# BANKING STRESS LIQUIDITY PREDICTION USING MACHING LEANING

Réalisé par
**Adel TAMART**
*Consultant Expert Quant/Risk*

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# INTRODUCTION

Liquidity stress constitutes an on-going threat to financial stability in the banking sector. A bank that manages its liquidity inadequately might find itself unable to meet its payment obligations. These liquidity issues, in turn, can negatively impact the liquidity position of many other banks due to contagion effects. For this reason, central banks carefully monitor the payment activities of banks in financial market infrastructures and try to detect early-warning signs of liquidity stress. In this article, we will see what the Banking Risk Liquidity is meaning. Differentiate between various types of Banking Liquidity, including funding, operational, strategic, contingent, and restricted liquidity. Finally, we explain how banks, by using technical maching learning, can perform their liquidity-stress.

## What is Banking Liquidity Risk?

Liquidity in the banking system refers to readily available cash that banks need to meet short-term business and financial needs. It is the nature of banks to attract deposits and provide loans. Bank lending finances investments in relatively illiquid assets, but it funds its loans with mostly short-term liabilities. The mismatch of short-term deposits versus long-term loans makes banks vulnerable to liquidity risk. Thus, one of the main challenges to a bank is ensuring its own liquidity under all reasonable conditions. Liquidity Risk is the risk that a firm will not be able to ensure that sufficient funds are available at a reasonable cost to meet potential demands from both funds providers and borrowers. When a bank does not manage its liquidity adequately, it might find itself unable to fulfill short-term payment obligations and face bankruptcy, this can easily trigger a domino effect across payment systems and effect the liquidity position of many other banks.

## Differentiate between various types of Banking Liquidity?

Liquidity is used for four purposes, namely operational, contingent, restricted and strategic liquidity. Operational liquidity involves the cash needed for daily funding of the business and the orderly clearing of payment transactions. Restricted liquidity entails liquid assets maintained to be used mainly for specifically defined purposes. Contingent liquidity characterizes the liquidity available to meet general financial obligations under a stress scenario. The liquidity is in the form of the institution’s liquid asset buffer, which entails access to high-quality financial assets that are readily convertible to cash without incurring a fire sale price. Strategic liquidity involves the cash an institution holds for future business needs that may arise without the course of normal operations such as funding future acquisitions or capital.

