RESEARCH ARTICLE OPEN ACCESS

A Big Bang – Big Crunch Optimized Type-2 Fuzzy Logic Based System for Default Prediction in Sudanese Banking Sector

Ahmed Salih [1], Hani Hagras [2]

[1] (Department of Computer Science, Sudan University of Science and Technology (SUST))-Sudan
[2] (The Computational Intelligence Centre, School of Computer Science and Electronic Engineering University of Essex)-United Kingdom

ABSTRACT

The recent global financial-economic crisis has led to the collapse of several companies from all over the world. This has created the need for powerful frameworks which can predict and reduce the potential risks in financial applications. Such frameworks help organizations to enhance their services quality and productivity as well as reducing the financial risk. The widely used techniques to build predictive models in the financial sector are based on statistical regression, which is deployed in many financial applications such as risk forecasting, customers' loan default and fraud detection. However, in the last few years, the use of Artificial Intelligence (AI) techniques has increased in many financial institutions because they can provide powerful predictive models. However, the vast majority of the existing AI techniques employ black box models like Support Vector Machine (SVMs) and Neural Network (NNs) which are not able to give clear and transparent reasoning to explain the extracted decision. However, nowadays transparent reasoning models are highly needed for financial applications. One transparent modelling approach is via employing type-2 fuzzy logic systems. However, type-2 fuzzy logic systems rule bases can suffer from the curse of dimensionality problem when the input features increase. This paper presents an optimized type-2 fuzzy logic system for predicting customers default within the Sudanese banking sector. We have employed real datasets collected from the banking sector in Sudan. The proposed system resulted in transparent outputs which could be easily understood, analyzed and augmented by the human stakeholders. Furthermore the optimized proposed model provide a very light rule base that contains only 400 rules reflecting an effective improvement in the system's performance. Besides, the proposed system resulted in an average recall of 84%, which outperformed its type-1 counterpart by 21%.

***Keywords* —** Big bang – Big Crunch, Type-2 fuzzy logic system, default, prediction model.

I. INTRODUCTION

During 2008 economy crisis, several companies financially collapsed around the world. For example, the United State housing market lost $3.4 Trillion in real estate wealth [1]. This was equivalent to $30,300 per U.S. household. Stock wealth lost $7.4Trilion equivalent to $66,200 per household. 5.5 Million jobs were lost in the American job market. All of these factors have taken hold despite the existent of predictive models to help forecast crisis before they happen. More emphasis on finding ways to minimize the impact of potential risks on businesses becomes evident among researchers.

In Sudanese banks there is no loan default predictive model applied in order to eliminate the potential risks. The mechanism which is used by central bank of Sudan (CBOS) simply maintains a black list shard among the commercial banks this list contains all defaulter customers in all Sudanese banks. Any bank can update this black list by adding its own defaulter customers. This mechanism is less efficient because it cannot identify the default until it's really happen.

There are numerous Artificial Intelligent (AI) prediction models which have been presented to predict default in financial sector, and most of these models have achieved hopeful results, but most of them are considered to be black box models which are not able to give clear and transparent reasoning to explain the extracted decision.

Extended to our previous work [2] which is used type-2 Fuzzy Logic Systems (T2FLSs) to build white box predictive model to predict loan default in Sudanese banking sector using real dataset extracted from financial institutions in Sudan, this paper employ "Big Bang Big Crunch (BB-BC) optimization algorithm, to optimize the rule base in order to produce readable rule base with small number of short rules providing less computational overhead model.

The rest of the paper is structured as follows: the following section presents a brief overview of predictive models for Financial Applications followed by an overview of Type-2 Fuzzy Sets and Systems, then we will give an introduction on Big Bang–Big Crunch (BB-BC) evolutionary method followed by section dedicated to proposed optimized Type-2 Fuzzy Logic Based System (T2FLS) prediction model for the Sudanese financial sector. After that we will present and discuss the results of proposed model and the paper will conclude with a list of findings and recommendations for future work.

II. PREDICTIVE MODELS FOR FINANCIAL APPLICATIONS OVERVIEW

In general, there are four different techniques to build predictive models employed by financial firms. There are:

- Statistical-based.
- Operation research-based.
- Artificial Intelligence (AI) based.
- Hybrid artificial intelligent based.

The statistical-based predictive models contain many techniques like:

- Dicremenant Analysis (DA).
- Statistical Regression (SR).
- Factor Analysis (FA)

The techniques are wildly used because they are easy to develop. However, they capture only information that can be used within mathematical models. The output in this case is binary either a 0/1 or black/white [3]. Moreover, these techniques assume existence of mathematical relationship between input and output which is necessarily true in the real-world data.

Operation research-based predictive models contain many techniques like:

- Linear Programing (LP).
- Data Envelopment Analysis (DEA).
- Quadratic Programing (QP).

These techniques are used widely because of their development simplicity but they are complicated to use and can lead to complicated semi-black box models.

Artificial Intelligence (AI)-based predictive models can be subdivided into two sections:

- **Black-box:** containing techniques such as Support Vector Machine (SVM) [4] and Neural network (NN) [5]
- **White-box:** containing techniques such as Case Base Reasoning (CBR), Rough Set Theory, Decision Tree (DT), and Fuzzy logic (FL) [6].

