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Flexible Decision Support System for Algorithmic Trading: Empirical Application on Crude Oil Markets

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ABSTRACT Generating reliable trading signals is a challenging task for financial market professionals. This research designs a novel decision-support system (DSS) for algorithmic trading and applies it empirically on two main crude oil markets. The novel DSS enables investors to interactively build algorithmic trading strategies by fine-tuning various predefined integral elements. The main novelty of this study is the forecasting procedure encompassed into the DSS, and the flexibility of the system that allows users to adjust the parameters of the predictive model embedded and the length of the recursive window, based on individual preferences and the trade-off between prediction accuracy (increased computing intensity) and computing efficiency. The DSS also introduces two new steps into a standard fixed-length recursive window out-of-sample forecasting technique. It first estimates a universe of candidate models on each rolling window and then applies a fitness function to optimize model fit and produce more reliable one-step predictions from each recursive forecasting origin. Point-forecasts are subsequently fitted into algorithmic trading strategies, whose absolute and risk-adjusted performance is finally evaluated by the DSS. In implementing the DSS-based algorithmic trading strategies, the system performs 60760 estimations and 1736 optimizations for each market. In robustness checks, an additional number of 8 DSS's are designed and evaluated. The results confirm the superiority of DSS-based algorithmic trading strategies in terms of predictive ability and investment performance for both markets. Hence, owing to its performance, flexibility and generalizability, the DSS is an important tool for prediction, decision-making, and algorithmic trading in the financial markets.

INDEX TERMS Algorithmic trading, COVID-19, decision support system, expected shortfall, oil price forecasting, Sharpe ratio, trading performance, trading signals.

I. INTRODUCTION

Technology has transformed the way financial markets operate and assets are traded [36]. With the advent of computational intelligence, algorithmic (or automated) trading has become integral to the operation of capital markets [83], and it dominates the equity, futures, and Treasury markets, among others, in the United States and across the world [19]. Currently, it is estimated that approximately 70-80 percent of the overall trading volume in the US stock market and many other mature financial markets is generated through algorithmic trading [70]. Moreover, the proportion of participants trading 80 percent or more of their portfolio via algorithmic trading nearly doubled over the last year, reaching 20.75 percent in 2021 from 10.98 percent in 2020 [79]. This trend is expected to continue and even intensify, as world financial markets become increasingly reliant on computer-driven algorithms [83] and automated trading is regarded as the ''lynchpin of a successful trading strategy'' [45].

Unsurprisingly, numerous research efforts have been dedicated to understating how this intense automation of trading impacts market dynamics [13]. Previous studies have found that algorithmic trading improves market liquidity [37] and facilitates price discovery [12], [11], and [38], also contributing to decreasing trading costs [21] and [47]. Nonetheless, it is important to underline that these positive externalities have been validated during ''normal'' market evolution [83], whereas algorithmic trading can diminish liquidity and exacerbate volatility during distressed markets, with dire economic consequences [80].

By definition, in computer science an algorithm is described as ''*a finite, deterministic, and effective problem-solving method suitable for implementation as a computer*

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program" [73]. In the context of electronic financial markets, algorithmic trading refers to the use of computer programs to automate one or more steps of the trading process: pre-trade data analysis, trading signal generation, and order execution [63]. Consequently, algorithmic trading strategies encompass pre-set rules that are coded into a computer program and that issue signals on which trading decisions are based [78]. This study proposes an integrated decision support system (DSS) aimed at building a trading algorithm that covers all three steps of the trading process, while also performing post-trading performance evaluation. Additionally, the robustness of the novel approach is tested by estimating the performance of empirical portfolios constructed with the novel trading algorithm on main crude oil markets on absolute and risk-adjusted terms relative to various benchmark strategies.

The predictive ability and trading performance of any algorithmic trading strategy intrinsically depend on the pre-set rules coded into the algorithm, and their ability to predict market movements through reliable trading signals. Trading rules are thus the lifeblood of any trading strategy and have the potential to create the link between automated trading and automated trading success. The embedded pre-set rules are in turn based on two important factors: (i) the predictive model encompassed into the algorithm; and (ii) the procedure employed to produce forecasts based on the predictive model.

The predictive model can range from simple indicators pertaining to technical analysis to complex forecasting models. Mainly, starting from Breiman [10] two main cultures or schools of thoughts in the field of data modeling have been identified, econometrics (statistical methods) and machine learning (self-learning systems, capable of learning from data to improve their performance), respectively [16]. The two frameworks bring distinct benefits and drawbacks [56], but share two common (altough differently prioritized) goals: information and predictability [48]. Thus, statistical methods focus on the construction and fitting of a dataset-specific probability model employed for inference, whereas machine learning techniques concentrate on prediction and make minimal assumptions about the data-generating systems [42]. The optimal model is ultimately specific to the data-generating process and is strongly linked to the main research goal. In this research, we rely on previous findings and on distributional characteristics of data to make our choice for the base model (i.e. a bivariate ARMA (p,q)-GARCH(1,1)), while we canalize our interest and efforts on the second element of crucial importance for the performance of the trading rules embedded into the integrated algorithm, i.e. the forecasting method. The algorithm is flexible and can accommodate any predictive model, as such the base ARMA (p,q)-GARCH(1,1) framework employed in this study serves as an initial example.

The forecasting procedure is at least as important as the predictive model itself. However, in the field of financial markets, time series forecasting remains a challenging task [74]. A recognized issue in forecasting continues to be the instability of parameters (Goyal and Welch, 2003; Paye and Timmermann, 2006; Giacomini and Rossi, 2009). To handle the problem of parameter instability, the recursive (or rolling) out-of-sample forecasting procedure that uses a fixed number of the most recent data (i.e. window) at each point of time emerged as the accepted optimal solution [43]. This procedure also brings additional advantages, such as more efficient splitting rules of the time series, distinct error distributions by lead time, and elimination of sensitivity to specific events, with further benefits when recalibration of the parameters at each iteration is also performed [77]. However, the empirical evidence on the forecasting performance of the fixed rolling scheme, as it emerges from the extant literature, although superior relative to other techniques, is unconvincing in absolute terms. Hence, the need for its improvement has emerged [43]. One direction in this respect has been towards the optimization of the window size employed in rolling estimation and forecasting. Some authors (i.e. Pesaran and Timmermann, 2007); Pesaran *et al.*, 2013; Giraitis *et al.*, 2013, and Inoue *et al.* [43]) propose different solutions for window size optimization and show the forecasting superiority of the approach. In this paper, we develop a new approach for improving the forecasting performance of the rolling out-of-sample forecasting procedure. More specifically, unlike previous studies that fit the predictive model to empirical time series, on a static or sliding window, and further employ fitted parameters to forecast future price movements (i.e. for the first two iterations, this approach implies the sequence of steps: Estimation on first window of data (one model specification)-Prediction-Recalibration on the second window of data (one model specification)-Prediction), this study uses computational intelligence to optimize model-fit daily (i.e., the first two iterations now take the form: Estimation on first window of data (multiple model specifications)-Selection (fitness function)-Prediction- Recalibration on the second window of data (multiple model specifications)- Selection (fitness function)-Prediction sequence approach). The proposed approach allows model parameters to adapt daily through the fitness function applied following multiple recalibrations at each iteration, and hence to achieve improved forecasting accuracy and superior trading performance. The novelty of the study and its superiority relative to previous attempts lies in the multiple specifications of estimated models and the selection step introduced into the recursive forecasting sequence. Whereas in the standard rolling window out-of-sample forecasting technique the model parameters also adapt at each iteration following model recalibration on the new fixed window of data, our approach re-estimates an array of model specifications at each iteration and then applies a fitness function to identify and select the best fit model among multiple candidates for each window, which is subsequently employed to issue the one-step-ahead forecast using a rolling fixed-length window of data. The algorithm thus re-estimates at each iteration (daily) the parameters of an array of ARMA(p,q)-GARCH(1,1) models (i.e. $[(p \times q) - 1]$

parameters) and applies the fitness function to identify the optimal parameters set (p,q) from the universe of $[(p \times q) - 1]$ candidates. The best-fit model is then employed to issue one-step-ahead forecasts, used by the algorithm to trigger buy and sell signals, and execute the trade. This is repeated recursively over the testing period.

