MVA Optimization with Machine Learning Algorithms

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Abstract

MVA (Margin Valuation Adjustment) is becoming a dominant component of the price in interdealer derivatives trading. MVA is always a cost because of non-rehypothecability of the initial margin posted under the margin rules covering non-centrally cleared derivatives. This prompts dealers to **investigate MVA optimisation**.

The dealers face a complex non-linear optimisation problem: MVA is a **non-linear function** in **continuous trade parameters** such as tenor and notional, but also a function of **discrete variables** such as counterparty and underlying asset.

Many standard optimisation algorithms based on the continuity or convexity of the objective function are no longer suitable due to the non-linear and the mixed discrete and continuous nature of the problem.

At the same time we observe, mainly on the buy side, increasingly widespread usage of Machine Learning techniques in quantitative finance.

This work is about novel applications of Genetic Algorithm and Particle Swarm Optimisation to the problem of MVA optimisation.

Main equations

$$MVA = \int_0^T f(u)\exp\left(-\int_0^u f(s)ds\right) Q(u) EIM(u) du$$

Where:
- Q(u) is the counterparty survival probability
- f(u) continuously compounded funding spread
- EIM(u) expected Initial Margin at time u

$$\varphi(\text{solution}) = \Delta MVA(\text{solution}) + Cost(\text{solution})$$

$$\Delta MVA(\text{solution}) = MVA(\text{existing portfolios} + \text{proposed trades}) - MVA(\text{existing portfolios})$$

$$Cost(\text{solution}) = \frac{1}{2}\sum_{i=1}^{2} spread_i \, |\text{DV01}|_i$$

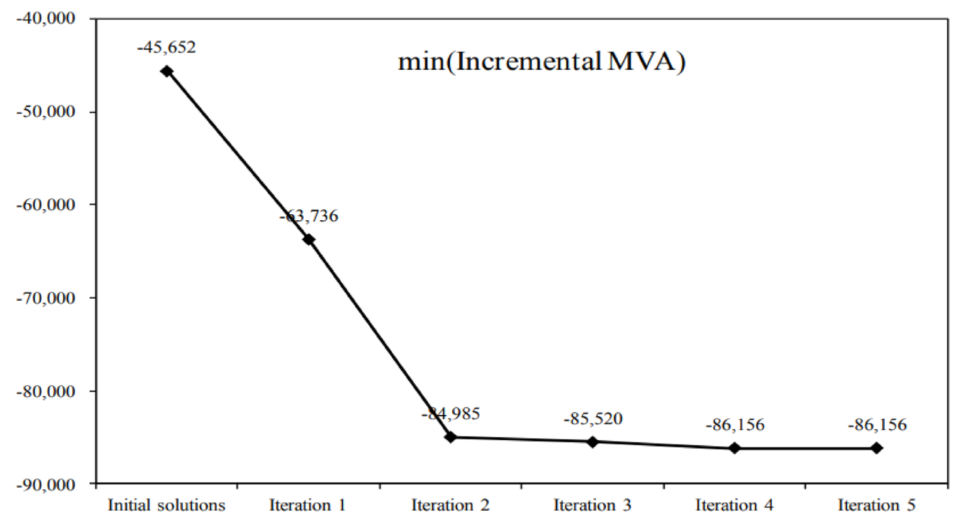
Method 1: Genetic Algorithm

The population of solutions undergoes a simulated evolution with relatively good solutions producing offsprings that subsequently replaces inferior ones.

The Genetic Algorithm for MVA optimisation consists of the following steps:
- Generation of N initial solutions through a random draw from the pools of possible gene values
- Evaluation of the objective function for each solution
- Ranking of solution from best to worst
- Selection of M best solutions and production of N new solutions by mutation or crossover
- Evaluation of the objective function...

Solution / chromosome:	Dealer A	Dealer B	300m	INR	5y
	Pool of dealers	Pool of dealers	Pool of standard notional values	Pool of non-clearable currencies	Pool of standard tenors
Number of independent gene values	~10²	~10²	~10²	~10	~10

GA operates on a function of discrete variables
Discretized continuous parameters

