ONE MODELLING TECHNIQUE APPROACH FOR OPERATIONAL RISK PREDICTION

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Abstract

In this paper we approximated operational risks in banks with artificial neural networks. Typically, operational risk losses in banks are grouped in a number of categories: People risk (Incompetence, Fraud), Process risk (Model risk, Transaction risk, Operational control risk), and IT risks. These categories can be further aggregated to the three levels of nominal, ordinary and exceptional operational risks. The Basel Committee on banking supervision at the Bank for international settlements imposes to financial institutions to meet capital requirement based on VaR estimates. Value at Risk (VaR) is very simple in itself, but it is inadequate when applied to operational risk. Until now, no one single method developed for the assessment of operational risk has managed to provide satisfactory results. In these circumstances, new alternative models are needed that can assess small and medium values, predict the probability of extreme events, reflect asymmetric behavior at the output and analyze nonlinearity of the input-output values. As the comprehensive and accurate solution for this problem we suggest using artificial neural networks. Neural network methods, offer a powerful alternative to linear models for forecasting, classification, and risk assessment in finance and economics. In this paper the neural network model is presented. This model is based on back propagation neural network with sequence generator for input data. We observed four different categories of losses: internal causes of business breakdown, external causes of business breakdown, IT risks and non-adhering to working practice and mistakes in execution and management. The data were analyzed separately and cumulatively. The results show that predicted values are very close to real data and that the model can be used in real financial environment.

Keywords: Modelling, Neural network, Operational risk, Risk prediction.

Presenting Author's biography

Ana Savić. She is currently a Ph.D. student in the Faculty of Economics, University of Belgrade. She obtained as M.Sc. degree from the same faculty. Her research interests include risk management, operational risks in banks, and quantification of financial risks. She is the author and coauthor of several economic papers. Now, she works in ICT College in Belgrade, and before that she used to work in several banks.

1 Introduction

The assessment and control of operational risk differs from that of other banking risks. This is because of the heterogeneous nature of operational risk which covers all internal and external causes of business breakdown, and the inherent inability to entirely predict the consequences of a total crash on a financial institution [1,2]. This makes the creation of a systematic and coherent system of assessment and regulation very complex [3].

Operational events are very specific, so even the standard assessment model 'Value at Risk' (VaR) [4], which is very simple in itself, is inadequate when applied to operational risk [5]. Until now, no one single method developed for the assessment of operational risk has managed to provide satisfactory results. Even after the clear separation between the severity and frequency of operational risks, the operational VaR which is generated through these two processes does not provide optimal results.

In these circumstances, new alternative models are needed that can assess small and medium values, predict the probability of extreme events, reflect asymmetric behavior at the output and analyze nonlinearity of the input-output values [6]. These obvious asymmetries and nonlinearities cannot be assumed away.

As the only comprehensive and accurate solution for this problem we suggest using neural network modeling [5,7]. Neural network methods, offer a powerful alternative to linear models for forecasting, classification, and risk assessment in finance and economics [8].

Neural networks can approximate a multifactorial function in such a way that creating the functional form and fitting the function are performed at the same time, unlike nonlinear regression in which a fit is forced to a prechosen function. This capability gives neural networks a decided advantage over traditional statistical multivariate regression techniques [8,9].

2 Measuring operational risk losses

Operational risk is "the risk of losses resulting from inadequate or failed internal processes, people and systems or from external events" [1] in the bank. It can also be defined as "a measure of the link between a firm's business activities and the variation in its business results" [3].

Modern risk management in general, and operational risk management more in particular, is confronted with serious challenges which bring the analysis of heterogeneous events to the forefront.

Operational risk deals mainly with tail events rather than central projections or tendencies, reflecting aberrant rather than normal behavior. For this reason, the exposure to operational risk is less predictable and very hard to model.

