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Modular Software Framework for Financial Risk Evaluation

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ABSTRACT

To effectively manage the various types of financial risk faced daily by institutions in the sector, national and international regulatory bodies have established a range of monitoring and control tools. Central to these tools is the quantification of risk, which enables financial institutions to estimate potential losses and based on these estimations, to design and implement procedures that include the formulation of general policies and risk mitigation strategies. In alignment with these efforts, the University of Medellín has developed a software application named **SICRIF** a modular suite designed to support the measurement of liquidity risk, market risk, and operational risk through specialized components.

Keywords: software engineering; software suite; liquidity risk; operational risk; market risk.

INTRODUCTION

The new regulatory capital framework provides a macroprudential dimension to address systemic risks, i.e. the risk of disruptions to the financial system that could destabilize the macroeconomy. While strengthening banks' capital bases will strengthen the banking system, it is not enough to focus on individual institutions, as the risk to the system as a whole is greater than the sum of the risks of each institution, as was evident during the 2007 financial crisis (Escudero 22024). In this regard, one of the key lessons of the crisis has been the need to strengthen risk coverage within the capital framework.

One of the main destabilizing factors during the crisis was the inability to properly capture the major on- and off-balance-sheet risks, as well as derivatives-related exposures. In response to the need to strengthen mechanisms that allow for adequate risk management and administration, the financial engineering and systems engineering groups at the University of Medellín developed a software tool called SICRIF. It is a suite composed of specialized modules that allow for the quantification of liquidity, market, and operational risk.

The software allows for the generation of different scenarios regarding the loss events that may arise due to the risk exposure of any financial institution, which could have a significant impact on its operations. It also allows for the identification of relevant statistical information to quantify and make provisions to cover any loss events that affect the entity's optimal performance.

This article is divided into four sections, in this section a brief introduction is developed, in section II the concept of Value at Risk is defined and the different methodologies for its estimation are presented, section III describes the methodology and the results obtained from the implementation of the SICRIF software for the estimation of market, liquidity and operational risks, and section IV presents the most relevant conclusions.

METHODS

Value at Risk (VAR): Sean Xa random variable in a probability space $(\Omega, F, \wp)$, F_X its distribution function and F_X^{-1}its generalized inverse function (Cousin & Di Bernardino, 2013). For a confidence levelα, with $\alpha \in [0,1]$, VaR is defined as a threshold value that should not be exceeded with a certain probability $1-a$, Formally,

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$$VaR_\alpha = inf\ \{x \in R:\ F_X(x) \geq \alpha\}. \qquad (1)$$

In other words, the $Our$is the α-th quantile of the distribution function of F:

$$VaR(X) = F_X^{-1}(\alpha).$$

Typical values forα are α = 0.95 o α = 0.99.

For the estimation of VaR, various approaches are usually known, classified as parametric (characterized by a density function) and non-parametric (distribution-free) (Alexander, 2008), (A. J. McNeil, 2015.).

1. Parametric approach

Under these methodologies, the calculation of VaR depends crucially on obtaining good estimators for the parameters of the density function.$f_\theta(x)$, where θ∈Θ is unknown. In particular, it is of great interest to have a good estimate of the variance, given that one of the most characteristic facts of financial variables is that their volatility changes over time and therefore knowing it is crucial because an excess of volatility could mean huge losses, in this sense, models that assume constant volatility (Delta-normal, Delta t-Student, etc.) and models that assume non-constant volatility (Moving Average Model, EWMA Model, and the econometric models of the GARCH family) are frequent in the literature, see (Valadez 2024). (McNeil, 2005) and (Engle, 2001), for a detailed description. The most used model is the Delta-normal which assumes that the distribution function is normal with constant volatility over time (Vasileiou 2024).

a. Delta-Normal

The main characteristic of this methodology is the assumption that the sample distribution is normal (Melo Velandia & Becerra Camargo, 2005).

