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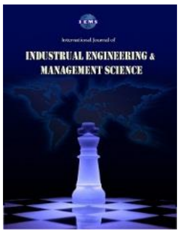

A Novel Approach for Circular Trade Detection in Mercantile Exchange

Zainabolhoda Heshmati[a,*], Ramin Salahshour[a]

[a] *Amirabad, North Kargar Street, Faculty of New Sciences and Technologies, University of Tehran*
[b] *University of Tehran*

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A B S T R A C T

The derivatives market having a significant number of investors trading in futures contracts, is vulnerable to manipulation by some perpetrators. Protecting market participants from a prevalent manipulation called circular trading and providing a fair market has always been a challenging task for regulators. This kind of malpractice is represented by the trading behaviors of a group of investors who trade among themselves frequently to increase the price of a commodity and consequently make forged prosperity. This type of securities fraud is also very similar to the well-known pump and dump strategy which involves artificially inflating the price of an owned stock, in order to sell the cheaply purchased stock at a higher price. This paper presents a network-based approach for detecting investors involved in such circular trading in the futures market. This is done initially by constructing the daily networks of investors' trades, then, extracting all trade cycles of various lengths from these daily networks to arrive at the group of initial suspicious cycle traders. Finally, in order to exclude investors who are randomly involved in suspicious cycles, price fluctuations over time were analyzed. The proposed approach has been conducted on real data from Iran Mercantile Exchange (IME) and as a warning system, has succeeded in detecting anomalous traders effectively.

1. Introduction

Illegal or misconduct that appears in the financial market includes behaviors such as financial fraud, insider trading, bribery, self-dealing, money laundering, tax evasion, corruption and a specific category of malpractices like broker embezzlement, Pyramid scheme, Ponzi scheme and circular trading known as market manipulation. Market manipulation, which is the target field in this study, involves individuals or a group of people attempting to deliberately interfere with the fair and orderly operation of the market and create false or misleading appearances of the price of a commodity to gain personal profit (See Reurink (2016)).

Circular trading is still one of the biggest concerns of investors and regulators in the capital markets, although many efforts have been made to reduce the effects of such malpractice on the markets reliability. Circular trading is described as the trading behavior of a group of accomplice investors who trade among themselves frequently to generate an apparent short

* Corresponding author, zheshmati@ut.ac.ir

term price trend, which in turn incentivizes other investors to follow them and consequently create a false market. This manipulative trading strategy is very similar to what is known as "pump and dump" in the securities market. The manipulators would pump up the price by buying aggressively within their trading cycle, and then dump what they bought at the new higher price. In this scenario, irrational investors may also be attracted to come into the market because of the false belief that the price is going up. The same is also true for a downward price trend, where the manipulators would exploit by selling into the market and then covering the short sales when other investors begin selling too.

In Choi and Skiba (2015) These accomplice investors are in fact herding the other investors into trading based on a new inflated price. Some of the researchers like Xuan et al. (2017) has also attempted to survey the presence of herding behavior and its underlying reasons. Their findings indicate that herd behavior is evident during high and low trading volume days and does not exhibit during public meltdown. They also observed that it is stronger in post-crisis than pre-crisis. But, according to investigations, it is not complicated for a group of influential investors to manipulate the market and herd the other investors, but the real challenge for them is to make the manipulations profitable.

To facilitate fair trade, the competent authorities keep applying various guidelines to be followed by all participants in market activities, as well as developing smart systems to monitor their actions. These widespread monitoring systems which usually use machine learning techniques are generally unable to detect minute by minute occurrences of complex types of malpractices like circular trading because they naturally need access to the history of each investor's transactions which are mostly classified and inaccessible at the moment. In fact, they cannot analyze short-term trading data in the available limited time. Such systems could be preventive provided that they detect circular trading premature. Also, mechanical factors such as margin calls have no effect on this kind of market manipulation since they are calculated on a daily basis. This means settlement price calculations (which margin calls are based on) are done after market closure at the end of the day, yet, circular trades happen in one trading day. However, to detect and label a group of accomplice investors as fraudulent, such a manipulative act must be repeated on more than one occasion.

