Authority for
Consumers & Markets

Public

Algorithmic Trading in Wholesale Energy Markets

Key findings of an exploratory market study by the ACM

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Markets that work well for people and consumers

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Management summary and key findings

The Netherlands Authority for Consumers and Markets (ACM) has conducted an exploratory market study into algorithmic trading in wholesale energy markets. The aim is to further enhance the knowledge on this increasingly significant trading method. The study investigates overall trends in the use of algorithms, the types of algorithms used, the motives for market participants to engage in or abstain from algorithmic trading, possible impacts on the wholesale energy market, and the procedures that trading companies employ to ensure algorithms perform as intended. The primary focus is to gain insights into industry and pertinent stakeholder perspectives as well as to observe and interpret emerging developments. ACM has the duty to monitor and enforce compliance with the EU Regulation on Wholesale Energy Market Integrity and Transparency (REMIT).

This market study is carried out in collaboration with the Dutch Authority for the Financial Markets (AFM). The AFM has provided valuable input based on their experience. As a regulator of the financial markets, the AFM has examined developments in algorithmic trading in earlier studies, among other things for the purpose of their oversight of financial markets. The ACM and the AFM share the responsibility for the oversight of the integrity and transparency of wholesale energy market trading in the Netherlands, including trading via algorithms. Each organisation does this based on its own competences.

The objective of this publication is to share the overall findings of our exploratory market study. ACM aims to enhance publicly available knowledge on algorithmic trading, specifically within the energy markets. The insights of the study also hold relevance for policymakers, regulatory authorities, trading platforms, and market participants. Additionally, with this publication, ACM emphasises the importance of market participants understanding their responsibility to ensure and document that their algorithmic trading activities comply with the revised REMIT, which came into effect in May 2024. As a National Regulatory Authority, ACM is responsible for monitoring and enforcing compliance with these obligations in wholesale energy trading in the Netherlands.

Research approach: ACM conducted interviews and a survey among market participants and trading platforms, complemented by desk research. The exploratory market study included interviews with a diverse group of market participants, trading platforms, and a technology provider of surveillance services. Additionally, a survey was conducted among a larger group of market participants, and the study included desk research. While not all perspectives from the entire population of parties active in the wholesale energy market were gathered, the broad and diverse range of contributors provides that the findings are valuable and reflective of a broad spectrum of views. The study did not involve data-analysis by the ACM, or in-depth analysis of the algorithms used by market participants. Furthermore, the study did not assess or verify the extent to which the interviewed market participants and survey respondents effectively implement the compliance procedures regarding the use of algorithms in energy trading as outlined in this study.

Scope of the study: the study focuses on spot markets for power and gas trading, encompassing market players identified by ACM as companies engaged in trading energy products with delivery within a 48-hour timeframe. Many participants in the spot market are also active in derivatives and futures trading. The study incorporated insights related to these markets where relevant. However, it did not exclusively focus on players in those areas.

The key findings of the market study:

Algorithms are increasingly prevalent in wholesale energy markets.

- Algorithmic trading is a process where a computer algorithm determines trading parameters such as price, quantity and whether to initiate an order with limited or no human intervention. In many cases the trader only monitors the performance of the algorithm.
- There are different types of algorithms: execution algorithms, trading algorithms and signal generators. These all might vary in complexity, from simple rule-based algorithms to advanced machine-learning techniques.
- Trading with the help of algorithms is usually part of a broader trading strategy, which might also encompass (simultaneous) manual trading. Various strategies are employed with algorithmic trading, for instance, spreading volume over time or markets in order to reduce price impact, spread trading, market making and relative pricing in the orderbook.

The energy transition moves market participants to use algorithms, as the need for constantly balancing positions increases especially during last-minute trading.

- The use of algorithms in energy market trading is growing and it is expected to increase further. There is an increasing number of pure algorithmic trading market participants.
- A key driver behind expected further growth of algorithmic trading is the energy transition, as the necessity to balance positions at short notice keeps increasing, because it is more difficult to predict renewable energy production.
- In the power spot market, algorithm use in trading is widespread, while in the gas spot market, algorithm use is somewhat less frequent, yet it keeps increasing.
- Motives for the use of algorithms mentioned by market participants are efficiency, asset optimisation and risk mitigation. Reasons for abstaining from such are IT and knowledge requirements, as well as a perceived lack of necessity or interest. In certain markets, trading without algorithms is becoming increasingly difficult, due to some disadvantages related to the slower speed of manual trading.

Positive outcomes and risks can be associated with algorithmic trading; as a regulator, ACM continues to stay alert.

- Possible market outcomes resulting from algorithmic trading include increased liquidity and refined, accelerated price formation. On the downside, there is also a recognised risk of a disconnect emerging between fundamental market information and algorithm-driven trading behaviour.
- Algorithmic trading may increase volatility through feedback loops and rapid response to market signals, which can amplify existing market movements. However, some argue that it does not fundamentally change volatility dynamics. Well-programmed algorithms incorporate safety measures to prevent excessive volatility and can even serve as a useful tool in highly volatile markets.
- Market transparency can be affected due to frequent price movements, complicating price determination, especially for manual traders. While algorithms also might enhance transparency by documenting trading decisions, their complexity - especially in machine learning - may hinder explainability, impacting transparency.
- Some suggest possibilities of (unintended) manipulation through algorithms, with concerns including algorithmic sensitivity to manipulated data input and the speed at which manipulative actions can occur. Others, however, view that algorithmic trading can reduce vulnerability to manipulation by adding liquidity.

- The complexity and high frequency of trading orders in algorithmic trading changes the approach in identifying suspicious trading patterns from a monitoring perspective, requiring a thorough and data-intensive approach.

Compliance and internal checks and balances are essential when using algorithmic trading. Such measures are in place in the industry, though the effectiveness thereof was not assessed in this study.

- All interviewed and surveyed market participants have told ACM that they have compliance and risk measures in place regarding their algorithm(s), though to varying extents. In this study ACM has not assessed whether the procedures are put into practice. This concerns a variety of measures, such as limiting the price and volume of orders within certain ranges, and a kill functionality that enables the trader to stop all algorithm trading at once when needed.
- Since this study is exploratory in nature, ACM has not assessed the effectiveness or the implementation of the compliance and risk measures from a regulatory perspective, as this is beyond the scope of the study.
- Risks of adverse behaviour may remain present, even when compliance measures are in place. For example, the effectiveness of applied controls and limits depend on specific input values. In case the input values are set too high or too wide, the controls and limits may not be restrictive enough in practice.
- Trading platforms maintain several conditions for market participants to employ algorithms on their platforms, mainly to ensure stability of the trading system and the quality of price discovery.

The ACM continues to monitor and regulate the algorithmic trading and the compliance by market participants of the obligations based on the revised REMIT.

- The REMIT revision imposes new obligations on EU wholesale energy market participants engaged in algorithmic trading to mitigate associated risks. Market participants engaged in algorithmic trading must implement effective risk management systems, adhere to trading thresholds and limits, ensure business continuity, and notify regulatory authorities of their algorithmic trading activities.
- The REMIT revision strengthens ACM's oversight of algorithmic trading in the Dutch energy market. ACM continues to monitor and regulate trading behaviour by market participants, thereby also focusing on compliance of the obligations regarding algorithmic trading.
- ACM continues to work closely together with the AFM and other regulatory bodies.

The insights from the present market study enhance ACM’s understanding of algorithmic trading and will be applied in future market oversight in cooperation with the AFM. Throughout this exploratory market study, the objective was not to draw definite conclusions about specific trading behaviours. Various topics of interest for future market study or market oversight include developments in algorithm use, specifically in TTF gas market futures trading, advancements in self-learning algorithms within energy market trading, detection and analysis of potential suspicious behaviours involving algorithms, and to what extent market participants adhere to their compliance procedures that are said to be in place. The ACM and AFM will continue to cooperate in the future: sharing knowledge, furthering knowledge building and joining forces in market oversight and enforcement of the obligations for market participants.

Managementsamenvatting en belangrijkste bevindingen

De Autoriteit Consument en Markt (ACM) heeft een verkennend marktonderzoek uitgevoerd naar algoritmische handel op de groothandelsmarkten voor energie. Het doel is om de kennis over deze steeds belangrijker wordende handelsmethode verder te vergroten. De studie onderzoekt algemene trends op het gebied van het gebruik van algoritmes, de soorten algoritmes die worden gebruikt, de motieven voor marktdeelnemers om al dan niet deel te nemen aan algoritmische handel, mogelijke gevolgen voor de groothandelsmarkt voor energie en de procedures die handelaren gebruiken om ervoor te zorgen dat algoritmen zich gedragen zoals bedoeld. De primaire focus ligt op het verkrijgen van inzicht in de sector, relevante perspectieven van belanghebbenden en op het observeren en interpreteren van recente ontwikkelingen. De ACM houdt toezicht op en handhaaft de naleving van de regels in de Europese Verordening inzake integere en transparante handel op de groothandelsmarkten voor energie (REMIT).

Deze marktstudie is uitgevoerd in samenwerking met de Autoriteit Financiële Markten (AFM). De AFM heeft waardevolle inbreng geleverd op basis van hun ervaringen. Als toezichthouder op de financiële markten heeft de AFM eerdere studies uitgevoerd naar algoritmische handel en neemt dit mee in het toezicht op de financiële markten. De ACM en AFM delen de verantwoordelijkheid voor het toezicht op de integriteit en transparantie van de Nederlandse groothandelsmarkten voor energie, met inbegrip van handel via algoritmes. Elke organisatie doet dat vanuit zijn eigen bevoegdheden.

Het doel van deze publicatie is om de belangrijkste bevindingen van de marktstudie te delen. De ACM wil bijdragen aan de beschikbare kennis over algoritmische handel, specifiek binnen de energiemarkten. De inzichten uit het onderzoek kunnen relevant zijn voor beleidsmakers, toezichthouders, handelsplatformen en marktdeelnemers. Bovendien benadrukt de ACM met deze publicatie het belang dat de ACM hecht aan het bewustzijn van marktdeelnemers van hun verantwoordelijkheid om ervoor te zorgen en te documenteren dat hun algoritmische handelspraktijken in overeenstemming zijn met de in mei 2024 herziene REMIT. Als nationale energietoezichthouder heeft de ACM de taak om toezicht te houden op de naleving van deze verplichtingen met betrekking tot de groothandel in energie in Nederland.

Onderzoeksaanpak: interviews, een enquête onder marktpartijen en handelsplatformen en deskresearch. Het verkennende marktonderzoek bestond uit het afnemen van interviews met een diverse groep marktdeelnemers, handelsplatformen en aanbieders van surveillancediensten. Daarnaast is er een enquête gehouden onder een grotere groep marktpartijen en deskresearch uitgevoerd. Hoewel de studie niet alle standpunten van alle marktdeelnemers op de groothandelsmarkt voor energie omvat, zijn de bevindingen van waarde dankzij de brede en diverse groep partijen die hebben bijgedragen, wat een vertegenwoordiging biedt van diverse visies. De studie omvatte geen data-analyse door de ACM of diepgaande analyses van door marktdeelnemers werkelijk gebruikte algoritmes. Ook is niet onderzocht of getoetst hoe adequaat de geïnterviewde partijen en respondenten in de enquête hun compliance procedures toepassen met betrekking tot het gebruik van algoritmes, voor zover ze dit tegen de ACM hebben verteld.

Reikwijdte van het onderzoek: spotmarkten voor de handel in elektriciteit en gas. De reikwijdte omvat marktpartijen die actief zijn op de spotmarkten, waarbij de ACM doelt op bedrijven die energieproducten verhandelen met levering binnen een termijn van 48 uur. Veel spotmarktdeelnemers zijn ook actief op derivatenmarkten en doen aan termijnhandel. Waar relevant is in het onderzoek rekening gehouden met de inzichten met betrekking tot deze markten, hoewel dit onderzoek zich niet specifiek heeft gericht op spelers die alleen daar actief zijn.

De belangrijkste bevindingen van het marktonderzoek:

Algoritmen komen steeds vaker voor op de groothandelsmarkten voor energie.

- Algoritmische handel is een proces waarbij een computer algoritme handelsparameters bepaalt, zoals prijs, hoeveelheid en of een order moet worden geïnitieerd, met beperkte of geen menselijke tussenkomst. In veel gevallen monitort de handelaar alleen het gedrag van het algoritme.
- Er zijn verschillende soorten algoritmen: uitvoeringsalgoritmen, handelsalgoritmen en signaalgeneratoren. Deze kunnen allemaal variëren in complexiteit, van eenvoudige, op regels gebaseerde algoritmen tot geavanceerde technieken voor *machine learning*.
- Handelen met behulp van algoritmen maakt doorgaans deel uit van een bredere handelsstrategie, die ook (gelijktijdig) handmatig handelen kan omvatten. Bij algoritmische handel worden verschillende strategieën gebruikt, bijvoorbeeld het spreiden van volume over de tijd of markten om de prijsimpact te verminderen, handel door middel van *spreads*, *market making* en relatieve prijsstelling in het orderboek.

De energietransitie zet marktdeelnemers ertoe aan algoritmen te gebruiken omdat de behoefte aan het voortdurend balanceren van posities toeneemt, vooral tijdens last-minute handel.

- Het gebruik van algoritmen bij de handel op de energiemarkt groeit en zal naar verwachting nog verder toenemen. Er is een toenemend aantal pure algoritmische handelsmarktdeelnemers.
- Een belangrijke drijfveer achter de verwachte verdere groei van algoritmische handel is de energietransitie, omdat de noodzaak om posities op korte termijn in evenwicht te brengen steeds groter wordt.
- Op de elektriciteitsspotmarkt is het gebruik van algoritmen bij de handel wijdverbreid, terwijl op de spotmarkt voor gas het gebruik van algoritmen iets minder frequent is, maar ook blijft toenemen.
- Door marktpartijen genoemde motieven voor het gebruik van algoritmen zijn efficiëntie, asset-optimalisatie en risicobeperking. Redenen om af te zien van algoritmen zijn IT- en kennisvereisten, evenals een waargenomen gebrek aan noodzaak of gebrek aan interesse. Op bepaalde markten wordt handelen zonder algoritmen steeds moeilijker, vanwege enkele nadelen die verband houden met de lagere snelheid van handmatig handelen.

Positieve resultaten en risico's kunnen in verband worden gebracht met algoritmische handel; als toezichthouder blijft de ACM alert.

- Mogelijke marktresultaten die voortvloeien uit algoritmische handel zijn onder meer verhoogde liquiditeit en verfijnde, versnelde prijsvorming. Aan de andere kant bestaat er ook een risico dat er een kloof ontstaat tussen fundamentele marktinformatie en door algoritmen gestuurd handelsgedrag.
- Algoritmische handel kan de volatiliteit vergroten via feedbackloops en snelle reacties op marktsignalen, waardoor bestaande marktbewegingen kunnen worden versterkt. Sommigen beweren echter dat dit de volatiliteitsdynamiek niet fundamenteel verandert. Goed geprogrammeerde algoritmen omvatten veiligheidsmaatregelen om buitensporige volatiliteit te voorkomen en kunnen zelfs dienen als een nuttig hulpmiddel in zeer volatiele markten.
- De transparantie van de markt kan worden beïnvloed door frequente prijsbewegingen, wat de prijsbepaling bemoeilijkt, vooral voor handmatige handelaren. Hoewel algoritmen ook de transparantie kunnen vergroten door handelsbeslissingen te documenteren, kan hun

complexiteit – vooral op het gebied van *machine learning* – de uitlegbaarheid belemmeren, wat van negatieve invloed is op de transparantie.