And $X \sim_{iid} N(\mu, \sigma^2)$, so:

$$P(X \leq VaR) = P\left(\frac{X-\mu}{\sigma} \leq \frac{VaR-\mu}{\sigma}\right) = \alpha$$

Then

$$\frac{VaR-\mu}{\sigma} = \Phi^{-1}(1-\alpha) \equiv z_\alpha$$

Where $\Phi^{-1}(\alpha)$is the inverse function of the cumulative normal distribution and $z_\alpha$is the αth quantile of the standard normal distribution. From the above, we have the following expression known as the Delta-Normal VaR.

$$VaR = \mu + \sigma z_\alpha. \qquad (2)$$

Among the methodologies that consider non-constant volatility that has been quite appropriate given that it only requires the calculation of one parameter is the Exponentially Weighted Moving Average, briefly described below.

b. Exponentially Weighted Moving Average (EWMA)

Under this methodology the standard deviation in period t is a weighted average of past observations (Morgan/Reuters, 1996), that is,

$$\hat{\sigma_t}^2 = \sum_{i=1}^{n} \alpha_i {x_{t-i}}^2$$

Where $\alpha_i \to 0$ when $i \to n$ and $\sum_{i=1}^{n} \alpha_i = 1$.

Assuming that the weights decay exponentially, i.e.$\alpha_{i+1} = \lambda\alpha_i$, with $0 < \lambda < 1$, or equivalently $\alpha_{i+1} = \lambda^i \alpha_1$, where from, $\sum_{i=0}^{n-1} \lambda^i \alpha_1 = 1$, then $\alpha_1 = 1 - \lambda$. Assuming a large n

$$\hat{\sigma_t}^2 = \sum_{i=1}^{n} \alpha_i {x_{t-i}}^2 \approx (1-\lambda) \sum_{i=1}^{n} \lambda^{i-1} {x^2}_{t-i}$$

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Therefore

$$\lambda\widehat{\sigma_{t-1}}^2 \approx (1-\lambda)\sum_{i=1}^{n}\lambda^i {x^2}_{t-i-1}$$

Subtracting the last two expressions

$$\widehat{\sigma_t}^2 - \lambda\widehat{\sigma_{t-1}}^2 \approx (1-\lambda){x_{t-1}}^2$$

Finally, it has to be

$$\widehat{\sigma_t}^2 \approx (1-\lambda){x_{t-1}}^2 + \lambda\widehat{\sigma_{t-1}}^2$$

Where x_{t-1} and σ_{t-1}correspond to the observation and the estimated standard deviation for the period $t-1$, respectively, both calculated from historical data. To determine the value ofλmost suitable is commonly sought λthat minimizes some measure of goodness of fit (root mean square error (RMSE), mean absolute percentage error (MAPE), root mean square error (RMSE).

Basel recommends a value λ of 0.94 for daily data and 0.97 for monthly data. From all the above, if $X \sim N\left(\mu, \widehat{\sigma_t}^2\right)$ then by a reasoning like that developed to obtain (2) we have that:

$$VaR = \mu + \widehat{\sigma_t}^2 z_\alpha \qquad (3)$$

2. Focus on parametric:

Nonparametric estimation refers to a variety of estimation techniques that do not explicitly involve parameter estimation. This approach makes no assumptions about the distribution of data, nor does it assume any type of parameter behavior. One of the most widely used nonparametric approaches is Historical Simulation, which is briefly described below.

a. Historical Simulation (SH)

In this methodology, VaR is calculated as the α th quantile of empirical or sample distribution, assuming that history will repeat itself from a risk perspective (Landazury et al 2025). Under this approach, current historical data are reorganized, usually ordered from lowest to highest, and given a confidence level, the value at thatα-th quantile in the distribution represents the VaR. If we denote the ordered values of the data by $X_{t-n+1,n}, \ldots, X_{t,1}$, the VaR by historical simulation is given by:

$$VaR_\alpha = X_{[n(1-\alpha)],n}$$

Where $[n(1-a)]$ denotes the largest integer that does not exceed $n(1-a)$.

