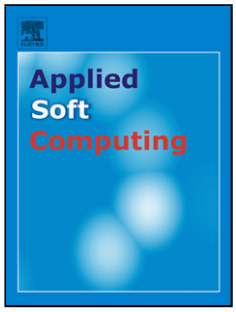

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Flexible inverse adaptive fuzzy inference model to identify the evolution of Operational Value at Risk for improving operational risk management

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Abstract

Operational risk was one of the most important risks in the 2008 global financial crisis. This is due to limitations of the applied models in explaining and estimating this type of risk from highly qualitative information related to failures in the operations of financial organizations. A review of research literature on this area indicates an increase in the development of models for the estimation of the operational value at risk. However, there is a lack of models that use qualitative information for estimating this type of risk. Motivated by this finding, we propose a Flexible Inverse Adaptive Fuzzy Inference Model that integrates both a novel Montecarlo sampling method for the linguistic input variables of frequency and severity that allow the characterization of a risk event, the impact of risk management matrices to estimate the loss distribution and the associated operational value at risk. The methodology follows a loss distribution approach as defined by Basel II. A benefit of the proposed model is that it works with highly qualitative risk data and it also connects the risk measurement (operational value at risk) with risk management, based on risk management matrices. This way, we mitigate limitations related to a lack of available operational risk event data when assessing operational risk. We evaluate the experimental results obtained through the proposed model by using the Index of Agreement indicator. The results provide a flexible loss distribution under different risk profiles or risk management matrices that explain the evolution of operational risk in real time.

Keywords: operational risk, adaptive fuzzy inference model, Montecarlo sampling, loss distribution approach, operational value at risk, risk management matrix, Basel Committee on Banking Supervision, Basel II.

1. Introduction

Operational Risk was one of the most important risks in the 2008 global financial crisis as the applied models have limitations in explaining and estimating this type of risk from highly qualitative information related to failures in the operations of a business and, in particular, in operations of financial organizations. According to the Basel II agreement, established through the Basel Committee on Banking Supervision (BCBS), operational risk (OpRisk) is defined as *"the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events"* [1]. This means that this type of risk occurs when business processes and units do not perform well and when different qualitative elements are involved, which are not static and evolve over time.

The operational value at risk (OpVaR) is defined as the maximum loss which can be expected given a specific confidence level (α) in a certain period of time. This value can be estimated based on a loss distribution (LD)) which can be built using the frequency and severity of a set of operational risk events generated within a certain period of time by OpRisk events in a particular business line associated with a particular risk type, such as fraud for example [2, 3]. However, when it comes to measuring OpRisk, one problem is that compared with other types of risk data, like credit or market

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