- Sommigen marktpartijen suggereren mogelijkheden voor (onbedoelde) manipulatie door middel van algoritmen, waarbij zorgen bestaan over onder meer de algoritmische gevoeligheid voor gemanipuleerde gegevensinvoer en de snelheid waarmee manipulatieve acties kunnen plaatsvinden. Anderen zijn echter van mening dat algoritmische handel de kwetsbaarheid voor manipulatie kan verminderen door liquiditeit toe te voegen aan de markt.
- De complexiteit en hoge frequentie van handelsorders bij algoritmische handel veranderen de aanpak bij het identificeren van verdachte handelspatronen vanuit een toezichtperspectief, wat een grondige en data-intensieve aanpak vereist.

Compliance en interne *checks and balances* zijn essentieel bij het gebruik van algoritmische handel. Dergelijke maatregelen zijn in de sector van kracht, hoewel in dit onderzoek niet is beoordeeld in hoeverre deze toereikend zijn.

- Alle geïnterviewde en geënquêteerde marktdeelnemers beschikken over compliance- en risicomaatregelen met betrekking tot hun algoritme(n), zij het in verschillende mate. Het gaat hierbij om een verscheidenheid aan maatregelen, zoals het beperken van de prijs en het volume van orders binnen bepaalde marges, en een kill-functionaliteit waarmee de handelaar alle algoritmehandel in één keer kan stopzetten wanneer dat nodig is.
- Omdat dit onderzoek een verkennend karakter heeft, heeft de ACM de implementatie van de compliance- en risicomaatregelen en de mate waarin ze toereikend zijn niet beoordeeld vanuit toezichtperspectief, omdat dit buiten de reikwijdte van het onderzoek valt.
- Risico's op ongewenst gedrag kunnen aanwezig blijven, zelfs als er compliance-maatregelen zijn getroffen. De effectiviteit van toegepaste controles en limieten is bijvoorbeeld afhankelijk van specifieke invoerwaarden. Als de invoerwaarden te hoog of te breed zijn ingesteld, zijn de controles en limieten in de praktijk mogelijk niet beperkend genoeg.
- Handelsplatforms hanteren verschillende voorwaarden voor marktdeelnemers om algoritmen op hun platforms te gebruiken, voornamelijk om de stabiliteit van het handelssysteem en de kwaliteit van de prijsstelling te garanderen.

De ACM blijft toezicht houden op algoritmische handel en de naleving door marktpartijen van de verplichtingen op basis van de herziene REMIT.

- De REMIT-herziening legt nieuwe verplichtingen op aan marktpartijen op de groothandelsmarkt voor energie in de EU die zich bezighouden met algoritmische handel om de daarmee samenhangende risico's te beperken. Marktdeelnemers die zich bezighouden met algoritmische handel moeten effectieve risicobeheersystemen implementeren, zich houden aan handelsdrempels en -limieten, de bedrijfscontinuïteit waarborgen en regelgevende instanties op de hoogte stellen van hun algoritmische handelsactiviteiten.
- De REMIT-herziening versterkt het toezicht van de ACM op algoritmische handel op de Nederlandse energiemarkt. De ACM blijft toezicht houden op het handelsgedrag van marktpartijen en richt zich daarbij ook op de naleving van de verplichtingen op het gebied van algoritmische handel.
- ACM blijft nauw samenwerken met de AFM en andere toezichthouders.

De opgedane inzichten vergroten de kennis van de ACM over algoritmehandel verder en worden gebruikt in het toekomstige markttoezicht in samenwerking met de AFM. De aanpak van deze verkennende marktstudie was er niet op gericht om vergaande conclusies te trekken over bepaalde vormen van handelsgedrag. We zien meerdere onderwerpen voor verder onderzoek waaronder de ontwikkelingen met betrekking tot gebruik van algoritmes specifiek in de TTF future markten, verdergaande ontwikkelingen met betrekking tot de inzet van zelflerende algoritmes in energiehandel, de detective en analyse van bepaalde vormen van mogelijk verdachte handel waar algoritmes worden gebruikt, en in hoeverre de marktdeelnemers daadwerkelijk de procedures volgen die ze zeggen te hebben als het gaat om prudent gebruik van algoritmes. De ACM en AFM zullen blijven samenwerken in de toekomst: op gebied van kennis uitwisselen, gezamenlijk verder met kennis opbouwen, en door de handen ineen te slaan als het gaat om het monitoren van de markt en de handhaving van de verplichtingen voor marktpartijen waar dit bijdraagt aan integere en transparante groothandelsmarkten voor energie, en daarmee eerlijke energieprijzen voor consumenten en bedrijven.

Abbreviations

ACER	Agency for the Cooperation of Energy Regulators
ACM	Netherlands Authority for Consumers and Markets
AFM	Dutch Authority for the Financial Markets
DSO	Distribution System Operator
EU	European Union
ICE	Intercontinental Exchange
IT	Information Technology
MIFID	Markets in Financial Instruments Directive
MTF	Multilateral Trading Facility
MW	Megawatt
MWh	Megawatt Hour
NRA	National Regulatory Authority
OMP	Organised Market Place
OTC	Over-the-Counter
OTF	Organised Trading Facility
REMIT	Regulation on Wholesale Energy Market Integrity and Transparency
TSO	Transmission System Operator
TTF	The Title Transfer Facility
TWh	TeraWatthour, measure for produced energy

Content

1 Introduction

In today's world, automated digital processes are becoming increasingly integral to our lives. So called algorithms enable the processing of large quantities of data and provide useful insights to users. The examples are numerous: algorithms simplify our daily tasks by saving us time and enabling us to make better informed choices. Yet, each of us is also familiar with publicly known excesses and unwanted outcomes.

Algorithms play a significant role in the world of trading companies and their traders. This trend has been ongoing in the financial world for several decades. Data analysts and programmers are indispensable for many trading firms. But also on a smaller scale, trading robots are for instance increasingly available for smaller traders. Trading in wholesale energy markets is – following the financial world – more and more done with the help of trading algorithms.

Algorithmic trading in energy markets is of great interest for the ACM as an energy regulator for several reasons. To start with, to effectively interpret developments and to be able to act against possible prohibited trading behaviour, it is necessary to have a clear understanding of market developments. The ACM receives an increasing number of indications of possible market abuse involving algorithmic trading. Moreover, the Regulation on Wholesale Energy Market Integrity and Transparency (hereinafter: REMIT)[1] has been reinforced in May 2024, introducing new obligations for trading companies applying algorithmic trading. The ACM keeps active oversight of compliance with these rules among participants in the Dutch energy markets and works closely together with the Authority Financial Markets (AFM).

The ACM carried out an exploratory market study on algorithmic trading in energy markets. The study aims to further build and increase the current knowledge, with the emphasis on gaining insights from the market and its participants. The study investigates several key questions: what are the motives behind algorithm usage? Are there parties that do not currently use algorithms (yet), and what are their observations? What risks do market participants perceive, and how do they deal with them? How do energy companies organise their internal processes around algorithmic trading? And what are the implications to regulators of the energy markets that have the duty to monitor market developments, and to detect and act against market manipulation?

1.1 Research approach and scope

The approach of the market study comprises several elements:

- Interviews. The ACM carried out twelve interviews with a diverse group of relevant stakeholders: energy companies/traders, trading platforms and a technology provider of surveillance services. The selection ensured a diverse representation, encompassing traders mostly active in gas or electricity markets, suppliers to end users, producers, pure traders without physical assets, manual traders, among others. Participation in the interviews was voluntary.

- Survey. Following the interviews, the ACM conducted a voluntary survey among a larger group of traders. The survey recipients were selected based on the trading volume on the spot gas and power markets in the Netherlands. Market participants with less than one trade per day on

[1] Regulation (EU) 2024/1106 of the European Parliament and of the Council of 11 April 2024 amending Regulations (EU) No 1227/2011 and (EU) 2019/942 as regards improving the Union's protection against market manipulation on the wholesale energy market (Text with EEA relevance) [2024] OJ L, 2024/1106.

average were excluded. The response rate was approximately 20%.[2] While this percentage does not allow for fully substantiated conclusions about the entire trader population, the responses came from a diverse group, providing valuable insights according to the ACM.

- Literature investigation. Furthermore, the ACM conducted a concise literature review of public sources to gather common knowledge on algorithmic trading. To our knowledge, there is limited published research on algorithmic trading in the EU and/or Dutch wholesale energy markets. The literature that is reviewed predominantly comprises algorithmic trading in financial markets, with less focus on algorithmic trading in energy markets specifically. ACM is aware of the specific characteristics of energy wholesale markets compared with the broader financial markets and took these differences into account in interpreting the literature.

The scope of the study focuses on traders in spot markets for energy. Spot markets encompass wholesale energy markets where the energy is delivered on the same day (intraday/within-day market) or the following day (day-ahead market). Additionally, many traders active in spot markets also trade in derivatives markets, such as options and longer-term contracts. Insights gathered from these players regarding other markets than the spot markets were incorporated into the study where relevant, although this was not the primary focus. The rationale for focusing on traders in spot markets lies in the dominant link to physical delivery of traded commodities, potentially bringing different market characteristics and dynamics compared with derivatives trading. Additionally, as an energy regulator, ACM is responsible for the oversight of the integrity and transparency of spot markets. Traditionally, oversight of derivatives traded on exchanges was primarily the domain of the AFM, but following the recent REMIT revision, this oversight is now shared between AFM and ACM.

It is important to acknowledge the heterogeneity of the research population. This diversity underscores the nuanced dynamics of the energy market, wherein different types of market participants may exert varying impacts on the markets.

The ACM conducted the study with the help and expertise of the AFM. The AFM provided valuable insights to the ACM at various stages of the investigation. In the recent past, the AFM has conducted market studies on algorithmic trading in financial markets. The insights from these studies are applied in the present exploratory market study on energy market trading, where applicable. The ACM and AFM will continue working together in this area to further build knowledge. Furthermore, the AFM and ACM will jointly keep a close watch on algorithmic trading activities and on the compliance of trading companies with the current rules.

This publication provides an overview of the findings from the ACM market study on algorithmic trading in energy markets. It begins by explaining how energy markets function in practice (chapter 2). Subsequently, it delves into the specifics of algorithmic trading (chapter 3), and the application of algorithmic trading in the energy sector, and the motivations behind its use (chapter 4). Chapter 5 explores the potential market impacts, followed by an overview in chapter 6 of how market participants ensure control over their algorithms. Finally, chapter 7 outlines the specific rules on algorithmic trading under the revised REMIT and its implications for market participants using algorithmic trading, as well as for national regulatory authorities.

[2] The respondents that are active in gas, trade on average less in terms of total volume and number of transactions compared to the population (i.e., the group to which the survey was sent). For power, the respondents trade on average more in terms of total volume and number of transactions compared to the population.

2 Background on energy market trading

For a broader audience of interested readers, beyond market insiders, it is necessary to understand the general mechanisms of trading in energy markets to comprehend the developments in algorithmic trading. There are several links in the chain of energy supply concerning natural gas and electricity between the moment of production / generation / extraction on the one end, and consumption on the other end. This market study focuses on the wholesale energy markets. It is on these wholesale energy market where, among others, suppliers to end-users buy their electricity and gas, and producers sell their generated volumes. But there are many other types of traders active. And besides this ‘trading chain’, there is a chain of physical transport and distribution.

There are many different types of companies active in trading in energy wholesale markets, each with their own individual interests and strategies. Examples of these companies are electricity producers (both conventional and renewable), natural-gas producers, suppliers to end consumers, large users, storage operators, other types of intermediaries / aggregators between supply and demand, commodity traders, proprietary trading companies, investment firms, hedge funds, etc. Each of these entities has its own trading strategy based on its own interests in the market, such as (expected) demand of their customers, expected production (increasingly influenced by the weather), geopolitical developments, broader (national, European, worldwide) economic developments and outlook, etc. In many cases trading in various energy products and its derivatives is a way to hedge its positions and interests, while at the same time for many companies trading in energy markets is also a speculative activity. Algorithmic trading, if used, is a method of trading within the overall trading strategy of a company.

It is important that the supply is in constant balance with the demand on the wholesale markets for physical delivery of gas and electricity. For electricity this necessity is even more prominent than for natural gas, where there is some more leeway, but here too, there is a limited bandwidth for imbalance due to physical constraints. The reason for this is the interaction with the underlying physical network of gas transport (operated by Gasunie Transport Services) and electricity transmission (operated by TenneT). These Transmission System Operators (TSOs) are responsible for the prudent functioning of the physical network, and enable market participants to constantly balance their position via a mechanism based on market principles. For example: electricity producers must constantly make sure the volume of generated electricity (mostly indicated in MWh[3]) is bought by a supplier to consumers, or a different re-seller.

Both natural gas and electricity have their own market-based mechanisms for active market participants to balance their positions. For the gas market, it is possible to trade in within-day products and next hour products. Within-day products are for delivery of natural gas during the rest of the day respectively the whole next day, while next hour products concern delivery during the following hour. At the end of the day, market participants must balance their own physical positions to ensure the balance in the entire gas network is within certain safe limits. It is more work to balance the electricity network, and there are more trading products in order to do so. During the whole day, it is possible to trade in quarterly and (half) hourly products, entailing products for delivery of electricity during the agreed 15 minutes, or (half) hour. There are also day-ahead products where physical delivery for the next day is concerned.

Time horizons and locational delivery are important aspects of trading in wholesale energy markets. It is possible to trade in volumes of electricity and natural gas with many different longer timeframes for delivery, such as weekend(s), week(s), month(s), quarter(s), season(s) and year(s) ahead. The locational aspect is relevant as well, when speaking of the Dutch wholesale energy markets, we mean trading in electricity and/or natural gas products for delivery in or from the Netherlands.

[3] The abbreviation MWh denotes megawatt-hour.

Besides, various different derivatives are traded, such as options (where the buyer acquires the right to buy/sell a certain volume for an agreed price at a specific date) and spreads (such as locational spreads, where a trader offers to buy a volume in one delivery area, and sell an equal amount in another area, if the price difference meets a certain threshold).[4] Wholesale energy markets are commodity markets where the traded (underlying) product itself is largely homogeneous.

In practice, trading takes place either via an exchange platform, via a broker platform or bilaterally between the trading parties themselves. Several exchanges exist where energy products are traded. Traders are able to place orders anonymously on the ‘screen’ where other traders might be interested in, or to enter into a transaction with an already outstanding order. Orders are typically automatically matched by the exchange, resulting in trades. For each of the trading parties, the clearing bank of the exchange is their counterparty. Most of the spot market trading occurs via exchanges. A brokerage firm is an intermediary that tries to match outstanding / potential orders by their clients, based on its knowledge about their interests. There are about ten to twenty brokers that intermediate into energy market products for delivery in the Netherlands.[5] There are several ways broker transactions might take place, either digitally inserted in the used trading portal or by telephone / e-mail contact and confirmation. Lastly, trading may take place bilaterally between the trading parties themselves. They can agree on specific requirements, only relevant for them, other than the standard contracts that are traded on exchanges. Bilateral and broker trading account in general for larger volumes per trade.

Market participants and trading venues both have requirements they need to fulfil. In order to comply with REMIT, market participants are obliged to register with the competent regulators when first starting trading. In this respect, all energy market participants active in one or more EU member states, need to have a REMIT-registration in an EU member state: either in the member state where the company is located, or in case of non-EU market participants, in the member state where most of its trading takes place. This obligation is also true for market participants that are no member of an exchange themselves, but trade via Direct Market Access provided by another market participant, who facilitates access to the trading platform. Furthermore, market participants need to fulfil all necessary requirements and be in possession of relevant licences, such as those of the TSO and the trading venues. Obviously, market participants need to follow the rules for transparency and integrity of trading and do not engage in market abuse (or in attempts thereof). The trading venues have the obligation to detect, and report possible suspicious trading behaviour to the relevant authorities such as the energy regulators and the financial regulators.

