to the previous scenario is higher, and we can see that clearly through the following figures.

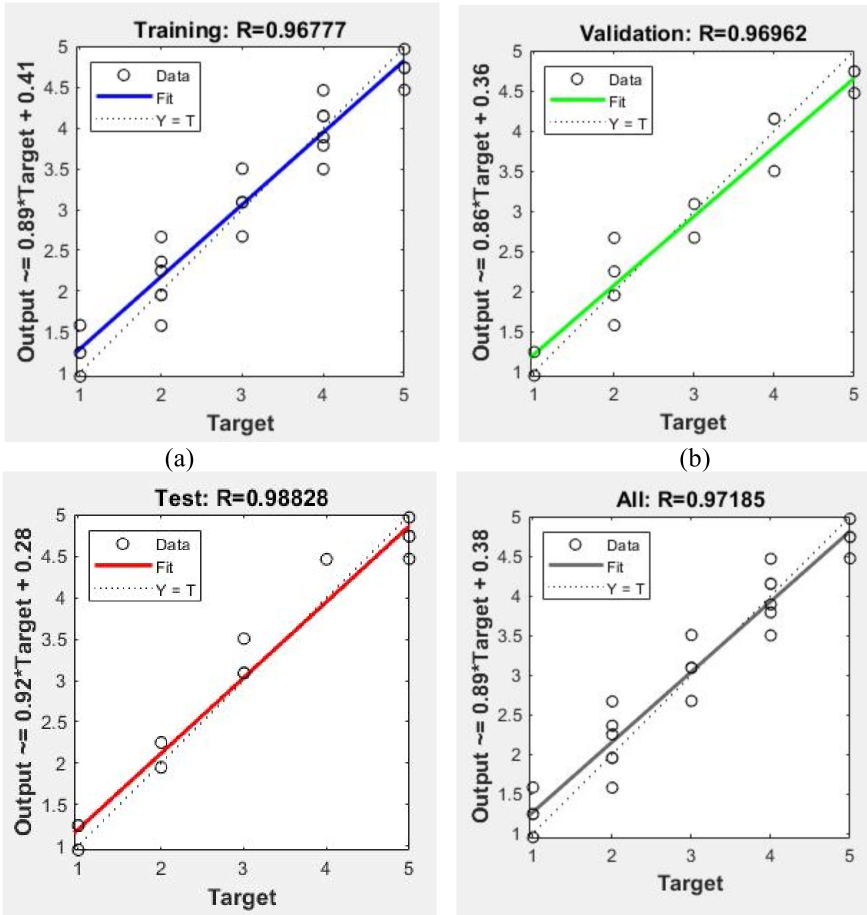


Figure 5. The results of the 2nd scenario: (a) Training (70%), (b) validation (15%), (c) Testing (15%), and (d) All results.

d) The Third Scenario

In this scenario, the percentage of data distribution on the training, validation, and testing is changed. The training was 80%, the validation was 10%, and the testing a 10%. The other specifications are kept as in the second scenario. Tables 8 and 9 provide the obtained results. In this scenario, we got results near the first scenario, and we can also see that from the simulation time and the minimal performance error.

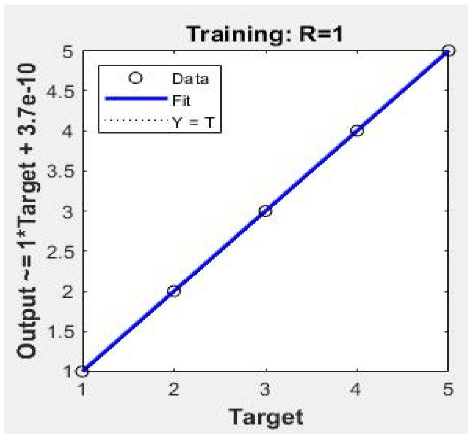
Table 8. The results of MSE and Regression for all samples (3rd scenario)

