

INTELLIGENT DECISION SUPPORT SYSTEMS FOR FINANCIAL RISK MODELING AND ANALYSIS

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The article examines approaches to financial risk analysis based on mathematical models and intelligent decision support systems (IDSS). The study describes key types of financial risks and the properties of economic processes that complicate modeling, such as non-stationarity, nonlinearity, and heteroscedasticity. It outlines the main stages of model construction – from data preprocessing and structure identification to parameter estimation and adequacy assessment. Classical risk management models, including BIA, LDA, and IMA, are analyzed, and the potential of Bayesian networks and fuzzy logic methods for handling uncertainties is highlighted. The article demonstrates that specialized IDSS, designed according to the principles of systems analysis, improve the quality of risk assessment and provide users with recommendations on model selection, uncertainty mitigation, and evaluation of forecasting performance. It is emphasized that the use of such systems reduces the labor intensity of analysis and increases the accuracy of forecasting potential financial losses.

Keywords: financial risks; risk analysis; non-stationary processes; nonlinear models; heteroscedasticity; Bayesian networks; fuzzy logic; Loss Distribution Approach; Basic Indicator Approach; Internal Measurements Approach; risk modeling; forecasting; decision support system (IDSS).

1. INTRODUCTION

Analysis of financial risks is in the focus of attention for many researchers and practitioners worldwide, as effective risk management plays a crucial role in ensuring the stability and resilience of financial institutions and economic systems. Among the most frequently encountered categories of financial risks are market, credit, and operational risks, each of which may significantly influence the performance and sustainability of financial activities. The analysis of such risks typically involves several fundamental components, including the identification of the underlying financial processes, appropriate data preprocessing, construction and validation of mathematical models, and estimation of potential losses together with their associated probabilities. Equally important is the task of forecasting future losses, which allows decision-makers to anticipate adverse events and implement preventive or mitigating strategies.

In modern financial environments characterized by increasing volatility, structural changes, and expanding volumes of heterogeneous data, the development of reliable methods for risk analysis has become increasingly complex. This complexity necessitates the application of advanced modeling techniques capable of capturing non-linear relationships, dynamic variance, non-stationary behavior,

and various sources of uncertainty inherent in financial data. As a result, constructing accurate, robust, and interpretable models of financial risks remains a critical and demanding task, motivating ongoing research in the field.

2. BACKGROUND AND RELATED MODELS

The most often met types of processes in analysis of financial process are non-stationary and non-linear. The reasons for non-stationary behavior are as follows: availability of deterministic or stochastic trend (integrated processes); variance may change in time (heteroscedastic processes). Non-linear behavior can be induced by observed nonlinear components in variables or parameters [1]. The models of such processes can be multidimensional, sophisticated and contain deterministic and stochastic components. It means that modeling of the processes can require substantial efforts and time [2, 3].

The spectrum of models applied to describing financial processes is very wide and includes at least the following: linear and non-linear regression, models of dynamic variance, state space models, polynomials of various types, generalized linear models (GLM), generalized additive models (GAM), distributions of various types, neural networks, Bayesian networks, combined models (linear plus non-linear components) and others. Adequate model can be constructed after appropriate preparing statistical data: filtering, normalizing, missing values imputation etc. Usually the modeling procedure is implemented as shown in Fig. 1.