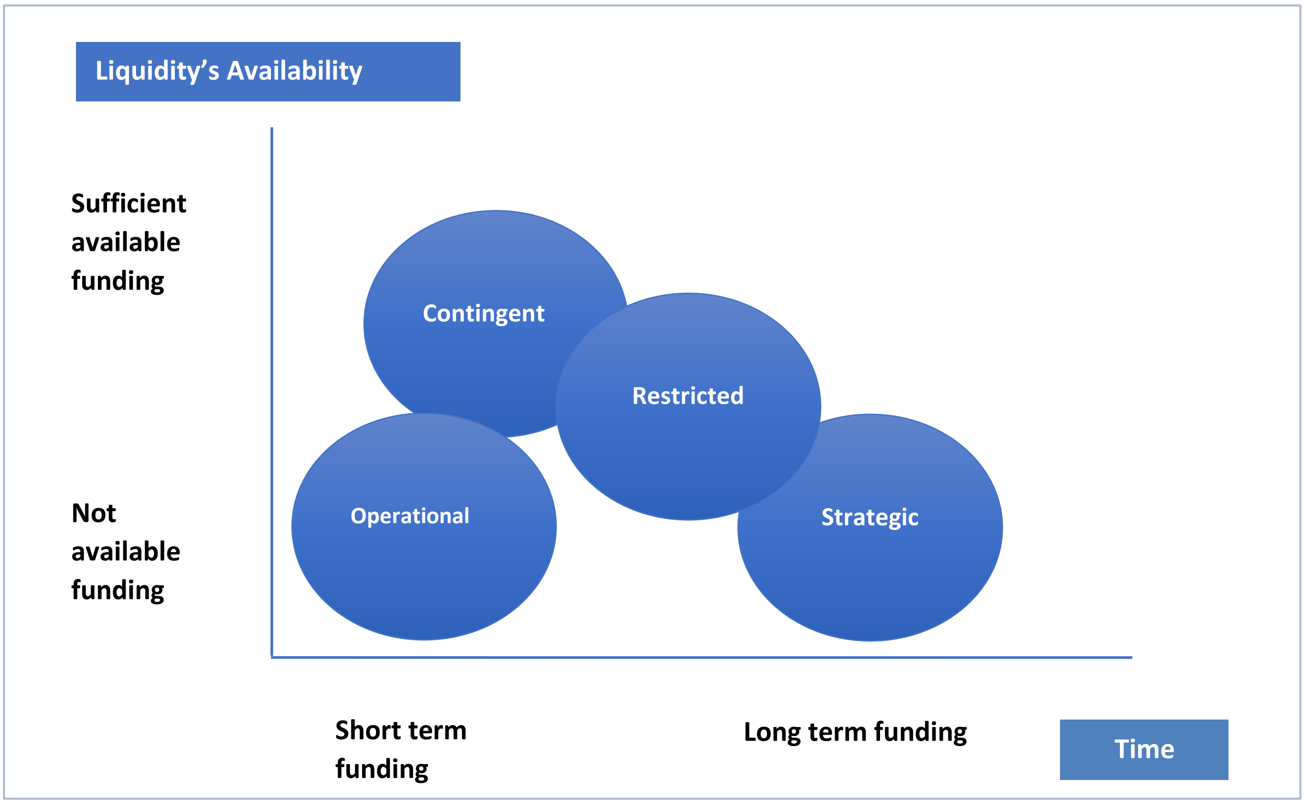


*Figure name: Classification of Banking Liquidity types*

From the financial crisis, Basel Framework introduces important reforms to enhance high liquidity risk coverage. It is essential that a high-quality capital base back banks' liquidity risk exposure. The main capital requirement measure proposed is the Capital Adequacy Ratio (CAR). Otherwise known as Solvability Ratio.

The CAR ratio can be defined as:

$$\textbf{CAR ratio} = \frac{\textbf{\textit{TIER 1 + TIER 2}}}{\textbf{\textit{RWA's}}}$$

where:

Tier 1: represent bank's core capital and it is the amount of immediate reserves on hand that a bank can use to fund its activities. Tier 1 capital is composed of excess reserves, common stock, and preferred stock.

Tier 2: is bank's supplementary capital and it is an amount that a bank must keep as part of its required reserves. Tier 2 capital is composed of revaluation reserve, undisclosed reserves, hybrid security, and subordinate debt.

Risk Weighted Asset (RWA): represent a measure of the riskiness of a bank's assets. It is based on a risk assessment for each type of bank risk exposure. The riskier the asset, the higher the RWAs.

Actually, strong buffers of capital are necessary to enhance the risk coverage but are not sufficient only by themselves. A bank needs a strong liquidity base as well. The Basel Framework establishes minimum liquidity requirement to achieves two objectives. The first is to promote short-term resilience by ensuring that the bank has enough liquid asset to survive an acute shock of short-term duration. The second is to promote long-term resilience by incentivizing a bank to fund its activities with stable funds. For measuring the capacity of a bank to fulfill its short and long term liquidity requirement. Basel committee within Basel III introduced two new ratios. They are Liquidity Coverage Ratio (LCR) and Net Stable Fund Ratio (NSFR).

The LCR ratio can be defined as:

$$\textbf{LCR ratio} = \frac{\textit{High Quality Liquid Assets}}{\textit{Total Net Cash Flow}}$$

The NSFR ratio can be defined as:

$$\textbf{NSFR ratio} = \frac{\textit{Available Amount of Stable Funding}}{\textit{Required Amount of Stable Funding}}$$

The interactions between the solvency and the liquidity of the banks are well identified analytically. The literature has identified several transmission channels in the event of financial shocks, such as financing costs, emergency sales of assets at “slashed” prices (discounts), uncertainty about the quality of assets, confidence or return on assets. In the event of a crisis, a problem that initially only seems to affect a bank's liquidity can quickly turn into a serious solvency problem and lead to the bank's bankruptcy. Indeed, more capital means a larger share of stable funding, which is supposed to increase the liquidity coefficient. Conversely, during a liquidity crisis, a bank may encounter difficulties in obtaining financing or obtaining it at higher costs. This increase in financing costs reduces its profits, which implies that a lower amount of income can be set aside to increase equity. In addition, in the face of a liquidity crisis, a bank may resort to emergency asset sales to raise liquidity, resulting in losses if the assets are marked to market and reducing the bank's solvency. More than likely that, when a shock materializes in one systemic bank, its impact is transmitted directly or indirectly to the financial sector.

