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Identification and risk management related to construction projects

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Abstract. This paper presents a study conducted with the aim of developing a model of tendering based on a technique of artificial intelligence by managing and controlling the factors of success or failure of construction projects through the evaluation of the process of invitation to tender. Aiming to solve this problem, analysis of the current environment based on SWOT (Strengths, Weaknesses, Opportunities, and Threats) is first carried out. Analysis was evaluated through a case study of the construction projects in Algeria, to bring about the internal and external factors which affect the process of invitation to tender related to the construction projects. This paper aims to develop a mean to identify threats-opportunities and strength-weaknesses related to the environment of various national construction projects, leading to the decision on whether to continue the project or not. Following a SWOT analysis, novel artificial intelligence models in forecasting the project status are proposed. The basic principal consists in interconnecting the different factors to model this phenomenon. An artificial neural network model is first proposed, followed by a model based on fuzzy logic. A third model resulting from the combination of the two previous ones is developed as a hybrid model. A simulation study is carried out to assess performance of the three models showing that the hybrid model is better suited in forecasting the construction project status than RNN (recurrent neural network) and FL (fuzzy logic) models.

Keywords: risk management; construction projects; recurrent neural network; fuzzy logic; hybrid model

1. Introduction

The management of a project is a systematic process of identification, evaluation of the risk of the project Jayasudha *et al.* (2014); the construction project involves many actors and several disciplines during the various stages of a single project in accordance with the relevant codes and the standards Sudarshan and Rakesh (2014).

For providing a competitive advantage in the invitation to tender and increase the principal chances of the project meeting in an efficient way Rafiq and Khurram (2013). Risk management is essential to the construction activities in reducing the losses and increasing profitability Kansal *et al.* (2012). However, risk management is somewhat neglected because of lack knowledge and consciousness among construction all the people Sathishkumar*et al.* (2015).

There are many internal and external factors which carry enormous risks in the construction industry; these factors are interdependent and require a great deal attention in identifying and

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evaluating the project success chances in being carried through while remaining within budget limits. There are more challenging in construction projects tough cuts budget and requirement represents a major challenge for the different type of project Murat and Ahmad (2018). The risk factors involved during construction to reduce the time and cost to increase the quality of risk analysis in the planning Cheng (2013). Thus, the management in the construction is designed to plan, monitor and control necessary measures to prevent and to assess the risk Agnieszka and Mariuez (2015). For these reasons, the identificationof the risk affecting factor on the process of invitation to tender of the construction project must subjected a SWOT analysis, aiming at identifying threat-opportunities and strength-weaknesses of the project related to its environment to help decide whether to continue the project or not.

It is the aim of his paper to develop models of risk management for construction projects in Algeria using more rigorous and more precise mathematical models. The practice of these methods is today necessary for treating its factors, and minimizing the level of risk which can be accepted. For that, the identification and the evaluation of the risks in the stage of invitation to tender for the construction projects will lead to the best estimate of the gain increase beyond the cost and the deadline Surabni and Brajesh (2016), Renuka *et al.* (2014). Consequently, Ubani *et al.* (2015) has confirmed that the level of sensitizing and the implementation of the process of the risk management in the sector of construction are low. When, the analysis of sensitivity could be used to analyze various answers Juan *et al.* (2013). Therefore, the treatment of the possible hazards, thus identified will be based on the consideration of the techniques of avoidance taking into account the level of the techniques of avoidance or tolerance and taking into account the level of estimates in the techniques of the answer to the invitation to tender Patel *et al.* (2013). These techniques are used very little because of less knowledge projects Jayasudha and Vidivelli (2016). Consequently, these risks are minimized by the functional use of the tools. Planning the techniques must be applied in all construction projects, which could make a process of invitation to tender more competitive of the notes of the risk to raise the critical points Hesham *et al.* (2016). Therefore, one should use construction projects to support project managers and the owners companies in decision making. During the last decade, the technical intelligence cuts have increasingly applied to the research area of construction project management, when were already applied in civil engineering to resolve a wide variety of issues Hocine *et al.* (2018). Use nape methods facilitated risk analysis. Mahmoud and Hassan (2015), Sotoudeh *et al.* (2015) used fuzzy logic to overcome the lack of data and uncertainty in preparation for future construction project and their impact. In addition, Sotoudeh *et al.* (2011) tried to identify and give priority of the risk in the life cycle of the construction projects by the fuzzy technique, which has to determine the report of a set of criteria evaluation and the points of the groups of the risks. Then, Radek (2016) they classified the factors internal and external. Each group is composed of several factors to which the project is exposed. These factors are examined by fuzzy analytical hierarchy process (FAHP). For the total evaluation of the risk, Sotoudeh *et al.* (2012) they proposed fuzzy model based on the RIPRAN method (Risk PRoject ANalysis), to simulate the values total of the risks of the project and uncertainty which are always associated with the actual value of the project. Mohsen *et al.* (2017) proposes a method that can provide an overall framework for three aspects of risk management in highway construction projects by fuzzy FMEA and fuzzy AHP, analyzed the usual state to determine the criteria of risk. Mehdi and Reza (2014) utilized fuzzy analytic hierarchy process (AHP) for priory's factors on the risk because they classified factors influencing the failure and the success of the construction in Iran. In the last years the researchers compared the results of different methods, KANSAL *et al.* (2012) developed a regression model and its results were compared with ANFIS, the classification of the factors on the risk is laid out in a hierarchical systematic structure that has to leave the determination of their priorities in each stage and to increase the reliability of the success of the construction project risks.