In this paper we present a novel network-based approach that is able to discover anomalous traders. This approach is applied to data from Iran Mercantile Exchange (IME) market. IME is a commodities exchange located in Tehran, Iran. Various products and commodities are listed and traded in IME including industrial products and commodities, oil products and petrochemicals, agricultural, and futures contracts of gold coin. For the purpose of this research, data from the gold coin futures contracts have been used.

The remainder of this paper is organized as follows: In the next section, a survey of some related works is provided. In the following section, the basic approach for detection of anomalous traders, including data preparation, extraction of all trade cycles, investigation of transactional behaviors of traders involved in such cycles has been described. Then the results section provides experimental analysis and elaborates on the results, as well as suggestions for future research directions. Finally, the last section concludes the paper.

2. Related work

Graph structure is an expressive data structure model which is able to examine relationships among objects in applications such as transport networks, biological networks, computer and telecommunication networks and social networks. Recently, graph based approaches and algorithms have been considered as a powerful tool to analyze financial networks like the network formed by investors' transactions (see Lillo and Valdés (2016)).

There are many different models of graph-based methods being used in financial networks, each one assessing a different aspect of connectivity and dynamism. In some approaches like Dehmamy et al. (2016) and Hemenway and Khanna (2016) and Sun et al. (2005), the network is defined such that there is no links or communication between nodes of the same kind such as sellers with other sellers, or buyers with other buyers. Hence this leads to creation of bipartite graphs where sellers or assets are placed in one part and buyers or investors, in the other part.

Moreover, it is possible to categorize all nodes to three groups such as fraudster, accomplice and normal (see Chau et al. (2006)) and as fraudsters and their accomplices probably form a bipartite graph, a Markov random field model could be built from the transaction history amongst all traders, then the belief propagation algorithm is applied to calculate the probabilities of fraudster, accomplice and normal user for each node in the resulted graphs.

Jallo et al. (2013) and Liu and Chi (2012) and Li et al. (2015) have developed another set of methods and are using other coefficients and indices like correlation coefficient and assortative index to construct the network's graph by measuring the similarity between stocks; clustering dependent ones that tend to trade only with one another. These approaches also investigate the network's components and their impacts on market dynamics which are mostly due to fluctuations in financial variables like turnover and volatility.

In recent years, a new model of graph-based methods has been used in a few studies. This category of approaches is based on extracting building blocks of graphs like cliques, motifs or other topological structures and scrutinizing them to find anomalous groups or behaviors. Wang et al. (2012) proposed a method to detect hidden collusive cliques of traders collaborating to manipulate the market and mislead other investors to maximize their personal benefits. They calculated correlation between any pairs of time series of orders in the futures market and then combined the daily weighted graphs into an integrated graph in which the fully connected subgraphs (or cliques) are extracted as the suspect collusive cliques. Jiang et al. (2013) investigated three specific abnormal motifs comprised of self-loop, two-node loop and two-node multiple arcs and their evolution in a time-varying network of traders' transactions. They further studied the dynamics of financial variables around the transactions associated with the mentioned motifs. Xie et al. (2014) constructed dependence networks from weighted friendship networks of avatars in virtual societies of a massively multiplayer online role-playing game. They examined the evolution of thirteen kinds of triadic motifs in dependence networks and distribution of their occurrence frequency and relations between their counts.

To the best of our knowledge, there is no work that develops an approach to extract trade cycles of various lengths as topological structures from traders' network of future contracts as proposed in this paper. The novelty of this approach is that after extracting the frequency of each daily trade cycle over a period of time, it will then compare and trace their behavior over that time period to ensure market manipulation. Results are later verified by the market experts.