During the last years, risk management in banks gained great importance due to increase in the volatility of financial markets and a desire to assess less fragile financial system. Value-at-Risk (VaR) models have been implemented throughout the financial industry, as the key and standard measure that financial analysts use to quantify risk [1,2,10]. VaR is defined as the predicted worst-case loss at a specific confidence level over a certain period of time [11]. It is a number that indicates how much a financial institution or an investor can lose with a given probability over a given time horizon. The Basel Committee on banking supervision at the Bank for international settlements imposes to financial institutions to meet capital requirement based on VaR estimates [1].

It is crucial to provide accurate estimates. If the risk is not properly estimated, these can lead to a sub-optimal allocation. A key element to VaR calculation is the distribution function chosen for the specific change that leads to some observed result [10,12]. Over years, VaR became a common means of communication about aggregate risk within an institution.

Unfortunately, the recent banking crisis highlighted some problems underlying VaR–based risk management [13]. At this point, risk managers are primarily concerned with the risk of low-probability events that could lead to catastrophic losses [14,15,16]. Traditional VaR methods tend to ignore extreme events and focus on risk measures that accommodate the whole empirical distribution of returns [17].

Recent financial crisis imposed a need to review and make recommendations for reforming international approaches to the way banks are regulated, and the risks are measured. Taking an in-depth look at the causes of the financial crisis, some recommendations were made to the international community, to enhance regulatory standards, supervisory approaches and international cooperation and coordination. The recent Turner Review, "A regulatory response to the global banking crisis", published in March 2009 by the FSA [17], among many things, emphasizes the bad handling of operational events and the problems underlying VaR–based risk management. Some relevant quotes are:

"Misplaced reliance on sophisticated maths. The increasing scale and complexity of the securitized credit market was obvious to individual participants, to regulators and to academic observers. But the predominant assumption was that increased complexity had been matched by the evolution of mathematically sophisticated and effective techniques for measuring and managing the resulting risks. Central to many of the techniques was the concept of Value-at-Risk (VaR), enabling inferences about forward–looking risk to be drawn from the observation of past patterns of price movement. This technique, developed in the early 1990s, was not only accepted as standard across the industry, but adopted by regulators as the basis for calculating trading risk and required capital, (being incorporated for instance within the European Capital Adequacy Directive). There are, *however, fundamental questions about the validity of VAR as a measure of risk . . .*"

"*The use of VAR to measure risk and to guide trading strategies was, however, only one factor among many which created the dangers of strongly procyclical market interactions.* More generally the shift to an increasingly securitized form of credit intermediation and the increased complexity of securitized credit relied upon market practices which, while rational from the point of view of individual participants, increased the extent to which procyclicality was hard–wired into the system".

"*Non–normal distributions*. However, even if much longer time periods (e.g. ten years) had been used, it is likely that estimates would have failed to identify the scale of risks being taken. Price movements during the crisis have often been of a size whose probability was calculated by models (even using longer term inputs) to be almost infinitesimally small. This suggests that the *models systematically underestimated the chances of small probability high impact events. ...* it is possible that *financial market movements are inherently characterized by fat–tail distributions*. *VaR models need to be buttressed by the application of stress test techniques which consider the impact of extreme movements* beyond those which the model suggests are at all probable."

A typical profile of losses caused by operational risk contains extreme losses in addition to frequent cases of low values losses [13]. Banks divide operational risk losses into: expected loses (EL) which are covered by net profit, and unexpected losses (UL) which are covered by risk reserves through core capital and/or hedging [13].

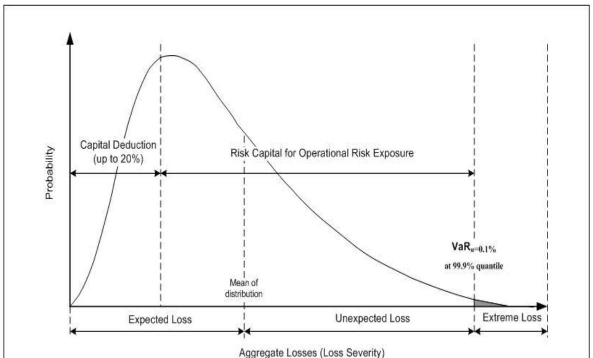


Fig.1. Typical loss profile due to operational risk [13]

