



On Wash Trade Detection in Energy Markets

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Abstract — A wash trade in energy markets refers to entering into arrangements for the sale or purchase of a financial or physical instrument, a related spot commodity contract, or an auctioned product based on emission allowances, where there is no change in beneficial interests or market risk or where beneficial interest or market risk is transferred between parties who are acting in concert or collusion. Market abuse scenarios such as wash trade compromise the efficiency and integrity of energy markets. The research of abusive trading behavior in financial markets is well ahead of peers in energy markets. Effective solutions for monitoring abusive scenarios such as wash trade in energy markets have yet to be developed. This paper describes a practical implementation example of detecting wash trade behavior in energy markets using simple techniques. An easily reusable method is then proposed to detect the potential wash trade activities involved in an instrument by first detecting trades resulting in no overall change in market risk and then further identifying the collusive behavior between the counterparties. The proposed method is tested and evaluated on energy instruments order data sets from the Trayport trading platform. We find that the proposed approach can effectively detect all primary wash trade indicators across energy instruments.

Keywords— *Energy markets; market abuse; wash trade*

I. INTRODUCTION

Recent regulatory changes in Europe are likely to result in increased enforcement against market abuse in energy markets. Enforcement activity under the Regulation on Wholesale Energy Markets Integrity and Transparency (REMIT) [1] is expected to step up. REMIT is a European Union regulation designed to deter market abuse in energy markets, and also requires disclosure of price-sensitive information regarding energy generation, storage and transmission. In addition, the Market Abuse Regulation (MAR), a European Union directive applicable from July 2016[2], will widen the scope of the existing regulatory framework applicable to certain energy derivatives and related products. European Securities and Markets Authority published a report where a detailed technical advice on detection of manipulative scenarios such as wash trade were discussed [3].

Traditionally, market abuse cases have concentrated around financial instruments. However, energy markets have some features which may be important in any analysis relating to alleged market abuse:

- Some segments of energy markets are driven by few main players and, other segments, dominated by a single entity;

- The supply and demand in energy markets should balance in real time, hence demand and supply can be insensitive to price in the short term. Similarly, small changes in the supply-demand balance may result in significant changes in prices;
- Some segments of the market are less liquid; and
- Trade is often conducted over-the-counter (OTC) and may be less transparent than exchange based trading;
- Data availability for analysis

While financial and energy markets share some of the same mechanisms, energy market's more granular feature (various venues, various instrument characteristics, delivery types etc.) energy markets must be given separate consideration in any analysis of alleged abuse in such markets.

A representative example of distinct characteristic of an energy market instrument could be a typical structure for long-term Gas or Power Agreements which are priced based on trusted indices rather than fixed in absolute terms. An index in this regard could be a reference to the average price of Platts' 3 month-ahead assessment of the Gaspool price, averaged over the previous month. The abusive behavior could be achieved by a utility's generation unit signing the long-term contract, and utility's trading unit biasing Platts' assessment of the Gaspool price downwards, reducing the price paid on its long-term contract.

Due to rapid regulative activity, existing Market Abuse Surveillance Systems functioning well in financial markets were not ready to cater for energy markets characteristics. Many energy companies committed to implement existing standard solutions, but had to scrap the configuration work and start in-house development [11].

During the last year we tried to convert ESMA's technical advice into tangible detection algorithms based on statistical methods. We've build an automated system and formulated a smooth process enabling the compliance officers to monitor the abusive scenarios and react accordingly. In this paper we attempted to describe how we implemented the wash trade detection monitor in an environment where no prior implementations exist in the industry and license to operate is at stake.

The reminder of the paper is organized as follows. In Section II we review the work related to detection of wash trade activity. In section III we describe data mining techniques for energy trade logs as well as propose the actual detection

algorithms. We evaluate in section IV and conclude in section V.

II. RELATED WORK

There are a number of approaches for detecting abusive behavior in different markets. While pattern recognition and outlier detection are applicable when comparable examples exist, rule induction social network analysis and visualization are widely used with unlabeled data sets [4].