A. OIL PRICE FORECASTING: A LITERATURE REVIEW

The proposed algorithm is applied to the task of forecasting and trading the crude oil market. The choice of the oil market for the empirical investigation is motivated by several factors. First, the oil market is the biggest and most liquid commodity market [53], it is also a highly oscillated market, due to its ''financialization'' process with the increasing use of oil as a financial asset ([84], Schmidt, 2017; Nguyen *et al.*, 2020). Second, oil is a significant impact factor for stock markets [3], [46], [65], [90]. Third, WTI and Brent are major benchmarks in the world of international trading [15]. Fourth, the crude oil markets have been catastrophically impacted by the ''*once-in-a-century*'' COVID-19 pandemic [30] that has shrunk global energy demand, with crude oil prices plunging to historic lows. Additionally, the effect of oil shocks on stock returns is more pronounced during crisis periods [4]. Not in the least, oil is a notoriously unpredictable market, which might explain the significant decrease in automated trading for crude oil contracts, as opposed to other commodities and financial assets [35]. All these factors suggest that a trading algorithm capable of superior performance on crude oil markets is of particular interest to financial markets practitioners and are thus important motivators for this study. Moreover, forecasting crude oil prices and volatility facilitates macroeconomic and capital market policymaking [50], further spurring our research interest, as well as the relevance of results.

Previous studies employ various models to understand and predict the behavior of crude oil prices, pertaining to both cultures described by Breiman [10]. Thus, while some authors estimate statistical models on crude oil series, i.e. the vector autoregressive (VAR) model [7], Dynamic Model Averaging (DMA), and Dynamic Model Selection (DMS) [22] and [61], ARIMA-GARCH models [57], [71], [92], [85], [88], and [26], forecast combinations [8] and [89], other studies employ machine learning techniques, such as neural networks [33], [87], decision tree models [64], [17], and support vector machines (SVMs) [93]. However, no technique has emerged as particularly successful; the non-linearity and non-stationarity of data, the complex supply-demand relationships, the various unanticipated events, and unpredictable factors that destabilize market equilibrium, are all sources of crude oil price forecasting failures [20]. Consequently no ''optimal'' or commonly accepted method for forecasting the crude oil price exists [22].

Nonetheless, the empirical literature does agree that oil returns distributions present excess kurtosis, negative skewness, and significantly deviate from normality, while volatility in oil returns is clustering and persistent. See among others [6], [58], [71], and [92] these empirical properties of the oil time series indicate that ARMA-GARCH models would be fit to consistently capture its properties. The statistical properties that emerge from our data sample echo these previous findings and justify our choice of the model embedded in the proposed DSS for algorithmic trading.

Some authors that employ GARCH-family models to predict crude oil returns go one step further and compare their results in terms of return enhancement and/or risk reduction strategies, with divergent results. Among these studies, [5] investigate the relationships between oil prices (Brent) and stock returns in Europe from a sector perspective (DJ Stoxx 600 and twelve European sector indices) and provide evidence of the out-of-sample benefit from portfolio diversification by applying some index-based investment strategies and constructing several portfolios composed of both stocks and oil with different allocation rates. Results show that introducing the oil asset into a diversified portfolio of stocks allows to significantly improving its risk-return characteristics. On the other hand, [86] also investigate whether the inclusion of crude oil futures benefits typical stocks and bonds portfolios. They find optimal asset weights based on forward-looking estimates of expected returns (derived via various forecasting techniques, including GARCH-family models) and conclude that crude oil futures do not enhance the out-of-sample portfolio performance of a stock and bond portfolio. However, previous research does not focus on constructing and optimizing trading strategies specifically on the crude oil market, but mainly assesses the importance of adding crude oil in terms of portfolio diversification benefits. The current study, different from prior research, focuses on the two main crude oil markets (WTI and Brent) and constructs energy portfolios based on algorithmic trading strategies drawn from the novel DSS within the crude oil market, whose trading performance is subsequently evaluated in both absolute and risk-adjusted terms relative to the buy-and-hold strategy and strategies drawn from alternative DSSs. A particular interest is on performance evaluation during distressed market periods, and thus the COVID-19 pandemic deserves special attention. This approach is further motivated by the fact that most markets have experienced disastrous losses after the pandemic out-break in the first trimester of 2020 and have been moving at a very similar trend at least during the first months of the world pandemic [51]. As a result, a within-market optimized trading strategy, contrary to diversification, would be able to add value to energy portfolios. Consequently, the results of this research have direct applications for portfolio and risk management on crude oil markets.

Compared with previous research, this paper makes several contributions to the literature, as follows.

First, it develops a new approach for improving the standard recursive out-of-sample forecasting technique, which offers important advantages over existing methods. It solves the parameter instability problem by multiple model fitting and selection (through applying a fitness function) on each recursive window of data. In-sample model fit (parameter adjustment to new data) is hence continually and dynamically optimized. From each rolling forecasting origin, only the best-fitted model is employed to produce forecasts throughout the lead-time. This procedure, which we call dynamically optimized recursive window forecasting (or DOR), can embed a wide range of predictive models. The ARMA-GARCH framework employed in this study serves as an initial example. DOR is further flexible by allowing the user to fine-tune pre-defined integral elements, including the length of the recursive window and the parameters of the predictive model that it embeds. This choice is the prerogative of the user, and must consider the trade-off between forecasting accuracy and computing efficiency. In robustness checks, alternative settings for various integral elements are specified, including distinct window lengths and a restricted optimization procedure, where the fitness function is applied at each iteration within a narrow universe limited to three candidate models. By all accounts, this restricted optimization is nonetheless superior in terms of forecasting ability to the standard recursive forecasting technique encountered in the literature that recalibrates step-wise the predictive model without applying a fitness function, but inferior to the base DOR proposed in the study. On the other hand, it brings important gains in term of computing efficiency when incorporated into an automated forecasting mechanism. DOR also permits adaptation of the fitness function, allows multiple-step-ahead forecasting, can be automated and is feasible in practice. We thus empirically assess the practical value of the technique for forecasting crude oil prices. Equally importantly, DOR offers generalizability, as it can be easily applied to other financial markets as well. To the best of our knowledge, this is the first study to propose and apply this approach for forecasting financial time series, and its findings are particularly relevant to policymakers that incorporate oil price predictions in their policymaking process.

Second, it designs an integrated decision support system (DSS) that encompasses the improved DOR forecasting procedure. The DSS serves for algorithmic trading covering all three steps of the trading process and also performs post-trading evaluation. To this aim, the paper goes further than previous related literature that evaluates model in-sample and out-of-sample performance by comparatively estimating model fit and/or forecasting-fit metrics, and proceeds to show the practical value of the integrated DSS. Hence, algorithmic trading strategies drawn from the DSS are implemented on two crude oil markets, and their predictive ability and performance over January 2014 - April 2021 is assessed in absolute and relative terms, considering the buy and hold strategy as benchmark. The outcome of algorithmic strategies based on four alternative DSSs for each crude oil market is additionally investigated in robustness checks. The onset of the COVID-19 pandemic (i.e. January 2020 – April 2021) is analyzed in a separate investigation. The findings show that the optimized DSS-based algorithmic strategies are able not only to avoid losses but also even achieve profits in turbulent markets. These findings have important consequences for market professionals, contributing to enhanced risk management and performance of crude oil portfolios by showing that investors don't need to sustain losses or exit crude oil markets in times of turmoil, but instead follow superior investment strategies.