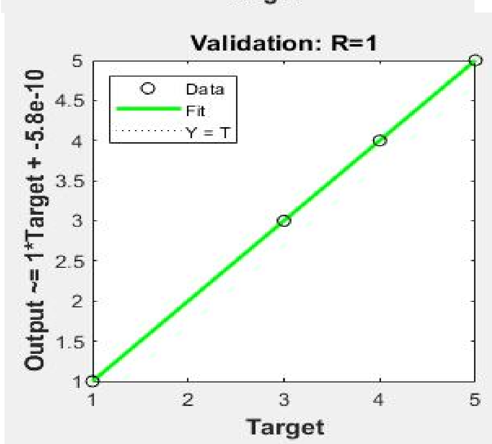
	Samples	MSE	R
Training	96	5.06E-19	1
Validation	12	1.45E-18	1
Testing	12	2.40E-18	1

Table 9. The results for the training of the ANN (3rd scenario)

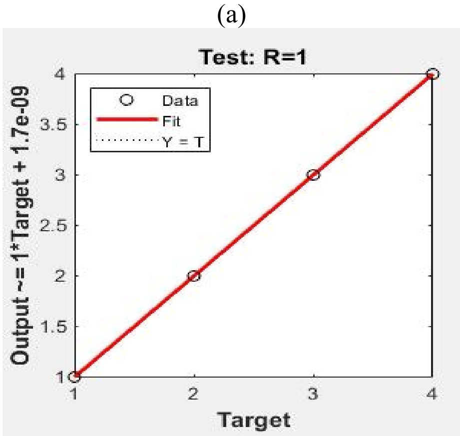
Scenario no.	Third
Epoch	24

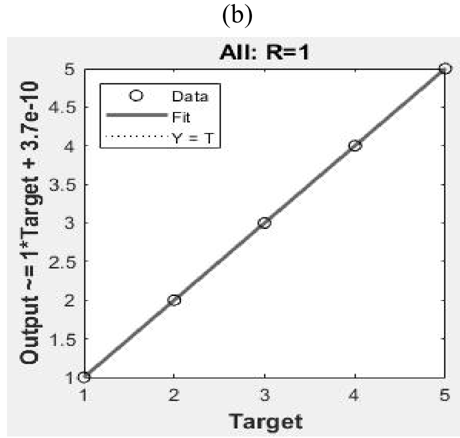
Time	0.12 sec
Performance	5.06E-19
Gradient	1.27E-09
μ	1.00E-08
Validation Checks	0
no. of neurons in the hidden layer	10





(a) (b)





(c) (d)

Figure 6. The results of the 3rd scenario: (a) Training (80%), (b) validation (10%), (c) Testing (10%), and (d) All results

Investigating Figure 6, it can be noticed that the obtained results with changing the ratios were also satisfactory, as the error rate is low.

e) Comparing The Three Scenarios

In Table 10, we can note that the first and third scenarios gave the best results despite changing the portion of data between training, validation, and testing. This is evident from the performance value, which represents a minimal value for the error made from the training process according to the proposed scenarios. Besides, the more neurons in the hidden layer, the more accurate the results are. Based on the obtained results, it is found that five neurons or more gave acceptable results with the experiment.

Table 10. The results of three scenarios

Scenario no.	One (Base)	Second	Third
Epoch	19	11	24
Time	3 sec	2 sec	0 sec
Performance	3.07E-19	1.00E-01	5.06E-19
Gradient	9.64E-10	2.48E-06	1.27E-09
μ	1.00E-08	1.00E-11	1.00E-08
Validation Checks	0	6	0
no. of neurons in the hidden layer	10	1	10
Data distribution (training, validation, testing)%	(70, 15, 15) %	(70, 15, 15) %	(80, 10, 10) %

f) The Obtained Results of Twenty Samples

In this section, 20 samples were proposed to test the system used in this study, and in this section, the results obtained from applying the 20 samples to the proposed system were presented, as shown in Table 11.