While the amount of papers in the area is growing rapidly, we found no related work on the detection of wash trade activities in energy markets. The closest by nature and complexity of instruments research is work on detection of collusive trading in futures markets, based on identifying threshold tolerance on correlation between the eligible unified aggregated time series [5]. The trader behavior was represented by an aggregated time series of signed volumes of submitted orders. The similarities of behaviors among multiple traders are measured by Pearson’s product-moment coefficient, and the cliques with a coefficient higher than a user-specified threshold were considered as suspicious collusions. Further there’s an extensive research dedicated to the abusive trading activities in financial markets. A spectral clustering-based approach was developed [6], where a trading-behavioral network is generated and any behavior that deviates from the network is reported as an irregularity. Authors assume that there is a strong correlation between trader’s current behaviors and his/her previous trading network. A graph clustering algorithm for detecting a set of collusive traders has been proposed in [7]. Some authors believe it is unacceptable to ignore the order price information, which not only distinguishes traders’ intention, but is a key feature of wash trade activity [8], [9], [10]. The lack of the surveillance mechanisms for wash trades with multiple orders or traders left it possible for collusive parties to create a number of transactions that give a false appearance of large trading volumes [10]. Just like in the case of Vancouver based Gordon Eberwein who during 2013 wash traded in Ackroo shares through four different accounts in his possession and led to misleading appearance of trading activity [13]. Sometimes misleading appearance of a wash trade is enough for allegation irrespective of the intention [14], [15]. The academic research in this area has mainly focused on detecting the overall trading collusions according Social Network analysis or outlier detection. While these approaches are good for regulators, and overall exchange surveillance, they may require too much resources to develop for compliance purposes. Thus the industry adopted relatively simple techniques of wash trade scenarios, which can be bypassed by slightly more sophisticated manipulation pattern. We found no simple suggestions in the analysis of wash trade strategic behavior and the design of a detection approach identifying any tactics of attempts of wash trade for industry practice. Thus we propose a universal wash trade monitor that would allow easy implementation by industry practitioners from the self-surveillance perspective. Adopting these techniques would help the energy trading companies to prevent market abuse and stay compliant with a strict regulation.

III. PROPOSED METHOD

The monitor is developed to identify behavior where a trader executes trades for no, or little, change in overall economic position or benefit – often to artificially stimulate broker commissions for illicit reasons or to create false or misleading impression of trading activity. Based on this formulation we model the following ways wash trading can occur:

- Trading which results in no overall change in market risk (e.g. the company trading on exchange where the counterparty is not known).
- Trading with a colluding counterparty where trades are pre-arranged or coordinated resulting in no change in market risk or overall economic position.
- Trading with self

Since latter is to be addressed more broadly by another monitor, only the first two points are explicitly captured in by this method.

A number of challenges arise when practically implementing such a monitor for wash trades in energy markets e.g.

- The nature of energy trades makes it possible, at least in theory, to use different but related instruments to engage in wash trading
- Fragmented, illiquid markets (typical to some energy markets) in contrast to deeper, more liquid markets make it more challenging to apply a single monitor to cover all potential eventualities

An example includes the window within which wash trades might take place may differ between liquid and illiquid markets potentially requiring an adjusted approach for each – this is likely however to substantially increase the complexity of the monitor.

A. Data set

We use daily order log file from Trayport. ICE, EEX and other Exchanges haven’t opened feeds for market abuse regulation monitoring yet. The file contains contains all the order and trade activity of the traders who submitted their orders via Trayport’s trading system. For many companies in the market Trayport is the only gateway to trade on energy markets so far.

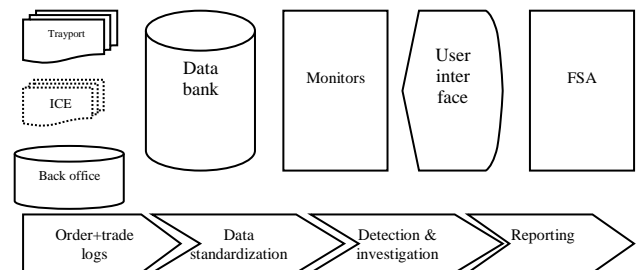


Fig. 1. Data collection and monitoring process.