3. Dataset

In the futures market, there are several types of data, including order records, positions and match trades. Order records consist of information about investors such as their decisions to buy or sell, the volume and price of their requested commodity as well as the corresponding times. The exchange market's internal computer system then compares all the order records to find pairs with the same requested value of commodity, while one is for a seller and the other, a request to buy. The system will then change the investors' positions and report their orders as an integrated trade record in the match trades data.

The dataset under investigation is the match trades data related to four future contracts of gold coin traded in Iran Mercantile Exchange (IME) during 618 trading days from April 2013 to January 2016. The data set contains 1,600,000 match trades records and 2095 market participants.

Table 1. Sample view of the dataset.

Contract-Id	No. of Gold packs	Price	Seller		Buyer		Time
			Investor	Broker	Investor	Broker	
1354872	2	1,078,540	0x11FB3AE	0x5G4E27D	0x9F8EAB6	0x8A6B18F	2015-01-13 11:00:27:387
1367529	3	1,046,890	0x1E345DB	0x723F4E6N	0x87C43B2	0x243D5A7	2015-02-17 14:23:37:522

Each match trades record contains the following information: contract id, that could be used as a unique key in the database, number of gold coin packs, as the contract size (each pack contains 10 gold coins), price of each gold coin in that specific contract, encrypted identity of the brokers and investors and the last column is also time stamp of the contract.

As to brokers and investors, commodity broker is a firm or individual who executes orders to buy or sell commodity contracts on behalf of the clients and charges them a commission. An individual who trades for his own account is called a trader or investor. A sample view of this dataset is illustrated in Table 1.

4. Methodology

In this section, the details of the various steps taken to detect anomalous traders, are described. First of all, the daily graphs of traders need to be constructed in order to be examined by three main modules of the proposed approach. We have called these modules: Trade Cycle Extraction (TCE), Suspicious Cycles Selection (SCS) and Transactional Behaviors Evaluation (TBE) which have to be executed respectively. In the TCE module, all cycles of various lengths are extracted from all daily graphs. The SCS module is in charge of selection of initial cycles that are suspected regarding the defined conditions of being anomalous. In the TBE module, transactional behaviors of the traders involved in the suspicious cycles selected by the SCS module are investigated to verify their suspicious activities.

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5. Graph Construction

To construct the trading graph, it is essential to determine the types of nodes and edges (i.e. connections between two nodes). In this study, we consider each investor as a node and each transaction as a directed and weighted edge from seller to buyer. The weight of the edge is shown by an ordered pair in which the first element contains the price of the gold coin in that specific transaction and the second element holds the timestamp of the transaction.

In the future contracts of gold coin (or any other commodity), investors are allowed to trade with one another without any limits, therefore we will have a multi-edged graph. On the other hand, investors cannot trade with themselves, hence there are no self-loops in the graph. On the whole, the resulted graph is a multi-edged directed and weighted graph without self-loop, similar to the sample graph depicted in Figure1.

As it is likely for an investor to trade in one day and then not participate in the market for several days, therefore, each trading day is investigated independently and daily trade graphs are constructed and analyzed. Hence, we will have 618 graphs, each one being created based on a specific day's transactions.

6. Trade Cycle Extraction (TCE)

A circular trade as referred to here is the same as a cycle in the corresponding directed trade graph. To detect anomalous traders who are involved in circular trades, we need to extract all cycles of various lengths from all 618 constructed graphs of daily trading networks. To simplify the method, we have concentrated initially on cycles with an upward price trend, however, the same logic and principles will apply in detecting downward price trends too. The following example will clarify the scenario in discussion.

Figure 2 shows a sample circular trade detected in a daily trade graph. As it is clear, investor A buys 10 packs of gold coin for the base price of one million Toman (Iranian currency) and then sells two of these packs to one of his accomplices, investor B, with a 1% increase in price. Then, investors B, C and D follow the same procedure and sell those two packs among themselves, increasing the price by approximately 1% each time, until it reaches back to investor A. So, investor A, who sold those two packs to investor B in the first place, now becomes the buyer after a cycle of trades, and buys them again from investor D. He will then sell them, with about 5% increase in price, to an investor who has been impressed by the market's fake prosperity. Finally, investor A participates in the market affected by a fake prosperity and sells the remaining of those 10 packs of gold coin which he has bought initially and not traded yet. Consequently, investors A, B, C and D are anomalous traders who manage to benefit from the false increase of commodity price in the market.

