

Compression Algorithms and Their Utilization in the OTC Market

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Abstract

Due to the 2008 financial crisis, with the rise of regulatory restrictions and the increasing importance of reducing operational and counterparty exposures, compression algorithms have played an essential role in optimizing the OTC markets such as CDS, derivatives, and interest rate swaps. However, even with the emergence of portfolio compression, little academic research has been done to understand compression algorithms. This thesis observes the emerging technology of compression algorithms, how and why they work, and the ways that they are continuously being improved and deployed. Their recent use cases in OTC markets, quantifiable evidence on their proven market optimization, and other applications are covered.

Introduction to Compression Algorithms

Compression algorithms are a relatively new computer science technology that is constantly being deployed in new and innovative ways. For the scope of this thesis, the focus will be on compression algorithms used in graph reduction rather than those that compress data, such as what is used when a folder is compressed into a ZIP file. Graph compression, or graph reduction, was first researched by Chris Wadsworth in 1970. The goal of his research was to show how effective graph reduction would help to advance the development and use of functional programming languages.¹ Functional programming languages are software programming languages that have arisen in the field of computer science as they pose a number of benefits, such as parallel programming, efficiency, and nested functions. Python and Haskell are among the most popular programming languages used in the present day.²

The issue with functional programming languages, however, is that they require efficiently organized data, typically stored as graphs, to optimize the use of memory and storage.³ Thus, the research of many others since Wadsworth has focused on improving graph compression algorithms to become as efficient as possible. Yet, as the world has technologically advanced since 1970, graphs have become ubiquitous in their deployment. It is not uncommon “to find graphs with millions of nodes and billions of edges in, e.g., social networks.”⁴

The use cases of graph algorithms are thus just as numerous as graphs themselves, and they will be discussed later in this thesis. However, with so many different use cases, it is important to differentiate between different types of graph reduction. The first significant separator in graph reduction is the allowance of node and edge reduction versus solely edge reduction. After, follows another division between algorithms that can create new edges between nodes in order to allow for the possibility of deleting more edges or algorithms that are strictly able to reduce graphs from what they currently are while maintaining reachability, which is the condition that the nodes of both the reduced graph and original graph are all reachable from the same point.⁵

Among the most important of all the different types of graph compression is query preserving graph compression. Wenfei Fan describes query preserving graph compression best saying that a query preserved compression is:

¹ Wadsworth, Chris. “Graph Reduction: A Retrospective.” *Electronic Notes in Theoretical Computer Science*, vol. 2, 1995, p. 286. *DOI.org (Crossref)*, DOI:10.1016/S1571-0661(05)80207-5.

² *Functional Programming - Introduction - Tutorialspoint*. https://www.tutorialspoint.com/functional_programming/functional_programming_introduction.htm. Accessed 6 Apr. 2020.

³ *Functional Programming - Introduction - Tutorialspoint*. https://www.tutorialspoint.com/functional_programming/functional_programming_introduction.htm. Accessed 6 Apr. 2020.

⁴ Fan, Wenfei, et al. “Query Preserving Graph Compression.” *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, Association for Computing Machinery, 2012, pp. 157–168. *ACM Digital Library*, doi:10.1145/2213836.2213855.

⁵ *Reachability Graph - an Overview | ScienceDirect Topics*. <https://www.sciencedirect.com/topics/computer-science/reachability-graph>. Accessed 6 Apr. 2020.

“a small G_r from a graph G such that (a) for any query $Q \in Q$, $Q(G) = Q'(G_r)$, where where $Q' \in Q$ can be efficiently computed from Q ; and (b) any algorithm for computing $Q(G)$ can be directly applied to evaluating Q' on G_r as is.”⁶

Something to note about these query preserved compressions is that their complexity is identical to the graphs they were compressed from. However, they do exhibit less data and take up less memory and space than the graphs prior to reduction.⁷

There are also different types of query preserving compression algorithms, and they can be split up into either multilateral or bilateral compression. The former options rely on market participants revealing their positions and the entire network of trades being manipulated for optimization. The latter work within the confines of the current compression tolerances, which are guidelines that the algorithms must follow due to real life regulation. In this case the tolerances are that banks do not disclose their positions publicly and so compression only takes place between each pair of market participants (bilaterally).⁸

For the scope of the technical overview, we will examine query preserved graph compressions of when used in optimizing OTC markets to reduce the amount of gross notional outstanding while ensuring that banks have the same net positions that they held prior to compression. This allows the entire financial system to have less systemic and counterparty risk, which is of rising importance since the 2008 financial crisis, when one bank failure would lead to another.⁹

⁶ Fan, Wenfei, et al. “Query Preserving Graph Compression.” *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, Association for Computing Machinery, 2012, pp. 157–168. *ACM Digital Library*, doi:10.1145/2213836.2213855.

⁷ Fan, Wenfei, et al. “Query Preserving Graph Compression.” *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, Association for Computing Machinery, 2012, pp. 157–168. *ACM Digital Library*, doi:10.1145/2213836.2213855.

⁸ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

⁹ Elliot, Matthew, et al. “Financial Networks and Contagion.” *The American Economic Review; Nashville*, vol. 104, no. 10, American Economic Association, Oct. 2014, pp. 3115–53. *ProQuest*, doi:http://dx.doi.org.proxy.library.upenn.edu/10.1257/aer.104.10.3115.

Introduction to Over the Counter Markets

In today's financial system, over-the-counter (OTC) markets play a critical role in allowing banks (dealers) and investors (buyers or sellers) to hedge investments and decrease or increase their exposure to market risk. Of all of the different types of securities traded in an OTC manner, credit default swaps (CDS) represent the largest asset class. A CDS is "a financial derivative or contract that allows an investor to "swap" or offset his or her credit risk with that of another investor."¹⁰ In other words, a CDS works similar to the way insurance does, in that one party can purchase protection by paying a monthly or annual payment such that it would be reimbursed for a partial or full amount of its loss in the case that the event specified occurs. When searching for protection against certain events, hedge funds and other buyers/sellers purchase CDS's to offset risk from their positions, so hence their asset class has a massive magnitude measured at \$3.68 trillion.¹¹

Given the way that CDS's are structured, in that they are personalized contracts in some cases, it is only possible for them to be traded in an OTC market rather than a centralized one, such as stocks that trade on an exchange. In an OTC market, securities will be traded between two parties in which one is the buyer and the other is the seller, and prices are not standardized across the market.¹² Between the buyer and seller is a dealer, which is usually a bank. Banks do not want the same exposure to the market as buyers and sellers, rather seeking solely to make as many trades as possible because of the commission that they earn in doing so.¹³ However, what this entails for the structure of the CDS market, and other OTC markets, is "increased financial interdependencies among many kinds of organizations – governments, central banks, investment banks, firms, etc. – that hold each other's shares, debts, and other obligations."¹⁴

Defined more formally, the interdependencies can be referred to as gross notional outstanding, which is the total sum of all the securities' spot prices that are currently in the market.¹⁵ For example, if a market were to consist of only 3 CDS contracts worth \$3, \$4, and \$5, respectively, its gross notional value would be \$12. However, the idea of gross notional outstanding value should be held in contrast with net positions. A bank could be holding multiple contracts which have offsetting positions, and if this is the case then that bank is both a buyer and seller, which is very typical of banks to do, and it would have a net position less than

¹⁰ Kuepper, Justin. "Credit Default Swap (CDS) Definition." *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/c/creditdefaultswap.asp>. Accessed 25 Mar. 2020.