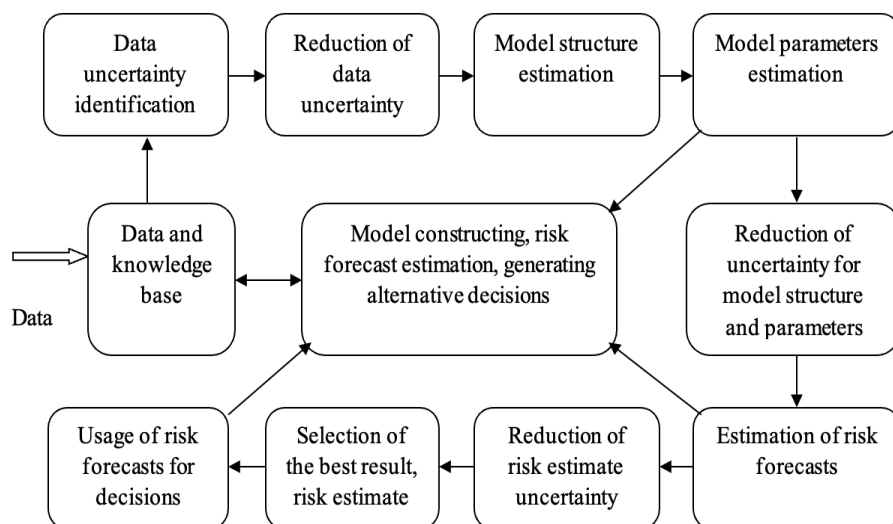


Figure 1. The flow chart of modeling procedure

3. METHODOLOGY OF FINANCIAL RISK MODELING

Model constructing using statistical data requires solution of two main problems: estimation of model structure and its parameters. Model structure is estimated with application of correlation techniques to data like correlation matrix, autocorrelation etc. To estimate model parameters various methods are applied like linear and nonlinear least squares, maximum likelihood, Markov Chain Monte Carlo (MCMC) and other possibilities. The MCMC procedure is universal to some extent and can be applied to parameter estimation of linear and nonlinear models. Approximate functional diagram of the decision support system is shown in Fig. 2.