Thirdly, unlike most of the previous studies that focus only on one crude oil market, (usually the US market), it includes the two most important crude oil markets, which are also two relevant benchmarks for international trading, WTI and Brent crude, respectively. This further assures the robustness of the algorithm based on the novel DSS and increases the relevance of results for market professionals.

The paper proceeds as follows. Section II presents the dataset, and contains a discussion on the evolution of the crude oil market over the analysis period. Section III describes and motivates the integral elements of the decision support system, designs the integrated DSS, and proposes robustness checks for the system. Empirical findings that emerge from implementing algorithmic trading strategies drawn from the novel DSS on the two main crude oil markets over two separate sample periods are contained in Section IV, which also included a discussion of the results and robustness checks. Finally, Section V concludes the study.

II. DATA AND METHOD

A. DATA

This subsection provides a quick overview of the oil market's evolution, as well as the dataset for the current study and key descriptive statistics.

1) THE EVOLUTION OF THE CRUDE OIL MARKET OVER THE LAST DECADES

The most popular traded grades of oil are Brent North Sea Crude (commonly known as Brent crude and sourced from the North Sea between the Shetland Islands and Norway) and West Texas Intermediate (commonly known as WTI, sourced from U.S. oil fields). Their origin has a direct impact on transportation costs. Thus, as Brent Crude is produced near the sea, transportation costs are significantly lower, whereas West Texas Intermediate is produced in landlocked areas, which in turn increases its transportation costs. While WTI stands as the major oil benchmark for the North American market, Brent fulfills this task for Africa, Europe, and the Middle East, whereas the price differential between the two is called a spread. It is apparent in Figure 1, which reflects the average weekly price evolution of the two crude oil markets over the January 2014 – April 2021 period, that realignment in the spread usually takes place during distressed markets. It happened over 2014-2015, a challenging time for crude oil markets globally, with both crude oils prices plunging from levels above 100$ per barrel at the beginning of 2014 to under 40$ per barrel by the end of 2015. This price drop was primarily caused by the sharp rise in U.S. oil production due to advancements in oil drilling and fracking (the so-called

"*American shale revolution*"), and was further exacerbated by the lifting of the export ban on U.S. crude that occurred at the end of 2015.

FIGURE 1. Average weekly price evolution of WTI and Brent crude oil over the 2014-2021 period, source of data: FRED, Federal Reserve Bank of St. Louis. Author's representation.

Most recently, the ongoing COVID-19 pandemic has significantly affected the global energy market and has again caused realignment in the spread over the first stages of the pandemic outbreak. However, the crude oil prices deviated again shortly by mid-April 2020 with the historical plummet of the WTI market, before realigning. Moreover, as demand for oil and gas fell sharply worldwide, a price war between Saudi Arabia and Russia further contributed to put an exceptional downward pressure on crude oil prices. After trading at over \$61 per barrel in the beginning of 2020, both crude oils prices plummeted to two-decade lows by April 2020 as the pandemic spread, (with WTI even entering into uncharted negative territory for future prices). WTI registered a negative price for the first time in history, closing at −\$37.63/bbl on April 20th 2020. The dramatic situation on WTI oil market was mainly caused by financial long positions on WTI crude oil futures for May 2020 that were too large to be physically accommodated because of the devastating collapse in demand and scarcity of storage capacity caused by the COVID-19 pandemic, while contract expiry was approaching. As an immediate response measure, OPEC members and other oil-producing nations, including Russia, Azerbaijan, Malaysia and Mexico, agreed in April 2020 that total global output should be reduced by around 9.7 m barrels per day (bpd) in order to help stabilize oil prices, which corresponds to about 10 percent reduction of world production. The 23-nation group known as OPEC+ has further decided to intervene and cap oil production during 2020. All these efforts, along with increased optimism about post-COVID19 economic recovery with the advent of new vaccines, have contributed to a recovery of the oil prices to a level of above \$60 per barrel by the end of March 2021.

2) DATA SAMPLE

The research conducted in this paper employs daily spot prices of the two main grades of crude oil (Brent crude and WTI), sourced from the Federal Reserve Bank of St. Louis's (FRED) database, which at its turn collects data from the U.S. Energy Information Administration (EIA). The sample period extends from January 2, 2014 to April 4, 2021 and therefore includes 1857 observations for each crude oil series. The timeframe provides a sufficing sample that includes tranquil, as well as highly volatile (historically turbulent) periods through which the predictability and performance of algorithmic trading strategies can be tested.

Crude oil price series are subsequently turn into daily return series in the manner described in Eq. (1) (the estimation of logarithmic returns is avoided due to the aforementioned negative value encountered in the closing prices of WTI on April 20th):

$$r_{i,t+1} = \frac{Index_{i,t+1}}{Index_{i,t}} - 1 \tag{1}$$

where $r_{i,t+1}$ is the return of the Index i on trading day $t+1$.

3) DESCRIPTIVE STATISTICS

Table 1 presents the descriptive statistics of the Brent and WTI crude oil return series over the January 2014 - April 2021 period.

TABLE 1. Descriptive statistics of one-day returns (%) for WTI crude oil and Brent crude oil (January 2, 2014–April 4, 2021).

	WTI crude	Brent crude
Min	-301.97	-47.47
Max	53.09	50.99
Range	355.05	98.45
Sum	-275.65	35.03
Median	0.06	0.00
Mean	-0.15	0.02
SE mean	0.19	0.08
CI, mean, 0.95	0.38	0.15
Variance	69.28	10.72
SD	8.32	3.27
Coef of var.	-56.07	173.58
Skewness	-27.20	0.80
Kurtosis	956.25	68.87
Shapiro-Wilk test	0.19	0.69
P ADF1	0.01	0.01
P KPSS	0.14	0.17

[1] PADF and PKPSS are p-values of the ADF and KPSS unit root tests, respectively. The null of ADF test is the existence of a unit root, whereas the KPSS tests the null of stationarity.

As expected, the crude oil markets exhibit significantly high volatility on average, with a daily volatility of 3.27% for Brent crude and 8.32% for WTI crude over the analyzed period. The Brent crude oil market is also more rewarding in terms of returns, with an average daily return of 0.02% compared to a negative daily return of −0.15% for the WTI crude market over the same period. Also, the distributions of the crude oil markets daily returns series are highly leptokurtic, with huge excess kurtosis especially for the WTI series. The leptokurtic behavior implies returns are likely to produce outliers, and this behavior is present, with fat tails, in both series. The Shapiro-Wilk test rejects the normality assumption at any level of statistical significance for both crude oil series. This reflects the importance of the non-normality assumption when estimating the predictive model. ADF unit root tests and KPSS stationarity tests consistently indicate a stationary return sequence for both crude oil series.

Next, Figure 2 plots the WTI and Brent crude returns over 2014-2021.

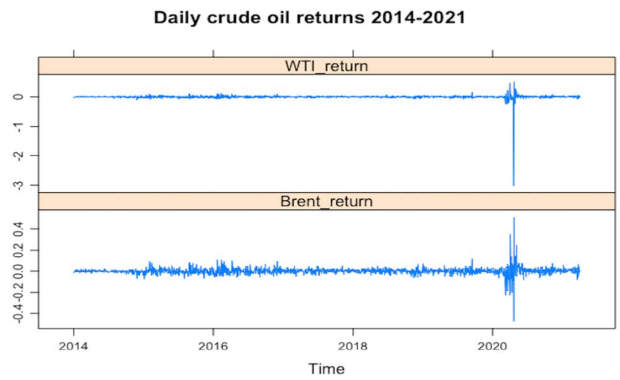

FIGURE 2. **Daily crude oil returns over 2014–2021.**

There is a clear indication of volatility clustering in the series. Indeed, the visual examination of crude oil daily return series supports the volatility clustering hypothesis of Bollerslev [9], meaning low volatility usually follows low volatility and vice versa, unless a disruptive event impacts the market. This empirical characteristic is also relevant for determining the optimal predictive model embedded into the novel forecasting procedure that is further encompassed into an integrated DSS used for algorithmic trading. Significant volatility is apparent on both crude oil markets over the first trimester of the COVID-19 pandemic, with the WTI experiencing the most dramatic one-day fall in history (over 300%) on April 20th. Hence, the recent dramatic evolutions of crude oil markets reflect the need for trading rules capable to issue reliable trading signals and further construct resilient (and even over-performing) portfolios during turmoil.