[4] Derivatives are financial instruments whose value is derived from the performance of an underlying asset, such as commodities, currency exchange rates, interest rates etc.
[5] Please see the REMIT PORTAL (acer-remit.eu) for a complete list of the registered organised market places.

3 What is algorithmic trading?

Key points:

- Algorithmic trading is a process where a computer algorithm determines trading parameters such as price, quantity and whether to initiate an order with limited or no human intervention. In many cases the trader only monitors the performance of the algorithm.
- There are different types of algorithms: execution algorithms, trading algorithms and signal generators. These all might vary in complexity, from simple rule-based algorithms to advanced machine-learning techniques.
- Trading with the help of algorithms is usually part of a broader trading strategy, which might also encompass (simultaneous) manual trading. Various strategies are employed with algorithmic trading, for instance, spreading volume over time or markets in order to reduce price impact, spread trading, market making and relative pricing in the orderbook.

3.1 Definition of algorithmic trading

According to the recently revised REMIT (REMIT II) 'algorithmic trading' means:

i. trading, including high-frequency trading, in wholesale energy products
ii. where a computer algorithm automatically determines
    a. individual parameters of orders to trade such as whether to initiate the order, the timing, price or quantity of the order; or
    b. how to manage the order after its submission,
iii. with limited human intervention or no such intervention at all,
iv. not including any system that is only used
    a. for the purpose of routing orders to one or more organised marketplaces; or
    b. for the processing of orders involving no determination of any trading parameters; or
    c. for the confirmation of orders or the post-trade processing of executed transactions.[6]

This definition is almost identical to the one which has been in use in regulation for the financial sector since 2014.

3.2 Different types of algorithms

The below section gives an overview of the different types of algorithms that are relevant in wholesale energy market trading. This information is mostly based on interviews with stakeholders and the survey ACM carried out among market participants.

This distinction is made by ACM for the purpose of this study alone. This conceptual description of the different algorithm types is based on the types of trading methods the interviewed and surveyed market participants use in practice. The current publication does not further define which types of algorithms are in scope for the legal definition of algorithmic trading in the context of the revised REMIT. Any further guidance on the scope is coordinated by ACER.

[6] Regulation (EU) 2024/1106 of the European Parliament and of the Council of 11 April 2024 amending Regulations (EU) No 1227/2011 and (EU) 2019/942 as regards improving the Union's protection against market manipulation on the wholesale energy market (Text with EEA relevance) [2024] OJ L, 2024/1106, article 2(g)(18).

3.2.1 Three main types of algorithms

Generally, there are three types of algorithms in the context of energy trading:

- **Execution algorithms:** Execution algorithms are used to execute a trading decision made outside the algorithm. Parameters of execution algorithms are set outside the algorithm, after which the algorithm places orders on the trading platform in an optimal way through a specified method, usually within certain price and volume limits.
- **Signal generators:** Signal generators are algorithms that – based on a set of inputs – signals trading opportunities or other supporting information for trading decisions to traders or execution algorithms.
- **Trading algorithms:** Trading algorithms differ from execution algorithms in one important respect: the algorithm additionally decides whether an order should be submitted on the trading platform or not. That is the case when signal generators are directly linked to execution algorithms.

The different types of algorithms use varying inputs. Execution algorithms use a list of parameters to execute the order in a predefined way. In addition to the price and volume information of the order, this can include a number of controls and limits such as maximum and minimum price (price limit) and volume (volume limit); chapter 6 contains more information on controls and limits. Execution algorithms also make use of historical trading patterns in determining for example where to position the order in the orderbook, which can be based on technical analysis such as the historical maximum volatility in a five-minute period. Depending on the level of complexity, trading algorithms, and signal generators can use hundreds of parameters as input. These can be based on fundamental data such as weather data or data provided by TSOs or market participants. Technical data includes, for example, historical and current prices and price volatility in different time frames.

The output varies between different types of algorithms. The output generated by both an execution and trading algorithm is an order sent to the trading platform. Signal generators provide a prediction and/or advice to a manual trader or another algorithm. A prediction can include, for example, the expected price, supply, demand, volatility or portfolio. An advice can be a particular preferred strategy accompanied by a probability a particular strategy is justified based on certain market conditions and/or predictions.

3.2.2 Varying complexity: from simple rule-based algorithms to machine learning

The algorithms vary in complexity. Each type of algorithm (execution, trading or signal generators) could be programmed relatively simple or more advanced. A relatively simple algorithm is rule-based; the algorithm consists of predefined rules. For example, an execution algorithm following the rule 'place an ask (order) with a specified volume (X MWh) if the market price is at maximum Y euros per MWh'. A next step is when the algorithm itself determines what the algorithm parameter values should be in the given example. Then only the structure of the rule is specified in advance and the algorithm updates the parameters in the rule as new information becomes available.

There are even more complicated self-learning algorithms that determine the structure of the rule themselves. They must discover the relationship between the variables in the input dataset themselves and determine which variables are relevant to include in a trading decision and how much weight a variable should receive. Such machine-learning algorithms are usually trained with historical data and so they can learn, for example, how much profit a choice yields in a certain situation (state of the order book, for example) and thereby finds the best choice in the future. The algorithm itself learns when it is best to initiate a trade and with what properties (price, volume, etc.).

Type of algorithm	Design of algorithm	Market analysis	Trading strategy	Placing order in the order book
Signal generator	Trader/analyst designs the algorithm such that it signals trading opportunities based on the market conditions	Algorithm analyses market data and signals trading opportunities	Trader chooses strategy and which order(s) to place	Trader places the order
Execution algorithm	Trader/analyst designs algorithm(s) for execution optimisation	Trader analyses the market	Trader chooses strategy, which order(s) to place and input parameters of the algorithm	Algorithm places the order optimally given chosen strategy
Trading algorithm	Trader/analyst designs the algorithm such that it can decide whether and which order should be placed (based on market conditions) and how	Algorithm analyses market data and signals trading opportunities	Algorithm chooses trading strategy and which order(s) to place	Algorithm places the order optimally given chosen strategy

Trader monitors algorithm

Figure 1: A schematic overview of the different types of algorithms

3.2.3 The use of the different types of algorithms in gas and power spot markets

The results of the survey indicate that, in the natural-gas market execution, algorithms are more frequently used than signal generators and trading algorithms, while, in the power market, all types of algorithms are used to the same extent. The survey results on the use of different types of algorithms on the gas and power markets are shown in Figure 2. As described earlier, the surveyed market participants are selected because they are at least active in the spot market, although their answers might also include their activity in forward / future markets. Out of a total of 8 respondents that use and/or develop algorithms for gas trading, 6 respondents report the use of execution algorithms, and 3 respondents report the use of signal generators and trading algorithms. In the power market, execution algorithms, signal generators and trading algorithms are applied to approximately the same extent (approximately 9 out of 12 respondents that use and/or develop algorithms for power trading). A number of respondents uses algorithms based on machine learning techniques. Figure 2 shows that for both gas and power markets, machine learning is mainly used or developed for generating trading signals. Unlike the natural gas-market, machine learning is also applied to trading algorithms on the power market.

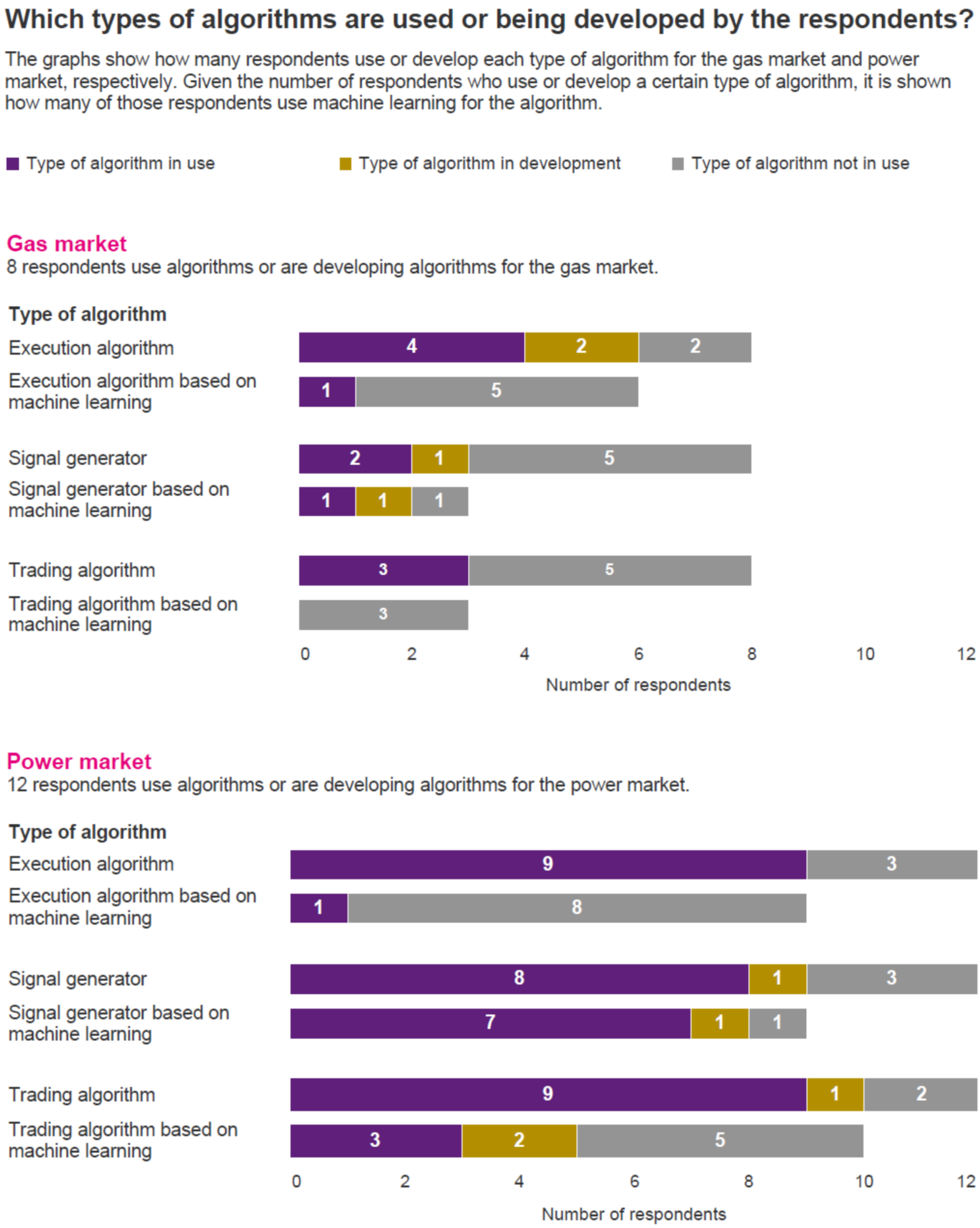


Figure 2: Survey results on the type of algorithms used on the gas and power markets

3.3 Strategies behind algorithmic trading

Trading via algorithms generally is a part of a broader overall trading strategy of the market participant. Market participants use the trading strategies and methods they believe that are necessary for achieving their goals: trading manually, algorithmic or both simultaneously. For example, the algorithm trades based on a market making principle, while at the same time a trader trades manually to balance the physical portfolio. Different trading methods – trading with (multiple) algorithms and manually – can also be applied simultaneously based on the same strategy: more advanced machine learning models in addition to automatic trading (or semi-automatic) algorithms and manual trading. Furthermore, it is common for a trading company to employ multiple algorithms simultaneously, each potentially pursuing different strategies.

Algorithms are used to deploy several strategies. These strategies are not exclusively used in algorithmic trading but can also be implemented in manual trading. However, employing these strategies with algorithmic trading can potentially offer the user certain advantages. Some of the most frequently mentioned strategies are described below in more detail:

1. **Spreading the order volume over the trading session**
This is a way of trading where the algorithm can minimise the price impact of its trading by spreading the needed volume over time and/or across markets. Trading large volumes in smaller batches and spreading them over time prevents too large a portion of the order book from being traded at any one time. This should prevent the matching of multiple price levels in the order book and thereby minimising the deviation from perceived fair value. There are various ways how to do that. For example, the algorithm may take into account trading volume patterns in the recent past and adjusts the volume brought to the market accordingly. The algorithm then trades more volume when there is more trading activity on the market. The aim of this strategy is, for example, to achieve a price similar volume weighted market price over a certain period. Another strategy of algorithms is to distribute the desired volume in smaller batches linearly over a predetermined period. This helps to reduce exposure to price fluctuations that can occur as a result of trading large volumes at once. Multiple interviewed market participants ensure that their traded volumes do not exceed a certain percentage of the total trade on the market. This prevents having too much of an impact on the market.

2. **Spread trading**
Spread trading is a trading strategy in which a trader attempts to profit from the difference between the prices for: 1) different products, for example the difference between the revenue of electricity sold and the costs of buying gas and emissions allowances (clean spark spread); 2) markets, for example the difference between TTF and Zeebrugge; and/or 3) time frames, for example the difference between summer and winter gas prices. According to an interviewed trading platform, this type of arbitrage is the most often used strategy. Multiple interviewed market participants employ this strategy using algorithms. For this, the trader inserts the parameters such as the desired volume and the price spread between the contracts to be traded. The algorithm executes the trade once the given price spread is reached and can thus take advantage of price differences between markets. Examples of spread trading are: 1) transformation of the product (for example gas to electricity); 2) transformation of location (buying gas in one country and selling in another country); 3) transformation over time (via the use of, for example, gas storage); and 4) transformation of trading platform (intervenue arbitrage). An example is buying natural gas day-ahead at a discount compared with the front month price, stored in gas storage and then sold on the TTF front month.

3. **Market making**
Market making is a strategy that basically comes down to trying to be present in the market on both sides of the orderbook during the whole trading day or a large part thereof. This is done with the intention to have no remaining physical position in the end, i.e., to have equal volumes sold and bought. There are roughly two strategies when employing market making: either strive for a larger bid-ask spread, which generally leads to lower transaction volumes; or a smaller bid-ask spread, which usually leads to higher transaction volumes.[7] When choosing between them, the trader maximises total profit by seeking the balance between profitability per unit volume and transaction

[7] The bid-ask spread represents the difference between the maximum price a buyer is willing to offer (the bid price) and the minimum price a seller is willing to accept (the ask price).

volume while managing any open position. Overall, the intention is to sell at a higher price than purchase price for the same volume. Trading platforms might also provide financial incentives for trading companies to be frequently present on both sides of the order book.

Market making is an example of a strategy where the algorithm places an order at a certain position relative to all orders in the orderbook. For example, the algorithm might have the aim to have the best price on the screen on both buy and sell side of the order book. The risk is that the party only finds a match with a counterparty on one side of the order book and concludes transactions. When no opposing transaction follows, the market participant remains with an open position. To manage this risk, parameters can be given to the algorithm. Algorithms managing relative order placement in the order book are also used in other strategies, for example in spread trading.

4 Algorithmic trading in Dutch energy markets in practice

Key points:

- The use of algorithms in energy market trading is growing and it is expected to increase further. There is an increasing number of pure algorithmic trading market participants.
- A key driver behind expected further growth of algorithmic trading is the energy transition, as the necessity to balance positions at short notice keeps increasing, because it is more difficult to predict renewable energy production.
- In the power spot market, algorithm use in trading is widespread, while in the gas spot market, algorithm use is somewhat less frequent, yet it keeps increasing.
- Motives for the use of algorithms mentioned by market participants are efficiency, asset optimisation and risk mitigation. Reasons for abstaining from using algorithms are IT and knowledge requirements, as well as a perceived lack of necessity or interest. In certain markets, trading without algorithms is becoming increasingly difficult, due to some disadvantages related to the slower speed of manual trading.