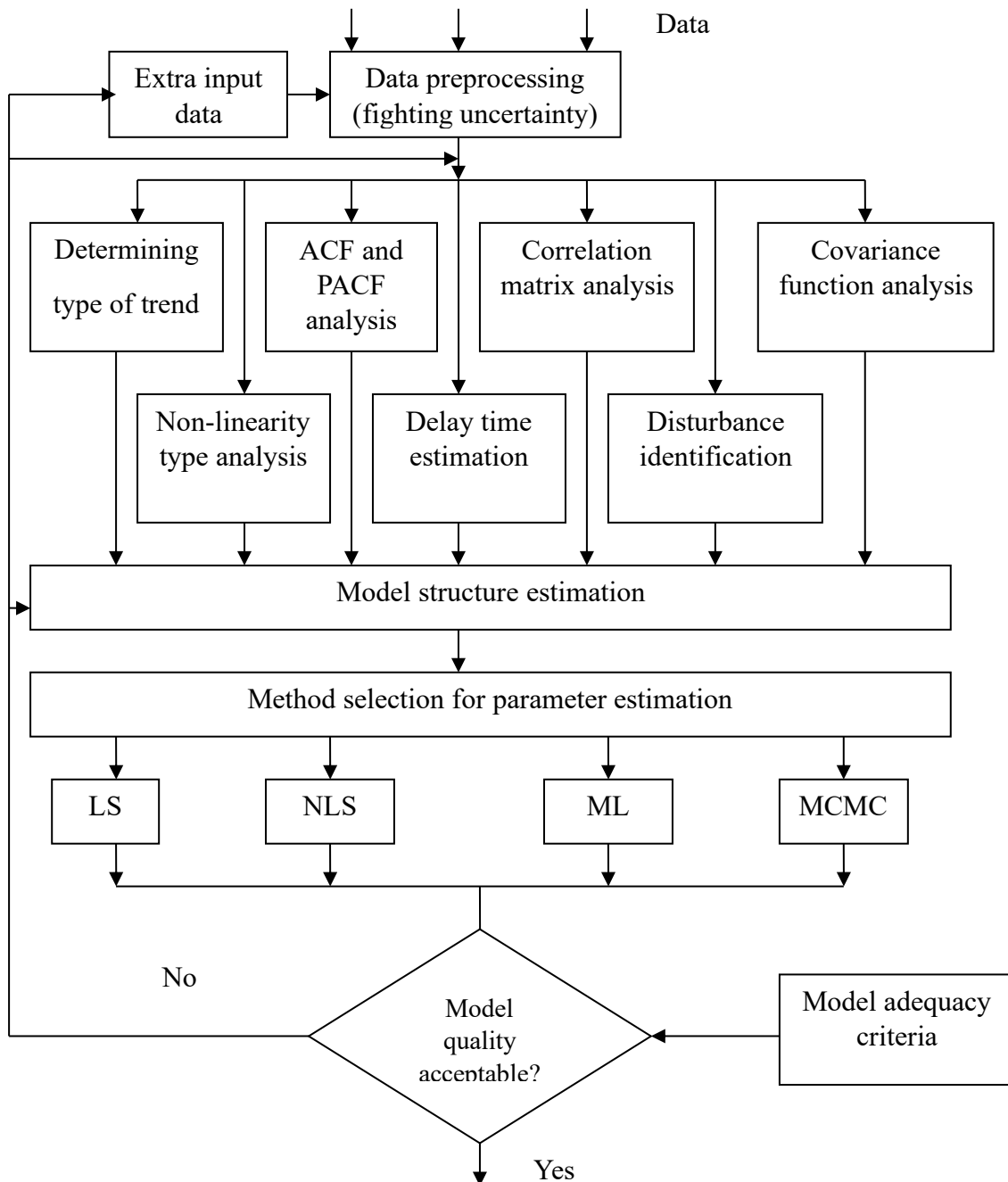


Figure 2. Approximate functional chart of intellectual decision support system

After parameter estimation model adequacy is analyzed using appropriate statistical parameters (statistics). Besides application of these parameters each model constructed can be tested on the quality of forecasting immediately after constructing. The forecasting capability of the models is important from the point of view of predicting possible future loss. Especially important is possibility for high quality forecasting of dynamic variance with heteroscedastic process models because the variance is basic parameter for estimating possible loss in many cases of financial risk estimation, for example market risk.

4. INTELLIGENT DECISION SUPPORT SYSTEMS (IDSS)

Of particular importance for applications in financial risk analysis are probabilistic models like Bayesian networks, decision trees, various distributions etc. The models provide the possibility for taking into consideration probabilistic and some other types of uncertainties that accompany financial risk management. Especially flexible are Bayesian networks that exhibit many advantages of modeling complex multivariable processes [4]. The models dimensionality can be very high, they can include discrete and continuous variables, and they are compatible for constructing combined models [5]. Besides, there exist multiple methods for the model structure and parameter (conditional probabilities) estimation, and for computing final result – marginal probabilities.

To analyze financial process and estimate financial risks it is recommendable to construct specialized intellectual decision support systems (IDSS) that already found wide applications in many applied areas [6]. IDSS designed on the principles of system analysis is very convenient instrument for researchers, engineers and students; such systems provide substantial help in modeling, forecasting and decision making.

Among substantial advantages of IDSS are following:

- correctly organized functioning of IDSS provides a user with recommendations regarding selection of data preprocessing methods, especially the methods for fighting statistical uncertainties often available in collected data (external disturbances, missing measurements etc.);
- statistical uncertainties of data are practically always available, and the means to fight them can be incorporated into IDSS itself what makes easier usage and modification of the methods if necessary;
- next the recommendations can be generated regarding possible types of mathematical models to be constructed in each specific case and algorithms for their constructing; this is especially convenient for the users who still do not have enough experience of analyzing non-stationary and non-linear processes;
- the IDSS is usually directed towards solution of specific problems – for example, constructing models for risk estimation can include necessary (available and designed for specific tasks) statistical quality criteria providing the possibility for thorough analysis of model adequacy and forecast quality;
- the system provides a user with necessary recommendations in cases when a model constructed does not exhibit necessary adequacy and quality of forecasting is not satisfactory; these recommendations indicate what other model type can be constructed or what additional data processing like fighting uncertainties can be performed;
- besides, specialized IDSS may include all necessary additional information (like special data and model tests, indications to processes simulation; constants, etc.).

The experience of practical application of specialized IDSS shows that quality of risk analysis is substantially higher with constructing the specialized system. Also necessary time for carrying out the analysis is usually shorter.

5. CLASSIFICATION OF FINANCIAL RISK MODELS

Consider some types of mathematical models that are used in financial risk analysis. The models can be classified by the use of the distinguishing features (criteria) considered below. Generally financial risks can be classified from the point of view of input factors, and from the point of view of consequences of the events linked to risks. Mathematical models used for describing risks can also be divided into two classes: models related to analysis of consequences (or on *up down analysis*), and models based upon analysis of risk factors (or on *bottom up analysis*).

On the other side, as distinguishing feature of a model can be considered the problems that could be solved with the model. For example, the models directed on function construction for mean

distribution of loss, can be used for estimating mean and maximum loss at given level of significance (Table 1).