And finally there is "extreme" or catastrophic loss, which is not covered and can possibly be protected through insurance. The operational risk loss is represented by the graph in Figure 1[2,13] :

In reality, an analysis of operational risk data for their density, distribution, tail, mean, variance, mode, skewness and kurtosis [2,12], shows that these data do not follow the pattern of normal distribution for parametric values, but instead produce the best fit curve with a strong positive skew, as represented in Figure 2.

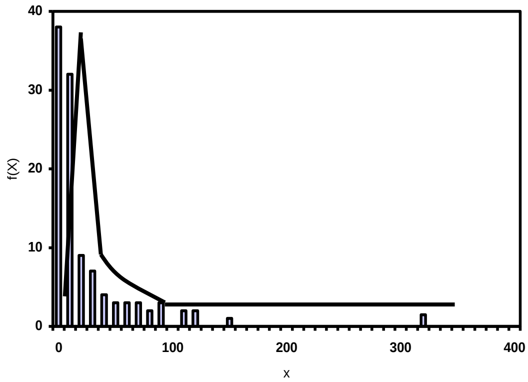


Fig.2. Operational losses represented as modelled continuous density

Typically, operational risk losses in banks are grouped in a number of categories (People risk: Incompetence, Fraud. Process risk: Model risk, Transaction risk, Operational control risk. IT risks). These categories can be further aggregated to the three levels of nominal, ordinary and exceptional operational risks [1].

One of the main tasks of operational risk management is to help to avoid large losses due to breakdowns in systems and controls, i.e. to predict all types of operational risks, even exceptional ones [14,15,16]. Looking back in time, many of the largest losses incurred by investment banks have happened due to operational risk [3]. These famous losses include Societe Generale (5,4 billion $), Sumimoto Corporation (2.6 billion $), Barings bank (1.4 billion $), Orange County (1,7 billion $), BCCI (10 billion $), Allied Irish Banks (0.7 billion $), Daiwa bank (1.1 billion $)…

Based on the previous graphs, and supported also by a definition of operational risk that includes a very heterogeneous group with a large number of unconnected events, one must bear in mind that the nature of operational risk is fundamentally different from that of credit and market risks. Finally, confirmed by exact measurements, we can conclude that it is highly unlikely that a classical Gaussian distribution, used to measure other type of risks, can be used for operational risks. The analysis of operational risk requires different types of distributions to be used, like logarithmic functions, Weibull, Pareto or alpha-stable distributions, although many authors use Poisson or Binomial distribution

[10]. These distributions can be very useful for modeling some operational events (extremes or high frequency/low severity events), but assessing overall measure of operational risk still remains very challenging task.

We suggest that the standard measurement of VaR, although conceptually very simple, when applied to operational risk will not fulfill expectations. No other currently available methods can produce satisfactory results. Even after the clear separation of two main elements which are functionally aggregated in the VaR assessment - the severity and frequency of operational events - it was not possible to obtain optimal results. A logarithmic expression of operational events failed to assist in the modeling of operational risk due to its strong nonlinearity, as mentioned above. The VaR, although being a standard measure of risk in banks, must be adjusted when used for operational risk.

Under these circumstances new alternative models are needed, ones that can measure events of small and medium value and at the same time be able to predict the probability of extreme events, to reflect an asymmetrical distribution of events. As the comprehensive and accurate solution for this problem we suggest using artificial neural networks.

Using evolutionary computation with neural network models greatly enhances the likelihood of finding globally optimal solutions, and thus predictive accuracy [5,8,18].

3 The use of artificial neural networks in financial environments

Neural network methods, coming from the brain science of cognitive theory and neurophysiology, offer a powerful alternative to linear models for forecasting, classification, and risk assessment in finance and economics [8]. A neural network is a highly complex nonlinear system [19].

