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# INTEGRATION OF MODELLING METHODS FOR FORECASTING THE QUALITY OF BANK'S LOAN PORTFOLIO

***Based on the analysis of the current tools available for quality assessment of the loan portfolio a conclusion has been made about their retrospective nature on the whole, where as the contemporary environment, being mobile and unstable, challenges for the methods of perspective analysis and forecasting. The proposed method of integrating ARIMA and ARIMA-LI for the quality assessment of loan portfolio in the short term will allow control the quality, and not just state its status. The analysis of quality of banking system loan portfolio of Ukraine during 2008–2011 is carried out. Numerical results using the software package STATISTICA 8.0 are presented and recommendations are given.***

***Keywords:*** *loan portfolio; quality; forecast; ARIMA; integration of methods.*
***JEL Classification: C53.***
***AMS Classification: 62M20.***

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# ІНТЕГРАЦІЯ МЕТОДІВ МОДЕЛЮВАННЯ ДЛЯ ПРОГНОЗУВАННЯ ЯКОСТІ КРЕДИТНОГО ПОРТФЕЛЮ БАНКУ*

***У статті проаналізовано сучасні інструменти оцінювання якості кредитного портфелю, зроблено висновок, що вони переважно ретроспективні, в той час як сучасне фінансове середовище, яке постійно змінюється та є вкрай нестабільним, потребує методів перспективного аналізу та прогнозування. Запропонований метод інтегрує в собі методи ARIMA та ARIMA-LI для оцінювання якості кредитного портфелю у короткотерміновій перспективі, що дозволить контролювати його якість на майбутнє. Аналіз якості кредитних портфелей проведено на даних банківської системи України за 2008–2011 роки. Для аналізу використано пакет STATISTICA 8.0. За результатами аналізу розроблено рекомендації для банків.***

***Ключові слова:*** *кредитний портфель; якість; прогнозування; ARIMA; інтеграція методів.*
***Рис. 4. Табл. 2. Літ. 1.***

**Мария Н. Квасний**

# ИНТЕГРАЦИЯ МЕТОДОВ МОДЕЛИРОВАНИЯ ДЛЯ ПРОГНОЗИРОВАНИЯ КАЧЕСТВА КРЕДИТНОГО ПОРТФЕЛЯ БАНКА

***В статье проанализированы современные инструменты оценки качества кредитного портфеля, сделан вывод, что они в основном ретроспективны, в то время как современная финансовая среда, постоянно изменяющаяся и нестабильная, требует методов перспективного анализа и прогнозирования. Предложенный метод интегрирует ARIMA и ARIMA-LI для оценки качества кредитного портфеля в краткосрочной перспективе, что позволит контролировать его качество в будущем. Анализ качества кредитных портфелей проведён на данных банковской системы Украины за 2008–2011 годы. Для анализа использован пакет STATISTICA 8.0. По результатам анализа даны рекомендации для банков.***

***Ключевые слова:*** *кредитный портфель; качество; прогнозирование; ARIMA; интеграция методов.*

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**Introduction.** Due to the growth of credit operations volumes and a significant share of problem loans in banks there is a need for improving the existing methods of enhancing the quality of credit portfolio of depository corporations. In such conditions it is crucial to make a forecasting of the dynamics of portfolio quality. Therefore, the problem of the adequate quality of forecasting is paramount, because today to have a retrospective of financial condition is insufficient, there is a need for faster methods of the analysis of perspectives, which would allow reduce the risks of losses and increase profits.

The analyses of latest researches and publications showed that issues of further improvement of the banking system functioning, in particular the process of bank's credit portfolio management, attracts the attention of many scientists, among whom A. Gerasimovych, M. Alekseenko, I. Parasiy-Vergunenko (2004), A. Halafyan (2007), K. Holden et al. (1996), A. Yerina (2001) et al. They describe the problems of formation and monitoring of loan portfolio, give the classification characteristics of loans and the risks associated with them, and other relevant aspects of credit operations in commercial banks. However, analysis and forecasting of the credit portfolio quality is not sufficiently elaborated, thus making this research relevant.