III. METHOD

A. SETTING UP THE SYSTEM

Each individual building block of the proposed DSS is presented next.

1) THE FORECASTING METHOD

The primary objective of this study is to produce more accurate forecasts of the oil price, and then incorporate the novel forecasting method into a decision-support system employed for constructing and implementing algorithmic trading strategies. The system embeds a novel method for estimating and predicting oil price movements based on a recursive (or rolling) fixed-size window approach, that is capable of capturing any structural break in the dataset (Sermpinis *et al.*). This technique requires the division of the historical data series of length N into a training (or fit) period and a test period, where the final observation in the training period indicates the *forecasting origin* and the time being forecast is the *lead time* (or the *forecasting horizon*) [77]. For our purposes, the training set equals the length of the recursive window (i.e. hereafter using the notation S_{li} for the recursive window of length l and with i $\in$ [1; N $- \, l -$ 1]), whereas the lead time is thus equal to the testing period, or [l + 1; N]. This approach allows capturing any structural break in the rapidly changing crude oil market that is used in this study as the playground for the novel DSS. Subsequently, the rolling out-of-sample forecasting method successively updates the forecasting origin through the interval [l; N $-$ 1] and produces one-step-ahead return forecasts r_i from each new origin (point-forecasts correspond to each first day of the lead time, such as i $\in$ [[l + 1; N]), as depicted in Figure 3.

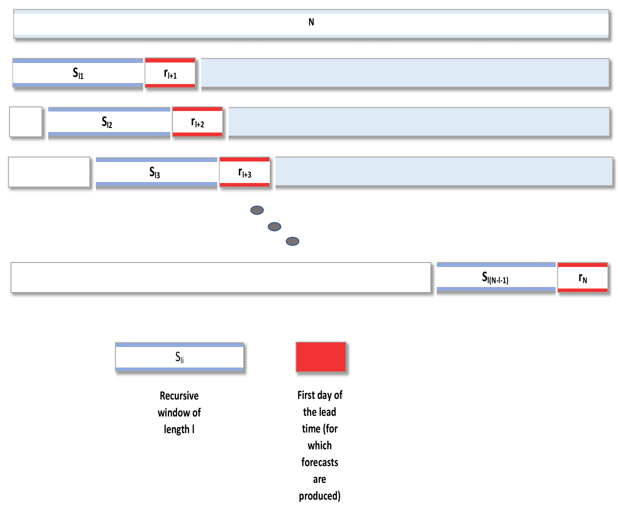

FIGURE 3. **The fixed-length recursive window out-of-sample forecasting technique embedded in the DSS.**

The novelty of our approach consists in the way estimations and predictions are made through the rolling window approach. More specifically, whereas the standard method involves fitting the predictive model to empirical time series on the rolling window, and further employ fitted parameters to forecast future price movements (i.e. for the first two iterations in the inner loop, this approach implies the following sequence:

1. Estimation (fit one model specification on the first window of data, i.e. S_l);
2. Prediction with model fit on S_l (i.e. one step-ahead forecast of r_{l+1})
3. Recalibration (fit the same model specification on the second window of data, i.e. S_{l+1})
4. Prediction with model fit on S_{l+1} (i.e. one step-ahead forecast of r_{l+2})),

this study uses computational intelligence to optimize model-fit daily (i.e., the first two iterations now involve a more complex sequence:

1. Estimation (estimate multiple model specifications on the first window of data, S_l)

2. Selection (identify optimal model specification for S_l with the fitness function)
3. Prediction with optimal model for S_l (i.e. prediction of r_{l+1})
4. Recalibration (re-estimate multiple model specifications on the second window of data, i.e. S_{l+1})
5. Selection (identify optimal model specification for S_{l+1} with the fitness function)
6. Prediction with optimal model for S_{l+1} (i.e. prediction of r_{l+2})).

Thus, the novel methodology proposed here estimates multiple model candidates at each iteration (each recursive window) and applies a fitness function that automatically searches over a feature space (pool of covariates or model parameters) to select the optimal model specifications (i.e. the optimal parameter set (*p,q*)) for each recursive window). This is repeated recursively a total of [$N - l - 1$] times.

2) THE FITNESS FUNCTION

The choice of the fitness function embedded into the automated trading strategy is a subject by itself. Here, we justify this choice by considering several factors. The Akaike Information Criterion (AIC) [2] and the Bayesian Information Criterion (BIC) [72] have emerged as the simplest, most computationally tractable model selection tools. They generally show superior model-fit performance relative to more sophisticated, computationally intensive methods [25] and are especially convenient when the main task is to automate forecast generation, where oftentimes there is a clear trade-off between computational efficiency and forecasting accuracy. In addition, AIC has predictive optimality not possessed by BIC [14], whereas BIC carries the additional fault of being too conservative [69]. Moreover, minimizing AIC is asymptotically equivalent to minimizing the cross-validation statistics for any model [75]. Consequently, this property makes AIC particularly valuable in model selection when the central goal is prediction [41].

The fitness function that automatically goes over the pool of covariates at each inner loop is thus specified as:

$$\mathrm{AIC} = -2\log(\text{maximum likelihood}) + 2\mathrm{k}, \tag{2}$$

where k is the number of estimated parameters. Since the AIC is estimated by maximum likelihood, adding additional model parameters contributes to better model fit, whereas the risk of over-fitting is eliminated by the penalty function [81].

3) THE PREDICTIVE MODEL

The choice of the predictive model embedded into the novel forecasting methodology and further integrated into the decision-support system for algorithmic trading constitutes a secondary, but nonetheless integral element of the DSS. We should mention that the predictive model is not the focal point of this study, which rather focuses on bettering the forecasting technique, or how the model is used by the automated system to issue daily-forecasts. Here, the empirical distributional characteristics of data, in light of previous findings in the literature, indicate that ARMA-GARCH models are capable of explaining and predicting oil price movements.

The ARCH model introduced by Engle [24], the Generalized ARCH (GARCH) model introduced by Bollerslev (1992) and their developments have been extensively used for estimating and forecasting return and volatility in financial time series. The main appeal of the GARCH approach consists in the fact that the model that explains the conditional variance or volatility is estimated jointly with a model for asset returns [19]. In constructing the bivariate model, this study first relies on results of Costello *et al.* [18] and assumes that the crude oil return series follow an autoregressive moving average (ARMA) model developed by Box and Jenkins (1970), with p autoregressive and q moving average terms. Second, considering that a more complicated GARCH specification does not improve on the forecasting performance of basic GARCH(1,1) (i.e. [1], [27], [34], [71], [19], and [29] the study proceeds) with a GARCH(1,1) order specification for the conditional variance. Consequently, two equations are combined to obtain an ARMA (*p,q*) –GARCH(1,1) model that is embedded in the decision-support system for forecasting next day's crude oil returns. The conditional mean equation has thus an ARMA (*p,q*) specification, allowing for the possibility of returns being auto-correlated and dependent on the previous error terms in the following manner:

$$r_{i,t} = c_i + \sum_{j=1}^{p} k_{i,j} r_{i,t-j} + \sum_{j=1}^{q} \mu_{i,j} \varepsilon_{i,t-j} \tag{3}$$

where p and q describe the number of autoregressive and moving average terms, respectively, $k_{i,j}$ is the autoregressive constant, and $\varepsilon_{i,t-j}$ is the realized error.