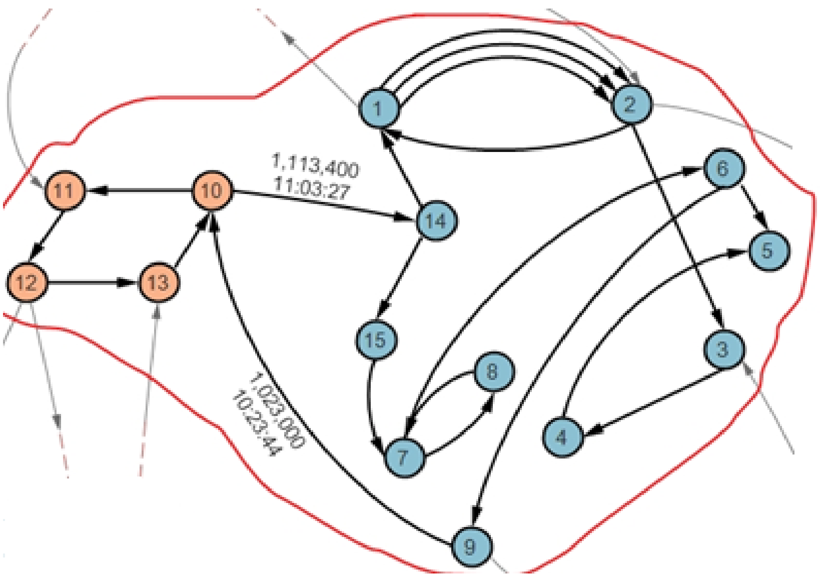

Fig. 1. A sample of daily trade graphs from the IME – a multi-edged directed and weighted graph without self-loop