The computational power and methods for more accurate diagnostics, forecasting, and control are available with neural networks methodology, especially in volatile, increasingly complex and multidimensional environments, such are financial ones [18].

A major focus in financial market research today is volatility and forecasting, rather than return. Volatilities, as proxies of risk, are asymmetric and nonlinear.

We can go beyond linearity and normality in our assumptions with the use of neural networks. For that reason, the aim of the model that will be presented is to gain predictive power concerning operational risks in banks [8].

The basic idea is that reactions of economic decision makers are not linear and proportionate, but asymmetric and nonlinear, to changes in external variables [6]. Neural networks *approximate* this behavior of economic and financial decision making in a very intuitive way.

In this important sense neural networks are different from classical econometric models [8].

In the neural network model, one is not making any specific hypothesis about the values of the coefficients to be estimated in the model, nor, for that matter, any hypothesis about the functional form relating the observed regressor x to an observed output y. Most of the time, the interpretation of the meaning of the coefficients estimated in the network cannot be made in the same way we can interpret estimated coefficients in ordinary econometric models, with a well-defined functional form. In that sense, the neural network differs from the usual econometrics [12], where considerable effort is made to obtain accurate and consistent estimates of particular parameters or coefficients.

The difference between a neural network and the other approximation methods is that the neural network makes use of one or more hidden layers, in which the input variables are squashed or transformed by a special function, known as a logistic or log sigmoid transformation [19,20]. While this hidden layer approach may seem esoteric, it represents a very efficient way to model nonlinear statistical processes.

In this context, the meaning of the hidden layer of different interconnected processing of sensory or observed input data is simple and straightforward [21]. Current and lagged values of interest rates, exchange rates, changes in GDP, and other types of economic and financial news affect further developments in the economy by the way they affect the underlying subjective expectations of participants in economic and financial markets.

These subjective expectations are formed by human beings, using their brains, which store memories coming from experiences, education, culture, and other models [19]. All of these interconnected neurons generate expectations or forecasts which lead to reactions and decisions in markets, in which people raise or lower prices, buy or sell. Basically, actions come from forecasts based on the parallel processing of interconnected neurons [18].

A general function approximation theorem has been proven for three-layer neural networks [20]. This result shows that artificial neural networks with two layers of trainable weights are capable of approximating any nonlinear function [19]. This capability gives neural networks a decided advantage over traditional statistical multivariate regression techniques [7].

The neural network performs at least as well as or better than all of these more familiar methods for predicting default in credit cards and in banking-sector fragility [8], which is part of operational risks. The neural network is much more precise, relative to the other methods, across a wide set of realizations [8].

Relatively simple feed forward neural nets outperform the linear models in some cases, or do not do worse than the linear models. Since the neural networks never do appreciably worse than linear models, the only cost for using these methods is the higher computational time [8].

Generally, a network model should do better in terms of overall explanatory power than a linear model.

4 Proposed model for prediction of the operational loss system

Algorithm shown in this paper is based on well known back propagation neural network [19]. Weight coefficient corrections is realized as in [20] and given in (2, 3).

At the start, we need to calculate the local gradient and corrections of the weight coefficients for the neuron in the output layer are as follows [20]:

$$\delta_o = (y - \vartheta) \cdot \vartheta \cdot (1 - \vartheta) \quad (1)$$

Where y represents an expected value, and ϑ is the output of the neural network.

The local gradient and weight coefficient corrections for each of the neurons in the hidden layer (*hidden layer* 1, *hidden layer* 2, *hidden layer* 3, are calculated as follows [19,20]:

$$\delta_j(s) = x_j(s) \cdot (1 - x_j(s)) \cdot \sum_k \{\delta_k(s+1) \cdot w_{kj}(s+1)\} \quad (2)$$

$$\underbrace{\Delta w_{ji}(s)}_{(k+1)-step} = l_c \cdot \delta_j(s) \cdot \{x_i(s-1) + k \cdot \delta_i(s-1)\} + M(\underbrace{\Delta\omega_{ji}(s)}_{k-step}) \quad (3)$$

where $\delta_j(s)$ represents a local gradient, $x_j(s)$ is the output from the j[th] neuron of the s^{th} layer, w_{kj} is weight coefficient, $\Delta w_{ji}(s)$ is corrections of the coefficient, lc is the speed of training, k is step number, and $M()$ is the mathematical expectation.

