Evaluation and Optimisation of Trading Strategies for EEX Financial Gas Futures on the TTF DA Market

A Master's Thesis

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Preface and reading guide

This thesis is written to complete the master Industrial Engineering & Management with the specialisation Financial Engineering & Management at the University of Twente. I would like to thank a couple of people for their efforts and contributions in my research. First, I thank the company, BCI, and the manager, Wouter Alblas. They welcomed me with open arms and facilitated me with the right materials and resources. I remember my time at the company as very pleasant. This is because BCI gave me the ability to sit in the office amongst other colleagues. Every person was very friendly, and questions were appreciated. I especially would like to thank my supervisor at the company, Jonas Amtsfeld. Here, questions about the data and the assessment of these were answered with ease. At BCI, I had a great learning experience on how such a company in general operates but also on how it operates in this specific sector. The experiences gained will surely benefit me in the future. Finally, I would like to thank Reinoud Joosten and Berend Roorda, my supervisors at the university, for their insights and guidance throughout the research.

Executive summary

BCI trades EEX Financial Gas Futures on the Title Transfer Facility Day-Ahead gas market on behalf of its clients. Traders manually trade based on experience and intuition. This is challenging due to the dynamic and volatile nature of the market. Therefore, BCI is interested in a systematic trading strategy which exploits the opportunities in the market. We determined our best trading strategy by applying a top-down approach. Here, we initially investigate the potential of existing strategies. Then, we make a selection for further development, backtesting, and optimisation. We realise this with the Backtesting.py library in Python, which meets all our criteria. On this, we optimise the strategies by maximising our defined objective function with grid search optimisation. We analyse the strategies based on multiple performance indicators, benchmarks, Walk-Forward Analyses, heatmaps, and quarterly results. These components construct a blueprint which explains how the most suitable strategy can be identified. Additionally, we test the strategies on the weak form of the Efficient Market Hypothesis (EMH). Based on the results, we conclude that the strategies outperform the market, suggesting that we reject the weak form of the EMH. Furthermore, with our blueprint, we conclude that the so-called EMA cross-over strategy is the most suitable.

To realise the development and assessment of the trading strategies, we investigated the following topics:

- Dynamics of the TTF DA market.
- Trading theory.
- Trading strategies.
- Testing platforms.
- Performance indicators.
- Walk-Forward Analysis.

Based on these investigations, we develop and assess multiple trading strategies which have a high potential in the market. This results in the following items:

- **Strategy set justification**
  We conduct a literature review on various trading strategies and explain why we selected

certain trading rules and strategy characteristics over others for our strategy set. The criteria used to establish our set of strategies include *Profitability*, *Intraday trading focus*, and *Non-stock*.

- **Strategy formulation**
  We provide the formulation of our trading strategies to ensure repeatability. This includes the detailed definitions of the trading rules, specifically the entry, exit, stop, and target rules, and the position sizing technique employed. Additionally, the strategies are provided in scripted form using Python, supported by the Backtesting.py library. These scripts can be used for further development and analysis and are available in Appendix C.

- **Blueprint**
  We develop a blueprint which selects the most suitable strategy for a given set of strategies. This selection is based on several metrics regarding the performance of the strategies. These metrics are: The objective function, the heatmap of the grid search optimisation, the quarterly performance, the Sharpe ratio, the Profit Factor, the Walk-Forward Analysis, the alpha and beta derived from the TTF DA benchmark, and the comparison with the S&P500 benchmark. This blueprint can also be applied to other markets.

- **Advisory report**
  During the development, we have noticed some shortcomings or potential improvements which could benefit the performance of the trading strategies. Therefore, we recommend the following:

  - Test strategies periodically and simultaneously.
  - Optimise risk management.
  - Consider multi-timeframe strategies.
  - Add more trading rules.
  - Investigate distribution of drawdown lengths.
  - Apply strategies to Monte Carlo simulations and predictive models.
  - Fit equity curves to exponential formulae.

- **Disclaimers**
  Our strategies have a couple of disclaimers with regard to the execution in practice.

  - During backtesting, slippage is not taken into account. In practice, orders might not be directly executed due to low traded volumes in the market. Therefore, orders might not be executed at the intended prices.
  - When backtesting, the last close price is used as entry price, not the bid and ask price. In practice the bid and ask price are used which are probably less beneficial for the profitability of the strategies.
  - Automation of the strategies is time-consuming, as systems need to be integrated with the software, and most likely a new programming language needs to be learned in which the strategies must be defined.
  - Especially in a volatile and dynamic market, historical performance is not a guarantee for similar future performance. Market conditions are likely to change in the long run, resulting in different performances.
  - To assess the performance of a strategy in real time, a long predefined testing period is required, as drawdown periods can be long, masking the true potential of the strategy.

Contents

List of Acronyms

ATR	Average True Range
BCI	Brainchild Commodity Intelligence
CAPM	Capital Asset Pricing Model
CET	Central European Time
DA	Day-Ahead
DCS	Donchian Channel Strategy
EEX	European Energy Exchange
EGSI	European Gas Spot Index
EMA	Exponential Moving Average
EMH	Efficient Market Hypothesis
EoD	End-of-Day
IS	In-sample
LNG	Liquefied Natural Gas
MDD	Maximum Drawdown
MSE	Mean Squared Error
OF	Objective Function
OHLCV	Open, High, Low, Close, Volume
OOS	Out-of-sample
ORB	Opening Range Breakout
PF	Profit Factor
RRR	Reward to Risk Ratio
RSI	Relative Strength Index
SMA	Simple Moving Average
SQN	System Quality Number
TR	True Range
TTF	Title Transfer Facility
TTS	Turtle Trading Strategy
WFA	Walk-Forward Analysis
WFE	Walk-Forward Efficiency
WFT	Walk-Forward Test
WR	Win Rate

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1 Introduction

Brainchild Commodity Intelligence (BCI) is an intermediary providing energy market access to its clients while managing their portfolios. The firm is active on multiple trading platforms and trade in financial products derived from energy sources, such as oil, coal, natural gas, wind, and solar. Furthermore, the firm is trading in emission rights of carbon dioxide. BCI provides insights and information to its clients about current developments in the energy markets. One of the services provided is enabling clients to hedge against the financial risks of the gas market.

1.1 EEX Financial Gas Futures

Clients can hedge their expenditures in natural gas by buying EEX Financial Gas Futures, traded on the Title Transfer Facility gas market (TTF). This is the largest and most liquid gas trading hub of Europe, located in the Netherlands. The futures are cash-settled against the European Gas Spot Index (EGSI), which is based on the trades executed on all EEX natural gas markets in Europe. More precisely, calculated as the volume-weighted average price, based on all Day-Ahead transactions of the day (8:00 a.m. to 6:00 p.m. CET) (EEX, 2024). When the futures expire, owners receive a cash-settlement equal to the EGSI times the volume they have in futures. For example, if a client buys futures in December for the month March for a volume of 5 MWh per day at a price of €10/MWh, he pays an initial amount of 5*10*24*31 = €37,200 for 3,720 MWh. The day before the 1st of March, 5*24 = 120MWh of financial gas is traded on the Day-Ahead market. When the market closes that day, the client receives a cash-settlement which is equal to the EGSI times the volume. Let's say this EGSI equals €11/MWh during all 31 days. Therefore, in the end the client receives a total of €11*3,720 MWh = €40,920.

Because external parties deliver physical gas on the next day at the price of the EGSI, clients can use EEX gas futures to hedge against financial risk in the gas market. In our example, the client has to pay the external party a total of €40,920. However, due to the hedge with futures the client essentially only paid €37,200. This results in a profit for the client of €40,920 – €37,200 = €3,720. On the contrary, the gas price (EGSI) can also drop to €9/MWh, the total payoff in this second scenario is only: 9*3,720 = €33,480. The client fixed its price at €37,200, and therefore has a loss of €40,920 - €37,200 = €3,720. As can be observed in Table 1, EEX financial gas futures enable clients to fix their gas prices which hedges against price increases, but not against price decreases.

Table 1: Client's Perspective.

Client	**€/MWh**	**MWh**	**Total (€)**
Futures price	-10.00	3720	-37,200
EGSI scenario 1	11.00	3720	40,920
EGSI scenario 2	9.00	3720	33,480
Profit client scenario 1			3,720
Profit client scenario 2			-3,720

BCI makes profits by selling futures of clients on the Day-Ahead market for prices which are above the EGSI. Take our first scenario where the EGSI is €11.00/MWh. Here, BCI sells the futures for €11.50/MWh on each day. BCI realises a profit of (11.50-11)*3,720 = €1,860. This can also be the case in the second scenario where the client is unprofitable with an EGSI of €9/MWh. If BCI sells at €9.50, they again make a profit of (10-9.50)* 3,720 = €1,860. As can be seen in Table 2, the profitability of the client has no effect on the profitability of BCI. Of course, at the start of the day, BCI does not know what the EGSI of that day is going to be. Therefore, BCI attempts to sell at the highest prices possible on a daily basis, and most ideally outperform the EGSI. Currently, the best price is realised by individual traders who manually trade based on experience, fundamental analysis, and intuition rather than a quantitative trading approach.

Table 2: BCI's Perspective.

BCI	**€/MWh**	**MWh**	**Total (€)**
EGSI scenario 1	11.00	3720	-40,920
EGSI scenario 2	9.00	3720	-33,480
BCI selling price scenario 1	11.50	3720	42,780
BCI selling price scenario 2	9.50	3720	35,340
Profit BCI scenario 1			1,860
Profit BCI scenario 2			1,860

1.2 Market environment

The TTF DA gas market is a unique market which distinguishes itself from equity, forex, and commodity markets. It is essential to know the market dynamics before developing a strategy. The TTF DA market is connected to the global gas market which is known to had a high volatility in the past years due to geopolitical turmoil. The price is mainly determined by supply and demand. This is in contrast to stocks, which are often valued using fundamental analysis on financial statements. Furthermore, stocks generally increase in price in the long run as companies grow when reinvesting profits and gaining market shares. This does not apply to gas. For our research we use a unique dataset with OHLCV-values on 1-minute timeframes, between the 2$^{\text{nd}}$ of January 2020 until the 12$^{\text{th}}$ of April 2024. The price movements of the TTF DA gas market are illustrated in Figure 1.

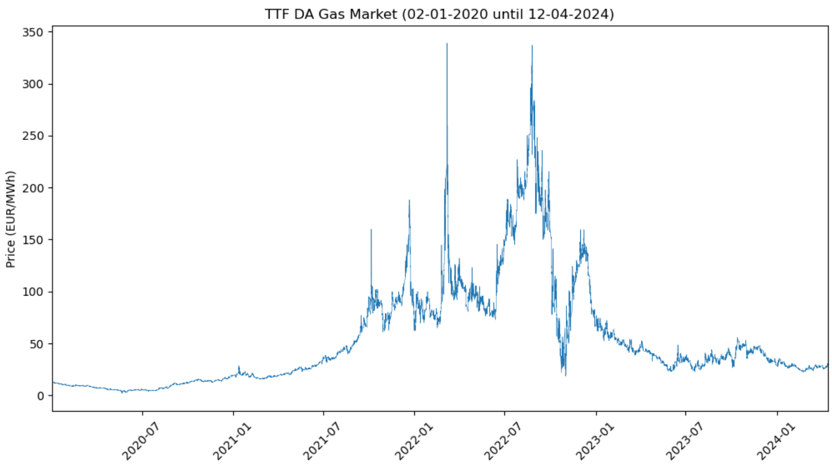

Figure 1: Prices TTF DA Gas Market.

Another factor making the market unique is the Day-Ahead component. Here the gas price is settled for the next day. This results in a unique volume pattern in comparison to other markets. In Figure 2, we provide a bar chart with the average volumes for each 5-minute interval. We observe that in the first hour after the market open at 08:00, almost no trades are made on average. Contrarily, the average volume around 17:20 makes a big jump. Main reason for this is that positions in this market must be liquidated before the end of the day to secure a better payoff. Therefore, many market participants sell their positions before the market close at 18:00.

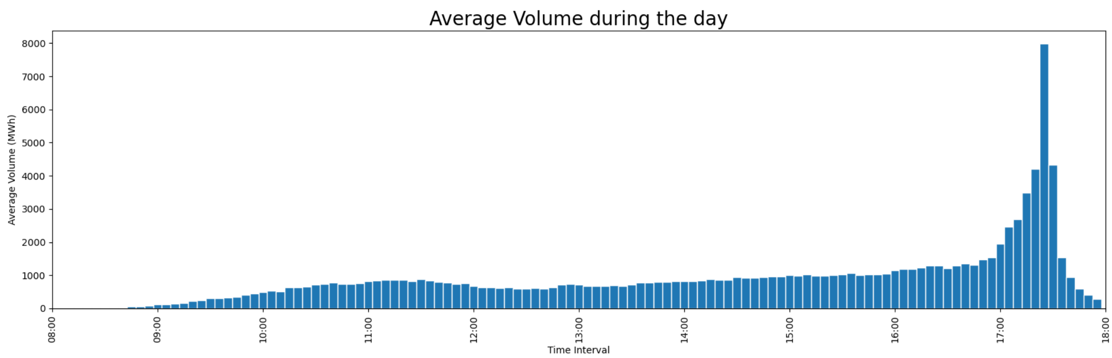

Figure 2: Average Volumes TTF DA Gas Market.

1.3 Geopolitical influences

Lately, there has been a shift in the dynamics of the gas market. Due to tensions around Russia, Ukraine and NATO, the United States imposed sanctions on the Nord Stream pipeline (Reuters, 2021). This pipeline has been constructed to transport natural gas from Russia to Germany through the Baltic Sea, bypassing Ukraine. Nord Stream is primarily owned by Gazprom, a Russian state-owned gas company. On 26$^{\text{th}}$ September 2022, its pipeline was sabotaged by a series of underwater explosions (Reuters, 2024). This rendered three of the four pipelines inoperable, while losing vast quantities of pressurised natural gas. At the time, Europe was dependent on Russian gas for 45% (NGI, 2022). An alternative for Russia is to deliver gas to Europe with ships transporting Liquefied Natural Gas (LNG) (S&P Global, 2024).

However, the LNG network must be expanded to handle the volumes that were previously supplied through the Nord Stream pipeline. This led to a lot of uncertainty about gas supply to Europe. As a result, the volatility in the gas market increased significantly (Chen et al., 2023). This volatile environment adds challenges to traders. On the other hand, bigger fluctuations in gas prices also offer more trading opportunities as more profit can be generated when bought at lower prices and sold at higher prices.

2 Problem identification & Approach

BCI aims to outperform the EGSI when selling their hedged volume in the TTF DA market. This could be achieved using an exit strategy, where the optimal selling (exit) point is determined. Unlike a normal trading strategy, the exit point in this strategy is independent of the entry point, as profits are generated when prices are closed above the EGSI. In contrast, normal trading strategies depend on the entry price and offer more profit potential. This is due to three key reasons: first, there is a wider profit margin between the entry and exit prices than between the EGSI and the exit price, as the EGSI is the volume-weighted average of the day. Second, multiple trades can be executed within the same day. Third, normal strategies allow both long and short positions, enabling traders to capitalise on market reversals during the day. As a result, the EGSI becomes irrelevant as a benchmark for normal strategies. Based on this insight, BCI decided to develop a normal trading strategy that better exploits opportunities in the TTF DA market. Additionally, it provides BCI with deeper insights into systematic trading and its application in this market.