## What is Banking Stress Liquidity Testing?

Liquidity stress tests examined the capacity of banks to withstand large withdrawals of funding of different maturities caused by liquidity risk factors, including policy changes, macroeconomic fluctuation, unexpected events, etc.

The objective of liquidity stress testing is to analyse whether an institution has sufficient sources of funding to withstand unexpected market disturbances. Although, not being seemingly straightforward, it appears that implementing a system that effectively achieves this goal in a repeatable and automated fashion is complex.

## Detection of banking liquidity stress using Maching Leaning Technics

To anticipate early signs of the liquidity stress, banks traditionally proceed by using supervised approaches example of regression logistics methods or one of the three approaches namely historical statistical techniques, deterministic models or Monte Carlo simulation. These traditional methods that depends on observations of the historical volatility of cash flow variables are less favorable in times of financial crisis. For improving the signaling power of an early warning system in order to predict individual banks stress liquidity and therefore future financial crash, Richard Heuver and Ron Triepels are given their first contribution to this field with the application of maching learning such as neural network to a dynamic balance sheet liquidity stress testing. The two authors have formulated their work for liquidity stress detection by taking a set of European well-known banks $\beta = \{b1 \ldots bn\}$ and comparing their payment behaviour, including their liquidity position, over an interval of time. They used a probabilistic classifier that classifies whether or not the corresponding bank faces liquidity stress. The classifier is a probability function:

$$\boldsymbol{f}: \boldsymbol{X} \rightarrow [\mathbf{0}, \mathbf{1}]$$

where:

$\boldsymbol{f}(x_i^{(k)})$ is the conditional probability that a bank $bk$ faces liquidity stress given that we observe feature vector $x_i^{(k)}$ at time interval $\mathcal{T}_i$

$$\boldsymbol{f}(x_i^{(k)}) = \boldsymbol{P}(y_i^{(k)}) = \mathbf{1}|x_i^{(k)}$$

A bank is classified as under liquidity stress if $\boldsymbol{f}(x_i^{(k)})$ higher than a certain threshold $\zeta \in [0,1]$.

$$\boldsymbol{\Phi}(x_i^{(k)}, \zeta) = \begin{cases} \mathbf{1}, \boldsymbol{f}(x_i^{(k)}) \geq \boldsymbol{\zeta} \\ \mathbf{0}, \boldsymbol{otherwise} \end{cases}$$

**$\zeta$:** Determines how the confident the classifier needs to be to classify a feature vector as belong to a stress bank.

To estimate this function $\boldsymbol{f}(x_i^{(k)})$, they have compared the result of using a Logistic Regression Model (LRM) and Multi-Layer Perception Network (MLP-N).

- For Logistic Regression Model they have considered $\hat{y}_i^{(k)}$ is an estimate of $\boldsymbol{f}(x_i^{(k)})$

  $$\hat{\boldsymbol{y}}_{\boldsymbol{i}}^{(\boldsymbol{k})} = \boldsymbol{\sigma}(\boldsymbol{w}\mathbf{x}_{\boldsymbol{i}}^{(\mathbf{k})} + \boldsymbol{b})$$

  where: $\boldsymbol{w}$ is an m-dimensional row vector of weights, $\boldsymbol{b}$ is a bias term, and $\boldsymbol{\sigma}$ is the sigmoid function.

- For Multi-Layer Perception Network, the have considered the output $h_\delta$ that is an estimate of $\boldsymbol{f}(x_i^{(k)})$

  $$\hat{y} = h_\delta = \boldsymbol{\sigma}(\boldsymbol{W}_\delta \boldsymbol{h}_{\delta\text{-}1} + \boldsymbol{b}_\delta)$$

where: $\boldsymbol{w}_\delta$ is m-dimensional row vector of weights, $\boldsymbol{b}_\delta$ is a bias term and $h_{\delta-1}$ is the last hidden layer processed through a single sigmoid.