Based on relations (1-3) we have made neural network function, which is represented as block shown on figure 3.

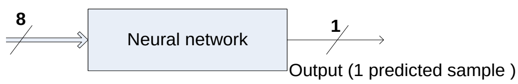


Fig.3. Block diagram of neural network

In this study we used the data on operational losses from the Basel Committee on Banking Supervision, QIS3, for 2002 [22]. The data are collected from 89 banks and cover a period of one year. According to QIS3, there are 7 different types of risk events:

1. Internal fraud
2. External fraud
3. Employee behavior and workplace security
4. Clients, products and business practice
5. Property damage
6. Systems breakdown and interruption of business
7. Execution, delivery, and process management

The losses that result from operational risk, for the purpose of this study, are classified in the following four major categories:

1. Internal causes of business breakdown,
2. External causes of business breakdown,
3. IT risks,
4. Non adhering to working practice and mistakes in execution and management.

These classifications are based on the nature of the available data; however different data would require different classifications which could include more or fewer parameters. In each of the four categories m_i and n_i are defined according to the QIS3 data. These data are used as input sequences for the model.

Walczak has examined the issue of length of the training set or in-sample data size for producing accurate forecasts in financial markets [18]. He found that for most exchange-rate predictions (on a daily basis), a maximum of two years produces the "best neural network forecasting model performance" [18]. We used a one year set.

Operational risk information is very sensitive, is kept confidential by individual banks and is not publicly available. Therefore, our study has utilized annual data obtained from the QIS3 as no weekly or daily data were available to us. Nevertheless, this algorithm can be used by other banks inputting their own data which are relevant to their specific types of losses.

4.1 Sampling algorithm

For operational risk assessment it is essential to use the input data of daily events. As the only available data that were available to us were provided in a cumulative annual format, we have had to create an additional algorithm to distribute the available cumulative annual loss data into daily losses. It was especially important during this process to keep the severity of the losses and their frequency in accordance with the actual circumstances. To achieve this, the frequency distribution for the following losses: IT, external fraud, inadequate business practice and property damage should not be random; whilst the losses due to internal fraud, employee behavior and workplace security, none adhering to working practice and mistakes in execution and management, Execution, delivery, and process management should remain random. The same should apply to the severity of the losses.

The severity of the loss of the i^{th} event (Si) is obtained by the generalization of the sequence of the n sample from the interval [0-m]. n represents a number of events which have caused individual losses in each of the risk categories in one year. The extent of the loss i^{th} can be determined by the difference between i^{th} and i-1 unit (Figure 4), and can be calculated by the following expression:

$S_i = \Delta r * \frac{m}{r_{\max}}$, where m represents a total loss per category (system breakdown), and S is the extent of the loss of 1 event in this category (Extent of the loss on the 3rd day, due to a systems breakdown)

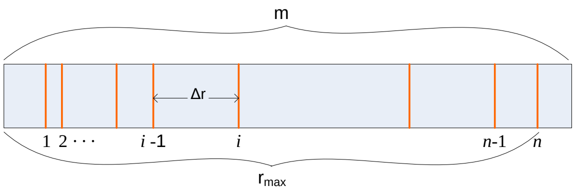


Fig.4. Extent of loss i^{th} is defined by the difference between the i^{th} and i-1 sample

The difference between two selected units follows the characteristics of the samples themselves, being interrelated to the size of the loss between consecutive events. In the case of interdependency a conditional probability is used for the sample generation.