The requirements of BCI can be understood through the lens of an action problem. An action problem arises when there is a discrepancy between the reality and the norm perceived by the problem owner (Heerkens & van Winden, 2017, p. 22). In this context, reality refers to the current situation: BCI lacks a profitable trading strategy that effectively exploits market opportunities and instead relies on individual traders who manually trade based on experience and intuition. The norm, on the other hand, is the desired goal of BCI, which is to have a profitable trading strategy that leverages a quantitative approach to capitalise on market opportunities. To bridge the gap between reality and norm, we need to transform the current reality. Therefore, we must develop a profitable systematic trading strategy for BCI that addresses this discrepancy and resolves the action problem.

A trading strategy can be developed using two approaches (Pardo, 2008, p. 44), the scientific and the empirical approach. With the former, every element must make sense before the testing process starts. With this approach, the trading strategy is transparent. The strategy developer knows which trading rules are used and why the trading strategy makes specific trades. Due to this transparency, observations can be made, supporting further development. The empirical approach uses machine learning techniques. This approach has gained a lot of popularity over the last years due to its accuracy, and its ability to effectively process vast amounts of data, further enhancing its predictive abilities (Ghotbi & Zahedi, 2024). Despite its popularity, the empirical approach has some disadvantages. It often results in complex trading patterns that are hard to comprehend. Also, empirically derived strategies are more likely to be curve-fitting and there are high costs and time efforts associated with the creation and validation of empirically derived strategies (Pardo, 2008, p. 47).

We decide to use the scientific approach for the development of our trading strategy. We prefer to have a transparent strategy, rather than a black-box strategy. This is less stressful for the trader of the strategy, especially during times the strategy generates consecutive losses. Besides, due to the transparency of the strategy, flaws can easily be detected which is beneficial for further optimisation and development.

3 Development framework

The development framework of the scientific approach is based on the following steps mentioned by Pardo (2008, p. 43):

1. Formulation.
2. Specification in computer-testable form.
3. Preliminary testing.
4. Optimisation.
5. Evaluation of performance and robustness.
6. Refinement and evolution.

3.1 Formulation

A trading strategy begins with an idea (Pardo, 2008, p. 49). We identified two approaches to generate this idea: the top-down and bottom-up approach. The top-down approach involves conducting a literature review on various trading strategies that have been successful in the past, which are then optimised for a specific market. In contrast, the bottom-up approach focuses on investigating the components, or trading rules, of trading strategies and assembling these components into a potentially effective strategy. The likelihood of developing a successful trading strategy using the bottom-up approach is lower than with the top-down approach. The primary reason for this is that it is more challenging to justify why specific combinations of components are chosen over others. Additionally, the top-down approach provides a set of strategies that have been proven successful in the past, thereby increasing the chances of selecting an effective strategy. This approach is also more valuable for BCI, as it offers insights into the performance of multiple potentially successful trading strategies rather than focusing on a self-constructed strategy that may have a higher likelihood of failure. Therefore, we adopt the top-down approach to develop our set of strategies. However, we may need to adjust the selected trading strategies to fit the specific characteristics of the TTF DA market. To accomplish this formulation, we must answer the following knowledge questions:

1. Which trading strategies are acceptable for our set?
2. In which ways do we adjust our trading strategies to the TTF DA market while retaining the strategies' original underlying ideas and logical basis?

3.2 Specification in computer-testable form

For the strategies to be testable, we translate them into a language format that our selected testing platform understands. This testing platform processes the price data from the TTF DA market. We select our testing platform based on multiple criteria. Based on these criteria, we select the testing platform that fulfils our needs the best. Therefore, we have the following knowledge question:

3. Which testing platform fulfils our needs?

3.3 Preliminary testing

We prepare the dataset of the TTF DA market for preliminary testing on our testing platform. Furthermore, we evaluate whether our trading strategies do what they are supposed to do and obtain an indication on how our set of strategies perform. If performance disappoints when compared with literature, we must reformulate the strategy or ultimately remove it from our set of trading strategies.

3.4 Optimisation

The formulated strategies are optimised using a search algorithm, which identifies the maximum value of our defined objective function by adjusting the parameters of the trading rules. The choice of search algorithm depends on the one provided by our selected testing platform. To ensure the strategy is robust and not curve-fitted, we compare the objective function values and other performance metrics between in-sample and out-of-sample data. To carry out this optimisation phase, we must address the following knowledge question:

4. Which performance indicators do we use in our objective function?

3.5 Evaluation of performance and robustness

We evaluate the optimised strategies based on the output values of the objective function. Besides, we use additional metrics to assess the robustness and risk of the strategies. Based on the results, we select the best trading strategies, and combine them, if possible, for real-time implementation. We have the following knowledge question:

5. How do we assess the risk and robustness of the optimised strategies?

3.6 Refinement and evolution

Based on the outcomes, we give a conclusion and discussion. We also provide recommendations for further research and improvements in our advisory report. Furthermore, disclaimers are given about potential disadvantages and pitfalls.

3.7 Scope

We have to develop, optimise, and select our trading strategy within a six-month period. This time constraint served as our killer requirement (Heerkens & van Winden, 2017, p. 77), limiting our ability to conduct deeper follow-up research on certain aspects of the strategy. However, we will highlight potential areas for further research and development in our advisory report. The level of modularity of our trading strategy is arbitrary. This means that it is in our own hands what level of complexity we want to give our strategy. A strategy can be really simple, or complex. Simplicity might come at the cost of performance, as it likely to be already exploited by other strategy developers. Contrarily, complexity comes at the cost of time and transparency. We must manage time properly and develop an adequate strategy which has an advantage in the market.

4 Research design

To realise the steps of our development framework, we must answer the identified knowledge questions. For further insights into the development framework and project schedule, we refer to the Gantt chart in Appendix A.

4.1 Knowledge questions

1. **Which trading strategies are acceptable for our set?**
   We conduct a literature review on different trading strategies. We want these strategies to be successful in similar markets or environments as the TTF DA market. This means that we prefer our strategies to be successful in an intraday trading environment, which is not a stock market. With the use of this literature review, we are able to select and formulate the trading strategies that have high potential of success in the TTF DA market.

2. **In which ways do we adjust our trading strategies to the TTF DA market while retaining the strategies' original underlying ideas and logical basis?**
   We investigate the complications of the TTF DA market. Based on these complications, we assess whether our selected strategies do have any shortcomings in the TTF DA market. If this is the case, we slightly alter the strategy to make it functional in the TTF DA market, while retaining the same underlying idea and logic.

3. **Which testing platform fulfils our needs?**
   To implement our selected trading strategies, we need to select a testing platform. We set multiple criteria for this platform. Based on these criteria, we make the choice for our testing platform.

4. **Which performance indicators do we use in our objective function?**
   Trading strategies can be assessed with the use of a wide variety of performance indicators. In the basis, the selection of performance indicators is quite subjective as traders have different trading styles and perceptions of risk. Based on the type of strategy we determine what performance indicators are of great importance. Furthermore, we apply the preferences of BCI in combination with our own logic to make a selection of performance indicators for the objective function.

5. **How do we assess the risk and robustness of the optimised strategies?**
   Besides, the profitability and success of the trading strategy, we also must assess whether the strategies are robust, meaning that they consistently perform in a profitable manner, despite the market movements. Furthermore, we would also like to assess the risk of the trading strategy with the use of different metrics. To realise this, we conduct a literature review on different ways to assess the robustness and risk of a trading strategy.

4.2 Validity

Validity can be seen from two perspectives, external and internal. External validity is the data's ability to be generalised across persons, settings, and times (Schindler, 2008, p. 237). The external validity of our strategy is debatable. The reason for this is that the characteristics of financial markets are always changing due to technical, political, and environmental changes. Therefore, results are likely to be different for different periods. However, as markets do not shift quickly, the blueprint has an adequate external validity in the short term.

Internal validity is about the ability of a research instrument to measure what it is purported to measure (Schindler, 2008, p. 237). In other words, does our blueprint really select a suitable trading strategy? Different performance indicators are used among traders to measure their strategies' performances dependent on their trading style and requirements. Therefore, it is debatable whether our designed blueprint offers a high internal validity. However, our blueprint is backed with valid arguments, concrete values from multiple performance indicators, and logical reasoning. This enhances the internal validity of the blueprint's outcome.

4.3 Deliverables

In the end, we deliver the following items:

- **Strategy set justification**
  We provide a literature review on various trading strategies and explain why we select certain trading rules and strategy characteristics over others for our set of strategies. Our choices for strategies are based on a set of defined criteria.

- **Strategy formulation**
  We provide the formulation of our trading strategies to ensure repeatability. This includes the definitions of the trading rules that we use and the underlying assumptions. Additionally, we define our trading strategies in a scripted form which can be understood by our selected testing platform.

- **Blueprint**
  During the process of our research, we develop a blueprint which selects the most suitable out of a set of given strategies. This blueprint makes use of multiple performance metrics. With the blueprint, we make a conclusion about what the best most suitable is. This blueprint is applicable to other markets.

- **Advisory report**
  During the development and optimisation of the trading strategies, we come across several shortcomings or alternative ideas. Due to our killer requirement, we are not able to implement all of these alternative ideas. Therefore, we recommend and mention these in the advisory report.

- **Disclaimers**
  During the research and development, we discovered potential pitfalls or shortcomings regarding the execution in practice of the trading strategies. We mention potential disclaimers which we discovered during the research and development of these.

5 Literature review

We investigate the core components of trading theory. Furthermore, technical analysis is often a core component in systematic trading strategies. Therefore, we introduce the state of the art of technical analysis. Additionally, we introduce the Efficient Market Hypothesis. In the end we investigate multiple trading strategies that meet our criteria. The aim is to obtain a set of strategies with high potential which can eventually be formulated for backtesting.

5.1 Trading theory

It is essential to introduce the basic elements used in the discipline of trading. A trading strategy can consist of the following elements:

1. Entry & Exit.
2. Stop & Target.
3. Position sizing technique.
4. Timeframe.

Entry & Exit

An entry is the point where a trade is entered. This is a long (short) position when the trader expects the market to go up (down). Here, we speak of a bullish (bearish) trend. In trading strategies, technical indicators are used to determine when to enter the market and whether to take a long or short position. An exit is the point where the trade is exited, preferably at a winning position. The perfect exit is when there is no more advantage to be obtained from the trading position. Also, exits make use of technical indicators to determine when to exit the trade. An entry and an exit together are considered to be a trade.

Stop & Target

Stops and targets are optional, and are a form of risk management, as they minimise losses or lock in profits, respectively. Losses are minimised with stops, or stop-losses. Stop-losses close the trade when the price goes to a less profitable direction to a certain extent. On the other hand, targets close the trade when the trade is in a profitable position to a certain extent. All in all, stops and targets are a form of risk management regarding the profitability of a trade.

Position sizing technique

Another form of risk management is the position sizing technique. This determines the quantity invested in each trade. This quantity can be determined with a fixed percentage of the total equity available, or a dynamic percentage based on real time performance of the strategy. Besides a fixed unit size, other formulae are also possible. The goal of the position sizing technique is to maximise profits, while managing the risk of losing the total equity available.

Timeframe

Trading strategies can be applied to different timeframes, which determine the data used to calculate technical indicators for entries, exits, stops, and targets. In a 5-minute timeframe, five types of data are used for each 5-minute interval: the first price (Open), the highest price (High), the lowest price (Low), the last price (Close), and the quantity traded (Volume). These OHLCV values are the inputs for calculating technical indicators. The selection of the timeframe influences the performance of the trading strategy as it determines the granularity and precision of the data, as well as the level of exposure to market noise.

5.2 Technical analysis

Three types of analysis in the field of security analysis are fundamental, sentiment, and technical analysis. Fundamental analysis assesses the intrinsic value of a security by analysing financial statements, external influences, events, and industry trends. Sentiment analysis investigates the contents of posts on social media, news articles and words spoken by CEOs in interviews, to obtain an indication whether the sentiment is optimistic (bullish) or pessimistic (bearish).

Technical analysis can be defined as the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends (Murphy, 1999). Technical analysis consists of two categories: charting techniques, and technical indicators. Charting involves the visual identification of patterns in price charts, such as channels and trends. Based on these patterns, future price movements are predicted. Charting techniques are generally applied by visual inspection, being rather subjective. On the contrary, technical indicators are concrete statistical rules which provide buy and sell signals (Popov & Madlener, 2014). Technical indicators provide a more consistent and disciplined approach than charting techniques. Due to their concreteness, technical indicators are ideal for computerisation and systematic trading strategies in contrast to charting techniques.

5.3 Efficient Market Hypothesis

Technical indicators reject the Efficient Market Hypothesis (EMH), which states that it is impossible to consistently achieve superior returns to those of the market on a risk-adjusted basis by using historical information (Fama, 1970). There are three levels of market efficiency. These are the weak, semi-strong, and the strong form. The weak form of the EMH, states that the prices of securities reflect all available public market information. Historical information regarding price, volumes and returns are independent of future prices. Therefore, it dismisses the usefulness of technical analysis. With the semi-strong EMH not only the weak form holds, but it also expands on the hypothesis that prices adjust quickly to publicly announced news. Therefore the semi-strong form not only dismisses the usefulness of technical analysis, but also of fundamental analysis. With the strong form, not only the semi-strong form holds, but it also expands on the hypothesis that prices in the market reflect private information. Therefore, according to the strong form, not even insider knowledge can give investors an advantage. The EMH is supplemented with Random Walk theory, which suggests that trading rules are useless for predicting future price movements. Therefore, returns are random. In this perspective, successful investors are seen as lucky, as they consist of a small group of outliers (Malkiel, 1996) (Statman, 2002).

The question if markets are truly efficient has been a major debate among academics and investors for decades. Multiple studies support (Malkiel, 1996) and reject (Jagadeesh and Titman, 1993) the EMH. Brock et al. (1992) supports the efficiency of technical indicators and rejects the weak form of the market hypothesis. On the contrary, critics claim that the efficiency of technical analysis is solely based on the self-fulfilling prophecy effect (Merton, 1948) where bullish or bearish patterns cause periods of buying and selling. Despite comprehensive research in this field, there is still no consensus. In our research, we test the gas market for the weak form EMH, where our strategies are solely based on past prices.

5.4 Trading strategies

We conduct a literature review on multiple trading strategies. The end goal of this literature review is to gain knowledge about the underlying idea and logic of these strategies in order to formulate them on our testing platform and eventually optimise them. We have multiple criteria for the trading strategies. Based on these criteria, we select the strategies that we want to formulate.

5.4.1 ORB Strategy

A commonly used strategy in intraday trading is the n-minute Opening Range Breakout (ORB) strategy. During the first n minutes of the day, two thresholds are created. When in the period after the first n minutes, the upper (lower) threshold is crossed, a long (short) position is taken if the trend was bullish (bearish) in these first n minutes. Profits are taken at exits or at the end of the day (Target EoD). Losses are limited with the use of different types of stop-losses.