This paper provides a comparison between three models including ANFIS, RNN and FL in predicting the status projects in Algeria.

2. Methodology

A SWOT analysis of the environment of the project is first carried out using a reference mark which makes it possible to simplify the analytical expressions; in practice, the choice is done according to the objectives of the application. Artificial intelligence techniques such as ANN and FL are then used to develop relevant risk management models, simulation study is then carried out followed by results evaluation.

After a SWOT analysis, then a study of mathematics, we have created models based on a technique of artificial intelligence to process these data. The basic principle consists of interconnecting together a great number of the factors to model this phenomenon. Initially, we created a neuronal model, under the name of 'recurrent neural network'. The training of the model before the application, formed to determine a reasonable relation between the inputs and the output through the hidden layers. Then, we proposed algorithm of fuzzy logic. The combination of these two models neuronal makes it possible to have a model neuron-fuzzy, which theoretically remains most powerful. Lastly, one encloses by a comparison between the different models.

2.1 SWOT analysis

Professor K. Andrews proposed abbreviation SWOT (Strengths, Weaknesses, Opportunities and Threats) in 1963 at a conference held at the Harvard and dedicated to the issues of business policies. At first, the SWOT analysis is set in the structure of the knowledge of the Harvard Business School (Learned; Christensen *et al*. 1965), the method comprised external and internal factors but effective planning within the organization to be recognition of these factors.

Therefore, it is a strategic within the organization to be recognition of these factors. Therefore, it is a strategic planning technique for understanding your strengths, weaknesses and for identifying the opportunities and threats related to project planning. The SWOT method is an impact analysis technique for decision making, planning, by analysis to identify the external and internal analysis as an impact of the environment of an organization. The simplest practical methods are a strategic assessment that is widely used for the analysis of different kinds of risks, its strategic forecasting by analyzing the status and prospects of development of enterprises based on the internal and external factors (Vladimir *et al*. 2016).

3. Soft computing techniques

Soft computing is an innovative approach made up of complementary elements of artificial neural networks and fuzzy logic, genetic algorithms, that parallel the remarkable ability of the human mind as a role model, and learn in an environment of imprecision but solutions that can be used for complex computational problems, to be particularly useful for handling classification and regression problems. Therefore, is which of the constituent a separate methodology for dealing with the problem in his field. The techniques of soft computing are today being used successfully in various applications in practice, became a field of study in computer science in the 1990s.

The main soft computing techniques used, is explained in the following section.

3.1 Recurrent Neural Network (RNN)

Generally, recurrent neural network is a system developed for information processing with exciting performance improvements in series data modeling, thus it consists of units interconnected interacting not linearly and for which there exists at least one cycle in the structure.

The techniques of training of the network are the same ones as for the classical networks, nevertheless of the gradient to learn to memorize last events. Many examples of recurrent neural network enclose the Hopfield network (Hopfielf 1982) and the Elman neural network (Jeffrey 1990) and the Jordan network (Micael 1986).

3.2 Fuzzy Logic (FL)

Lotfi Zadeh introduced fuzzy logic for the first time in 1965. It is an approach of reasoning that resembles human reasoning, and has been applied to many fields, which is a generalization of the control theory of artificial intelligence.

In this perspective, this method has been used defuzzification output membership functions into a crisp output value that can be used for control purposes.

3.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an artificial intelligence technique based on the combination from the fuzzy logic and artificial neural networks of the smaller squares evaluation and gradient descent algorithm, to construct a relation between inputs and outputs based on available data sets, the connections of the layers are weight equal to one (Jyh 1993).

A Neuro-fuzzy is a fuzzy system is used learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) using data processing samples. To use ANFIS in a more efficient and perfect way, one can use the best standards that have been obtained by genetic algorithm.

4. Results and discussions

4.1 SWOT analysis (Strengths, Weaknesses, Opportunities, Threats)

Our main aim is to make an analysis of the current environment of the project of invitation to tender related to the construction project in Algeria during all these processes. We applied this tool of choice to prepare the necessary information and to obtain a better quality of the construction projects with an aim of identifying threats-opportunities and the strength-weaknesses of the project related to his environment, which could affect the success or failure of the project. The factors of realization are shown in Fig. 1.

From an analysis the environment of the construction project by SWOT analysis, we will identify those following factors, then, these factors will be confirmed by a statistical analysis:

