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Prediction of Firm Value with Financial Structure Items: An Implementation on Metal Industry

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Abstract.
Firm value is an important measure for creditors on credit process and for investors in investment decisions. So estimating of firm value is important previously. In this study, a model which estimates firm value was established, by using the values of capital structure like short term liabilities, long term liabilities and equity capital. The research sector is Metal Industry and Metal Goods, Machinery And Tool Industry and the used data which covers 2004-2008 years gathered from the official web site of Istanbul Stock Exchange (ISE). By using Adaptive-Network-based Fuzzy Inference System (ANFIS) firm values were estimated. It is clear that at the end of the study ANFIS model has predicted the market value of the firm in (t+1) period with small error rates.
Key words: firm value, capital structure, ANFIS modeling

Introduction

Changing and globalizing economic conditions changed the success criteria of firms. Nowadays, increasing the market value becomes important factor while profit maximization was on the top of the priorities list of firms in 1900s. Firm value concept which becomes popular lastly creates an important study field for the finance society.

Firm value can be defined as "the value if firm is sold with its whole tangible and intangible assets." The concept of firm value changed with time. Cash flows were important for the firm valuation in past while firm value is evaluated in a wide range by using different approaches called as modern approaches that emerges nowadays. These approaches advocate that firms don't consists of from cash flows but there are other variables that can have impact on firm value.

Aim of firm value evaluation in all approaches and methods is to maximize firm value. For this purpose, it is important that resources of firms, equity capital and liability which generate capital structure and the ratio of equity capital and liability.

Artificial intelligence models are based on neural networks, genetic algorithm and fuzzy neural techniques. These techniques can learn to detect complex patterns that are hidden in data and cannot be uncovered easily. Mathematically, these AI techniques are universal non-linear function predictors capable of capturing and modeling almost any input output relationships (Tan et. al. 2011). AI models also have advantages over statistical models. Relatively, they are more efficient and effective than statistical models in prediction and pattern recognition. Unlike most of the statistical models, they do not require any specific distribution of data or underlying theory. They are able to manage non-linear or complex relationships better and at the same time accommodate relatively larger number of variables.

Soft computing techniques are widely applied to stock market problems. They offer useful tools in forecasting noisy environments like stock markets, capturing their non-linear behavior (Atsalakis & Valavanis, 2009). Although Anfis has been applied in several studies, few of these have contributed to research in the financial area. This study contributes to the field of financial research. The main goal of this study is to explore the predictability of firm value on ISE index of metal goods by using ANFIS modeling. Index of Metal Goods includes the manufacturers of; gas cylinder, home appliances, nail, air conditioning, solar collectors, welded pipes, agricultural machinery, nuts and bolds, rim, motor casting parts, metal pipes and cables. This industry covers different sub sectors because of its structure and it realizes the production of variety of end products. The firms who products the inputs to the above mentioned firms are also in this index. Construction firms need the products of metal goods and this increases the importance of the value of the firms that are operating in metal goods.

According to the projections of Oxford Economics construction sector is expected to growth with 5.2% while this ratio is 6.4% and 10.1% in automotive and metal goods respectively. With these projections the importance of the firm values in the metal goods sector becomes clearer. This study will contribute to the

literature with examining this subject. This study is also important, because it tries to predict the values of the firms in such a big growing sector (Iron and Steel Sector Report, 2010).

Literature review

There are a lot of studies in literature. Huge part of this studies are about the firm value and the capital structure (Modigliani and Miller, 1958), (Elton and Gruber, 1971), (Özaltın, 2006),(Burca, 2008) or relationship between firm value and dividend allocation policies (Miller and Modigliani, 1961),(Doğukanlı, 1994),(Ünsal, 1998),(Karaca, 2007),(Belkayalı, 2004).

Masulis (1993) developed a linear regression with least squares method in order to determine the effect of the change in the capital structure to the firm value. At the end of his studies he found a positive relationship between firm value and changes in stock prices. And there is a positive relationship between the change of firm value and change in debt.

Yenice (2001) aimed to measure the effect of the capital structure on the firm value and the efficiency in his study. He used the data of 37 firms that operates in a subfield of production industry between the years of 1999-2000. His results indicate no meaningful relations.

Bayrakdaroğlu and Ege (2008), examined the three-month financial statements of insurance firms that are in the index of IMKB between the years 2000 and 2004. They used multivariate regression analysis in order to put forward the relationship between debits, provisions and other debits and current value and the efficiency of firm. According to their results there is no statistically meaningful relationship between firm value and capital structure but there is a negative relationship between firm efficiency and the capital structure.

Other studies about this fields firm value is handled with different aspects. In 1992 Fama and French researched the relationship between firm value and stock returns. Firm value is represented by Book Value / Market Value (BV/MV). Results indicate positive relationship between firm value and returns. (Fama and French, 1992:427-465).

Arkan (2010) prepared a study about the relationship between financial structure of firms and the value of firm. He conducted multiple regression analysis and correlation to the data including 127 firms on the index of ISE. According to his results a 1% increase or decrease in equity leads to a 1.1% increase or decrease in firm value.

Anfis is generally used in the prediction of the returns of stocks in literature. Grosan et. al. (2005) used a new artificial intelligence technique called Multi Expression Programming (MEP) in prediction of stock index and compared the results with artificial neural network with Levenberg-Marquardt learning algorithm, support vector machine, Takagi-Sugeno Neuro-Fuzzy model and Difference Boosting Neural Network. Results indicate a lower error rate in MEP when compared with other AI techniques.

Afoloabi and Olude (2007) used Self Organizing Maps with ANFIS for predicting the stock price. At the end of the study it becomes clear that SOM are showed less variance than other techniques.

Yunos et al. (2008) developed an ANFIS model in order to predict the daily movements of Kuala Lumpur Compound Index (KLCI). In order to verify the efficiency of ANFIS model they made two experiments and results indicate the efficiency of ANFIS.

Abbasi and Abouec (2009;11336) tried to predict price trend of the Khodro Company operating in Tahran Stock Exchange with ANFIS. Results indicate that ANFIS can predict the stock prices with small error rates.

Atsalakis and Valavanis (2009) tried to predict the other day's stock price with ANFIS. In this study a lot of possibilities are tried with changing the parameters via trial and error method. Results indicate the sufficiency of the model to predict the stock price prediction.

Boyacıoğlu and Avcı (2010) used ANFIS to predict the stock market returns. There were 9 input variables, 6 of which macroeconomic variables. At the end of their study they were 98.3% successful in the prediction of the ISE-National 100.

ANFIS is being used in financial studies because it makes easier the prediction of future values. But it hasn't been used in firm value foresight. The importance of this study is that it is the first study that uses the ANFIS to predict the firm value.

Theory of adaptive neuro-fuzzy inference system (ANFIS)

A specific approach in neuro-fuzzy development is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which has shown significant results in modeling nonlinear functions (Jang et al., 1997). The ANFIS is a new improved tool and a data driven modeling approach for determining the behavior of imprecisely defined complex dynamical systems (Kim & Kasabov, 1999). The basic idea behind the neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modelling procedure to learn about

the data set, and to compute membership function parameters that will best suit the associated fuzzy inference system (FIS) for given input/output set. The ANFIS learning method works similarly to the neural networks one (Jang, 1993)

The advantages of FL for grade estimation is clear because it prepare a powerful tool that is flexible and in lack of data with its ability which is if-then rules would able to solve the problems. As discussed, one of the biggest problems in FL application is the shape and location of membership function for each fuzzy variable which solve by trial and error method only. In contrast, numerical computation and learning are the advantages of neural network, however, it is not easy to obtain the optimal structure (number of hidden layer and number of neuron in each hidden layer, momentum rate and size) of constructed neural network and also this kind of artificial intelligent is more based on numerical computation rather that than symbolic computation. Both FL and NN have their advantages, therefore, it is good idea to combine their ability and make and strong tool and also a tool which improve their weak as well as lead to least error. Jang (1993) combined both FL and NN to produce a powerful processing tool named NFSs which is a powerful tool that have both NN and FL advantages and the most common one is ANFIS.

Neural Networks and Fuzzy Logic are the two key technologies that have recently received growing attention in solving real world, nonlinear, time variant problems. Because of their learning and/or reasoning capabilities, these techniques do not need a mathematical model of the system which may be difficult, if not impossible, to obtain for complex systems. Although these techniques have had successes in solving many real world problems, they have limitations as well. Intelligent combinations of these two technologies can exploit their advantages while eliminating their limitations.

It consists of five layers. The first layer carries out a fuzzification process. In the second layer, each node output is the product of the antecedent part of the fuzzy rules. The third layer normalizes the membership functions (MFs). The fourth layer executes the consequent part of the rules and the fifth layer computes the overall output as the addition of all incoming signals.

Adaptive-Network-based Fuzzy Inference System (ANFIS) is a Sugeno-type (Sugeno & Kang, 1988) fuzzy system in five-layered feed-forward network structure. ANFIS can be used to optimize membership functions and has the advantage of being able to construct fuzzy IF-THEN rules representing these optimized membership functions.

Since ANFIS is much more complex than the fuzzy inference systems discussed so far, you are not able to use all the available fuzzy inference system options. Specifically, ANFIS only supports Sugeno systems subject to the following constraints:

- First order Sugeno-type systems
- Single output derived by weighted average defuzzification
- Unity weight for each rule

An error occurs if your FIS matrix for ANFIS learning does not comply with these constraints. Moreover, ANFIS is highly specialized for speed and cannot accept all the customization options that basic fuzzy inference allows, that is, you cannot make your own membership functions and defuzzification functions; you'll have to make do with the ones provided. Using the Adaptive Neuro-Fuzzy Inference System (ANFIS) Editor, you can shape membership functions by training them with input/output data rather than specifying them manually. The toolbox uses a back propagation algorithm alone or in combination with a least squares method, enabling your fuzzy systems to learn from the data.

The most important reason for combining fuzzy systems with neural networks is to use learning capability of the neural network. While the learning capability is an advantage from the view point of a fuzzy system, from the viewpoint of a neural network there are additional advantages to a combined system. Because a neuro-fuzzy system is based on linguistic rules, we can easily integrate prior knowledge in to the system, and this can substantially shorten the learning process. One of the popular integrated systems is an ANFIS, which is an integration of a fuzzy inference system with a back-propagation algorithm (Jang, 1997; Lin, 1996).

In order for a FIS to be mature and well established so that it can work appropriately in prediction mode, its initial structure and parameters (linear and nonlinear) need to be tuned or adapted through a learning process using a sufficient input–output pattern of data. One of the most commonly used learning systems for adapting the linear and nonlinear parameters of an FIS, particularly the first-order Sugeno fuzzy model, is the ANFIS. ANFIS is a class of adaptive networks that are functionally equivalent to fuzzy inference systems (Jang, 1993).

Data set

The data which belongs to the firms that are registered to ISE index of Metal Industry and Metal Goods, Machinery and Tool Industry are used. Data also covers the years 2004-2008. In order to realize the purpose of the study secondary data is used. Data collected from the financial statements of firms for related years.

Firm value is an important measure for creditors on credit process and for investors in investment decisions. So estimating of firm value is important previously. In this study, a model which estimates firm value was established, by using the values of capital structure like short term liabilities, long term liabilities and equity capital. The research sector is metal industry and the used data which covers 2004-2008 years gathered from the official web site of Istanbul Stock Exchange (ISE).

In this study input variables are as follow: short term liabilities, long term liabilities and equities. Output variable is firm value. Market values that are issued by Istanbul Stock Exchange were used as firm value. Market value variable is the value in the period of (t+1).

Short term liabilities are the liabilities that have to be paid at most in one year or at the end of the activity period. Long term liabilities are the liabilities that are gathered from credit institutions, capital markets or the third part institutions and have a due date more than one year. Equities are representing the investments that come from firm owner or partners, priorities and undistributed profits.

To get a better ANFIS model and increase the performance, a data normalization process needs to be done. In the process of normalization the data is ranged between [0,1] or [-1,1]. This process is required in order to optimize the input and output neurons (Doğan, 2010:83). Normalized data is separated as 75% for training and 25% as test data.

Development of ANFIS models

Fuzzy Logic Toolbox of MATLAB was used to build an ANFIS model. Using membership functions (MFS) of all types (trimpf, trampf, gauss etc.) for all input variables and linear for all outputs, the number of MFs assigned to each input variable is chosen by trial and error. After training and testing the number of MFs was fixed for each input variable, when the ANFIS model reaches to the acceptable satisfactory level. ANFIS architecture and training parameters at satisfactory level were illustrated in table 1.