Sönnert (2015) applied an ORB strategy on the gold futures market and concluded that ORB strategies could be profitable when using narrow thresholds. Zarattini and Aziz (2024) proved that day trading can be profitable by using the ORB strategy with leveraged trades. They found that the best results are achieved with tighter stops and large profit targets, which is in line with the findings of Sönnert (2015). This empirically confirms the correctness of the commonly used saying to cut losses quickly and to let profits run. In other research, Zarattini et al. (2024) discovered that a smaller opening range results in more profitable performance of the ORB strategy. The ORB strategy can be enhanced by implementing the *Relative Volume*. This is a statistical comparison of the day's trading volume during the first n minutes, against the average volume from previous days. *Relative Volume* has the following formula (Zarattini et al., 2024):

$$\text{RelativeVolume}_t = \frac{\text{ORVolume}_t}{\frac{1}{14}\sum_{i=1}^{14} \text{ORVolume}_{t-i}}. \tag{1}$$

Here, the *ORVolume* is the volume during the first n minutes on trading day t. When the *Relative Volume* of a security is high, the security is considered to be "in play". Meaning that some catalyst has triggered abnormal trading activity. Zarattini et al. (2024) found that there is a strong correlation between the *Relative Volume* and the profit of a trade when using the ORB strategy. Because of this, Zarattini et al. (2024) implement the *Relative Volume* to select specific stocks that are in play. This resulted in remarkably better results than the initial n-minute ORB strategy. In the TTF DA market, we do not have the advantage to choose stocks with a high *Relative Volume*. In spite of this, *Relative Volume* might still play a pivotal role in determining whether we enter a position in the gas market or not.

5.4.2 Cross-over strategies

Cross-over strategies are often used with moving averages. There are two types of moving averages (MAs). These are the Simple Moving Average (SMA) and the Exponential Moving Average (EMA). SMAs use the averages of prices during a specified window. For example, the 50- and 200-day SMA cross-over strategy is often used. When the 50-day SMA crosses above the 200-day SMA, it is a so-called "golden cross", an indication of a long-term bullish market (Schwab, 2023). When the 50-day SMA crosses under the 200-day SMA it is a so-called "death cross", an indication of a long-term bearish market (Schwab, 2023). Moving averages are lagging indicators as their value is determined by the average of historical data. Due to this lagging characteristic, moving averages do not always suggest tops and bottoms in the market when crossed. Especially for smaller timeframes, when there is a lot of market noise, SMAs are not efficient indicators for intraday trading strategies. In spite of this, SMAs are commonly used as trend confirmation. For example, when the SMA with a small window crosses above the bigger window SMA, it confirms a sudden rise in price, indicating a potential start of a bullish trend. This trend confirmation can be used in combination with other technical indicators, resulting in more accurate entries or exits of trades.

The EMA is more responsive than the SMA. This is because it assigns greater weights to more recent prices than older ones. The EMA can also be used in cross-over strategies in a similar way as explained for the SMA. Because of its characteristics, the EMA cross-over strategy is more efficient for intraday trading than an SMA cross-over strategy. Due to its commonality, EMAs are used by traders in all kinds of markets. The formula for the EMA is as follows (Capital, 2024):

$$\mathrm{EMA}_t = \frac{P_t - \mathrm{EMA}_{t-1}}{k+1} + \mathrm{EMA}_{t-1}. \tag{2}$$

Here:

$$\begin{aligned} EMA_t &: \text{Exponential moving average at time } t. \\ EMA_{t-1} &: \text{Exponential moving average at time } t-1. \\ P_t &: \text{Price at time } t. \\ k &: \text{Smoothing factor, number of periods minus 1.} \end{aligned}$$

5.4.3 Turtle Trading Strategy

The Turtle Trading Strategy (TTS) has been developed by Richard Dennis and William Eckhardt (Covel, 2009). The TTS is considered one of the most famous trading strategies ever applied in history. In an experiment, the strategy was provided to participants without any initial trading knowledge. The participants only traded commodities. With this strategy and the provided starting capital, the participants earned over one hundred million dollars in four years. Based on this, Richard Dennis claimed that "everyone can be a great trader when being disciplined and consistent in following a set of trading rules". Because of the popularity of this "market legend", we are interested in the actual potential of the TTS.

In the simplified TTS, a trade is entered when the price crosses the highest close of the last 20 days, assuming a further trend upwards. Therefore, the turtle strategy can be considered as a breakout strategy (Donchian, 1960). These highest and lowest closes during a certain period are called Donchian Channels (DCs) when graphed. Therefore, such strategies are often referred to as Donchian Channel Strategies (DCSs). The trade is exited when the close crosses the lowest close in 10 days. Also, a stop-loss is used which is triggered when the close is equal to the entry price minus two times the Average True Range (ATR).

The ATR is often implemented in stop-losses because it incorporates the volatility of a security. It measures the market volatility by decomposing the entire range of an asset price over that period (Wilder, 1978). When using the ATR, we use $n = 14$ periods. The ATR was initially developed for commodities (Wilder, 1978) and is considered to be a useful tool to incorporate in a trading system as a risk management tool. The general formula for the ATR is as follows:

$$\text{ATR} = \frac{1}{n}\sum_{i=1}^{n} \text{TR}_i. \tag{3}$$

Here:

$$\begin{aligned} \text{TR}_i &: \text{True Range of period } i. \\ n &: \text{number of periods.} \end{aligned}$$

$$\text{TR} = \max\left[(H - L), |H - C_p|, |L - C_p|\right]. \tag{4}$$

Here:

$$\begin{aligned} H &: \text{Today's high.} \\ L &: \text{Today's low.} \\ C_p &: \text{Yesterday's closing price.} \end{aligned}$$

The trading rules for the simplified TTS can be summarised as follows:

Entry:	if Close is equal or higher than the highest close in 20 days.
Exit:	if Close is equal or less than the lowest close in 10 days.
Stop:	if Close is equal or less than entry price minus 2*ATR.

In today's market conditions, the TTS does not perform well on a daily timeframe. However, by adjusting the entry and exit conditions, this system can become a profitable strategy. Bruch (2024) demonstrates that this strategy can become profitable for historical gold prices by adding a trend filter. This is done by adding an SMA cross-over condition to the entry condition. However, this adaptation of the TTS does not fit with our intraday criterion. This is because this adaptation uses a daily timeframe. However, we can still apply the original underlying idea and adapt it in our own way to make it work for the TTF DA market.

5.4.4 RSI strategy

One of the most popular technical indicators is the Relative Strength Index (RSI). The RSI is classified as a momentum indicator. It measures the rate at which the price increases or decreases (Zatwarnicki et al., 2023). When the RSI reaches high levels, for example above 70, the market is considered overbought. Vice versa, the market is considered oversold when the RSI is below 30. The RSI is calculated as follows (Wilder, 1978):

$$\mathrm{RSI} = 100 - \frac{100}{1 + \mathrm{RS}}. \tag{5}$$

Here:

$$\mathrm{RS} = \frac{\text{Avg. Gain}}{\text{Avg. Loss}}. \tag{6}$$

In this formula the RSI is dependent of a period of 14 intervals on which the averages are calculated. A common strategy is to go long when the RSI crosses below 30 and to short when the RSI crosses above 70. In research, the RSI assists with predicting price movements and significantly reduces the risk when trading cryptocurrencies (Zatwarnicki et al.,2023). They tested this strategy on a daily timeframe to overcome complexity and avoid the problem of data availability for smaller timeframes.

5.4.5 Candlestick trading

Japanese candlesticks have been developed by Munehisa Honma, a Japanese rice merchant that traded on the Dōjima Rice Exchange in Osaka during the Tokugawa Shogunate. One candle depicts the Open, High, Low, and Close price (OHLC) during a specific period. A candlestick contains all OHLC data for a specified timeframe. A visual representation of a candle stick is provided in Figure 3. Here, a white (black) candle depicts a bullish (bearish) period.

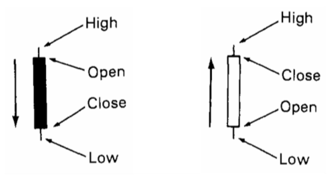

Figure 3: Candlestick explained.

Certain relations between these OHLC values, or specific sequences of these, can be an indication of a specific market direction in the future (Nison, 2001). There are many candlestick patterns that can indicate a market reversal, such as the *bullish engulfing*, *bearish harami*, *morning star*, or *tweezer tops* as shown in Figure 4. The *bullish engulfing pattern* is an indication of a market reversal from bearish to bullish. In this case, the open of the second day is lower than the close of the previous day, but despite the "bad start", the close of the second day is even higher than the open of the previous day, indicating more buyers entering the market, indicating a market reversal to the upside. Son et al. (2018) analysed the predictability of multiple candlesticks patterns on the Vietnamese stock market. They found that the *bullish harami*, *bullish engulfing*, and the *piercing pattern* obtain the best results in profitability, despite being well above the 5% significance level. The *piercing pattern* was the rarest, but the *harami* and *engulfing pattern* are the most common patterns.

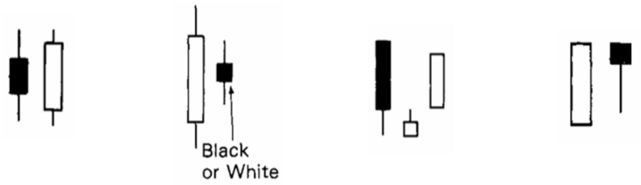

Figure 4: Bullish Engulfing, Bearish Harami, Morning Star, and Tweezer Tops.

Candlesticks draw a lot of criticism. This is because trading techniques that are focused on price action suffer from the disadvantage of market's noise (Chandrinos and Lagaros, 2018). For example, one candlestick might provide a long signal, and the next a short signal. This noise comes from the interaction between traders and institutions attempting to establish their opinion in the market (Chandrinos and Lagaros, 2018). However, Martinsson and Liljeqvist (2017) used the candlestick patterns in combination with technical indicators, such as the RSI to cancel this noise. They found this can have a positive effect on the profitability of a trading strategy. Another way to solve the noise of candlesticks is with the use of Heikin-Ashi or Renko charts (Chandrinos and Lagaros, 2018).

5.4.6 Criteria

For our strategies, we set multiple criteria. These criteria are based on the conditions of the TTF DA market, and the preferences of BCI. The criteria that our strategies must satisfy are:

- **Profitability**
  The strategy has performed well in history. This means that the strategy was able to realise a reasonable return over time, preferably in a consistent and non-volatile manner.
- **Intraday trading focus**
  The strategy should exploit the opportunities in the TTF DA market. The Day-Ahead market implies that we have to trade intraday. Intraday means that trades are made within the day. This is in contrast to interday trading, where entries and exits can be on different days. Because the strategy has to support intraday trading, profits must be realised within short time frames. Therefore, the strategy has to perform well with small time frames, such as 1min, 5min, 10min, 15min or 30min.
- **Non-stock**
  The strategy has to be tested in similar market environments as the TTF DA market. This market is more dependent on technical analysis, due to less fundamental indicators, unlike stock markets. Therefore we want our strategies to be applied in non-stock markets. We prefer the strategies showing promising results in commodity, forex, or crypto markets. These are less dependent on fundamental analysis as no fundamental analysis on financial statements can be performed in these markets.

When we assess the strategies on these criteria, we obtain the following results in Table 3:

Strategy	Profitability	Intraday trading focus	Non-stock
ORB	Good	Applicable	Yes
DCS	Good	Applicable	Yes
RSI	Medium	Applicable	Yes
Candlestick	Questionable	Applicable	No
SMA cross-over	Medium	Inefficient	Yes
EMA cross-over	Good	Applicable	Yes

Table 3: Comparison of trading strategies.

We observe that the most promising strategies are the ORB, DCS, and EMA cross-over. We include these in our set of strategies. Furthermore, we decide to exclude the candlestick strategy from our set of strategies. The reason for this is that the candlestick strategies have not been backtested in a similar market environment, and their profitability is questionable. Furthermore, there is a lot of criticism towards Japanese candle sticks. Besides, there is a high number of candlestick patterns, for both long and short positions, which makes developing such a strategy rather time-consuming, which interferes with our killer requirement. We also decided to exclude the SMA cross-over strategy. This is because the EMA cross-over strategy is more efficient than the SMA, due to its higher level of responsiveness. As for the RSI strategy, we have no objections as it has reasonable results in our table. Therefore, we also include the RSI strategy in our set of strategies.

6 Backtesting preparation

6.1 Market complications

The uniqueness of this market brings some complications. The limited volume during the first hour can bring some issues for existing strategies to perform as they are supposed to. Either the dataset must be altered in such a way that the strategies perform well, or the strategies must be adapted to the current market dynamics. Both options have their advantages and disadvantages.

When we change the dataset, for example we cut off the first hour after the open, Our strategies are more likely to operate in the way we want. However, the question is whether some technical indicators in these strategies are measured correctly. For example, moving averages are not measured in the first hour. We are not sure whether such indicators give a good reflection of the market, despite the low volume in the first hour. We have similar issues with the opening range. When we use the opening range an hour later, it is debatable whether the original underlying idea of the ORB strategy still holds, which is that an external catalyst in the market affects the price movement in the opening range.

If we adapt our strategies to the dataset, we also run the risk of eroding the underlying ideas of the strategies. Some technical indicators behave strangely due to the lack of price movements in the first hour. This is especially the case with moving averages, Donchian Channels, and the RSI. Moving averages come unnecessarily close to the actual price during the first hour. Donchian Channels represent the highest and lowest prices during the last n periods, which are easily broken when trades are made after the first hour, due to the long period of no price changes. Because of this period of no price movements, calculations of the RSI are more likely to obtain divide-by-zero errors.

Our scope is to develop a strategy that is suitable for implementation in the TTF DA market. Therefore, we want to apply these strategies on a dataset which is highly representative with the TTF DA market. Therefore, we do not remove or alter major parts of our dataset. Instead we adapt our strategies to the market, despite the downsides.

6.2 Testing platform selection

To specify our trading strategy in computer testable form, we must select a testing platform. For our testing platform, we have the following criteria:

1. **Dataset implementation.**
   We have a unique dataset which cannot be easily uploaded to testing platforms. We have a Microsoft Excel dataset with the OHLCV values on 1-minute timeframes. Our testing platform has to load this dataset and interpret it in the way it is supposed to.
2. **No indicator limitations.**
   Sophisticated trading strategies often consist of multiple technical indicators. Some online testing platforms allow you to use a limited number of these. We prefer to have a testing platform where the number of technical indicators that can be used is no limitation.
3. **Zero cost.**
   We prefer a testing platform with zero cost.
4. **Optimisation.**
   In addition to backtesting, optimising the trading strategy is crucial for identifying the most optimal parameters. Therefore, it is essential for our testing platform to include a built-in function that optimises the strategies we formulate.

	1	2	3	4
AmiBroker	No	Yes	No	Yes
Backtesting.py	Yes	Yes	Yes	Yes
MetaStock	No	Yes	No	No
TradeStation®	No	Yes	No	Yes
TradingView PineScript™	No	Yes	Yes	No

Table 4: Comparison of testing platforms.

Five testing platforms have been analysed for each criterion in Table 4. The Backtesting.py library in Python satisfies all our needs. Therefore, we select this as our testing platform.