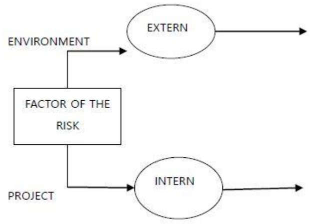


Fig. 1 The factors of realization according to SWOT analysis

Table 1 SWOT matrix of the construction project in Algeria

Strenghts	Weakeness
- Large number of tender and of corporation concerned by the project - Time between the publication date of the invitation to tender and the date of limit of submission is sufficient to allow for a good study of the tender dossier. - Contract is awarded to the best tendered - Geographical presence - Number of projects which are the object of invitations to tender at the same time. - Calendar of the invitation to tender adapted to periods of time allocated for the invitation to tender and construction adequate. -Good competence in project management -Good competences in expert testimony.	-Time inadequate for the tender of the offers -Bad knowledge of the project market. -Time between the publication date of the invitation to tender and the date limit of tender is insufficient -Lack of training -Absence of protection mechanism of the information obtained tenders - Information consigned in the life of offer of the project is not always supplemented. -Lack of resources and formation of invitation to tender - Absence of a rejection threshold of the tenders -Absence of procedures and mechanisms to prevent profitability project. -Lack of equipment. -The procedure has all the acceptable tenders possible to contribute. - Offers are open only at the expiry of the period, at the time of the grand opening and publication of the offers. - Negotiations are allowed only with the selected supplier after examination of the various offers.
Opportunities	**Threats**
-Tenders are responsible for detailed examinations of the site. - Emergence of new regulation. - Opening of new markets. -Emergence of a new technology -Customer acceptance of the specifications and any modification not brought there -The employer agreed to finance examinations of ground additional -It exactly describes specifications which were technical, aesthetic and contractual requirements. -The system of quality assurance entrepreneur to control it and to provide a permanent support in terms of new approaches in matter of engineering and management.	- Existence of competitor projects in the same moment of launching of invitation to tender. - Absence of antecedents of failure markets during the five last years before the deadline of presentation of tender. - Inflation - Existence of an unspecified conflict of interest. - Existence of another project in the same zone. - Capacity of the customers to acquire the future project - Performance of the competitor project exceeds your project. - Impossibility to construct in the relevant zone - Rupture with the partners. - Results of qualifications of tender are not adequate.

4.1.1 Data description

The data used in this piece of research were collected from local companies in Algeria, over the past ten years between the periods of 2006 to 2016. One hundred and twenty construction projects from different council based on bills of quantities, which concern the estimation the final cost of each for different types of projects, were used for training and testing purposes. The results are shown in Table 2.

4.2 Recurrent Neural Network (RNN)

The recurrent neural networks are adapted for a given variable entry of size. It is appropriate in individual for the analysis of time secrets. The six stages involved are listed below

4.2.1 Data collection

Input data: A set of data, including 120 coming from construction projects. Those, 96 projects of data through the method of analysis were used for the network, and the rest (24 projects), randomly selected and were used for testing.

Output data: the state of the construction project (success or failure of the construction project). The table 3 which follows the characteristics was selected to predict the status of construction projects.

The developed RNN model for predicting the project status according to the various factors is shown in Fig. 3. The vectors of inputs are made up of the five characteristics of the construction project X= [Experiment in the sector of construction, Standard deviation of the cost, Rate of advance, Experiment of carried out project similar in the 5 last years, Flows of treasury of works carried in the 5 last year's]. The vector of output contains T= [Success or failure of the project].

4.2.2 Separation of the database

The second step is the learning, which consists in initializing the coefficients of correlation of the three phases (training, test and validation), then initialize the number of neurons per hidden layer, knowing that we tested a hidden layer, then two hidden layers, the structure uses eight neurons in one only hidden layer, and the learning parameters can be found in Table 4.

4.2.3 Neural network selection

The creation of a new neural network which contains standardized inputs and outputs, one certain hidden number of layer and neurons per layer, passes by the use of a transfer function. After several attempts, Table 5 summarizes a comparison between various algorithms of training in terms of iteration count maximum, in our case on the fixed 1000 iteration.

4.2.4 Formatting the data for a neural network

We used a network with 5 inputs and only one neuron at the output. The inputs correspond to the states boxes of the position given. The value given by the neuron among and of exit being able to take all the values understood in the interval [-1 1]. We proposed a loop of back propagation in the hidden layer; it thus does not affect the layer of entry in the phase of propagation ahead.

4.2.5 Learning phase

They currently do not output methods to find the optimal configuration. We thus tested several networks and kept the best. The configuration retained in our study is a neural network with one

Table 2 Description of data and assessment approach

	Evaluation criteria	Scale	Assessment approach
Inputs variables	Experiment in the sector of construction (ESC)	20 points	More than 15 years: 20 points Between 10 and 15 years: 10 points Between 1 and 10 years: 5 points
	Standard deviation of the cost(Standard deviation)	20 points	< 5%: 20 points (5-15)%: 10 points > 15%: 5 points
	Rate of advance	20 points	(75-100)%: 20 points (50-75)%: 10 points < 50%: 5 points
	Experiment of carried out project similar in the 5 last years (EPS)	20 points	More than 5 projects: 20 points Between 3 and 5 projects: 10 points From 1 to 3 projects: 5 points
	Flows of treasury of works carried in the 5 last years (Flows of treasury)	20 points	- Equal to or greater than total amount of works contracts: 20 points -Less than total amount of works contracts: 10 points.
Output variables	The success or the failure of the project.	100 points	After the evaluation: A project that has been a total of less than 50 points is loss. A project > 50 points is successful.

Table 3 Characteristics of indicators used in the model

Type of parameter	Indicators	Quantitative/ Qualitative	Continuous/ Discrete	Terminals
Inputs	Experiment in the sector of construction	Quantitative	Discrete	[01 year: more than 15 years]
	Standard deviation of the cost	Quantitative	Discrete	[0.5 : > 15 %]
	Rate of advance	Quantitative	Discrete	[<50% : 100%]
	Experiment to carry out project similar in the 5 last years	Quantitative	Discrete	[1 project : 5 projects]
	Flow if treasury of works carried in the 5 last years	Quantitative	Discrete	[0 DA: 500000000 DA]
Output	The success or the failure of the Project	Qualitative	Discrete	[Weak : Very good]