4.1 The use of different types of algorithms in Dutch energy markets

4.1.1 Overall developments on the use of algorithms in Dutch energy markets

The interviewed trading platforms and market participants observe an increased use of algorithms. The possibilities that algorithmic trading technologies offer, are embraced by all kinds of energy market participants, varying from producers and suppliers to proprietary traders. The types of simple or advanced algorithms they use, and the intensity thereof, depends on their trading strategies. Some interviewed parties observe a distinction in the extent of algorithm use on the wholesale energy market between market participants with and without a physical portfolio. It is argued that, at least traditionally, proprietary traders without a physical portfolio use advanced algorithmic trading for strategies such as market making and spread trading. However, the results of the survey and interviews reveal that all sorts of companies use algorithms.

The interviews indicate that the number of pure algorithmic traders, including market-makers and arbitrage traders, is growing. This group includes companies from various sectors, such as financial markets or quantitative-data analysts, attracted by the fundamental data of the energy market. One interviewed trading platform depicted that the presence of non-asset players has increased significantly, with currently around 50% of trading volume on the power intraday market, combined with the day-ahead auction market, that share is around 30%. This causes traditional market participants with physical assets to realise that they need to embrace these technologically advanced strategies to remain competitive.

Several interviewed market participants expect a further increase in the use of algorithms in the future. The growing availability of good 'off-the-shelf' algorithms makes it easier for market participants to use them without having to set up a complete in-house development team, is one of the arguments given in an interview. The survey results show that currently the majority of market participants develop the algorithms themselves (8 out of 15 in total). A smaller group (6 out of 15 in total) uses both in-house developed algorithms and purchased algorithms. One market participant only uses algorithm(s) purchased from a third party.

The energy transition is mentioned by several interviewed parties as one of the key drivers behind the current need and further expected growth of algorithm use in the energy markets. The increasing importance of renewable energy sources often requires actions and adjustments closer to delivery, with algorithms playing a crucial role for market participants that have an extensive portfolio of renewables. Even with weather forecasts from multiple providers, it remains difficult to make accurate predictions – especially longer ahead – given the unpredictable nature of weather conditions, as even a small cloud can have a significant effect on solar energy production. This makes it difficult to accurately predict trading volumes, which therefore requires constant adjustment based on changing weather predictions. It would cost too much manpower if all trading decisions in, for example, quarterly power products were carried out by people. In this context, one interviewed trading platform also mentioned that the increase in renewable energy sources comes with more data available, and algorithmic trading is attracted by data availability.

Algorithmic trading and the energy transition

The amount of power produced must always match the amount of power consumed.

Figure 3: Decorative image on the balance between power produced and power consumed

Power is increasingly generated by renewable energy sources.

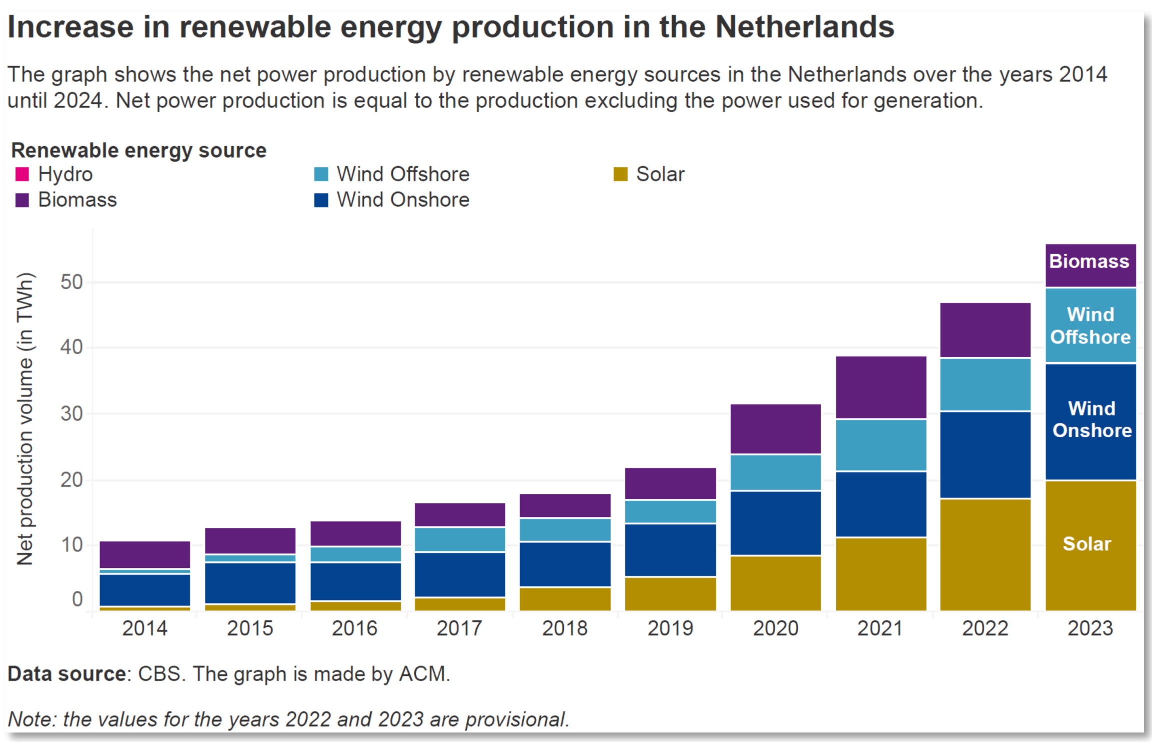


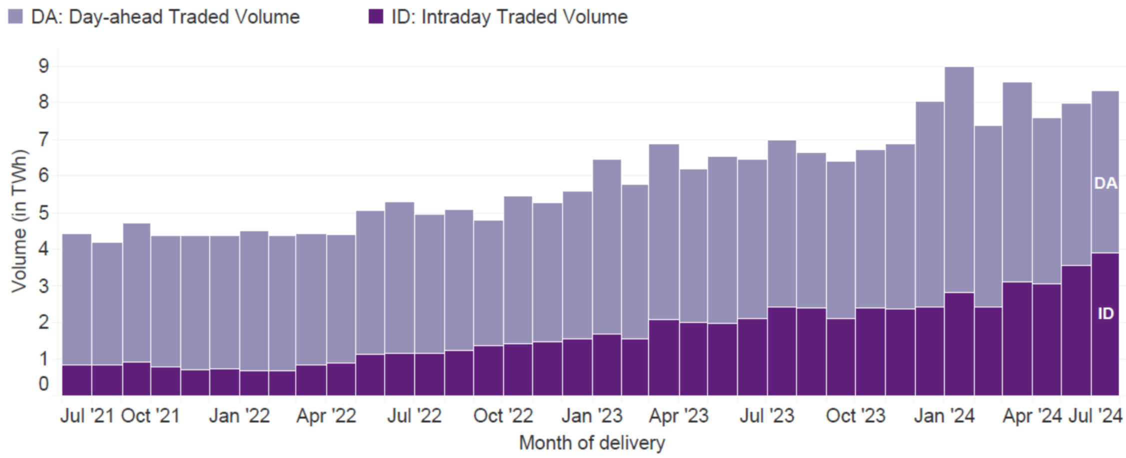
Figure 4: Graph on the increase in renewable energy production in the Netherlands[8]

As a growing share of electricity production in the Netherlands is generated from wind turbines and solar panels, more last-minute trading on spot markets is required to balance trading positions based on changing weather forecasts.

[8] CBS had no involvement in making the graph and does not necessarily endorse its content.

Increase in power spot trading in the Netherlands

The graph shows the traded volume on the day-ahead market and the intraday market per month of delivery over the period from July 2021 until July 2024. The graph includes trades of power bought or sold in the Netherlands as reported by the data sources; trades on other trading platforms like ETPA are not included.



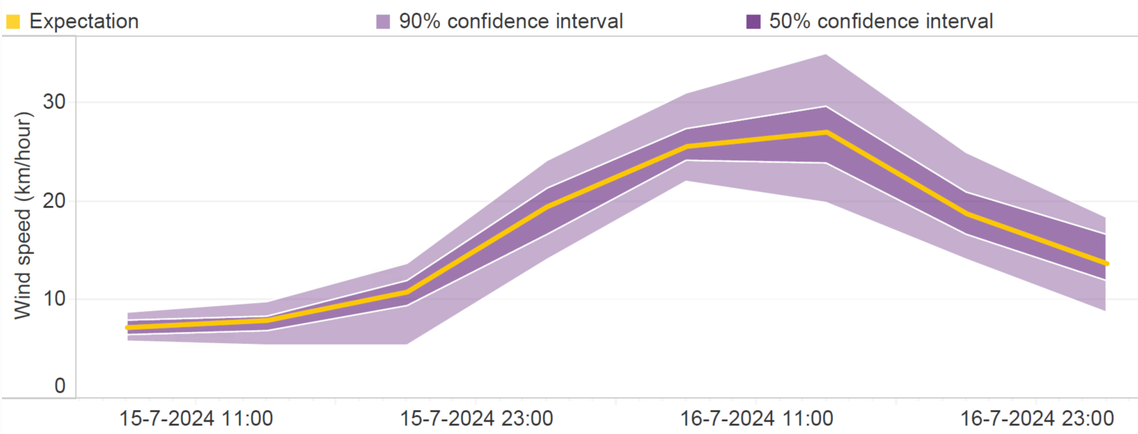
Data sources
- EPEX SPOT (day ahead auction, intraday auctions, intraday continuous trade)
- Nord Pool (day ahead auction, intraday continuous trade)
- ICIS (information service reporting on day ahead over-the-counter trade)
- EEX (day ahead continuous trade)

Figure 5: Graph on the increase in power sport trading in the Netherlands

Weather forecasts become increasingly accurate closer to the delivery time. There is a lot of data available on weather forecasts. Algorithms can translate each new data update into trading actions, such as adjusting trading positions and buying or selling required quantities multiple times a day. This trading encompasses a wide range of products, such as hourly products, half-hourly products, and quarter-hourly products. An algorithm can efficiently manage this multitude of diverse data compared to a trader who would need to continuously trade each product separately.

Weather predictions come inherently with a margin of uncertainty

The graph shows the expected wind speed at 00:00h on 15 July 2024, for the coming two days. The purple area indicates the uncertainty margin around the expectation in yellow. Wind speed is relevant for the power production by wind turbines.



Data source: KNMI. The graph is made by ACM.

Figure 6: Graph on prediction for wind speed[9]

[9] KNMI had no involvement in making the graph and does not necessarily endorse its content.

4.1.2 The use of algorithms per type of market: spot, OTC and financial trading

Algorithms are widely used on the power spot market, as indicated by the survey results and supported by the insights from the interviews. Figure 3 shows how many market participants in the survey are active on each market, how much they trade on average on that market and whether they use or develop algorithms for this (note: the scale of the axes for the average traded volume for gas and power are different). Furthermore, it is visible that not a single respondent uses algorithms on the over-the-counter (OTC) market (physical or financial). Although market participants trade less volume on average on the power market (in terms of TWh), algorithms are used there relatively more often than in the gas spot market. These observations are similar to the overall impression by the interviews that are carried out among a diverse group of energy market participants and trading platforms.

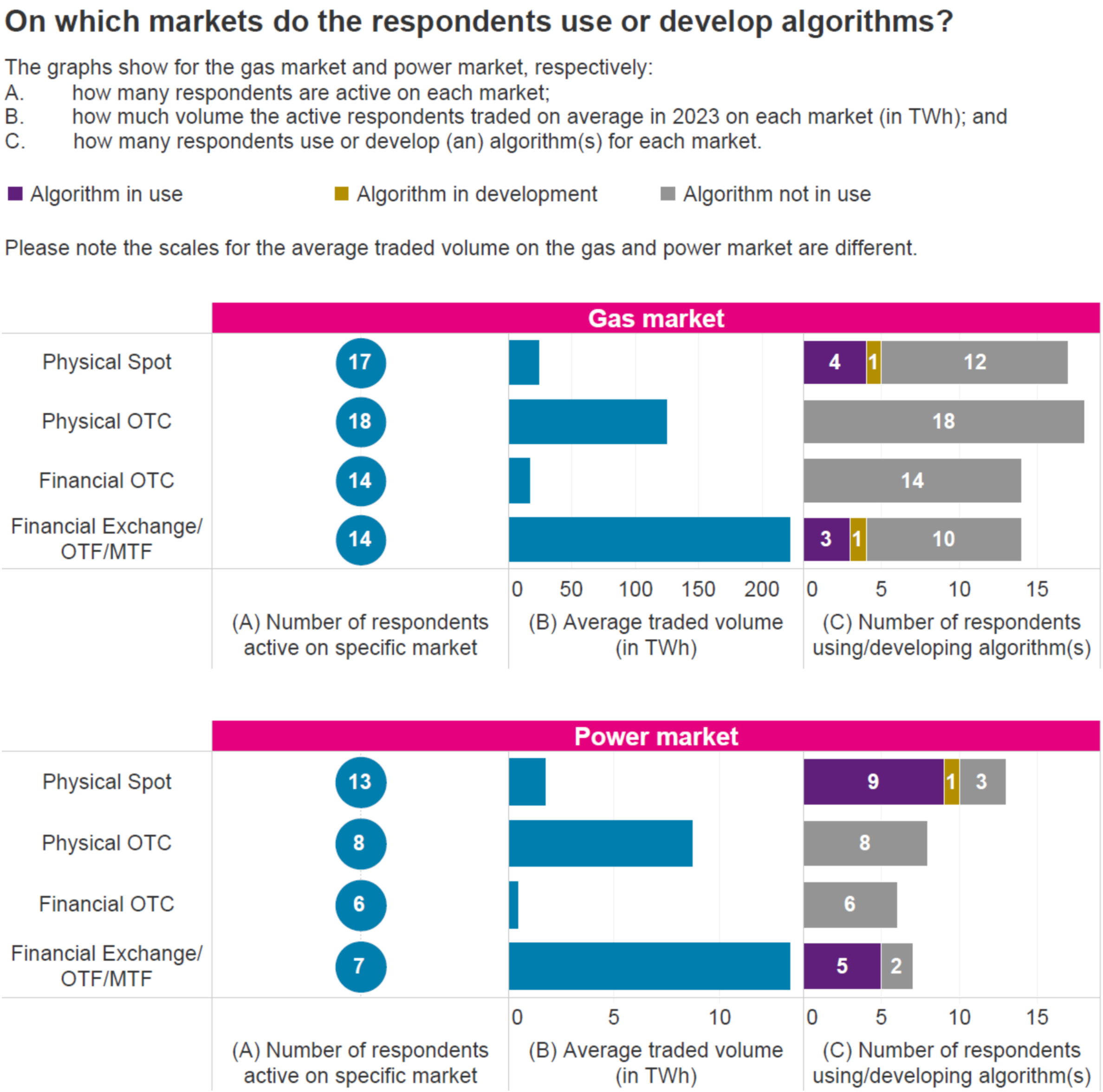


Figure 7: Survey results on algorithm use on different markets for gas and power

The interviewed parties also observe a shift towards automation in the gas spot markets. It has been mentioned that algorithms are now more frequently used in gas spot markets compared to a few years ago. The competition arising from the growing number of traders employing algorithms induces others to develop their own algorithms in order to be able to keep up with market dynamics. The use of algorithms is strongly related to the degree of liquidity on the market. The observation that algorithms on the power intraday markets are more prominent than on the gas spot markets, might for a part be explained because short-term gas trading, such as within-day and day-ahead, generally includes only a limited number of product per country, making it more manageable for traders, while power intraday includes many products: hourly products, half-hourly products and quarter-hourly products. Moreover, the gas market is less volatile, which means traders have more time to respond to developments and therefore have less need for algorithms.