6.3 Data Preparation

We obtained a dataset for the 1-minute intervals on the TTF DA market between 2^{nd} of January 2020 to 14^{th} of April 2024. Due to the low number of trades within these 1-minute timeframes, we decided to alter the dataset to 5-minute timeframes. In the original dataset, some 1-minute timeframes have no volume and therefore no data. We temporarily fill these spaces with the latest data. The problem now is that, sometimes when there is no volume, non-identical OHLC values are repeated. We must solve this as there is no price action in these timeframes. Therefore, we change all OHLC values with the latest close price, when there is no volume. If there was no volume until the market open, the close price of the market open is used.

We obtain OHLCV values for each 5-minute timeframe. The open of the 5-minute timeframes equals the first Open of each set of five 1-minute timeframes. Furthermore, the High is the Maximum, the Low is the Minimum, and the Close is the last close of each set. The Volume is the sum of the volumes of each set. After this, we remove the rows in our data set with dates and times when no trades are made. These are the following dates and times:

- All times outside of the trading hours of 8:00 - 18:00.
- Weekend days.
- Trading/banking holidays:
  - New Year's Day.
  - Good Friday.
  - Easter Monday.
  - Labour Day.
  - Christmas Day.
  - Boxing Day.

7 Formulation

We formulate the strategies that we use as a basis for our optimisation process. Due to the nature of the Day-Ahead market, we cannot trade interday, but only intraday. We solved this problem by adding an End of Day (EoD) target. This closes the position right before the market close. Our idea is that when we enter a trade, we expect it to become profitable, therefore trades entered should at the end of the day have a profit on average. For all our strategies, we use 5-minute timeframes. If applicable, we use a common stop for our strategies which equals the entry price minus (plus) two times the ATR for long (short) positions. We use a position sizing technique where a position is taken of 20% of the total equity available for each trade, with a starting equity of €1,000. Furthermore, the commission costs are €0.0085/MWh.

We test the set of strategies using 5-minute timeframes. The issue with using larger timeframes is that indicators, such as an SMA with a window of 5 on a 10-minute timeframe, are essentially equivalent to those with a window of 10 on a 5-minute timeframe. As a result, enlarging the timeframe does not necessarily yield a more precise or optimal strategy for our set of strategies.

Additionally, increasing the timeframe reduces the granularity and specificity of the data, potentially missing price swings within those intervals. These are lost opportunities for profitable trades. For more insights into the Python code of the following strategies, we refer to Appendix C.

ORB

The problem with the TTF DA market is that mostly in the first two hours after the open, there is no volume. This is quite contradictory to the underlying idea of the ORB strategy in the literature. To solve this problem, we select the 10:00 – 10:10 interval as ORB. In this way we skip the first two hours with low volume. Based on this "opening range" we obtain our high and low ranges, which determine our entry conditions. Of course, trades can only be made after this interval, because from then we know the high and low ranges of the ORB. The formulation is as follows:

Long position:

Entry:	ORB close > ORB open, and close > ORB high.
Stop:	Entry price – 2 * ATR.
Target:	EoD.

Short position:

Entry:	ORB close < ORB open, and close < ORB low.
Stop:	Entry price + 2 * ATR.
Target:	EoD.

DCS

The Donchian Channel Strategy (DCS) consists of two technical indicators. These are the high (DCH) and low (DCL) bands of the Donchian Channel. The trading rules for a long position have a DCH and DCL with a window of $n1 = 10$, and $n2 = 20$, respectively. For the short position the DCH and DCL have a window of $n3 = 20$ and $n4 = 10$, respectively. This is based on the original system 1 TTS (OxfordStrat, 2003). The formulation is as follows:

Long position:

Entry:	Close = DCH($n1$), and DCH($n1$) > previous DCH($n1$).
Exit:	Close = DCL($n2$), and DCL($n2$) < previous DCL($n2$).
Stop:	Entry price – 2 * ATR.
Target:	EoD.

Short position:

Entry:	Close = DCL($n3$), and DCL($n3$) < previous DCL($n3$).
Exit:	Close = DCH($n4$), and DCH($n4$) > previous DCH($n4$).
Stop:	Entry price + 2 * ATR.
Target:	EoD.

EMA

For the EMA cross-over strategy, we do not use a stop-loss. This is because when the strategy exits a long position, it directly enters a short position and vice versa. Therefore, a stop-loss is not necessary. For the small window EMA, we use $n1 = 12$ timeframes, and for the big EMA window we use $n2 = 26$ timeframes. The formulation for the EMA strategy is as follows:

Long position:

Entry:	EMA($n1$) > EMA($n2$).
Exit:	EMA($n1$) < EMA($n2$).
Target:	EoD.

Short position:

Entry:	EMA($n1$) < EMA($n2$).
Exit:	EMA($n1$) > EMA($n2$).
Target:	EoD.

RSI

For the RSI, we use the recommended window of 14 timeframes (Wilder, 1978). We enter (close) a long (short) position when the RSI is below 10. This indicates that the market is heavily oversold. We close (enter) a long (short) position when the RSI is 90, which indicates that the market is heavily overbought. We use the RSI(10, 90) over the standard RSI(30, 70) because with extremer values, there is a stronger likelihood of a trend reversal. Besides, more distant RSI values reduce the frequency of trades to more realistic proportions. The formulation for the RSI strategy is as follows:

Long position:

Entry:	RSI < 10.
Exit:	RSI > 90.
Stop:	Entry price – 2 * ATR.
Target:	EoD.

Short position:

Entry:	RSI > 90.
Exit:	RSI < 10.
Stop:	Entry price + 2 * ATR.
Target:	EoD.

8 Blueprint

We develop a blueprint which assists in selecting the most suitable for a given set of strategies. This blueprint, a design which explains how the most suitable strategy can be identified, uses multiple metrics and benchmarks to compare and assess the performances of the strategies.

8.1 Performance indicators

We conduct a literature review on different performance indicators. Based on this, we select the most suitable indicators for our objective function based on logic and our reasoning. The objective function enables us to optimise and compare our set of strategies.

Win Rate

We noticed that many traders use the Win Rate (WR) to assess their strategies. This is the percentage of profitable trades (Investopedia, 2022). However, this may give a false perception of the performance of a trading strategy. If many winning trades have tiny profits and a few losing trades have huge losses, the WR is high, but the profitability is low. We rather make money than be right most of the time. Therefore, we decide to not implement the WR in our objective function. The formula for the WR is as follows:

$$WR = \frac{\#\text{ profitable trades}}{\#\text{ trades}}. \tag{7}$$

Maximum Drawdown

The Maximum Drawdown (MDD) is the largest drop in equity measured from equity high to a succeeding equity low (Pardo, 2008, p. 83). The MDD is considered to be one of the best measurements of the overall risk of a trading strategy (Pardo, 2008, p. 83). However, it is still an approximation of overall strategy risk (Pardo, 2008, p. 83). Statistically, there is likely to be some degree of variability in all performance statistics calculated by historical simulation. Therefore, the MDD is often multiplied by a safety factor which mitigates this variability (Pardo, 2008, p. 83).

$$\text{MDD}(\%) = \max_t D_t = \max_t \left(\frac{M_t - P_t}{M_t} \right). \tag{8}$$

Here M_t is the running maximum of the portfolio:

$$M_t = \max_{0 \leq s \leq t} P_s. \tag{9}$$

D_t is the drawdown at current time t.

Profit Factor

The Profit Factor (PF) is the ratio of gross profits to gross losses (Investopedia, 2022). It shows how many euros you gain for each euro that you lose on average. A PF higher than 1 indicates that profits outweigh losses. Between 1.5 and 2.0 it is considered good, and a PF above 2.0 is considered as extremely profitable. A high PF is also desirable as it indicates less big drawdowns.

$$\text{PF} = \frac{\text{Gross Profit}}{\text{Gross Loss}}. \tag{10}$$

Reward to Risk Ratio

The Reward to Risk Ratio (RRR) is calculated by dividing the Net profit by the MDD. A large RRR implies that the reward per trading dollar is more relative to its risk. As a rule of thumb, the RRR should be at least 3 (Pardo, 2008, p. 273). By maximising this ratio, large drawdowns are minimised while maximising net profits.

$$\text{RRR} = \frac{\text{Net Profit}}{\text{MDD}}. \tag{11}$$

Sharpe ratio

A well-known metric for optimisation is the Sharpe Ratio (Pardo, 2008, p. 94). It calculates the performance of the strategy compared to a risk-free asset, after adjusting for its risk. More precisely, it is the difference between returns of the strategy and the risk-free return, divided by the standard deviation of the strategy returns (Stanford University, 2024). As known, high returns often come with high risk. With the Sharpe Ratio we can offset these variables to each other and analyse whether the amount of risk related to the return is high or not.

$$\text{Sharpe ratio} = \frac{R_S - R_F}{\sigma_S}. \tag{12}$$

Here:

R_S : Return of strategy.

R_F : Risk free rate of return.

σ_S : Volatility of strategy returns.

A disadvantage of the Sharpe ratio is that it does not take tail risk into account. This is because the volatility is based on a normal distribution, which is not the case in financial markets (Mandelbrot, 1963). Here, extremely high and negative returns appear more often when compared to a normal distribution. This creates thicker tails in the distribution of returns. However, we mitigate the tail risk with the use of stop-losses to cut extreme losses. Besides, we further mitigate this risk with the use of a position sizing technique which makes sure to only use a fixed percentage of the total equity for a trade.

Sortino ratio

The Sortino ratio differs slightly from the Sharpe ratio (Red Rock Capital, 2024). It uses the standard deviation of the negative strategy returns, or downside volatility. The Sortino ratio appears to give a better view on the strategy's performance on a risk-adjusted basis since positive volatility is a benefit. The Sortino ratio has the following formula:

$$\text{Sortino ratio} = \frac{R_S - R_F}{\sigma_d}. \tag{13}$$

Here:

R_S : Expected return of strategy.

R_F : Risk free rate of return.

σ_d : Volatility of strategy's negative returns.

Calmar ratio

The Calmar ratio is the annualised return divided by the MDD (Young, 1991). It is another way to measure a strategy on a risk-adjusted basis. A possible downside of the Calmar ratio is that its interpretation of risk is only based on the MDD and not on the volatility. The formula for the Calmar ratio:

$$\text{Calmar ratio} = \frac{\text{Annualised Return}}{\text{MDD}}. \tag{14}$$

Van Tharp's System Quality Number

The System Quality Number (SQN) is designed to find good quality trading strategies (Van Tharp, 2013). A high quality strategy is both tradeable and efficient. A strategy is considered tradeable when it has a low volatility. It is efficient when it generates reasonable amounts of profit (IndexTrader, 2020). The SQN can be calculated with the use of the formula (Van Tharp, 2013):

$$\text{SQN} = \frac{\text{AverageReturn}}{\sigma_S} \times \sqrt{\text{Trades}}. \tag{15}$$

$$\begin{aligned} &\text{Here:} \\ AverageReturn &: \text{Expected return of strategy.} \\ \sigma_S &: \text{Volatility of strategy returns.} \\ Trades &: \text{Number of trades.} \end{aligned}$$

The values of the SQN can be interpreted according to the table below (IndexTrader, 2020):

SQN	System Quality
<1	Hard to trade
1-2	Average
2-3	Good
3-5	Excellent
5-7	Superb
7>	Holy Grail

Table 5: SQN and system quality.

Unfortunately, the SQN has some downsides (IndexTrader, 2020). The first factor shows a bias for strategies with a narrow distribution of reward/risk ratios. Because of this, the SQN favours mean-reverting strategies (IndexTrader, 2020). The second factor shows that the SQN increases when the number of trades increases. This makes it difficult to compare strategies with different numbers of trades. Van Tharp acknowledges this last point and suggests traders to use 100 arbitrary trades when a strategy has more than 100 trades (IndexTrader, 2020). However, this leaves too much space for variability.

8.2 Objective function

We discuss the components that are included in the objective function to realise the optimisation and comparison of the strategies.

8.2.1 Sharpe ratio & Profit Factor

We conclude that the Sharpe ratio and Profit Factor are the best indicators for our objective function, as they both aim to maximise profitability and minimise risk. Maximising the Sharpe ratio increases returns while reducing both systemic and non-systemic risk by lowering volatility. Similarly, maximising the PF increases the number of profitable trades while decreasing the number of unprofitable ones. This, in turn, suggests a positive impact on the Sortino ratio, as fewer unprofitable trades lead to reduced downside volatility. Additionally, a higher PF improves both the Calmar ratio and the Reward to Risk Ratio, since fewer unprofitable trades result in smaller drawdowns. Therefore, the PF is positively correlated to many performance indicators, making it an almost ideal metric. The Sharpe ratio complements the PF by incorporating systemic and non-systemic risk. The PF complements the Sharpe ratio by reducing the number of losses, resulting in less frequent and smaller drawdowns. Therefore, the product of the Sharpe ratio and PF is perfect as a basis for the objective function.

8.2.2 Commission costs

Additionally, we also want to incorporate commissions in our objective function. Some strategies make more trades, resulting in higher profitability. However, this also leads to more commission costs. It is realistic to incorporate those costs in our objective function to find the most profitable trading strategy while taking commission costs into account. The total commission cost of BCI on the TTF DA equals €0.0085/MWh. We calculate the total commission costs of the strategy at the end of the backtesting session. In this way, we prevent commission costs to influence the position sizing of our strategy. Thus, commission costs are not included in the drawdowns. We assume that commission costs do not have a significant effect on the drawdowns of a trading strategy, because these are relatively small when compared to the absolute profits and losses. We include the commission costs in the PF and the annualised return of the strategy.

8.2.3 Volatility

For the Sharpe ratio, we must calculate the annualised volatility of the returns. To calculate this, we use the daily returns from the equity portfolio. The daily returns are compounded, which results in the final equity of our portfolio. Concluding, we have the following formula for the annual return:

$$R_A = \prod_{t=1}^{T} (1 + R_{D,t}) - 1. \tag{16}$$

Here:

$R_{D,t}$: Return on day t.

T : Number of trading days in a year (255).

To calculate the mean and volatility of the annualised return, we use the following formulae derived by Tobin (1965):

$$\mu_A = (1 + \mu_D)^T - 1. \tag{17}$$

$$\sigma_A = \sqrt{(\sigma_D^2 + (1 + \mu_D)^2)^T - (1 + \mu_D)^{2T}}. \tag{18}$$

Here:

$$\begin{aligned} \mu_A &: \text{Annualised geometric mean of returns.} \\ \sigma_A &: \text{Annualised volatility of returns.} \\ T &: \text{Number of trading days in year.} \\ \mu_D &: \text{Geometric mean of daily returns.} \\ \sigma_D &: \text{Volatility of daily returns.} \end{aligned}$$

Where:

$$\mu_D = e^{\frac{1}{N}\sum_{t=1}^{N} \ln(1+R_{D,t})} - 1. \tag{19}$$

$$\sigma_D = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N} (R_{D,t} - \mu_D)^2}. \tag{20}$$

Here:

$$N : \text{Total number of trading days in data sample.}$$

For more insights into the proof of the annualised mean and volatility we refer to Appendix B. For the calculation of the daily volatility, we apply Bessel's correction (Bessel, 1818). This is because the historical data that we use is part of all historical data. Furthermore, it can also be interpreted as a sample of all possible data. Therefore, we use the formula for the sample variance which applies Bessel's correction (*N-1*), to obtain a more realistic measure of the strategy's volatility.