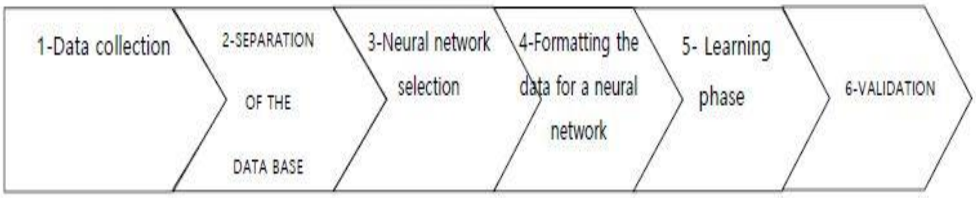


Fig. 2 Steps of developing the model

Table 4 Optimized parameters

Parameters	Optimized value	
Rule of training	Back propagation of the errors	
Number of neurons	Input layer / Output layer	05/01
	Hidden layer	08
The function of transfer	Hidden layer	Sigmoid
	Output layer	Linear
Database (Learning/ Test)	96	24

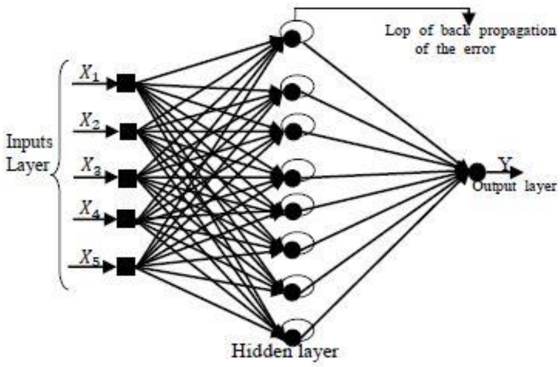


Fig. 3 Recurrent neural network topology used

Table 5 Comparison between the algorithms of training

Algorithm	Number of iteration	Performance
Lm (Train levenberg marquardt)	1000	$5.16\ e^{-8}$
gda (Train gradient descente with adaptive learning rate	990	$8.72\ e^{-7}$
bfg (Train BFGS quasi neuron)	800	$7.16\ e^{-5}$
gdm (Train descente gradient and moneutum)	850	$3.21\ e^{-5}$
oss (Train one step secant)	900	$5.01\ e^{-6}$
br (Train bayesian regulation)	930	$4.88\ e^{-6}$

sleep hidden of 08 neurons. The learning technique is a method of Levenberg Marquedt retro-propagation. The determination of the weights and skews of the network, which are the parameters carry out via supervised learning.

We used 80% of the dataset to train and validate the recurrent neural network model, and the rest 20% of the data projects were used for testing purpose, so this provided 96 projects for training and 24 projects for testing. The training set is utilized to modify the networks weights and biases in order to minimize the network error. The feedback propagation algorithm was used to train the model; the purpose of this algorithm provides a certain desired response for some neurons at suitable instants, with a feedback loop, it does not therefore affect the input layer at the stage of forward propagation. The principle of this algorithm is to propagate the error of the hidden layer to the output layer, then the input layer with some modification of weight and neural activation functions.

The weights of recurring connections are updated with the same principle as the gradual feedback propagation algorithm. This algorithm reduces the error between the model output and the target output by minimizing the mean square error (MSE) over a set of training set. Therefore, the (MSE) is used as a competing criterion for determining how well the models perform. The mean square error is as follow

$$MES = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(Y_i - T_i\right)^2 \quad (1)$$

Where N is the number of projects in the training set, Y_i is the model output to the sample, and T_i is the target output.

4.2.6 Validation

The analysis of the results got started from the phases of training, test and validation leads to use of a network of size 'RNN 05-08-01' for forecasting construction project status. Iteration count 1000 and following transfer function:

- Transfer function 'Tansig' for the hidden layer

-Transfer function 'Purelin' for the output layer and the performance equal $5{,}1594e^{-08}$.

The mean squared error between the network output and the target was used in train, test and validation sets. The results are shown in Fig. 4.

The coefficient of correlation of measurements of the force and the direction of a linear relation tender two variables and the value of R varies between -1, and 1.

The coefficients of correlation obtained during the training and validation, testing for the best neurons and layer so that it advertises very good linear relation between the output and the parameter of the input obtained. A better forecast ability of the algorithms, the result is shown in Fig. 5.

4.2.7 Test

In this step, 24 projects were used for testing. A spreadsheet simulation program on Microsoft excel was used for testing our model accordingly to the transfer function used.

The test of the calculation algorithm has been written by Microsoft Excel, was used of verification our model as result to the weights adopted. This approach is being studied to determine the percentage error (Error), the mean error (ME) which can be expressed by Eqs. (2) - (3) in the following

$$Error = \left(\frac{Estimated\ value\ of\ risk - Actual\ value\ of\ risk}{Actual\ value\ of\ risk}\right) * 100\% \quad (2)$$

$$ME = \left(\frac{1}{N}\right)\sum_{i=1}^{i=N} Error_{(i)} \quad (3)$$

Where: N is the number of projects to be evaluated in the testing phase.

The resulting model developed is calculated from the test cases are presented in Table 6.