We classify each record according to action type as follows:

TABLE I. ORDER ACTION TYPE DESCRIPTION

#	Order Action Type	
	Order Action Type	Description
1	“Insert”	An order is added to the queue
2	“Update”	The attribute of an order is updated
3	“Partially dealt”	The order is partially filled
4	“Cancelled”	The order is cancelled and removed from the queue
5	“Dealt”	The order is dealt

We identify our company’s activity by user names where all other market participants have an anonymous trader name. Each file contains approximately 2 mln. records for one day. We exclude all order types other than “Firm” and “Venue Implied” due to their visibility to other counterparties in the market and potential tradability. We start our analysis from 01. July 2016, where the regulation first entered the force and the data was officially made available for extraction.

B. Data Processing

At the first stage we collect all trade logs into a database (see Fig. 1). The database also contains the deal capture information for counterparty data. Daily files are tested against inspection rules defined as representative of abusive behavior.

It is obvious that each order has its life span l represented as follows:

$$l = \begin{cases} (\text{Inserted}), t_0 \\ (\text{Updated or Partially dealt}), t_2 \\ \dots \\ (\text{Cancelled or Dealt}), t_n \end{cases}$$

We track each order using the corresponding ID columns. as follows:

TABLE II. ORDER LIFECYCLE EXAMPLE

Action	Side	Order ID Group	Order ID	Price	Volume	Time stamp
Inserted	Ask	1	1	100	20	09:00:00
Updated	Ask	1	2	100	25	09:00:01
Dealt	Ask	1	3	100	25	09:00:10
Inserted	Bid	2	1	99	10	10:00:00
Updated	Bid	2	2	98	10	10:00:15
Cancelled	Bid	2	3	98	10	10:00:50

Table II depicts the mechanism of grouping orders into a logical continuation for each trader and instrument.

C. Test

Assuming the traders ability to avoid risk the following two indicators were developed and tested.

Indicator 1: Wash Trade

Opposite transactions in the same instrument executed by the same trader within calibratable time intervals differ $< 1\%$ in price (calibratable)

and

Opposite transactions in the same instrument executed by the same trader within same calibratable time intervals differ $< 1\%$ in volume (calibratable)

In other words a situation like presented in the following table would generate an alert for further investigation in case of time interval calibration of 2 hours:

TABLE III. WASH TRADE INDICATOR 1

Action	Side	Trader	Instrument	Price	Volume	Time stamp
Inserted	Bid	Z1	X.Q1.19	100	100	09:00:00
Updated	Bid	Z1	X.Q1.19	100	100,5	09:00:01
Dealt	Bid	Z1	X.Q1.19	100	100,5	09:00:10
Inserted	Ask	Z1	X.Q1.19	100	100	10:00:00
Updated	Ask	Z1	X.Q1.19	100,5	100	10:00:15
Dealt	Ask	Z1	X.Q1.19	100,5	100	10:00:50

Both the volume and the price difference between buy and sell transactions (Dealt) is less than 1%.

Indicator 2: Collusion

There is > 1 buy-sell pair (calibratable) for a given instrument with the same counterparty within calibratable time intervals (excluding exchanges)

and

Net trading volume for a given instrument with the counterparty represents < 3 percent (calibratable) of the total sum of buy and sell transactions volume with the counterparty within calibratable time intervals (excluding exchanges)

We exclude exchanges in this indicator because the exchanges hide the real counterparty information.

In table IV we represent an ideal situation where two different traders in the company accomplish more than one roundtrip within two hours interval and their resulting position ends in zero-sum:

TABLE IV. WASH TRADE INDICATOR 2

Action	Side	Trader	Volume	Counterparty	Instrument	Time stamp
Dealt	Bid	Z1	100	Y	X.Q1.19	09:00:10
Dealt	Ask	Z1	500	Y	X.Q1.19	09:30:50
Dealt	Bid	Z2	600	Y	X.Q1.19	09:45:10
Dealt	Ask	Z2	200	Y	X.Q1.19	10:00:50

IV. RESULTS AND ANALYSIS

Preliminary results of both indicators detected 4 cases (2 cases in each of October and November data set) of potential wash trade activity using indicator 2. In order to test the performance of Indicator 1, we injected manually generated order activity into the data feed, and rerun the inspection. As a result all of the injected data points were detected 100% by the algorithm.