¹¹ Kuepper, Justin. "Credit Default Swap (CDS) Definition." *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/c/creditdefaultswap.asp>. Accessed 25 Mar. 2020.

¹² Murphy, Chris B. "Over-The-Counter (OTC)." *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/o/otc.asp>. Accessed 25 Mar. 2020.

¹³ Craig, Ben, and Goetz von Peter. "Interbank Tiering and Money Center Banks." *Journal of Financial Intermediation*, vol. 23, no. 3, July 2014, pp. 322–47. *DOI.org (Crossref)*, doi:10.1016/j.jfi.2014.02.003.

¹⁴ Elliot, Matthew, et al. "Financial Networks and Contagion." *The American Economic Review; Nashville*, vol. 104, no. 10, American Economic Association, Oct. 2014, pp. 3115–53. *ProQuest*, doi:<http://dx.doi.org.proxy.library.upenn.edu/10.1257/aer.104.10.3115>.

¹⁵ Nickolas, Steven. "Notional Value vs. Market Value: What's the Difference?" *Investopedia*. www.investopedia.com, <https://www.investopedia.com/ask/answers/050615/what-difference-between-notional-value-and-market-value.asp>. Accessed 31 Mar. 2020.

the gross notional outstanding that it is contributing to the market.¹⁶ Thus, it follows that although every market has its inherent level of risk associated with the trades that make up that market, a market can be further prone to risk if it has a much larger amount of gross notional outstanding than needed to fulfill its net positions.¹⁷

During the 2008 financial crisis, the entire financial market suffered due to a magnification of credit defaults that was a product of network effects. Interdependencies formed due to significant gross notional amounts in the OTC derivatives markets created a large number of counterparty risk for banks rather than solely the market risk that they wanted to take on. Although some blame should fall on the net positions that financial institutions held at the time, much of it is attributable to the large gross positions that they held, creating a considerable systemic risk rather than just market exposure.¹⁸ Since the 2008 crash, the network profile of the financial market has been a focus in recent years as legislators aim to lessen interconnectedness, and compression has served as a solution for banks to reduce counterparty risk while maintaining market exposure.

Three major regulations were passed since the Great Recession, including but not limited to the Dodd-Frank Act (2010), Basel III (2011), and European Market Infrastructure Regulation (2012). The Dodd-Frank Act imposed many regulations on banks with the purpose of limiting systemic risk. First of all, banks would have to split up their investing and servicing platforms and, by the Volcker Rule, would not be allowed to take the same inherently risky positions that they could hold prior. Second, banks would have to increase their reserve requirements. This meant that banks would be able to have less outstanding trades on their balance sheets in proportion to the cash that they had on hand.¹⁹ Combining this with the passing of European Market Infrastructure Regulation (EMIR), which forced banks to include OTC derivatives markets in their outstanding trades, banks now have a need to find ways to reduce their gross notional outstanding while fulfilling their net positions.²⁰ The Basel III framework gives more stringent regulations on the reserve requirements that banks must uphold and installed a liquidity coverage ratio so that banks would be forced to keep a percentage of its positions in securities that could be sold within 30 days.²¹

This increased regulation of banks has led to the need for portfolio compression, defined below:

“a process of replacing multiple offsetting derivatives contracts with fewer deals of the same net risk to reduce the notional value of the portfolio. It can be carried out between

¹⁶ “How Gross and Net CDS Notionals Really Work.” *Financial Times*. ftalphaville.ft.com,

<http://ftalphaville.ft.com/2011/10/27/713826/how-gross-and-net-cds-notionals-really-work/>. Accessed 31 Mar. 2020

¹⁷ in 't Veld, Daan, and Iman van Lelyveld. “Finding the Core: Network Structure in Interbank Markets.” *Journal of Banking & Finance*, vol. 49, Dec. 2014, pp. 27–40. *DOI.org (Crossref)*, doi:10.1016/j.jbankfin.2014.08.006

¹⁸ Elliot, Matthew, et al. “Financial Networks and Contagion.” *The American Economic Review; Nashville*, vol. 104, no. 10, American Economic Association, Oct. 2014, pp. 3115–53. *ProQuest*, doi:<http://dx.doi.org.proxy.library.upenn.edu/10.1257/aer.104.10.3115>.

¹⁹ Kenton, Will. “Dodd-Frank Wall Street Reform and Consumer Protection Act.” *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/d/dodd-frank-financial-regulatory-reform-bill.asp>. Accessed 31 Mar. 2020.

²⁰ “Derivatives / EMIR.” *European Commission - European Commission*. ec.europa.eu, https://ec.europa.eu/info/business-economy-euro/banking-and-finance/financial-markets/post-trade-services/derivatives-emir_en. Accessed 31 Mar. 2020.

²¹ *Basel III: International Regulatory Framework for Banks*. 7 Dec. 2017. www.bis.org, <https://www.bis.org/bcbs/basel3.htm>.

two or more counterparties (bilateral and multilateral compression, respectively). The idea is to reduce the gross notional exposure in derivatives portfolios, which counts towards regulatory requirements such as the leverage ratio.”²²

In simpler terms, compression aims to provide banks with the same access to market risk with less counterparty risk, or the risk that a counterparty on one of their trades is not able to fulfill its contractual obligations. The mechanics of portfolio compression will be covered more deeply in later sections of this thesis, but there are two main factors that allow compression to be effective. The first factor is that compression algorithms are able to cancel existing trades between counterparties and replace them with less or smaller trades that maintain the same market risk of the two counterparties. The second is that a Central Clearing Counterparty does not need to be used.²³

The introduction of the Volcker Rule in 2010 also required banks to clear OTC trades via Central Clearing Counterparties (CCPs).²⁴ CCPs are normally banks or other financial institutions that aim to solve the same issue that portfolio compression does. CCPs work as intermediaries between buyers and sellers and guarantee both sides of an OTC trade in the case that one counterparty cannot fulfill its obligations. In addition, CCPs must clear every trade, meaning that fewer trades are occurring in the market and forcing traders to be more efficient with their trades (reducing the amount of redundant trades that they submit to the CCPs).²⁵ The effect of CCPs is that they do reduce counterparty risk. However, systemic risk will still be present as the CCPs themselves could fail. It can be said that CCPs do benefit the OTC market in making it more efficient but fail in terms of reaching a level of stability that one would need to prevent a cascade of failures as was, seen in the 2008 Great Recession.²⁶ Thus, although helpful, CCPs are less effective than portfolio compression via compression algorithms in making the OTC market more efficient and stable as they can only help stabilize the market bilaterally and not multilaterally. It has even been researched how portfolio compression reduces the benefits that CCPs can provide and renders them pointless.²⁷

Compression algorithms are an important emerging technology that helps banks reduce their balance sheets and gross notional outstanding while maintaining the net positions that they seek to hold in relation to the market, and further research into improving them can free up more capital in banks so that they can take on other positions and create a more stable financial system.