Table 1. ANFIS architecture and training parameters

Membership Functions (MF) type	Gaussmf
Number of nodes	286
Number of linear parameters	500
Number of nonlinear parameters	30
Total number of parameters	530
Number of training data pairs	23
Number of checking data pairs	8
Number of fuzzy rules	125
NumMFs input 1	5
NumMFs input 2	5
NumMFs input 3	5

ANFIS models defined with rules and membership functions that are in convenient with input-output sets. In the process of defining the suitable membership function, the results are examined for every membership function. The membership function that returns the least error rate has been chosen.

Results and discussions

The accuracy of the results of the developed models are assessed using some statistical verification criteria such as R2, MSE and MAE corresponds to the coefficient of correlation, mean square error and the mean absolute error.

R2 measures the statistical correlation between the predicted and actual values. This method is unique in that it does not change with a scale in values for the test cases as the previously mentioned measures do. Also note that here a higher number means a better model, with a 1 meaning perfect statistical correlation and a 0 meaning there is no correlation at all. This performance measure is only used for numerical input and output.

MSE is the principal and most commonly used measure; sometimes the square root is taken to give it the same dimensions as the predicted value itself. Many mathematical techniques (such as linear regression) use the mean-squared error because it tends to be the easiest measure to manipulate mathematically.

MAE is an alternative: just average the magnitudes of the individual errors without taking account of their sign. Mean-squared error tends to exaggerate the effect of outliers—instances whose prediction error is larger than the other but absolute error does not have this effect: all sizes of error are treated evenly according to their magnitude.

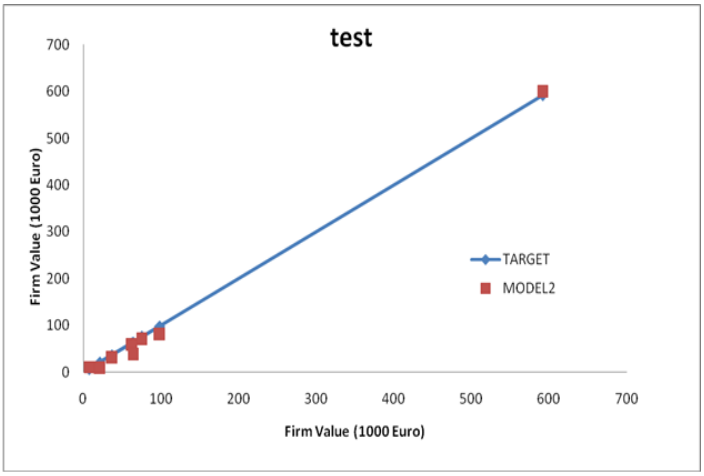


Figure 1. The relationship between predicted values and actual values for testing data.

In this Figure 1, the predicted values can be seen. ANFIS model returns quite well for predicting the future firm value.

Conclusion

As a result predicting the firm value with one year before is performed with low error rates. The correlation rate between the predicted firm values and actual ones are quite high on both of the train and test data (Train: 0.998. Test:0.987).

In this study different from other studies about the relationship between capital structure and firm value the relationship is investigate with ANFIS model. This model facilitated to research the relationship between capital structure and firm value. Also it allows calculating the firm value with financial structure items. It is thought that this study will be useful to see the usage of ANFIS model on the future studies and researches on financial field.

This study can also be improved with different time series or with different data set belong to various industries.

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Electronic Expert System in Life Insurance Underwriting: The Case of Saman Insurance Underwriting Portal

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Abstract.

Issuing individual life insurance started in the seventies in Iran but after nearly forty years, due to the lack of documented data, the insurance companies cannot easily access to insured proposal data and their medical history. Because of this the underwriting is based on personal experience or reference book instead of real data. Nowadays by information technology, data mining through medical data and documents is possible. This paper describes the process of issuing life insurance by electronic documents at Saman Insurance and advantages and disadvantages have been reviewed.

Life insurance underwriting is a complex and a sensitive operation. In this paper we describe how to use Microsoft SharePoint in underwriting life insurance.

Some steps are:

1. Data entry
2. Attaching scanned of proposal and previous medical documents.
3. Determining the required medical tests automatically.
4. Determining the substantial rate related to age, sum insured, occupation… automatically.
5. Sending emails to physicians for supplementary review and register their comments.
6. Sending emails to underwriter to gather and records their comments.
7. Updating the status

Keywords: expert system, issuing policy, underwriting, life insurance

Introduction

Hard copy documents play a major role in the insurance industry. Archiving documents is an integral part of the insurance process. Since this process is time consuming and hard copies are quite expensive, is insurance companies are motivated to find alternative ways. Using new technologies is a good way to speed up the process and reduce the costs. Gathering credible, documented and audited data is another advantage of using new technology in insurance industry. Data classification greatly increases the efficiency of financial system in insurance and will accelerate the customer service process.

In the view of insurance analysts, having good performance, efficient operation and management are the best representation and advertisement for the company. Increasing procedures' efficiency and enhancing leadership result in a rise in company's profit. Information technology helps companies to reach multiple objectives by redesigning the procedures. American Express, for example, set out to reduce the cost, time and to improve the process of making credit authorization decisions by embedding the knowledge of its best authorizers in an "Authorizer's Assistant" expert system. This successful redesign led to a 7 million dollar annual reduction in costs due to credit losses, a 25% reduction in the average time for each authorization, and a 30% reduction in improper credit denials [1].

It is estimated that about 30% of staff time is wasted in handling paper documents daily. So using an electronic system in which all documents are virtually stored and all processes are followed is very important for an insurance company.

Underwriting

Risk is the probability or threat of quantifiable damage, injury, liability, loss, or any other negative occurrence that is caused by external or internal vulnerabilities, and that may be avoided through preemptive action. Insurance is one of the most common ways that individuals and organizations protect themselves against financial losses. Insurers have significant expertise in risk management.

Insurer must make complex decisions about selecting and pricing risks and adjusting losses as well. This process called underwriting. In recent years, these decisions are taken only by experts who have enough skills and the experience. However nowadays, decision-making processes can be planned in advance. Indeed, certain percentage of underwriting decisions is automated and for human decision maker, provides assistance.

Underwriting is a plenary process in which decision making about risks is done based on actuarial and business principals. Underwriting involves measuring risk exposure and determining the premium that needs to be charged. Generally, underwriting inspects a particular risk; classifies exposures- i.e. people- into groups of homogeneous risks, and calculates financial impacts of potential losses.

In life insurance, risk has different aspects: health, finance and occupation issue. Underwriting should be regarding competitive market and adjusting expected losses by expected investment income and reserves.

A precise underwriting makes an insurance company competitive. On the other hand, poor underwriting can cause major losses during time.

Risk classification and assessment in life insurance is very important. Determining occupational risk categories using mortality tables, medical tests and … are some attempt to a precise underwriting.

Electronic expert system

The tools by which processes to be redesigned are identified and prioritized is one of the key issues in process redesign. This is often difficult because most managers do not think of business operations' processes. There are two major approaches in this issue. The first, we labeled as "exhaustive", attempts to rigorously identify all processes in organization and then to prioritize them to redesign urgency. The second, which we refer to as "high-impact", attempts to identify only the most important processes or those most in conflict with the business vision and process objectives, using a minimum of time and effort [1].

An expert system is a computer based system which emulates the decision-making ability of a human expert. In simple words, such systems contain knowledge derived from an expert in some narrow domain. Expert systems are meant to solve real problems which normally would require a specialized human expert [2].

The process of issuing universal life policy in terms of time, cost and quality is one of the most important processes at Saman Insurance Company. Currently, redesigning process is done via "high-impact" approach.

Already, most insurance companies use integrated system for issuing policies. In addition to scientific evidence, underwriting process requires underwriters' experiences and should be done by hand, in part.

In Saman Insurance Company underwriting process is automated. Required medical exams are specified in the electronic system and referral letter to lab is generated automatically. Moreover substantial rates are determined by expert system related to occupational and medical history of the insured.

Advantages and Disadvantages of Electronic Expert System

Some advantages of applying electronic expert system in insurance are:

- Cost reduction in documenting and archiving
- Easy and quick access to required data
- Speeding up customer service
- Classified data
- Extracting analytical reports
- Analyzing expense
- Integrated sales channels systems

Most insurance companies can redesign their processes based on information technology. However, electronic systems may have some limitations.

Organizations that have redesigned key processes will also need to establish an ongoing organization to oversee continuous redesign and organizational "tuning", and to ensure that information systems support process flows. In most companies, required analytical skills for redesigning processes are most likely found in the IT functions. However, individuals in the IT function will also require a high degree of interpersonal skills to be successful as the "new industrial engineers". The ideal group would combine the responsibilities of multiple

functional areas, e.g., information systems, industrial engineering, quality and process control, finance, and human resources.

There are a few emerging examples of groups that aim to redesign processes. Silicon Graphics has created a specific process consultation group for ongoing process management; it is headed by a director-level manager. On a project basis, Ford Motor increasingly combines IT function employees with industrial engineers to redesign key processes, as it did recently on a redesign of the pans warehousing process [1]

Electronic Expert System in Universal Life Insurance Underwriting at Saman Insurance Company

Universal Life Plan is a whole life regular premium plan with a pre-defined death benefit (called Sum Assured) payable on the event of the death of the policyholder in addition to the Cash Value. The policyholder can change the death benefit and the amount/timing of premium payments from time to time.

In this article using new technology Microsoft SharePoint in underwriting universal life is described.

Microsoft SharePoint is a Web application platform developed by Microsoft, First launched in 2001. SharePoint has historically been associated with intranet content management and document management, but recent versions have significantly broader capabilities. SharePoint comprises a multipurpose set of Web technologies backed by a common technical infrastructure. By default, SharePoint has a Microsoft Office-like interface, and it is closely integrated with the Office suite. The web tools are designed to suits non-technical users. SharePoint can be used to provide intranet portals, document & file management, collaboration, social networks, extranets, websites, enterprise search, and business intelligence. It also has system integration, process integration, and workflow automation capabilities (Wikipedia).

One of the most important properties of this portal is in defining work flows (such as underwriting process, registering proposal…) and monitoring the state of a proposal at any time.

Microsoft SharePoint is integrated with other Microsoft products such as: Microsoft Office, Microsoft Project Server, Microsoft SQL Server, Microsoft Exchange Server, Microsoft Windows Server, Microsoft Visual Studio.

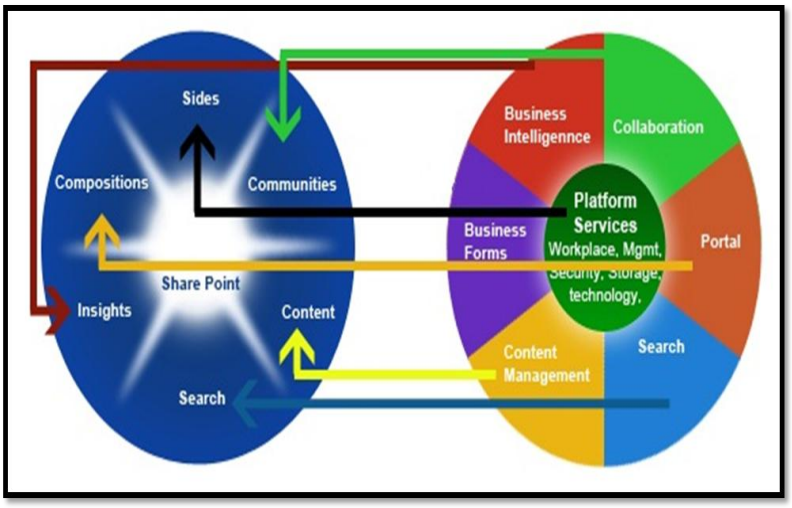


Figure 1

Some features of Microsoft SharePoint are:

- Powerful, reliable server platform
- Powerful, fast search engine
- Flexible web server
- Content Management
- Workflows engine

There are several ways to implement processes in SharePoint. We use Nintex workflow engine. Nintex Workflow adds a drag-and-drop workflow designer, connectivity and advanced workflow features to the Microsoft SharePoint platform. Business users and IT Professionals alike will be empowered to quickly and easily automate business processes; from a simple leave approval request, to complex integration across external applications, cloud services and data sources.

For designing life proposal we use Microsoft Office InfoPath.

First we designed life proposal in InfoPath (Figure 2).