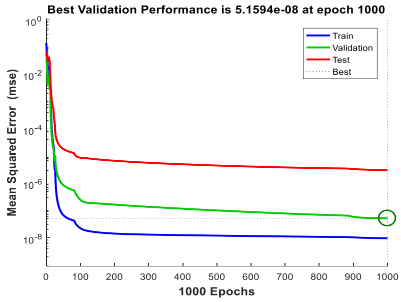


Fig. 4 Mean squared error of learning epochs

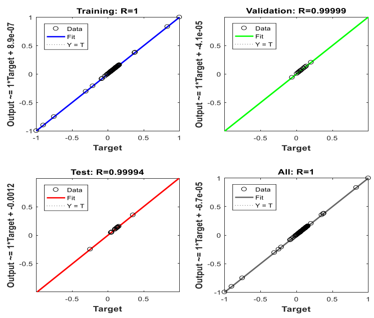


Fig. 5 Diagram of regression

Table 6 Results of recurrent neural network in the test phase

Project N°	Estimated value of risk by RNN (Points)	Actual value of risk (Points)	Error (%)	Mean error (ME)
1	80	83	-3.614	
2	50	57	-12.281	
3	64	68	-5.882	
4	70	75	-6.667	
5	60	60	0.000	
6	50	55	-9.091	
7	67	73	-8.219	
8	75	80	-6.250	
9	50	55	-9.091	
10	60	65	-7.962	
11	57	62	-8.065	
12	50	56	-10.714	-7.228
13	51	53	-3.774	
14	80	90	-11.111	
15	60	70	-14.286	
16	52	58	-10.345	
17	81	85	-4.706	
18	82	90	-8.889	
19	50	56	-10.714	
20	79	80	-1.250	
21	45	48	-6.25	
22	65	70	-7.142	
23	62	67	-7.462	
24	86	90	-4.444	

4.3 Fuzzy Logic (FL)

The next part describes in detail the steps which are followed to build the program based on our fuzzy approach.

- Identification of input and output variables

Data regarding a fuzzy system's input and output are expressed in terms of the learning function.

Based on the collected data, the system outputs and inputs were clarified, and Tables 7 and 8 provides a linguistic values and fuzzy values for inputs and outputs variables, following a comprehensive study of the combination of the corresponding input and output variables.

- Defuzzification: Used to convert the variant of fuzzy order into a digital value applies to the interval [-1, +1], of the universe of the speech. We chose method of the centre of gravity to apply this stage. It consists in to search the centre of gravity of a system of fuzzy subsets whose weights are their coefficients of membership.

- The rules of inference are described by a matrix known as of inference representing the vague whole of the variability of output defined by the function “Trimf”. The reasoning used in a vague

system of inference can be carried out in three stages (fuzzification, the rules of inference, defuzzification), whatever the number used of rules. The inference rules is shown in Fig. 6, by inference rules follow a triangular distribution by a function

$$f(X;a,b,c)=\max\left(\min\left(\frac{X-a}{b-a},\frac{c-X}{c-B}\right),0\right) \tag{4}$$

Where: *a* and *c* is the feet of the membership function, and b defines its peak, and X is the inputs variables.

The graph which follows watches a sample of the process of evaluation of the projected based on the model of fuzzy logic is shown in Fig. 7.

The validation of the system was used in practice after it has been adapted, and as tested with real data. The model developed using 18 numbers of membership function with If-then rules. The rules based on fuzzy logic shown in Fig. 8. In this figure inputs (ESC = 4.13, Standard deviation=5.71, Rate of advance = 5.71, EPS = 5.43, Flow of treasury = 8.04), and the output (The success of the project = 0.185).

The rule 4 and rule 10 are then aggregated to produce a final output, a crisp output of 0.185, which means that the risk of the project status is large.

- Test:

In order to, validate if the values at the output of defuzzification is good. The soundness of the calculation of this function has been tested on Microsoft Excel, using the following formulas Eqs. (2) - (3) and the results of the test are presented Table 9.

4.4 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Network ANFIS was programmed in this work, with which one built the fuzzy rules with their functions of memberships appropriate to seven units, while respecting the following stages:

- Most important stages for the generation of the structure of the network Neuro-fuzzy establishment of the rules of inference. The rules are defined like combinations of the function variable of input.

Table 7 Linguistic values and fuzzy values for inputs variables

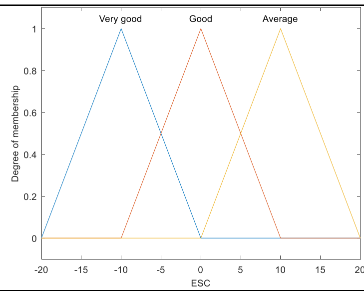
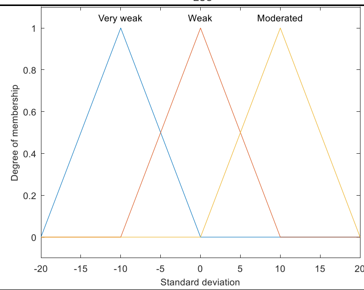
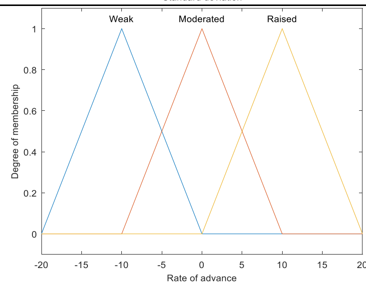
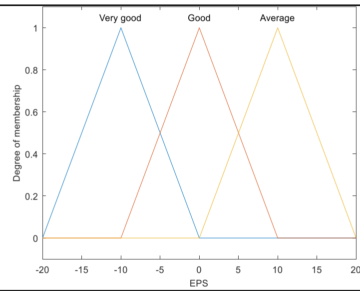
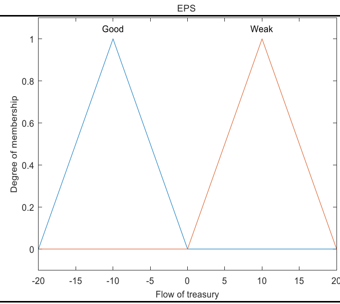
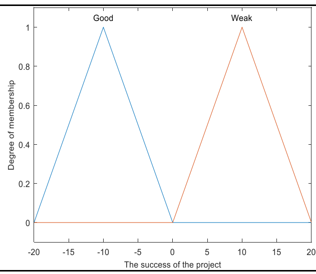
N	Inputs variables	Linguistic value	Fuzzy value	Graphical presentation
01	Experiment in the sector of construction (ESC)	Very good	(-20 -10 0)	
		Good	(-10 0 10)	
		Average	(0 10 20)	
02	Standard deviation of the cost (Standard deviation)	Very weak	(-20 -10 0)	
		Weak	(-10 0 10)	
		Moderated	(0 10 20)	
03	Rate of advance	Weak	(-20 -10 0)	
		Moderated	(-10 0 10)	
		Raised	(0 10 20)	
04	Experiment to carry out project similar in the 5 last years (EPS)	Very good	(-20 -10 0)	
		Good	(-10 0 10)	
		Average	(0 10 20)	
05	Flow if treasury of works carried in the 5 last years (Flows of treasury)	Good	(-20 -10 0)	
		Weak	(0 10 20)	