²² “Portfolio Compression Definition.” *Risk.Net*. www.risk.net, <https://www.risk.net/node/2270600>. Accessed 5 Apr. 2020.

²³ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

²⁴ Kenton, Will. “Dodd-Frank Wall Street Reform and Consumer Protection Act.” *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/d/dodd-frank-financial-regulatory-reform-bill.asp>. Accessed 31 Mar. 2020.

²⁵ Andrew Bloomenthal. “The Core Role of a Central Counterparty Clearing House—CCP.” *Investopedia*. www.investopedia.com, <https://www.investopedia.com/terms/c/ccph.asp>. Accessed 5 Apr. 2020.

²⁶ Duffie, Darrell. “Resolution of Failing Central Counterparties.” *SSRN Electronic Journal*, 2014. *DOI.org (Crossref)*, doi:10.2139/ssrn.2558226.

²⁷ Duffie, Darrell, and Haoxiang Zhu. “Does a Central Clearing Counterparty Reduce Counterparty Risk?” *Review of Asset Pricing Studies*, vol. 1, no. 1, Dec. 2011, pp. 74–95. *DOI.org (Crossref)*, doi:10.1093/rapstu/rar001.

Technical Overview of Compression Algorithms

The technical aspects of compression algorithms will now be discussed in the scope of the financial system. First, it is necessary to formally define the OTC financial market as a graph. Marco D’Errico and Tarik Roukny put it best:

“The network or graph G is the pair (N, E) where N is a set of institutions present in the market and E is a set of directed out-standing fungible obligations (i.e., edges) between two institutions in the market. An outstanding obligation is represented by e_{ij} whose value corresponds to the notional value of the obligation and the directionality departs from the seller i to the buyer j with $i, j \in N$.”²⁸

It is important for the algorithms that will be discussed that the edges are directed. It is obvious that if the edges were not directed that not enough information would be obtained from the graph since the nature of trades is that one counterparty is the buyer and one is the seller.

When examining markets as graphs, we can identify a party’s gross position and net position almost immediately. The gross position, representing the gross notional outstanding as discussed above, is found by adding the face values of all directed edges that stem from or go into a node. The formal definition is:

$$“v_i^{gross} = \sum_j e_{ij} + \sum_j e_{ji}”^{29}$$

The net position is found by taking the total weight of the outward edges and subtracting the weight of all inward edges.

$$“v_i^{net} = \sum_j e_{ij} - \sum_j e_{ji}”^{30}$$

Not only is it possible to find the positions of individuals, but one can also find the gross notional outstanding of the entire graph by adding the weights of all of the edges that exist within the graph. D’Errico and Roukny define gross notional outstanding as x , where:

$$“x = \sum_i \sum_j e_{ij}”^{31}$$

Finally, it is possible to define market excess quantifiably. Excess in the market was already defined above as the difference between a market’s gross notional outstanding and the minimum gross notional outstanding to satisfy its net risk profile, but D’Errico and Roukny provide a measurable definition:

²⁸ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

²⁹ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

³⁰ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

³¹ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

$$\Delta(G) = \sum_{i=1}^n \sum_{j=1}^n e_{ij} - \sum_{i: v_i^{net} > 0} v_i^{net},^{32}$$

This definition just takes the gross notional outstanding of the entire market graph and subtracts the sum of all the net positions of nodes that have a position weight. The ultimate goal is to perform a reduction on the directed graph while keeping v_i^{net} constant for all vertices and maximize $\Delta(G)$. An example is given in Figure 1, taken from D’Errico and Roukny.

D’Errico and Roukny find a corollary that stems from this definition. The authors “identify a necessary and sufficient condition for excess to emerge in a market: the existence of intermediation.”³³ This entails that all OTC markets will exhibit excess since it is the nature of OTC markets that dealers facilitate trades between buyers and sellers. Thus, the dealers will have gross positions larger than their net positions, and excess will emerge. This also leads to the conclusion that markets with centralized trading platforms, such as the New York Stock Exchange, will exhibit no excess and have no need for compression.³⁴

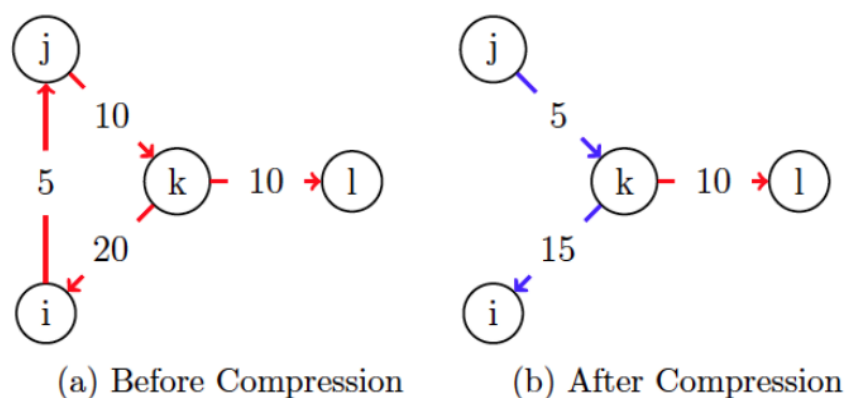


Figure 1: A graphical example of portfolio compression. Graph (a) shows a market consisting of 4 institutions as nodes i, j, k, l , and positions as edges. Graph (b) shows a compression solution to the market. Positions were removed and replaced with new positions, which reduced the overall market positions by 15 units.³⁵

It also follows that different compression algorithms would have different levels of effectiveness. And, this effectiveness can be measured by the magnitude of market excess ($\Delta(G)$) that each algorithm can remove from the graph. While it is impossible to find the best possible compression algorithm, as more efficient ones are being created every day, we will examine three different algorithms that Dominic O’Kane presented in his 2014 paper.

³² D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. DOI.org (Crossref), doi:10.2139/ssrn.2962575.

³³ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. DOI.org (Crossref), doi:10.2139/ssrn.2962575.