The **Black Box** models are used on a wide spectrum of financial applications such as [12] and they produce a good level of prediction accuracy. However, these models are hard to understand and analyze by financial analysts since black-box models don not produce clear evidence-based decisions. This is considered an important requirement by the financial market nowadays due to the intense competition and race to winning customer confidence.

The term **White Box** refers to AI techniques that can provide transparent reasoning behind extracted decisions. This has motivated users to apply white box techniques for normal end usages [6]. The White box models uses the following techniques:

- Case-based Reasoning
- Decision Trees
- Fuzzy Logic

Fig.1 shows a schematic of white-box model where decisions are provided with justifications. In the following section a summary of these techniques will be provided. The Case-Based Reasoning (CBR) is one of the white box methods that attempts to solve new problems based on solutions of similar past problems [7], [8].

Decision trees (DT) uses recursive partitioning algorithm to produce rules on a specific data set [9]. DT algorithms take training data set and extract decision boundaries. These decision boundaries are then used to build a decision tree. From the constructed decision tree, the model will be able to extract decision rules which can provide reasoning tools which can provide clear understanding about the extracted decisions. However, DTs have many limitations such as inability to handle uncertainty. DT also utilize recursive partitioning operation which may leads to hard decision boundary extraction [10].

Lotfi Zadeh [11] have proposed the Fuzzy Logic Theory (FL) in order to provide a framework that is capable of handling uncertainties associated with natural languages. The FL tries to mimic a human's way of reasoning in order to think in approximate ways rather than precise ways. The FL systems is built based on fuzzy set theory which provides means of calculating intermediate values between absolute true and absolute false. The resulting values range between 0 and 1 leading to smooth transition between different sets. Fuzzy Logic Systems (FLSs) have been employed widely in financial applications.

J. Andres et. al. [12] have proposed fuzzy-rule-based classifiers for bankruptcy prediction problem and compared their classifier with logit and perceptron NN techniques. It was concluded that NN and fuzzy rule-based classifier outperformed logistic regression. The FL can provide transparent reasoning model; however, type-1 FL cannot handle a high level of uncertainty. The FL systems suffer from the dimensionality problem where number of rules tends to be enormous. This render them tedious to read and analyze by humans.

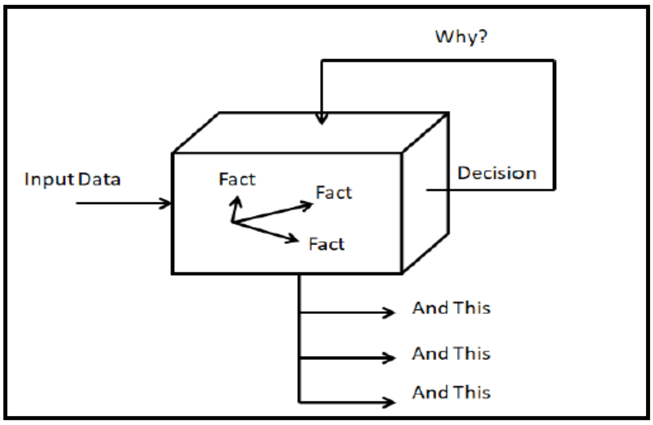


Fig. 1 A simple visualization for white box model

Hybrid Intelligent Technique: This term refers to the AI technique which tries to combine more than one AI technique to take advantage of each technique individual features and overcome each system limitation. S. Michael et. al.[13] presented the combined use of a fuzzy rule generation method and a data mining technique for the assessment of financial risks. A comparison between developed model with DA, logit analysis, and probability analysis concluded that fuzzy rule-based classifier outperformed other methods.

III. TYPE-2 FUZZY SETS AND SYSTEMS

Type-2 Fuzzy sets initially introduced by L. Zadeh[11] in 1975 as an extension of Type-1 fuzzy set. The membership grades of the Type-2 fuzzy sets are of Type-1 fuzzy sets. These Type-2 fuzzy sets are very useful when it is difficult to determine an exact membership function as in Type-1 fuzzy sets [14]. When there is no membership uncertainty, the set reduces to Type-1 fuzzy set.

Fig.2 shows Type-2 fuzzy set which is characterized by a fuzzy Membership Function (MF). The MF will assume membership value (or membership grade) for each element on the fuzzy set between [0, 1]. The grade will be of an interval set of values rather than a single value. In contrast, the Type-1fuzzy set the membership grade is a crisp and single value falling between “0” and “1”. From Fig 2, when the Upper Membership Function and Lower Membership Function coincides, the Figure reduces to Type-1 Fuzzy set. This indicates that the FOU region is eliminated in Type-1 Fuzzy set in accordance to the definition.