This InfoPath file consists of several pages to register insured and policyholder's properties, as paper based proposals.

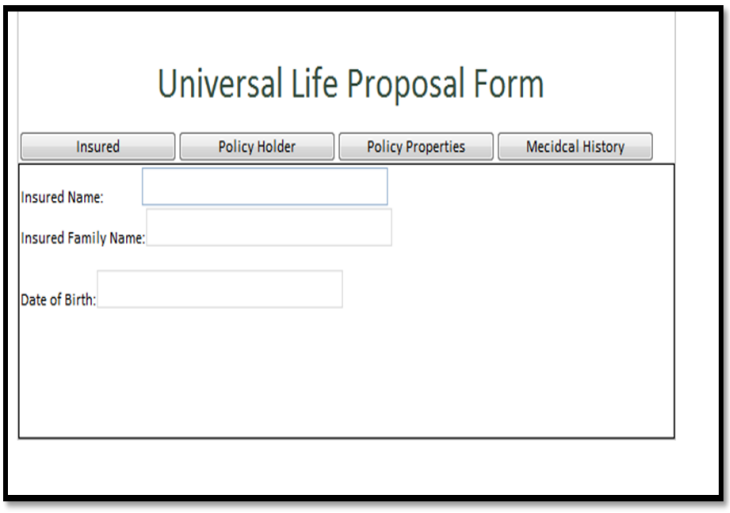


Figure 2

All agents and sales channels have access to this InfoPath form via SharePoint portal. They enter all data fields of the proposal in this form. Further, it's possible to attach the scanned proposal form to the portal (Figure 3).

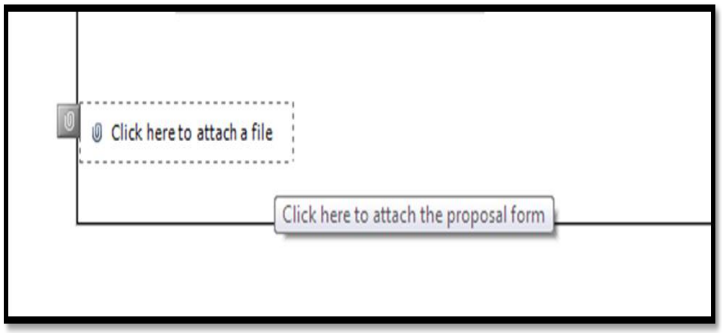


Figure 3

After submitting InfoPath form, proposal data are exported to a list in SharePoint and upon this proposal's status will be 'Initial Registration' (Figure 4).



Figure 4

Consequently, agents and sale channels' permission change to read only and they can only follow the underwriting process or print the referral letter to lab. The general required medical tests will be determined by the system as well.

Now, underwriters can see the proposal in the portal and start the underwriting process. There are some workflows (designed by Nintex) that underwrites should start with. The insured age, basic required medical tests; occupational as well as medical substantial rates are specified by workflows (Figure5).

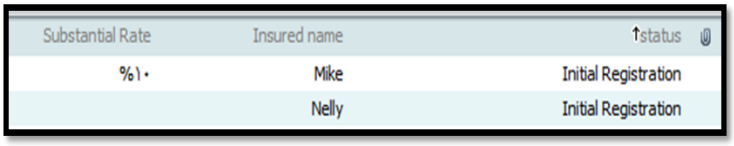


Figure5

Several underwriters and doctors may survey the proposal, so all steps of survey are automated in SharePoint portal by Nintex. Due to the integration of SharePoint and Microsoft Outlook all processes can be monitored by email. For underwriter and doctor, it suffices to use their emails and answer some questions about the specified proposal.

Below, underwriting steps are summarized:

1) Starting underwriting workflow (Figure 6).



Figure 6

2) Registering underwriter's comments (Figure 7).

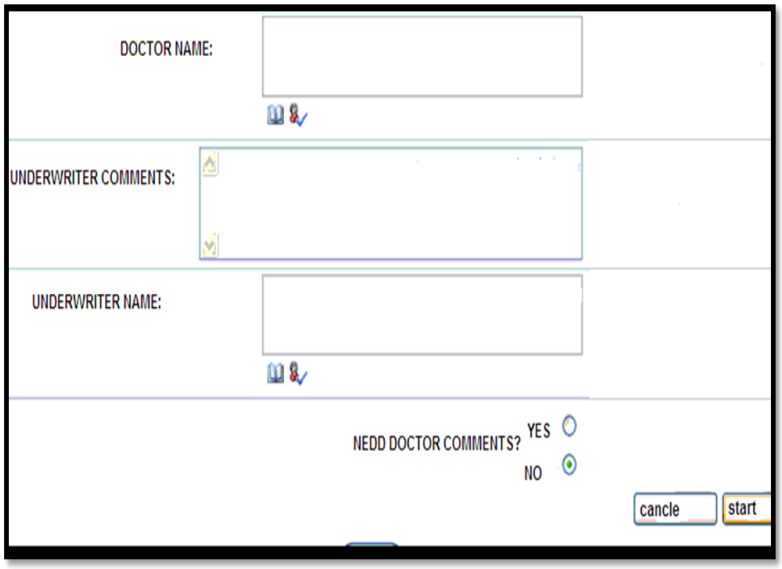


Figure 7

3) Sending email to doctor and registering doctor's comments (Figures 8 and 9).

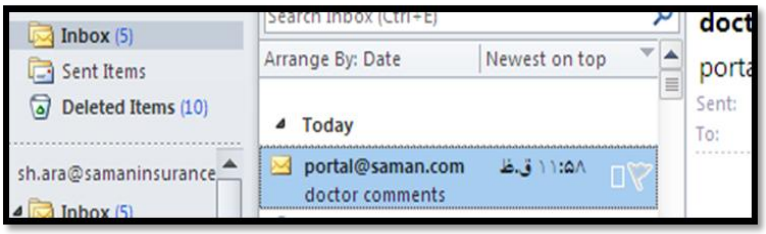


Figure 8

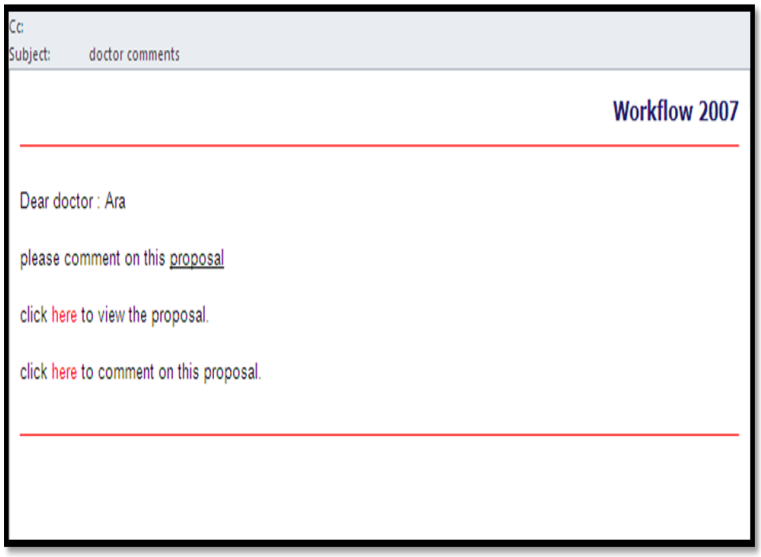


Figure 9

4) After gathering all comments (from underwrites, doctors…) the policy is ready to be issued. Underwriter checks all comments and decides to issue the policy under general and special conditions and substantial rate as well. Underwriter may decide not to issue the policy because of the high risk. In each case, the proposal's status will change (Figure 10).

status	Insured name
Initial Registration	Mike
Issued by Substantial Rate	John
Not Issuable	Sarah

Figure 10

Conclusion

In this article, we showed how to use simple technologies such as SharePoint to automate underwriting process and to reduce its cost.

Below are our suggestions to speed up the processes:

1. Culture of using information technology should be integrated into insurance industry and become conventional.
2. Insurance companies should improve their systems and train the staff instead of outsourcing.

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Fitting Generalised Linear Models to Car Claims data

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Abstract.
Generalised linear models (GLMs) overcome the limitations of Normal regression models since they can accommodate any distribution that is a member of the exponential family. These models allow transformation of the response variable through the canonical link function. This paper presents two GLMs to analyze a data set provided by a car insurance company. The first model is a lognormal regression model that relates claim size to a number of demographic, car-related and policy-related predictors and the second model is a Poisson regression model that relates the number of claims filed by a policy holder to these explanatory variables. An appropriate model that describes the aggregate claim amount in a portfolio of insurance contracts during a fixed period combines both claim size and number of claims through a compound Poisson distribution.

Key words: Poisson and Lognormal distributions, Iterative reweighted least squares algorithm, Generalized Linear Models, Compound Poisson distribution

Introduction

One of the most far-reaching contributions in statistical modelling is the concept of generalized linear models introduced by John Nelder and Robert Wedderburn (1972). These models relate the response variable to the linear predictor (non-random component) through any invertible link function and accommodate any error distribution that is in the exponential family. Analyzing car claim data using traditional ordinary least squares regression models and ANOVA methods can be problematic. Firstly the distribution of car claim size is very often right skewed and do not follow a Normal distribution; secondly the number of claims made by a policyholder is a discrete variable and would be better accommodated by a discrete distribution. GLMs, on the other hand, provide an integrated conceptual and theoretical framework that can be used to analyze both continuous and categorical response data. Logistic and Probit regression models are appropriate to analyze Binomial response data; whereas Loglinear models are suitable to analyze Multinomial and Poisson response data. The iteratively re-weighted least squares algorithm that maximizes the log-likelihood function in Generalized Linear models makes use of Fisher scoring. Although GLMs accommodate most of the assumptions of Regression models they still rely on the assumption that the responses are independent.

Estimation

The unity of several statistical methods to analyze response data that departs from the normality assumption was demonstrated by (Nelder and Wedderburn, 1972) using the idea of a generalized linear model. This section provides an outline of the properties of GLMs as a comprehensive structure.

Consider a random variable Y_i whose probability mass function, if it is discrete, or probability density function, if it is continuous is assumed to follow the form of the exponential family of distributions.

$$P(Y_i = y_i) = \exp\left[\frac{y_i\theta_i - b(\theta_i)}{a_i(\phi)} + c(y_i, \phi)\right]$$

It is assumed that the responses Y_i are independent and identically distributed and the distribution of each Y_i is a member of the exponential family. Moreover the known values of the explanatory variables influence the distribution of Y_i through a single linear function or linear predictor η_i

$$\eta_i = \sum_{j=1}^{p} x_{ij}\beta_j$$

It is also assumed that the mean $\mu_i = E(Y_i)$, and linear predictor η_i are related by a smooth invertible link function $g(\cdot)$.

$$\eta_i = g(\mu_i)$$

Considering the likelihood L as a function of $\boldsymbol{\beta}$, one can find the maximum of L by maximizing $\log L = \sum_{i=1}^{n} l_i$ where $l_i = \log P(Y_i = y_i)$. This is realized by solving the maximum likelihood equations $\frac{\partial l_i}{\partial \beta_j} = 0$ for $j = 1,..., p$

$$\frac{\partial l_i}{\partial \beta_j} = \frac{\partial l_i}{\partial \theta_i}\frac{\partial \theta_i}{\partial \mu_i}\frac{\partial \mu_i}{\partial \eta_i}\frac{\partial \eta_i}{\partial \beta_j}$$

Since $l_i = \frac{y_i\theta_i - b(\theta_i)}{a_i(\phi)} + c(y_i, \phi)$, $\mu_i = E(Y_i) = b'(\theta_i)$ and $\eta_i = \sum_{j=1}^{p} x_{ij}\beta_j$ then

$$\frac{\partial l_i}{\partial \theta_i} = \frac{y_i - b'(\theta_i)}{a_i(\phi)} = \frac{y_i - \mu_i}{a_i(\phi)},\ \frac{\partial \mu_i}{\partial \theta_i} = b''(\theta_i) \text{ and } \frac{\partial \eta_i}{\partial \beta_j} = x_{ij}$$

Moreover, by setting $d_i = \frac{\partial \eta_i}{\partial \mu_i}$ then $\frac{\partial l_i}{\partial \beta_j} = \frac{y_i - \mu_i}{a_i(\phi)}\frac{1}{b''(\theta_i)}\frac{1}{d_i}x_{ij}$