The following section describes the estimation of the functionality of each of the modules in obtaining Market risk, Liquidity risk and Operational risk respectively.

TECHNOLOGY DESCRIPTION

Implementation: Sicrif Software

The purpose of estimating VaR for financial risks is to provide an overview so that an institution or investor does not suffer intolerable economic losses, thus improving the financial performance of said economic agent and providing a short-term perspective for their investments by adjusting their positions to risk. To effectively identify risks and obtain a good VaR estimate, it is necessary to consider their nature when a transaction occurs. Market risks are associated with price volatility, operational risk is associated with human or system failures, and liquidity risk involves the available cash resulting from the company's operations. The following describes how the different financial risks are measured using the SICRIF tool.

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1. Sicrif: Market Risk Estimate

Market risk is the potential loss in the value of financial assets due to adverse movements in the risk factors (interest rates or exchange rates that determine their price (Buriticá Chica, Orozco Arboleda, & Villalba Marín, 2016). Financial studies are usually conducted on returns, not prices, as indicated by (Melo Velandia & Becerra Camargo, 2005).

The market VaR, under the parametric method, is calculated using the variable of asset returns, where it is assumed that these are distributed with a normal distribution function with mean equal to zero, (Yang, 2011) (Pérez Hernández & Sotirova, 2015) and (Alonso & Arcos, 2016).

To calculate the value at risk, the model described in (2) is taken as a reference and considering that the total amount of the investment (capital) or the total exposure to risk as shown (from Lara Haro, 2008), then the market risk (MVaR) is given by the expression:

$$MVaR = \sigma z_\alpha * S$$

In (Buriticá Chica, Orozco Arboleda, & Villalba Marín, 2016) they explain that financial assets can be divided into three groups: variable income assets (or equity securities), fixed income assets and derivative instruments.

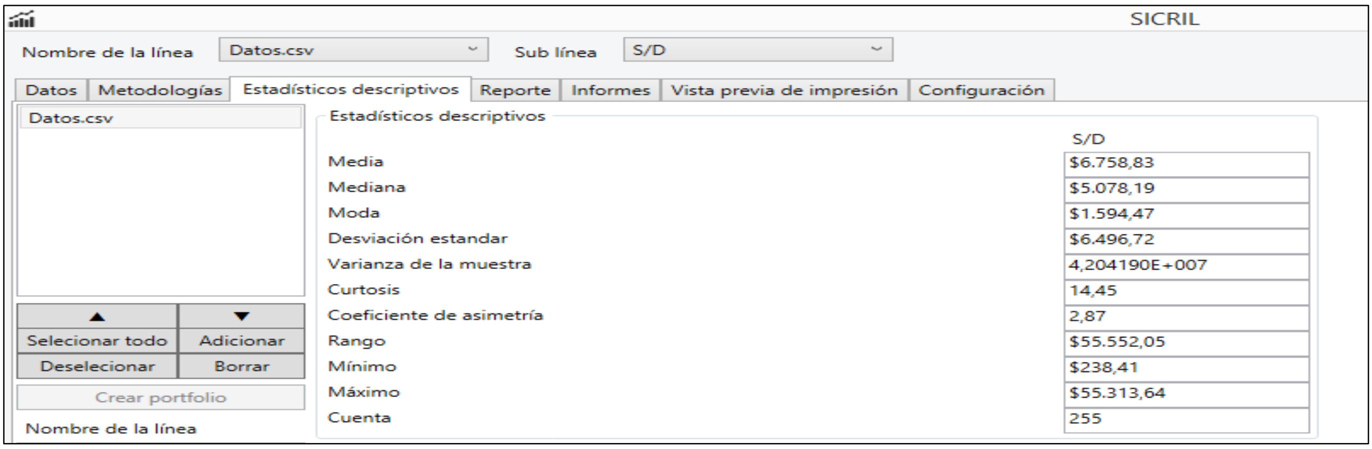
$$MVaR = \frac{D}{1+r} F(\sigma z_\alpha * S).$$

Market VaR estimates were run in the SICRIF information system, as described below:

To obtain the results, 501 data were analyzed, of which a mobile window of 250 days was used to obtain the VaR and another 250 for the test Back Testing, in all cases an α of 5% was taken, which is equivalent to a confidence level of 95%.