8.2.4 The Function

For convenience, we assumed a risk-free rate of zero. Additionally, we incorporated the commission costs in the PF and annualised return of the strategy. This results in the following objective function (OF):

$$\text{OF} = \max\left(\frac{\mu_A - R_F}{\sigma_A} \times \frac{\text{Gross Profit}}{\text{Gross Loss} + \text{Commission Costs}}\right). \tag{21}$$

Here:

$$\begin{aligned}
\mu_A &: \text{Annualised return of the strategy, commission costs included.}\\
R_F &: \text{Risk free rate.}\\
\sigma_A &: \text{Annualised volatility of strategy returns.}\\
\text{Gross Profit} &: \text{Total profit from trades.}\\
\text{Gross Loss} &: \text{Total loss from trades.}\\
\text{Commission Costs} &: \text{Volume traded (MWh)} \times \text{€}0.0085.
\end{aligned}$$

8.3 Benchmarks and risk assessment

Besides the optimised performance obtained from the objective function, we want to perform a deeper analysis into the performance of the trading strategies. Therefore, we compare our trading strategies with a TTF DA and S&P500 benchmark.

8.3.1 TTF DA benchmark

We compare our strategies with a simple buy-and-sell strategy on the TTF DA market. Due to the market environment, we are not able to buy and hold the futures, as positions must be liquidated before the end of the day. Therefore, we compare our strategies with a buy-and-sell strategy. Here, futures are bought at the open and sold at the close of each day. Based on this benchmark, we determine whether our strategies outperform the TTF DA market. Additionally, we calculate the alpha and beta of our strategies with this benchmark.

Capital Asset Pricing Model
We use the TTF DA benchmark in the Capital Asset Pricing Model (CAPM), to calculate the excess expected return adjusted to the risk (alpha), and the systematic risk (beta) (Hull, 2018. pp. 1-13). A positive alpha means that we have an "edge" and outperform the TTF DA market. The beta in the CAPM resembles the systematic risk of the trading strategy compared to the TTF DA benchmark. A beta of 0, implies no systematic risk. A beta of 1, implies that we have the same systematic risk as the benchmark. The alpha and beta are calculated as follows according to the CAPM:

$$\alpha = R_S - R_F - \beta(R_M - R_F). \tag{22}$$

$$\beta = \frac{\text{COV}(R_S, R_M)}{\text{VAR}(R_M)}. \tag{23}$$

Where:

$$\begin{aligned}
R_S &: \text{Return of the strategy.}\\
R_F &: \text{Risk-free interest rate.}\\
R_M &: \text{Return of the market.}\\
\text{COV}(R_S, R_M) &: \text{Covariance of } R_S \text{ and } R_M.\\
\text{VAR}(R_M) &: \text{Variance of } R_M.
\end{aligned}$$

8.3.2 S&P500 benchmark

Besides the performance of the strategy, we also want our strategies to perform better than a simple buy-and-hold strategy on the S&P500. It is illogical to put many efforts in a trading strategy, while a simple buy-and-hold strategy on another market outperforms this strategy. Therefore, we identify the return of a long-term investment in the S&P500 as an opportunity cost for BCI. We consider our strategy to be interesting when it outperforms the S&P500 benchmark.

8.3.3 Fat tail risk

Fat tail risk suggests that price changes tend to follow distributions with fat tails rather than normal distributions. This means that extreme price movements occur more frequently than predicted by normal distributions (Mandelbrot, 1963). The Value at Risk (VaR) and Expected Shortfall (ES) can be used to assess the risk of fat tails for specific confidence intervals (Hull, 2018, pp. 269-291). We obtain more reliable measurements of the VaR and ES when we have a big sample size of trades. For most of our strategies, we have a relatively small sample size of trades. Therefore, we cannot fully rely on the outcomes of these metrics. Fortunately, we already mitigate most of this fat tail risk by applying stop-losses and a position sizing technique. This prevents exceptionally large losses. Therefore, we do not incorporate the VaR and ES in our blueprint.

8.3.4 Quarterly performance

We want our strategy to make consistent returns despite changing market conditions. We prefer the returns to be evenly distributed across the testing period. Therefore, we investigate the number of trades per quarter and the quarterly returns on equity. Based on this, we calculate the geometric average return per trade. In this way, we assess whether the frequency and average returns on trades have been stable.

8.4 Walk-Forward Analysis

We assess the strategies' ability to adapt to changing market conditions, also known as the robustness of the strategy (TradeStation, 2024). To assess the robustness, we apply Walk-Forward Analysis (WFA). With WFA, the entire data set is split up into multiple segments which are trained and tested, also known as Walk-Forward Tests (WFTs) (Pardo, 2008, p. 238). We can distinguish two types of WFA: the Anchored and the Rolling WFA (TradeStation, 2024). In the first case, the training period is extended from the starting point. Each WFT extends with the same length of the testing period. Here, the WFTs proportionally include more historical data. A downside is that the strategy adapts less fast to more recent data during the optimisation process as training periods become larger. A method that tackles this problem is the Rolling WFA. Here, the length of the training period stays constant and moves each WFT the same length of the testing period, as can be observed in Figure 5. Therefore, Rolling WFA adapts more to recent market conditions.

In our example, the dataset consists of 2 years, or 8 quarters. In the first WFT, the training period (In-sample) consists of the 1^{st} quarter until the 3^{rd} quarter, in which the strategy is optimised, see Figure 5. The retrieved optimal parameters are tested in the 4^{th} quarter, which is the testing (Out-of-sample) period. After this, the same process is repeated, but now the training data consists of the 2^{nd} until the 4^{th} quarter and the testing period is the 5^{th} quarter. This process is repeated until the testing period reaches the 8^{th} quarter. In this case, we have 8 - 3 =

5 WFTs, of which the results can be compared.

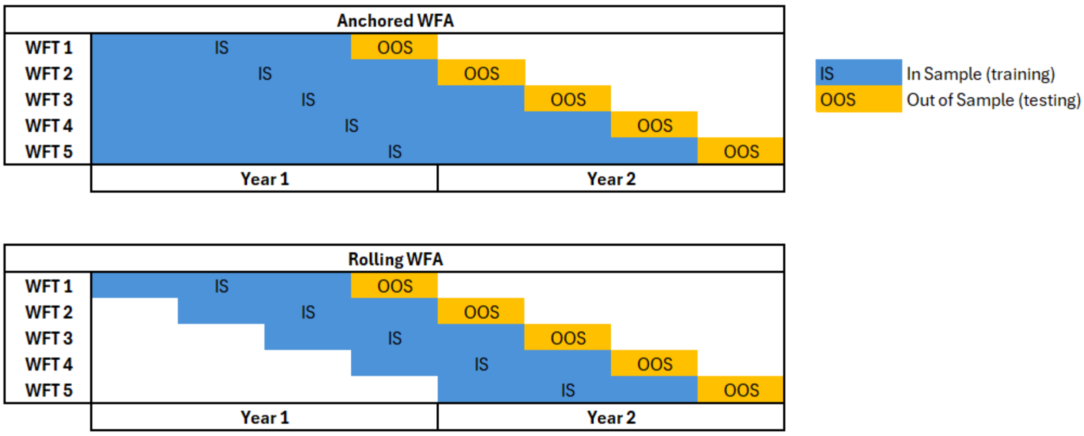

Figure 5: Anchored and Rolling WFA.

The robustness is assessed by calculating the Walk-Forward Efficiency (WFE) (Pardo, 2008, p. 239). To calculate this, we divide the average out-of-sample (OOS) performance by the average in-sample (IS) performance. The formula for the WFE can be written as follows:

$$\text{WFE} = \frac{1}{N} \sum_{i=1}^{N} \frac{\text{OOS performance}_i}{\text{IS performance}_i}. \tag{24}$$

Where:

N : Total number of WFTs.

$Performance$: Performance indicator value.

i : Stands for the i^{th} WFT.

When the OOS performance is on average better than the IS performance, we get a WFE $>$ 1, which is an uncommon optimal result. This indicates that the strategy is robust and is not overfitted to historical data. However, it can sometimes be a result of data snooping bias or luck rather than predictive power, if the WFE is too high. When the WFE < 0.5 the strategy is likely to be overfitted to historical data. A WFE close to 1 is an indication of a robust strategy.

For our Rolling WFA execution we must determine two things: The number of WFTs, and the OOS% for each WFT. A high number of WFTs should be performed to overcome random results. At least 10 WFTs approaches this reliability (TradeStation, 2024). For the OOS% we apply a value of 20% which is the recommended and default setting in most WFA systems (TradeStation, 2024). For more insights we also calculate the WFE on the profits, Profit factor and Sharpe ratio, besides the OF.

We want to have 20% OOS and 10 WFTs. We have 1099 trading days in our dataset. We also know that we want to have a warm-up period of 1 day for all of our indicators. Therefore, we must solve the following formula to know what the length of the OOS (x) is: 5x + 9x = 1099 - 1. This results in approximately 78 days, and 312 days for the IS.

9 Results

9.1 Preliminary Testing

To get a first impression of the performance of the strategies prior to optimisation, we calculate intermediate results based on the default parameter settings mentioned in the formulation section. This includes returns, volatility, OF values, performance indicators included in the OF, benchmarks, and the alpha and beta derived from the TTF DA buy-and-sell benchmark.

Strategy	Return	Volatility	Sharpe	MDD	PF	Trades	Alpha	Beta	OF
EMA	847%	34.09%	2.01	13.41%	1.34	4079	71.15%	-0.01059	2.69
DCS	792%	36.75%	1.80	24.64%	1.23	6419	74.96%	-0.01220	2.21
RSI	453%	24.86%	1.96	13.40%	1.61	2081	50.29%	-0.03815	3.16
ORB	16%	20.05%	0.19	28.69%	1.06	825	5.38%	-0.02655	0.20
TTF DA	-21%	163.10%	-0.03	92.55%	0.997	1099	0	1	-0.03
S&P500	57%	22.45%	0.51	34.10%	-	-	-	-	-

Table 6: Intermediate Results.

Concluding from Table 6, the RSI strategy is the best according to the OF. Furthermore, it has the lowest MDD, a relatively low volatility. Interestingly this result is achieved with only 2081 trades, in contrast to the high number of trades of the EMA and DCS strategies. Furthermore, the ORB strategy is the worst performing strategy. The main reason for this is probably that the 10:00 - 10:10 interval does not provide much information to achieve a high profitability. We solve this issue in the optimisation process, by analysing the performance of the strategy for multiple ORB intervals.

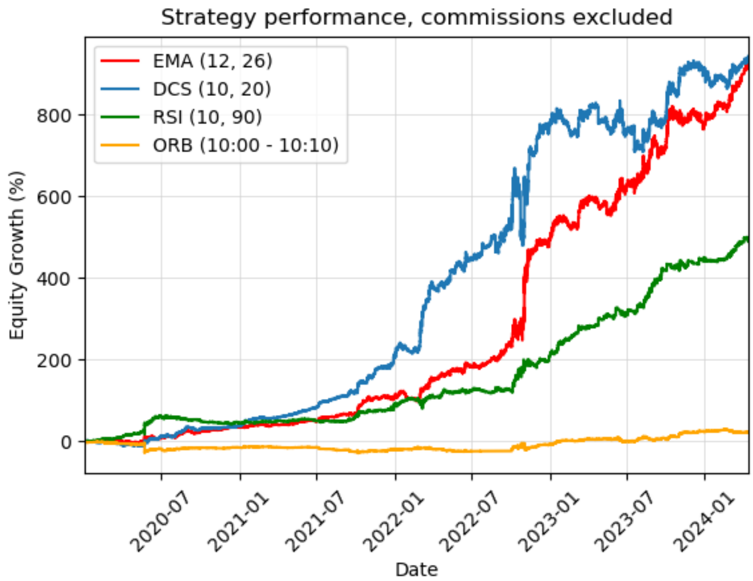

Figure 6: Equity curves of strategies.

In Figure 6 the equity curves of the strategies are illustrated. Here, commissions costs are excluded. Interestingly, the EMA and the DCS have similar final equity. However, the DCS is more volatile than the EMA strategy, resulting in the EMA having a better Sharpe ratio. Furthermore, the EMA has a higher value for the objective function, as can be read from Table 6.

9.2 Optimisation

During the optimisation process, we perform an optimal grid search, provided by the backtesting.py library. With the optimal grid search, we search for the optimal parameters resulting in a maximum value of our objective function. Furthermore, the optimal grid search provides us with heatmaps, showing the areas where the most optimal OF values occur. These optimal values have a yellow colour, while the least optimal have a dark indigo colour. We assess the optimised strategies with the use of our blueprint.

ORB

From the heatmap of the ORB strategy in Figure 7 we can conclude multiple things. The first thing is that the strategy is not profitable when an opening range is chosen within the first hours of a trading day. We already expected this, due to the low liquidity in those hours, failing to fully represent the sentiment/trend in the market. We also notice that late end-times for the opening range are not beneficial for the performance of the strategy. This is logical because there is less time to realise large profits as the market closes soon after these times. For some end times even no trades are made at all. We can also conclude from the heatmap that there is a concentrated area with high OF values, indicating that the performance of the strategy is sensitive to market changes. Another thing that is remarkable is that the optimised strategy has a WR of 54.84%, which can be further exploited with proper risk management.

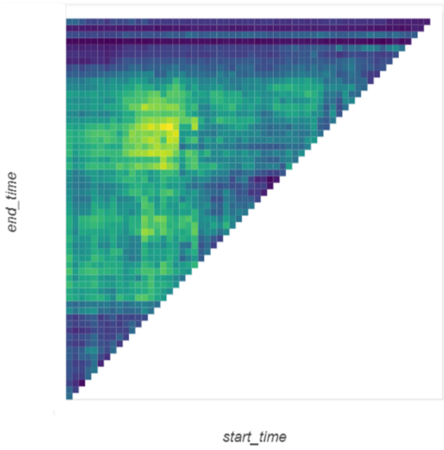

Figure 7: Heatmap ORB strategy.

When we analyse the quarterly results in Table 7, we observe that the number of trades does not deviate much, meaning it observes an equal amount of opportunities in the market despite the changing market conditions. Contrarily, the returns generated within the quarters deviate a lot. Fortunately, the equity only decreased 2 out of the 17 quarters with minor losses. This gives confidence in future profitability.

Table 7: Quarterly performances ORB.

Quarter	End date	Equity change [%]	Trades	Geom. avg. [%]
2020Q1	2020-03-31	-0.49	45	-0.01
2020Q2	2020-06-30	2.38	45	0.05
2020Q3	2020-09-30	7.93	37	0.21
2020Q4	2020-12-31	3.39	31	0.11
2021Q1	2021-03-31	4.52	41	0.11
2021Q2	2021-06-30	2.01	44	0.05
2021Q3	2021-09-30	5.22	38	0.13
2021Q4	2021-12-31	1.92	46	0.04
2022Q1	2022-03-31	7.16	39	0.18
2022Q2	2022-06-30	-1.01	40	-0.03
2022Q3	2022-09-30	9.61	37	0.25
2022Q4	2022-12-31	30.38	48	0.55
2023Q1	2023-03-31	1.01	43	0.02
2023Q2	2023-06-30	3.03	47	0.06
2023Q3	2023-09-30	5.52	42	0.13
2023Q4	2023-12-31	8.22	46	0.17
2024Q1	2024-03-31	6.00	40	0.15

DCS

Because the DCS strategy has 4 parameters to be optimised, it is time-consuming to optimise all at once. We tackle this curse of dimensionality by splitting up the DCS into a long and short strategy with each 2 parameters, resulting in less calculation time. We observe from the heatmap in Figure 8 that the original parameter values of the TTS of $n1 = 20$ and $n2 = 10$ are not applicable in the TTF DA market. It appears on the heatmap that these windows are much closer to each other than one would expect. Due to the fact that high OF values are not concentrated in a specific area, it is less likely that the strategy is sensitive to market shifts. When we combine the optimal parameters for both long and short DCSs, we obtain the results in Table 11.