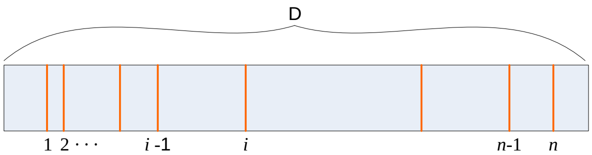


Fig.5. Frequency of operational risk events created/occurring over 250 days

We have created an event frequency for D=250 days (Figure 5), taking into account the interdependency of these events.

For the purpose of this study we have used the value of the four categories of operational risks, taking the total annual loss and the total number of events, defined as

$M = \sum_{i=1}^{4} m_i$, where m_i represents the extent of the loss within a single category.

$N = \sum_{i=1}^{4} n_i$, where n_i represents the number of events within a single category.

For these purpose, we used M = 500 000 euro, and N = 1000.

4.2 Proposed neural network model to predict losses of operational risks

In each of the four categories m_i and n_i are defined according to the QIS3 data [22]. These data are used as input sequences for the model in Figure 6.

A separate neural network based on the proposed theoretical model has been created for each of the categories, with the aim of predicting specific daily losses at its output.

The algorithm for the sample creation was used to transform the losses from the cumulative annual report (including all loss categories) into their particular categories for the daily occurrence of these losses, including the severity and frequency of the losses. These input data are further used for training the proposed neural network model in order to predict the loss in each category at a daily level. This is represented as a block diagram in Figure 6.

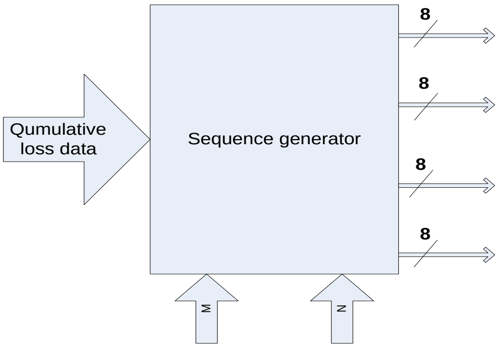


Fig.6. Block diagram of the system of a proposed neural network model that can predict each of the daily loss categories/or predict the losses for each of the categories.

Each of the neural network blocks undergoes changes according to the aforementioned special project solutions for each of the four categories (Figure 7). In this way individually predicted loss values are presented, with each of the four categories operating independently, without affecting each other either through their inputs or predictions (output levels).

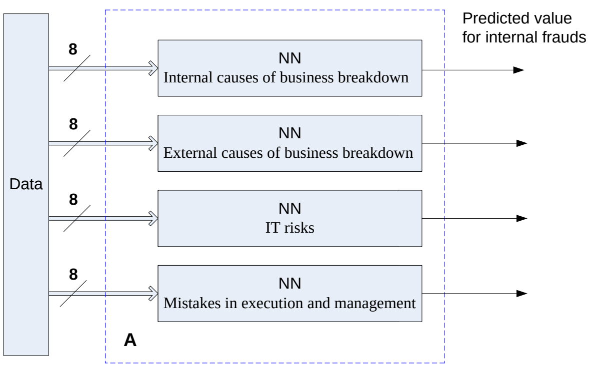


Fig.7. Generation of predicted values for each operational risk category

In order to view the predicted data cumulatively but this time at a daily level for the purpose of bank management, or in order to assess the exact amount of regulatory capital required for covering operational losses, the system should be modified according to Figure 8. This figure shows a proposed model for the prediction of the loss for operational risks, where block A gives the prediction value for each of the aforementioned four categories. These values are then integrated into block B and provide a comprehensive prediction for the overall daily losses incurred through daily operational risks in the bank.