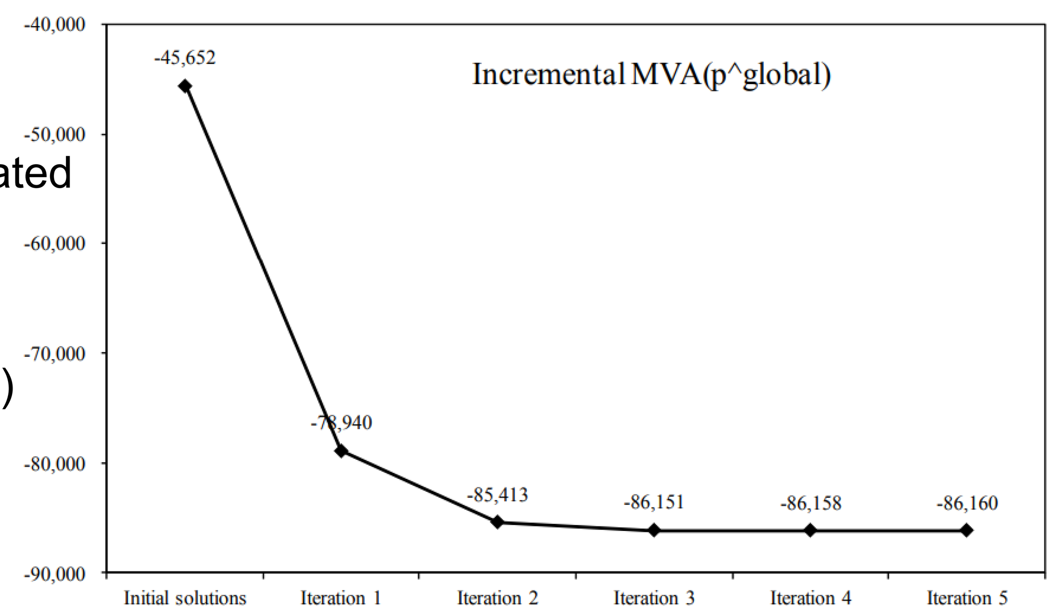


Method 2: Particle Swarm Optimisation

A number of particles are placed in the solution space and each evaluates the fitness at its current location.

-Particle = Solution (e.g. Pair of offsetting trades)
- Swarm of particle = Set of solutionsthat evolve over time
- Particles move in the solution space (solution parameters are updated at each iteration)
  - Position of particle i at time k is a n-dimensional vector x
  - Velocity of particle i at time k is an n-dimensional vector v
  - n= number of solution parameters (tenor, notional, ccy, etc)

-Particle velocity is changing at each iteration and is influenced by current motion, particle own memory and swarm influence.



PSO operates on a function of continuous variables
Continuous counterparts for categorical parameters

$$\mathbf{x}_0^i = \mathbf{x}_{\min} + \omega_x(\mathbf{x}_{\max} - \mathbf{x}_{\min}) \qquad \mathbf{x}_{k+1}^i = \mathbf{x}_k^i + \mathbf{v}_{k+1}^i \Delta t$$

$$\mathbf{v}_0^i = \frac{\mathbf{x}_{\min} + \omega_v(\mathbf{x}_{\max} - \mathbf{x}_{\min})}{\Delta t} \qquad \mathbf{v}_{k+1}^i = w\mathbf{v}_k^i + c_1\omega_1 \frac{(\mathbf{p}^i - \mathbf{x}_k^i)}{\Delta t} + c_2\omega_2 \frac{(\mathbf{p}_k^{global} - \mathbf{x}_k^i)}{\Delta t}$$

What about machine learning?

Single incremental MVA calculation = 100 milliseconds Possible solutions = 10^8	115 days to evaluate the objective function on the set of solutions

Tuning the parameters of GA and PSO by training the optimiser on sample inputs with known optimal solutions. The parameters are tuned for quick convergence to the optimum.

Conclusion

In this work, we explored the use of Machine Learning and metaheuristics for MVA optimisation and found that:

• Evolutionary heuristics are able to optimise non-convex or discontinuous functions

• Genetic Algorithm and Particle Swarm Optimisation work well when parameters are tuned by training the optimiser.

• Comparison with other Machine Learning techniques as future work and expect more techniques to emerge as the usage of Machine Learning techniques becomes more widespread for optimising valuation adjustments.

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References

1. MVA Optimisation with Machine Learning Algorithms,; Alexei Kondratyev and George Giorgidze
2. Credit Exposure in the Presence of Initial Margin,; Leif Andersen, Michael Pykhtin and Alexander Sokol
3. A comparison of Particle swarm optimization and the Genetic Algorithm; Rania Hassan, Babak Cohanim and Olivier de Weck
4. Margin requirements for non-centrally cleared derivatives; BCBS 261, 2013