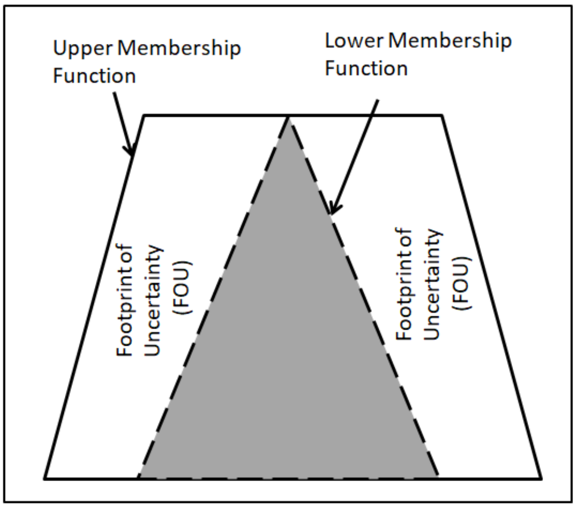


Fig. 2 A Type-2 Fuzzy Set

Type-2 fuzzy set is bounded from bottom by a Lower Membership Function and bounded from top by an Upper Membership Function. The membership functions of Type-2 fuzzy sets are 3D dimensional and include a Footprint Of Uncertainty (FOU). The combination of the Type-2 third-dimension and the FOU provides additional degrees of freedom that enables direct modelling and uncertainties handling.

In Type-2 fuzzy logic system each input and output will be represented by a large number of Type-1 fuzzy sets, which are embedded in the Type-2 fuzzy sets. The concept of a principal membership function also illustrates the fact that a Type-1 fuzzy set can be thought of as a special case of a Type-2 fuzzy set. We can think of a Type-1 fuzzy set as a Type-2 fuzzy set whose membership grades are Type-1 fuzzy singletons. Also, having secondary membership equal to unity for only one primary membership and zero for all others [15].

In Fig.3, the structure of a standard Type-2 Fuzzy Logic System (FLS) is presented. The crisp inputs are first fuzzified i.e. inputs are converted to input Type-2 fuzzy sets. Then, the inference engine identifies the rules fired from a previously defined rule base. Then combining these rules to produce output Type-2 fuzzy sets. Subsequently, the Type-2 fuzzy output sets are reduced and mapped to Type-1 fuzzy sets. This process is also known as type-reduction technique indicated by the Type Reducer block in Fig. 3. In this process, the Type-2 fuzzy sets outputs are reduced to Type-1 fuzzy sets by performing centroid calculation. Finally, the Type-1 reduced fuzzy sets are defuzzified i.e. by taking the average of the type-reduced set to obtain a crisp output [16][17],[18].

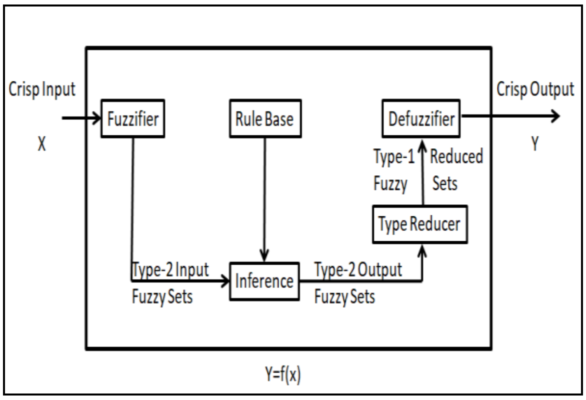


Fig. 3 Standard Type-2 FLS

Type-1 FLSs cannot fully handle or accommodate the high levels of linguistic and numerical uncertainties. This is due to usage of precise Type-1 fuzzy sets and membership functions [19]. For example, for a house environment, a “Moderate” temperature could be associated with the triangular Type-1 fuzzy membership function. However, the center of this triangular membership function and its endpoints vary according the user of the system where different users will have different preferences. Even for the same user, his/her preference will vary according to the season of year, his mode, country, context, and room location in the house. For example, “Moderate” temperature in the kitchen will be different to “Moderate” temperature in the living room.

IV. BB-BC OPTIMIZATION METHODS

The Big Bang–Big Crunch (BB-BC) is an optimization method originally invented by Erol and Eksin[20] this method inspired from the beginning of the universe in astrophysics, namely Big Bang – Big Crunch Theory. The main benefits of BB-BC are it’s easily to implement, has low computational overhead, and fast convergence [21]. It has two main phase: Big Bang phase and Big Crunch phase. The following steps demonstrates the BB-BC algorithm [22]:

Step 1: (Big Bang Phase): In this step an initial generation of N candidates is generated like other evolutionary search algorithms.

Step 2: After generate initial generation computes the cost function values of all the candidate solutions.

Step 3: (Big Crunch Phase): this phase can be considered as convergence operator and in this step you can computes either the best fit individual or the center of mass. The following equation can used to computes center of mass:

$$x_c = \frac{\sum_{i=1}^{n} \frac{x_i}{f_i}}{\sum_{i=1}^{n} \frac{1}{f_i}} \qquad (1)$$

Where xc is the position of the center of mass, xi is the position of the candidate, fi is the cost function value of the i^{th} candidate, and ***n*** is the population size.

Step 4: This step generate new candidates around the new point calculated in Step 3 and this achieved by adding or subtracting a random number whose value decreases as the iterations elapse as follow:

$$x^{new} = x_c + \frac{\gamma p\,(x_{max} - x_{min})}{k} \qquad (2)$$

Where γ is a random number, ρ is a parameter limiting search space, x_{min} and x_{max} are lower and upper limits, and k is the iteration step.