Although more algorithms are observed on the gas spot market over the years, algorithm use is not as significant as in the gas month ahead product. Gas trading on the TTF Front Month in particular is dominated by algorithms. One interviewed market participant has the impression that hedge funds trade on the TTF front month without physical assets only to hedge 'exposure' or to trade speculatively. On the gas spot market, traders are mainly concerned with managing their physical needs.

Algorithms are mainly used in liquid markets to arbitrage the spread. One market participant notes that the more liquid the product is, the more often the price changes. This phenomenon is less pronounced in products further along the curve, such as winter products two years ahead where less trade takes place. In illiquid markets, further along the curve, such as calendar products two or three years ahead (cal ’26 or cal ’27), manual trading can still take place.

4.2 Reasons behind using or not using algorithms

Automation and efficiency are the most frequently mentioned cited reasons for algorithm use among the surveyed market participants and is also mentioned by several interviewed market participants. It is explained that automation enables tasks to be executed faster and more consistently than is possible manually, thereby enhancing efficiency and allowing trading activities to proceed uninterrupted. For instance, trading in power intraday products encompasses a relatively large number per delivery day (i.e., 168 products in total for the Netherlands: 24 hour products, 48 half-hour products and 96 quarter-hour products per delivery day). In that context, it is noted that the use of algorithms reduces the workload of shift traders/dispatchers. According to some interviews, in certain energy markets, manual trading is becoming increasingly challenging, if not impossible.

Other reasons mentioned for using algorithms, both in the survey and during interviews, include asset optimisation, forecasting and risk management. For instance, several interviewed parties indicate that algorithms are better capable of handling large volume orders by dividing them in smaller batches, thereby mitigating the risk of causing a price impact on the market. In addition, it is noted that algorithms are capable of processing lots of data (updates). Speed advantage and profitability are also mentioned as reasons for employing algorithms.

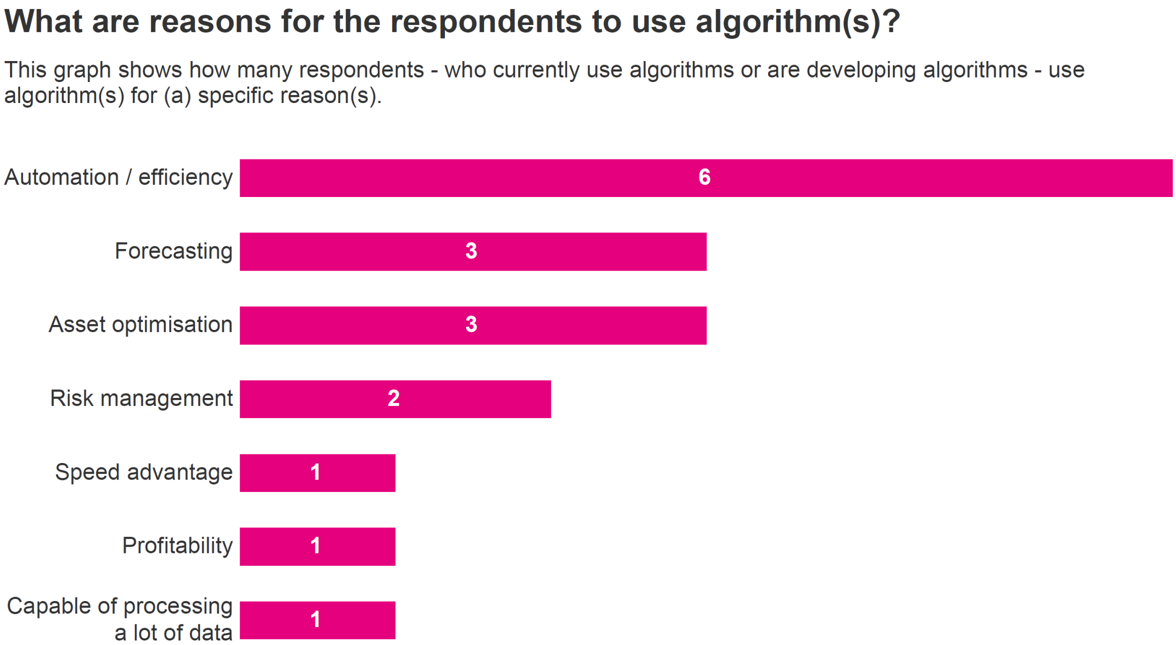


Figure 8: Survey results on reasons for algorithm use

Considerations for not using algorithms include the costs to invest in knowledge building, expertise and IT or a lack of interest. One interviewed market participant thinks algorithms are less suitable for commodities markets and currently offer little added value for physical traders; this opposed to equity markets, where algorithms are perceived more common.

5 Impact of algorithmic trading on wholesale energy markets

Key points:

- Possible market outcomes resulting from algorithmic trading include increased liquidity and refined, accelerated price formation. On the downside, there is also a recognised risk of a disconnect emerging between fundamental market information and algorithm-driven trading behaviour.
- Algorithmic trading may increase volatility through vicious cycles and rapid response to market signals, which can amplify existing market movements. However, some argue that it does not fundamentally change volatility dynamics. Well-programmed algorithms incorporate safety measures to prevent excessive volatility and can even serve as a useful tool in highly volatile markets.
- Market transparency can be affected due to frequent price movements, complicating price determination, especially for manual traders. While algorithms also might enhance transparency by documenting trading decisions, their complexity - especially in machine learning - may hinder explainability, impacting transparency.
- Some suggest possibilities of (unintended) manipulation through algorithms, with concerns including algorithmic sensitivity to manipulated data input and the speed at which manipulative actions can occur. Others, however, view that algorithmic trading can reduce vulnerability to manipulation by adding liquidity.
- The complexity and high frequency of trading orders in algorithmic trading changes the approach in identifying suspicious trading patterns from a monitoring perspective, requiring a thorough and data-intensive approach.

5.1 Impact of increasing algorithmic trading activity on market outcomes

When considering the market impact of algorithms, a distinction is commonly drawn in literature between periods of 'normal' market functioning and those characterised by heightened volatility. In the financial markets it is suggested that algorithms offer benefits, such as enhanced liquidity, during normal market conditions.[10] However, during periods of heightened volatility, while there may be some advantages, algorithms also pose significant risks and may cause illiquidity.[11] The findings from the survey and the interviews substantiate this perspective, with respondents emphasising the positive effects, but also acknowledging nuances.

The survey reveals that market participants predominantly view algorithms as positively impacting the energy markets. The majority agrees on algorithms facilitating increased liquidity (17 out of 19 respondents) and efficient price discovery (13 out of 19 respondents). They expect narrower price spreads, increasing market efficiency, competition, and transparency in price discovery. However, some foresee negative effects, such as increased volatility (7/19), higher risk of (unintended) market manipulation (6/19), and amplification of price movements (4/19). While acknowledging potential negative effects, one respondent does not consider them to be the primary outcome of algorithms. Conversely, another notes adverse effects of the high speed of algorithmic trading, namely market disruption and extreme price movements. Additionally, it is noted that the liquidity or depth of the order book may be smaller than initially perceived, as algorithms withdraw orders when only a portion of the order is executed, posing challenges when wanting to trade volumes larger than a minimum clip size.

[10] Martins Pereira (2020), Regulating algorithmic trading in the new capital markets: a critical analysis of the European Union regime, sections 3.2.2.1 and 3.2.2.2 and the references.
[11] OECD (2021), Artificial Intelligence, Machine Learning and Big Data in Finance, p. 8.

Do the respondents expect effects of algorithms on the functioning of energy markets?

The graph shows how many respondents do expect algorithms to have the certain effect (yes) and how many do not expect the effect (no).

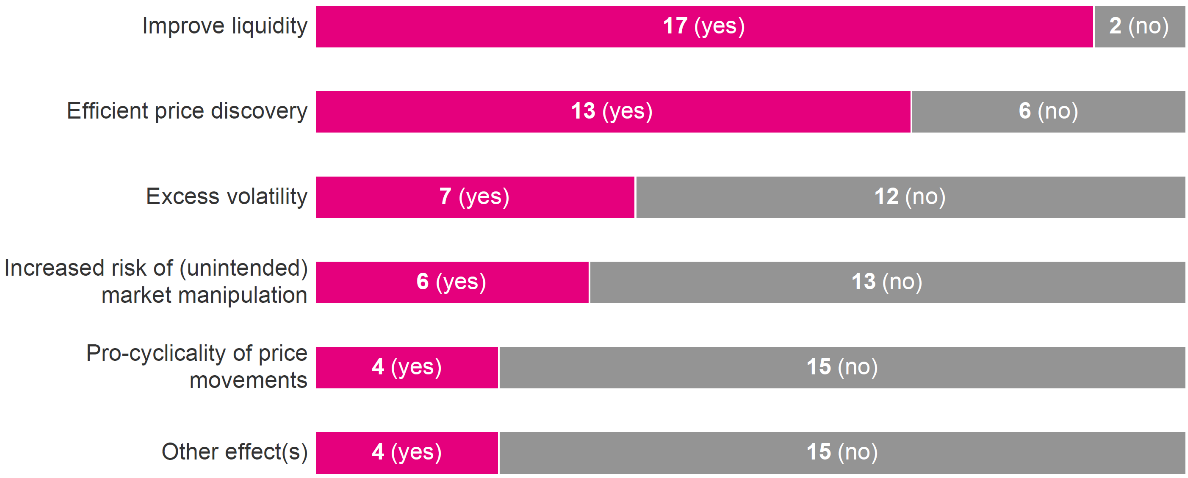


Figure 9: Survey results on the expected effects of algorithms on the functioning of energy markets

5.1.1 Price formation and liquidity

According to the literature, algorithms can play a significant role in shaping the dynamics of price formation.[12] Their rapid processing of new information exceeds human capabilities in data processing, thereby accelerating price formation.[13] Furthermore, the efficiency generated by algorithms reduces trading costs compared with manual trading and their immunity to emotions and biases results in fewer errors (excluding coding errors).[14] This fast data processing provides a comprehensive market overview, refines prices, narrows bid-ask spreads and enhances liquidity.[15] The liquidity is further improved by market-making activities, particularly in the electricity market, fostering increased market entry, competition, and a level-playing field among vertically integrated companies and independent companies.[16]

The interviews as well as the survey results confirm a notable liquidity surge in energy markets together with the increase of algorithmic trading. The interviewed trading platforms noted that the liquidity increase is attributed to the deployment of market-making algorithms. The market-making practices enhance competition and compel market participants to align more closely with optimal market prices. It is observed by several market participants that heightened liquidity positively influences price formation and reduces the bid-ask spread on the energy wholesale markets. The decrease in price spread across markets can also be attributed to increased spread trading, a trend less prevalent in previous years as certain markets required more time to adapt to new price dynamics. Participants mentioned other benefits associated with increased liquidity, such as mitigating the effects of network

[12] Price formation refers to the establishment of prices (for energy commodities) through the interplay of supply and demand, market conditions, and trading activities among participants. This process ensures that energy prices accurately reflect market fundamentals and economic conditions.
[13] SEC (2020), Staff Report on Algorithmic Trading in U.S. Capital Markets, p. 77, Maechler, A. M. (Bank for International Settlements, 2020), FX execution algorithms and market functioning, p. 2. AFM (2023), Market Watch #8, Algorithmic Trading, p. 7.
[14] Menkveld, A. J. (2016), The economics of high-frequency trading: Taking stock, Annual Review of Financial Economics, figure 2 and section 3.4.
[15] SEC Staff Report on Algorithmic Trading in U.S. Capital Markets (2020), p. 71. Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011), Does algorithmic trading improve liquidity?, The Journal of Finance, 66(1), p 1-33.
[16] ACER (2022), ACER's Final Assessment of the EU Wholesale Electricity Market Design, p. 75.

imbalances, providing hedging opportunities within less liquid markets and decreasing vulnerability to market manipulation.[17] However, manipulation may still occur, albeit with less price impact.

On the other hand, the literature indicates that other market participants who take more time to react to new information may become risk-averse due to concerns about being disadvantaged by algorithms. This behaviour may contribute to a widening of the bid-ask spread as manual traders may integrate risk costs into their pricing.[18] In line with this, as mentioned in the interviews, the bid-ask spread may sometimes present a distorted view of the market. Some of the interviewees note that the best bid and offer prices correspond to small volumes. When manual traders execute trades with a relatively small volume at these best prices, they might establish a new, elevated price level, consequently driving up those prices. Accordingly, the majority of traded volume tends to take place at less favourable price levels, at least for manual traders.

In some interviews it is suggested that the presence of algorithms also has the risk to lead to a disconnect between the fundamental market information and the trading behaviour dictated by these algorithms in commodity markets. This phenomenon, commonly referred to as the *financialisaton of commodity markets*, denotes an increased portion of trading driven by speculative motives rather than motives relating to physical assets. However, despite sharing similar concerns, some interviewees view commodities markets as distinct from financial markets because of their inherent reliance on fundamental factors. Although a disconnect from market fundamentals caused by algorithms are observed at times, they perceive them to be typically short-lived. Market dynamics tend to realign with stable fundamental factors such as storage levels, which act as stabilising forces in the market. Some consider that supply-and-demand dynamics are the primary drivers of price movements, with algorithms playing a subordinate role.

Lastly, the literature indicates that increased algorithmic use may heighten entry barriers for market participants, requiring investments in both data and expertise to compete with established algorithms. This might potentially impact market liquidity and price formation negatively.[19] Nevertheless, some interviewees observe a trend towards increasingly accessible advanced off-the-shelf algorithms over time, which could increase opportunities for more market participants to engage in algorithmic trading activities.

5.1.2 Volatility

The literature presents a nuanced perspective on the use of algorithms during times of increased volatility in financial markets. While algorithms can mitigate volatility by avoiding immediate market exits and occasionally taking counter positions during extreme price shocks, there is also a recognised risk of them getting trapped in a vicious cycle. This cycle amplifies significant price shocks to the extent that algorithms ultimately withdraw from the market in large numbers.[20] Due to the rapid pace at which algorithms operate, any potential errors, whether originating from human traders or the algorithms themselves, can exert a substantial impact on the market. Additionally, even in the absence of erroneous decisions, algorithms can amplify market trends due to their differential processing of various data types (e.g., financial figures compared with news articles).[21]

[17] ACER Guidance, 6th Edition, section 6.2: provides further details on ACER's views on the definition of (attempted) market manipulation within the meaning of REMIT.
[18] SEC (2020, Staff Report on Algorithmic Trading in U.S. Capital Markets (2020), p. 73.
[19] AFM (2023), Market Watch #8, Algorithmic Trading, p. 7. See also: FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 22.
[20] Maechler, A. M. (2020), FX execution algorithms and market functioning, p. 2. See also SEC (2020), Staff Report on Algorithmic Trading in U.S. Capital Markets, p. 78-79.
[21] Martins Pereira (2020), Regulating algorithmic trading in the new capital markets: a critical analysis of the European Union regime, p. 67.

Studies indicate that the risk of volatility is rooted in the correlation between algorithms, i.e., algorithms acting similarly to each other. Algorithms may be programmed, whether unintentionally or intentionally, to respond in the same way to certain information.[22, 23] This correlation is intensified when market participants use similar algorithms, especially if they are sourced from third parties.[24] Consequently, there is a risk that errors in the data may spread similarly across various algorithms, impeding price formation, particularly when multiple algorithms rely on the same flawed data or reference prices from less reliable illiquid markets.[25]

The survey results and the interviews show that the respondents have differing views on whether algorithmic trading might result in increased market volatility. Approximately two-thirds of the survey respondents do not foresee a risk of increased volatility, while the remaining respondents hold a different view. This sentiment is reflected, to some extent, in the interviews.

