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Discovering Decision Rules in the Commodity Options Market for Hedging Against Oil Price Fluctuations

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ABSTRACT

High volatility of commodity prices is due, among others, to sudden global events. Only recently, COVID-19 pandemic and the war in Ukraine have caused crisis in commodity markets. In particular, the prices of strategic goods such as oil have become very volatile. To hedge against adverse price movements in this commodity, business and investors use commodity options. However, making reasonable buy/sell decisions requires a good mix of market understanding, technical and fundamental analysis, and risk management. In this paper, we use association analysis to discover buy decision rules for the investors in the WTI crude oil options market. The rules are discovered based on moving averages of WTI crude oil prices and the price differences of this commodity between selected days. The effectiveness of the discovered rules is evaluated using indicators related to the level of payout of the buyer of call options and the cost of acquiring these options. The results of experiments on data from 26 August 2008 and 15 November 2022 indicate that the decision rules discovered can effectively support decisions to take a long position in call options and can significantly contribute to effective hedging against unfavorable oil price movements.

Keywords: WTI Oil, Option Hedging, Association Analysis, Decision Rules, Price Risk
JEL Classifications: D81, G32

1. INTRODUCTION

Energy commodity prices are highly volatile. This is mainly due to sudden events that disrupt the supply chain and affect lead times, delivery times and production costs. For example, in March 2020, the supply and demand for energy commodities was disrupted when many governments decided to freeze retail trade and other economic activities to limit the spread of the COVID-19 pandemic (Yang and Deng, 2021). Various restrictions and the resulting slowdown in production during the first wave of COVID-19 (and the first shutdowns) significantly reduced demand for oil and consequently caused the fall of oil prices (Qin et al., 2020). The COVID-19 pandemic also made the oil market inefficient, and it was difficult to predict oil price movements (Gil-Alana and Monge, 2020). In other words, COVID-19 has not only caused death of millions of lives but also proved to be a serious threat to the global economy (Alfaro et al., 2020; Ding et al., 2020), including the stability of the oil market (Mensi et al., 2020).

The war in Ukraine, which began in February 2022, has also increased oil price volatility. It has triggered several geopolitical and economic responses that have contributed to increased uncertainty and volatility in world energy markets. Ukraine is not a major oil producer itself, but the conflict has affected neighboring regions and raised concerns about potential disruptions of oil supplies from Russia, which itself is one of the largest oil exporters in the world. These concerns have led to market speculation about possible supply disruptions, and what follows a rapid rise in oil prices.

The increased volatility of energy commodity prices became particularly visible after the events that took place in April 2025.

The US imposed an astounding 104% in tariffs across all Chinese imports as part of an unfolding global trade war. In return, China has raised its tariffs on US products to 125%. This escalation in trade tensions has increased concerns about a global economic slowdown and reduced demand for energy commodities, including oil. As a result, WTI prices fell more than 4% reaching $57.12 per barrel, the lowest since February 2021 (Jao, 2025). In response to rising trade tensions and concerns about demand, eight OPEC+ member countries announced plans to increase oil production by 411,000 barrels per day starting from May 2025. The unexpected move added pressure on oil prices, which were already weighed down by concerns about oversupply and falling demand (Ballard, 2025).

These decisions forced financial institutions such as Goldman Sachs and JP Morgan to revise their forecasts regarding the growth of oil prices. Goldman Sachs lowered its global oil demand growth forecast for 2025 to 300,000 barrels per day, citing weak growth prospects due to the ongoing trade war (Reuters, 2025a). Similarly, JP Morgan lowered its oil price forecasts, predicting an average WTI price of $62 per barrel in 2025, down from a previous forecast of $73 per barrel (Reuters, 2025b). All these events indicate that during the upcoming months the oil market will be highly volatile, which may pose a significant challenge for companies selling and processing oil. High volatility of prices will undoubtedly translate into high variability in supply costs and revenues from oil sales.

At a time of increasing uncertainty in commodity markets, it is not surprising that areas of research aimed at hedging against this type of risk are developing. Many academic studies show that recent years have also witnessed the rapid development of Internet technology, generating huge amounts of data that, among other things, facilitate decision-making in financial markets. On the other hand, huge amounts of data pose new challenges to financial activities in terms of acquiring, processing and analyzing multiple sources of information (Xiao and Ke, 2021) and the relationships between them. Nonlinear and complex relationships between various financial factors from large data sets can be modeled effectively using deep learning (DL) and reinforcement learning (RL) methods. Thus, these methods can effectively support decision-making processes in various financial tasks – especially in conditions of high market uncertainty, which is common in commodity markets. Another important tool for supporting decision-making processes in various financial tasks is knowledge discovery in databases (KDD). KDD is a data science process that involves finding useful patterns or relationships in large amounts of data that are not readily apparent due to their complexity. KDD consists of several stages of data handling, such as selection, preprocessing, transformation, and data mining (Pardasani, 2023). Data mining techniques include regression, classification, as well as association and decision rules.