Table 1. Model classification for risk management

Class of models	Data distribution identification and risk classification into critical groups	Model application for mean loss estimation	Possibility of model application for estimation of maximum loss	Possibility of model application for risk factor identification
Models related to analysis of consequences (<i>Top Down</i>)				
BIA			+	
IMA			+	
LDA	+	+	+	
Models based upon analysis of risk factors (<i>Bottom Up</i>).				
Sb-AMA	+	+	+	
Method of functional correlations	+	+	+	
Regression analysis	+	+	+	+
Bayesian networks	+	+	+	+
Fuzzy logic	+			+

The models based upon analysis of consequences are mostly constructed using the techniques of mathematical statistics. This group of methods uses collecting and analysis of data related to loss during previous periods of time with subsequent extrapolation of values on future periods. The most widely used are the following models:

BIA – Basic Indicator Approach;
LDA – Loss Distribution Approach;
IMA (Internal Measurements Approach).

The BIA model describes requirements regarding necessary volume of capital for covering loss due to risks. It was proposed for solving the problem of estimation maximum possible loss at given level of significance (99%). In application to analysis of operational risk the model is based upon initial idea that operational loss is estimated as residual of general loss relevant to other types of risks. The quintile of interest of random value x , that characterizes volume of loss is determined via the formula:

$$\hat{Q}_{99\%} = \overline{GI} \cdot \alpha, \quad (1)$$

where $\hat{Q}_{99\%}$ is an estimate of quintile at the level 99% of the random value that characterizes the loss (actually this requirement to the capital necessary to cover possible loss); $\overline{GI}$ is mean net income for three previous years that showed positive net annual income; $\alpha = 15\%$ is coefficient, determined by the Basel Committee on the bases of bank statistics.

Practical application of the model is based upon general estimate of risk (possible loss) that is principally possible. The general estimate of possible loss is based upon reports about loss in former time periods with correction on business scale. The coefficient α should be corrected to cover the risk of fraud. The drawback of the model is that estimate of fraud is dependent on business volume, and does not depend on the quality of monitoring procedures that should identify the cases of fraud.

The models based upon LDA (Loss Distribution Approach). The model constructing is based upon assumption that random value x , that characterizes the loss within time period t , can be defined as follows:

$$x = \sum_{i=1}^{n(t)} L_i, \quad (2)$$

where $n(t)$ is a random number that characterizes number of cases when loss was observed of the same type within time period t ; L_i is a set of random values that characterize separate loss for each observation. It is supposed here that the values of, L_i , are independent and equally distributed for selected types of loss.

To construct the model an analysis is performed for selected period of time for each pair “business line”/“type of loss”. Using the data regarding frequency of loss and volume of loss (observed in former periods) a mean frequency of loss is calculated (risk events), $(E(n(t)))$, and mean value of loss for each risk event, $(E(L))$. The next task is estimation of distribution type for the random values, $n(t)$ and L . In practice, the standard distributions are used, for example, Poisson or negative binomial, and empirical ones using historical data. Parameters of standard distributions are estimated with statistical data.

The distribution functions constructed for random values, $n(t)$ and L , allow for constructing distribution function for x . To fulfill the task as a rule Monte-Carlo method is applied using expression (2) that characterizes general loss for specific risk type. Next the point estimate of loss is possible, and/or quintile of given level of significance that allows (for example) estimation of OpVaR (Operational Value-at-Risk). Graphical representation of the LDA method is given in Fig. 3.

