Financial Market Reform Project
Desktop Review of Methodologies for Initial Margin Calculation

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1 Purpose

This paper examines the pros and cons of potential approaches for the calculation of initial margin for participant FTR portfolios, and recommends two options to proceed forward with for development of proof-of-concept models and associated back-testing.

2 Summary

Margin is the amount of **financial** collateral deposited by a market participant with the Central Counter-Party (CCP) to collateralize trade exposures introduced by the participant. Margins are the CCP's first line of defense in the event of the market participant's default, to satisfy the financial obligations of that participant. The margins are designed to cover the market risk of a market participant's portfolio with high level of confidence. There are two principal forms of margin: Variation Margin (VM) and Initial Margin (IM).

Initial Margin is the main focus of this paper. IM is the amount of collateral needed to cover the 'replacement cost' of unwinding a market participant's portfolio in the case of default. These are the costs incurred during the liquidation period – the time period between the last VM posting and the complete portfolio closeout time.

In this paper we describe two principal approaches to IM calculation: Historical Simulation (HS) approach and Monte-Carlo (MC) approach. In the Historical Simulation method, past auction price volatilities are used to calculate the CCP's exposures during the liquidation period.

The Monte-Carlo approach is based on generating a range of LMP sets using economic dispatch software (PROMOD, PLEXOS, etc.) and a set of stochastic primary drivers: load, generation, transmission, fuel prices, etc. This approach would utilize knowledge of the statistical properties of these primary drivers to calculate changes to market participants' portfolio values under each simulated scenario, and based on this, forward looking CCP risk.

In this paper both methods are described, together with the methodology for their validation.

3 Initial Margin

Initial Margin (IM) is a good-faith deposit, posted by a trading participant as collateral to protect against the financial consequences of default. It typically represents the potential losses that would be incurred by the counter-party – or frequently, as in this case, the Central Counter-Party (CCP) – should the participant default, calculated to a high degree of statistical likelihood, across the participant's entire portfolio. In order to do this, it must cover the time period between when the position was incurred or variation margin (VM) last levied (whichever is the latter), and when it could be liquidated or taken to final settlement (whichever is the sooner) in the event of default. This time period is called the Market Period of Risk (MPOR), and is also known as "liquidation period".

The correct calculation and levying of IM is an essential – but not the sole – defense in protecting the market from the failure of any of its individual participants.

4 Review of the Academic Literature[1]

Early models quantifying potential exposure of Central Counter-Parties (CCPs) can be divided into three main categories:

- Statistical Models: assume simple underlying dynamics, such as geometric Brownian motion, and derive the probability for the IM to be exceeded within a given time horizon. For instance, Figlewski (1984) calculated the probability of a margin call given a certain percentage of Variation Margin (VM) and Initial Margin (IM).
- Optimization Models: calculate margins in a way that balances the resilience of CCPs and costs to their members. For example, Fenn and Kupiec (1993) and Baer et al (1996) built models along these lines by minimizing the total sum of margin, settlement and failure costs.
- Option Pricing-Based Models: explore the fact that the exposure profile of a CCP is approximately equivalent to a combination of call and put options because a GCM can strategically default if the contract loses more value than the posted IM. (This is largely a theoretical possibility.) Day and Lewis (1999) used this framework and estimated prudent margin levels for specific instruments.

When designing its defenses, a CCP has to analyze losses conditional on exceeding margins. By its very nature, extreme-value theory (EVT) can be used for this purpose; it has been exploited by several researchers (see, for example, Longin 1999; Broussard 2001). While the use of EVT to set up margins for a single contract is straightforward, it is much more difficult to do this at a portfolio level. Accordingly, CCPs tend not to use EVT directly, relying instead on the intuitive Standard Portfolio Analysis of risk (SPAN) methodology and its variations (see Kupiec 1994). In practice, SPAN has severe limitations when applied to complex portfolios. The value-at-risk-based (VaR-based) IM system, which is better suited for such a task, was discussed by Barone-Adesi et. al. (2002).

More recently, some fundamental topics related to the clearing process have come into focus. For instance, Duffie and Zhu (2011) questioned the premise that central clearing of OTC derivatives can substantially reduce counterparty risk. They argued that some of the expected benefits are lost due to the fragmentation of clearing services, since there is no allowance for interoperability across asset classes and/or CCPs. They argued that the benefit of multilateral netting among many clearing participants across a single class of derivatives over bilateral netting between counterparties across assets depends on the specifics of the clearing process and could be absent in practice.

Arnsdorf (2012) showed that a clearing GCM's CCP risk is given by a sum of exposures to each of the other clearing members, which arises because of the implicit default insurance that each member has provided in the form of mutualized, loss sharing collateral. He calculated the exposures of GCMs by explicitly modelling the capital structure of a CCP as well as the loss distributions of the individual member portfolios. Arnsdorf assumed that all GCMs are equivalent, which is not the case in practice.