- **Some interviewees suggest similar risks as described above, indicating that algorithms may have the potential to amplify existing market movements, although not necessarily being the primary cause.** For example, events like *short squeezes*, where sudden price spikes force short sellers to cover positions, can lead to significant market exits. The potential pro-cyclical behaviour of algorithms, along with their rapid execution and responsiveness to market signals, could potentially intensify these market movements, thereby increasing volatility. Even minor volume increases can induce additional price reactions by algorithms, heightening market unpredictability.
- **According to other interviewed market parties, price dynamics are predominantly influenced by supply and demand forces.** They argue that algorithmic trading does not necessarily change the fundamental dynamics of volatility. Although the number of orders has increased due to algorithmic trading, this does not automatically equate to a higher frequency of transactions. Moreover, it is noted in some interviews that algorithms help maintain market stability by keeping prices in check and mitigating market impact. Unlike human traders, who may require breaks and face difficulties to adjust orders quickly in fast-moving markets, well-programmed algorithms maintain constant attention and reliability, particularly in highly volatile markets where quick price adjustments are crucial for achieving better prices.

5.1.3 Traded volumes

Another development of algorithmic trading influencing the functioning of the market is the reduction in traded volumes per transaction compared to manual trading alone. Several of the interviewed parties observe that average transaction volumes have decreased enormously, making it challenging for manual trading to keep pace. Previously, 100 MWh transactions were typical in e.g., the intraday power market, but now they have declined to transactions as small as 0.01 MWh. This reduction is viewed as a benefit by some interviewed parties, as algorithms enable the splitting of large orders into numerous smaller ones, thereby reducing their impact on the market.

As the volume of orders has notably shrunk, trading with larger quantities has become more complicated, particularly for manual traders. Moreover, manual traders are no longer able to place their orders in the market with competitive prices and wait for execution, because algorithms often place a slightly better priced order on the screen within milliseconds. This poses difficulties for manual traders to execute larger volumes without affecting prices. Consequently, manual traders may need to execute more or all orders in the order book to secure volumes. This may lead to higher costs, especially during price increases, as they are no longer able to wait for favourable price movements as they used to do.

[22] Ibid.
[23] Another partially related risk is that algorithms might lead to explicit or tacit collusion between competitors. While not within the scope of this market study, ACM, as a competition authority in addition to its role as an energy regulator, keeps a close watch on these potential risks.
[24] OECD (2021), Artificial Intelligence, Machine Learning and Big Data in Finance, p. 28.
[25] FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 7.

5.1.4 Impact on the transparency and explainability of trading and market outcomes

The rapid pace of algorithmic trading poses challenges for the transparency of the market, according to some interviewed market participants. Frequent and rapid price fluctuations on trading screens can complicate the accurate determination of prices. This disruption in the market forces manual traders to wait until these feedback loops subside. Furthermore, excessive liquidity can result in disorderly order books (quote stuffing), impeding transparency.[26] As a preventive measure, certain exchange platforms impose limits to cap the number of orders each participant can make within a short time frame. Once this limit is reached, traders are required to wait for at least one second before placing or adjusting further orders. Further details on this are elaborated in section 6.2.

Based on the interviews, algorithms have an ambiguous effect on transparency in the trading process. Some interviewees argue that algorithms enhance transparency by accurately documenting all trading decisions and actions, which facilitates ongoing oversight. However, algorithms can also negatively affect transparency across various aspects. As algorithms become more intricate, they become increasingly challenging to comprehend. This challenge is particularly pronounced with machine learning algorithms, which learn by experience and may exhibit different responses in similar situations. Following the insights gathered from the interviews, there are suggestions that machine learning could hinder transparency, particularly in comprehending the rationale behind algorithmic decisions, thus impacting the explainability of an algorithm.

Some studies imply that the increasing complexity of predicting and explaining algorithm behaviour emphasises the importance of thorough testing of algorithms. One interviewee also emphasises the importance of accurate testing environments, highlighting the necessity for trading platforms to simulate realistic market scenarios in their test environments. However, the focus on testing might shift the attention away from the explainability of an algorithm, leaving the oversight over algorithms without this crucial insight.[27] Complexity also emerges in integrating different components within an algorithm, each possibly comprising distinct algorithms. The overall behaviour of such an algorithm may diverge from expectations due to uncertainties surrounding the interactions among its various components.[28]

The literature indicates that, in financial markets, transparency could also be negatively affected by certain types of strategies or methods used by algorithms to place orders in the market. For instance, strategies such as the division of orders into smaller batches (spreading order volume over the trading session) or using partially hidden order volumes (iceberg orders) to execute large volumes. Dividing larger orders into smaller ones reduces market impact, but also means that the size of the order book is a less reliable indicator of market functioning. This is partly due to market participants not knowing if and how much hidden volume is behind the orders in the order book. In this context, an interviewee mentioned that the best priced orders usually involve small volumes, and most of the volume is seen at less favourable prices. Consequently, additional indicators may be necessary to interpret the market accurately. One such indicator could be the rate of which liquidity enters the market. This influx of buying and selling interest can indicate a more transparent market interest and help traders better understand market direction and sentiment.[29] It is important to note, however, that the abovementioned strategy is often also implemented by manual traders, e.g., by using available tools in trading software.

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[26] ACER Guidance, 6th Edition, section 6.3.2: Quote stuffing involves entering a large number of orders to trade and/or cancellations and/or updates to orders to trade so as to create uncertainty for other participants, slowing down their process, and/or to camouflage one's own strategy.
[27] AFM (2023), Market Watch #8, Algorithmic Trading, p. 14.
[28] FMSB (2020): Emerging themes and challenges in algorithmic trading and machine learning, p. 13.
[29] Maechler, A. M. (2020), FX execution algorithms and market functioning, p. 1-2.

5.2 Effects of algorithmic trading on market manipulation

5.2.1 Possible risks of market manipulation by algorithmic trading

While the majority of the survey responses and interviews mainly highlight the positive effects of algorithmic trading, some also recognise potential risks of (un)intended market manipulation in wholesale energy markets. Regarding the risks of algorithmic trading on market manipulation, opinions varied among interviewees. One highlighted perspective is that algorithmic trading adds liquidity to the market, generally resulting in reduced vulnerability to manipulation. Besides, it is mentioned by some interviewees that market manipulation via algorithmic trading is not fundamentally different from market manipulation via manual trading. Some interviewees add that the intentions behind the orders or transactions ultimately dictate the behaviour. For specific examples of risk factors and market manipulation by algorithms, please see section 6.5.

Some interviewees perceive risks of market manipulation through algorithmic trading. It is mentioned that manipulation can still persist even in liquid markets. With algorithmic trading, manipulative activities often involve small amounts such as one cent or a mere profit of one euro, but are executed repeatedly throughout the day. Another interviewee argues that algorithms might be even more susceptible to manipulation than manual trading due to their reliance on processing vast amounts of data. Manipulating input information could potentially influence an algorithm's output and subsequent actions.

An example of possible manipulative behaviour involving algorithms occurs in situations where so-called 'robot battles' take place between two algorithms. Such rapid actions can sometimes exhibit behaviours suggestive of layering/spoofing, where false or misleading signals are sent to the market. In this scenario, two algorithms compete with each other for the best (highest) buy order[30] through a series of order adjustments. This competition continues until the algorithm representing the 'suspect' party reaches its price limit. At this point, the party sells at the highest priced buy order of the other party and swiftly removes its own buy order. The concern would be that the purchase price is being manipulated, given that it is pushed up to its maximum limit through layering / spoofing behaviour, which involves the rapid removal of an order on one side of the book after a transaction on the opposite side. Such adverse behaviour, if unintended, could be prevented by effective controls and compliance measures, see also chapter 6.

Another example of possible manipulative behaviour where algorithms are involved, is where the order activity is so extreme that it disrupts the visibility of the order book for other market participants. This situation can arise from the correlation between algorithms that leads to improvement loops or feedback loops. These loops manifest through upward and downward order price movements, where two or more algorithms compete to optimise their orders. Imagine a situation where two algorithms compete to be the best (lowest) sell order in the order book. When algorithm 'A' adjusts its price to a level that is below the price limits of algorithm 'B', then algorithm 'B' no longer alters its price such that it is lower that algorithm 'A'. Instead, algorithm 'B' changes its price to be the second-best price in the order book, just slightly better than the former second-best order in the order book. Subsequently, algorithm 'A' follows suit by adjusting its price which slightly betters the new second-best price in the order book of algorithm 'B'. With the best price (of algorithm 'A') again being within the price limits of algorithm 'B', algorithm 'B' then pursues to have the best price again by slightly bettering the price of algorithm 'A'. These price adjustments continue, leading to upward and downward movements. The duration of such patterns depends on the programming of the algorithms. In specific circumstances, very rapid adjustments (imagine thousands of adjustments per minute) might lead to a situation where the order book is no longer visible for other traders. Within this context, some interviewed market participants acknowledge the existence of improvement loops, but highlight the implementation of

[30] A similar scenario can be correspondently described when two algorithms compete for the lowest sell order.

control mechanisms, such as maximum price deltas and controls on the last traded price that mitigate such cyclic movements. As shown in chapter 6, market participants actively maintain limits and safeguards within their algorithmic trading activities to preserve market stability.

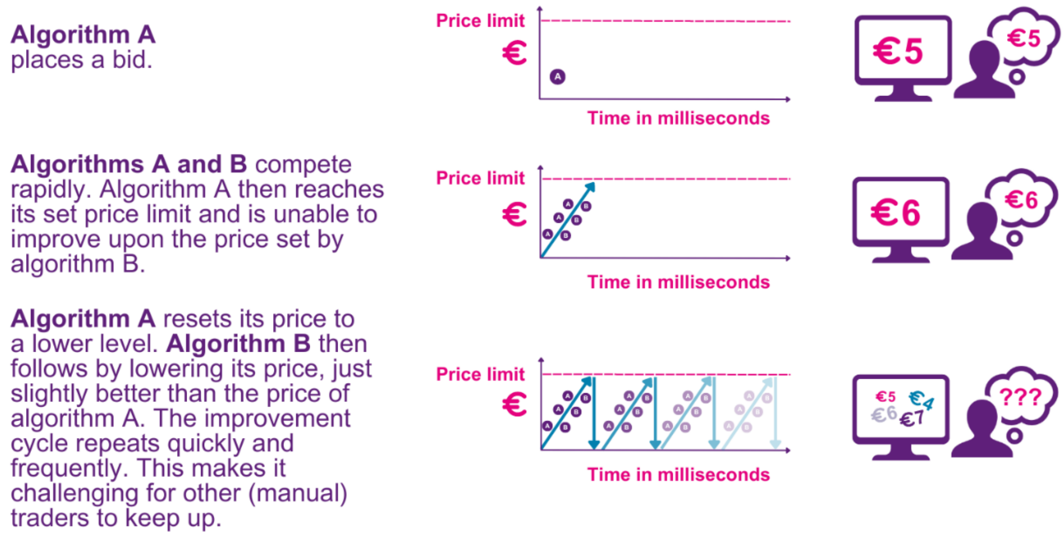


Figure 10: A schematic illustration of an improvement loop. The prices on the right are fictitious; in practice, the price steps often amount to cents.

5.2.2 Implications of algorithmic trading on the surveillance of suspicious behaviour by regulatory authorities and trading platforms

Complex and high frequency algorithmic trading requires a different approach in identifying suspicious trading patterns. Trading platforms have the responsibility to detect suspicious trading behaviour and report this to the authorities.[31] Additionally, energy and financial regulators conduct their own market surveillance. The complex nature and high frequency of trading orders make it challenging to identify the risks of certain behaviours and detect possible suspicious trading. The rapid pace of trading sequences in algorithmic trading can occur within milliseconds. Moreover, total order and transaction activity has increased rapidly over the years.

The increased use of trading algorithms has led to changes in surveillance methods. Investigating suspicious algorithmic trading behaviours now demands a more data-intensive approach compared with manual trading. There is now a shift towards quantitative data analysis and the development of advanced detection tools. Regulators therefore invest in expertise and IT infrastructure to enhance their ability to detect and analyse such trading behaviours.

[31] Pursuant to article 15 of REMIT, this applies to Persons Professionally Arranging or Executing Transactions.

6 Compliance and internal checks and balances

Key points:

- All interviewed and surveyed market participants have told ACM that they have compliance and risk measures in place regarding their algorithm(s), though to varying extents. In this study ACM has not assessed whether the procedures are put into practice. This concerns a variety of measures, such as limiting the price and volume of orders within certain ranges, and a kill functionality that enables the trader to stop all algorithm trading at once when needed.
- Since this study is exploratory in nature, ACM has not assessed the effectiveness or the implementation of the compliance and risk measures from a regulatory perspective, as this is beyond the scope of the study.
- Risks of adverse behaviour may remain present, even when compliance measures are in place. For example, the effectiveness of applied controls and limits depend on specific input values. In case the input values are set too high or too wide, the controls and limits may not be restrictive enough in practice.
- Trading platforms maintain several conditions for market participants to employ algorithms on their platforms, mainly to ensure stability of the trading system and the quality of price discovery.

6.1 Measures taken by market participants

All interviewed and surveyed market participants, who currently use algorithms or are developing algorithms, have – to varying extents – procedures in place concerning the development, testing, employment, and monitoring of algorithms. These procedures are detailed and (in some cases) periodically reviewed. As this study is exploratory, ACM has not assessed the effectiveness or implementation of the compliance and risk measures from a regulatory perspective, as this is beyond the scope of the study. Please note that this study has been conducted before the revision of REMIT came into effect in May 2024. Since then, REMIT includes, among other things, several obligations for market participants regarding risk controls, compliance, and testing and monitoring systems, please see chapter 7 for more information on this.

6.1.1 Developing and testing phase

Developing algorithms usually starts with market and data analysis. Market participants then formulate the rationale or strategy for a (new) algorithm. Certain checks are prerequisites such as on data quality and whether the data is transferred properly between applications.

Market participants consider multiple criteria when testing algorithms. The most mentioned criteria by market participants are as follows:

- *The algorithm behaves as expected.* The behaviour of the algorithm is checked by feeding in realistic or historical data and often under a variety of market conditions. Additionally, market participants check whether the algorithm properly interacts with other algorithms that are active on the market at the same time. Sometimes these checks are automated and sometimes performed manually.
- *The algorithm performs well.* Simulated trading is a common step in the testing phase. In realistic simulations – often using actual order book data of the exchange(s) – the performance of the algorithm is being evaluated in terms of expected profit.
- *The algorithm contains all required elements.* Most market participants have a checklist of required elements for the algorithms. This includes for example price and volume limits.

All surveyed and interviewed market participants test their algorithm(s) during development. Almost all surveyed market participants (that is, 13 out of 15 respondents) test their algorithm(s) after every change to the algorithm. The majority of market participants also test their algorithm (again):

- when entering a new trading venue (11 out of 15 respondents);
- after changes to the venue's systems (10 out of 15 respondents); and
- periodically in general (10 out of 15 respondents).

The interviews gave similar results as the survey.