Figure 1.

Calculation of statistics for performance.



From Fig. 1 it can be observed in the last column that the average return for an investment of $1,000,000 is $6,494, which indicates that the entity obtains profits in daily market operations and that its investments can report some utility, the minimum value is $238, and the maximum is $55,313.

According to the standard deviation, which measures market volatility, the result indicates that for every million pesos invested in this instrument, the price fluctuates by $6,496 relative to the average, indicating high volatility for the asset, as it is above the calculated average value. The calculated asymmetry coefficient is 2.87 (positive), which implies that returns are asymmetric to the right; that is, higher returns are less likely to occur given market conditions. A kurtosis of 14.45 > 3 indicates to the structuring expert that returns around the central tendency measures are more likely to occur; it also indicates that extreme values may be present.

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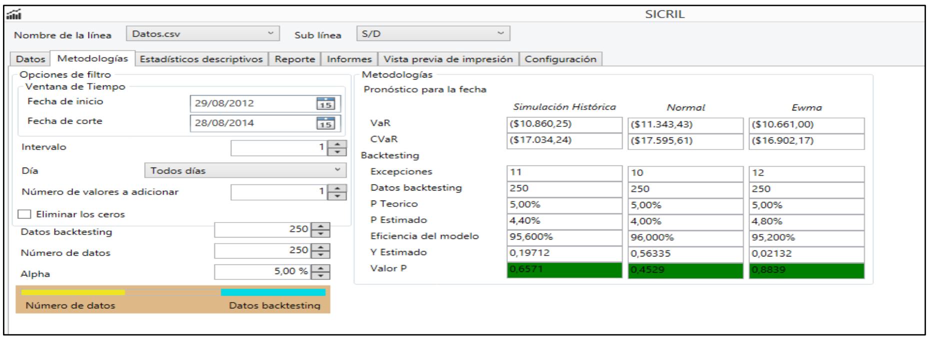
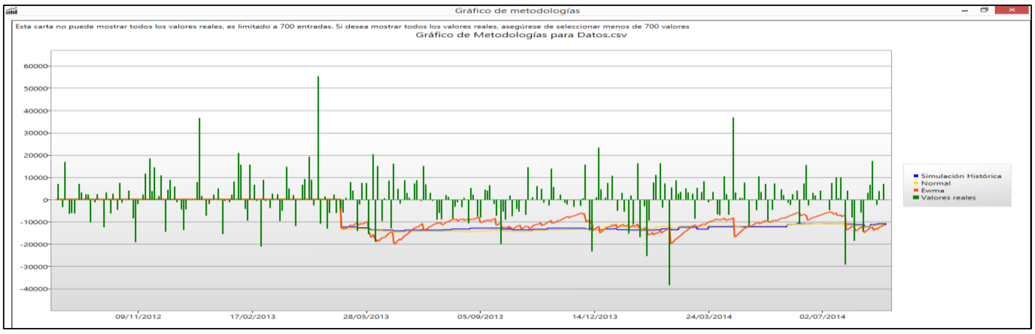
Figure 2. *Results of the application of methodologies: historical simulation, Normal and Ewma.*



The most relevant data for the analysis of market risk exposure is shown in Fig. 2. The first row indicates, with 95% confidence, that the maximum loss for this portfolio, where the investment is $1,000,000, is $10,860 for SH, $11,343 for Normal, and $10,661 for EWMA. These values must be insured daily to guarantee the entity's solvency and assume the market losses of the following day. Fig. 6 also presents the data required to perform the back testing test, which, as mentioned above, is the test that determines the reliability and accuracy of the models. The software indicates that when forecasting using the S.H. methodology, 11 exceptions were presented, that is, 11 scenarios in which actual returns exceed estimates. Similarly, 10 exceptions were presented for Normal and 12 for EWMA.