Step 5: Continuously return to step 2 until stopping criteria have been met.

V. PROPOSED BB-BC OPTIMIZED TYPE2 FUZZY SYSTEM:

The proposed model is an optimization for our previous work [2] which is A Type-2 Fuzzy Logic Based System for Decision Support to Minimize Financial Default in the Sudanese Banking Sector. Our previous research [2] is implementation of system this system take the customer's information as an input and provides classification of this customer (default/ not default). It has two main phase: Modelling phase and prediction phase. In the **modelling phase** two components have been constructed: The fuzzy sets Membership Function (MFs) and the rule base. In order to construct the MFs Fuzzy C-Means clustering algorithm (FCM) [23], [25] have been used to construct Type-1 Fuzzy Sets . Due to the high level of uncertainty associated with the financial data the Type-1 fuzzy sets transformed in to Type-2 fuzzy sets. The second component which is rule base have been learned from the real dataset belong to Alshimal Islamic Bank using the extracted Type-2 fuzzy sets. There are many issues regard to the rule extraction have been taken in the consideration like rule conflict which have been solved by using "***weighted scaled dominance***" approach introduced by [3] and "***weighted confidence***" which is presented by [26]. **The second phase** is prediction phase which used the extracted model to predict if the customer is default or not.

The resulting previous model provided a white box prediction model which can easily identify why this customer is classified with associated class (default/ not defuel) due to the if-then rule in the rule base, But on the other hand the number of rules in the rule base is very high -refer to our previous experiment is 8214 rules- which is difficult to analyze by human decision maker and increase the computational cost[27], furthermore the rule itself had many number of antecedents. For example Table I shows example of extracted rule from the previous model [2].

I. TABLE

EXAMPLE OF EXTRACTED RULE FROM THE PREVIOUS MODEL

N	*Rule*
R1	*if age is **Young** & sex is **Male** & marital_Status is **Married** & no_Dep_Child is **Mid** & income is **Low** & no_Dep_Spouses is **Low** & accupation is **Basic** & Avg_Month_Exp is **High** & live_Country is **SD** & live_City is **Khartoum** & tot_Amoount is **Low** Then class is **default***
R2	*if age is **Young** & sex is **Male** & marital_Status is **Married** & no_Dep_Child is **High** & income is **Low** & no_Dep_Spouses is **Low** & accupation is **HigherEducation** & Avg_Month_Exp is **Low** & live_Country is **SD** & live_City is **Khartoum** & tot_Amoount is **High** Then class is **default***

In order to enhance our previous model the proposed model use the BB-BC optimization method in order to optimize the rule base size by minimize it into rational number of rules each of them contains small number of antecedents which can enhance the readability of rule base by human decision maker and reduces the computational cost. Furthermore BB-BC optimization method also used to optimize the fuzzy set in order to achieve acceptable accuracy. Fig. 4 shows the structure of the optimized proposed model.

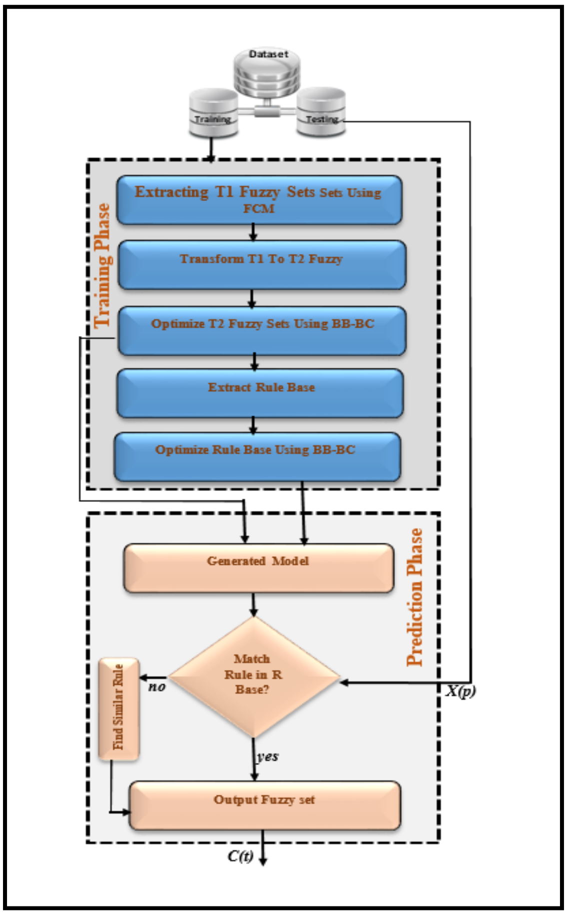


Fig. 4 Structure of the optimized proposed model

As appear in Fig. 4 the structure of the proposed model is same as our previous model [2] except that the proposed optimize model has new additional properties which is: optimization of the components of the type-2 fuzzy logic System (extracted rule base and fuzzy sets). The following subsection describe the optimization of type-2 fuzzy logic system's components.