Table 11. The results of the proposed cases of twenty inputs by using ANN

Case no.	Strength of Interest	Inclusion of Interest	Expectation Of Interest	Fields of Interest	Degree of Priority	
1	1	1	1	1	1	**Lowest**
2	1	1	1	1	1	**Lowest**
3	2	2	2	2	3	**Medium**
4	3	2	1	2	4	**High**
5	3	3	1	3	4	**High**
6	1	3	2	3	2	**Low**
7	1	4	1	4	2	**Low**
8	2	1	1	4	2	**Low**
9	3	1	2	5	4	**High**
10	3	2	1	1	4	**High**
11	1	2	1	1	1	**Lowest**
12	1	3	2	2	2	**Low**
13	2	3	1	2	3	**Medium**
14	3	4	1	3	5	**Highest**

15	3	1	2	3	4	**High**
16	1	1	1	4	1	**Lowest**
17	1	2	1	4	1	**Lowest**
18	2	2	2	5	3	**Medium**
19	3	3	1	1	4	**High**
20	3	3	1	1	4	**High**

g) The Confusion Matrix of Results

In this section the confusion matrix of our system will be discussed depending on one of the above shown scenario to show the effectivity of it and we can decide whereas the system works properly or not. And we must indicate that we neglected the fourth factor of the input data to make the calculations easier and in the same time this factor was not effective on our calculations as shown before in the data set. The confusion matrix of our system is shown below in Table 12.

Table 12. The confusion matrix of the system

PREDICTED LABEL

TRUE LABEL	HIGHEST	HIGH	MEDIUM	LOW	LOWEST
HIGHEST	6	0	0	0	0
HIGH	0	8	1	0	0
MEDIUM	0	1	4	1	0
LOW	0	0	1	7	1
LOWEST	0	0	0	0	6

(Highest) TP = 6	(Highest) TN = 30	(Highest) FP = 0	(Highest) FN = 0
(High) TP = 8	(High) TN = 31	(High) FP = 1	(High) FN = 1
(Medium) TP = 4	(Medium)TN = 28	(Medium) FP = 2	(Medium) FN = 2
(Low) TP = 7	(Low) TN = 26	(Low) FP = 1	(Low) FN = 2
(Lowest) TP = 6	(Lowest) TN = 29	(Lowest) FP = 1	(Lowest) FN = 0

Overall accuracy = 31/36 = 86.1 %

Precision (Highest) = TP / (TP+FP) * 100% = 6 / (6+0) * 100% = 100%

Precision (High) = TP / (TP+FP) * 100% = 8 / (8+1) * 100% = 88.8%

Precision (Medium) = TP / (TP+FP) * 100% = 4 / (4+2) * 100% = 66.6%

Precision (Low) = TP / (TP+FP) * 100% = 7 / (7+1) * 100% = 87.5%

Precision (Lowest) = TP / (TP+FP) * 100% = 6 / (6+1) * 100% = 85.7%

Recall (Highest) = TP / (TP+FN) * 100% = 6 / (6+0) * 100% = 100%

Recall (High) = TP / (TP+FN) * 100% = 8 / (8+1) * 100% = 88.8%

Recall (Medium) = TP / (TP+FN) * 100% = 4 / (4+2) * 100% = 66.6%

Recall (Low) = TP / (TP+FN) * 100% = 7 / (7+2) * 100% = 77.7%

Recall (Lowest) = TP / (TP+FN) * 100% = 6 / (6+0) * 100% = 100%

Specificity (Highest) = TN / (TN+FP) * 100% = 30 / (30+0) * 100% = 100%

Specificity (High) = TN / (TN+FP) * 100% = 31 / (31+1) * 100% = 96.8%

Specificity (Medium) = TN / (TN+FP) * 100% = 28 / (28+2) * 100% = 93.3%
Specificity (Low) = TN / (TN+FP) * 100% = 26 / (26+1) * 100% = 96.3%
Specificity (Lowest) = TN / (TN+FP) * 100% = 29 / (29+1) * 100% = 96.6%

5. Conclusion

Based on the preceding, it shows us the proposed system's ability to deal with managerial decisions and prioritize them based on the available dataset. The system can also deal with other factors that may have an impact on the decision. The accuracy of the system and its ability to simulate human thinking depend mainly on the amount of dataset available for machine learning and several other factors such as the number of hidden layers in the system, the activation function, and others. The goal to be worked on is to develop the model and introduce other factors that affect the administrative decision-making process and help determine priority more specifically.

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