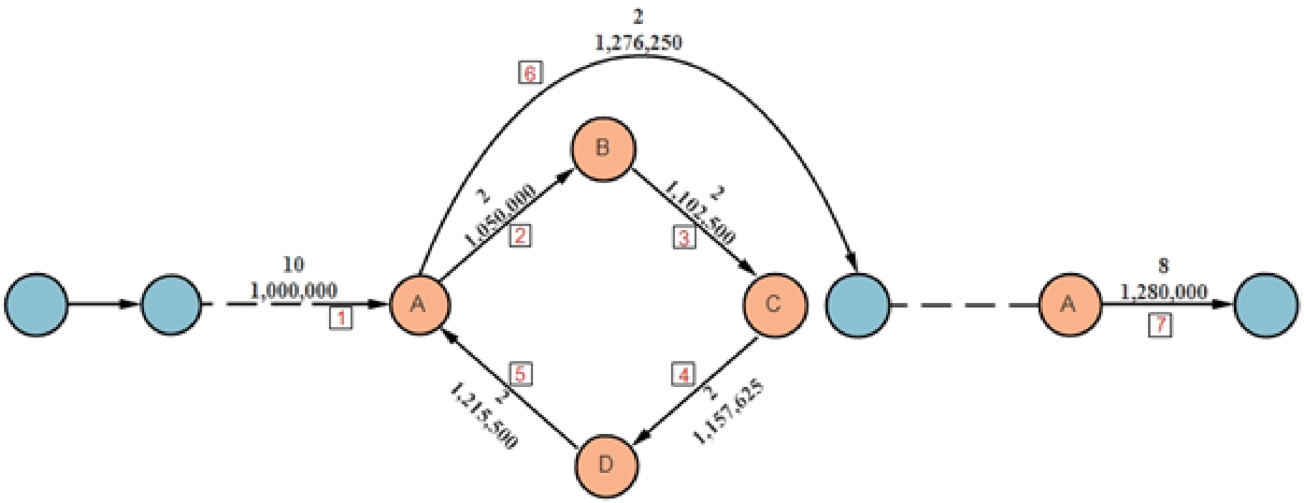

Fig. 2. A sample circular trade detected in a daily trade graph

After extraction of all cycles from the given daily trade graphs, it was noticed that there were no cycles with more than 5 nodes involved. Hence, all retrieved cycles were cycles with 3, 4 or 5 nodes like those shown in figure 3. An explanation for this could be because in the futures contracts market, there is a daily price fluctuations limit of up to ±5% based on the settlement price of the previous working day.

7. Suspicious Cycles Selection (SCS)

Amongst the extracted cycles, there were a few cycles that had been repeated in several trading days. Also, there were a handful of cycles that had identical subsequences inside one another, i.e. same order of nodes in the cycle. As it is indicated in figure 3, the subsequence X-Y has appeared in three cycles of different lengths.

Eventually, it was required to scrutinize cycles and count the frequency of their occurrences and also compare all their subsequences with each other to find similar ones. Therefore, that seemed reasonable to choose those traders who had been involved in repeated cycles and subsequences as the initial suspicious participants as the outputs of this step of the approach**.**

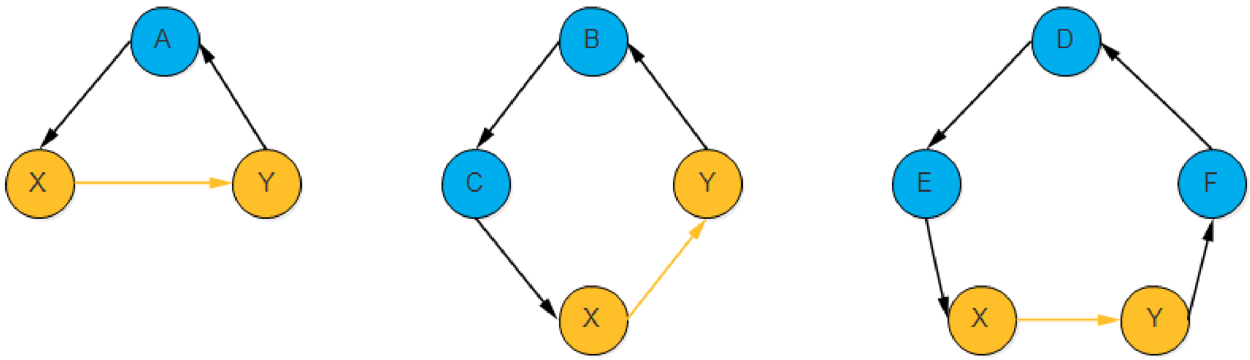

Fig. 3. Same subsequence of traders (X-Y) in three different cycles of different lengths

8. Transactional Behaviors Evaluation (TBE)

After extracting the initial suspicious cycles based on their repetition, we need to examine the transactional behaviors of the traders involved in the cycles. This is because it is possible for some traders to have unintentionally fallen within a trade cycle. Also, it is important to monitor the traders' benefits or loss, in order to verify suspicious trader activities.

In order to examine the transactional behaviors of such suspicious cycles, we need to plot the time series of the price fluctuations of the commodity relating to the corresponding trading days. Each time series is then divided into three time windows and each one is analyzed independently. Figure 4, shows an instance of time series for the day when a circular trade occurred, plus a sample of a normal day without any circular trade to compare. It is worth noting that the time series plot contains all the (matched) price fluctuations of the commodity (in this case gold coin future contracts), from the moment the market opens until the end of the day. As an example, the time series for 23rd of May 2015 is highlighted with the three time windows clearly shown in figure 4. The first window covers the time from market opening to just before a circular trade occurs. The second time window covers the span of time while circular trade is occurring. As was predicted and can be seen from the results, it shows an increasing trend in the price. The third time window, then shows the interval between the moment that circular trade terminates until the end of that trading day. For comparison, the time series for 14th of Feb 2015 is also shown on the same exhibit, as an example of a normal trading day along with the usual price fluctuations.