Optimizing Type-2 Fuzzy logic System Using BB-BC:

In order to optimize the rule base using BB-BC the proposed model optimize the rule base in two deferent levels the first one is in term of the rule base by reducing the number of rule in the rule base into rational number of rules. The second level is in term of rule itself which is need to be shrinking by reducing the number of antecedents for the rule. In order to implements the BB-BC for the two levels; firstly the rule base parameters should be encoded in form of population [21]. The rule base can be represented as shown in Fig.5.

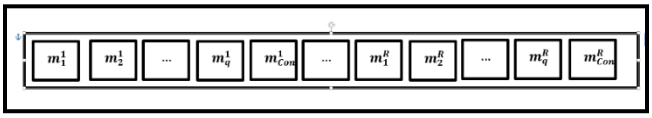


Fig. 5 Rule base representation in form of population

As appear in Fig. 5 m_j^r are the antecedents and O_{Con}^R is the consequent of each rule respectively, where j = 1,…, q, q is the number of antecedents; r = 1,…, R, and R is the number of the rules to be tuned. However, the values describing the rule base are discrete integers while the BB-BC supports continuous values. Thus, as an alternative of equation (2) the following equation is used in the BB-BC model to round off the continuous values to the nearest discrete integer values modelling the indexes of the fuzzy set of the antecedents or consequents [21].

$$D^{new} = D_c + round\left[\frac{y\,p(D_{max} - D_{min})}{K}\right] \qquad (3)$$

Where Dc is the fittest individual, r is a random number, ρ is a parameter limiting search space, $Dmin$ and $Dmax$ are lower and upper bounds, and k is the iteration step.

In this research the rule base constructed from our previous work [2] is used as the initial generation of candidates. After that the rule base can be tuned with BB-BBC using the average recall as cost function since the proposed model is binary classifier. The AVG-Recall could be calculated in a confusion matrix which displays information about predicted and actual classification done by a classifier [28]. This information is used to measure the classifier's performance. For example If there exist an input item and two classes (positive and negative), then there would be four possible cases that can occur. These would be:

- The input item is positive and the classifier classifies it truly as positive and this case is known as **True Positive (TP)**.
- The input item is negative and the classifier classifies it as positive and this case is known as **False Positive (FP)**.
- The input item is positive and the classifier classifies it as negative and this case is known as **False Negative (FN)**.
- The input item is Negative and the classifier classifies it truly as negative and this case is known as **True Negative (TN)**.

From the information provided by the confusion matrix we can calculate Recall which is called sensitivity for both classes (positive and negative) as follow [29]:

$$Recall\ Positive\ Rate = \frac{TP}{TP+FN} \qquad (4)$$

$$Recall\ Negaitive\ Rate = \frac{TN}{TN+FP} \qquad (5)$$

We can calculate the AVG-Recall which is used as cost function of the proposed model as follow [3]:

$$Avg\ Recall = \frac{Recall_{Positive} + Recall_{Negative}}{2} \qquad (6)$$

To optimize the fuzzy set using BB-BC optimization method likely way of optimizing the rule base using BB-

BC is used, the parameters of the MFs are encoded into a form of a population [21] as shown in Fig.6

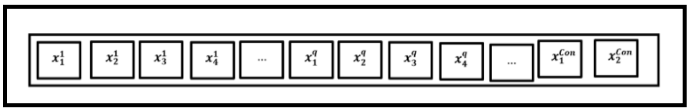


Fig. 6 Fuzzy set representation in form of population

VI. EXPERIMENTS & RESULTS

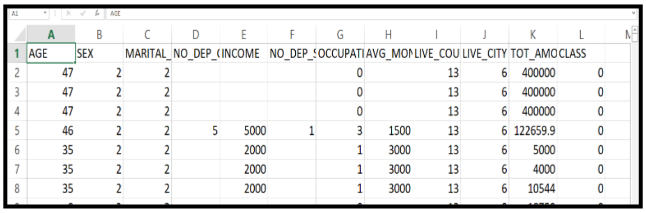
The proposed model is evaluated using real-time financial data extracted from Sudanese banking sector. The data collection and analysis technique will be described in this section.

Data collection and Analysis:

The data set which was used to test the proposed model is Real data collected from Al-Shimal Islamic Bank, Sudan. The researcher got an authorization from the administration of the bank to use the data. Because the costumer financial data is confidential data all personal information field was omitted. The data set is characterized as follows:

- Contains records dating back to the period between 2007 and 2017.
- Contains 101,257 records
- Contains 1,120 records categorized as defaults
- Contains 100,137 categorized as non-defaults
- Collected from 23 bank branches distributed across Sudan.

In order to implement the BB-BC all linguistic data fields are transformed into numerical representation Fig.7 shows a snapshot of data set after transformation.