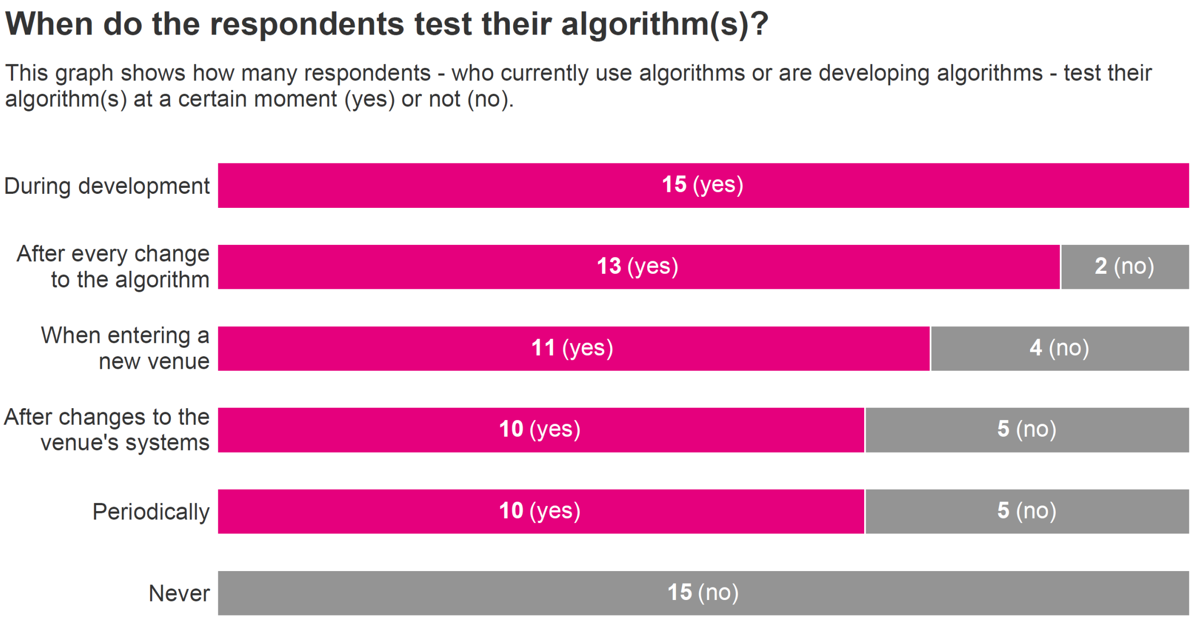


Figure 11: Survey results on when algorithms are tested

Usually, multiple persons or departments are involved when testing and approving an algorithm. For example, some market participants ensure two people check the algorithm (four eyes principle). For other market participants several departments – e.g., compliance-, IT- and risk department – need to approve the use of the algorithm. A single market participant also asks a third party for a check. Another market participant has a dedicated a committee for algorithm governance, in which several areas of expertise are centred (risk, compliance etc.).

After approval of an algorithm, some interviewed market participants closely monitor the performance of the algorithm on the market. When the algorithm proves successful and no undesired risks materialise, then the increased monitoring efforts at the start of employment will be decreased over time until eventually only the trader monitors the algorithm.

6.1.2 Information storage on algorithms

Market participants document several types of information on the development and use of (an) algorithm(s). The interviewed market participants gave the following examples on types of information that are being stored:

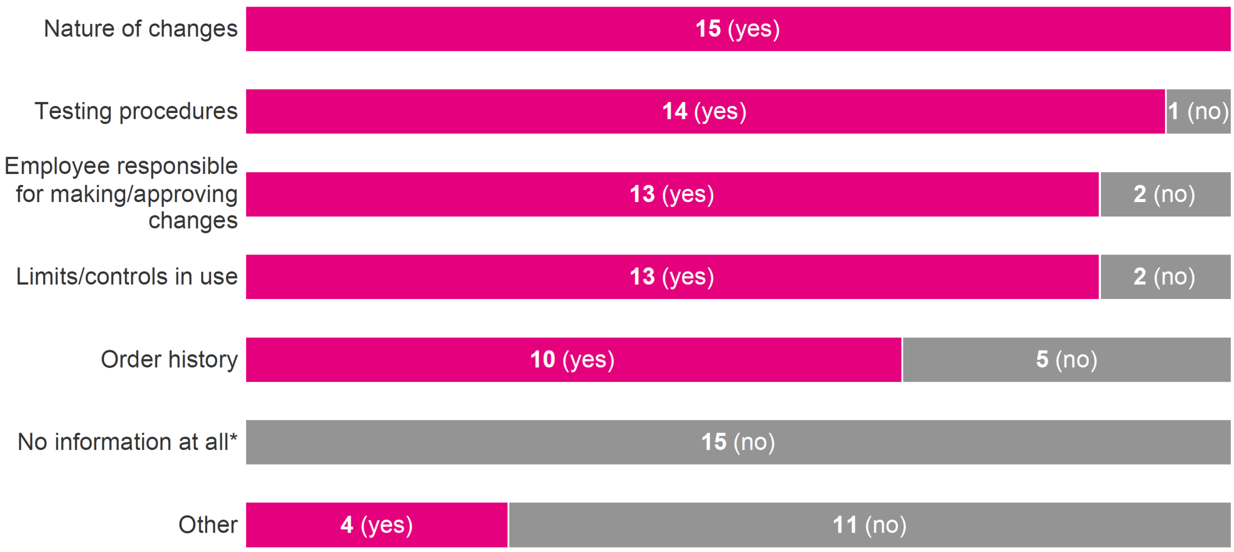
- logic and rationale behind the algorithm and/or configuration of the algorithm;
- tests conducted;
- programming code of the algorithm (including version control);
- logging files, including per algorithm output information on produced orders and trades (information is kept over a historical period of 5 years);

- possible risks (sometimes using a template with standard questions on possible risks);
- information concerning registration of algorithm(s) with exchanges.

Every surveyed market participant – that is currently using or developing (an) algorithm(s) – stores at least some information on the algorithm development and use. Almost all market participants store information on changes to algorithms, testing procedures, employee responsible for making and/or approving changes, and applied limits/controls. Two-thirds of the market participants (10 out of 15 market participants) also store information on order history.

What types of information do respondents store regarding the development and use of algorithms?

This graph shows how many respondents - who currently use algorithms or are developing algorithms - store the type of information (yes) or not (no).



** With respect to the category 'No information at all': "no" means that the respondent does store (some) information.*

Figure 12: Survey results on information storage

6.1.3 Controls and limits

All interviewed and surveyed market participants use pre-trade controls and limits in algorithmic trading. Pre-trade controls determine how individual orders must be verified before they are submitted using certain limits. Pre-trade limits apply to the (aggregated) characteristics of all orders in a specific trading session. For example, the total number of outstanding orders.

The majority of the surveyed market participants use multiple types of pre-trade controls for their algorithms. The most often used pre-trade controls concern maximum order volume (14 out of 15 market participants use this limit); time limit (12 out of 15); maximum message limit (12 out of 15); maximum order value (10 out of 15); and order price (9 out of 15). Roughly half of the surveyed market participants apply controls on the number of executions and market/credit risk (both 7 out of 15). Five surveyed market participants also mentioned other controls, for example: maximum total traded volume, maximum number of active orders (per specific short time period); and prevention against self-trades. The specific controls are also frequently applied by the interviewed market participants.

Which pre-trade controls do the respondents use for their algorithm(s)?

This graph shows how many respondents - who currently use algorithms or are developing algorithms - use a certain type of pre-trade control (yes) or not (no).

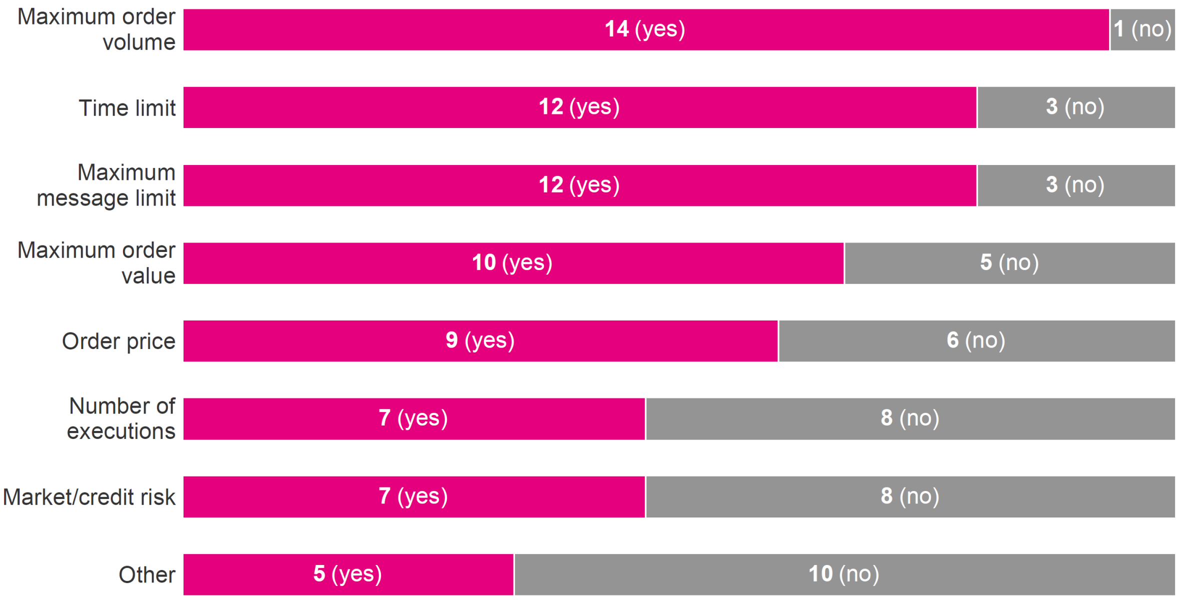


Figure 13: Survey results on pre-trade controls in use

Most of the surveyed and interviewed market participants, who currently use algorithms or are developing algorithms, apply many pre-trade limits. Based on the survey, the following pre-trade limits are used (ordered by descending use intensity):

- *Strategy positions.* 14 out of 15 market participants use limits to ensure the strategy is executed properly in terms of positions.
- *Order price.* 13 out of 15 market participants have limits in place around the pricing of an order.
- *Order value.* 12 out of 15 market participants have limits in place around the value of an order.
- *Number of outstanding orders*. 11 out of 15 market participants have limits in place regarding the number of outstanding orders active in the order book at any time.
- *Frequency limit*. 10 out of 15 market participants have specific limits in place around the amount of order placements or changes per particular time period.
- *Specific tradeable instruments.* 9 out of 15 market participants have limits in place regulating which specific instruments can be traded by the algorithm.
- *Specific trading venues accessible.* 8 out of 15 market participants have limits in place regulating which specific venues are accessible by the algorithm.

5 out of 15 market participants also mentioned other pre-trade limits such as data integrity, market impact, and interaction with other algorithms.

Which limits do the respondents use for their algorithm(s)?

This graph shows how many respondents - who currently use algorithms or are developing algorithms - use a certain type of limit (yes) or not (no).

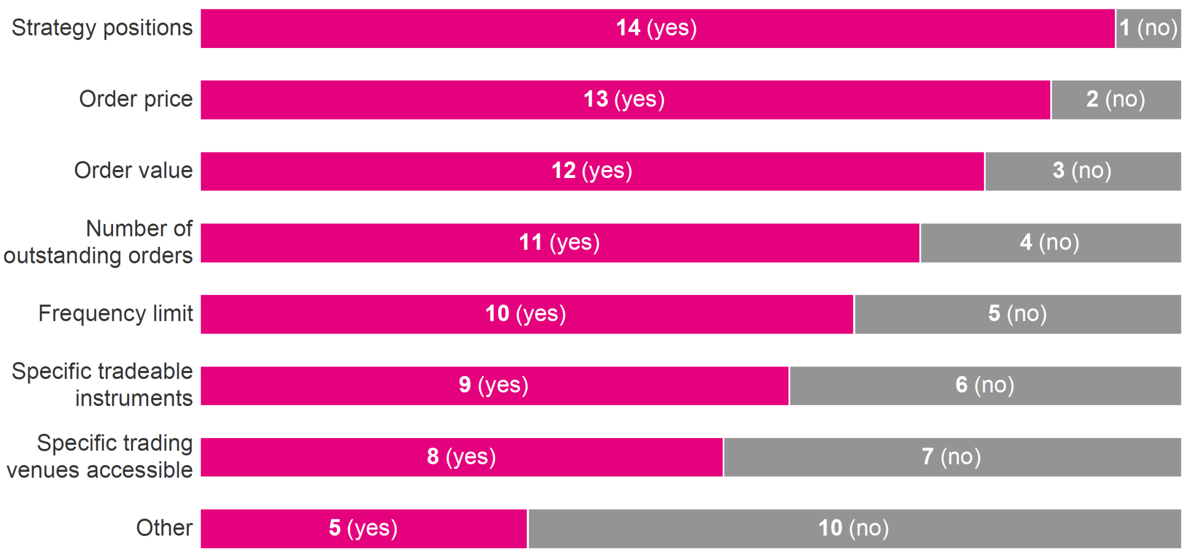


Figure 14: Survey results on limits in use

Price and volume limits are the most often mentioned limits in the interviews. These limits protect against fat finger errors – human mistakes in input for order price and volume. The order price can be limited between some absolute minimum and maximum values and/or the price can be limited relative to a reference price such as the last traded price. Such price limits prevent that the algorithm – in competing with another algorithm for the best price (also known as an improvement loop) – will exceed certain price levels. Through volume limits a minimum and maximum volume per individual order can be set. A position limit prevents that the algorithm buys or sells too much.

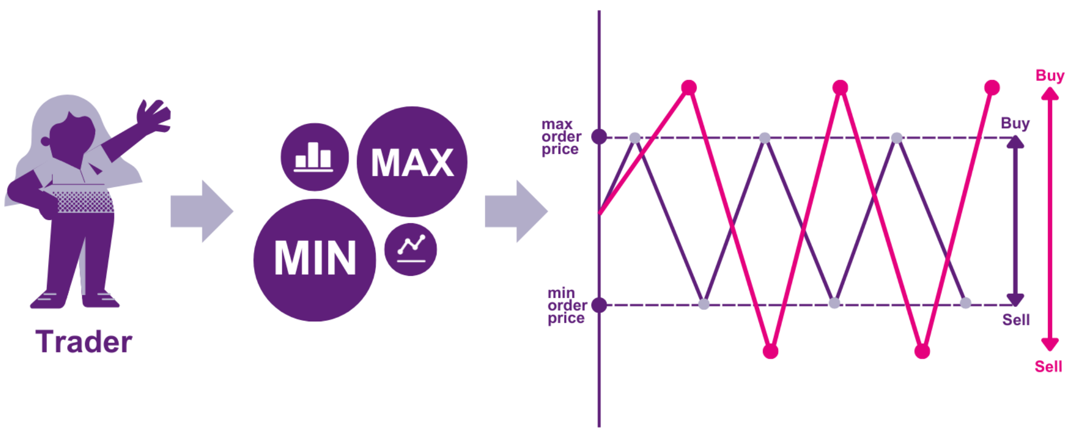


Figure 15: A schematic illustration of order price limits. The algorithm is confined to operate within the purple price bandwidth. Without price limits in place, the algorithm may operate freely outside the price bandwidth as indicated by the pink line.

Frequency limits are also applied often by the interviewed market participants as well as controls to prevent self-trades. Technically an algorithm is able to update orders on the trading platform millions of times per second. A frequency limit puts a maximum on the number of orders or order updates that can be inserted by the algorithm on the trading platform within a certain short time period (per second for example). As such, it prevents overloading the order book and having a disorderly effect on the market. Some market participants use multiple algorithms on the same market at the same time. Therefore, a control is needed to prevent that the algorithms of one market participant trade with one another which would lead to self-trades.[32] Other market participants solve that issue by first inserting a new order on an internal market (within the company) and only bringing remaining net positions to the market.

ACM's impression, based on the assessment of cases of possible suspicious trading behaviour, shows that the use of controls and limits differ between market participants. Some market participants put more responsibility on the monitoring of the trader, while other market participants show many similarities in the applied controls and limits compared to the interviewed and surveyed market participants. In several cases the ACM looked into, the market participants involved incorporated new checks to ensure that the algorithm properly interacts with other algorithms.