A rules engine is an efficient, cost-effective choice for businesses that prioritize consistency, simplicity, and speed in decision automation. Therefore, the observed increase in volatility in energy commodity markets and the rapid development of artificial intelligence technologies have led us to an attempt to identify decision rules for call options on WTI crude oil. Commodity derivatives now play an important role in global commodity trading (Christensen et al., 2010). This is because, by their very nature, they allow future deliveries to be settled at a price set at the time the contract is entered into. Thanks to this form of settlement, each counterparty knows exactly how much it will pay or receive for future deliveries of the commodity and can therefore plan future expenditures. An important group of commodity derivatives are, as already mentioned, options, which are characterized by asymmetric risk distribution and the possibility of fixing the total cost (maximum loss) on the day the position is opened.

Puka et al. (2023) discovered the buy/sell decision rules for the WTI crude oil options market in the period 2008-2022 based on implied volatility and the Greeks (delta, gamma, vega, theta). However, we believe that in the situation of highly volatile WTI oil prices, decision rules should be discovered for a narrower group of options and based on factors that are strictly related to oil prices. Therefore, in this paper, we discover the buy/sell decision rules based on moving averages of WTI oil prices and the differences of oil prices between selected days and we only consider options with an execution time that did not exceed 30 days. We evaluate the effectiveness of the developed rules using indicators such as the total payout for taking a long position in a call option and the ratio of the sum of these payouts to the sum of the cost of acquiring the option (Puka et al., 2023).

The remainder of the article is structured as follows. Section 2 provides an overview of related work. Data used in the study and their characteristics are described in Section 3. The proposed methods and performance indicators used in the analyses are presented in Section 4. The results obtained are presented in Section 5. The article ends with a discussion and concluding remarks in Section 6.

2. LITERATURE REVIEW

The rapid development of artificial intelligence (AI) has led to its widespread use in various fields, including financial markets. As Masood (2024) notes, AI has profoundly impacted financial markets by improving efficiency and accuracy across multiple areas, including trading, and risk management. Sophisticated machine learning models enable high-frequency trading and predictive risk analysis, enhancing market adaptability. For example, Goldman Sachs and Morgan Stanley use AI for predictive analytics, improving their ability to anticipate market trends and dynamically adjust portfolios (Turmanidze, 2024).

In recent years, AI and machine learning have been extensively used to solve problems related to the oil market. Sequential models based on neural networks, especially LTSM (Long Short-Term Memory) architectures, have gained considerable attention. Their ability to discover long-term dependencies makes them more adequate than statistical tools to predict prices of raw materials (Guo et al., 2025; Foroutan and Lahmiri, 2024). For example, Gao et al. (2022) have compared the effectiveness of several ML algorithms and LSTM, in forecasting oil prices during the COVID-19 pandemic. They showed that LSTM can learn nonlinear patterns better than classical methods, though in their experiments LightGBM (Light Gradient Boosting Machine) showed the best accuracy. Jahanshahi et al. (2022) have focused on investigating the impact of global crises (COVID-19 pandemic and the war in Ukraine) on oil prices. They used both classical (SVM, linear regression, random forest) and deep neural networks (LSTM and BiLSTM).

However, not only neural networks, but also classical machine learning methods are used in literature to forecast oil prices. Ensemble algorithms such as random forest or gradient boosting (e.g., eXtreme Gradient Boosting – XGBoost, Light Gradient-Boosting Machine – LightGBM) often compete in terms of efficiency with deep learning models. For example, Gao et al. (2025) observed that LightGBM slightly outperformed other ML models (including XGBoost, random forest, k-NN, linear regression and neural network) for the problem of short-term forecast of oil price in a period of major market disruptions. They trained six ML models based on the extended set of features (such as data on internet search, cryptocurrency, and COVID-19 statistics), which highlights an increasingly common practice to enrich input data with non-obvious factors.

Accurate forecasts of oil prices straightforwardly impact on risk management – the smaller the prediction error, the better the decisions regarding hedging or capital allocation. Many of the AI/ML models discussed above can foresee the upcoming trend changes or volatility jumps, allowing investors and businesses to take safe positions. However, risk management is something more than prediction of average prices. An important part of risk management is discovering patterns and market anomalies. Both of these can be done efficiently using Knowledge Discovery in Databases (KDD).

The term was first used at the KDD workshop in 1989 to emphasize that knowledge is the ultimate product of data-driven discovery (Mirończuk and Maciak, 2009). KDD is a multifaceted process for extracting valuable and understandable patterns from large data sets. The process involves several steps, from data preparation to pattern evaluation, and relies heavily on domain knowledge to improve the quality of the discovered patterns. The last and very important step for the final effect of using KDD is data exploration. This step can be accomplished by using decision rules which provide a ready-made pattern for dealing with the conditions, trading decisions, guiding investment strategies and managing risk. These rules can be derived using a variety of methodologies, including rule-based systems (Puka et al., 2021; Li et al., 2023), decision markets (Wang and Pfeiffer, 2022) and investment valuation techniques (Schoenmaker and Schramade, 2023).

Recent years have also demonstrated the value of KDD, particularly decision and association rule mining, in improving understanding of energy commodity markets. These techniques complement traditional analysis by uncovering complex, multivariate patterns and presenting them in an accessible, rule-based format. Ongoing research is making these tools more powerful (through hybrid models and better validation) and extending them to new problems.