Since $\sigma_i^2 = \text{var}(Y_i) = a_i(\phi)b''(\theta_i)$ then

$$\frac{\partial l_i}{\partial \beta_j} = \frac{y_i - \mu_i}{\sigma_i^2 d_i}x_{ij}$$

The log-likelihood function is maximized by solving the equations $\frac{\partial l}{\partial \beta_j} = 0$ for $j = 1,..., p$. Let U_j be the scores with respect to parameters β_j such that

$$U_j = \frac{\partial l}{\partial \beta_j} = \sum_{i=1}^{I}\frac{\partial l_i}{\partial \beta_j} = \sum_{i=1}^{I}\frac{(y_i - \mu_i)x_{ij}}{\sigma_i^2 d_i}$$

In general the equations $U_j = 0$ for $j = 1,..., p$ are non-linear and they have to be solved by numerical iteration. The Newton-Raphson approach to solving these equations would be to set up an iterative scheme for the vector $\boldsymbol{\beta}$. The m^{th} approximation is given by

$$\hat{\boldsymbol{\beta}}^{(m)} = \hat{\boldsymbol{\beta}}^{(m-1)} - \mathbf{H}^{-1}\mathbf{U}^{(m-1)}$$

where $\mathbf{H} = \left[\frac{\partial^2 l}{\partial \boldsymbol{\beta}\,\partial \boldsymbol{\beta}'}\right]$ is the Hessian matrix evaluated at $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}^{(m-1)}$ and the score vector $\mathbf{U}^{(m-1)}$ is also evaluated at the previous iteration. These second derivatives are often complicated to calculate. An alternative procedure, which is sometimes simpler than the Newton-Raphson method is called the Fisher scoring technique. It involves replacing the matrix of second derivatives by its matrix of expected values where

$$\Psi_{jk} = -E\left[\frac{\partial^2 l}{\partial \beta_j \partial \beta_k}\right] = E\left[\frac{\partial l}{\partial \beta_j}\frac{\partial l}{\partial \beta_k}\right] = \sum_{i=1}^{I}\frac{x_{ij}x_{ik}}{\sigma_i^4 d_i^2}E\left(Y_i - \mu_i\right)^2$$

Since $E(Y_i - \mu_i)^2 = \text{var}(Y_i) = \sigma_i^2$ then $\Psi_{jk} = \sum_{i-1}^{I}\frac{x_{ij}x_{ik}}{\sigma_i^2 d_i^2}$

So $\boldsymbol{\Psi} = \left[\frac{\partial l}{\partial \boldsymbol{\beta}} \frac{\partial l}{\partial \boldsymbol{\beta}'}\right]$ can be expressed as $\mathbf{X'WX}$, where $\mathbf{W}$ is a diagonal matrix whose diagonal elements are $w_{ii} = 1/(\sigma_i^2 d_i^2)$ and $\hat{\boldsymbol{\beta}}^{(m)} = \hat{\boldsymbol{\beta}}^{(m-1)} + \left[\boldsymbol{\Psi}^{(m-1)}\right]^{-1} \mathbf{U}^{(m-1)}$. Multiplying throughout by $\boldsymbol{\Psi}^{(m-1)}$ we get $\boldsymbol{\Psi}^{(m-1)}\hat{\boldsymbol{\beta}}^{(m)} = \boldsymbol{\Psi}^{(m-1)}\hat{\boldsymbol{\beta}}^{(m-1)} + \mathbf{U}^{(m-1)}$. The right hand side of this iterative scheme can be written as:

$$\boldsymbol{\Psi}^{(m-1)}\hat{\boldsymbol{\beta}}^{(m-1)} + \mathbf{U}^{(m-1)} = \sum_i \frac{x_{ij}}{\sigma_i^2 d_i^2}\left[\sum_k x_{ik}\hat{\beta}_k^{(m-1)} + d_i\left(y_i - \mu_i\right)\right] = \mathbf{X'Wz}$$

where $z_i = \sum_k x_{ik}\hat{\beta}_k^{(m-1)} + d_i\left(y_i - \mu_i\right) = \eta_i + d_i(y_i - \mu_i)$

$$\left(\mathbf{X'WX}\right)\hat{\boldsymbol{\beta}}^{(m)} = \mathbf{X'Wz} \text{ and } \hat{\boldsymbol{\beta}}^{(m)} = \left(\mathbf{X'WX}\right)^{-1}\mathbf{X'Wz}$$

The generalized linear model maximum likelihood estimators are obtained by an iterative weighted least squares procedure.

Application

To implement the theory of GLMs we utilized a data set provided by a local insurance car company, to relate the number of claims filed annually by each policyholder and the claim size made by each claimant to a number of predictors. These explanatory variables included policy-related variables (cover subscription, premium paid annually by policyholder), car-related variables (number of owned cars, engine size) and individual covariates (age of policyholder). Premium paid annually and claim size are continuous variables; number of claims and number of owned cars are discrete variables; whereas cover subscription (Third party only, third party fire and theft, fully comprehensive), engine size (less than 1100, 1100-1500, more than 1500cc) and age of policy holder (18-30, 31-50, more than 50 years) are categorical variables.

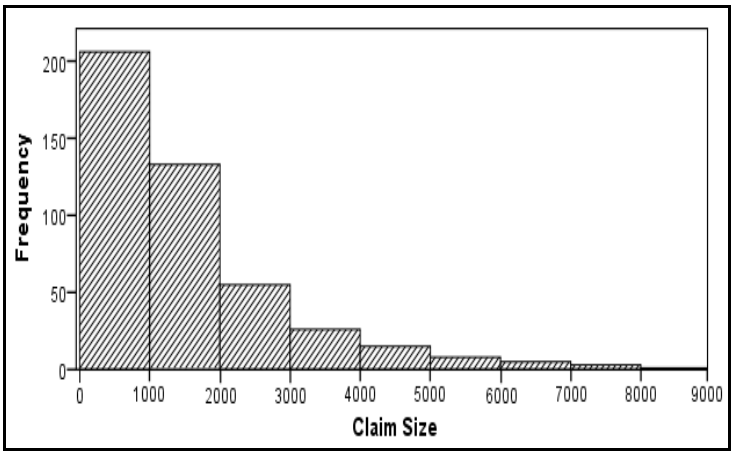


Figure 1. Frequency distribution of car claim size

The data comprised 9107 policyholders of which 497 made at least one claim. The frequency distribution of claim size, displayed in Figure 1, was considerably right skewed and fitting a Normal regression model to this data was not deemed appropriate. EasyFitXL was used to identify the best contender for the distribution of claim size using the Kolmogorov Smirnov, Anderson Darling and Chi squared criteria. Undoubtedly the Lognormal distribution is identified as the best fitting distribution for claim size.

Table 1. Goodness of fit using Lognormal and Normal distributions

Distribution	Kolmogorov Smirnov		Anderson Darling		Chi squared	
	Statistic	Rank	Statistic	Rank	Statistic	Rank
Lognormal	0.0231	1	0.2676	1	4.1677	2
Normal	0.1701	17	26.127	17	131.54	18

Figure 2 displays that 94.5% of policyholders made no car claims throughout a year, 5.2% made one claim and the remaining 0.3% made at least two claims. The Poisson distribution is appropriate for the number

of claims made yearly by a policyholder because this random variable is discrete, does not have an obvious maximum and making a claim is considered to be a rare event.

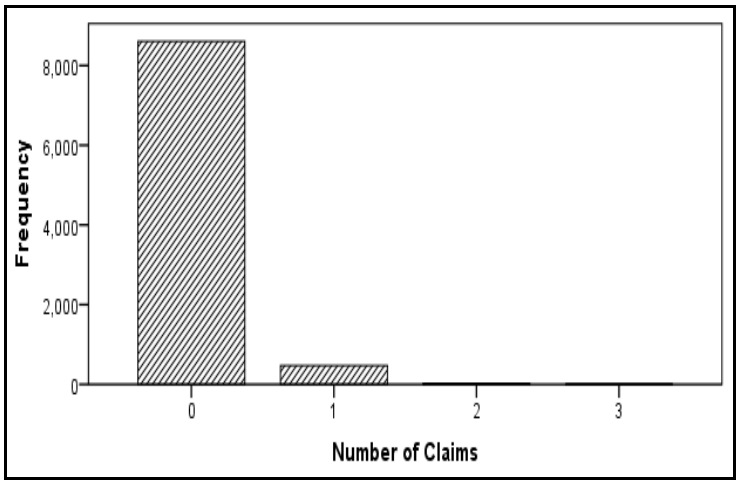


Figure 2. Frequency distribution of number of car claims

Fitting a Lognormal regression model to car claim size

If the logarithm of the response variate $\log(y_i)$ has a Normal distribution with mean μ_i and variance σ^2 then y_i has a lognormal distribution. Assume that claim sizes $y_i,\ i = 1,...,n$ are independent and follow a lognormal distribution whose density function is:

$$f(y_i) = \frac{1}{y_i\sqrt{2\pi\sigma^2}} \exp\left[\frac{(\log y_i - \mu_i}{2\sigma^2}\right]^2 \qquad y_i > 0.$$

The mean and variance of y_i are respectively

$$E(Y_i) = \exp\left(\mu_i + 0.5\sigma^2\right) \text{ and } \mathrm{Var}(Y_i) = \exp\left(2\mu_i + \sigma^2\right)\left[\exp\left(\sigma^2\right) - 1\right]$$

If an identity link function $(\eta_i = \mu_i)$ is assumed, one can compute the linear predictor η_i, the predicted values μ_i, the iterative weights $w_{ii} = 1/\sigma_i^2$ and the working variate $z_i = y_i$, at each iteration.

Table 2. Tests of model effects

Predictor	Wald Chi-Square	df	P-value
Intercept	6957.628	1	0.000
Engine size	3.875	2	0.144
Age-Group	2.205	2	0.332
Cover	0.380	2	0.827
Premium paid annually	4.988	1	0.026

The tests of model effects displayed in table 2 indicate that the premium paid annually (in thousands of Euro) is the best predictor of car claim size. This is followed by engine size, age of policyholder and cover subscription. This four-predictor model explain 15.7% of the total variance in the responses indicating that there are other important predictors that contribute significantly in explaining variation in car claim sizes.

Table 3. Parameter estimates and corresponding 95% confidence intervals

Term	Parameter	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
Intercept	6.898	0.113	6.676	7.120
Engine size (less than 1100cc)	-0.236	0.140	-0.510	0.038
Engine size (1100-1500cc)	0.033	0.099	-0.162	0.229
Engine size (More than 1500cc)	0	.	.	.
Age-Group (18-30 years)	0.254	0.171	-0.081	0.589
Age-Group (31-50 years)	0.047	0.097	-0.144	0.237
Age-Group (More than 50 years)	0	.	.	.
Cover (Third party only)	-0.064	0.110	-0.280	0.152
Cover (Third party fire and theft)	0.007	0.130	-0.247	0.262
Cover (Fully comprehensive	0	.	.	.
Premium	0.351	0.157	0.043	0.659
(Scale)	0.830	0.059	0.723	0.953

The parameter estimates, displayed in table 3, reveal interesting contrasts between the levels of the main effects. Policyholders that pay large premiums tend to make bigger claims than other policyholders; young claimants tend to make bigger claims than older ones. Moreover, policyholders possessing small sized engine cars tend to make smaller claims than those possessing large sized engine cars and claimants who insure their cars under a third party cover tend to make smaller claims than those who insure their cars under a third party fire and theft or a fully comprehensive cover. The residual plot displayed in Figure 3 exhibits no systematic patterns indicating no model misspecifications. Approximately 95% of all Pearson residuals lie between the ± 2 threshold values which conform to what is expected.