The conditional variance equation given by GARCH(1,1) then takes the following form:

$$\sigma^2_{t|t-1} = \omega + \alpha_1 a^2_{t-1} + \beta_1 \sigma^2_{t-1|t-2} \tag{4}$$

All estimations are performed under the assumption of a skewed generalized error distribution (SGED) for the error process (as in [27]). Lee *et al.* [49] define the probability density function for the SGED.

4) THE POOL OF COVARIATES

Whereas the equation for conditional variance stays restricted based on the aforementioned arguments, the mean equation is subject to an automated optimization process within the system. The algorithm thus re-estimates at each iteration (i.e. daily) the parameters of an array of ARMA(*p,q*)-GARCH(1,1) models (i.e. [$(p \times q) - 1$] parameters) and applies the fitness function to identify the optimal parameters set (*p,q*) from the universe of [$(p \times q) - 1$] candidates. The best-fit model is then employed to issue one-step-ahead forecasts, used by the algorithm to trigger buy and sell signals, and execute the trade. This is repeated recursively over the testing period. In empirical investigations performed in this study, the system is set to allow the parameters p and q in the conditional mean equation to vary in the interval [0:5], thus estimating 35 different candidate models at each iteration (i.e. $6 \times 6 - 1$, as the (0,0) pair is excluded). This is the pool of covariates over which the fitness function searches the optimal model for each window S_{il}. This approach of using a universe of 35 different candidate models on each recursive window l is selected based on a trade-off between the model performance (in-sample fit and subsequent predictive ability) and the computational intensity needed for its estimation on the dataset and for the execution of the integrated trading algorithm. Given that the algorithm is intended for real world trading, where rapid trade execution is most often crucial for trading success, this is a non-trivial issue.

In subsequent robustness checks, a so-called "restricted optimization" where the two parameters are only allowed to vary in the interval [0:1] (i.e. at each iteration the fitness function goes over a pool of 3 candidate models) is also embedded into a DSS employed for automated trading.

5) THE TRAINING AND TESTING SETS AND THE WINDOW LENGTH

The data sample covers a training period set for the first l days in the sample, and a testing period of length $N - l$, where N is the total number of observations, i.e. 1857. For each trading day n in the testing interval $[l + 1{:}N]$, the return is predicted after the rolling window of l past crude oil daily returns (i.e. S_{li}, $i \in [1;N - 1 - 1]$ has been used to identify the optimal ARMA (p,q)-GARCH(1,1) model specifications for S_{li}. To this end, the system fits ARMA models of order (p,q) for the mean, where $(p,q) \in \{0,1,2,3,4,5\}$ and for each recursive window S_{li} the optimal pair of (p,q) is chosen by applying the fitness function over the pool of 35 covariates. Secondly, a GARCH (1,1) model is fitted for the conditional variance, and these ARMA (p,q)-GARCH(1,1) specifications are then used to forecast the crude oil price return for each day n in $[l + 1;N]$. This sequence is repeated recursively over the testing period.

The system first sets the lengths of the rolling window to 120 days, or approximately 6 months of trading. The narrow rolling window eliminates the risk of failing to capture the quickly evolving energy market events that a longer length window would carry. Additionally, another argument for the choice of l length relies on the work of Menkhoff [55], which showed that practitioners have most often a trading horizon of up to 6 months when they trade through technical trading strategies. As the algorithm proposed in this study works in a similar way by signaling market entries and exits, we argue that a rolling window of 1/2 years is appropriate. As a result, the forecasting model trains on the first 120 days of data (S_{l1}) and then rolls over in a daily sequence through the subsequent recursive windows S_{li}, $i \in [2{:}N - l - 1]$. Overall, the system embeds a total of $N - l - 1$ iterations, implying that the rolling window goes through 1736 days (1857-120-1]). For each time series, the DSS reestimates daily 35 candidate models (i.e. $p \times q - 1$), and applies the fitness function 1736 times, for a total of 60760 estimations (i.e. 35×1736) and 1736 optimizations. DSS has the advantage of flexibility, so that users can fine-tune the size of the pool of covariates (p and q) and the length of the rolling window l, based on the individual preference for the trade-off between prediction accuracy (that increases with an increase in p and q, and with a decrease in l, but also spurs computational intensity) and computational efficiency (that requires lower values for p and q and increasing recursive window length l). Basically, the DSS performs a number of $[(p \times q - 1) \times (N - l - 1)]$ model estimations and $N - l - 1$ optimizations, the exact specifications being the prerogative of the user. Another important advantage of the DSS is its generalizability, as it can be easily applied to other financial markets as well. This can in turn also influence this choice, particularly with respect to the window size l, which is dependent on market structure.

B. THE INTEGRATED DSS

The automatic forecasting procedure described earlier (integrating the predictive model, the fitness function, and the forecasting technique, together with the specifications of its integral elements) is further combined with a trading strategy and embedded together into an integrated trading algorithm.

The predictions issued automatically through the dynamically optimized forecasting procedure work as trading signals and for each forecasting origin n_i ($i \in [l;\ N - 1]$) the pre-programmed rules instruct the system to go long (buy) if the one-step-ahead forecast is positive ($r_{i+1} > 0$), go short (sell) if the one-step-ahead forecast is negative ($r_{i+1} < 0$), and stay out of the market otherwise, including in the event that $r_{i+1} = 0$. Hence, the algorithm proceeds accordingly to the signals issued from the decision-support system and executes trades following these rules at the closing price in the recursive forecasting origin, i.e. P_i.

Lastly, the system performs the final task and assesses the predictive ability and trading performance of the algorithmic trading strategy based on the novel DSS in absolute and relative terms. The steps involved for this particular task are summarized below:

1. Set up the empirical portfolio drawn from DSS-based algorithmic trading strategies (i.e. the DOR A-G120 portfolio);
2. Implement the corresponding basic buy-and-hold (BH) trading strategy on the same dataset;
3. Compute risk and return of the DOR A-G120 and BH portfolios;
4. Estimate risk-adjusted performance measures of the DOR A-G120 and BH portfolios (the Standard Deviation Sharpe ratio and the Conditional or Expected Shortfall Sharpe ratio;
5. Create and print the cumulative return plot for the DOR A-G120 and BH portfolios.

The Sharpe ratio is a measure of risk-adjusted performance, estimated as the return over the risk-free rate per unit of risk. In the classic case of the Standard Deviation Sharpe (SD Sharpe), the unit of risk is the standard deviation of the returns. In addition, the DSS estimates a conditional Sharpe ratio, defined as the ratio of expected excess return to the expected shortfall. In this study, the risk-free rate is assumed 0% in all estimations.

Expected Shortfall attempts to measure the magnitude of the average loss exceeding the traditional mean-VaR and is able to capture all of the nonlinearities and asymmetries of the return distribution. Thus, while the numerator of the conditional Sharpe ratio is identical to that in the SD Sharpe ratio, the denominator replaces standard deviation with the Expected Shortfall or the Expected Tail Loss (ETL), giving a more relevant reward-to-risk measure for practitioners. Also, a more conservative approach is taken and the conditional ES Sharpe ratio is estimated at a 99% confidence level within the DSS.

Summing up the above discussion, there are overall seven major phases integrated in the proposed decision-support system (DSS) for algorithmic trading, namely: (a) data retrieval, (b) data preprocessing and dataset generation, (c) model estimation (multiple candidates), (d) model feature selection (fitness function), (e) oil return prediction, (f) trading signal generation and trade execution, and (g) performance evaluation. The phase's c-f make up the novel forecasting procedure embedded into the DSS and are repeated recursively over the testing period. The novelty of the study and its main contribution to the extant literature hence lies in phases *c* and *d* of the proposed DSS, consisting in the re-estimation of an array of model specifications at each iteration and the application of a fitness function to identify and select the best fit model among multiple candidates for each recursive window.