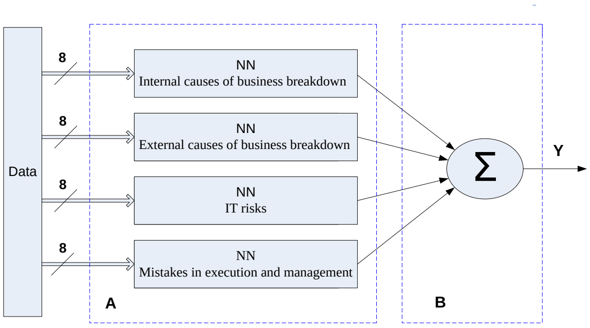


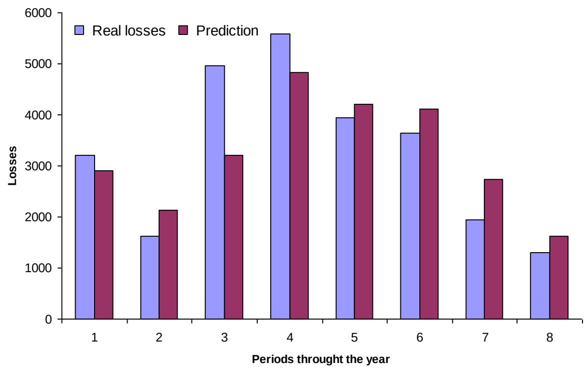
Fig.8. Proposed model for the system of predicting losses due to operational risks

4.3 Experimental results

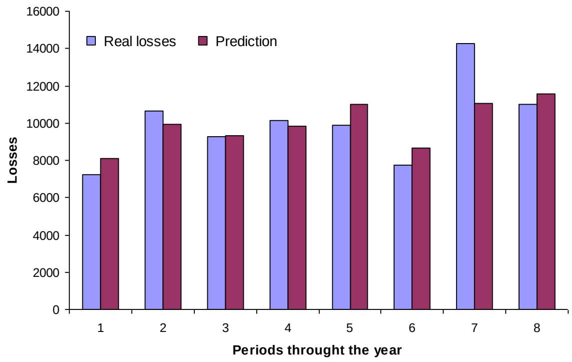
Based on proposed algorithm we have made several tests. Starting from cumulative losses given in [22], using the procedure given in 4.1. and prediction of daily losses given in 4.2. by sequence generator, we've calculated the input data for proposed neural network model.

According to Figure 7, we have made individual predicted value for each operational risk category.

On the Figure 9 is presented diagram with real and predicted losses for 8 periods throughout the year (250 working days divided into 8 periods), for: Internal causes of business breakdown, External causes of business breakdown, IT risks and Non adhering to working practice and mistakes in execution and management.



a)



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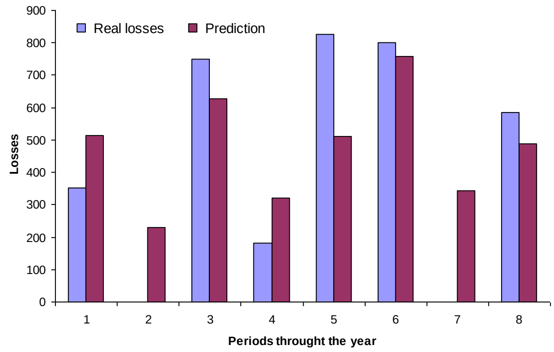
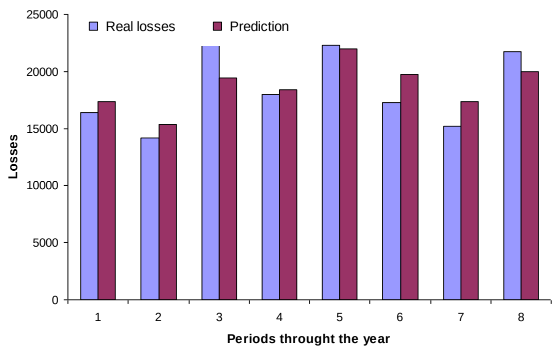


c)



d)

Fig.9. Real and predicted losses for 8 periods throughout the year for a) Internal causes of business breakdown, b) External causes of business breakdown, c) IT risks and d) Non adhering to working practice and mistakes in execution and management.