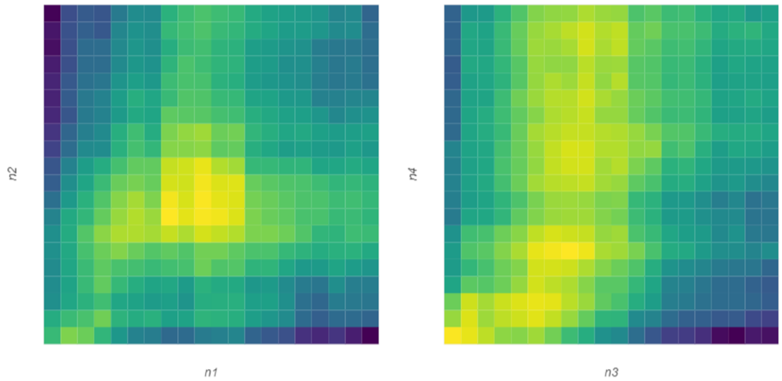

Figure 8: Heatmaps long and short DCS.

In the quarterly results in Table 8, we notice some fluctuations in the frequency of trades per quarter. This is also true for the changes in equity for each quarter. This makes the strategy less reliable. Contrarily, for the majority of quarters, positive returns are generated. Furthermore, it is noticeable that the average geometric return per trade is much smaller than for the ORB strategy.

Table 8: Quarterly performances DCS.

Quarter	End date	Equity change [%]	Trades	Geom. avg. [%]
2020Q1	2020-03-31	-8.08	200	-0.04
2020Q2	2020-06-30	15.36	201	0.07
2020Q3	2020-09-30	2.75	200	0.01
2020Q4	2020-12-31	-1.01	217	-0.00
2021Q1	2021-03-31	8.35	209	0.04
2021Q2	2021-06-30	0.45	205	0.00
2021Q3	2021-09-30	4.97	189	0.03
2021Q4	2021-12-31	22.79	185	0.11
2022Q1	2022-03-31	38.07	169	0.19
2022Q2	2022-06-30	15.34	199	0.07
2022Q3	2022-09-30	10.63	193	0.05
2022Q4	2022-12-31	20.85	167	0.11
2023Q1	2023-03-31	0.72	201	0.00
2023Q2	2023-06-30	2.27	190	0.01
2023Q3	2023-09-30	2.18	192	0.01
2023Q4	2023-12-31	11.25	183	0.06
2024Q1	2024-03-31	0.99	196	0.01

EMA

Concluding from the heatmap, high OF values are obtained in the lower window values. Indicating that for this strategy more recent data matters for achieving high OF values. We can also observe that high OF values can be obtained in still a wide range of parameters for *n1* (small window) and *n2* (large window) in the left bottom. This suggests that the strategy is less sensitive to market changes.

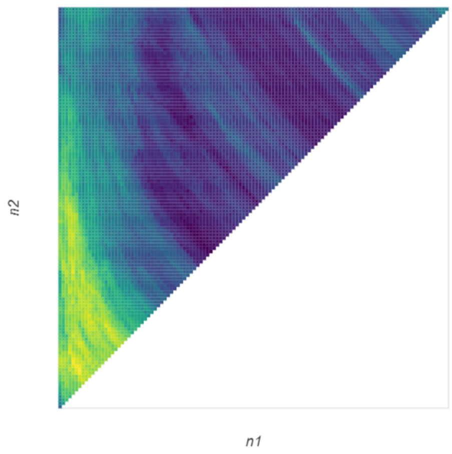

Figure 9: Heatmap EMA cross strategy.

The quarterly results in Table 9 show us that the frequency of trades per quarter is quite high. Besides, the number of trades for each quarter fluctuates a lot. However, there is only one of the 17 quarters that performs bad. This is a small decrease in equity. Furthermore, the geometric average return for a trade contributing to the total equity appears rather small in comparison with the ORB strategy. This strategy can become unprofitable when commission costs increase.

Table 9: Quarterly performances EMA.

Quarter	End date	Equity change [%]	Trades	Geom. avg. [%]
2020Q1	2020-03-31	-0.10	469	-0.00
2020Q2	2020-06-30	23.02	413	0.05
2020Q3	2020-09-30	10.99	449	0.02
2020Q4	2020-12-31	5.27	440	0.01
2021Q1	2021-03-31	12.98	427	0.03
2021Q2	2021-06-30	8.83	423	0.02
2021Q3	2021-09-30	15.79	419	0.03
2021Q4	2021-12-31	38.60	392	0.08
2022Q1	2022-03-31	79.61	379	0.15
2022Q2	2022-06-30	20.77	396	0.05
2022Q3	2022-09-30	46.67	369	0.10
2022Q4	2022-12-31	64.31	473	0.11
2023Q1	2023-03-31	23.69	448	0.05
2023Q2	2023-06-30	16.86	437	0.04
2023Q3	2023-09-30	12.25	464	0.02
2023Q4	2023-12-31	4.78	467	0.01
2024Q1	2024-03-31	6.82	450	0.01

RSI

Due to the three dimensions, three heatmaps are generated which show the relation between all three parameters. In Figure 10, we observe that the OF values are closely related to what window is chosen. However these values are quite concentrated, suggesting that the strategy might be sensitive for market changes.

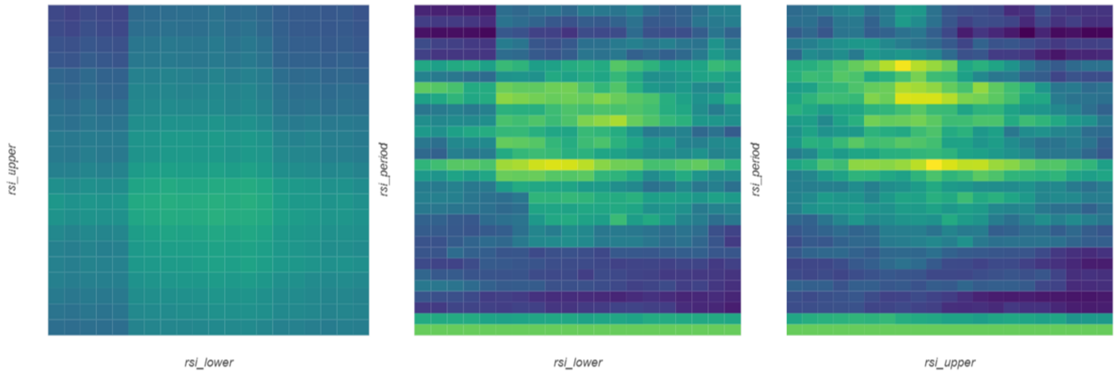

Figure 10: Heatmaps RSI.

From the quarterly results in Table 10, we observe that this strategy might be the least consistent through time. Firstly, the number of trades appears to reduce as we come closer to the present. Besides, the changes in equity seem to have big fluctuations when quarters are compared next to each other. The geometric averages seem to have one of the highest values next to the geometric averages of the ORB strategy.

Table 10: Quarterly performances RSI.

Quarter	End date	Equity change [%]	Trades	Geom. avg. [%]
2020Q1	2020-03-31	11.27	152	0.07
2020Q2	2020-06-30	45.28	199	0.19
2020Q3	2020-09-30	-5.78	206	-0.03
2020Q4	2020-12-31	-3.71	165	-0.02
2021Q1	2021-03-31	2.50	102	0.02
2021Q2	2021-06-30	-1.80	131	-0.01
2021Q3	2021-09-30	7.47	141	0.05
2021Q4	2021-12-31	21.51	140	0.14
2022Q1	2022-03-31	9.10	138	0.06
2022Q2	2022-06-30	11.19	164	0.06
2022Q3	2022-09-30	3.48	121	0.03
2022Q4	2022-12-31	32.92	111	0.26
2023Q1	2023-03-31	23.17	91	0.23
2023Q2	2023-06-30	16.17	95	0.16
2023Q3	2023-09-30	27.55	77	0.32
2023Q4	2023-12-31	6.73	58	0.11
2024Q1	2024-03-31	6.51	67	0.09

Summary

In Table 11, we observe the summarised results of all strategies. They all outperform the TTF DA and S&P500 benchmarks. Also, they all have a relatively low beta, which implies that they have low systemic risk. A few other things are noticeable in this table. Firstly, the ORB strategy scores the highest based on the value from the objective function and the Profit Factor, while having the lowest amount of trades. Furthermore, the EMA cross strategy scores best on the Sharpe ratio and the return.

Strategy	Return	Volatility	Sharpe	MDD	PF	Trades	Alpha	Beta	OF
EMA	2311%	45.58%	2.40	22.26%	1.27	7383	120.45%	0.00049	3.04
DCS	980%	38.02%	1.94	19.21%	1.23	5620	81.38%	-0.01532	2.38
RSI	531%	26.00%	2.05	14.02%	1.65	2171	55.39%	-0.03179	3.39
ORB	142%	10.94%	2.08	9.26%	1.82	713	24.55%	0.00747	3.79
TTF DA	-21%	163.10%	-0.03	92.55%	0.997	1099	0	1	-0.03
S&P500	57%	22.45%	0.51	34.10%	-	-	-	-	-

Table 11: Optimised results.

9.3 Walk-Forward Analysis

For the WFA, we use slightly different parameter dimensions to make the WFAs less time-consuming. These dimensions are based results of the grid search optimisation, showing us in which dimensions optimal results are likely to be obtained. For the RSI, we optimise for the upper limit from 80 to 100, and the lower limit from 1 to 20. For the EMA, we optimise for both windows from 1 to 20. For the DCS, we optimise DCS long and DCS short from 1 to 20 for all parameters. For the ORB strategy, we perform the WFA with the start times and end times from 10:00 to 17:00.

ORB

The results of the WFA of the ORB strategy in Table 12 show that the WFEs are relatively low when compared to other strategies. The objective function has a WFE of 0.46, which is not sufficient to assume robustness. All OOS/IS values of the OF seem rather low. The WFE of the Sharpe ratio and Profit Factor are 0.52 and 0.69, respectively. Also indicating that the robustness of the strategy is not strong. On the other hand, the WFE of the annualised return is 0.87. However, this is mainly due to the OOS/IS value of the 6^{th} WFT. When this value is excluded and the WFE is calculated for the remaining WFTs, we get a WFE of 0.41. We can conclude that the ORB strategy is not robust and is overly reliant on past data.

Table 12: WFA ORB.

WFT	OF			Sharpe			PF			Return (Ann.) [%]		
	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS
1	5.93	0.88	0.15	2.41	0.68	0.28	2.46	1.29	0.52	25.10	1.58	0.06
2	5.95	0.11	0.02	2.40	0.11	0.05	2.48	0.99	0.40	24.73	0.69	0.03
3	8.72	5.02	0.58	3.59	2.63	0.73	2.43	1.91	0.79	20.81	23.71	1.14
4	7.67	0.92	0.12	3.35	0.79	0.24	2.29	1.16	0.51	23.14	7.14	0.31
5	7.00	6.25	0.89	3.07	2.88	0.94	2.28	2.17	0.95	41.12	55.77	1.36
6	5.81	8.15	1.40	2.85	2.91	1.02	2.04	2.80	1.37	21.06	104.84	4.98
7	6.85	1.53	0.22	2.83	1.14	0.40	2.42	1.34	0.55	42.51	7.88	0.19
8	6.47	0.96	0.15	2.64	0.80	0.30	2.45	1.20	0.49	75.55	10.38	0.14
9	6.80	2.77	0.41	2.70	1.75	0.65	2.52	1.58	0.63	41.18	15.16	0.37
10	6.66	2.49	0.37	2.96	1.72	0.58	2.25	1.45	0.64	56.76	10.33	0.18
WFE			0.46			0.52			0.69			0.87

DCS

For the WFA of the DCS, we did two WFAs to tackle the curse of dimensionality. We did an WFA for the short and long strategy. In Table 13 we can see that the WFEs of the Sharpe ratio and the Profit Factor for the long strategy are the highest, with excellent scores of 0.90 and 0.91, respectively. However, this does not imply a high WFE for the OF, because this is only 0.51. This means that there is some degree of robustness, but may still be sensitive to market changes. The WFE for the annualised return is 0.78, which suggests that it has some robustness and is less reliant on past data.

Table 13: WFA DCS long.

WFT	OF			Sharpe			PF			Return (Ann.) [%]		
	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS
1	2.42	16.88	6.96	1.77	6.75	3.81	1.37	2.5	1.82	27.09	57.35	2.12
2	4.11	4.80	1.17	2.55	3.00	1.18	1.61	1.6	0.99	42.09	41.68	0.99
3	6.32	4.39	0.69	3.51	2.71	0.77	1.80	1.62	0.90	36.89	50.37	1.37
4	6.70	5.04	0.75	3.66	2.74	0.75	1.83	1.84	1.01	57.61	84.69	1.47
5	6.09	3.87	0.64	3.22	2.48	0.77	1.89	1.56	0.83	50.16	23.84	0.48
6	6.66	2.62	0.39	3.60	1.78	0.49	1.85	1.47	0.79	84.82	96.39	1.14
7	4.64	0.11	0.02	2.73	0.11	0.04	1.70	0.97	0.57	70.14	1.08	0.02
8	3.62	1.48	0.41	2.32	1.25	0.54	1.56	1.18	0.76	51.93	13.14	0.25
9	2.48	1.36	0.55	1.84	1.19	0.65	1.35	1.14	0.84	47.15	15.33	0.33
10	1.83	0.00	0.00	1.39	0.00	0.00	1.32	0.79	0.60	41.02	-14.18	-0.35
WFE			0.51			0.90			0.91			0.78

In Table 14 it can be seen that for the short strategy, the Sharpe ratio and Profit Factor have less robustness, but still reasonable WFEs of 0.62 and 0.88, respectively. Despite their lower robustness, the WFE is higher for the OF than in for the long strategy. Furthermore, the WFE for the annualised return is 0.85, which is an excellent score, indicating robustness. All in all, we can conclude that the DCS strategy is fairly robust.

Table 14: WFA DCS short.