Figure 4 summarizes the integrated decision-support system employed for algorithmic trading.

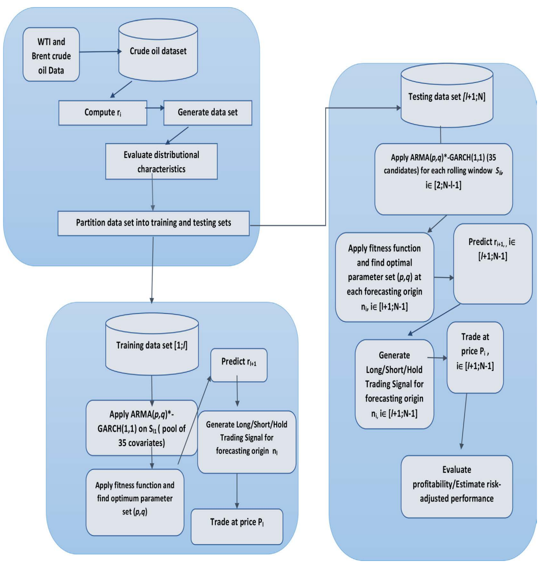

FIGURE 4. Schematic outline of the decision support system for algorithmic trading (source: own design).

C. ROBUSTNESS CHECKS

To assure the robustness of results, the aforementioned strategy is subsequently tested on a rolling window of length 250, corresponding to approximately one year of trading, while keeping the same pool of covariates. In this scenario, the DSS thus performs a number of 56210 model estimations (i.e. 35 × 1606) and 1606 optimizations (i.e. N − l − 1, or 1857-250-1). The sensitivity of the strategy performance to the length of l is thus also tested.

Additionally, the robustness of results will be further tested by discarding the optimization procedure for the mean equation and instead employing a so-called "restricted optimization" procedure where parameters (p,q) are only allowed to take values in [0:1], except the (0,0) pair. For each iteration, the restricted optimization will thus choose the optimal parameter pair by minimizing the AIC from a restricted universe of three possibilities. The optimal model is then fit to the rolling window of length l of data and the return for the next day forecasted. The algorithm will then buy when a positive return is forecasted and sell when a negative return is forecasted, or stay out of the market in all other situations. As in the case of the "full" optimization procedure, the restricted optimization is run for l = 120 and for l = 250. The DSS automatically performs 5208 (3 x 1736) model estimations and 1736 optimizations in the first case (when l = 120) and 4818 model estimations (3 × 1606) and 1606 optimizations in the second case (when l = 250), for each of the two crude oil series.

This allows analyzing the value of the model selection and model fit optimization steps introduced in the classical fixed-length recursive window forecasting technique, in terms of trading strategy predictive ability and performance.

The robustness of results is further assessed through considering a separate time interval corresponding to the onset of the COVID-19 pandemic. This approach has a secondary research purpose, being further motivated by the generalized market downturn produced in the first trimester of 2020 that suggests the theoretical superior performance of a within-market strategy, relative to diversification strategies. Hence, the actual performance of trading strategies constructed and executed through the trading algorithm drawn from the novel decision-support system over the period January 2020 – April 2021 is assessed in both absolute an relative terms.

Consequently, as our study involves two crude oil markets (WTI and Brent), two separate time frames over which the analysis is conducted (i.e. 2014-2021 and 2020-2021), two model-fit and selection strategies (selection from a pol of 35 candidates versus a pool of 3 candidates, or full optimization versus restricted optimization) and also two distinct lengths for the recursive window (i.e. 120 and 250), it requires the construction and implementation of eight different trading-decision systems for algorithmic trading.

IV. RESULTS AND DISCUSSION

A. EMPIRICAL RESULTS

Figure 5 shows the cumulative returns achieved by the algorithmic trading strategy drawn from the DSS that embeds the proposed dynamic optimized recursive (DOR) forecasting method, while specifying the length of 120 days for the rolling window and encompassing the ARMA (*p,q*)-GARCH (1,1) predictive model, applied on the Brent crude oil market over January 2014- April 2021.

It is obvious that the algorithm-based strategy consistently outperforms the BH benchmark throughout the 2014-2021 period, with some interim exceptions over the bull market around 2018. The overall cumulative returns of the DSS-based algorithmic trading strategy are positive during the bear market periods in 2014-2015 and also over the outbreak of the COVID-19 pandemic. Strategy returns fall into negative territory for most of the subsequent period, but nonetheless manage to significantly surpass the BH returns throughout the remaining sample period.

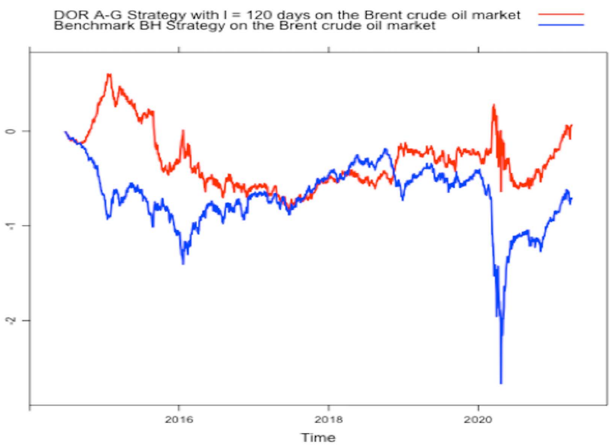

FIGURE 5. Performance (Log of cumulative gross returns) of the optimized DSS-based algorithmic trading strategy versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length = 120 days on the Brent crude oil market. The dynamic optimized model embedded into the DSS trains on the first 120 days in the sample, finds the optimal pair of (*p,q*) in [0:5] and then makes its first prediction for Brent returns on the first day in the lead time, i.e. 20.06.2014 (day $l+1$), subsequently rolling over and forecasting daily returns 1736 times until April 4th, 2021.

Similar patterns are found for the WTI crude oil market (the optimized DSS-based algorithmic trading strategy on the WTI crude oil market is visually presented in Figure 6). These results indicate that trading strategies based on the new dynamically optimized recursive forecasting method are able to achieve superior returns relative to the BH strategy and are capable to protect portfolio from heavy losses during crisis periods.

B. RISK-ADJUSTED PERFORMANCE EVALUATION

To further confirm the findings above, the risk-adjusted performance of the DSS-based algorithmic trading strategy over the entire period and over the outbreak of the COVID-19 pandemic is also analyzed. To this end, two risk-adjusted performance measures are estimated: the Standard Deviation Sharpe ratio and the conditional Sharpe (or Expected Shortfall Sharpe) ratio.

Table 2 shows both the performance and the risk-adjusted performance for the overall period (January 2014- April 2021) and separately for pandemic times (no allowance for transaction costs). Results confirm the over-performance of the DSS algorithmic trading strategies based on a dynamically optimized forecasting technique both in terms of absolute returns and risk-adjusted returns.

FIGURE 6. Performance (Log of cumulative gross returns) of the optimized DSS-based algorithmic trading strategy versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length = 120 days on the WTI crude oil market. First daily WTI return prediction is made for day 20.06.2014 (first day of the lead time) and is repeated recursively 1736 times until April 4, 2021.

Over the entire period, the base strategy produces a daily excess return of 0.0442% (0.0631% for the optimized DSS algorithmic strategy relative to 0.0189% for the BH on the Brent market). In annual terms, this translates into 11.8% excess return produced over the 2014-2021 period. On the Brent market, the optimized DSS algorithmic strategy managed to additionally improve the risk-adjusted performance, both in terms of the SD and in terms of the conditional (ES) Sharpe ratio. The over-performance is more spectacular over the pandemic out-break. The strategy eliminates losses (i.e. the Brent market daily return averaged a negative −1.3% over the outbreak of the COVID-19 pandemic), and gains a positive average daily return of approximately 1%. This further translates into an average excess daily return of 2.29% (300% annualized), too high to be explained by transaction costs (that have been neglected in estimations).