Now, according to experts' knowledge, there is a condition to discern a real malicious circular trade from a simple cycle which has been made randomly and unintentionally. As was explained in the trade cycle extraction step, traders who commenced a suspicious circular trade must have participated in the market during the first time window and bought some commodity (packs of gold coin) with a price cheaper than the average price of the day. Then, during the second time window it is expected that the price rises significantly (above the average fluctuations) due to the frequent trades among teamed-up investors. These investors are trading a small amount of commodity (gold coin packs), bought within the first time window, as a leverage to create a false market. Finally, through the third time window, we are now faced with a market following a trend of price increase which is fake. It is in this time window that the initial member of the suspicious trade cycle, attempts to sell the rest of the batch commodity, which had not been traded during the second time window, based on the new soared price. This is something that must be verified by analyzing each of the consecutive time windows per trading day. Hence after this step, those trade cycles that fit such activities are verified and their members are introduced as suspicious cycle traders.

9. Time Complexity

Computational complexity of the proposed approach is linear with respect to the complexity of three main modules of the approach namely the Trade Cycle Extraction (TCE), the Suspicious Cycles Selection (SCS) and the Transactional Behavior Evaluation (TBE) which are represented by the pseudocode given in figure 5.

According to the algorithm shown in figure 5, the TCE module can be calculated in O(n). Besides, the SCS module and the TBE module add a similar O(n) to the complexity of the proposed approach, leading to an overall linear complexity. Moreover, there are some constants such as number of trading days or number of investors in a single day that will not affect the order of computational complexity.

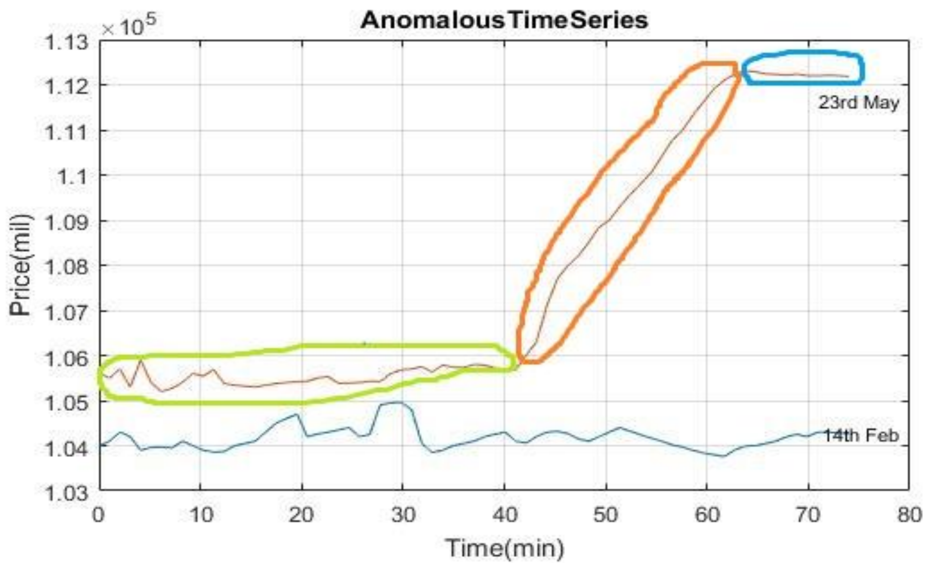

Fig. 4. A sample of two daily time series of price fluctuations in the market corresponding to an anomalous (23rd May 2015) and a normal (14th Feb 2015) trading day

Input: Data set D ordered by Time, Array T includes unique codes of traders, Condition of being anomalous
Output: Array N contains the names of anomalous traders
List L, List Suspicious;

```
For each daily graph Do
    Extract cycle C from D
    Add C to L
End
For each cycle C in L Do
     F = Count the frequency of C
     If (F >= 1) then
         Add C in Suspicious
     end
     Compare C with the rest of cycles
     If (Common Subsequence) then
        Add the Subsequence in Suspicious;
     end
 End
For each Node n in Suspicious Do
     Analyze the trading behavior;
     If (Condition) then
          Add n to N;
     end
End
Output N;
```