WFT	OF			Sharpe			PF			Return (Ann.) [%]		
	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS
1	1.61	1.88	1.17	1.33	1.46	1.10	1.21	1.29	1.07	15.00	8.92	0.59
2	3.20	2.38	0.74	2.22	1.65	0.74	1.44	1.44	1.00	27.05	29.15	1.08
3	2.61	6.97	2.67	1.88	3.40	1.81	1.39	2.05	1.47	17.98	66.11	3.68
4	6.14	13.15	2.14	3.20	4.78	1.49	1.92	2.75	1.43	43.86	128.35	2.93
5	9.65	0.00	0.00	4.02	0.00	0.00	2.40	0.81	0.34	86.26	-12.61	-0.15
6	7.46	0.64	0.09	3.64	0.51	0.14	2.05	1.26	0.61	85.26	24.14	0.28
7	4.15	0.00	0.00	2.37	0.00	0.00	1.75	0.97	0.55	123.34	-7.52	-0.06
8	3.12	0.85	0.27	2.15	0.79	0.37	1.45	1.08	0.74	107.95	13.16	0.12
9	1.61	0.00	0.00	1.27	0.00	0.00	1.27	0.96	0.76	39.07	-6.40	-0.16
10	1.34	0.61	0.45	1.04	0.56	0.54	1.29	1.09	0.84	32.25	4.88	0.15
WFE			0.71			0.62			0.88			0.85

EMA

In Table 15 we can see that the WFE for the objective function is 0.76. This is based on OOS/IS values of which 70% has at least a value of 0.5. Furthermore, the WFE for the Sharpe ratio and Profit Factor are 0.92 and 0.91, also based on fairly stable OOS/IS values. The WFE for the annualised return is 0.94. However, this high value is obtained from the OOS/IS value of the 4^{th} WFT. When we consider this as a circumstance of luck and calculate the WFE for the remaining 9 OOS/IS values, we obtain a WFE of 0.60. Therefore, it can still be considered as fairly robust. All in all, the results show that the EMA strategy can be considered as a quite robust.

Table 15: WFA EMA.

WFT	OF			Sharpe			PF			Return (Ann.) [%]		
	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS
1	2.74	6.16	2.25	2.06	4.05	1.97	1.33	1.52	1.14	58.42	50.45	0.86
2	3.64	4.60	1.27	2.58	2.95	1.14	1.41	1.56	1.11	65.29	71.88	1.10
3	4.87	0.47	0.10	3.10	0.44	0.14	1.57	1.06	0.68	53.24	6.68	0.13
4	7.44	9.33	1.25	4.40	4.30	0.98	1.69	2.17	1.28	128.94	517.52	4.01
5	8.17	5.82	0.71	4.28	3.71	0.87	1.91	1.57	0.82	191.51	103.09	0.54
6	7.84	2.07	0.26	4.19	1.49	0.36	1.87	1.39	0.74	233.41	273.58	1.17
7	3.57	3.14	0.88	2.35	2.36	1.00	1.52	1.33	0.88	112.04	38.08	0.34
8	3.91	1.68	0.43	2.46	1.39	0.57	1.59	1.21	0.76	116.87	37.96	0.32
9	3.56	4.46	1.25	2.33	3.12	1.34	1.53	1.43	0.93	110.69	78.57	0.71
10	3.50	2.39	0.68	2.33	1.91	0.82	1.50	1.25	0.83	111.28	26.02	0.23
WFE			0.76			0.92			0.92			0.94

RSI

In Table 16, we observe immediately that all WFEs have values above 1. For the OF, we obtain a WFE of 1.38, which is relatively high. This may be an indication of circumstances of luck or anomalies. We see that the OOS/IS values of the OF deviate a lot. The WFEs for the Sharpe ratio and Profit Factor are 1.07 and 1.04, respectively. Those WFEs are based on fairly stable OOS/IS values where at least 70% has at least a value of 0.5. Indicating that the strategy is robust for the Sharpe ratio and Profit Factor. The WFE for the annualised return is 1.08. Here the OOS/IS values fluctuate a bit more. It indicates that the results of annualised returns are somewhat reliant on new market data. All in all, we can conclude that the RSI strategy is fairly robust.

Table 16: WFA RSI.

WFT	**OF**			**Sharpe**			**PF**			**Return (Ann.) [%]**		
	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS	IS	OOS	OOS/IS
1	2.95	0.68	0.23	1.93	0.64	0.33	1.53	1.07	0.70	41.29	4.68	0.11
2	1.89	4.87	2.58	1.38	2.69	1.95	1.37	1.81	1.32	25.95	61.71	2.38
3	1.29	2.54	1.97	1.03	1.66	1.61	1.25	1.53	1.22	11.07	29.63	2.68
4	3.89	0.27	0.07	2.37	0.24	0.10	1.64	1.13	0.69	38.25	3.30	0.09
5	3.00	1.22	0.40	2.03	0.98	0.48	1.48	1.24	0.84	40.71	10.67	0.26
6	3.59	3.63	1.01	2.27	1.87	0.82	1.58	1.94	1.23	44.84	109.65	2.45
7	2.87	8.82	3.07	1.72	3.46	2.01	1.67	2.55	1.53	49.76	65.79	1.32
8	4.04	3.50	0.87	2.17	2.07	0.95	1.86	1.69	0.91	69.12	39.00	0.56
9	5.23	6.09	1.16	2.39	2.94	1.23	2.19	2.07	0.95	82.64	43.23	0.52
10	5.60	7.30	1.30	2.48	3.03	1.22	2.26	2.41	1.07	74.46	30.29	0.41
WFE			1.38			1.07			1.04			1.08

10 Advisory report

We have provided a blueprint for assessing trading strategies, designed to select the most suitable strategy from a given set. However, we have identified certain areas that may require further investigation or clarification to enhance the blueprint's effectiveness and the strategies' performance. These topics are addressed in the following sections of this advisory report.

10.1 Backtesting

We recommend testing multiple trading strategies simultaneously to enable comparison and selection with the blueprint. This allows BCI to quickly determine which strategy aligns best with their preferences. To ensure the selected strategy continues to perform optimally in the current market, we advise periodic testing. Based on these tests, the strategy can be re-optimised if necessary. This is especially crucial in the TTF DA market, due to its volatile and dynamic nature.

10.2 Risk management optimisation

We optimised the entry and exit conditions of the strategies. Trading strategies can be further optimised by adjusting the parameters related to the stop-loss conditions or by changing the position sizing technique. For instance, we can reduce the Maximum Drawdown (MDD), by optimising the ATR window and factor used for stop-losses. With a reduced MDD, we can increase the position sizing percentage, potentially resulting in higher returns over time. Furthermore, it would be interesting to investigate the effectiveness of trailing stop losses, which move along with profitable price movements, securing profits during the trade.

For our strategies, we apply a fixed position sizing technique, allocating 20% of our total equity to each trade. Depending on the strategy, other position sizing techniques may be used. An example is the Kelly Criterion (Pardo, 2008, p. 90) which requires a trading strategy to have a win rate (WR) of at least 50%. Since most of our strategies are trend-following systems, which typically have WRs below 50%, we did not apply this technique. However, it could be applicable to the ORB strategy, as it often meets the WR requirement. The formula for the Kelly Criterion is (Pardo, 2008, p. 90):

$$\text{Kelly Criterion} = \frac{\text{Win\%} - \text{Loss\%}}{\frac{\text{Average Profit}}{\text{Average Loss}}} \tag{25}$$

10.3 Multi-timeframe strategies

We used 5-minute timeframes for testing our strategies to maintain high data granularity while preserving valuable information. There is potential in strategies that analyse indicators across different timeframes simultaneously, such as for trend confirmation. However, we did not implement this approach due to its complexity and limited theoretical support. Nonetheless, it is worth considering that such strategies could yield good results.

10.4 Additional trading rules

We recommend adding more trading rules, particularly for strategies with a low average profit per trade and a high frequency of trades. Stricter conditions from additional rules could increase both the WR and average profit per trade. Moreover, it would reduce the frequency of trades, lowering total commission costs. This could make such strategies more profitable.

10.5 Distribution of drawdown period lengths

It is useful to investigate the likelihood of drawdown period lengths. Occasionally, drawdown periods of around 150 days can occur, meaning a strategy must be tested over a long duration to draw accurate conclusions about its performance. By analysing the distribution of drawdown period lengths, one can estimate the likely duration of a drawdown when the strategy is implemented in practice. This allows for a better estimation of how long it will take to assess the strategy's performance accurately.

10.6 Monte Carlo simulation & Predictive models

To ensure good future performance, it would be interesting to test the strategies on Monte Carlo simulations and predictive models. With Monte Carlo simulations, the trading strategies are tested on different price paths that might occur in the future. It would also be interesting to incorporate predictive models to test multiple strategies periodically and simultaneously. This enables us to switch from strategy each period to obtain optimal results.

10.7 Exponential formula

Due to the reinvestment of returns, the equity curves increase exponentially, assuming a positive average return per trade. This exponential characteristic can be observed in Figure 6. It is interesting to fit an exponential formula to these equity curves, by finding the growth factor which minimises the Mean Squared Error (MSE). With this MSE, we get an additional measurement of the stability of the strategies. Furthermore, we get a growth factor. Both of these metrics can be used for the comparison of strategies in our blueprint.

11 Disclaimers

We address different pitfalls regarding the application of trading strategies, and some potential disadvantages which may occur when putting a strategy into practice.

11.1 Slippage

We do not account for the risk of slippage, which occurs when orders are not executed at the intended prices due to limited volumes at certain timeframes. This can negatively impact the overall performance of the strategy. We decided not to include this risk in our assessment because of its predictive complexity. It is important to note that slippage may occur during real-world implementation.

11.2 Bid-Ask spread

In reality there is a bid-ask spread present. The bid price is the highest price that a participant wants to buy for, and the ask price is the lowest price a participant wants to sell for. The bid-ask spread is the difference between the bid and ask prices. In our simulation, entry prices are executed for the close price of the last timeframe. Considering a long position, the latest close is not necessarily equal to the current ask price. Vice versa, in the context of exits, the bid price can be different than the latest close. It is likely that the strategies are less profitable as they portray. This is because the Bid-Ask spread can decrease the profitability for each trade.

11.3 Automation duration

Automating the strategies is time-consuming. First, all systems need to be correctly integrated. Next, the strategies must be defined in a programming language suitable for the chosen trading platform that facilitates automated trading. Learning a new programming language takes time. Once the strategy is defined, it must be backtested and analysed to ensure it performs as desired. Only then can we automate our trading strategy.

11.4 Ex-post performance

Since our focus was on developing a trading strategy, we did not create a predictive model for future prices in the TTF DA market. The performance of the strategies is based on historical data, which does not guarantee similar results in the future. To assess the robustness of the strategies better, we calculated the Walk-Forward Efficiency (WFE), which averages the results of multiple Walk-Forward Tests (WFTs). Despite a high WFE, the remarkable deviation among the WFT results reduces its reliability.

11.5 Drawdown periods

Most strategies have relatively long periods of drawdown. This is especially the case with trend following strategies, which attempt to ride profits as long as possible, and exit losing positions as quickly as possible. In this case, there are many losing trades with small losses, and a few winning trades with large profits. The losing trades may be more prevalent at first, resulting in long periods of drawdown. Sometimes we see strategies with a maximum drawdown period of around 150 days. This means that for real time assessment of the strategy, it at least needs to be put into practice for a year to make a reasonable assessment.

11.6 Prepared dataset

In the prepared dataset, we use the most recent close prices for periods with no volume, to prevent rises in volatility, and represent market prices as accurately as possible. There is a possibility that this causes technical indicators to obtain unintended values, resulting in unintended triggers (false positives) or unintended non-triggers (false negatives). This makes the performance of the strategies sub-optimal, and suggests that there is room for improvement.

12 Conclusion

We selected, developed, tested, and optimised a set of trading strategies on EEX Financial Gas Futures traded in the TTF DA gas market. This has never been performed before in the academic field. We tested the set of strategies against the weak form of the Efficient Market Hypothesis (EMH) and developed a blueprint which selects the most suitable strategy from the set. All strategies have higher Sharpe ratios and returns than the TTF DA and S&P500 benchmarks, see Table 11. Therefore, we conclude that our strategies outperform the benchmark, suggesting we beat the weak form of the EMH.

Based on our blueprint, we eliminate the Donchian Channel Strategy, because it has the lowest Sharpe ratio, PF, and therefore lowest OF. This makes the DCS inferior compared to the others. We also eliminate the RSI strategy, as it has a lower Sharpe ratio, lower PF, and therefore lower OF than the ORB strategy. Despite that the EMA cross-over strategy has a lower OF than the RSI strategy, we keep the EMA because it has the highest Sharpe ratio of all strategies. Therefore, we identify two candidates for the most suitable strategy: the ORB strategy and the EMA cross-over strategy.

When we compare the ORB and EMA cross-over strategy with the use of our blueprint, we see in Table 17 that the ORB scores better on the PF and OF. However, the ORB strategy scores worse on the heatmap and WFE. These low scores for the heatmap and WFE suggest that the strategy is more sensitive to new market data, and is less likely to obtain similar results in the future when market conditions change. Therefore, it has a low robustness. The quarterly results show that the strategy has few trades with high profits. This indicates less market exposure and suggests that the performance is less sensitive to changes in commission costs.

The EMA scores less on the OF and PF than the ORB. However, it has a better return and Sharpe ratio. This means that the strategy is able to get higher returns, while having less risk in proportion with its returns. Furthermore, the EMA scores well on the heatmap and WFE. This suggests that the strategy is less sensitive to market changes and is likely to have similar performance in the future. The quarterly results show that the strategy has many trades with small profits. This makes the strategy vulnerable for rises in commission costs.

We summarised the comparison in Table 17. We conclude that the best strategy for BCI is the EMA cross-over strategy. This is because the aim of BCI is to have a trading strategy which maximises profitability, minimises relative risk, and has a high robustness. The EMA cross-over strategy meets all of these criteria, the ORB strategy does not. This is because the ORB strategy has a low robustness, a lower sharpe ratio, and a much lower return, as can bee seen in Table 17. We assume that the practical implementation of the strategies does not result in any significant rises in commission costs.

Strategy	OF	Sharpe	PF	Heatmap	Overall WFE	Quarterly	Return
ORB	3.79	2.08	1.82	Vulnerable	0.635	Few trades, large profits	142%
EMA	3.04	2.40	1.27	Less vulnerable	0.885	Many trades, small profits	2311%

Table 17: Comparison of ORB and EMA strategies.

13 Discussion

Our strategies have been tested during a period with exceptional geopolitical shifts. This resulted in an increase in volatility, and exceptional price movements. Therefore, it is debatable whether our strategies are tested on a dataset which is representative for future price movements. Problem is that we cannot predict the future. Nevertheless, we tested the strategies during this period with many dynamic and volatile market conditions. Despite this, the strategies have profitable performance, indicating that they can withstand times of turmoil within the market. Furthermore, we did a WFA, in multiple segments of the dataset, including more calm periods. This resulted in good WFEs for all strategies, except for the ORB strategy. Furthermore, the quarterly results, including calm periods, also show that the strategies are profitable in different market conditions. This suggests that most of the strategies' performances are reliable, and are likely to have positive results in the future.

Our Objective Function (OF) is based on our reasoning and metrics drawn from the literature. During our literature review, we did not find a universally accepted method to quantify the performance of a trading strategy. This is because the definition of a good strategy is often subjective, depending on the trader's risk perception and objectives. It is debatable whether our OF reliably selects the most suitable strategy. Since the OF is the product of the Sharpe ratio and Profit Factor, one metric can dominate the other during optimisation. This results in high OF values while still allowing for a low Sharpe ratio or Profit Factor. Despite an increased OF, we do not prefer strategies with low values in either metric.