To do this comparison they have taken into consideration features, which describes the payment behaviour of a list of seven European banks on daily basis over the last ten years.

Data and information's are taken from Eurosytem Target 2 and concerns:

- Payment features:

  - **Daily net value of payment**

    $$[\sum \text{cash inflow} - \sum \text{cash outflow}]$$

  - **Daily number of transactions**

    $$[\sum \text{number of incocmming payments} - \sum \text{number of outgoing payments}]$$

  - **Daily net payment time by value and number of transactions**

    $$[\text{Weighted incoming payment time} - \text{Weighted outcoming payment time}]$$

  - **Daily end-of-day account balance**
  - **Daily minimum account balance** i.e. the lowest value within the day

- Money market features
- Collateral amounts management features

For the validation of each model, they split data used into two sets. A set of training and a set of testing.

As the Multi-Layer Perception Networks have some hyper-parameters that needed to be tuned, they optimized them by using the technical of K-fold cross validation and choose the configuration having the lowest loss averaged over the all-holdout folds. Also, to avoid the discrepancy of scale and easily compare the feature vectors of one bank to another bank, they have normalized the value of features vectors of each bank separately by z-normalization. The mean and standard deviation are estimated only on the training dataset and then applied to validation sets to avoid data leakage.

To measure the performance of the probabilistic classifier model, which model better classifies whether the corresponding bank faces liquidity stress, they used Precision[1], Recall[2], *F1*-score[3] and weighted cross entropy loss for accuracy[4] as evaluation metrics with a threshold of $\zeta = 0.9$.

For definition:

- *Precision:* is the probability that a feature vector belongs to a stressed bank given that a classifier predicted liquidity stress.

$$(1)\ \ldots\ \textbf{Precision}\ (\zeta) = \frac{True\ Positive\ (TP)}{\text{True}\ Positive\ (TP)\ \ +False\ Positive\ (FP)}$$

- *Recall:* is the probability that a classifier predicts liquidity stress given that a feature vector belongs to a stressed bank.

$$(2)\ \ldots\ \textbf{Recall}\ (\zeta) = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP)\ \ +False\ Negative\ (FN)}$$

- *F1*-score: is the harmonic mean of precision and recall and constitutes an overall measure to compare the performance of a set of competing classifiers.

$$(3)\ldots\ \textbf{F1-score}\ (\zeta) = 2\ X\ \frac{Precision\ (\zeta)\ X\ Recall\ (\zeta)}{Precision\ (\zeta) + Recall\ (\zeta)}$$

- *Accuracy:* is the probability that a feature belonging to a correct class when predicting a stressed or no stressed bank.

$$(4)\ldots\ \textbf{Accuracy}\ (\zeta) = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{\text{True}\ Positive\ (TP)\ \ +False\ Positive\ (FP) + True\ Negative\ (TN) + False\ Negative\ (FN)}$$

With this experience, the detection of stress liquidity is much well identified by using the Multi-Layer Perception Networks Model than Logistic Regression Supervised Model. The result of the prediction error drops significantly under the deep leaning approach. The MPL-N achieve an average of *F*1-score of 42% with an average precision of 70% and average recall of 34% while the LR model achieve a similar F1-score but with much lower precision (average precision 47%).

| | *ζ = 0.9* | ***Precision*** | ***Recall*** | ***F1-score*** |
|---|---|---|---|---|
| **Accuracy Weighted Average** | ***LR*** | *0.47* | *0.39* | *0.41* |
| | *MLP-N* | *0.70* | *0.34* | *0.42* |

*Figure name: LR & MLP-N performance results or Banking Liquidity Stress detection*

# CONCLUSION

At the end of these few lines of this article, nowadays in the context of the downward economic pressure and the recent economic crisis, the banking system, more than ever, will absolutely go through a difficult period and banks may be more exposed to serious liquidity risk. The use of deep learning models could be an innovative expertise for detecting earlier banking liquidity stress.

Given the good predictive performance obtained using Network Models, developing new Advanced Machine Learning tools have a potential to be a game changer as the technological progress and financial innovation for banks. They could be useful instrument for regular monitoring exercises, as they can help central banks to detect in advance banks that could be in need of central bank's emergency liquidity assistance.

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