³⁴ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. DOI.org (Crossref), doi:10.2139/ssrn.2962575.

³⁵ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. DOI.org (Crossref), doi:10.2139/ssrn.2962575.

One of the first compression algorithms that was created for optimizing OTC markets was developed by TriOptima in 2012. TriOptima is the market leader in portfolio compression and was one of the pioneers of applying compression algorithms for OTC market solutions after the Great Recession.³⁶ TriOptima filed a patent in 2012, outlining a basic technique for OTC market compression using the Depth-First Search algorithm that is frequently spoken about in computer science classes. As is common knowledge to computer scientists, the DFS algorithm can list all closed loops in a directed edge graph, which the market graphs are.³⁷ The TriOptima algorithm runs DFS on the market graph, and all closed loops are found. The closed loops are cycles of trades that start at one counterparty and end with the same counterparty. Then, the TriOptima algorithm works on each of the closed loops found by the DFS algorithm. In each loop, the weight of the smallest edge will be deleted from the loop.³⁸

O’Kane points out that although the algorithm is effective in reducing gross notional outstanding without changing the net risk profile of the graph, it can be expensive in terms of time and memory. He also states that working with an algorithm of this nature in real life could prove to be problematic in that it would be hard to implement compression tolerances.³⁹ Compression tolerances are the “potential restraints...set by both individual participants and regulators.”⁴⁰ For example, in some CDS compressors, only units of 5 million to 10 million dollar transactions are compressed or only trades that have been originally created can be used such that the creation of new contracts is not allowed.⁴¹

A large downfall with this traditional DFS greedy approach is that it does not take account for loops which sum to zero. A method to get around this is to enumerate the closed loops and associate a value to it. This is not ideal as closed loops can grow exponentially with the number of nodes.⁴²

Another method for compression is using algorithms that try to minimize the entry-wise exposure of a graph. To represent a graph, a matrix representation will be used. Each row and column represent a node, and the matrix entry represents an edge. The value of edge $C_{1,2}$ is the position between customer 1 and customer 2. $C_{i,i}$ will always be zero due to a customer unable to buy or sell to themselves. In addition, the graph will be antisymmetric. In order to keep track of our algorithm using the matrix representation, we calculate the matrix norm and use the first and second orders as our entry-wise exposure.⁴³

³⁶ *TriReduce*. www.trioptima.com, <https://www.trioptima.com/trireduce/>. Accessed 14 Apr. 2020.

³⁷ *Data Structure - Depth First Traversal - Tutorialspoint*.

https://www.tutorialspoint.com/data_structures_algorithms/depth_first_traversal.htm. Accessed 14 Apr. 2020.

³⁸ Brouwer, Derk Pieter. *System and Method of Implementing Massive Early Terminations of Long Term Financial Contracts*. US20120023002A1, 26 Jan. 2012. *Google Patents*, <https://patents.google.com/patent/US20120023002A1/en>.

³⁹ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴⁰ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

⁴¹ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴² O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴³ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

$$\|L(C, N)\|_p = \left(\frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N |C_{ij}|^p \right)^{\frac{1}{p}},^{44}$$

$$\|L(C, N)\|_1 = \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N |C_{ij}|^{45}$$

$$\|L(C, N)\|_2 = \sqrt{\frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N |C_{ij}|^2},^{46}$$

Table of Graph Matrix

	c_1	c_2	c_3	c_4	Net vertex value h_i
c_1	0	-2		-2	-4
c_2	2	0	-4		-2
c_3		4	0	1	5
c_4	2		-1	0	1

Figure 2: Matrix representation of the graph depicted in Figure 3 (this matrix is my creation, but I derived the idea of depicting a graph-matrix relationship in this manner from Dominic O’Kane).⁴⁷

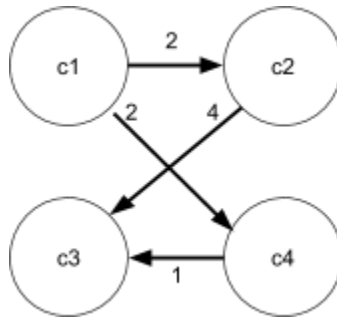


Figure 3: Graph representation of matrix depicted in Figure 2 (this graph is my creation, but I derived the idea of depicting a graph-matrix relationship in this manner from Dominic O’Kane).⁴⁸

⁴⁴ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴⁵ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴⁶ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴⁷ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁴⁸ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

The first of the two optimization methods minimize L_1 using a linear programming approach. The objective function of the linear program to be minimized is “ $\sum_{ij}^n |C_{ij}|$,”⁴⁹ which translates to minimizing the absolute values of all the exposures which is also equivalent to minimizing the L_1 function defined earlier.⁵⁰ The constraints which we want to satisfy are h_i (Figure 2 above), which is the net value of a particular vertex. In order to have a full linear programming problem, we will set:

$$C_{ij} = C_{ij}^+ - C_{ij}^-$$
⁵¹

Replacing the absolute value with the new variable results in the new objective function becoming:

$$\Omega(C) = \sum_{i=1}^N \sum_{j=1}^N (C_{ij}^+ - C_{ij}^-)$$
⁵²

The above equation is subject to the condition that “ $\sum_{j=1}^N (C_{ij}^+ - C_{ij}^-) = h_i$.”⁵³

The second method to optimize against is L_2 . The objective function of the linear program to be minimised is:

$$\Omega(C) = \sum_{i=1}^N \sum_{i=j+1}^N C_{ij}^2$$
⁵⁴

The above equation is subject to the condition that “ $\sum_{j=1}^N \hat{C}_{ij} = h_i$.”⁵⁵

The reasoning behind using a quadratic function rather than a linear one is to apply a greater cost penalty to large exposures which in turn should give us lower absolute exposures compared to using L_2 .⁵⁶ The matrix and antisymmetric structure of the graph give us an advantage of allowing us to use already developed solving methods such as linear programming to give us near optimal configurations or will have a GCD less than or equal to the original GCD divided by the number of counterparties.⁵⁷

⁴⁹ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵⁰ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵¹ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵² O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵³ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵⁴ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵⁵ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵⁶ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁵⁷ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

Application of Compression Algorithms in Optimization of OTC CDS Market

According to David Bachelier of Capitalab, another pioneer of portfolio compression technology along with TriOptima,⁵⁸ compression was lightly deployed in 2003 as “an IT and operational tool to reduce trade processing and the number of payments on derivatives; there was no leverage ratio.”⁵⁹ However, after the crash of 2008, with many banks defaulting and the entire system failing due to large amounts of systemic risk, compression became much more of a focus for banks and the government as both created measures to reduce the chance of a similar crisis occurring again.