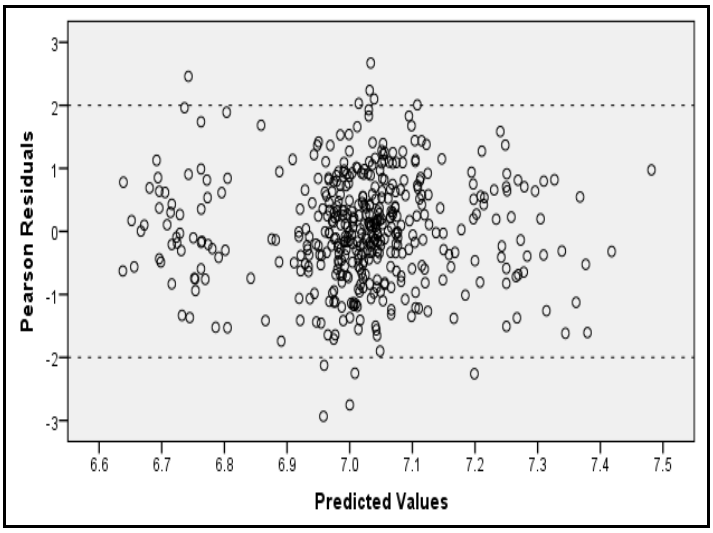


Figure 3. Residual plot

Fitting a Poisson regression model to number of claims

Suppose that the response variates $y_i,\ i = 1,...,n$ are independent and Poisson distributed $y_i :\ Poi(\mu_i)$ whose mass function is:

$$P(Y_i = y_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}$$

The log link is the canonical link function for a random variable having a Poisson distribution $\eta_i = \log \mu_i$. Given the fact that the mean and variance of y_i are both μ_i, one can compute the linear predictor η_i, the predicted values μ_i, the working variate $z_i = \eta_i + (y_i - \mu_i)/\mu_i$ and the iterative weights $w_{ii} = \mu_i$ at each iteration.

Table 4. Tests of model effects

Predictor	Wald Chi-Square	df	P-value
Intercept	2.050	1	0.152
Age-Group	3.094	2	0.213
Cover	47.627	2	0.000
Number of cars owned	15.198	1	0.000
Premium paid annually	6.558	1	0.010

The tests of model effects displayed in table 4 indicate that cover subscription is the best predictor of number of car claims. This is followed by the number of cars owned by policyholder, the premium paid annually (in thousands of Euro) and the age of policyholder. This four-predictor model explain 29.6% of the total variance in the responses indicating that there are other important predictors that contribute significantly in explaining variation in the number of car claims made annually by a policyholder.

Table 5. Parameter estimates and corresponding 95% confidence intervals

Term	Parameter	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
Intercept	-0.486	0.5841	-1.631	0.659
Age-Group (18-30 years)	0.131	0.1657	-0.193	0.456
Age-Group (31-50 years)	0.169	0.0967	-0.020	0.358
Age-Group (More than 50 years)	0	.	.	.
Cover (Third party only)	-0.667	0.1321	-0.926	-0.408
Cover (Third party fire and theft)	-0.675	0.1129	-0.896	-0.454
Cover (Fully comprehensive	0	.	.	.
Number of cars owned	2.228	0.5716	1.108	3.349
Premium paid annually	0.001	0.0002	0.000	0.001
(Scale)	1			

The parameter estimates, displayed in table 5, reveal interesting contrasts between the categories of the predictors. Policyholders that pay larger premiums tend to make bigger claims than other policyholders; old claimants tend to make fewer claims than younger ones. Moreover, policyholders who insure their cars under a Fully Comprehensive cover have a tendency to make more claims than others and the number of claims made annually increases with the number of cars owned by the policyholders. Approximately 95% of all Pearson residuals lie between the ± 2 threshold values which conform to what is expected.

The compound Poisson distribution

The decomposition of the aggregate claim amount *S* paid annually by the insurer allows consideration of the number of claims and corresponding claim amounts separately. A practical advantage of this is the factors affecting claim numbers and claim amounts may well be different. For instance, a prolonged spell of bad weather may have a significant effect on claim numbers but little or no effect on the distribution of individual claim amounts. On the other hand, inflation may have a significant effect on the cost of repairing cars, and hence on the distribution of individual claim amounts, but little or no effect on claim numbers.

If the random variable *N*, representing number of claims made by policyholders has a Poisson distribution with parameter λ and $X_1, X_2, ..., X_N$ are corresponding claim amounts which are assumed independent and identically distributed, then the total claim amount $S = \sum_{i=1}^{n} X_i$ has a compound Poisson distribution. This is obtained by marginalizing the joint distribution of (S, N) over *N*, which in turn is attained by joining the marginal distribution of *N* with the conditional distribution $S|N$. If the number of claims *N* has a Poisson distribution with mean λ and the total claim amount *S* has a compound Poisson distribution with parameter λ then,

$$E[N] = Var[N] = \lambda$$

$$M_N(t) = Ee^{tN} = \sum_{k=1}^{\infty} e^{tk} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{k=1}^{\infty} \frac{(\lambda e^t)^k}{k!} = e^{\lambda(e^t-1)}.$$

The expectation of *S* is obtained by applying the identity $E[S] = E[E[S \mid N]]$

$$E[S \mid N = n] = \sum_{i=1}^{n} E[X_i] = nm_1$$

and

$$E[S \mid N] = Nm_1$$
$$E[S] = E[Nm_1] = E[N]m_1 = \lambda m_1$$

The variance of *S* is obtained by using $Var[S] = E[Var[S \mid N]] + Var[E[S \mid N]]$

$$Var[S \mid N = n] = \sum_{i=1}^{n} Var[X_i] = n(m_2 - m_1^2)$$

and $Var[S \mid N] = N(m_2 - m_1^2)$

$$Var[S] = E[N(m_2 - m_1^2)] + Var[Nm_1] = (m_2 - m_1^2)E[N] + m_1^2 Var[N] = \lambda m_2$$

The moment generating function of *S* is the moment generating function of *N* evaluated at $\log M_X(t)$.

$$M_S(t) = Ee^{tS} = E[E[e^{tS} \mid N]] = Ee^{tNX} = E(M_X(t))^N =$$
$$= M_N(\log M_X(t)) = e^{\lambda(M_X(t)-1)}.$$

A very important property is that the sum of the independent compound Poisson random variables is itself a compound Poisson random variable. If $S_1, ..., S_n$ are independent random variables each having a compound Poisson distribution with parameters λ_i and $F_i(x)$ for $i = 1, ..., n$ where $F_i(x)$ is the distribution of individual claim amounts then $A = \sum_{i=1}^{n} S_i$ also has a compound Poisson distribution with parameters $\Lambda = \sum_{i=1}^{n} \lambda_i$ and $F(x) = \frac{1}{\Lambda} \sum_{i=1}^{n} \lambda_i F_i(x)$. Table 6 displays the distribution of claim size and the average number of car claims per age group and per cover.

Conclusion

The GLMs identified one significant predictor (premium paid annually) for claim size and three significant predictors (cover subscription, number of cars owned, premium paid annually) for number of filed claims. One of the limitations of this study is that the explanatory variables explained a small portion of the variation in the response variables. Indeed other explanatory variables, for instance, speed of car before impact and driving behaviour would have improved predictions if they were recorded.

Table 6. Distributions of claim sizes and mean number of claims

Age Group	Distribution of claim size	Mean number of claims
18 – 30 years	$\ln N(1277.5,\ 0.829)$	λ_1 = 0.05108
31 – 50 years	$\ln N(1117.4,\ 0.963)$	λ_2 = 0.06195
More than 50 years	$\ln N(1039.1,\ 0.967)$	λ_3 = 0.05334

Cover subscription	Distribution of claim size	Mean number of claims
Third party only	$\ln N(1112.9,\ 0.895)$	λ_1 = 0.03757
Third party fire and theft	$\ln N(1123.6,\ 0.871)$	λ_2 = 0.03907
Fully comprehensive	$\ln N(1117.4,\ 0.942)$	λ_3 = 0.08201

An alternative approach to address the data heterogeneity is by fitting Latent class models. These models assume that the observed data are actually composed of several homogeneous segments that are mixed together in unknown proportions. The segments are considered latent (unobserved) because the number of clusters and the number of individuals they comprise are unknown. The objective is to estimate the true number of segments and derive a prediction regression model for each segment using the expectation-maximization (EM) algorithm that maximizes the expected log-likelihood function. Indeed the main advantage of using these models over traditional clustering techniques is that estimation and segmentation are carried out simultaneously.

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Moderating Risk and Vagueness in the Process of Evaluating NPV using Fuzzy Decision Making

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Abstract.
In this paper we provide a fuzzy-based decision making for approximating NPV in the capital budgeting process. Many techniques and models are being used in this process for the purpose of determining risk and vagueness. They are not able to incorporate and value linguistic variables, however. The capital budgeting process has a couple of characteristics, such as the usual long-term cycle and the approximation of many variables, carried out by various managers and having a direct impact on the project's NPV. In order to display the usefulness of fuzzy logic and the valuation of experts expressed through qualitative opinions, i.e. linguistic variables in the process of capital budgeting, a study is presented for the prediction of the Net Present Value of one capital investment project.
Key words: Risk, Vagueness, Capital Budgeting, Fuzzy Decision, Triangular Numbers.

Introduction

Capital budgeting implies a complex process of predicting and anticipating future events that may occur, the probability of their occurrence, as well as planning for how those events will influence the capital budgeting process. A number of authors have studied the complexity of the capital budgeting process and all the risks that can have an impact on the capital investment (Merna and Smith 1996, quoted in Merna and Al-Thani 2005, 15). According to Ehsanifar, Motallebi, & Rezazad (2011), there exist "traditional methods, [that] initially, [and] may be seen as limited… when it comes to uncertainty dimension, nevertheless they are the basis for the development of sophisticated techniques which, at present time, have been used with great success". This subject has been treated by various authors who have conducted studies and examined novel techniques and methods in order to determine the variance of the probabilistic NPV, including, but not limited to Young and Contreras (1975), Zinn et al. (1977) Spahr (1982), Buck and Askin (1986), Tufecki and Young (1987) etc.

Fuzzy logic was first introduced by Lotfi Askar Zaheh (1965) by implementing fuzzy sets theory. With the application of fuzzy set theory to the capital budgeting process Chiadamrong (1999) presented a more efficient way for overcoming fixed-based variables within connected predictions and calculations. What is particularly interesting and meaningful is that fuzzy theory enables an evaluation of someone's opinion expressed through words i.e. linguistic variables. It is a bridge between modern quantitative theory and practical, real-life problem solving. McNeill and Thro contend that "many concepts are better defined by words than by mathematics, and fuzzy logic and its expression in fuzzy sets provide a discipline that can construct better models of reality" (1994, p. 11). It is precisely the valuation of someone's subjective opinion expressed through linguistic variables that may be one of the greatest contributions of fuzzy logic to modern science. As an innovative approach, it offers a new comparative advantage for qualitative variables and is on its way to being established as a standard method for moderating risk and vagueness in the capital budgeting process. The first part of this paper will therefore lay the foundations of triangular fuzzy numbers and fuzzy set theory. The second part will examine the mechanics behind implementing fuzzy decisions on the evaluation of net present value. Part three concludes.

Triangular Fuzzy Numbers and Fuzzy Set Theory

Gao, Zhang and Cao defined that "a fuzzy number is simply an ordinary number whose precise value is somewhat uncertain" (2009). In order to calculate fuzzy logic, many forms of numbers can usually be employed, but triangular fuzzy numbers and trapezoidal fuzzy numbers are the ones most often in use. A triangular fuzzy

number represents a set of three possible values, i.e. points and can be presented through real numbers A (a, b, c), where each number ranges between 0 and 1. A triangular fuzzy set can be interpreted as a membership function of $\mu_A(X)$, and the more that their value is closer to unity, the higher the grade of membership of the x in A. The membership function of triangular number is interpreted as:

$$\mu_A(X)=\begin{cases}0, & x<a\\ \dfrac{x-a}{b-a}, & a\le x\le b\\ \dfrac{c-x}{c-b}, & b\le x\le c\\ 0, & x>c\end{cases} \qquad 1.1$$

To get a crisp interval from an α -cut operation, it shall be obtained as $\forall\alpha\in[0,1]$ this can be written as:

$$\begin{aligned}&\frac{a^{(\alpha)}-a}{b-a}=\alpha,\\ &\frac{c-c^{\alpha}}{c-b}=\alpha\end{aligned} \qquad 1.2$$

From where it can be shown by the following expression:

$$\begin{aligned}a^{\alpha}&=(b-a)\alpha+a\\ c^{\alpha}&=-(c-b)\alpha+c\end{aligned} \qquad 1.3$$

Finally arriving at:

$$\begin{aligned}X_{\alpha}&=\left[a^{\alpha},c^{\alpha}\right]\\ X_{\alpha}&=\left[(b-a)\alpha+a,-(c-b)\alpha+c\right]\end{aligned} \qquad 1.4$$

The fuzzy set from above represents a collection of related items which belong to the set $\mu_A(X)$ of different degrees. In contrast to traditional set theory, moderate fuzzy set theory allows a partial, i.e. graded belonging to related item, and function values of relation are represented between intervals $[0,1]$ as shown in the following figure:

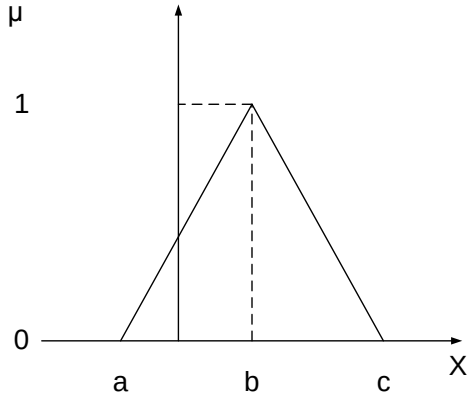


Figure1 Triangular fuzzy number X = (a, b, c)

The comparative advantage for the use of fuzzy logic in the capital budgeting process lies in that fuzzy sets can be described and operated as linguistic variables, i.e. terms used in fuzzy rules. Fuzzy rules are word like tall, high, large, good medium etc. that are fuzzy, i.e. qualitative and not precisely determined. Fuzzy variables can be described as human opinions that are fuzzy or other linguistic opinions and statements which are not precise or exactly measured.