	A	B	C	D	E	F	G	H	I	J	K	L
1	AGE	SEX	MARITAL_	NO_DEP_(	INCOME	NO_DEP_S	OCCUPATI	AVG_MON	LIVE_COU	LIVE_CITY	TOT_AMO	CLASS
2	47	2	2				0		13	6	400000	0
3	47	2	2				0		13	6	400000	0
4	47	2	2				0		13	6	400000	0
5	46	2	2	5	5000	1	3	1500	13	6	122659.9	0
6	35	2	2		2000		1	3000	13	6	5000	0
7	35	2	2		2000		1	3000	13	6	4000	0
8	35	2	2		2000		1	3000	13	6	10544	0

Fig. 7 snapshot of dataset after transformation

To build the proposed model, the data was divided randomly to 70% used in learning phase, and 30% used for testing phase. The dataset schema contains 12 parameters listed in Table II which shows parameters selected as inputs to the system with their description.

II. TABLE

PARAMETERS SELECTED AS INPUTS TO THE SYSTEM WITH THEIR DESCRIPTION

#	Parameter Name	Description
1	AGE	costumer's age
2	SEX	costumer's gender
3	M_STATUS	costumer's marital status
4	DEP_CHILDREN	number of costumer's dependent children
5	Income	costumer's income per month
6	DEP_SPOUSES	number of costumer's dependent spouses
7	OCCUPATION	costumer's occupation
8	MONTH_EXP	costumer's average monthly expenditure
9	LIVE_COUN	costumer's live country
10	LIVE_CITY	costumer's live city
11	TOT_AMOUNT	total costumer's loan amount
12	CLASS	costumer's class type(default/not default)

Constructing the fuzzy sets:

We started by constructing the Type-2 fuzzy sets using equal spaced fuzzy sets. Then the Fuzzy C-mean clustering algorithm (FCM) was exercised to generate the Type-1 fuzzy sets [30], as these will be used in the following iteration of the experiment. The FCM output shown in Fig. 8 represents distribution of the parameter age's data into three different clusters. Each of the clusters plays as a single fuzzy set i.e Young, Adult, and Old clusters. These sets can be approximated in order to construct the corresponding Type-1 fuzzy set membership function as shown Fig. 9.

Fig. 8 Output from FCM

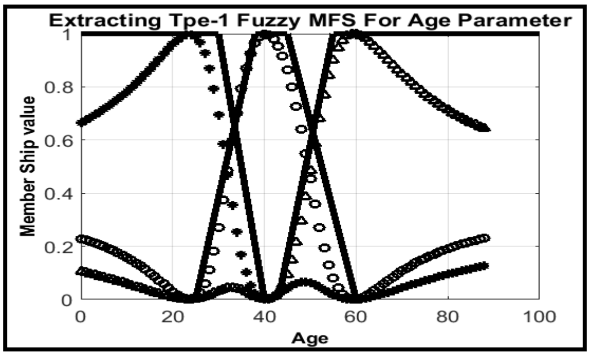


Fig. 9 Sample of constructed Type-1 Fuzzy set

The generated Type-1 fuzzy sets were then tuned by extending the FOU 10%, 20%, and 30% consequently. This to ensure that we can setup three different groups of Type-2 fuzzy sets that were used throughout the experiments. Then the three deferent group optimized using BB-BC. The sample of constructed Type-2 fuzzy set with 10 % FOU is shown in Fig 10.

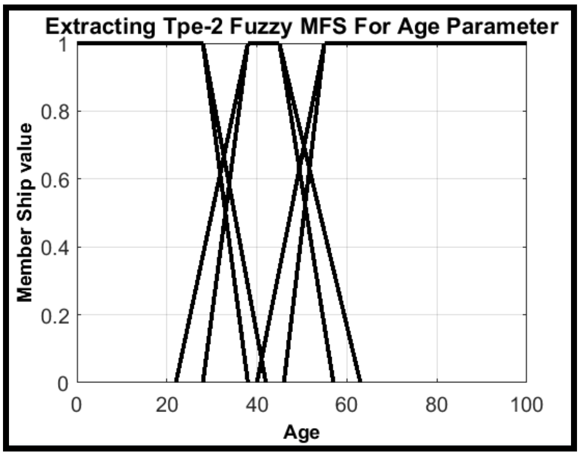


Fig. 10 Sample of constructed Type-1 Fuzzy set with 10 % FOU

An average recall (AVG-Recall) method was used to measure the proposed model accuracy as in equation (6). In order to evaluate the proposed model eight different experiments were conducted as follow:

1) Type-2 FLC using Type-2 fuzzy sets with equal space FOU.

2) Type-1 FLC using Type-1 fuzzy sets generated by FCM.

3) Type-2 FLC using Type-2 fuzzy sets generated by FCM with 10% FOU.

4) Type-2 FLC using Type-2 fuzzy sets generated by FCM with 20% FOU.

5) Type-2 FLC using Type-2 fuzzy sets generated by FCM with 10% FOU and optimized by BB-BC.

6) Type-2 FLC using Type-2 fuzzy sets generated by FCM with 20% FOU and optimized by BB-BC.

7) Type-1 FLC using Type-1 fuzzy sets generated by FCM and optimized by BB-BC.

Tables III and IV provide brief description for all conducted experiments. Table III summarizes the results extracted using testing data. Table IV shows the result of experiment that were extracted using the training data.