Compression is now a regular part of the CDS OTC market, and every bank uses compression to help optimize their portfolios. The market is also becoming more centralized in that the compression cycle occurs daily “just prior to the CDS auction process and its purpose is to reduce the number of participants in the CDS auction, the number of contracts which need to be settled, and the quantity of physical assets which are to be delivered.”⁶⁰ And, the effects of the deployment of this technology are well documented. According to TriOptima’s statistics alone, it eliminated \$30.2 trillion of CDS gross notional outstanding in 2008 and \$77 trillion in total. In only 2019, it eliminated \$250 trillion of gross notional outstanding over all of the OTC markets that it covers.⁶¹

If we are to look at the entire CDS market as a whole, we can see that compression has been ubiquitous since 2008. The “Bank for International Settlements (BIS) attributes the reduction of Credit Default Swap notionals to a sixth of the levels exhibited a decade ago to an extensive use of portfolio compression after the crisis.”⁶² In fact, looking at Figure 4 below, we can see that CDS gross notional outstanding peaked in 2007, the year before the Great Recession, and since then has decreased year-over-year to levels that provide less systemic risk.

⁵⁸ *Who We Are* | CAPITALAB. www.capitalab.co.uk, <https://www.capitalab.co.uk/who-we-are/>. Accessed 24 Mar. 2020.

⁵⁹ “The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity.” *Risk.Net*, 16 Apr. 2018. www.risk.net, <https://www.risk.net/node/5494961>.

⁶⁰ O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

⁶¹ *News*. www.trioptima.com, <https://www.trioptima.com/news/trioptima-sets-new-trireduce-record-250-trillion-g>. Accessed 15 Apr. 2020.

⁶² O’Kane, Dominic. “Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets.” *SSRN Electronic Journal*, 2013. *DOI.org (Crossref)*, doi:10.2139/ssrn.2273802.

Credit default swaps: interactive statistics

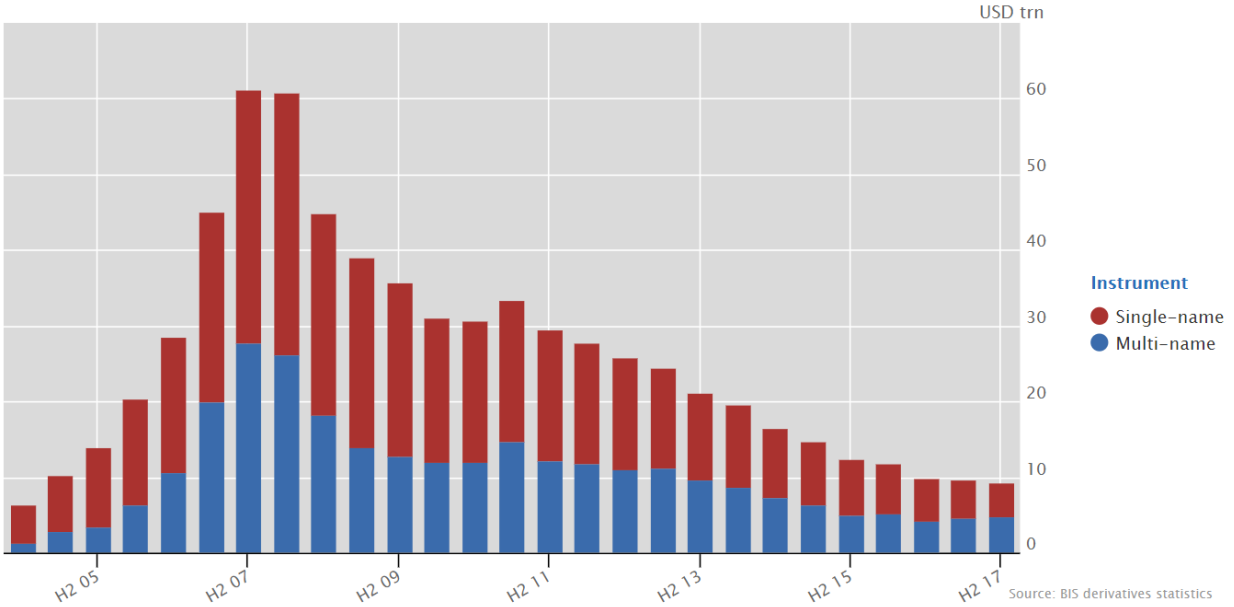


Figure 4: A breakdown of the gross notional outstanding in the CDS market broken down into single-asset and multi-asset backed CDS's.⁶³

In fact, something that is even more telling of compression's success is looking at the breakdown of gross notional outstanding being split into the counterparties that hold the gross notional outstanding, shown in Figure 5. From this graphic, it is evident that the most compression has been experienced by reporting dealers and banks and securities firms, which would make sense as these are the counterparties whose incentive is not to take on net risk, but to facilitate trades with other counterparties in order to make a commission off of those trades. Thus, they have successfully been able to reduce their systemic risk while maintaining their desired amount of net risk.

⁶³ Aldasoro, Iñaki, and Torsten Ehlers. *The Credit Default Swap Market: What a Difference a Decade Makes*. June 2018. www.bis.org, https://www.bis.org/publ/qtrpdf/r_qt1806b.htm.

Credit default swaps: interactive statistics

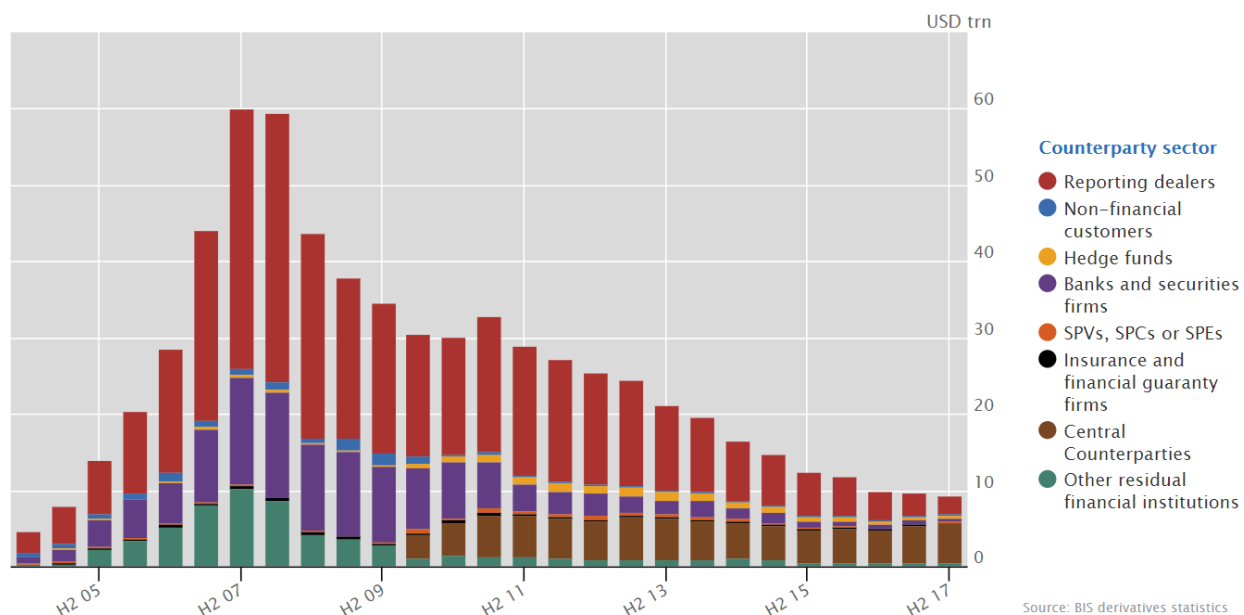


Figure 5: A breakdown of the gross notional outstanding in the CDS market broken down by counterparty sector.⁶⁴