As can be seen on Fig. 3, the S.I. allows generating the graph with a comparison of the values estimated by each of the methodologies. As can be seen, the normal and EWMA methods try to follow the volatility presented by the market, while the historical simulation assumes that the data will continue to be handled according to its past behavior.

Figure 3. *Methodologies Chart*



2. Sicrif: Liquidity Risk Estimation

Liquidity risk is associated with the possibility that a financial institution may be unable to adequately meet its obligations due to a lack of liquid resources. According to (Castillo Huerta, 2008) and (Echeverri-Arias, Arias-Serna, Murillo-Gómez, Klein, & Franco-Arbelaez, 2015), calculating the minimum amount of liquid assets requires analyzing the renewal and permanence patterns of each liability category. To avoid excessive liquidity risks, liquid assets should be considered at least equal to the LVaR. Liquidity must be sufficient to meet the institution's obligations without requiring recurring access to the most expensive or last-resort funding.

To calculate the liquidity VaR, it is defined XAs the variable that represents the mismatch, understood as the difference between assets and liabilities, as for any normal distribution, the expected mismatch will beμ, and volatility is defined as the variance of the distribution, that is, σ^2. Once it is considered that the pdf of the mismatch behaves as a normal distribution, obtaining the VaR as explained for obtaining equation (3) is given by:

$$LVaR = \mu + \sigma z_{\alpha}.$$

Like what was described in the previous section, the liquidity VaR estimates were executed as described below. The input data corresponds to the daily collections and disbursements of four portfolios. To obtain the results, 559 data

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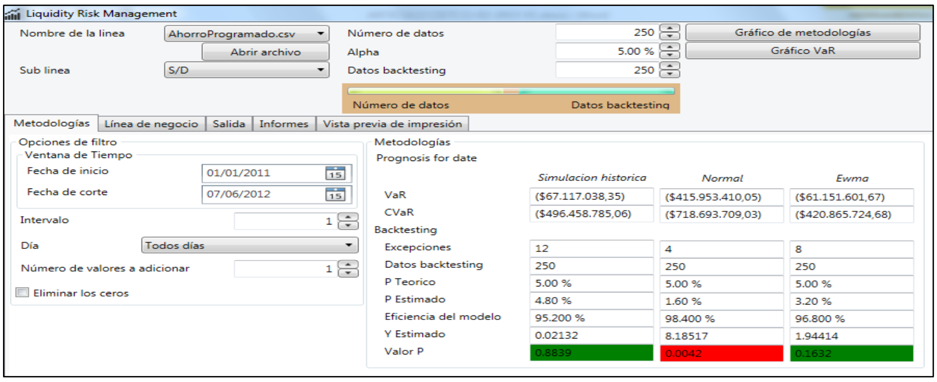
points corresponding to the Portfolio were analyzed. To avoid redundancy, we will limit the description of the features to the two most relevant features of the application.

The VaR estimates in the first row of Fig. 4 indicate, with 95% confidence, that the maximum amount of capital required to ensure the entity's solvency for the following day is $67,117,038 for SH, $415,953,410 for Normal, and $61,151,601 for EWMA. The data required to perform the Back Testing test are also presented, which, as mentioned above, is the test that determines the reliability and accuracy of the models. The software indicates that when forecasting using the S.H. methodology, 12 exceptions were presented, that is, 12 scenarios in which the actual mismatch exceeded the estimated one. Similarly, 4 exceptions were presented for Normal and 8 for EWMA. Knowing the number of exceptions also provides insight into the efficiency of the models in forecasting. That is, it provides a percentage of the total number of times the estimated mismatch covered the actual value reported by the entity. As can be seen, the efficiency of the models using all three methodologies exceeds 95%.