In the WFA, we analyse the robustness for different parameters. In this process we optimise the OF. It is debatable whether this results in accurate values for the robustness of the Sharpe ratio and Profit Factor, as these metrics are not solely optimised in the WFA. Sometimes, the WFE for the Sharpe ratio and Profit Factor is much higher than the WFE of the OF or vice versa. We do not know why this is the case and is reason for further investigation. Furthermore, sometimes the WFT results tend to be high due to what are possibly lucky circumstances. When such circumstances are ignored, the WFE turns out to be much lower. We only consider the lucky circumstances and not the circumstances with bad luck. In this way we build in a buffer and get an indication what the WFE at least is, approximately. We do this because it is debatable whether something is a result of luck or due to excellent performance of the strategy which exploited the opportunities in the market really well at that moment.

It is debatable whether the obtained performances are similar when implemented in real life, and whether we have truly rejected the weak form of the EMH. Sometimes, trades are performed in periods when there is no volume. In these cases, there is a high likelihood that orders are not executed in real life. This is also known as the risk of slippage. Furthermore, the trades are simulated based on the last close prices, instead of bid and ask prices, probably resulting in better entry and close prices than would be in practice.

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A Project Schedule

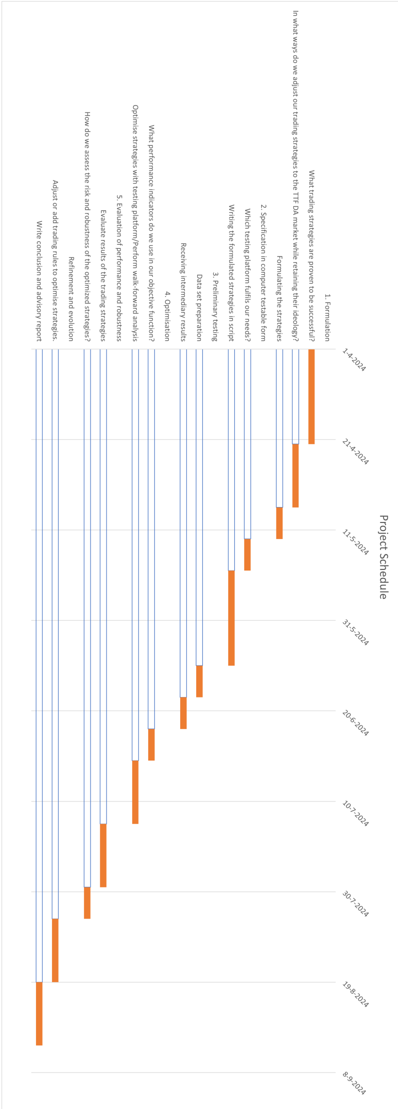

Figure 11: Project Schedule Gantt Chart.

B Proof for moments of multi-period returns

Let R_A, the annual return, be defined as:

$$R_A = \prod_{t=1}^{T}(1 + R_{D,t}) - 1$$

This gives us the mean of the annual returns:

$$\mu_A = E[R_A] = E\left[\prod_{t=1}^{T}(1 + R_{D,t}) - 1\right] = E\left[\prod_{t=1}^{T}(1 + R_{D,t})\right] - 1 = \prod_{t=1}^{T} E[1 + R_{D,t}] - 1$$

$$= (E[1 + R_D])^T - 1 = (1 + \mu_D)^T - 1$$

The annual variance of the returns:

$$\sigma_A^2 = \mathrm{Var}[R_A] = \mathrm{Var}[1 + R_A] = E[(1 + R_A)^2] - (E[1 + R_A])^2$$

$$= E\left[\prod_{t=1}^{T}(1 + R_{D,t})^2\right] - \left(E\left[\prod_{t=1}^{T}(1 + R_{D,t})\right]\right)^2 = \prod_{t=1}^{T}\left[E[(1 + R_{D,t})^2]\right] - \left(\prod_{t=1}^{T} E[1 + R_{D,t}]\right)^2$$

$$= \left(E[(1 + R_D)^2]\right)^T - \left((1 + \mu_D)^2\right)^T = \left(1 + 2\mu_D + E[R_D^2]\right)^T - (1 + \mu_D)^{2T}$$

The daily variance can be written as:

$$\sigma_D^2 = E[R_D^2] - \mu_D^2$$

$$E[R_D^2] = \sigma_D^2 + \mu_D^2$$

Substitution gives:

$$\sigma_A^2 = \left(1 + 2\mu_D + \sigma_D^2 + \mu_D^2\right)^T - (1 + \mu_D)^{2T} = \left(\sigma_D^2 + (1 + \mu_D)^2\right)^T - (1 + \mu_D)^{2T}$$

Hence, the volatility equals:

$$\sigma_A = \sqrt{\left(\sigma_D^2 + (1 + \mu_D)^2\right)^T - (1 + \mu_D)^{2T}}$$

C Python code of strategies

ORB

```
class ORB(Strategy):

    start_time = '10:00'
    end_time = '10:10'
    atr_period = 14
    market_close_time = time(17, 55)

    def init(self):

        # Convert data to pandas dataframe
        self.data_frame = pd.DataFrame({
        'High': self.data.High,
        'Low': self.data.Low,
        'Close': self.data.Close
        })

        # Process the external data to calculate the opening range
        self.external_data = TTF_DA_10min.copy()
        self.external_data['TradeTimestamp'] =
        ↪  pd.to_datetime(self.external_data['TradeTimestamp'])
        self.external_data.set_index('TradeTimestamp', inplace=True)
        self.external_data['Date'] = self.external_data.index.date
        self.external_data['Time'] = self.external_data.index.time

        self.calculate_opening_range()

        self.high_price = self.I(lambda:
        ↪  self.opening_range_high.reindex(self.data.index.date,
        ↪  method='ffill'), name='High')
        self.low_price = self.I(lambda:
        ↪  self.opening_range_low.reindex(self.data.index.date,
        ↪  method='ffill'), name='Low')
        self.open_price = self.I(lambda:
        ↪  self.opening_range_open.reindex(self.data.index.date,
        ↪  method='ffill'), name='Open')
        self.close_price = self.I(lambda:
        ↪  self.opening_range_close.reindex(self.data.index.date,
        ↪  method='ffill'), name='Close')

        # Calculate ATR
        self.atr = self.I(self.calculate_atr, self.data_frame['High'],
        ↪  self.data_frame['Low'], self.data_frame['Close'], self.atr_period)

        self.last_trade_date = None
```

```
def calculate_opening_range(self):
    self.opening_range_high =
    ↪   self.external_data.between_time(self.start_time,
    ↪   self.end_time).groupby('Date')['High'].max()
    self.opening_range_low =
    ↪   self.external_data.between_time(self.start_time,
    ↪   self.end_time).groupby('Date')['Low'].min()
    self.opening_range_open =
    ↪   self.external_data.between_time(self.start_time,
    ↪   self.end_time).groupby('Date')['Open'].first()
    self.opening_range_close =
    ↪   self.external_data.between_time(self.start_time,
    ↪   self.end_time).groupby('Date')['Close'].last()

def calculate_atr(self, high, low, close, period):
    tr1 = high - low
    tr2 = abs(low - close.shift(1))
    tr3 = abs(high - close.shift(1))
    tr = pd.concat([tr1, tr2, tr3], axis=1).max(axis=1)
    return tr.rolling(window=period).mean()

def next(self):

    close = self.data.Close[-1]
    high = self.data.High[-1]
    low = self.data.Low[-1]
    atr = self.atr[-1]
    current_time = self.data.index[-1].time()
    current_date = self.data.index[-1].date()

    high_range = None
    low_range = None
    open_range = None
    close_range = None

    # Get high and low range (choose last point of time interval so 10:00
    ↪   to 10:10 is 10:10)
    if current_time >= pd.Timestamp(self.end_time).time():
        high_range = self.high_price[-1]
        low_range = self.low_price[-1]
        open_range = self.open_price[-1]
        close_range = self.close_price[-1]

    # Check EoD close condition
    if current_time >= self.market_close_time:
        if self.position:
            self.position.close()
```

```
    return

#Ensure no trades are made before the end_time
if current_time < pd.Timestamp(self.end_time).time():
    return

#Ensure only one trade per day
if self.last_trade_date == current_date:
    return

# Check if we are in a long position
if self.position.is_long:
    entry_price = self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price - 2 * atr

    # Check stop-loss condition
    if close <= stop_loss_price:
        self.position.close()

# Check if we are in a short position
if self.position.is_short:
    entry_price = self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price + 2 * atr

    # Check stop-loss condition
    if close >= stop_loss_price:
        self.position.close()

# Check for long entry condition (bullish opening range and close above
↪  high range)
if high_range is not None and open_range is not None and close_range is
↪  not None:
    if close_range > open_range and close > high_range:
        if not self.position:
            self.buy(size=0.2)
            self.last_trade_date = current_date

# Check for short entry condition (bearish opening range and close
↪  below low range)
if low_range is not None and open_range is not None and close_range is
↪  not None:
    if close_range < open_range and close < low_range:
        if not self.position:
            self.sell(size=0.2)
            self.last_trade_date = current_date
```

DCS

```python
class DCS(Strategy):

    n1 = 10
    n2 = 20
    n3 = 20
    n4 = 10

    atr_period = 14
    market_close_time = time(17, 55)

    def init(self):

       # Convert data to pandas dataframe
        self.data_frame = pd.DataFrame({
            'High': self.data.High,
            'Low': self.data.Low,
            'Close': self.data.Close
        })

        #Calculate the Donchian Channel
        self.dc_high = self.I(self.calculate_donchian_channel,
        ↪   self.data_frame['High'], self.data_frame['Low'], self.n1, 'high')
        self.dc_low = self.I(self.calculate_donchian_channel,
        ↪   self.data_frame['High'], self.data_frame['Low'], self.n2, 'low')
        self.dc_low_20 = self.I(self.calculate_donchian_channel,
        ↪   self.data_frame['High'], self.data_frame['Low'], self.n3, 'low')
        self.dc_high_10 = self.I(self.calculate_donchian_channel,
        ↪   self.data_frame['High'], self.data_frame['Low'], self.n4, 'high')

        #Calculate ATR
        self.atr = self.I(self.calculate_atr, self.data_frame['High'],
        ↪   self.data_frame['Low'], self.data_frame['Close'], self.atr_period)

    def calculate_donchian_channel(self, high, low, period, channel_type):
        if channel_type == 'high':
            return high.rolling(window=period).max()
        elif channel_type == 'low':
            return low.rolling(window=period).min()

    def calculate_atr(self, high, low, close, period):
        tr1 = high - low
        tr2 = abs(low-close.shift(1))
        tr3 = abs(high-close.shift(1))
        tr = pd.concat([tr1, tr2, tr3], axis=1).max(axis=1)
        return tr.rolling(window=period).mean()

    def next(self):
```

```
# Get the latest values
close= self.data.Close[-1]
high = self.data.High[-1]
low = self.data.Low[-1]

# Get the latest calculated indicators
dc_high = self.dc_high[-1]
dc_low = self.dc_low[-1]
dc_high_10 = self.dc_high_10[-1]
dc_low_20 = self.dc_low_20[-1]
atr= self.atr[-1]

# Get current time
current_datetime = self.data.index[-1]
current_time = current_datetime.time()

# Check EoD close
if current_time >= self.market_close_time:
    if self.position:
        self.position.close()
    return

# Check if we are in a long positon
if self.position.is_long:
    entry_price = self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price - 2 * atr

    # Check stop-loss condition
    if close <= stop_loss_price:
        self.position.close()

    # Check exit condition
    if close <= dc_low:
        if len(self.dc_low) > 1 and dc_low < self.dc_low[-2]:
            self.position.close()

# Check if we are in a short positon
elif self.position.is_short:
    entry_price =  self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price + 2 * atr

    # Check stop-loss condition
    if close >= stop_loss_price:
        self.position.close()

    # Check exit condition
    if close >= dc_high_10:
```

```
        if len(self.dc_high_10) > 1 and dc_high_10 >
        ↪  self.dc_high_10[-2]:
            self.position.close()

# Check for long entry condition
elif close >= dc_high:
    if len(self.dc_high) > 1 and dc_high > self.dc_high[-2]:
        self.buy(size=0.2)

# Check for short entry condition
elif close <= dc_low_20:
    if len(self.dc_low_20) > 1 and dc_low_20 < self.dc_low_20[-2]:
        self.sell(size=0.2)
```

EMA

```
class EMA(Strategy):

    n1 = 12
    n2 = 26
    market_close_time = time(17,55)

    def init(self):
        close = self.data.Close
        self.ema1 = self.I(ta.trend.ema_indicator, pd.Series(close), self.n1)
        self.ema2 = self.I(ta.trend.ema_indicator, pd.Series(close), self.n2)

    def next(self):
        #Get current datetime
        current_datetime = self.data.index[-1]
        current_time = current_datetime.time()

        #EoD Target
        if current_time >= self.market_close_time:
            if self.position:
                self.position.close()
            return

        if crossover(self.ema1, self.ema2):
            self.buy(size=0.2)
        elif crossover(self.ema2, self.ema1):
            self.sell(size=0.2)
```

RSI

```python
class RSI(Strategy):

    rsi_period = 14
    atr_period = 14
    rsi_lower = 10
    rsi_upper = 90
    rsi_values = []
    market_close_time = time(17, 55)

    def init(self):
    #convert data to pandas dataframe
        self.data_frame = pd.DataFrame({
            'High': self.data.High,
            'Low': self.data.Low,
            'Close': self.data.Close
        })

        #calculate rsi
        self.rsi = self.I(self.calculate_rsi, self.data_frame['Close'],
        ↪   self.rsi_period)

        #Calculate ATR
        self.atr = self.I(self.calculate_atr, self.data_frame['High'],
        ↪   self.data_frame['Low'], self.data_frame['Close'], self.atr_period)

    def calculate_atr(self, high, low, close, period):
        tr1 = high - low
        tr2 = abs(low-close.shift(1))
        tr3 = abs(high-close.shift(1))
        tr = pd.concat([tr1, tr2, tr3], axis=1).max(axis=1)
        return tr.rolling(window=period).mean()

    def calculate_rsi(self, close, period):
        delta = close.diff()
        gain = (delta.where(delta > 0 ,0)).rolling(window=period).mean()
        loss = (-delta.where(delta < 0, 0)).rolling(window=period).mean()
        rs = gain / loss
        return 100 - (100 / (1 + rs))

    def next(self):
        rsi= self.rsi[-1]
        atr = self.atr[-1]
        close= self.data.Close[-1]

        # Get current time
        current_datetime = self.data.index[-1]
        current_time = current_datetime.time()
```

```
# Check EoD close
if current_time >= self.market_close_time:
    if self.position:
        self.position.close()
    return

#Check for long position
if self.position.is_long:
    entry_price = self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price - 2 * atr

    #check stop-loss condition
    if close <= stop_loss_price:
        self.position.close()

# Check if we are in a short positon
elif self.position.is_short:
    entry_price =  self.trades[-1].entry_price if self.trades else None
    if entry_price is not None:
        stop_loss_price = entry_price + 2 * atr

    # Check stop-loss condition
    if close >= stop_loss_price:
        self.position.close()

# Check for entry condition
elif rsi <= self.rsi_lower:
    self.buy(size=0.2)

# Check for short entry condition
elif rsi >= self.rsi_upper:
    self.sell(size=0.2)
```