Something to note is that the rise of Central Counterparties exhibits an inverse relationship with the decline of gross notional outstanding due to reporting dealers and banks and securities firms. As mentioned earlier in this dissertation, CCPs aim to solve the same issue that compression algorithms do, and much of the reduction in gross notional outstanding should be attributed to their increasing prevalence as well as compression algorithms such as TriOptima's. However, while their use does lessen gross notional outstanding, the CCPs themselves create a level of systemic risk as they can fail themselves. The amount of trades that they serve as counterparty to is depicted in Figure 5 as well in brown color, and their share of the market was recorded at 53% as of 2018.⁶⁵ Thus, this leaves much room for the improvement of the utilization of compression algorithms, as it seems the market has settled with the results of CCPs. TriOptima reported that although it was responsible for \$30.2 trillion in reductions in 2008, that number shrank to \$8.5 trillion in 2010 and \$3.5 trillion in 2012.⁶⁶ While O'Kane argues that this reduction can be attributed to the fact that many legacy positions were already compressed by 2012,⁶⁷ the fact remains that this decline also coincides with the rise of CCPs.

⁶⁴ Aldasoro, Iñaki, and Torsten Ehlers. *The Credit Default Swap Market: What a Difference a Decade Makes*. June 2018. [www.bis.org](https://www.bis.org/publ/qtrpdf/r_qt1806b.htm), https://www.bis.org/publ/qtrpdf/r_qt1806b.htm.

⁶⁵ Aldasoro, Iñaki, and Torsten Ehlers. *The Credit Default Swap Market: What a Difference a Decade Makes*. June 2018. [www.bis.org](https://www.bis.org/publ/qtrpdf/r_qt1806b.htm), https://www.bis.org/publ/qtrpdf/r_qt1806b.htm.

⁶⁶ News. [www.trioptima.com](https://www.trioptima.com/news/trioptima-sets-new-trireduce-record-250-trillion-g), <https://www.trioptima.com/news/trioptima-sets-new-trireduce-record-250-trillion-g>. Accessed 15 Apr. 2020.

⁶⁷ O'Kane, Dominic. "Optimizing the Compression Cycle: Algorithms for Multilateral Netting in OTC Derivatives Markets." *SSRN Electronic Journal*, 2013. DOI.org (Crossref), doi:10.2139/ssrn.2273802.

Other Applications

Network trafficking

Quality of Service (QoS) technologies are methods of improving the performance of a network. They are important in today's world as they allow a network to work with higher reliability for applications that demand large network capacity, such as streaming, video-conferencing, and online gaming. In all of these applications, lag and network performance is a major factor, and as more and more of everyday applications require stable network performance, QoS becomes more of a necessity.⁶⁸ QoS technologies work specifically on “bandwidth (throughput), latency (delay), jitter (variance in latency), and error rate.”⁶⁹

QoS technologies are best thought of as directors of traffic. There are large packets of data that different applications on the network need to send through the network, and the QoS technologies decide which paths through the network each packet of data should take and with what priority.⁷⁰ The methods of which QoS technologies can manipulate networks can be divided into five different categories:

1. Classification – Classifying data before it enters the network so that the network knows the priority of the data.⁷¹
2. Congestion management – The methods that handle the classified data and how priority data should be treated.⁷²
3. Congestion avoidance – The way that networks are monitored in real-time so that paths that are congested do not receive further packets of new data to transfer.⁷³
4. Policing – Limiting the traffic through the network to lower levels to avoid unexpected drops in reliability.⁷⁴
5. Link efficiency – Network paths are examined to find the shortest paths for each route that data needs to take.⁷⁵

⁶⁸ Kounev, Samuel, et al. *Autonomic QoS-Aware Resource Management in Grid Computing Using Online Performance Models*. 2007, p. 48. *ResearchGate*, doi:10.1145/1345263.1345325.

⁶⁹ *What Is Quality of Service? - Palo Alto Networks*. <https://www.paloaltonetworks.com/cyberpedia/what-is-quality-of-service-qos>. Accessed 18 Apr. 2020.

⁷⁰ Kounev, Samuel, et al. *Autonomic QoS-Aware Resource Management in Grid Computing Using Online Performance Models*. 2007, p. 48. *ResearchGate*, doi:10.1145/1345263.1345325.

⁷¹ *What Is Quality of Service? - Palo Alto Networks*.

⁷² “What Is QoS? Guide & Best Quality of Service Software 2020.” *DNSstuff*, 4 Oct. 2019. www.dnsstuff.com, <https://www.dnsstuff.com/what-is-qos>.

⁷³ “What Is QoS? Guide & Best Quality of Service Software 2020.” *DNSstuff*, 4 Oct. 2019. www.dnsstuff.com, <https://www.dnsstuff.com/what-is-qos>.

⁷⁴ “What Is QoS? Guide & Best Quality of Service Software 2020.” *DNSstuff*, 4 Oct. 2019. www.dnsstuff.com, <https://www.dnsstuff.com/what-is-qos>.

⁷⁵ “What Is QoS? Guide & Best Quality of Service Software 2020.” *DNSstuff*, 4 Oct. 2019. www.dnsstuff.com, <https://www.dnsstuff.com/what-is-qos>.