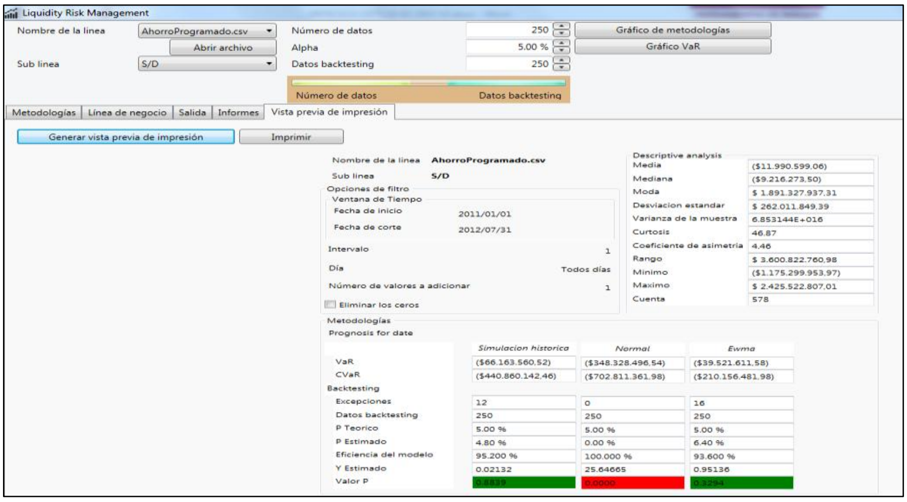
Figure 4. *Results of the application of methodologies: historical simulation, Normal, Ewma.*



In the last row of the S.I. (Fig. 6), the methodologies that satisfy the test value are indicated in green (P-value > 0.05) and those that do not are indicated in red. The purpose of this signaling is to indicate to the analyst that the values of $67,117,038 and $61,151,601 obtained from S.H. and EWMA are good forecasts for the next day's mismatch, while $415,953,410 obtained from the normality assumption might not be. It will be up to the analyst, based on their risk aversion, to decide what value to use as a forecast for the next day's mismatch.

Finally, Figure 5 shows that the S.I. allows generating and printing reports with the consolidation of all the results obtained (name of the portfolio, observation window, number of days being analyzed, descriptive statistics, VaR and Back Testing).

Figure 5. *Consolidated results report*



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3. Sicrif: Operational Risk Estimation

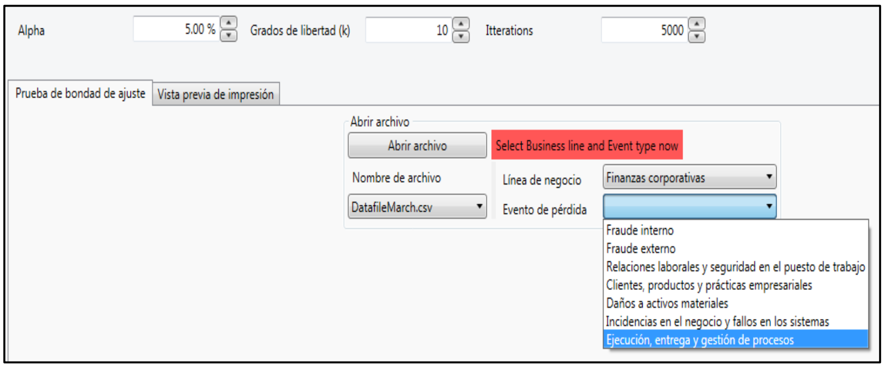
The Basel Committee defines operational risk as the potential for losses resulting from failures or inadequacies in internal processes, people, and systems, or external events. Operational risk is based on two fundamental variables: the frequency of occurrence of the risk and its severity, therefore, if X_i is the total amount of losses for frequency i and $S = \sum_{i=0}^{N} X_i$ is the random variable that represents the total losses, then the OpVaR is usually estimated according to (Murillo-Gómez, Franco-Arbeláez, & Arias-Serna, 2014) by:

$$Pr(S \leq OpVaR) = 1 - \alpha.$$

The results obtained from the implementation of the operational risk module are presented below. As described throughout this section, the application allows for: obtaining the distribution of aggregate losses by event/line of business, fitting data to probability distributions, modeling the distribution function of the frequency of occurrence for each operational event, modeling the distribution function of impacts or losses per event (severity), and constructing the loss matrix.