Fig. 5. Pseudocode showing the implementation of the main modules

10. Results

In this section we report on results obtained from applying our approach to real datasets, collected from Iran Mercantile Exchange (IME) during 618 trading days from April 2013 to January 2016. We ran the analysis on the 1,600,000 match trades records and 2,095 market participants.

In table 2, a breakdown of the all the examined cycles extracted from the daily graphs by the TCE module is given.

According to results in table 2, all the extracted cycles have less numbers of unique nodes than expected. For example, for 47 cycles of length 3 nodes, one would expect 141 unique nodes, yet there were 133 unique nodes, meaning that 8 nodes or approximately 6% of unique nodes have been repeated in some of the cycles. Accordingly, the percentage of similar nodes which have been repeated in several cycles, shown in table 2 as Nodes Overlap, increases from 6% in 3-node cycles to 28% in 5-node cycles. In fact, this increase is showing that larger cycles are more private than smaller ones and traders who are involved in them are familiar with one another, thereby reducing the likelihood of strangers entering their cycle and hence disturbing their malpractice.

Then, according to the SCS module we were supposed to select suspicious cycles and accordingly suspicious traders who highly probably were involved in repeated cycles and subsequences as the initial suspicious participants, because a group of anomalous traders, undoubtedly would not abandon the market after doing circular trade once, and tend to gain more profit from consequent circular trades. Therefore, we considered those 34 cycles from table 2 with more than one repetition and similar subsequences as our initial extracted suspicious cycles and also as the inputs to the TBE module for further evaluation, like the time series depicted in figure 6.

After time series evaluation of the 34 suspicious cycles found in the last step of the approach, we observed that some of these cycles (namely: four 3-nodes cycles, four 4-nodes cycles and two 5-nodes cycles) did not manage to create a sharp rise in the commodity price, and hence create a false market. Therefore, seven 3-nodes cycles, nine 4-nodes cycles and eight 5-nodes cycles, **24 cycles in total**, succeeded in faking a prosperity in the market and shaping a new trend of price based on circular trading. In other words, 97 traders who were involved in the mentioned 24 trade cycles, met the defined conditions of being anomalous. Hence, they are introduced as potential anomalous traders to market regulators for further probe**.**

Table 2. Information of all the examined cycles

Cycle Length	Number of Extracted Cycles	Number of Unique Nodes Involved in Cycles	Repeated Cycles and cycles with similar subsequences	Nodes Overlap
3	47	133	6 cycles with 2 occurrences during 1 month 2 cycles with 3 occurrences during 2 consecutive days 3 cycles with similar subsequences	6%
4	35	127	8 cycles with 2 occurrences during 1 month 3 cycles with 3 occurrences during 10 days 2 cycles with similar subsequences	10%
5	17	66	4 cycles with 2 occurrences during 2 consecutive days 2 cycles with 4 occurrences during 1 week 4 cycles with similar subsequences	28%
Total	99	176	34	