Cont and Avellaneda (2013) developed an optimal liquidation strategy for a defaulted GCM portfolio that is based on auctioning parts of the portfolio, unwinding other parts and selling the rest on the market. They modelled an auction with limits on how many positions can be liquidated on a given day due to liquidity considerations, and determined an optimal sale strategy to minimize market risk by using linear programming.

[1] This synopsis and more can be found in the paper by A. Lipton, "Systemic Risk in Central Counterparty Clearing House Networks", *Margin in Derivatives Trading, Ch. 16,* Risk, 2018.

Cumming and Noss (2013) assessed the adequacy of CCPs' default resources and concluded that the best way to model a CCP's exposure to a single GCM in excess of its IM and DF contribution is to use EVT. They drew a simple analogy between the risk faced by a CCP's default fund and that borne by a mezzanine tranche of a collateralized debt obligation (CDO) and used an established framework to model codependency of defaults based on a gamma distribution. Their model is a useful step towards building a proper top-down statistical framework for evaluating the risk of a CCP's member exposures.

Ghamami (2015) introduced a risk measurement framework that coherently specifies all layers of the default waterfall resources of typical derivatives CCPs, and produced a risk sensitive definition of the CCP risk capital.

Berlinger et al (2017) analyzed the effects of different margin strategies on the loss distribution of a CCP during different crises and found that anti-cyclical margin strategies might be optimal not only for regulators aiming to reduce systemic risk, but also for CCPs focusing on their micro-level financial stability.

Menkveld (2017) emphasized the fact that CCP risk management does not account for risks associated with crowded positions. He proposed an exposure measure based on tail risk in trader portfolios, which identifies and measures crowded risk and assigns it to traders according to the polluter-pays principle.

Lipton (2018) analyzed the pros and cons of moving trade execution, clearing and settlement to blockchain and concluded that the advantages of such a move are not as clear-cut as its proponents claim. Still, by using permissioned private ledger(s), costs can potentially be cut and the speed of clearing and settlement somewhat increased while the number of failures can be reduced.

5 Methodology Guidelines and Requirements

Objectives:

- Margin levels should correctly reflect the risk
- Margin calculation methodologies should be transparent and relatively simple
- Margin calculation methodologies should be replicable by counterparties to reduce dispute burdens
- Margin methodologies should take into consideration market liquidity and concentration

Guidelines from other markets:

- The BCBS-IOSCO guidelines (BCBS-IOSCO, 2015) define the IM requirement as an amount that "covers potential future exposure for the expected time between the last Variation Margin (VM) exchange and the liquidation of positions on the default of a counterparty". It is further specified that the calculation of this potential future exposure "should reflect an extreme but plausible estimate of an increase in the value of the instrument that is consistent with a one-tailed 99% confidence interval over a 10-day horizon, based on historical data that incorporates a period of significant financial stress".

  Note. The 10-day horizon in the guidelines above is the suggested length of the liquidation period for the markets trading frequently. The liquidation period for the FTR market will be substantially larger. We will also investigate the choice of confidence interval in the context of FTRs.

Methodologies similar to the one outlined in the above guidelines are called VaR-based methodologies (or, risk-based methodologies) and are widely accepted in different markets for calculating IM and for other capital requirements. We note that after choosing the target percentile, the collateral (capital) required for insurance against default or other adverse market events can be computed in several ways. It can be just the value corresponding to this percentile (VaR), or it can be the expected value of losses exceeding VaR. This expected value, called *expected shortfall* (ES), has recently become more and more frequently used in regulatory guidelines for capital requirements. For example, it is universally used for calculating regulatory capital under FRTB IMA guidelines.

Regardless of the choice of the capital calculation, one step is common – calculating the change (over the MPOR) in the MTA value corresponding to the target percentile. That step, in turn, requires determination of the distribution of these MTA value changes. More precisely, at time *t* (time of current auction) we need to determine the distribution of the random variable

$$d_t = MTA_{t+MPOR} - MTA_t \# (1)$$

Two principle ways of generating this distribution will be described in this paper – a method based on historical simulations, and one based on Monte-Carlo simulations.

6 Historical Simulation Approach

In this approach we use the historical time series for auction prices for all auction times preceding the current time *t.*

6.1 Simple Historical Simulation

Using historical time series of auction prices, we compute the changes of portfolio MTA values over the MPOR for all times $\tau,\ \tau \le t$, in our time series:

$$D_\tau = MTA_\tau - MTA_{\tau-MPOR}$$

- Sort D_τ and find the one corresponding to target percentile.
- Compute IM using VaR or ES approach.

6.2 Historical Simulation with Scaling: FHS (filtered historical simulations)

In this method we scale by the ratio of current volatility and long-term volatility to account for *procyclicality*.

6.3 Using Stress Period

In this method we use changes over the worst historical period (worst year, two years …) to get more conservative values of IM.

6.4 Liquidity Adjustment

Liquidity is taken into account by introducing liquidity horizons (*LH*) for each path and product, and by scaling historical changes by a factor proportional to $\sqrt{LH}$. The meaning of *LH* is that for certain paths/products the time to unwind is greater than for others.