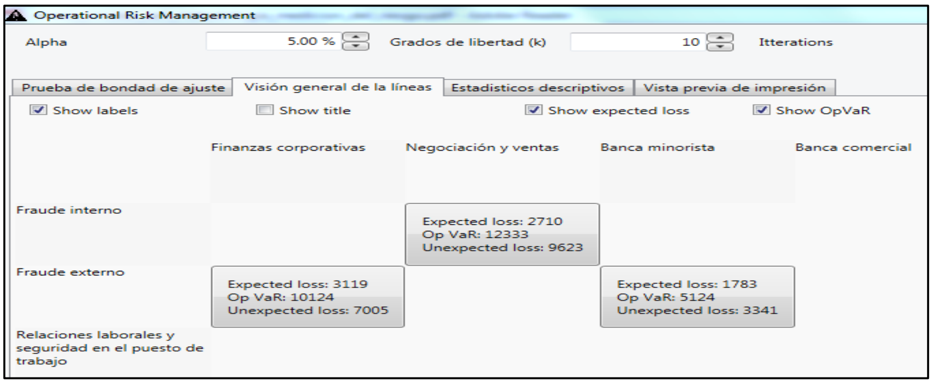
The system facilitates the configuration of three simulation parameters (see figure 6), which can be modified in each iteration; the parameters to be defined are: Degrees of freedom (k), required for the Chi-square goodness-of-fit test, significance level α (Alpha), required to calculate the expected and unexpected losses and finally the number of iterations: number of simulations to be executed in each run. (Murillo-Gómez, Franco-Arbeláez, & Arias-Serna, 2014), (Arias-Serna M. A., Caro-Lopera, Castañeda, Murillo-Gómez, & Echeverri-Arias, 2017), (Arias-Serna M. A., Caro-Lopera, Murillo-Gómez, Franco-Arboleda, & Echeverri-Arias, 2016).

Figure 6. *Line configuration and loss events.*



The operational risk losses experienced by the financial institution under study were expressed as a function of two random variables: frequency and severity. Discrete probability distributions were used for the number of events and continuous probability distributions for severity. These values were then used to construct a matrix summarizing the estimated losses, as shown in Fig. 7.

Figure 7. *Loss matrix*



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CONCLUSIONS AND FUTURE WORK

Understanding the risk assumed by organizations has become a critical success factor for competitiveness. For this reason, the system presented in this article seeks to ensure sound risk management and enable informed decision-making based on the degree of risk exposure calculated using VaR, based on various methodologies. The information provided by the software is aligned with the requirements presented by the Basel Committee.

The software allows for the generation of different scenarios regarding the loss events that may arise due to the risk exposure of any financial institution, which could have a significant impact on its operations. It also allows for the identification of relevant statistical information to quantify and make provisions to cover any loss events that may arise.

The efficiency of the VaR model using the three proposed methodologies exceeds 95%, which implies that the methodologies used are efficient.

Currently the Software is used by entities in the Colombian solidarity and financial sector who, using the tool, have achieved greater stability in their results, avoiding the materialization of negative events, in addition to the80% reduction in time spent on calculations and 50% reduction in financial losses.

In the future, we expect to include other variable volatility models, such as the ARCH and GARCH families. We also hope to add additional features to the system to estimate losses resulting from other financial risks, such as credit risk, counterparty risk, and the risk of money laundering and terrorist financing.

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