Table 8 Linguistic values and fuzzy values for output variable

N	Output variable	Linguistic value	Fuzzy value	Graphical presentation
01	The success or failure of the project	Good	(-20 -10 0)	
		Weak	(0 10 20)	

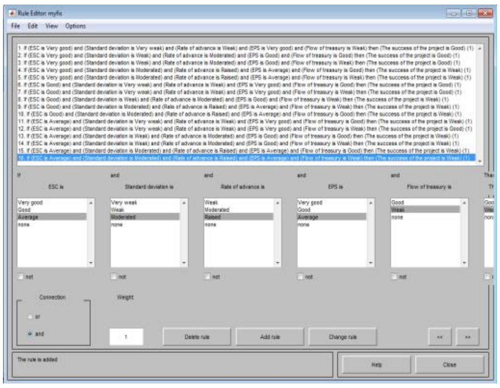


Fig. 6 The rules of regulators of fuzzy logic technique

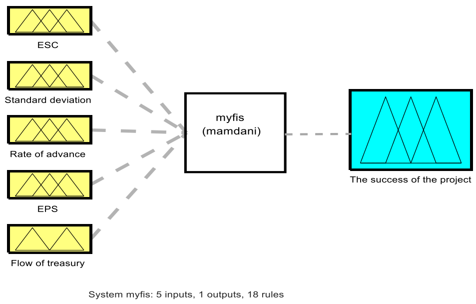


Fig. 7 Structure of the fuzzy logic model

Fig. 8 Rules viewer of fuzzy logic technique

Table 9 Results of fuzzy logic in the test phase

Project N°	Estimated value of risk by FL (Points)	Actual value of risk (Points)	Error (%)	Mean error (ME)
1	80	83	-3.614	
2	50	57	-12.281	
3	60	68	-11.765	
4	70	75	-6.667	
5	55	60	-8.333	
6	50	55	-9.091	
7	62	73	-15.068	
8	74	80	-7.500	
9	52	55	-5.455	
10	67	65	3.077	
11	50	62	-19.355	
12	51	56	-8.929	-7.640
13	52	53	-1.887	
14	86	90	-4.444	
15	66	70	-5.714	
16	50	58	-13.793	
17	81	85	-4.706	
18	79	90	-12.222	
19	50	56	-10.714	
20	77	80	-3.750	
21	56	60	-6.66	
22	75	80	-6.25	
23	40	50	-20	
24	40	45	-11.11	

• Have a problem to solve 5 inputs and only one output which represents 'will be learned' only once and the combination of the inputs of that having the smallest error of training will be selected.

• Fixed the number of the nodes at 2 data, and also we fixed the number of the iteration at 300 to ensure the conformity of data processing charged. The following Table 10 represents ANFIS model parameters, and this model composed as follows:

• Membership functions: Trimf
• 25 fuzzy rules
• 05 parallel layers
• 05 neurons in the first hidden layer (FUZZIFICATION).
• 25 neurons in the second hidden layer (FUZZY RULES).
• 25 neurons in the third hidden layer (STANDARDIZATION)
• 25 neurons in the fourth hidden layer (LINERAZATION).

Table 10 Specifications of the developed ANFIS model

Parameter	Description
Number of data	120
Number of inputs	5
Number of output	1
Number of iteration	300
Type of function of learning	Trimf
Training epoch number	100
Number of inputs membership functions	2 2 2 2 2
Algorithm of learning	Hybrid learning