**Problem definition.** The purpose of the article is the analysis of the existing methods and the development of the innovative ones to assess the quality of the credit portfolio of banks, selection of the forecasting tools, obtaining the numerical results with the application of the software package STATISTICA 8.0, formulation of recommendations.

The article defines the following objectives: to analyze the dynamics of the credit activity of banks in Ukraine; to define the features of the behavior of non-performing loans and loan portfolio in general; explore the available methods of assessing the quality of loan portfolio; to develop innovative tools for the analysis of quality; predict the dynamics of quality indicators in the short run; to establish the leading indicators; to use the method of ARIMA LI for recommendations for development of improving the quality of bank's loan portfolio.

**Theoretical framework.** For the banking activity it is important not to avoid risks altogether, but to foresight and decrease them to a minimum that is within the optimization of management. Under the risk we understand the threat of loss of the bank portion of its resources, loss of income or causing additional costs as a result of certain financial operations (Gerasimovych et al., 2004). Credit risk, or the risk of bad debt, can be industrial (associated with a probability of recession of production or demand for the products of a certain branch); risk arising from non-fulfillment of specific reasons contractual terms and conditions; the risk associated with the transformation of types of resources (often by date) and the risk of force-major circumstances.

The main task of bank risk management is to determine the admissibility of the risk and of the practical decision, aimed at the development of measures, which would reduce the possibility of losses. The worse are indicators of credit quality from the point of view of credit risk, the greater should be the degree of protection. To assess the quality of loan portfolio from the credit risk perspective the following indicators are applied: coverage ratio of classified loans, the weight of the weighed classified loans, the ratio of the weight of the problem and loss loans (Gerasimovych et al., 2004).

The listed indicators should be analysed in dynamics to identify the trend of their change and the causes of their deterioration. The calculation of these coefficients helps to determine the trend of deterioration of the financial state and the ways of increasing the economic efficiency of credit operations. The coverage ratio of classified loans is calculated as a ratio of weighted average interest rates to the bank's capital. This indicator comprehensively characterizes the quality of loan portfolio from the point of view of risk in conjunction with its protection of its own capital. Improvement of this ratio in the dynamics is regarded as a negative phenomenon and reflects the increase in the probability of losses in the future. Ratio of the weight of the weighed classified loans is calculated as the ratio of the weighted classified loans to total gross loans. Weighted classified loans are calculated by multiplying the amount of loans of a certain group of risk at the appropriate ratio. The analysis of credit operations should also be carried out in the direction of the assessment of the degree of protection from potential losses. To assess this level, we use the following indicators: the coefficient of loans; the coefficient of losses; the coefficient of security of loans from losses; the coverage of losses; the coverage ratio of the loans equity loans (Gerasimovych et al., 2004).

The quality assessment will be carrield out with the ratio of the weight of the problem and loss loans, since this indicator best reflects the losses of banks from lending activities and is essential for the functioning of the banking system. Calculating the value of this ratio, we get time series. Any dynamic range within a period of more or less stable conditions for development reveals a pattern of change of levels – the general tendency. One series has a tendency to growth, the other – the decreasing one, which, in turn, occurs in different ways: uniformly and rapidly or slowly. Often time series through the fluctuations of levels do not have a clear trend. To reveal and describe the basic tendency, we can apply different methods of smooth and analytic alignment of time series. The essence of anti-aliasing is in consolidating the intervals of time and the substitution of the initial number of average on intervals (Gerasimenko et al., 2000).