For example, Antomarioni et al. (2019) proposed a predictive maintenance policy for oil refineries based on association rule mining. Refineries are critical to the production of gasoline, diesel and LNG, and unplanned outages can disrupt supply and affect commodity prices. The authors compiled extensive equipment sensor and failure data and applied association mining to predict which components were likely to fail together or in sequence. The resulting decision rules identified patterns such as “IF pressure deviation in unit A AND temperature spike in unit B, THEN high risk of pump failure in unit C.” By incorporating these rules into a maintenance planning model, they were able to determine an optimal set of components to proactively repair during planned downtime (Antomarioni et al., 2019). The case study of a real refinery showed that this approach can minimize the probability of critical failures, thereby improving overall plant reliability.

In turn, Kim and Lee (2020) applied association analysis to patent data in the US shale oil and gas industry to uncover patterns of technological innovation [mdpi.com]. By treating International Patent Classification (IPC) codes as elements, they mined rules to see which technology areas frequently appeared together in patents, indicating converging areas of innovation (Kim and Lee, 2020). Their study found that although large-scale shale oil/gas production began around 2007, patent activity did not show a significant increase in technological development until after 2010 (Kim and Lee, 2020). In addition, the association rules revealed that two distinct technological domains emerged in shale oil/gas patents in 2010 [mdpi.com] - for example, certain drilling technologies were often associated with certain chemical engineering methods, forming clusters of innovation. In sum, the authors used KDD to identify priority technology domains (e.g., combinations of horizontal drilling and hydraulic fracturing techniques) that drove the US shale boom.

Si et al. (2021) applied unsupervised learning (clustering and association rules) to operational data from Canadian in-situ oil sands projects. Their goal was to discover patterns in steam-assisted heavy oil recovery processes that affect energy efficiency and production. After clustering similar production systems, they mined association rules within each cluster to determine which operational factors lead to better outcomes (measured by the Steam-Oil Ratio, SOR). The analysis of 35 million data (2015-2019) revealed several important rules. One rule showed that IF a project used cyclic steam stimulation (CSS) (an older extraction method) AND it was in later stages, THEN a high SOR (inefficiency) was likely - while another rule showed that IF it used steam-assisted gravity drainage (SAGD) (a modern method) AND project maturity was high, THEN the SOR remained low (Si et al., 2021).

To sum up, the recent literature reveals a diverse set of applications for decision and association rule mining in oil, gas and derivatives markets. Table 1 provides a summary of some of the key publications in recent years, highlighting their methods, focus commodities and main findings.

3. DATA

The data used in this study are the futures prices of WTI crude oil and the prices of call options written on this commodity between

Table 1: Selected studies on decision and association rule applications in energy commodity markets, with their methods, focus, and key findings

Authors (Year)	Title (Journal)	Methods	Commodity focus	Key findings
Antomarioni et al. (2019)	A predictive association rule-based maintenance policy to minimize the probability of breakages: application to an oil refinery (Int. J. Adv. Manuf. Technol.)	Association rule mining for predictive maintenance	Oil refinery (downstream)	Discovered rules linking equipment sensor anomalies to component failures; enabled a preventive maintenance schedule that reduces unplanned refinery outages.
Kim and Lee (2020)	Progress of Technological Innovation of the US Shale Petroleum Industry Based on Patent Data Association Rules (Sustainability)	Association rule mining (patent co-classification analysis)	Shale oil and gas (upstream innovation)	Identified emerging technology clusters in shale extraction after 2010; two distinct innovation domains and frequent IPC code co-occurrences driving shale oil and gas growth.
Si et al. (2021)	Discovering Energy Consumption Patterns with Unsupervised ML for Canadian *in Situ* Oil Sands Operations (Sustainability)	Clustering+Association rules (unsupervised KDD)	Heavy oil (oil sands) production	It was found that SAGD method yields lower Steam-Oil Ratios than CSS in later project stages, and gas co-injection strongly correlates with improved recovery efficiency (lower SOR). Validated associations with statistical tests.
Puka et al. (2023)	Knowledge Discovery to Support WTI Crude Oil Price Risk Management (Energies)	Association analysis+Decision rules (if-then patterns)	Crude oil options (WTI)	Mined decision rules for taking long positions in WTI call options based on implied volatility, time to expiry, and Greeks. Certain parameter ranges (e.g., moderate volatility, low delta) yield significantly higher option payoffs, providing clear hedging signals.

August 26, 2008 and November 15, 2022 (more than 3500 daily observations). They have been obtained from the QuikStrike options market analysis platform. The database is available on the CME Group website via Bantix Technologies LLC (2022).

In this study, American ATM (at the money) call options were used. They include options with a strike price set at the price of oil on the day the position was opened. Options with the shortest available maturity (maximum 30 days) are also selected. The reason for choosing such options is their great popularity among market participants, as options with an exercise date within the next month are characterized by the highest volume and the largest number of open positions. It seems, therefore, that the analysis of this group of options is particularly important from the perspective of options market participants.

To discover the decision rules for the period analyzed, we had to determine the values of two types of parameters, including:

- N-day moving averages of WTI oil prices (AvgN), where N $\in \{5, 10, 15, 20, \ldots, 90\}$
- Price differences between the WTI oil price of a given day and the oil price of N days before (DiffN), where N $\in \{5, 10, 15, 20, \ldots, 90\}$.