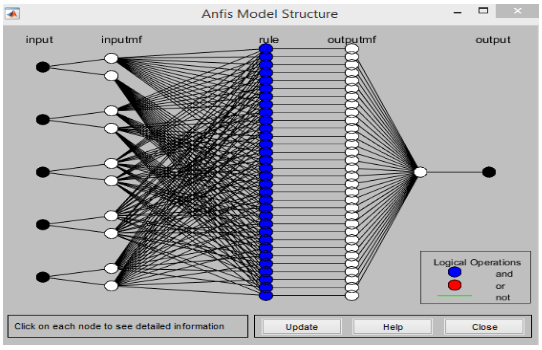


Fig. 9 the structure of ANFIS system

4.4.1 Learning of the ANFIS model

In a learning step, the model is trained until the results are obtained with minimum error. To design an ANFIS system for real world problems, it is essential to select the parameters for the training process (the state of the construction project). Were selected the parameters of training and testing data sets. During the learning process, the parameters of the memberships are updated, and error tolerance is used as a criterion for training stopping, which is linked to the size of the error. As a first step, we need to know what it forms a learning function we will choose to do our learning; afterwards from my database we can divide them into two parts. Part 1 will be used for training and part 2 will be used for checking. We will put 80% the data in the first, and the remaining 20% in the second. The training has been done on a number of loops during which the method will minimize the error made on the training part. The results are summarized in Table 11 below on the learning error. we are also trying to bring in forward will be to see whether how many a learning of function are useful for each inputs, by increasing the numbers of learning functions to 300 iterations up to the results better.

According to table we noticed that the function (Trimf), gave values similar to the real during the learning phase because they have small errors, same thing to the test phase. At last is the model ANFIS maintains its excellent accuracy prediction relative to the real case.

Training the ANFIS system with the training data set is shown in the Fig. 10. The training error is the difference between the training data output value, and the output of a fuzzy inference system corresponding to the same training data input value.

Testing the trained FIS is shown in Fig. 11. The average testing error for the training data set is 0.00312.

Table 11 Results of the learning functions

Type of function of learning	Number of inputs membership functions	Number of iteration	Learning error
Gaussmf	2 2 2 2 2	260	0.031
Psigmf	2 2 2 2 2	240	0.077
Pimf	2 2 2 2 2	200	0.159
Trampf	2 2 2 2 2	250	0.245
Tramp	2 2 2 2 2	200	0.301
Trimf	2 2 2 2 2	300	0.011

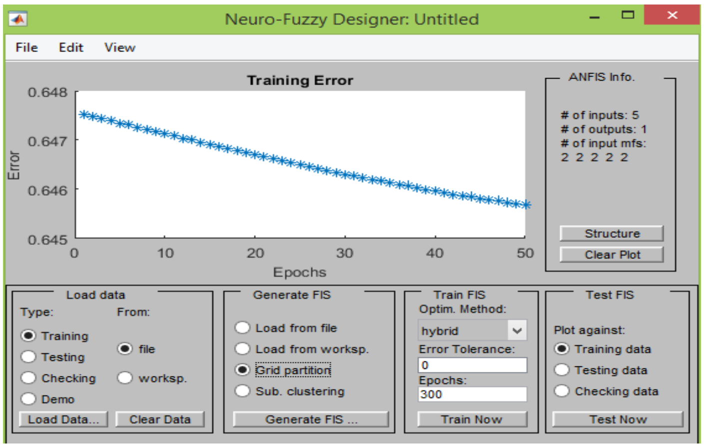


Fig. 10 Training error of model

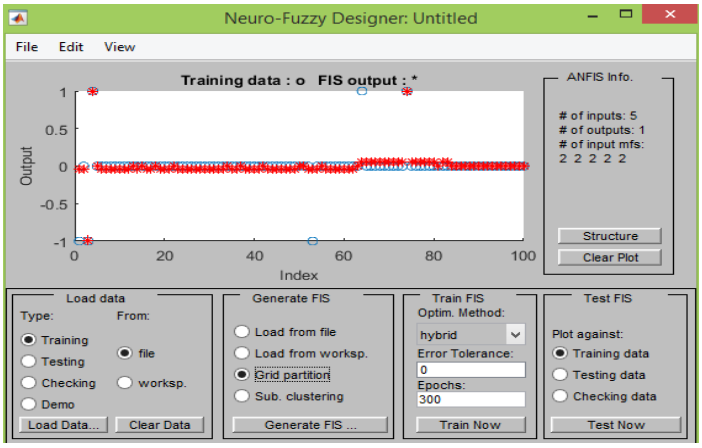


Fig. 11 Testing the FIS with learning data set

4.4.2 Test of the ANFIS model

The verification of the calculation algorithm has been borne of a simulation completely written in Microsoft Excel from which indicators of the test, using the following Eqs. (2) and (3). The results of the test are presented in Table 12

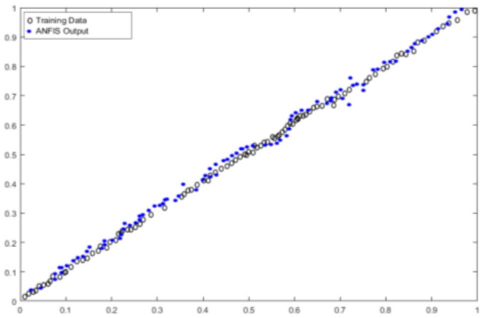
Table 12 Results of ANFIS in the test phase

Project N°	Estimated value of risk by ANFIS (Points)	Actual value of risk (Points)	Error (%)	Mean error (ME)
1	83	83	0.000	
2	56	57	-1.754	
3	68	68	0.000	
4	74	75	-1.333	
5	59	60	-1.667	
6	54	55	-1.818	
7	73	73	0.000	
8	80	80	0.000	
9	54	55	-1.818	
10	64	65	-1.538	
11	62	62	0.000	
12	53	56	-5.357	-1.317
13	53	53	0.000	
14	89	90	-1.111	
15	70	70	0.000	
16	59	58	1.724	
17	84	85	-1.176	
18	89	90	-1.111	
19	54	56	-3.571	
20	80	80	0.000	
21	88	90	-2.222	
22	76	80	-5	
23	73	75	-2.666	
24	78	80	-2.5	