The simple moving average (SMA) is among the most common and popular indicators in technical analysis. SMA is the usual simple average over a period (Halafyan, 2007). SMA belongs to the class of indicators, which follow the trend, help to determine the start of a new trend and its completion, by its angle you can determine the speed of movement, and it is also used as a basis for a large number of other technical indicators. Sometimes moving average is called the line of a trend. Averaging quality, which should always be for the main tendency of the market, we replace small fluctuations. The smaller is the parameter of the SMA, the faster it defines a new trend, but at the same time makes fluctuations more false, and conversely, the larger the key is, the slower a new trend is defined, but there are fewer false oscillations (Halafyan, 2007). However, this method has some disadvantages. In particular, using the method of SMA delays input to output of the trend, as a rule significant, so in most cases, a large part of the trend movement is lost. One of the major shortcomings of the SMA method is that it gives the same weight to new quality indicators as well as to older ones, although it is more logical to assume, that new indicators are more important, because they reflect modelling the market situation to the present moment.

**Integration of modeling methods: the results of the research.** ARIMA model is an important class of parametric models, which describes non-stationary series. They are called the models of Box-Jenkins (Holden et al., 1996). ARIMA model is formed, basically, at the autocorrelation data structure. In the methodology ARIMA is not assumed to be a clear model for the prediction of time series. It is only a general class of models, which describes time series and allows expressing the current value of the variable by its previous values. The internal parameters substituting the algorithm then choose the most appropriate forecasting model.

The forecasting methodology by Box-Jenkins is different from most of the methods in that it does not require a particular structure of time-series data, which is forecasted, and use an iterative approach to the definition of acceptable among the general class of models. Then the selected model is compared with historical data, to check the accuracy of the description of series. The model shall be considered acceptable if residues are mainly small, randomly distributed, and do not contain useful information. If you set the model unsatisfactory, the process is repeated, but with the use of a new improved model. This iterative procedure is repeated until there won't be found the correct model. From this moment, the given model can be used for prediction purposes. When modelling non-stationary economic processes, specification function is combined with other methods of analysis of dynamics: moving average, the trend, seasonal wave. The unification of different models in a single unit significantly expands the scope of their use. In addition, the models are based on the same statistical characteristics – autocorrelation functions, being developed by one algorithm for calculations of the parameters of models and forecasts. For the filtration of the linear trend of use of the difference of the first order for the filtration of parabolic trend – the difference of the second order etc. The difference $d$ should be stationary. In an ARIMA model the adequacy of real process and predictive properties depend on the order of autoregression $p$ and the order of the moving average $q$. Through the key moment of the simulation the identification procedure is considered – the justification of the model. ARIMA models are quite flexible and can describe a wide range of characteristics of time series, which are found in practice. The above factors indicate that these models work well in the case of the stable state of the process and cease to adequately reflect it, when significant changes are taking place. Forecasts of economic development can be based on elementary extrapolation of fine econometric models, methods of "technical analysis", consumer surveys and entrepreneurs, the formalization of the evaluations of experts and analysts. One of the most common methods of foresighting future economic dynamics is the use of the system of leading indicators. The idea underlying this approach is simple and obvious: to predict, the transition from boom to recession or from recession to recovery it is necessary to build an "early warning system" (Holden et al., 1996).

In the framework of this study the analysis of the quality of the loan portfolio with the position of the weight of bad loans in the total amount of the granted to non-financial sector of the economy for January 2008 – July 2011 (Figure 1) is carried out.

From Figure 1 we can see that time series should be divided into two parts, because from the first period and to the eleventh there is practically linear dynamics. In our opinion, the value of this part of series would not take into account the forecast. Such behavior explains the policy of the National Bank of Ukraine regarding the exchange rate. In the fourth quarter of 2008 of the National Bank let the exchange rate float freely. For further analysis let us consider the time series from January 2009 (Figure 2).