Compression algorithms work on two of the five methods, specifically congestion avoidance and link efficiency. When looking at a network and the routers and paths that comprise it, it can be thought of as a graph with directed edges. Thus, graph compression can be applied to network graphs in order to identify the paths that are currently congested and remove them from the graph in order to find more optimal paths for new data to be sent through (congestion avoidance) or to compress the graphs before any data is ready to be sent to create paths of minimum distance (link efficiency).⁷⁶

Currently, the main QoS technology used is called the Minimum Hop algorithm. This algorithm uses Breadth First Search, making it different from the typical DFS-powered compression algorithms. The Minimum Hop algorithm works as a QoS technology in the link efficiency factor, meaning that it is run prior to packets of data being sent so that path selection can be more optimal.⁷⁷ However, this algorithm does not change the graphs in any way in terms of link efficiency, and only identifies the existing shortest paths. J.J. Garcia-Luna-Aceves proved that much improvement could be made to the Minimum Hop algorithm to improve its effectiveness.⁷⁸

Casetti finds that applying compression algorithms as a QoS technology increases throughput by 15% compared to the typical Minimum Hop algorithm that is normally used.⁷⁹

Computational Memory and Logic Synthesis

Increasing computational power from computer processors has been increasing in demand. This is creating new challenges for engineers to decrease transistor sizes in chips and improve synthesis to meet demands.⁸⁰ This has manifested itself in Moore's Law, as more and more transistors must be fit inside of portable devices to make them smaller and more powerful.⁸¹ As a result, graph algorithms have been used to model logic gates as directed acyclic graphs. Engineers can use transitive reduction algorithms to affect the datapath and reduce the number of logical components, use faster logical components, or use less power. Cunxi Yu et al. have also proven that using graph reduction algorithms for Directed Acyclic Graphs (DAGs) and logic synthesis one is able to minimize the area of datapath designs.⁸² The DAG is a boolean

⁷⁶ Casetti, C., et al. "A New Class of QoS Routing Strategies Based on Network Graph Reduction q." *Computer Networks*, 2003, p. 13.

⁷⁷ Xin Yuan, and A. Saifee. "Path Selection Methods for Localized Quality of Service Routing." *Proceedings Tenth International Conference on Computer Communications and Networks (Cat. No.01EX495)*, 2001, pp. 102–07. *IEEE Xplore*, doi:10.1109/ICCCN.2001.956226.

⁷⁸ Garcia-Luna-Aceves, J. J. "A Minimum-Hop Routing Algorithm Based on Distributed Information." *Computer Networks and ISDN Systems*, vol. 16, no. 5, May 1989, pp. 367–82. *ScienceDirect*, doi:10.1016/0169-7552(89)90011-1.

⁷⁹ Casetti, C., et al. "A New Class of QoS Routing Strategies Based on Network Graph Reduction q." *Computer Networks*, 2003, p. 13.

⁸⁰ *Chipping Away at Moore's Law - ACM Queue*. <https://queue.acm.org/detail.cfm?id=3388515>. Accessed 28 Apr. 2020

⁸¹ *Engineering: Issues, Challenges and Opportunities for Development; UNESCO Report - UNESCO Digital Library*. <https://unesdoc.unesco.org/ark:/48223/pf0000189753>. Accessed 28 Apr. 2020.

⁸² Yu, Cunxi, Maciej Ciesielski, et al. "DAG-Aware Logic Synthesis of Datapaths." *Proceedings of the 53rd Annual Design Automation Conference*, Association for Computing Machinery, 2016, pp. 1–6. *ACM Digital Library*, doi:10.1145/2897937.2898000.

network representation where vertices are logic gates and edges represent connections between gates. As a result of graph reductions, we can increase processing power without solely counting on increasing the number of transistors added.⁸³

Visual Representations of Complex Social Networks

Graph reduction algorithms provide reduction of complex networks where edges are redundant. This leads to the visualization of networks and important clusters of people or places.⁸⁴ Social networks or corporate company communication networks such as emails can be represented as interaction maps between individuals which may involve thousands to millions of interactions. These relationships are complex and incredibly large, which result in difficulty in both analysis and visualizations.⁸⁵ While clustering has been used to see a high-level view of interactions, reduction algorithms can give a concise and easy to view alternative while keeping important properties of the network.⁸⁶

For example, in Vincent et al, the group analyzed emails from Enron after the fall out of the company. Emails of directors were gathered, and after reducing the graph to non-redundant edges, one can see both cycles and leaves forming out of specific vertices.⁸⁷

⁸³ Yu, Cunxi, Mihir Choudhury, et al. "Advanced Datapath Synthesis Using Graph Isomorphism." *2017 IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*, IEEE, 2017, pp. 424–29. *DOI.org (Crossref)*, doi:10.1109/ICCAD.2017.8203808.

⁸⁴ Fan, Wenfei, et al. "Query Preserving Graph Compression." *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, Association for Computing Machinery, 2012, pp. 157–168. *ACM Digital Library*, doi:10.1145/2213836.2213855.

⁸⁵ *Graph Pattern Matching Revised for Social Network Analysis / Proceedings of the 15th International Conference on Database Theory*. <https://dl.acm.org/doi/abs/10.1145/2274576.2274578>. Accessed 28 Apr. 2020.

⁸⁶ Dubois, V., and C. Bothorel. "Transitive Reduction for Social Network Analysis and Visualization." *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI'05)*, 2005, pp. 128–31. *IEEE Xplore*, doi:10.1109/WI.2005.152

⁸⁷ Vincent, D., and B. Cecile. "Transitive Reduction for Social Network Analysis and Visualization." *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI'05)*, IEEE, 2005, pp. 128–31. *DOI.org (Crossref)*, doi:10.1109/WI.2005.152.

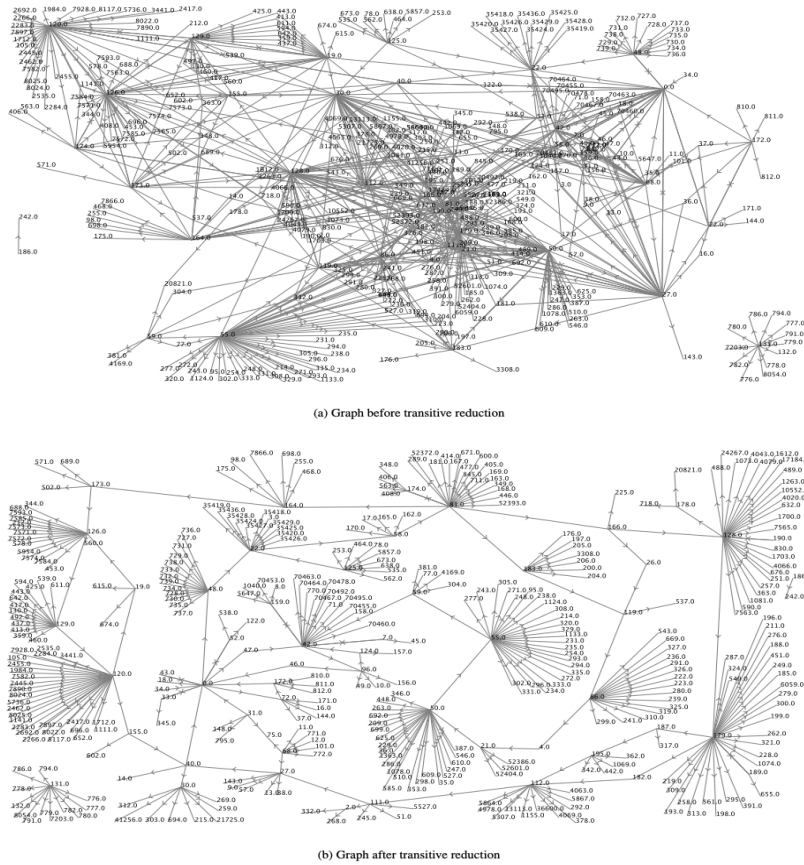


Figure 6: Graph of emails from Enron employee network.⁸⁸

It is much easier to deduce findings from graph b of Figure 6, than it is prior to graph reduction, and the validity of the findings still holds because it is query preserving.⁸⁹ In this case, the validity refers to the fact that it was more important in the Enron case to know who the emails were stemming from than who was receiving the emails.