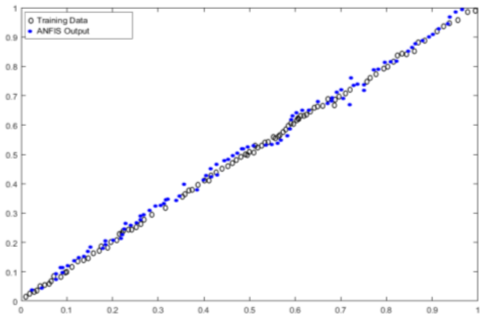
5. Comparative study of the various methods: RNN and FL and ANFIS

According to figures by noticing that, model ANFIS gave in the phase (Training), of the values, successes of the project (blue points) almost similar to those of reality (black points) during the phase of training. Figs. 12(a), (b) and (c)). Show the comparison between the training data the simulated values by the ANFIS and RNN, FL models.

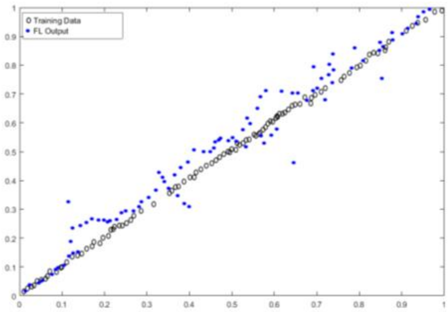
Fig. 13 shows comparison between the predicted value for RNN and FL and ANFIS models and the actual value, and the graph say that ANFIS model give more accurate result compared to RNN and FL.



(a) Learning of the data by ANFIS



(b) Learning of the data by RNN



(c) Learning of the data by FL

Fig. 12 Comparative studies of the various methods: RNN and FL and ANFIS

Table 13 Comparison between different methods ANFIS and FL and RNN

Indications of comparison	Models		
	RNN	FL	ANFIS
MPE	4.23	11.31	1.85
RMSE	0.70	0.75	0.86
MAPE	4.23	11.31	1.85
AA %	95.77	88.69	98.15

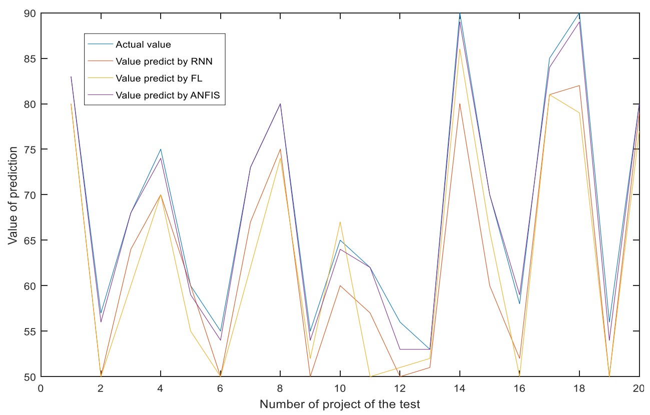


Fig. 13 Comparison between actual and predicted values by RNN and FL and ANFIS

The performances of RNN and FL and ANFIS were compared using the indices of comparison. The indices of comparison are defined in Eqs. (5) - (8)

$$MPE = \left\{ \sum_{i=1}^{n} \left(\frac{A-E}{A} \right) / n \right\} * 100\% \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (E-A)^2}{n}} \tag{6}$$

$$MAPE = \left\{ \sum_{i=1}^{n} \left(\frac{A-E}{A} \right) * 100\% \right\} / n \tag{7}$$

$$AA\% = 100\% - MAPE \tag{8}$$

Where MPE is the Mean Percentage Error, RMSE is the Root Mean Squared Error, MAPE is the Mean Absolute Percentage Error, AA% is the Average Accuracy Percentage; and n is the number of data, E is the forecast value, and A is the actual value of the projects.

Table 13 shows the comparison of ANFIS and RNN and FL models. The comparison reveals that these ANFIS are slightly better than the RNN and FL since they measure the statistical error. This is to say that the performance of ANFIS ahead exceeds that of other models. The evaluation indication MPE, RMSE, MAPE, and AA were taken as the reference to compare the best model and the very good coefficient of correlation to check the forecasting performance of the model.

Fig. 13 shows comparison between the predicted value for RNN and FL and ANFIS models and the actual value, and the graph say that ANFIS model give more accurate result compared to RNN and FL.

The tests carried out on the models show that the results practically coincide with the results obtained. Finally, these results show also that the ANFIS model is better for forecasting than that of RNN and FL.

6. Conclusions

This paper proves the applicability of the ANFIS and RNN and FL models in the prediction of the project status. According to the results obtained it can be seen that the neuro-fuzzy approach is a better technique to capture the relation of input-output and could be used for a good forecast of state of the project and especially to reducing the risk of failure of the project through various factors. We saw in the first part that the networks of neurons and fuzzy logic originated from a need to formalize inaccuracies. In spite of its simple rules, it is mathematically ready to model systems inference much.

For that, we used a technique of optimization of the vague system via a network of neuron (Neuro-fuzzy), thanks to which we obtained good performances in the forecast. According to the got results, we have to conclude that the model Neuro-fuzzy appears a good ranging between the characterization and effectiveness and precision of calculations.

This indicates that the ANFIS model gives a better result that the RNN and FL techniques for the forecast of the risk.

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