The role of trader changes when algorithms are used in trading. The trader performs many different activities, among which the following:

- *The trader now chooses upfront which (type of) algorithm to use and how*. For example, the trader chooses the input values of the algorithm parameters. One interviewed market participant explained that the signal generator sends to the trader a request to trade a certain amount of volume according to a certain strategy. Both the trader and the person responsible for the signal generator then verify the parameter values of that request.
- *The trader is responsible for the algorithm monitoring*. The traders of many interviewed market participants monitor the activities of the algorithm. When there is a shift in trading conditions, then the trader at one participant stops the algorithm and possibly continues manual trading, while the trader of another participant considers changes to the input values of the algorithm. The trader of yet another market participant receives a notification when the algorithm reaches certain predefined limits and needs to manually click on the screen whether or not to continue trading activities of the algorithm. Multiple interviewed market participants require the trader to monitor the algorithm at all times, not leaving the algorithm running unattended (besides some breaks). Therefore, one interviewee explained that algorithmic trading is only done during office hours. Another market participant does perform algorithmic trading outside of office hours, where overnight the algorithm monitoring is automated. The automated monitoring is based on a specific bandwidth around a fair market value, which is estimated using fundamental market information like fuel analyses and expected supply and demand. Additionally historical data is used as reference check.

6.1.4 Monitoring and other compliance measures

Many market participants have a real-time monitoring system in place and/or require the trader to monitor the algorithmic trading activities.[33] The majority of the surveyed market participants who currently use algorithms or are developing algorithms have an automated surveillance system in place (12 out of 15) and require the trader to always monitor the orders of the algorithm (12 out of 15). This also holds for the interviewed market participants. Generally, such a monitoring system generates alerts for several types of problems. Multiple market participants mentioned two main areas of focus: i)

[32] ACER's Guidance Note on Wash Trades (1/2017) provides further details on its views on the application of REMIT provisions in the context of wash trades in wholesale energy markets.
[33] With real-time monitoring, we are not necessarily referring to the definition from the financial markets, more so on the activities.

detection of trading patterns that could possibly be manipulative behaviour; and ii) the algorithm does not act as intended.

The trader intervenes when irregularities are detected. The irregularities in the algorithmic trading activities are detected by the trader and/or come from generated alerts by the monitoring system. The alerts are usually researched manually. The interviewed market participants do not have a list of predefined situations of irregularities in which cases intervention by the trader is needed. Instead, the traders check several indicators like actual compared with expected traded volume and use their expert knowledge for judgement. In this context, the market participants emphasise that traders have undergone training, also regarding REMIT topics.

Some market participants have bought such trading surveillance software from an external party, while others have developed it themselves. This holds both for the market participants in the interviews and ACM cases. There are also market participants who use both in-house developed and externally bought monitoring software.

Almost all surveyed market participants have a kill functionality built in their algorithms. This is true for 14 out of 15 surveyed market participants. Such a functionality – also known as a "kill switch" – enables the trader to stop all algorithmic trading activities at once when needed. One surveyed market participant additionally built in a 'regular' kill functionality, which stops the algorithmic trading when there has been no manual input for too long a time.

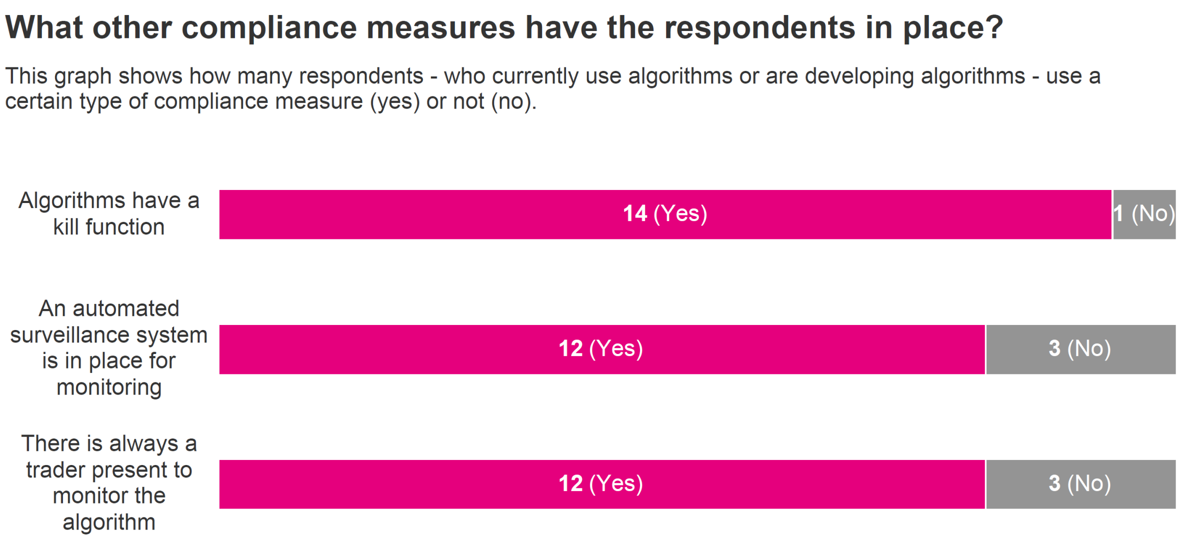


Figure 16: Survey results on other compliance measures

6.1.5 Prevention of adverse behaviour

Risks of adverse behaviour remain present even when compliance measures are taken with best efforts and intentions. Compliance measures minimise the occurrence of adverse behaviour, though some factors may still possibly lead to unwanted outcome. ACM monitors the market for these behaviours, see also section 5.2. Some examples of risk factors are the following.

- *When algorithms get more complex, the explainability decreases.* In those cases, the importance of testing of the algorithm grows, while it remains challenging to test for all possible trading scenarios.[34] This especially holds for machine learning algorithms that may react

[34] FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 13.

differently to certain situations over time when it develops further and is applied within an environment that is also changing.[35] [36]

- *When an increasing number of data sources and data types are fed to the algorithm, it gets more difficult to test whether a complex algorithm reacts as expected.*[37] The interaction between numerous data sources of various data types, like news items and social media, makes this task difficult. The risks arise that input data may be faulty, and that adverse behaviour may not be detected and corrected ex ante.[38]
- *The self-correcting tendencies of markets are less in illiquid situations according to an interviewed trading platform.* Vice versa, multiple interviewed trading platforms indicate that algorithms have less chance of manipulative market effects when markets are highly liquid.
- *Machine-learning algorithms may learn unintendedly that negative or even manipulative trading behaviour could result in more profit when programmed naively.*[39] [40] Trading companies perceive less risks for this when using supervised learning[41] instead of reinforcement learning[42].[43]
- *Code errors or technical problems around algorithms can last a long time when they remain undetected.* These issues may lead to incorrect decisions by the algorithm, which will only be solved through active intervention.
- *Self-learning algorithms may take less sound decisions in extreme market conditions.* Extreme market conditions are rare and may not be included in the dataset on which the algorithm is trained.
- *The effectiveness of applied controls and limits depend on specific input values.* In case the input values are set too high or too wide, the controls and limits may not be restrictive enough in practice.
- *When designing and employing algorithms, market participants must consider the occurrence of inside information.* Internal information, which possibly constitutes as inside information, must not be fed to the algorithm before it is published. In case the person responsible for an algorithm, somehow receives knowledge of inside information, they may not intervene with a running algorithm, i.e. “hands-off”.

6.2 Relevant conditions of trading platforms

The interviewed trading platforms maintain several conditions for allowing a market participant to use an algorithm on their platform. In all cases, the market participant remains responsible for the trading behaviour of their algorithm. Some examples of what trading platforms expect from market participants are the following:

- *Conformance test.* This technical test concerns the connection between the platform and the algorithm. Usually the application programming interface (API) is tested under a variety of circumstances, which is done in test environments facilitated by the trading platform. In this test the trading platform does not validate the logic or quality of the algorithm itself. The conformance test is repeated after particular changes to the system of the trading platform and in some instances when the market participant makes changes to the connection with the

[35] ACM (2020), Position Paper, Oversight of algorithms, p. 12.
[36] FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 18.
[37] Ibid., p. 18.
[38] FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 7.
[39] AFM (2023), Machine Learning in Algorithmic Trading, section 4.
[40] FMSB (2020), Emerging themes and challenges in algorithmic trading and machine learning, p. 4.
[41] With supervised learning, the model is trained using example data of which the input and the expected output are known. During the training phase, the algorithm learns what features of the input have an effect on the output and adjusts the model accordingly. Next, the model can be applied to new data. This method is therefore often used for predicting future situations on the basis of historical data.
[42] In reinforcement learning, the algorithm is trained using ‘trial and error’. Actions are rewarded or punished depending on whether steps in the right direction are made. This is an iterative learning process where the algorithm learns by maximising the reward and minimising the punishment. The main difference with supervised and unsupervised learning is that, in this method, the algorithm is not trained using training data.
[43] ACM (2020), Position Paper, Oversight of algorithms.

platform. One interviewed market participant indicated that 95% of the issues identified in testing are related to the communication between the algorithm and the trading platform.

- *Market disruption test.* One trading platform asks of market participants to test the algorithm to ensure it does not lead to disorderly trading conditions.
- *Notification.* One trading platform requests that market participants notify the platform when it plans to use an algorithm. The algorithm then gets a unique ID.
- *Compliance and monitoring system.* One interviewed trading platform mentioned the request that market participants must have a compliance and monitoring system in place. The market participants are obliged to monitor their own activities. Another trading platform requires market participants to store records/trading data for a period of 5 years in case of high frequency algorithmic trading.
- *Kill functionality in the algorithm.* A trading platform mentioned that a kill functionality must be incorporated in the algorithms. This functionality – also known as a "kill switch" – enables a trader to stop the operations of an algorithm at once.
- *Circuit breakers.* One interviewed trading platform mentioned that market participants active on their platform have better implemented its circuit breakers, since the trading platform altered its system to properly accommodate algorithmic trading. A trading platform incorporates circuit breakers in its system in order to, as it were, pause continuous trading in case there is an extreme price movement. This reduces the chance and extent of sudden extreme market movements.

The trading platforms also stipulate conditions during use of an algorithm on their platform. The interviewed trading platforms mentioned the following:

- *Number of active orders*. One trading platform maintains a limit on the number of orders a market participant is allowed to place on the platform in a longer timeframe. This prohibits that too many little, insignificant orders are in the order book. Thereby guaranteeing the stability of the trading system and the quality of price discovery.
- *Order frequency limit*. Multiple trading platforms have a rule in place to limit the number of orders a market participant may place in a time period of several seconds. This also guarantees the stability of the trading system and the quality of price discovery.
- *Limits to order volume and price.* One interviewed trading platform checks the order parameters before placement. This involves checks regarding order price and order volume in order to filter out extreme deviations from prevailing market conditions.

7 Recent legislative developments in the EU wholesale energy market

Key points:

- The REMIT revision imposes new obligations on EU wholesale energy market participants engaged in algorithmic trading to mitigate associated risks. Market participants engaged in algorithmic trading must implement effective risk management systems, adhere to trading thresholds and limits, ensure business continuity, and notify regulatory authorities of their algorithmic trading activities.
- The REMIT revision strengthens ACM's oversight of algorithmic trading in the Dutch energy market. ACM continues to regulate and monitor trading behaviour by market participants, thereby also focusing on compliance of the obligations regarding algorithmic trading.
- ACM continues to work closely together with the AFM and other regulatory bodies.

7.1 New obligations for market participants regarding algorithmic trading in the EU

On May 7th, 2024, the revision of REMIT came into effect, introducing new obligations for market participants using algorithmic trading, as well as new responsibilities for national regulatory authorities. These changes are designed to address the increasing risks associated with algorithmic trading on EU wholesale energy markets. Market participants and national regulatory bodies alike are bound to adapt their compliance strategies and oversight practices to meet the updated regulatory standards.

Pursuant to Article 5a of REMIT, market participants engaged in algorithmic trading on the wholesale energy markets are specifically required to:

(i) Implement effective systems and risk controls for their business activities to ensure resilience and sufficient capacity of their trading systems, and to ensure compliance with REMIT regulation and the rules of any organised market place (hereafter: OMP) to which they are connected.

(ii) Comply with appropriate trading thresholds and limits and prevent sending erroneous orders to trade or otherwise function in a way that may create or contribute to a disorderly market.

(iii) Establish effective arrangements to address business continuity in the event of any failure of their trading systems and ensure that their systems are fully tested and properly monitored to meet the requirements of REMIT.[44]

(iv) Notify the National Regulatory Authority (NRA) of the respective Member State where the market participant is established, as well as ACER, of their engagement in algorithmic trading. They may also be required to provide, on a regular or ad hoc basis, details of the trading parameters or limits to which the trading system is subject, key compliance and risk controls that are in place to ensure that the requirements of REMIT are satisfied and details of the testing of its trading systems. The market participant shall arrange for records to be kept for five years and shall ensure that those records are sufficient to enable the NRA of the Member State to monitor compliance with REMIT.[45]

[44] Regulation (EU) 2024/1106 of the European Parliament and of the Council of 11 April 2024 amending Regulations (EU) No 1227/2011 and (EU) 2019/942 as regards improving the Union’s protection against market manipulation on the wholesale energy market (Text with EEA relevance) [2024] OJ L, 2024/1106, article 5(a)(1).
[45] Ibid., article 5(a)(2).

(v) When a market participant offers direct electronic access to an OMP, the entity shall notify the NRA of its Member State of origin and ACER accordingly.[46]

The new obligations place a greater responsibility on market participants to ensure the integrity and stability of their algorithmic trading activities, requiring proactive oversight. They necessitate potential enhancements to trading systems, including improved management, testing, and monitoring processes, as well as accurate documentation, archiving, and ensuring accessibility of information.

7.2 New responsibilities and competences of ACM concerning algorithmic trading

The REMIT revision also describes the competences and duties regarding ACM's oversight of algorithmic trading. Market participants that are registered under REMIT with the ACM are now required to report their algorithm usage to ACM as well as ACER, necessitating the systematic management of this data by ACM.[47] Moreover, ACM as National Regulatory Authority, has the authority to request details and documents regarding algorithms to verify compliance with REMIT.

Overall, the REMIT revision enhances regulatory competences in relation to algorithmic trading in (Dutch) energy markets, including monitoring market parties' compliance and internal processes through a structured oversight process. ACM intends to incorporate the insights from the present market research on algorithmic trading into its surveillance of the Dutch wholesale energy market. By engaging in ongoing discussions with co-regulatory bodies including the AFM, ACM aims to establish collaborative efforts that synergise regulatory approaches and ensure comprehensive oversight.

7.3 Parallels to EU financial legislation and concerns related to algorithmic trading obligations under the REMIT revision

From the interviews, it seems that many traders have established a structured compliance framework around algorithmic trading, as outlined in chapter 6. Some have set measures in line with MiFID II RTS6 standards, anticipating that they already comply with REMIT II legislation and foresee minimal changes to meet the new requirements. Some internally document algorithms using self-assessment forms, implying that it covers REMIT II requirements. Additionally, exchange platforms require robust compliance systems, which already includes most of the REMIT II elements.

Some market participants have expressed worries or uncertainties regarding the requirements on algorithmic trading introduced by the revised REMIT. They seek further clarification or explanation on for instance technical standards to enhance their comprehension and implementation of the new obligations. One interviewed market participant holds that RTS 6 under MiFID II should not be applied directly in the wholesale energy market, considering that certain standards related to algorithmic trading are unsuitable due to the differing nature of energy markets compared with financial markets. The Agency for the Cooperation of Energy Regulators and the EU National Regulatory Authorities are taking the concerns expressed by stakeholders into serious consideration.

[46] Ibid., article 5(a)(3).
[47] Pursuant to article 5a of REMIT, this requirement applies to all market participants registered with their respective NRA.