From my own personal experience, I can attest to the value of graph reduction even in this seemingly elementary use. As corporations are getting larger and larger, and management of people is coming more into focus, graphs such as the Enron graph in Figure 6 are becoming used more. During a summer internship in the Summer of 2019, I was tasked with creating one of these graph networks to see which nodes had many incoming edges. We then recommended to the company that that node (person) hire someone for additional help and to improve the efficiency of operations. Had I been able to perform a graph reduction such as the one on the Enron employee graph, the insights would have been more obvious.

⁸⁸ Vincent, D., and B. Cecile. “Transitive Reduction for Social Network Analysis and Visualization.” *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI’05)*, IEEE, 2005, pp. 128–31. DOI.org (Crossref), doi:10.1109/WI.2005.152.

⁸⁹ Vincent, D., and B. Cecile. “Transitive Reduction for Social Network Analysis and Visualization.” *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI’05)*, IEEE, 2005, pp. 128–31. DOI.org (Crossref), doi:10.1109/WI.2005.152.

Challenges and Future Work

There are two main challenges that stand in the way of the further adoption of compression algorithms in making OTC markets more efficient. First, there is the rise of CCPs that compression algorithms, and specifically the companies that offer their service, face. As touched upon earlier in this dissertation, the fact that CCPs provide some of the same benefits as compression algorithms creates a question of whether further adoption is necessary for compression algorithms. The second main challenge that compression algorithms face is the fact that in real-world deployment, compression algorithms must be able to conform to different compression tolerances. As defined above, compression tolerances are important because they determine what the result of a compression algorithm will be, as the market as regulations that compression algorithms must follow. For example, the market may require that no new trades can be created as a result of compression.⁹⁰ Individual firms may also require compression tolerances specific to themselves, and thus compression algorithms must be nimble enough to adhere to these specific guidelines while remaining effective in reducing gross notional outstanding.⁹¹

In an interview with *Risk*, a financial journal, many important figures in the compression algorithm world shared their views in response to these challenges. According to Mike Sweeting, Head of Product at Capitalab, the issue with CCPs, other than the fact that they can also default, is that their compression runs are scheduled and each of those runs has limited spots.⁹² Thus, not every dealer can even enter, and compression is limited before it even takes place. The tipping point towards the use of compression algorithms for portfolio compression is thus its ability to support straight-through-processing (STP), or the ability to compress trades while they are taking place instead of having to coordinate compression with other banks during a set time.⁹³ However, as the Head of XVA Management at Credit Suisse, Philip Staddon, points out, this will require multiple banks to work with the same compression provider, which is tough to ensure as the compression space is a business with different servicers competing for clients after all.⁹⁴

In the rest of the interview, Gavin Jackson of Capitalab, Allan Guild of HSBC, and Edward Ground of JP Morgan, all mention that it is not the actual technology that is holding compression algorithms back, but instead the structure of their deployment. As of now, compression algorithms can support multiple types of compression tolerances while remaining effective, and they are actually achieving a more impressive compression than banks are looking

⁹⁰ D'Errico, Marco, and Tarik Roukny. "Compressing Over-the-Counter Markets." *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

⁹¹ D'Errico, Marco, and Tarik Roukny. "Compressing Over-the-Counter Markets." *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.

⁹² "The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity." *Risk.Net*, 16 Apr. 2018. *www.risk.net*, <https://www.risk.net/node/5494961>.

⁹³ "The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity." *Risk.Net*, 16 Apr. 2018. *www.risk.net*, <https://www.risk.net/node/5494961>.

⁹⁴ "The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity." *Risk.Net*, 16 Apr. 2018. *www.risk.net*, <https://www.risk.net/node/5494961>.

for, with a lot of banks setting individual tolerances to keep the compression more conservative.⁹⁵ The main factor impeding their success is that a large network must be made. After observing the technical aspects of compression algorithms, it follows that the larger the network, the better the compression would be. But with all of the different options in the market with CCPs and different portfolio compression providers, banks are split up into separate networks and are compressing at different times of each other.⁹⁶ The speakers agree that the winner out of CCPs vs compression algorithms will be the one that is operationally easier for banks to use. The main issue, outlined by Philip Staddon, is that banks have to implement teams in their own companies to consolidate their trades for both CCP and portfolio compression. If multiple banks are able to all submit their trades directly to Capitalab for STP compression, then compression algorithms will win the “battle” against CCPs and the market will exhibit more efficiency than it already does.⁹⁷

⁹⁵ “The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity.” *Risk.Net*, 16 Apr. 2018. [www.risk.net](https://www.risk.net/node/5494961), <https://www.risk.net/node/5494961>.

⁹⁶ “The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity.” *Risk.Net*, 16 Apr. 2018. [www.risk.net](https://www.risk.net/node/5494961), <https://www.risk.net/node/5494961>.

⁹⁷ “The Rapid Evolution of Compression: Keeping Pace with Optimisation Activity.” *Risk.Net*, 16 Apr. 2018. [www.risk.net](https://www.risk.net/node/5494961), <https://www.risk.net/node/5494961>.

Conclusion

With the understanding of how compression algorithms are currently deployed to optimize OTC financial markets, we can see the benefits that they bring to the financial system. There are three main factors that incentivize their utilization. First, is the reduction of systemic risk that they provide the system, which was covered earlier in this dissertation. Next, the compression algorithms shrink the portfolios that banks hold on their balance sheets, which helps them follow the new regulation restraints that were put in place after 2008. Lastly, “by reducing the number of contracts, compression leads to a reduction of operational risks and an improvement of management, including trade count reduction, speed to auction in case of default, lower cash-flow needed to settle obligations, fewer reconciliations, lighter burden of settlement, [and] lowered collateral and margin requirements.”⁹⁸

⁹⁸ D’Errico, Marco, and Tarik Roukny. “Compressing Over-the-Counter Markets.” *SSRN Electronic Journal*, 2017. *DOI.org (Crossref)*, doi:10.2139/ssrn.2962575.