Since we need to determine the size of the parameters used for rule discovery, i.e., N-day moving averages and N-day oil price differences, where the maximum value of N was set to 90, the final number of observations used in the analyses was 3464 (the first day for which all parameters were determined was January 05, 2009).

4. METHODOLOGY

This section discusses the methodology used to discover decision rules based on the data described in Section 3. We used the developed tool to analyze WTI crude oil call options. The discovered decision rules (Section 4.1) inform the trader whether to buy a call option on a given trading day. We evaluated the rule using three performance indicators, described in Section 4.2.

4.1. Association Analysis and Decision Rules

Association analysis is a data mining technique that identifies relationships between items in large datasets. In financial markets it uses various methods to discover relationships and patterns in financial data to help investors make decisions. This analysis is crucial for understanding market dynamics, predicting asset price movements, and optimizing investment strategies (Huang, 2022). It enables the identification of patterns (rules) that suggest a cause-and-effect relationship between the values (or range of values) of the analyzed variables and the occurrence of specific phenomena.

One of the outcomes of association analysis may be the development of decision rules. These rules are simple instructions used to classify or predict outcomes based on input data. They also form the basis for developing models in machine learning and decision support systems. Decision rules can be used to analyze data and draw conclusions that are easy to interpret, making them particularly useful in situations where an explanation of the decision-making process is required. Each decision rule consists of a premise (also called condition, predecessor) and a consequence (also called decision, successor in the implication). A premise specifies the conditions that must be met to apply the rule, while a consequence specifies the decision or action to be taken if the conditions are met.

In our study, we look for certain sets of variables related to the price of oil (moving averages and oil price differences on the days indicated) at which the parameters selected from the options market would be at a level favorable to the buyer of a call option. To determine the decision rules, we use an algorithm to search for all intervals of a given parameter that meet the following guidelines:

- The minimum number of observations in each interval is 10 (this is the minimum level of support for the rule at which the recurrence of a situation requiring hedging can be said to occur)
- The maximum number of observations in each interval is limited to 500 (to guarantee the reasonable computing time).

4.2. Indicators for Assessing Decision Rules

We use three indicators to evaluate the decision rules. Their values are calculated based on the final result obtained by the buyer of a WTI crude oil option and the cost of acquiring these options.

1. *Summary value of payoffs (P)*

$$P = \sum_{c \in C} P_c \tag{1}$$

where C is the set of all positions and P_c is the payoff from position c, calculated according to the following formula:

$$,P_c = \max\{F-K,\ 0\}-op_c \tag{2}$$

Where F is the future price of a good (here, crude oil) on the day of the option's expiration, K is the strike price of the option, and op_c is the option premium (for the strike price K) of position c.

2. *Average payoff per one position (AvgP):*

$$AvgP = \frac{1}{|C|}\sum_{c \in C} P_c \tag{3}$$

where |C| is the number of observations for which a given decision rule is satisfied.

3. Return of investment (ROI)

$$ROI = \frac{\sum_{c \in C} P_c}{\sum_{c \in C} op_c} \times 100\% \tag{4}$$

All these values have been calculated for ATM call options with a maturity of 30 days or less.

5. RESULTS

This section presents the highest rated (wrt the indicators: P, AvgP, ROI) decision (business) rules discovered with parameters such as N moving averages of oil prices (AvgN) or differences in oil prices over N recent days (DiffN), where N ∈ {5, 10, 15, 20,…, 90}. The discovered rules were sorted in descending order of the value of one of the three indicators. As a result, three lists were created for each of the indicators: P, AvgP and ROI. The lists contain the top five rules for each category, together with information on which parameter (AvgN or DiffN) was decisive in discovering the rule and in which range it fell. In addition, Figures 1-3 show information on the level of the rule evaluation performance indicators to better illustrate the effectiveness of the application of the discovered rules. The extended results (top 36 rules) from the perspective of maximizing the P, AvgP, ROI indicators are included in the appendix in Tables A1-A3, respectively.

Figure 1: P indicators (left axis) and AvgP and ROI indicators (right axis) for the top 5 rules obtained for maximizing P

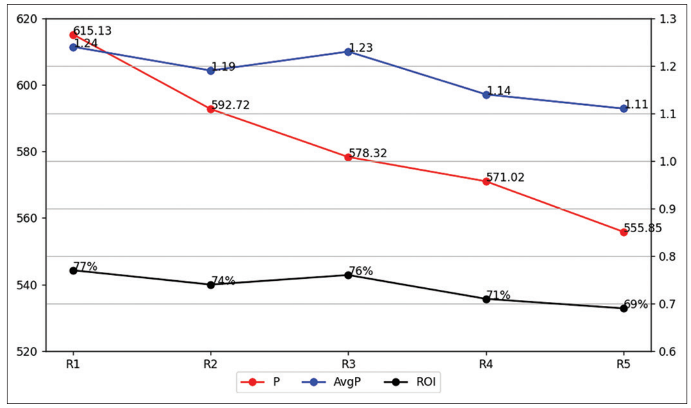


Figure 2: P indicators (left axis) and AvgP and ROI indicators (right axis) for the top 5 rules obtained for maximizing AvgP