Implementing Fuzzy Decisions in the Evaluation of Net Present Value

The vast majority of scientific research conducted on the matter of capital budgeting and determining the most widely acknowledged methods in the decision-making process of accepting or refusing an investment, emphasizes the importance of net present value and fuzzy logic as one of, if not the most, popular new methods for the decision-making process. The level of net present value depends on various factors, and only excellent cooperation within all division managers inside the company under the direction of the project manager can bring out a successful investment. These various variables that can influence the success of the capital investment have different origins:

- Sale; quantity and type of products sold,
- Price sale; depends on competition, period of year, purchase power, etc.,
- Variable and fixed cost; depends on level of sale and production,
- Cost of capital; it is directly connected to financial leverage, to the state on market, etc.,
- Risks; economic, political, ecological, etc.

Sometimes the financial experts can give different, and every so often, even totally opposite opinions (with great differences—they can move from positive to negative) on the net present value. Thus when a certain financial expert expresses an opinion given by means of a confidence interval, because all calculated NPV contains a certain amount of uncertainty. It should not be forgotten either, that all decisions and calculations are made under great subjective perception, thinking and judgment. According to the Merna and Al-Thani paper, "Subjectivity is a key factor in assessing risk. Whether a problem is perceived in terms of potential gains or losses [it] will not be assessed as a simple mathematical calculation of the problem, but as a subjective fear, often linked to the consequences of outcomes." (25-26). To reduce the uncertinty of predicted net present value a company can hire counter experts to reduce risk od just one opinion.

Table 1 Probabilities of the NPV

α	Minimum and maximum presumptions
0	Minimum 200.000
0.1	Low-low
0.2	Medium-low
0.3	Hi-low
0.4	Low-medium
0.5	Medium-medium
0.6	Hi-medium
0.7	Low-high
0.8	Medium-high
0.9	High-high
1	Very high 1.000.000

Table 2 Experts' Triples

		,3	,4
	,6	,9	
	,3	,5	,7
	,7	,8	
	,8	,9	
		,2	,3
	,5	,5	,5
	,3	,6	,9
	,4	,8	,9
0			,2

In the following case study, a company has proposed the net present value expressed in monetary units from a minimum (200.000) to a maximum (1.000.000). To reduce individual subjectivity, the company has engaged 10 experts, who have expressed their opinion in linguistic form by triples means of confidence with the range $[0,1]$, as shown in Table 2. Afterwards, it is possible to draw up the confidence triples gathering $\underset{\sim}{x}$ for every level $\alpha \in [0,1]$ the number of times that each presumption is repeated. Calculations of presumptions are presented in Table 3:

Table 3 Number of times of presumptions

α	Worst	Most likely	Best
0	1	1	1
0,1	0,7	1	1
0,2	0,7	1	1
0,3	0,7	0,9	0,9
0,4	0,5	0,6	0,8
0,5	0,4	0,6	0,7
0,6	0,3	0,6	0,6
0,7	0,2	0,5	0,6
0,8	0,1	0,5	0,5
0,9	0	0,3	0,5
1	0	0,1	0,3

Then through a formal matematical precedure it is possible to calculate ε(A) using means of the expected experts' triplets presumtions—x what can be written in modified formulae presented by Gil-Lafuente (2005)

$$\varepsilon(\underset{\sim}{A}) = A_x + (A^x - A_x) \cdot \varepsilon(\underset{\sim}{x})$$

Table 4 Construction of triangular fuzzy numbers on opinions of the experts

α	Worst	Most likely	Best
0	1.000.000,00	1.000.000,00	1.000.000,00
0,1	760.000,00	1.000.000,00	1.000.000,00
0,2	760.000,00	1.000.000,00	1.000.000,00
0,3	760.000,00	920.000,00	920.000,00
0,4	600.000,00	680.000,00	840.000,00
0,5	520.000,00	680.000,00	760.000,00
0,6	440.000,00	680.000,00	680.000,00
0,7	360.000,00	600.000,00	680.000,00
0,8	280.000,00	600.000,00	600.000,00
0,9	200.000,00	440.000,00	600.000,00
1	200.000,00	280.000,00	440.000,00
	534.545,45	716.363,64	774.545,45

In this way, the following triples (534,555; 716.364; 774.546) of the predicted net present value of the observed capital investment should be accepted as the aggregate estimation of the experts' opinions on NPV.

Conclusion

The modern business environment, which thrives on uncertainty and vagueness, needs a new set of financial modeling tools in order to anticipate and control the complexity of the decision-making process. Fuzzy logic offers a solution to the exigencies of the added complexity and subjectivity as it is a byproduct of the inability of classical logic to deal with behavioral biases and conventional rule-of-thumb heuristics present in managerial boardrooms.

The case study presented in this paper offers one more argument in favor of fuzzy logic, as it presents an ideal set of mathematical and logical tools for the calculating and determining of net present value in the capital budgeting process. By using the opinions of financial experts, it reduces imprecision and applies a formal decision-making method to real-life situations. In addition, the vagueness and risk that arise from individual subjectivity responsible for predicting, planning, calculating and decision-making in capital budgeting can be much better understood when using the presented method. Having examined the most commonly used methods for determining net present value by applying fuzzy logic concepts, it can be concluded that implementing capital budgeting decisions in the perpetually changing business world of today should be approached from a completely different angle. Fuzzy logic concepts and triangular fuzzy numbers should be recommended in the decision-making process of management, as they can not only complement, but single-handedly determine the net present value and profitability of a certain investment project.

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The Role of Sukuk (Islamic Bonds) in Economic Development

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Abstract.

Recent innovations in Islamic finance have changed the dynamics of the Islamic finance industry especially in the area of securitization, known as Sukuk or Islamic bonds. In the last ten years *Sukuk* have become increasingly popular both as means of raising government finance through sovereign issues, and as a way for companies to obtain funding through offering corporate *sukuk*. Beginning modestly in the year 2000 with total three sukuk worth USD 336 million to reach to a total volume of USD 197.203 billion, in all currencies, by the end of December 2010. The primary market of Sukuk grew between 2001 and 2010 at annual compounded rate (CAGR) of 57.0% which is 14.3% of the global Islamic finance assets. It has developed as one of the most significant mechanisms for raising finance in the international capital markets through Shariah-compliant structures. Today, local and multinational corporations, sovereign bodies and financial institutions are issuing sukuk as an alternative to syndicated financing, making sukuk an essential subset of the international financial system. Well-developed Sukuk markets would enhance access to financial services, deepen capital markets and create Sharia-compliant alternative for small and/or risk-averse investors.

This paper will trace the development of the fast growing Sukuk market and review the factors which have contributed to its development; in addition to exploring its role in the economic development of the Sukuk-issuing countries.

Keywords: Sukuk, Islamic Bonds, Securitization, Islamic Finance, Economic Development
JEL Classifications: E44, G31, G32

Introduction to Islamic Shariah

Shariah means the path to follow Allah's law. So, the Shariah is simply the Islamic law/jurisprudence. It controls, rules and regulates both public and private behaviour, such as prayers, fasting, Zakah, Hajj and many other religious matters. It can be also used as a guide to settle international disputes, conflicts and wars. Islamic Shariah derives its rules and principles from several resources, among which Quraan is the first (primary) one, and Sunnah is the second one.

Islamic Finance

In the Islamic finance, Shariah *compliant* services are the financial products that meet the requirements of Islamic law. Demand among Muslims for financial products and services that conform to the Shariah has led Islamic financial institutions to create Islamic financial alternatives based on Shariah and satisfy Muslims financial needs. The main characteristics of Islamic Finance can be summarized as follws:

- Making money from money is prohibited. Therefore, Islamic financial institutions cannot lend money to, or receive money from, someone and expect to benefit, which means that all types of interest (usury), known as "Riba" in Islam, are prohibited.
- The linking of finance to productivity, which means that wealth can only be generated through legal trade and/or investment in assets
- The desirability of profit sharing. Gains are shared between the party providing the capital and the party providing the expertise
- The prohibition of unethical investments, such as: Alcohol, Gambling, Tobacco, Pork products, and Sensual entertainment
- The emphasis on equitable contracts

Sukuk (Islamic Bonds)

Investment Sukuk (as defined by AAOIFI) are certificates of equal value representing undivided shares in ownership of tangible assets, usufruct and services. Sukuk should be tied to an eligible Sharia contract and would represent undivided ownership rights to the underlying assets and/or services

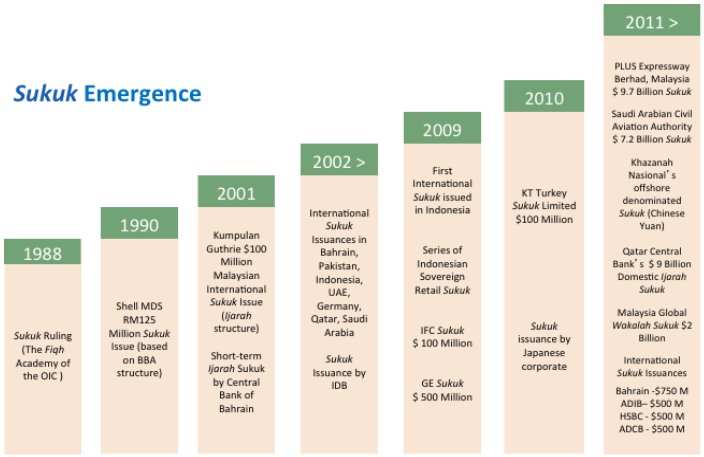
The Council of the Islamic Fiqh Academy of the Organization of Islamic Conference (OIC) in its Fourth Session held in Jeddah, Kingdom of Saudi Arabia from 6 – 11 February, 1988 legitimized the concept of Sukuk, which paved the way for an alternative source of financing to meet the needs of Islamic issuers and investors who are not allowed under the Shariah principles to invest in conventional bonds. Since that date, Sukuk market has dramatically grown up to become one of the fastest emerging alternative instruments and a significant capital markets tool which are increasingly used by governments, government-held entities and corporations, not only in the Middle East and South East Asia, but in a number of other countries across the globe.

In the year **1990**, the first Sukuk was issued in Malaysia by Shell MDS a foreign owned, non-Islamic corporation, with a value of RM 125 million (equivalent to $30 million), based on the principle of ***Bai' Bithaman Ajil.*** In the year **2000**, Sudanese Pound (SDG) 77 million domestic sovereign short-term Government ***Musharaka*** Certificates (GMC's) were issued by the Sudanese Government. In the year **2001**, the Sukuk market went international with the issuance of the first United States Dollar (USD) denominated international sovereign Sukuk ***Al Ijarah*** of $100 million (5 year tenor), and a series of domestic sovereign short-term (less than 1 year tenor) Sukuk ***Al Salam*** issued by the Central Bank of Bahrain on behalf of the Government of Bahrain. In the same year, the first 5 year international corporate Sukuk Al Ijarah of $150 million were issued by a Malaysian corporate Kumpulan Guthrie Berhad or Guthrie Group Limited. After that, many sovereign and corporate Sukuk issues (domestic and international) have been offered in various jurisdictions such as the United Arab Emirates (UAE), Saudi Arabia, Indonesia, Qatar, Pakistan, Brunei Darussalam, Singapore, Kuwait etc. Since then, the Sukuk market emerged as one of the main sections of the IFSI and a lot of innovation took place in its structures such as Ijarah, Musharaka, Mudaraba, Hybrid, Exchangeable and Convertible.