The performance of the optimized DSS-based algorithmic strategy on the WTI market is superior relative to results on the Brent market both in terms of absolute and risk-adjusted returns. The dynamically optimized forecasting method embedded into the designed DSS contributed to the strategy's average daily return of 0.106% over the entire period, relative to a negative average daily return for the WTI market (i.e. −0.148%) over the corresponding period. This implies an excess daily return of 0.254% over 2014-2021 (or 89.5% annualized) for the DSS-based algorithmic strategy. Sharpe ratios are higher than those estimated for the benchmark BH strategy over the same period and also surpass the risk-adjusted performance achieved by the DSS-based algorithmic strategy on the Brent market. Over the COVID-19 outbreak period (i.e. a severe bear market for WTI crude with average daily returns of −6.32%), the DSS-based algorithmic strategy performs exceptionally well, gaining 3.64% per day. The excess return of 9.96% per day well surpasses any possible transaction costs, while the level of risk that it assumes is similar to the risk level of the BH strategy.

TABLE 2. Risk, return, and reward-to-risk ratios of dynamic optimized algorithm-based trading strategies on the Brent crude oil market (Panel A) and on the WTI market (Panel B).

	Rdaily Whole period	SDdaily Whole period	SD Sharpe (Rf=0%, p=95%) Whole period	ES Sharpe (Rf=0%, p=99%) Whole period	Rdaily COVID-19 outbreak*	SDdaily COVID-19 outbreak	SD Sharpe (Rf=0%, p=95%) COVID-19 outbreak	ES Sharpe (Rf=0%, p=99%) COVID-19 outbreak
Panel A: Brent crude								
Optimized DSS-based algorithmic strategy 120	0.000631	0.0338	0.0187	0.00106	0.00995	0.13	0.0763	0.0215
BH Brent	0.000189	0.0327	0.00576	0.000327	-0.013	0.13	-0.0999	-0.0207
Panel B: WTI crude								
Optimized DSS-based algorithmic strategy 120	0.00106	0.086	0.0123	0.0131	0.0364	0.435	0.0836	0.0413
BH WTI	-0.00148	0.0832	x	x	-0.0632	0.432	x	x

*On January 30th, 2020, following the recommendations of the Emergency Committee, the WHO declared the novel coronavirus outbreak in China to be a public health emergency of international concern (PHEIC). At this time, crude oil markets have been already impacted by the shrinkage of global energy demand. Thus, although the official pandemic classification had only occurred on March 11th, 2020, in this study the "COVID-19 outbreak" interval spans January 2nd, 2020 - April 4th, 2021.

C. ROBUSTNESS CHECKS

Several robustness tests are performed to further confirm the above results. In this regard, first the optimized strategy is re-estimated by increasing the length of the rolling window to 250 days. Results presented in Figure 7 confirm that the novel optimized forecasting procedure has value for Brent crude oil traders, and cumulative returns of the DSS-based algorithmic trading strategy (DOR A-G) strategy generally stay over the BH returns for the whole period, with the exception of some temporarily under-performance. On the WTI market, increasing the rolling window-length from $l = 120$ to $l = 250$ eliminates over-performance. The strategy produces returns above the benchmark during the 2015- 2016 bear market, but is underperforming for the rest of the period (Figure 8).

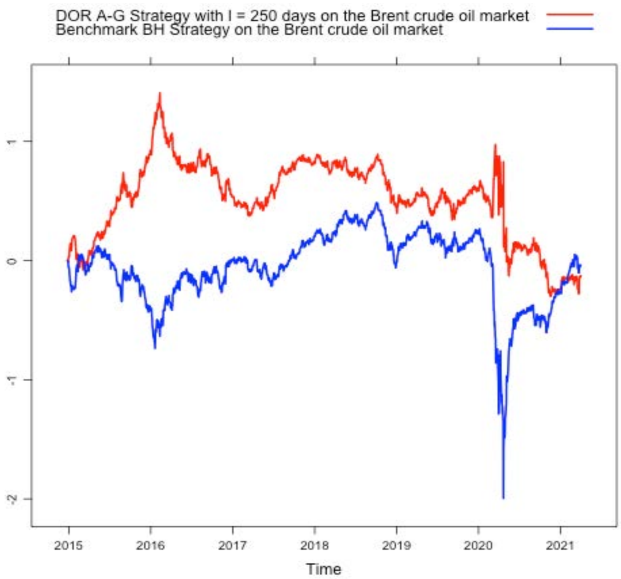

FIGURE 7. Performance (Log of cumulative gross returns) of the optimized DSS-based algorithmic strategy versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length l = 250 days on the Brent crude oil market. First prediction is made for Brent returns on 20.06.2014 (day $l + 1$).

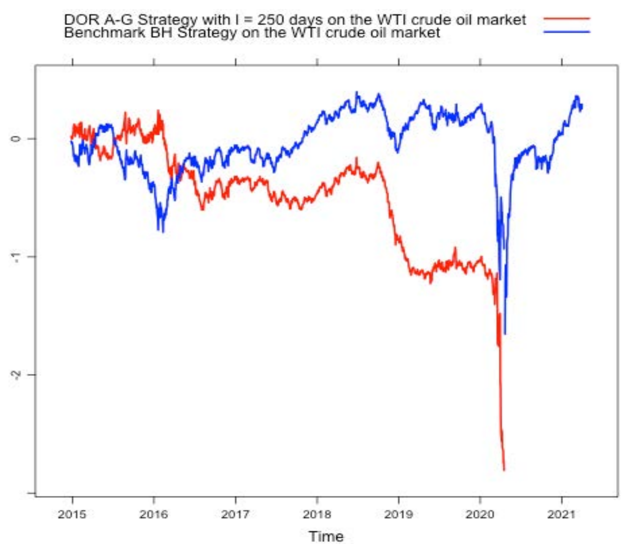

FIGURE 8. Performance (Log of cumulative gross returns) of the optimized DSS-based algorithmic strategy versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length $l = 250$ days on the WTI crude oil market. First prediction is made for WTI returns on 20.06.2014 (day $l + 1$).

In addition, the robustness of results is further tested by discarding the full optimization procedure for the (p,q) parameters of the predictive model and instead employing a so-called "restricted optimization" procedure were parameters (p,q) are only allowed to take values in [0:1], with the exception of the (0,0) pair. The restricted (minimally-optimized) models then roll over in a similar manner to produce daily forecast through the lead time. All estimations are again run for length of $l = 120$ days and for $l = 250$ days.

Next, Table 3 reports the risk-adjusted performance of all tested strategies on the two crude oil markets (results on the Brent crude oil market are presented in Panel A, whereas on the WTI crude oil market in Panel B).

For ease of comparison, the last two rows of each panel in Table 3 repeat the results for the BH strategy and for the base optimized DSS-based algorithmic strategy with window length $l = 120$ on the respective crude oil market.

For illustrative purposes, Figures 9 a,b - 10 a,b plot the cumulative return achieved by trading strategies based on restricted (minimally-optimized) rolling over ARMA(1,1)-GARCH(1,1) models with windows of 120 days and 250 days on the Brent and WTI market. Cumulative return of the buy-and-hold benchmark strategy is also presented.