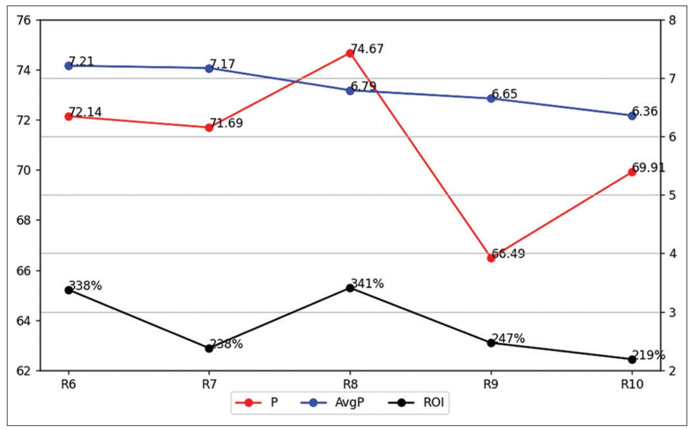
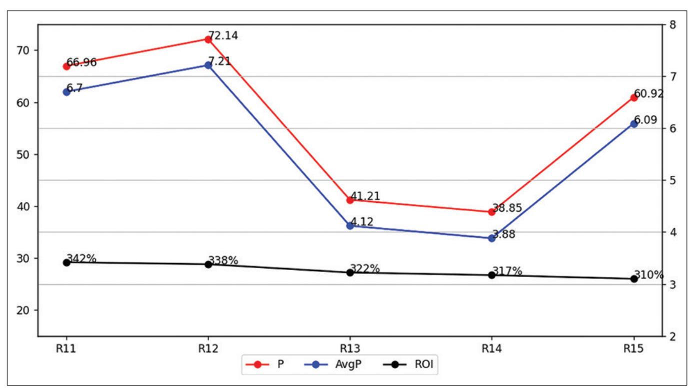


Figure 3: P indicators (left axis) and AvgP and ROI indicators (right axis) for the top 5 rules obtained for maximizing ROI



5.1. Decision Rules to Maximize P Indicator

The best five rules (R1-R5) determined by maximizing the P values are as follows:

- R1: IF Avg90 ∊ (35,2172; 47,469) THEN Buy Option
- R2: IF Avg85 ∊ (35,0139; 47,4189) THEN Buy Option

- R3: IF Avg80 ∈ (31,3131; 46,382) THEN Buy Option
- R4: IF Avg75 ∈ (30,3349; 46,6508) THEN Buy Option
- R5: IF Avg70 ∈ (34,1559; 47,0537) THEN Buy Option.

As can be seen, the best results, in terms of maximizing the P indicator, are produced by the rules developed based on the longest moving averages (here 90 days). Moreover, these averages are very similar for each of the top five rules. Their lower limits fluctuated around USD 30-35/barrel, whereas their upper limits were very similar and fluctuated around USD 46-47/barrel. It can also be noted that none of the top five rules do not include the second set of parameters (DiffN). The payouts obtained using the rules that maximize P were also analyzed in relation to the values of the other two indicators. The results are presented in Figure 1.

In summary, the best rule (R1) allowed call options to achieve a total payout (P indicator) of over $615 during the analyzed period, which was almost 4% better than the payout from the second rule (R2). The decline in the P indicator value for the subsequent rules was much smaller, ranging from 1.2 to 2.6%. It can also be observed in Figure 1 that the sum of the option payments decreases along with the values of the AvgP and ROI indicators. The exception is rule R3, for which these ratios reached the second highest values (just after R1).

5.2. Decision Rules to Maximize AvgP

The R6-R10 rules presented below were determined by maximizing the value of the AvgP indicator. This indicator showed the average result of acquiring a call option on the WTI crude oil price.

- R6: IF Avg40 ∈ (48,9565; 49,0308) THEN Buy Option
- R7: IF Avg20 ∈ (20,357; 22,73) THEN Buy Option
- R8: IF Avg55 ∈ (93,7738; 93,8749) THEN Buy Option
- R9: IF Avg15 ∈ (18,638; 21,7487) THEN Buy Option
- R10: IF Avg25 ∈ (21,0436; 23) THEN Buy Option.

The best rules in this category show a different trend than the rules R1-R5. Moreover, there is a much greater variation in the length of the moving averages used to find them. When optimizing the AvgP indicator, the best results were obtained when moving averages were calculated based on 15-55 observations. Furthermore, none of the moving averages for rules R6-R10 were used in the discovery of rules R1-R5. In the case of rules R6-R10, the ranges of average oil prices used were much more diverse and much narrower than in the case of rules R1-R6. Again, no DiffN parameters were used in the discovery of the best rules. The payouts produced by the rules that aimed at maximizing AvgP were also analyzed in terms of *P* and ROI values. The results are shown in Figure 2.

The R6-R10 rules undoubtedly achieved much higher average final results per call option purchased than the R1-R5 rules. The AvgP indicator for the best performing R6 and R7 rules in this category was USD 7.21/barrel and USD 7.17/barrel respectively, approximately six times higher than for R1-R5 rules. The ROI was also by far the highest, exceeding 200% for each of the rules in this set, with 338% and 341% for the R6 and R8 rules respectively. However, there was a marked decrease in the *P* indicator, and was about nine times lower for the R1-R6 rules.