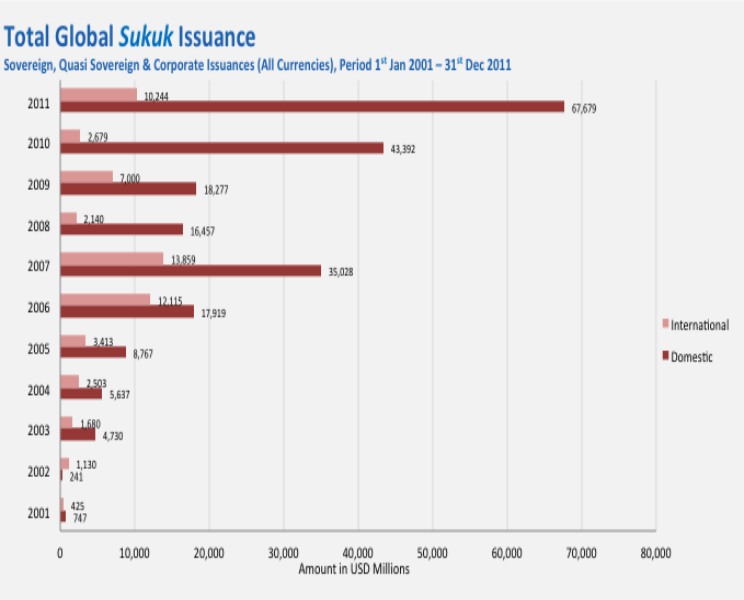
As far as the domestic Sukuk market is concerned, Malaysia has the lion's share in terms of both volume and value. Malaysia remains as the largest domestic issuer with 72% by value of domestic Sukuk issuance. The remaining 28% splits between a number of issuers, such as Sudan, Saudi Arabia, UAE, Bahrain, Brunei, Pakistan. Short-term Sukuk (maturity of 1 year or less) are essential for liquidity management purposes. Sudan is the leader in domestic short-term Sukuk issuances followed by Bahrain, Brunei and Malaysia. Bahrain has been the most active market within the GCC region and is a regular issuer of short-term Sukuk Al Salam and Sukuk Al Ijarah.

Overview & Trends in the Global Sukuk Market

a. The following chart refers to the historical trends in the global Sukuk market:



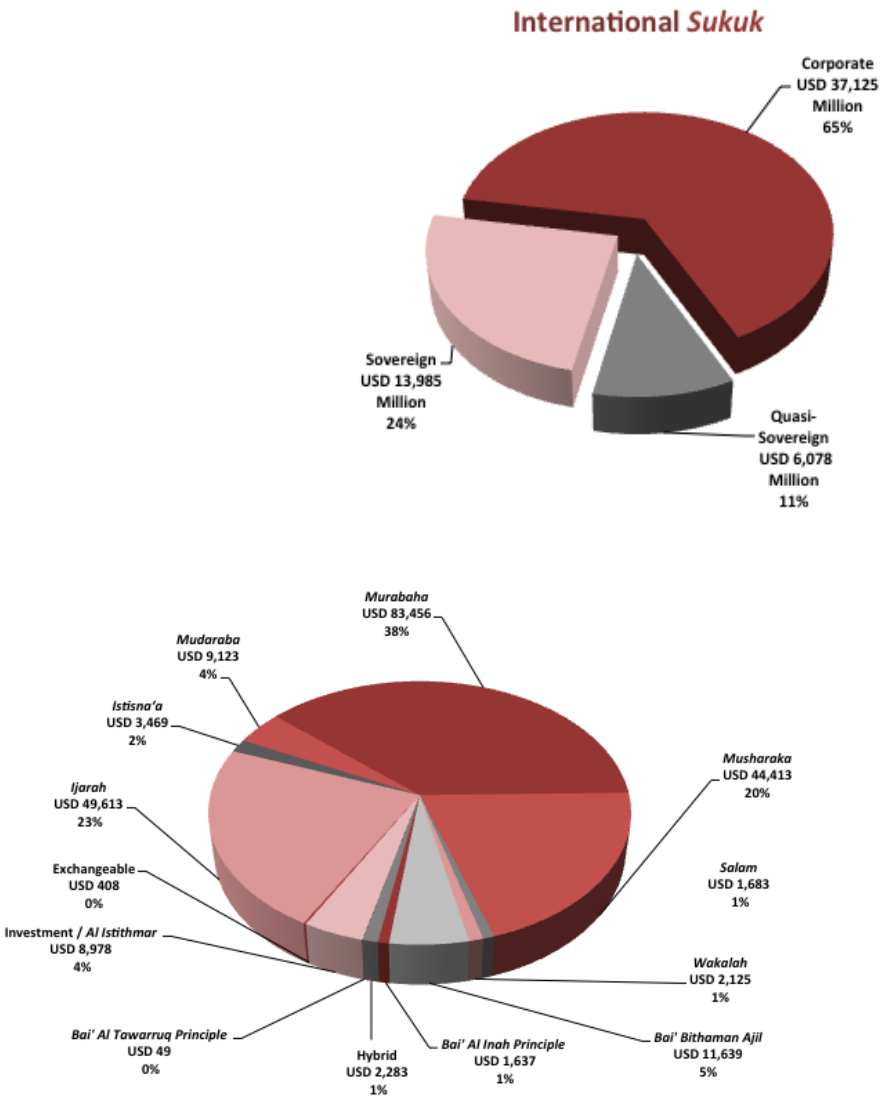
b. The following diagram represents the total global Sukuk issuance:



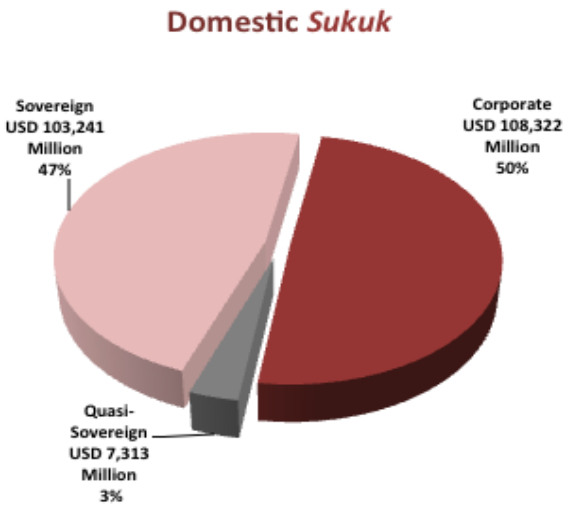
c. The following table shows a Country-wise breakdown of total global *Sukuk* issuance by volume:

Country	Number of Issues	Volume (US $ Million)	% of Total Value
Malaysia	2285	169,878	61.54%
UAE	43	32,946	11.93%
Saudi Arabia	25	17,099	6.19%
Sudan	23	13,344	4.83%
Qatar	7	11,568	4.19%
Bahrain	234	10,654	3.86%
Indonesia	75	6,780	2.46%
Pakistan	39	4,568	1.65%
Cayman Islands	6	2,679	0.97%
Kuwait	11	2,026	0.73%
Jersey	2	1,250	0.45%
Brunei Darussalam	21	1,176	0.43%
USA	3	767	0.28%
Turkey	2	450	0.16%
UK	2	271	0.10%
Singapore	5	192	0.07%
Germany	1	123	0.04%
Jordan	1	119	0.04%
Japan	1	100	0.04%
Gambia	49	30	0.01%
Iran	1	28	0.01%
Yemen	2	15	0.01%
Grand Total	2838	276,064	100%

d. The following chart displays a breakdown of total global Sukuk issuance by issuer status:



e. The following diagram displays a structural breakdown of domestic *Sukuk* issuance (% by volume)



Stoynov processes of second kind – definition and simulations

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Abstract: Stoynov distribution of second kind and the corresponding Stoynov process are presented. Simulation and graphics for both the distribution and the process in R language are done.

Key words: Stoynov distribution of second kind, Stoynov process of second kind, simulation

1.Introduction.

In Stoynov (2013), Stoynov process (of first kind) is defined and simulated. Here, we define and simulate Stoynov process of second kind.

2. Stoynov (switch time) family of distributions –STF(n,β).

We say that a random variable ξ with probability mass function $f_\xi(x)$ has distribution of $ST(n,\beta)$ family and denote this fact $\xi \in STF(n,\beta)$, if the probability mass function of ξ is given by the formula

$$f_\xi(x) = \begin{cases} \sum_{k=1}^{n+1} P(D^n = k) f_\xi(x \mid D^n = k) = \sum_{k=1}^{n+1} P(D^n = k) f_{G^k}(x), x \geq 0 \\ 0, x < 0. \end{cases}$$

where G^k are random variables with probability mass function $f_{G^k}(x) = f(k,\beta)$ and D^n are random variables taking values $k = 1,\ldots,(n+1)$ with probabilities $P(D^n = k) = \frac{C(n,\beta)n!}{\beta^k (n-k+1)!}, k = 1,\ldots,(n+1)$ where the coefficients $C(n,\beta)$ are given by the formulas:

$$C(n,\beta) = \frac{1}{I(n,\beta)},$$

$$I(0,\beta) = \frac{1}{\beta},$$

$$I(n,\beta) = \frac{1}{\beta} + \frac{n}{\beta} I(n-1,\beta), n = 1,2,\ldots$$

Also, variables $\tilde{D}^n = D^n - 1$ can be introduced taking values $k = 0,\ldots,n$ with probabilities

$$P(\tilde{D}^n = k) = \frac{C(n,\beta)n!}{\beta^{k+1}(n-k)!}, k = 0,\ldots,n.$$

Then the probability mass function $f_\xi(x)$ of ξ may be presented also by the formula

$$f_\xi(x) = \begin{cases} \sum_{k=0}^{n} P(\tilde{D}^n = k) f_\xi(x \mid \tilde{D}^n = k) = \sum_{k=0}^{n} P(\tilde{D}^n = k) f_{G^{k+1}}(x), x \geq 0 \\ 0, x < 0. \end{cases}$$

Here for G^k we may adopt different families of distribution. For example, if we take $G^k \in \Gamma(k,\frac{1}{\beta}) \equiv Erlang(k,\frac{1}{\beta})$, i. e. $\xi \mid D^n \equiv Erlang(D^n,\frac{1}{\beta})$, we obtain a distribution which we will call $ST1(n,\beta)$ distribution, having probability density function

$$f_{\xi}(x)=\begin{cases}C(n,\beta)e^{-\beta x}(1+x)^{n},\ x\geq 0\\ 0, x<0\end{cases}.$$

Indeed, we have:

$$C(n,\beta)e^{-\beta x}(1+x)^{n}=C(n,\beta)e^{-\beta x}\sum_{k=0}^{n}\binom{n}{k}x^{k}=\sum_{k=0}^{n}C(n,\beta)\binom{n}{k}x^{k}e^{-\beta x}=$$

$$=\sum_{k=0}^{n}\frac{C(n,\beta)n!x^{k}e^{-\beta x}}{k!(n-k)!}=\sum_{k=0}^{n}\frac{C(n,\beta)n!\beta^{k+1}x^{k}e^{-\beta x}}{\beta^{k+1}(n-k)!k!}=$$

$$=\sum_{k=0}^{n}\frac{C(n,\beta)n!}{\beta^{k+1}(n-k)!}\frac{\beta^{k+1}x^{k}e^{-\beta x}}{k!}=$$

$$=\sum_{k=0}^{n}P(D^{n}=k+1)f_{G^{k+1}}(x)=$$

$$=\sum_{k=1}^{n+1}\frac{C(n,\beta)n!\beta^{k}x^{k-1}e^{-\beta x}}{\beta^{k}(n-k+1)!(k-1)!}=$$

$$=\sum_{k=1}^{n+1}\frac{C(n,\beta)n!}{\beta^{k}(n-k+1)!}\frac{\beta^{k}x^{k-1}e^{-\beta x}}{\Gamma(k)}=\sum_{k=1}^{n+1}\frac{C(n,\beta)n!}{\beta^{k}(n-k+1)!}\frac{\beta^{k}x^{k-1}e^{-\beta x}}{(k-1)!}=$$

$$\sum_{k=1}^{n+1}P(D^{n}=k)f_{G^{k}}(x).$$

Special cases of $ST1(n,\beta)$ distribution are $ST1(0,\beta)\equiv Exp(\beta)$ and $ST1(1,\beta)\equiv Lindley(\beta).$ The case $n=2$ is considered for example in Stoynov (2011) where Moment Generating Function of $ST1(2,\beta)$ is derived.