LH values are typically the same for a specified group. We assign the lowest *LH* to the most liquid paths and higher values to the less liquid paths. Determining *LH* groupings and values will be one of our principal tasks.

6.5 Market Concentration Adjustment

Another objective of this project is to determine how to account for a concentrated trading position, i.e., a position that constitutes a large percentage of the total market exposure to the underlying product.

6.6 Generating Historical Time Series

Generating reliable historical time series is a key step for the success of HS methodology. This step requires proper concatenating, cleaning and analysis of various data streams as well as potential bootstrapping and proxying.

6.7 Validation of the Methodology: Back-Testing

Back-testing is a standard method for validating a particular trading or risk management methodology. We will also use it to choose between different IM methodologies under consideration.

For a given IM methodology the back-testing procedure works as follows.

- We fix a particular time *t* in the past and calculate IM using historical data for times preceding *t*.
- We then assume that default happens at time *t* and it takes a time period equal to MPOR to unwind the position.
- We then compare the loss during MPOR with the computed IM.
- We repeat this test for a number of times *t* and compute a percentage of times IM was less than actual loss.
- We check if this frequency is consistent with target risk percentile fixed in IM calculation methodology.

The comparison of these statistics for different methodologies also will allow us to choose a better IM methodology.

In addition to the procedure above we will include back-testing of a known default occurrence. Our goal is to analyze the performance of the IM algorithm during that time.

6.8 Final Thoughts about Historical Simulations Approach

Pros

- Standard risk-based approach used in majority of markets.
- Easy to implement.
- Transparent; low probability of dispute.
- No need to determine correlations between paths as there are built in the historical data.

Cons

- The method is based on historical price behavior; assumes stationarity; does not. take into account present and future systemic changes.
- Requires substantial historical data which may not be available.
- May generate unfeasible scenarios.

7 Monte-Carlo (MC) Simulation Approach

In this section we describe an alternative approach to simulating CCP exposure to a market participant over the MPOR. The main idea underlying this approach is that the congestion component of the LMP price at any node is a function of fundamental drivers, such as nodal loads, generation and transmission constraints, fuel prices, etc. Once the values of these fundamental drivers are specified, we can run an optimization program, such as PROMOD, PLEXOS, etc., to determine economic dispatch solution and LMP prices at every node x, and particularly its congestion component (*CLMP*)

$$c^x = \Phi(L^y, \dots, G^z, \dots, T^b, \dots U)\#(2)$$

where L^y denotes the load at a node y, G^z denotes generation constraints at the node *z*, T^b is the transmission constraint at the branch *b* and *U* is the vector of fuel prices.

The consequence of our ability to generate CLMPs as a function of primary drivers is that for any given path we can generate the distribution of CLMP price differentials for that path by generating the distribution of the primary drivers over the MPOR. The benefit of this approach is that the statistical properties of primary drivers (loads, fuel prices) are stable and their distribution can be reliably validated. Having the distribution of the path prices over MPOR will allow us to simulate the distribution of a market participant's portfolio values, which ultimately will lead us to the calculation of the IM.

We suggest two approaches to generation of the distribution of the primary drivers.

7.1 Using Historical Data to Generate Distributions of Primary Drivers

Let *t* denote the current date. We need to generate the distribution of the future primary drivers, say loads, for the month $t + MPOR$. We will produce this distribution by applying historical load changes over the same period to the expected load for the month $t + MPOR$. After the distribution for loads is constructed, we generate the distribution of FTR prices

Again, the advantage of the historical approach is that the distributions used in this approach are not parametric and we don't need to determine correlations between these drivers at different locations. Moreover, compared to the historical price simulation methodology the advantage of this approach is that statistical characteristics of primary drivers are much more stable than those of the prices, and thus, historical distribution of these drivers are more stable and reliable.

7.2 Using MC Simulations to Generate Distributions of Primary Drivers

In this approach we use pure MC simulations to generate joint distribution of LMP primary drivers. This approach allows us to generate as many scenarios as our hardware and efficiency of our software will allow us, thus, giving us an increased degree of confidence that we will cover most of the adverse future scenarios. In addition to scenarios on loads, generation and fuel prices we can also consider scenarios impacting grid topology. We should note here that even the pure MC simulations involve the usage of the historical data. We need it to determine parameters of the joint distribution, particularly, the correlation between different drivers.

7.3 Validation of the Methodology: Back-Testing

The back-testing methodology for MC approach is the same as the one proposed for HS methodology (see Section 6.7).

7.4 Add-Ons

Additional modifications, such as liquidity adjustments and concentration adjustments, will be considered for implementation as part of the MC approach, in the same way they are considered for the HS method (see Sections 6.4, 6.5).

7.5 Final Thoughts about MC Simulations Approach

Pros

- More flexibility; broader set of scenarios.
- Better risk determination; can better capture fat tails of loss distribution as we can analyze scenarios that HS cannot.

Cons

- Dependence on a choice of proprietary software.
- Potential for dispute if results are not easily understood (Solution: need to find a transparent way to communicate the process).
- More computationally intense; data requirements are high.