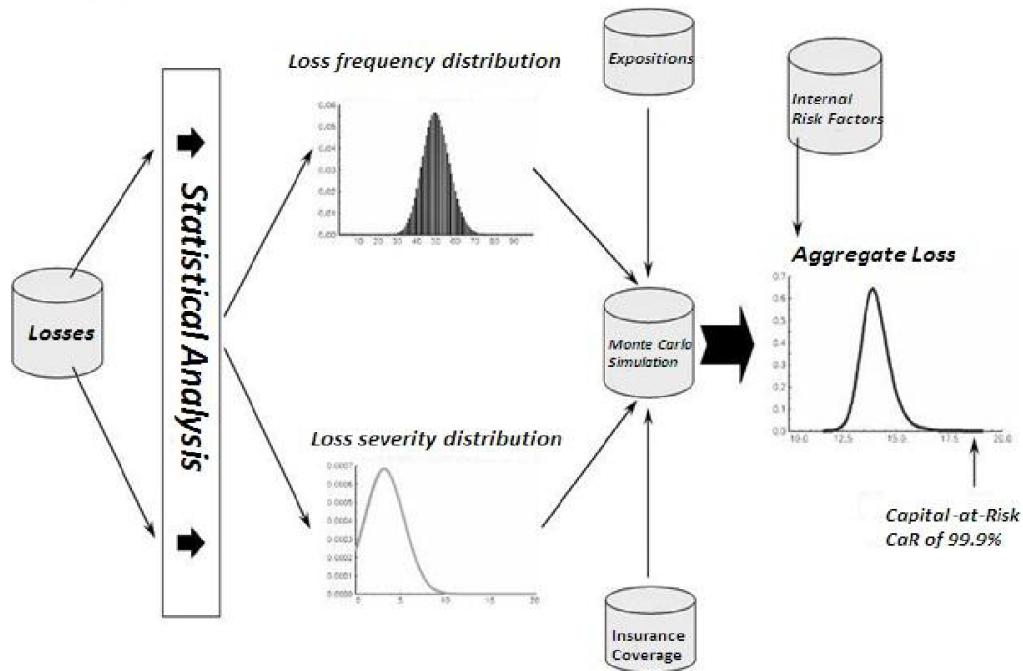


Figure 3. Graphical representation of LDA method

There exist various approaches to constructing model according to the LDA method; they can be divided into two groups.

The first group of models is based upon analysis risk events and respective loss without taking into consideration risk factors and cause and effect links. These models include estimation of distribution characteristics for risky events frequency and usage of the extreme value theory (EVT).

The second group of models takes into consideration wider set of parameters; besides risk

events risk factors are considered. Thus, in such models are used as parameters of distribution in the form of risk factors frequencies; such approach provides the possibility for taking into consideration interaction between risks.

The LDA class model can be hired for analysis of risks related to fraud (RF). In such cases it is necessary for each type of RF risk estimate distribution of its frequency, and distribution of loss using historical data. However, a distinguished feature of the fraud risk is that model is usually directed towards identification only a part of attempts to perform fraud. Another part of cases of general set available are not selected and analyzed. It means that empirical data should be supplied with other models to complete the picture.

The models built on the bases of Internal Measurements Approach (IMA).

This method provides a possibility for estimating maximum possible loss without constructing distribution for random value x , characterizing volume of loss. The approach to modeling is based upon assumption that all loss can be divided into expected (that is close to mathematical expectation of the loss within selected period of time), and non-predictable (that exceed mean value and belong to the “tail” of distribution. In simple case such model is represented by the linear equation:

$$\hat{Q}_{99\%} = EI \cdot PE \cdot LGE = \gamma \cdot EL,$$

where $\hat{Q}_{99\%}$ is estimate of 99-th quintile of the distribution for possible loss (volume of capital necessary for covering risk) related to specific type of events; PE is probability of negative event within the time period considered; EI is scale coefficient; LGE is mean value of specific loss under condition that negative event has occurred; γ is coefficient that allows to estimate requirements to capital via the estimate of expected loss EL . An integrated (total) estimate of maximum possible loss is determined as the sum of all risk estimates determined for possible risk events and business lines. The distinguished feature of this method comparing to LDA is that no assumption is made regarding distributions of $n(t)$ and L , that are not considered here. Instead an assumption is made regarding the volume of expected and unexpected loss. The use of the assumption requires application of additional coefficients (γ), and results in degrading the estimates to be found. On the other hand, IMA provides the possibility for estimating maximum loss without solving the problem of constructing distribution for X , characterizing total possible loss.

6. DISCUSSION

The short description of IDSS given above provides indications how to create practically operating system, and what functions it should perform to be effective assistant for a user. The system should be constructed on the use of system analysis principles – this is highly effective way for creating the best possible working instrument. Certainly, there are many useful ideas regarding the system functionality, and convenience to work with it, but the approach to design and implementation of it should be realistic.

7. CONCLUSIONS

The article demonstrated that specialized IDSS, designed according to the principles of systems analysis, helps to improve the quality of financial risk assessment and provide users with recommendations on model selection, uncertainty mitigation, and evaluation of loss forecasting performance. It is emphasized that the use of such system reduces the time and labor intensity for risk analysis and increases accuracy of forecasting potential financial loss. Thanks to modular construction of the system there exists a possibility for its modification: adding extra functions for risk analysis, criteria for testing intermediate and final results of computations, improving interaction with system etc.

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