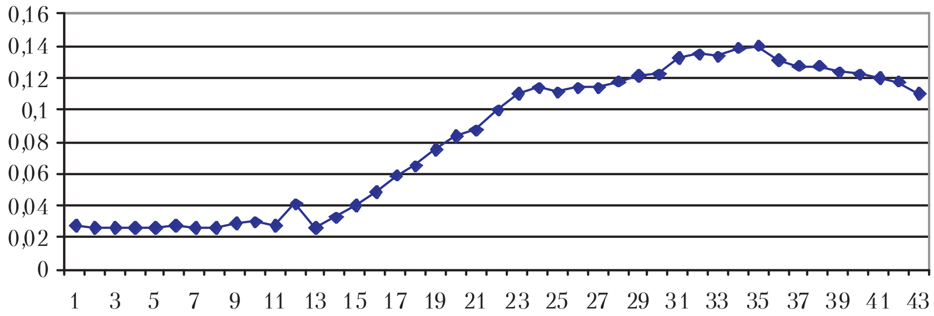


*Figure 1.* **Schedule of specific weight of bad loans, prepared by the author on the statistics of bank loans to non-financial sector** *(www.bank.gov.ua)*

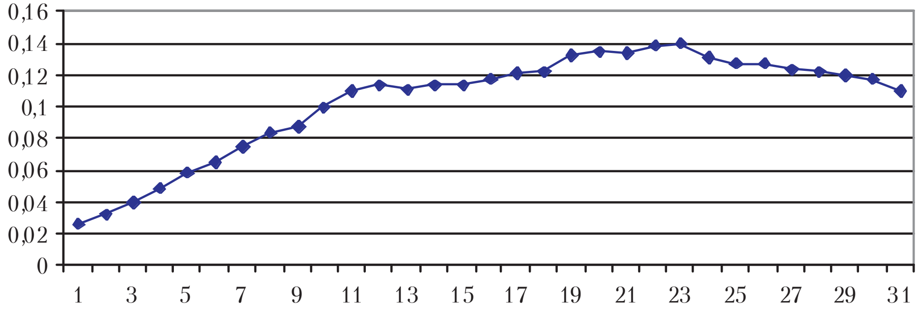


*Figure 2.* **Nonlinear part of the time series, prepared by the author on the statistics of bank loans to non-financial sector** (www.bank.gov.ua)

ARIMA models are built by using the statistical package STATISTICA 8.0. This package allows specifying the following parameters: *p* – order autoregressive, *q* – order moving average, *d* – order differences. To identify the model ARIMA means to determine these parameter (Yerina, 2001). The main criterion for identification is the behavior of autocorrelation and partial autocorrelation functions. Availability trend is the first sign of non-stationary (Figure 3).

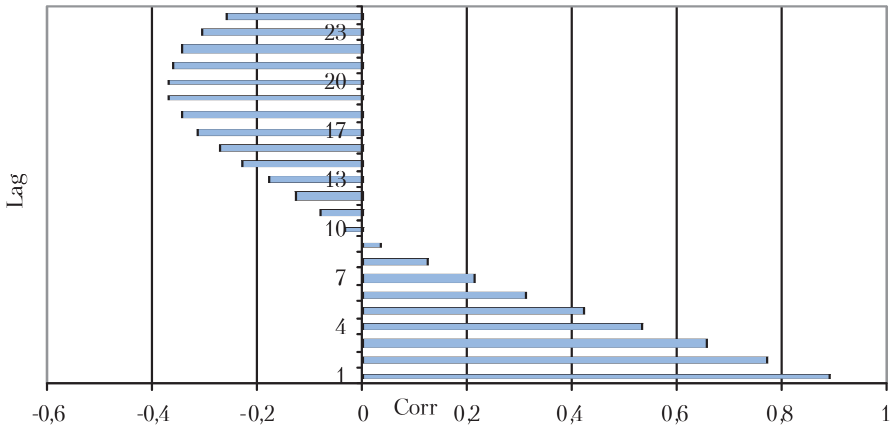


*Figure 3.* **Autocorrelation function of time series,** *made by the author*

As we can see (Figure 3) the autocorrelation function has no tendency to decay, so we conclude that series is non-stationary. Otherwise, you must take the difference as long as this function becomes stationary. After this iteration again, we obtain a stationary series for $d = 2$ (Figure 4).