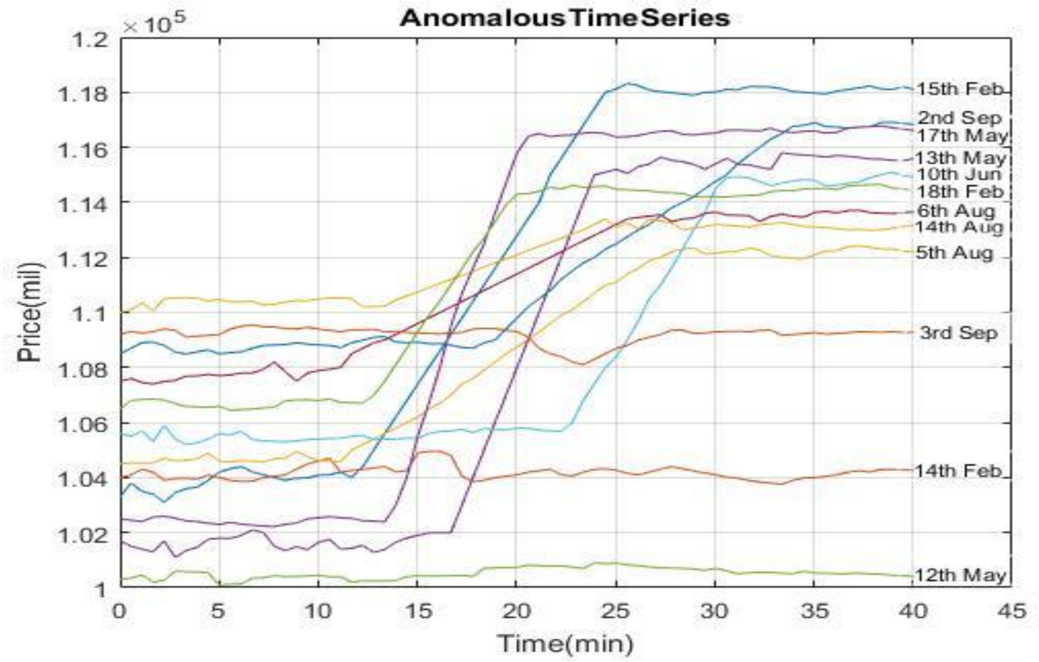

Fig. 6. 12 samples of anomalous and normal time series as our initial extracted suspicious cycles

Table 3 reports the final results of applying the proposed approach to the real data set of mercantile exchange which can confirm its effectiveness in detecting anomalous traders. As it is shown it table 3, of the 21 traders who were involved in 3-nodes anomalous cycles, 12 traders were confirmed as real fraudsters by the market regulators and experts. Also, 21 traders from the 4-nodes anomalous cycles and 26 traders from 5-nodes anomalous cycles were confirmed as real fraudsters by the experts.

Overall, more than 60% of the introduced anomalous traders were real fraudsters, which with respect to the linear complexity of the proposed approach and its duty as an alarm system, is acceptable.

Table 3. Analysis of the final output of the applied approach

Length of Cycle	Number of Extracted Cycles	Number of Suspicious Cycles	Number of Anomalous Traders	Number of Confirmed
3	47	11	21	12
4	35	13	36	21
5	17	10	40	26
Total	99	34	97	59

In this study, the verification process has been done by the market regulators and experts, because in the financial industry, it is against the rules to disclose market data or even history of investors, hence there are not enough information for researchers to label the data and verify the results. However, such results are very valuable to the market supervision division, which gives them some information on target or potential fraudsters for more investigation, rather than going through a huge amount of trading data.

11. Conclusions

In this research, a graph-based approach has been proposed to detect anomalous traders who are manipulating the price of the future contracts by circular trading in mercantile exchange. The suggested approach extracts all the cycles of various lengths from the defined multi-edged directed graph of investors. Then a group of suspicious cycles become selected based on the specific features of cycles to plot time series of price fluctuation relates to the days that they have been extracted from. Time series of some cycles showed their malpractice meeting the rule of being anomalous and finally those traders who have been involved in these anomalous cycles are introduced to market regulators for further probes.

In addition to the capability of suggested approach to both construct graphs of investors' networks and extract suspicious cycles from them as circular trades, it is also able to evaluate investors involved in suspicious cycles by time series analysis, prior to announcing them as anomalous investors to the market regulators.

As future work, we are considering to improve our approach to a real-time version to be able to warn market regulators as soon as a trade cycle is detected, whereas presently it is bound to have access to all records of a trading day together. Moreover, the present approach has only been applied to future contracts in mercantile exchange while other markets and financial instruments are severely suffering from circular trading and our approach with an alteration would be operative for them.

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