Table III

TESTING DATA RESULTS SUMMARY

Exp #	Model Type	BB-BC	FCM	FOU	Avg-Recall
1	T2	No	No	equal	0.79
2	T1	No	Yes	0	0.69
3	T2	No	Yes	10%	0.83
4	T2	No	Yes	20%	0.82
5	T2	Yes	Yes	10%	0.84
6	T2	Yes	Yes	20%	0.81
7	T1	Yes	Yes	0	0.75

TABLE IV

TRAINING DATA RESULTS SUMMARY

Exp #	Model Type	BB-BC	FCM	FOU	Avg-Recall
1	T2	No	No	equal	0.99
2	T1	No	Yes	0	0.91
3	T2	No	Yes	10%	0.99
4	T2	No	Yes	20%	0.96
5	T2	Yes	Yes	10%	0.99
6	T2	Yes	Yes	20%	0.98
7	T1	Yes	Yes	0	0.97

From Table III, it can be noticed that the Type-2 fuzzy based system using FCM with 10% FOU outperform Type-1 fuzzy based system using FCM. The improvement is computed as 20.66%. And the best fitted model of optimize proposed model which is labelled #5 in the Table III achieved little improvement in the accuracy.

The key main observation the rule base that generated by our previous non-optimized model contain 8214 rules which increased the computational cost. However the optimized proposed model extract rule base contain only 400 IF... Then rules; furthermore each rule contains only three antecedents which is decrees the computational cost. Table IV shows example of extracted rules by the proposed model. This provides an insight on the model operation as the main advantage provided by white box models. By analyzing these rules, the decision maker can reduce the potential risks that can face the organization as well as protecting customers form defaulting through advising in accordance to the analyzed information.

Table V shows example of rules extracted with the proposed optimized model if we compared with our previous model counterpart that appear in Table I we can show that the optimize rule base its very short contains only 3 antecedents per single rule which is easy to read an anlyse by human decision maker.

TABLE V

EXAMPLE OF RULES EXTRACTED WITH THE PROPOSED OPTIMIZED MODEL

N	Rule
R1	*if age is* ***Young*** *&no_Dep_Child is* ***Mid*** *& income is* ***Low*** *Then class is* ***default***
R2	*income is* ***Low*** *& Avg_Month_Exp is* ***High*** *& tot_Amoount is* ***High*** *Then class is* ***default***

VII. CONCLUSIONS AND FUTURE WORK

A Big- Bang optimized Type-2 Fuzzy logic model is proposed for decision support. The model is validated with real financial data extracted from Sudanese banking sector. The model has been able to identify financial default in the data and provided factors led to the decisions. The proposed system resulted in transparent outputs which could be easily understood, analyzed and augmented by the human stakeholders. The model has shown excellent average recall of 84%, which outperformed its Type-1 counterpart by 21%. Furthermore, the rule base which had been extracted by the proposed model is very small rule base which contain only 400 rule which decreased the computational overhead and provided a good tool to help decision makers analyse customer data and understand reasons behind model predictions. This an attractive feature to the organization as well as to the customer avoiding default situations. Such advantage cannot be provided by using black box models.

The banking sector in Sudan suffers from many problems in the recent period especially after revolution in December 2018, for example due to instability in the economic policies; the inflation rate is increasing reputedly. In our future works we will try to generalize our proposed optimized model in order to predict the inflation rate which can provides very valuable information to Sudanese banking sector.

REFERENCES

[1] P. L.Swagel, "Cost of the Financial Crisis", http://www.pewtrusts.org/en/research-and-analysis/reports/2010/04/28/the-impact-of-the-september-2008-economic-collapse, April 2010.

[2] A. Salih and H. Hagras "A Type-2 Fuzzy Logic Based System for Decision Support to Minimize Financial Default in the Sudanese Banking Sector" *SUST Journal of Engineering and Computer Sciences (JECS)*, Vol. 20, pp. 65-76, 2019.

[3] D.Bernardo ,H. Hagras, and E. Tsang, "A genetic type-2 fuzzy logic based system for the generation of summarized linguistic predictive models for financial applications", *Soft Computing*, vol.17,pp. 2185-2201, 2013.

[4] C. Robert West, "A factor-analytic approach to bank condition", *Journal of Banking & Finance*, vol.9, pp.253-266, 1985.

[5] H. Jae Min and Young-Chan Lee," Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters", *Expert systems with applications*, vol.28, pp.603-614, 2005.

[6] A. Salih and H. Hagras, "Towards a Type-2 Fuzzy Logic Based System for Decision Support to Minimize Financial Default in Banking Sector", In: *Proceeding of 10th Computer Science and Electronic Engineering (CEEC)*, Colchester, United Kingdom, 2018 ,pp:46-49.

[7] Karen Ketler, "Case-based reasoning: An introduction", *Expert systems with Applications* vol.6, pp. 3-8, 1993.

[8] Cheol-Soo Park, and Ingoo Han," A case-based reasoning with the feature weights derived by analytic hierarchy process for bankruptcy prediction", *Expert Systems with Applications,* vol.23, pp.255-264, 2002.

[9] P. Ravi Kumar and V. Ravi, "Bankruptcy prediction in banks and firms via statistical and intelligent techniques–A review", *European journal of operational research*, vol. 180, pp.1-28, 2007.