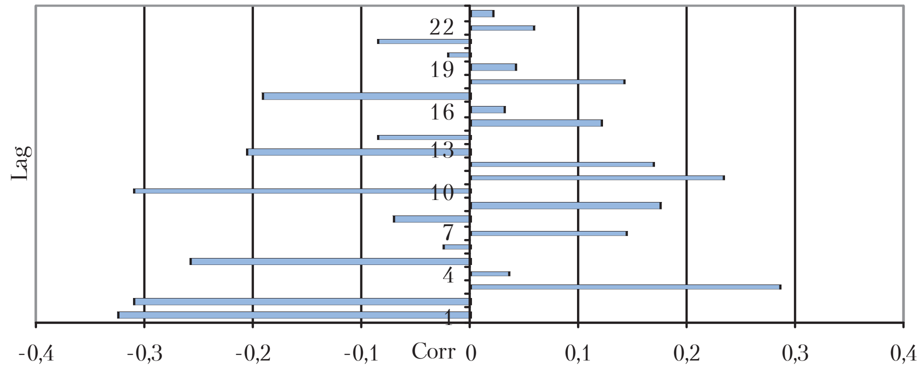


*Figure 4.* **Autocorrelation function of the time series at $d = 2$,** *made by the author*

The next step to determine the parameters $p$ and $q$. Analyzing the behavior of the autocorrelation function on Figures 3 and 4, we conclude that accurately present time series can be described by the second class of ARIMA models for witch $p = 2$, $q = 0$ (Table 1).

*Table 1.* **Evaluation of model parameters for the model ARIMA (2, 2, 0),** *calculated by the author*

| Paramet. | Coefficient | Stand. error | Asympt. t(25) | p-value | Lower 95% Conf | Upper 95% Conf |
|---|---|---|---|---|---|---|
| p(1) | 0.357297 | 0.185887 | 1.92211 | 0.066059 | -0.025545 | 0.740139 |
| p(2) | -0.447604 | 0.185920 | -2.40751 | 0.023769 | -0.830513 | -0.064694 |

Analyzing the parameters estimation in Table 1, we can conclude that the parameter $p$ (2) is statistically significant. Therefore, to further test the adequacy of this model we construct a forecast for existing data to see how many real values deviate from predicted. Now make a prediction using the model ARIMA (2, 2, 0) for 2 periods (Table 2).

*Table 2.* **Predictive values for 2 periods for the model ARIMA (2, 2, 0),** *calculated by the author*

| Case No. | Forecast | Lower 90.0000% | Upper 90.0000% | Stand. error |
|---|---|---|---|---|
| 32 | 0.110767 | 0.098990 | 0.122543 | 0.006894 |
| 33 | 0.101611 | 0.089105 | 0.114117 | 0.007321 |

Using ARIMA models to predict a confidence interval and the exact value of the series, which divides the interval by two. We propose to use the method of leading indicators to predict the peak and the bottom of economic cycles (Holden et al., 1996). After the economic analysis of factors influencing the share of problem loans, we have concluded that there are parameters that have the most significant impact. Thus, combining several methods of forecasting we managed to get a much more accurate predictive value compared with the predictions obtained by each method separately.

**Conclusions.** The analysis of the loan portfolio quality of a bank is a necessary stage in the assessment of bank liquidity, because of the high risk inherent to credit operations of banks. If the share of bad loans considerable, it is necessary to take all possible measures to improve the quality of the loan portfolio, as such a situation threats the economic security of a bank. The quality of loans portfolio is significantly influenced by the external environment, which a bank is unable to control. In particular, significant influence may have the number of unemployed persons (characterizes the level of population income), retail trade turnover (characterizes enterprises' incomes), as well as the stability of currency rates. These indicators should be considered to predict future values of the quality of loan portfolio, because they change with a high probability they will have an impact on the share of problem loans. In conclusion, the proposed method of integrating ARIMA with leading indicators (ARIMA-LI) for the assessment of the quality of the loan portfolio in the short term will allow control quality, and not just state its status. Obtained on the basis of ARIMA-LI forecasts show that the quality of the loan portfolio will be improved. Banks should take advantage of this situation to improve their financial results.

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