5.3. Decision Rules to Maximize ROI

The last indicator analyzed was the ROI, which can be interpreted as the return on investment of acquiring a call option. Rules R11-R15 were set to maximize the value of this indicator.

- R11: IF Avg55 ∈ (93,7773; 93,8749) THEN Buy Option
- R12: IF Avg40 ∈ (48,9565; 49,0308) THEN Buy Option
- R13: IF Avg85 ∈ (45,4661; 45,6604) THEN Buy Option
- R14: IF Avg70 ∈ (36,5537; 37,2699) THEN Buy Option
- R15: IF Avg35 ∈ (49,4; 49,4851) THEN Buy Option.

Once again, the research carried out showed that the parameters in the AvgN group should be used to find the best rules, with the number *N* varying from 35 to 85. The rules obtained for ROI optimization were also characterized by the smallest ranges of values of the moving averages of WTI oil prices. The lengths of these ranges were only 0.08-1.2 USD/barrel, and for the best R11 rule it was 0.1 USD/barrel. It is also worth noting that rule R12 is identical to rule R6, while rule R11 is very similar to rule R8. This may confirm that optimizing the AvgP and ROI indicators leads to much more convergent results (rules) than maximizing the *P* indicator. Figure 3 shows a comparison of the values of the analyzed indicators for rules R11-R15.

The best rules created for the ROI optimization problem indicate a relationship between the *P* and AvgP indicators, for which the resulting curves (Figure 3) are practically identical. This is because each of the rules found implied the acquisition of 10 call options during the period analyzed, and therefore the *P* indicator in this case is 10 times the AvgP indicator. Moreover, a high ROI value could have been achieved by one of two strategies:

1. Purchase of relatively expensive options with potentially high returns (R11, R12, R15)
2. Purchase options where the hedges are relatively cheaper but the potential income from their conclusion is also lower (R13, R14).

For each of these strategies, the ROI exceeded 300%.

5.4. Comparison of Results

As discussed in the previous subsections, the rules derived from autoregressive values were compared with those generated based on the Greeks (delta, gamma, vega and theta) and implied volatility values (referred as Greeks+). All rules were subject to the same constraint regarding the range of days to expiration (DTE): $1 \leq DTE \leq 30$. Table 2 provides a summary of the five best-performing rules for each indicator.

The attached results clearly show that using moving averages leads to better outcomes than relying on Greeks+ values. Higher performance was achieved with autoregressive-based rules in as many as 13 out of 15 analyzed rules. The two best results were obtained without the use of moving average values only in the case of the AvgP indicator. A particularly large difference is observed

Table 2: Comparison best autoregressive and Greeks+rules

Maximized indicator	Autoregressive rules			Greeks+rules		
	Parameter	Range of parameter values	Indicator value	Parameter	Range of parameter values	Indicator value
P	Avg90	(35.2172; 47.469)	615.13	Theta	(−0.051; −0.0418)	306.04
	Avg85	(35.0139; 47.4189)	592.72	Vega	(0.4139; 2.6585)	265.62
	Avg80	(31.3131; 46.382)	578.32	Volatility	(0.4737; 0.6831)	259.63
	Avg75	(30.3349; 46.6508)	571.02	Gamma	(0.0648; 0.0791)	245.65
	Avg70	(34.1559; 47.0537)	555.85	Vega	(3.1792; 4.1731)	191.66
AvgP	Avg40	(48.9565; 49.0308)	7.21	Vega	(13.4901; 13.501)	8.38
	Avg20	(20.357; 22.73)	7.17	Volatility	(1.792; 6.6148)	7.26
	Avg55	(93.7738; 93.8749)	6.79	Vega	(13.4079; 13.422)	5.75
	Avg15	(18.638; 21.7487)	6.65	Vega	(13.742; 13.7611)	5.64
	Avg25	(21.0436; 23)	6.36	Delta	(0.5944; 0.7569)	5.55
ROI	Avg55	(93.7773; 93.8749)	3.42	Gamma	(0.306; 0.3211)	3.04
	Avg40	(48.9565; 49.0308)	3.38	Theta	(−0.4815; −0.4531)	2.44
	Avg85	(45.4661; 45.6604)	3.22	Theta	(−0.0241; −0.0182)	2.3
	Avg70	(36.5537; 37.2699)	3.17	Vega	(0.4139; 0.7881)	2.11
	Avg35	(49.4; 49.4851)	3.1	Vega	(1.315; 1.3583)	2.11

for the P and ROI indicators, where the best Greeks+ rules perform worse than all the autoregressive rules.

6. CONCLUSIONS

Artificial intelligence is considered as an effective tool for dealing with data that is highly volatile, even over small time intervals thanks to its ability to extract patterns from large data sets. The high volatility of the oil market is a challenge for investors who include oil futures in their investment portfolios. Oil price volatility is also important for companies whose financial performance depends on both the price of oil and the price of the refined products derived from it. It seems, therefore, that any research aimed at increasing the effectiveness of managing the risk of oil price fluctuations is particularly important for the economy.