The performance evaluation of the proposed model is based on Sensitivity (SEN) and Specificity (SPE) confusion matrix, where a false positive (FP) is defined as a wash trade case detected as normal; a true negative (TN) is defined as a wash trade case detected as wash trade; a false negative (FN) defined as non-wash trade cases, and true positive (TP) defined as wash trade cases detected correctly. $SEN = TP/(TP+FN)$ and $SPE = TN/(FP+TN)$. Our findings showed that SPE and SEN values are optimal when the fuzzy matching level is at 1%, and the calibratable time intervals are set to 2 hours.

The experiments with injected orders also prove that proposed Indicator 1 approach captures all basic forms of single transaction wash trade behavior (common and easily detectable) covering both venue and broker activity. The ‘zero-net’ trade condition in Indicator 2 identifies where collusion may be evident with a single counterparty.

Results of all monitors are then presented to compliance officers who need to consider each case for investigation. They can confirm whether the trading data is factually consistent with the alleged market abuse framework. In fact, the confirmation of the existence of a specific trading strategy does not necessarily mean it was abusive. It might be the case that a strategy that appears to be abusive or manipulative is legitimate, and economically rational. Finally, if a manipulation is proven then the report is submitted to local FSA. Figures 1, 2, 3 show the examples of a system built by us.

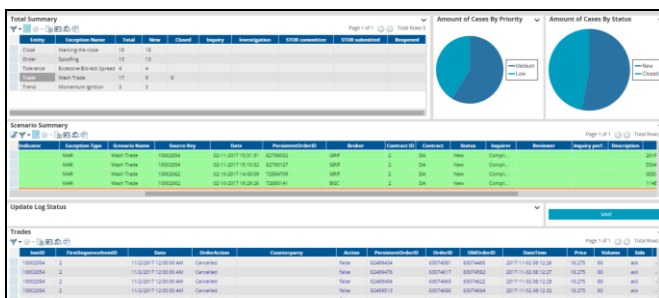


Fig. 2. Dashboard for wash trade suspects

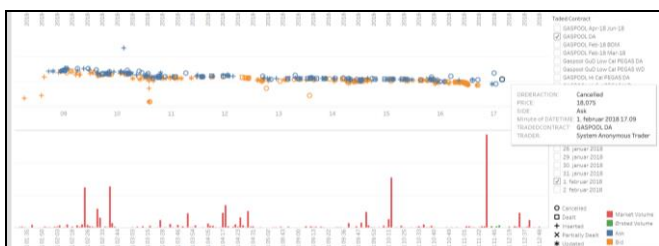


Fig. 3. Graphical representation of order activity

Future enhancements may include:

- to address the market liquidity point described in the section above, adapt the Monitor to introduce a liquidity based, market specific time window appropriate for each market.
- introduce a new indicator to identify related instrument/product types which, in varying permutations but equal volume, may indicate wash trade behavior
- employ social network analysis techniques.
- extend the functionality of communication channel (chat, telephone, email) surveillance with language process algorithms supporting collusion detection.

V. CONCLUSION

We propose a simple wash trade activity detection approach from self-surveillance point of view. After thoroughly studying the various scenarios of wash trade behaviors we build a system that is applicable for energy trading companies and utilities. The wash trade monitor examines instances of trade behavior by the same trader whose round-trip trades were fuzzy matched (i.e. price and volume are approximately equal) and an instance of a trade behavior where net trading volume with the same counterparty are zero over a specific rolling time. The underlying model has room for calibration of thresholds on time intervals and fuzzy match levels. This method differs from other proposed alternatives by simplicity of implementation taking into consideration the data availability in the energy markets and flexibility for extension. We propose fuzzy detection mechanism instead of equally priced buy/sell orders; universal collusion detection technique instead of costly network monitoring; flexible calibration across markets and instruments instead of fixed threshold. While such an approach is good for daily detection sprints, the increasing compute and storage power offered by cloud technologies, provides interesting insights for future development enabling real-time detection and reporting techniques.

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