[10] Halina Frydman, Edward I. Altman, and Duen-Li KAO, "Introducing recursive partitioning for financial classification: the case of financial distress", *The Journal of Finance,* vol.40, pp.269-291, 1985.

[11] L. A. Zadeh, "Fuzzy sets as a basis for a theory of possibility", *Fuzzy Sets and Systems,* vol.1, pp3-28. 1978.

[12] J. De Andrés, M Landajo, and P. Lorca, "Forecasting business profitability by using classification techniques: A comparative analysis based on a Spanish case", *European Journal of Operational Research,* vol.167, pp.518-542. 2005.

[13] S. Michael, D. Georgios, M. Nikolaos, and Z. Constantin,. "A Fuzzy Knowledge-Based Decision Aiding Method for the Assessment of Financial Risks: The Case of Corporate Bankruptcy Prediction", *In: Proc. European Symposium on Intelligent Techniques*, 1999, Crete, Greece.

[14] N. N. Karnik and J. M. Mendel, "Operations on type-2 fuzzy sets", *Fuzzy sets and systems,* vol.122, pp.327-348, 2001.

[15] N.N. Karnik, and J.M. Mendel, "Introduction to type-2 fuzzy logic systems, In Proc. *1998 IEEE International Conference on Fuzzy Systems* Proceedings. IEEE World Congress on Computational Intelligence, 1998, pp. 915-920, Anchorage, AK, USA.

[16] A. Bilgin, H. Hagras, J. Helvert, and D. Alghazzawi, "A Linear General Type-2 Fuzzy Logic Based Computing With Words Approach for Realising an Ambient Intelligent Platform for Cooking Recipes Recommendation", *IEEE Transactions on Fuzzy Systems*, vol. 24, pp.306-326, 2016.

[17] A.Bilgin, H. Hagras, A. Malibari, M. Alhaddad, D. Alghazawi, "Towards a linear general type-2 fuzzy logic based approach for computing with words", *International Journal of Soft Computing*,pp.2203-2222, May 2013.

[18] A. Starkey, H. Hagras, S. Shakya, and G. Owusu. "A Multi-Objective Genetic Type-2 Fuzzy Logic Based System for Mobile Field Workforce Area Optimization", *Journal of Information Sceinces,* vol. 333, pp.390-411, 2016.

[19]A. Sakalli, T. Kumbasar, E. Yesil, and H. Hagras, "Analysis of the performances of type-1, self-tuning type-1 and interval type-2 fuzzy PID controllers on the Magnetic Levitation system," *in Proceedings of the 2014 IEEE International Conference on Fuzzy Systems*, 2014.

[20]O. Erol and I. Eksin, "A new optimization method: big bang–big crunch," *Advances in Engineering Software*, vol.37, pp. 106-111, 2006.

[21] B. Yao, H. Hagras, D. Alghazzawi and M. J. Alhaddad, "A Big Bang–Big Crunch Type-2 Fuzzy Logic System for Machine-Vision-Based Event Detection and Summarization in Real-World Ambient-Assisted Living", *IEEE Transactions on Fuzzy Systems*, vol. 24, pp. 1307-1319, 2016.

[22] T. Kumbasar, I. Eksin, M. Guzelkaya and E. Yesil, "Adaptive fuzzy model based inverse controller design using BB-BC optimization algorithm," *Expert Systems with Applications*, vol. 38, pp.12356-12364, 2011.

[23] C. James Bezdek, Robert Ehrlich, William Full, "FCM: The fuzzy c-means clustering algorithm, *Computers & Geosciences,* vol.10, pp.191-203, 1984.

[25] S. Ghosh and S. Kumar "Comparative Analysis of K-Means and Fuzzy C-Means Algorithms" *International Journal of Advanced Computer Science and Applications,* vol. 4, pp.35-39, 2013.

[26] H. Ishibuchi, and T. Yamamoto, "Rule Weight Specification in Fuzzy Rule-Based Classification Systems", *IEEE Transactions on Fuzzy Systems,* vol.13, pp.428-435, 2005.

[27]V. Callaghan, M. Colley, H. Hagras, J. Chin, F. Doctor, G. Clarke, "Programming iSpaces: A Tale of Two Paradigms", *In the book entitled "Intelligent Spaces*: The Application of Pervasive ICT", (Eds: A. Steventon, S. Wright), Springer-Verlag, Chapter 24, pp.389- 421, December 2000
12, pp. 2185-2201, August 2013.

[28] Provost, F. and Kohavi, R., "Glossary of terms", *Journal of Machine Learning*, vol. 30, pp.271-274, 1998.

[29] H. Ishibuchi, and T. Yamamoto, "Rule Weight Specification in Fuzzy Rule-Based Classification Systems", *IEEE Transactions on Fuzzy Systems*, vol.13, pp.428-435, 2005.

[30]B. Yao, H. Hagras, M. Alhaddad, D. Alghazawi "A fuzzy logic-based system for the automation of human behaviour recognition using machine vision in intelligent environments*", International Journal of Soft Computing*, Vol. 19, No.2 , pp.499- 506, 2015.