This paper attempts to identify the business rules that support the decision to buy call options on WTI crude oil prices. During the period analyzed (2008-2022), it was possible to identify certain ranges of values of the moving averages of the crude oil prices for which the option buyer could count on high levels of payoff (*P* indicator), average opening profit (AvgP) or return on investment (ROI). When attempting to maximize the *P* indicator, the best rules found were characterized by long-term moving averages and an oil price level in the range of USD 35-47/barrel. These rules also required a significant number of options to be purchased (around 500 over the period analyzed), but at a relatively high initial cost and low ROI. The rules that aimed to maximize AvgP and ROI had a completely different nature. These rules involved the purchase of fewer options, resulting in significantly lower total option purchase payouts, but at the same time lower hedging costs and higher investment returns.

An important relationship discovered during the research was that high ROI could be achieved by two different strategies: buying a small number of expensive options with potentially large payoffs or buying a small number of low-cost options where the sum of the payoffs was much lower. Both approaches produced very high returns (over 300%). They can be interesting investing strategies, especially for individual investors who do not have a lot of personal capital and want to limit their initial costs. The research carried out showed that rules discovered from moving averages of WTI oil prices gave better results than those obtained using Greeks or implied volatilities (Puka et al., 2023).

The research carried out confirms the validity of using data mining methods in the decision support process for price risk management. In our future work, we plan to investigate the effectiveness of using more advanced decision rules in oil price risk management.

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APPENDIX A

Table A1: P, AvgP and ROI values for the best rules (one best rule for each of the considered values of the analyzed parameters) obtained by maximizing P

Number	Parameter	Range of parameter values	P	AvgP	ROI
1	Avg90	(35.2172; 47.469)	615.1282	1.235197	0.770478
2	Avg85	(35.0139; 47.4188)	592.7201	1.187816	0.740919
3	Avg80	(31.3131; 46.382)	578.3175	1.22785	0.760781
4	Avg75	(30.3349; 46.6508)	571.0247	1.144338	0.706587
5	Avg70	(34.1559; 47.0537)	555.8469	1.113922	0.692055
6	Avg5	(14.314; 45.908)	521.8693	1.052156	0.623179
7	Avg65	(33.6882; 47.0642)	518.5906	1.03926	0.647397
8	Avg35	(47.7731; 55.4814)	507.481	1.016996	0.690404
9	Avg30	(48.058; 55.4973)	487.9631	0.977882	0.661397
10	Avg60	(31.5473; 46.9422)	478.055	0.958026	0.588749
11	Avg40	(46.6962; 53.799)	469.2595	0.9404	0.643164
12	Avg10	(15.798; 45.348)	463.1459	1.052604	0.612194
13	Avg25	(48.2708; 55.5724)	459.5916	0.921025	0.622518
14	Avg45	(46.4627; 53.0122)	450.8929	0.933526	0.637758
15	Avg15	(18.3253; 45.84)	449.2169	0.941754	0.548539
16	Avg50	(45.9772; 52.7444)	437.2665	0.88695	0.594667
17	Avg55	(29.4704; 46.8202)	433.1353	0.86975	0.531549
18	diff65	(−2.12; 1.95)	424.8338	0.85825	0.520939
19	Avg20	(19.606; 46.011)	409.508	0.846091	0.491593
20	Diff90	(−61.97; −14.48)	370.1935	0.785973	0.348333
21	Diff80	(−52.06; −16.42)	361.6426	0.999013	0.434741
22	Diff85	(−51.81; −15.62)	349.4964	0.869394	0.373524
23	Diff70	(−0.89; 3.1)	328.0635	0.675028	0.425445
24	Diff75	(−0.21; 4.05)	318.8134	0.640188	0.410479
25	Diff55	(−1.67; 2.14)	293.2234	0.599639	0.364698
26	Diff20	(−9.1; −4.75)	274.7641	0.610587	0.336191
27	Diff60	(−4.35; −0.3)	257.4956	0.534223	0.327413
28	Diff25	(−14.51; −6.82)	244.3371	0.629735	0.307608
29	Diff40	(3.93; 6.92)	226.9875	0.478877	0.270958
30	Diff50	(−2.19; 0.71)	224.1561	0.579215	0.355954
31	Diff30	(−5.75; −2.38)	201.1547	0.421708	0.233354
32	Diff45	(−3.57; −0.11)	198.0968	0.415297	0.258257
33	Diff15	(−8.49; −4.6)	189.268	0.452794	0.24666
34	Diff35	(3.12; 6.04)	171.9237	0.368935	0.21923
35	Diff5	(1.73; 3.2)	169.6569	0.339994	0.192839
36	Diff10	(−7.7; −3.87)	146.6186	0.333224	0.17544

Table A2: P, AvgP and ROI values for the best rules (one best rule for each of the considered values of the analyzed parameters) obtained by maximizing AvgP