$ST1(n,\beta)$ distribution in the case $n=2$ is introduced in Stoynov (2010) and generalized in Stoynov (2012a) and Stoynov (2012b). Different application of $ST1(n,\beta)$ distribution are given in Stoynov (2011) and Kraynukov and Stoynov (2011, in Russian). $ST1(n,\beta)$ is defined and simulated in Stoynov (2013).

As another example we may consider negative binomial distribution for G^{k}, i. e. $G^{k}\in NB(k,e^{-\beta}).$ In this case, $\xi\mid D^{n}\equiv NB(D^{n},e^{-\beta})$ and we obtain a distribution which we will call $ST2(n,\beta)$ distribution.

Special cases of $ST2(n,\beta)$ distribution are

$$ST2(0,\beta)\equiv NB(1,e^{-\beta})$$

and

$$ST2(1,\beta)\equiv\frac{\beta}{\beta+1}NB(1,e^{-\beta})+\frac{1}{\beta+1}NB(2,e^{-\beta}).$$

We say that a random variable ξ has a negative binomial distribution (Pólya distribution) and write this $\xi\in NB(r,p)$, if its probability satisfies

$$P(\xi=k)=\binom{r+k-1}{k}p^{r}(1-p)^{k},\ k=0,1,2,\ldots$$

We may interpret this random variable as a counter of the failures till the r-th success in a sequence of Bernoulli trials.

As a third example we may consider $G^{k}\equiv\delta_{k}(x)$ - random variable which takes value k with probability one. Then $\xi\equiv D^{n}\in D^{n}(\beta).$ In this case, we say that random variable ξ has $ST3(n,\beta)$ distribution and denote $\xi\in ST3(n,\beta).$

Special cases of $ST3(n,\beta)$ distribution are $ST3(0,\beta)\equiv D^{0}\equiv 1$ and $ST3(1,\beta)\equiv D^{1}.$

3. Stoynov ST(n,β) processes.

We say that a process $X(t)$ is $ST1(n,\beta)$ ($ST2(n,\beta)$) and denote this fact $X(t)\in ST1(t;n,\beta)$ ($X(t)\in ST1(t;n,\beta)$), if it has the following properties:

1) $X(0)=0.$

2) The process has independent increments, i. e. for

$$0<t_1<t_2<\cdots<t_n$$

the random variables

$$X(t_1)-X(0), X(t_2)-X(t_1),\ldots, X(t_n)-X(t_{n-1})$$

are independent.

3) The process is continuous stochastically (continuous in probability), i. e.

$$\lim_{t\to s} X(t)=X(s),$$

where the limit is taken in probability.

4) $X(t)$ is pure jump process with jumps at times $T_{i'}, i=1,2,\ldots$ and jump sizes $\Delta X(T_i)=1.$

5) The intervals between two jumps are

$$\tau=T_i-T_{i-1}\in ST1(n-1,\beta)(ST2(n-1,\beta)), i=0,1,\ldots,T_0=0$$

The first three conditions mean that $ST1(n,\beta)$ ($ST2(n-1,\beta)$) process is an additive process. If we replace condition 4) with condition

4') $X(t)$ is pure jump process with jumps at times $T_{i'}, i=1,2,\ldots$ and jump sizes $\Delta X(T_i)=Y_i,$ where Y_i are independent and identically distributed random variables,

we say that $X(t)$ is compound $ST1(n,\beta)$ ($ST2(n,\beta)$) process.

It is interesting to see for $ST(n,\beta)$ processes the distribution of the number of jumps till time t which we denote $N^n(t).$

We start with $ST1(n,\beta)$ process. When $X(t)\in ST1(t;n,\beta)$, we consider first the case $X(t)\in ST1(t;1,\beta)$. In this case, $\tau=T_i-T_{i-1}\in ST1(0,\beta)\equiv Exp(\beta), i=0,1,\ldots,T_0=0$. In this case the process $N^1(t)$ is a Poisson process $N(t)$ and for it we have

$$P(N^1(t)=k)=\frac{(\beta t)^k}{k!}e^{-\beta t}.$$

In the case when $X(t)\in ST1(t;n,\beta)$ the intervals between two jumps are

$$\tau=T_i-T_{i-1}\in ST1(n-1,\beta)\equiv Erlang(D^n,\beta), i=0,1,\ldots,T_0=0.$$

First we will consider the case where

$$\tau=T_i-T_{i-1}\in Erlang(n,\beta), i=0,1,\ldots,T_0=0.$$

In this case, we have that the process which counts the jumps of an Erlang process till time t which we denote $N^E(t)$ is a Poisson process $N(t)$ with omitted $n-1$ jumps and actual jumps at every $n-$th jump of the Poison process, so

$$P(N^E(t)=k)=P(N(t)=kn)=\frac{(\beta t)^{kn}}{(kn)!}e^{-\beta t}.$$

So, in the case $X(t)\in ST1(t;n,\beta)$ we have

$$P(N^n(t)=k)=P(N(t)=kn)=\frac{(\beta t)^{kn}}{(kn)!}e^{-\beta t}.$$

4. Simulation of Stoynov process of second kind.

To make simulation of $ST2(n,\beta)$ process, the following algorithm can be applied:

1. Define interval $[0,T]$ of the simulation.
2. Set $k=0.$
3. While $\sum_{i=1}^{k}\tau_i<T$ do:

   3.1. Set $k=k+1$

   3.2. Generate $\tau_k\in ST2(n-1,\beta).$

3.3. Set $Y_k = 1$ for standard $ST2(n,\beta)$ process or simulate Y based on a given distribution f for compound $ST2(n,\beta)$ process.

Then the trajectory of $X(t) \in ST2(t;n,\beta)$ is given by the formula

$$X(t) = \sum_{i=1}^{N(t)} Y_i,$$

where

$$N(t) = \sum_i 1_{\{T_i < T\}}.$$

Here is the code for creating graphic representation of the $ST2(n,\beta)$ process:

```
# Theta_grid_sets Geometric ,NB, ST_type
T<-20
prob=0.7
Theta_geom_dist <- rgeom(1, prob)
while(max(Theta_geom_dist)<T) Theta_geom_dist <-
c(Theta_geom_dist,max(Theta_geom_dist)+ rgeom(1, prob))
m<-length(Theta_geom_dist)
Theta_geom_dist [m]<-T

# NB
r_NB <-2
m_NB<-m/r_NB
Theta_NB<- Theta_geom_dist [r_NB]
for (i in 2:m_NB)
{
Theta_NB<- c(Theta_NB, Theta_geom_dist [i* r_NB])
}


#ST_type
ST_n<-10
ST_beta<-1
n<-20
tvec<-T*0:n/n
In_beta<-function(n,beta, recursive=TRUE)
{if (n==0) return (1/beta) else return ((1/beta)+(n/beta)*In_beta(n-
1,beta))}
Cn_beta<-function(n,beta) {1/In_beta(n,beta)}
FDn_inverse<-function(y,n,beta){
Dn_values<-1:(n+1)
Dn_prob<-1:(n+1)
for (i in 1:(n+1))
{
Dn_prob[i]<-(Cn_beta(n,beta)*factorial(i-1)/beta^i)
}
Prob_acum<-Dn_prob[1]+Dn_prob[2]
for (k in 1:n)
{
if (y< Prob_acum) return (k)
else
Prob_acum<-Prob_acum+Dn_prob[k+2]
}
return(n+1)
}


#Dn_simulation<-function(n,ST_n,ST_beta){
```

```
Dn_values<-1:(n+1)
Dn_prob<-1:(n+1)
Dn_simulated<-1:n
for (i in 1:(n+1))
{
Dn_prob[i]<-(Cn_beta(n,ST_beta)*factorial(n)/(ST_beta^i*factorial(n+i-1)))
}
for (i in 1:n)
{
St_unif_value<- runif(1, min = 0, max = 1)
Dn_simulated[i]<-FDn_inverse(St_unif_value,ST_n,ST_beta)
}
#return Dn_simulated
#}
#Dn_simul=Dn_simulation(n,ST_n,ST_beta)

#acc_ST<-Dn_simul[1]
acc_ST<- Dn_simulated[1]

Theta_ST<- Theta_geom_dist[acc_ST]

while(acc_ST<m)
{
acc_ST<-(acc_ST+Dn_simulated[i])
if (acc_ST<=m)
Theta_ST<- c(Theta_ST, Theta_geom_dist[acc_ST])
}
Theta_ST
args_n<-10000
ST_type_proces_args<-T*(0:args_n)/args_n
ST_type_proces_values<- 1:length(ST_type_proces_args)
for (i in 1:length(ST_type_proces_args))
{
ST_type_proces_values [i]<-0
for (j in 1: length(Theta_ST))
{
if (ST_type_proces_args[i]> Theta_ST[j])

ST_type_proces_values[i]<- (ST_type_proces_values[i]+1)
}
}
title<-paste("ST_type_2(", round(ST_n,1), ",",round(prob,1),
",",round(ST_beta,1), ")")
plot(ST_type_proces_args, ST_type_proces_values,xlab="x",ylab="f(x)", type='l',
main=title)
```

The graphics of a trajectory of $ST2(n,\beta)$ process for the case $n=10$ and $\beta=1$ is given in Fig 1.
The graphics of a trajectory of $ST2(n,\beta)$ process for the case $n=5$ and $\beta=2$ is given in Fig 2.

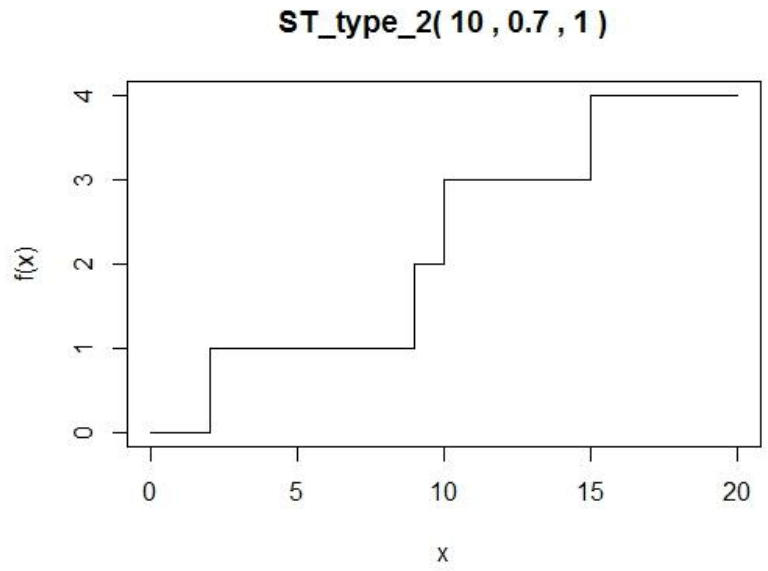


Figure 1. The graphics of $ST2(n,\beta)$ distribution for the case $n=10$ and $\beta=1$.

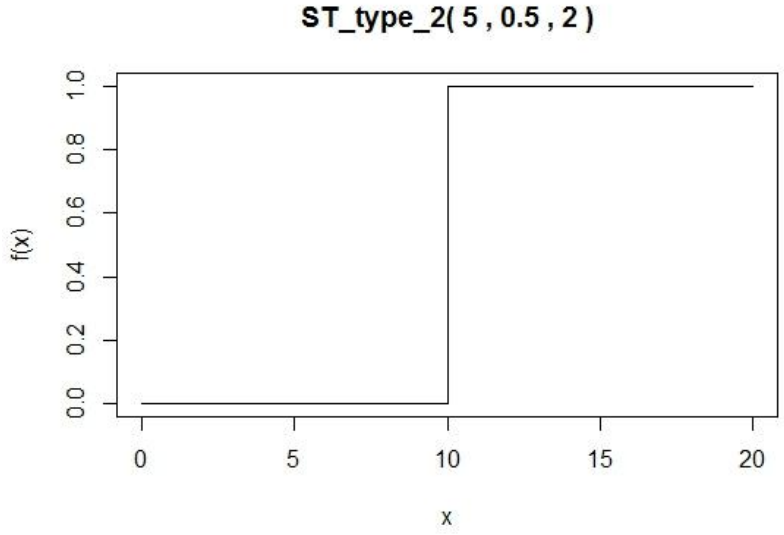


Figure 2. The graphics of $ST2(n,\beta)$ distribution for the case $n=5$ and $\beta=2$.

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