For all of the four categories, Figure 9 shows that the neural network can make good prediction if particular losses occur relatively often. Concerning category c), the mistake can be detected in prediction values. The reason for this is that banks usually don't report losses caused by IT risks. Based on the banking QIS classification of above mentioned categories [22], IT risks occupy only small percentage of total losses, which indicates that these losses won't have a big impact on total loss result. Nevertheless, we didn't omit this category, because we consider IT risks very important part of operational risks.

It is obvious on figure 10, that total operational losses can be modeled with artificial neural network, because the predicted value is relatively close to real data.

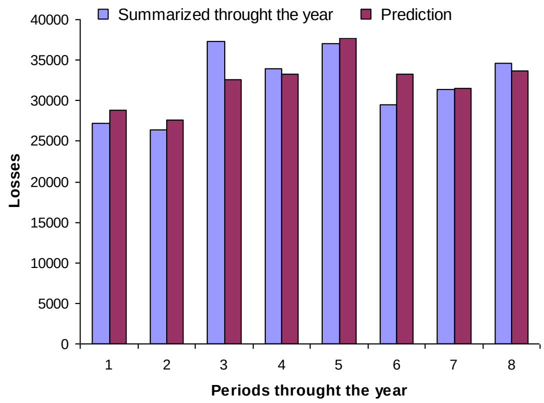


Fig.10. Summarized losses through the year

Comparison of the loss data from the QIS3 for 2001 with those obtained from our proposed neural network model which predicts losses for each of the categories for proposed period (with the option of producing cumulative results) has shown that our model is in agreement with the distribution of factual data.

5 Conclusion

Financial decision makers nowadays have available the computational power and methods for more accurate diagnostics, forecasting, and control in volatile, increasingly complex, multidimensional environments.

Researchers need no longer confine themselves to linear or log-linear models, or assume that underlying stochastic processes are Gaussian or normal in order to obtain forecasts. In short, we can go beyond linearity and normality in our assumptions with the use of neural networks.

Operational risk evaluation has been one of the most important focuses in the banking industry due to the recent financial crisis and the regulatory capital requirements under the recent Basel II Capital Accord. Since the classical normality assumptions with constant volatility or the linear and quadratic hypothesis are not appropriate for modeling the operational risk that requires the VaR calculation, the normality assumptions as well as the constant volatility hypothesis have to be corrected. Unfortunately, many statistical models cannot deal efficiently with the implicit nonlinear relationships between the characters and the results. For this reason, models based upon statistical techniques need alternatives. Currently, a predictive model modified to allow non-linear input-output relationships in operational risk events, auxiliary variables and small sample sizes is needed.

A lot of studies, in the last decade, revealed that artificial intelligent techniques are advantageous to statistical models for risk evaluation. Artificial neural networks are among the most effective learning methods currently known. Neural networks are an artificial intelligence method used for modeling complex target functions.

The important figure today is to assume the behavior of the market as a whole and separately by proxies of risk: from diverse signals, volatilities of different maturities, and the riskiness of different proxies. For a variety of implied volatility data, one nonlinear principal component can explain a good deal of the overall market riskiness, where it takes two or more linear principal components to achieve the same degree of explanatory power.

A major focus in financial market research today is volatility and forecasting, rather than return. Volatilities, as proxies of risk, are asymmetric and nonlinear processes. So nonlinear approximation methods such as neural networks may have a payoff when we examine such processes.

In this paper we suggest a neural network based model for operational risk prediction. Comparison of the loss data from the QIS3 for 2001 with those obtained from our proposed neural network model, has shown that our model is in agreement with the distribution of factual data. Our results show that this model can be useful in the case that losses are very frequent. In all of the categories, we've predicted losses that are very similar to the real ones, except for IT risks which are very specific, in the sense of frequency and intensity. Even bigger problem is the fact that banks usually hide real data concerning IT losses. Despite this fact, we suggest that IT risks should be observed together with other sources of operational risks, even predicted results for IT risks can be worse than in other categories.

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