Number	Parameter	Range of parameter values	P	AvgP	ROI
1	Avg40	(48.9565; 49.0308)	72.14	7.21	3.38
2	Avg20	(20.357; 22.73)	71.69	7.17	2.38
3	Avg55	(93.7738; 93.8749)	74.67	6.79	3.41
4	Avg15	(18.638; 21.7487)	66.49	6.65	2.47
5	Avg25	(21.0436; 23)	69.91	6.36	2.19
6	Avg10	(17.097; 22.115)	67.3	6.12	2.41
7	Avg35	(49.4; 49.4851)	60.92	6.09	3.1
8	Diff90	(−48.99; −46.69)	66.96	6.09	2.55
9	Avg80	(75.3693; 75.6599)	59.92	5.99	2.25
10	Avg70	(70.3941; 70.563)	59.73	5.97	2.54
11	Avg30	(21.5353; 23.2457)	59.57	5.96	2.1
12	Avg75	(70.3537; 70.6311)	59.38	5.94	2.53
13	Avg65	(94.0011; 94.1648)	62.65	5.7	2.88
14	Diff80	(−52.06; −47.64)	56.14	5.61	2.17
15	Diff85	(−50.49; −46.42)	88.65	5.54	1.94
16	Diff10	(−6.66; −6.54)	55.23	5.52	2.35
17	Avg60	(93.9257; 94.0203)	53.82	5.38	2.46
18	Avg5	(14.314; 20.998)	53.71	5.37	1.94
19	Avg85	(74.7325; 75.1746)	58.62	5.33	1.92
20	Diff70	(−42.76; −41.29)	52.2	5.22	1.62
21	Avg45	(84.7533; 85.0398)	49.67	4.97	1.54
22	Diff75	(−47.07; −44.85)	54.33	4.94	1.9
23	Avg90	(74.3609; 74.5013)	46.95	4.69	1.54
24	Diff50	(−42.44; −36.79)	45.04	4.5	1.39
25	Avg50	(48.6284; 48.7142)	43.66	4.37	2.18
26	Diff15	(−3.04; −2.98)	41.56	4.16	2.05
27	Diff25	(−0.63; −0.58)	40.4	4.04	2.13
28	Diff20	(−7.73; −7.49)	57.95	3.86	1.83
29	Diff60	(−1.29; −1.2)	37.79	3.78	2.11
30	Diff40	(−37.55; −30.92)	41.45	3.77	1.18
31	Diff45	(−33.17; −31.32)	37.45	3.75	1.21
32	Diff30	(−15.63; −15.28)	36.15	3.62	1.38
33	Diff65	(−41.3; −39.88)	36.01	3.6	1.8
34	Diff55	(1.22; 1.31)	35.1	3.51	1.87
35	Diff35	(3.12; 3.16)	33.52	3.35	1.56
36	Diff5	(2.39; 2.43)	27.97	2.8	1.46

Table A3: P, AvgP and ROI values for the best rules (one best rule for each of the considered values of the analyzed parameters) obtained by maximizing ROI

Number	Parameter	Range of parameter values	P	AvgP	ROI
1	Avg55	(93.7773; 93.8749)	66.96	6.7	3.42
2	Avg40	(48.9565; 49.0308)	72.14	7.21	3.38
3	Avg85	(45.4661; 45.6604)	41.21	4.12	3.22
4	Avg70	(36.5537; 37.2699)	38.85	3.88	3.17
5	Avg35	(49.4; 49.4851)	60.92	6.09	3.1
6	Avg90	(45.1159; 45.1792)	46.34	4.63	3.01
7	Avg20	(30.4065; 30.952)	47.71	4.77	2.94
8	Avg65	(94.0011; 94.1648)	62.65	5.7	2.88
9	Avg15	(30.4633; 31.11)	44.04	4	2.83
10	Avg45	(34.2296; 34.8896)	34	3.09	2.78
11	Avg60	(33.9377; 34.1503)	42.74	4.27	2.75
12	Avg25	(95.22; 95.2816)	47.94	4.79	2.7
13	Avg80	(87.0002; 87.498)	48.48	4.85	2.65
14	Diff90	(−48.99; −46.69)	66.96	6.09	2.55
15	Avg10	(47.926; 48.057)	35.62	3.56	2.54
16	Avg75	(70.3537; 70.6311)	59.38	5.94	2.53
17	Avg30	(95.1917; 95.3063)	48.31	4.39	2.52
18	Avg50	(34.1182; 34.7704)	33.93	3.08	2.46
19	Diff10	(−6.66; −6.54)	55.23	5.52	2.35
20	Avg5	(32.34; 33.23)	38.74	3.87	2.34
21	Diff40	(−1.18; −1.13)	30.26	3.03	2.19
22	Diff85	(−47.1; −45.42)	51.53	5.15	2.17
23	Diff80	(−52.06; −47.64)	56.14	5.61	2.17
24	Diff25	(−0.63; −0.58)	40.4	4.04	2.13
25	Diff35	(−9.02; −8.81)	29.63	2.96	2.12
26	Diff60	(−1.29; −1.2)	37.79	3.78	2.11
27	Diff15	(−3.02; −2.95)	32.68	3.27	2.07
28	Diff55	(−5.15; −5.06)	30.06	3.01	2.05
29	Diff75	(2.83; 2.89)	39.56	3.96	2.04
30	Diff20	(−7.64; −7.49)	41.58	3.78	2.01
31	Diff30	(7.29; 7.4)	23.24	2.32	1.98
32	Diff65	(−0.67; −0.59)	34.48	3.45	1.92
33	Diff50	(−22.92; −22.26)	43.47	3.34	1.89
34	Diff70	(11.28; 11.38)	21.81	2.18	1.85
35	Diff45	(−0.45; −0.37)	25.84	2.58	1.84
36	Diff5	(−0.31; −0.28)	27.73	2.77	1.52