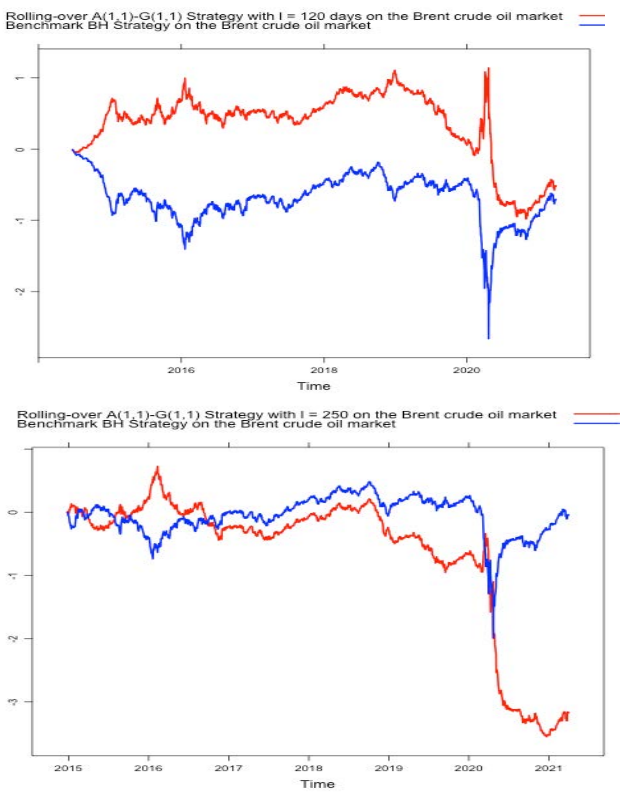

FIGURE 9. Performance (Log of cumulative gross returns) of the algo-trading strategy based on a DSS with restricted rollover ARMA (1,1)-GARCH (1,1) versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length $l = 120$ days (a) and $l = 250$ days (b) on the Brent crude oil market.

D. DISCUSSION

In calibrating the adaptive system on daily crude oil series for WTI and Brent spanning January 2014-April 2021, the paper confirms the phenomenon of volatility clustering and

TABLE 3. Risk, return, and reward-to-risk ratios of trading strategies on the Brent crude oil market (Panel A) and on the WTI market (Panel B).

Trading Strategy	Rdaily Whole period	SDdaily Whole period	SD Sharpe (Rf=0%, p=95%) Whole period	ES Sharpe (Rf=0%, p=99%) Whole period	Rdaily COVID-19 outbreak	SDdaily COVID-19 outbreak	SD Sharpe (Rf=0%, p=95%) COVID-19 outbreak	ES Sharpe (Rf=0%, p=99%) COVID-19 outbreak
Panel A: Brent crude								
Optimized DSS-based algorithmic strategy 250	0.000556	0.0349	0.0159	0.000956	0.0033	0.131	0.0252	0.00732
Rolling A(1,1) - G (1,1) 120 (Restricted)	0.000294	0.0338	0.0087	0.000509	0.0125	0.13	0.0961	0.0285
Rolling A(1,1) - G (1,1) 250 (Restricted)	-0.00131	0.0349	-0.0376	-0.00221	-0.0117	0.13	x	x
BH Brent	0.000189	0.0327	0.00576	0.000327	-0.013	0.13	x	x
Optimized DSS-based algorithmic strategy 120	0.000631	0.0338	0.0187	0.00106	0.00995	0.13	0.0763	0.0215
Panel B: WTI crude								
Optimized DSS-based algorithmic strategy 250	-0.00137	0.0892	x	x	-0.0435	0.435	x	x
Rolling A(1,1) - G (1,1) 120 (Restricted)	-0.00194	0.086	x	x	-0.0561	0.433	x	x
Rolling A(1,1) - G (1,1) 250 (Restricted)	-0.0000114	0.0893	x	x	0.0181	0.436	0.0416	0.0181
BH WTI	-0.00148	0.0832	x	x	-0.0632	0.432	x	x

TABLE 3. ***(Continued.)*** **Risk, return, and reward-to-risk ratios of trading strategies on the Brent crude oil market (Panel A) and on the WTI market (Panel B).**

Optimized DSS-based algorithmic strategy 120	0.00106	0.086	0.0123	0.0131	0.0364	0.435	0.0836	0.0413

The "COVID-19 outbreak" interval spans January 2nd, 2020- April 4th, 2021

x - Negative Sharpe ratios are unreliable because, counter-intuitively, when returns are negative, greater risk results in a higher Sharpe ratio. Thus, negative Sharpe ratios are not reported.

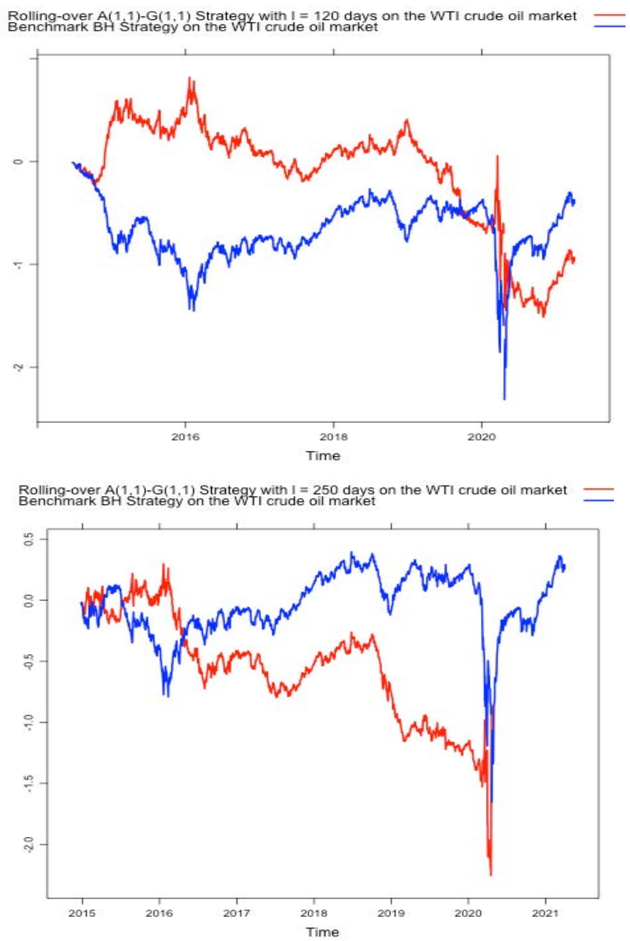

FIGURE 10. **Performance (Log of cumulative gross returns) of the algo-trading strategy based on a DSS with restricted rollover ARMA (1,1)-GARCH (1,1) versus performance (Log of cumulative gross returns) of the buy-and-hold strategy with rolling window length l = 120 days (a) and l = 250 days (b) on the WTI crude oil market.**

other empirical properties for crude oil empirical distributions reported by previous studies [6], [58], [71], and [92]: high volatility and high excess kurtosis (on both crude oil markets) and negative skewness (on the WTI crude oil market).

Results further confirm that the optimization of the recursive fixed-length window out-of-sample forecasting procedure through the introduction of the fitness function pays off in terms of the empirical performance of algorithmic strategies drawn from the integrated DSS. Additionally, algorithmic strategy performance is sensitive to the length of the rolling window specified in the DSS, with narrower windows being more reliable, which further confirms the rapidly changing evolutions of the crude oil market. On the Brent crude oil market, algorithmic trading strategies based on dynamically optimized DSS tents consistently outperform the BH over the entire period, but are more successful over the COVID-19 outbreak, while the length of the rolling window directly affects strategy performance. On the WTI crude oil market, the algorithmic strategy drawn from the base DSS with $l = 120$ (DOR A-G 120) is significantly over-performing both over the entire period and exceptionally during the COVID-19 outbreak, but again increasing window length to $l = 250$ eliminates its success. The findings thus suggest that evolutions on the crude oil markets happen so fast that a longer window is unable to appropriately capture them. Results are also in line with the finding of Menkhoff [55] in what the timeframe for trading decisions- making is concerned. Results also echo those of Pesaran and Timmermann (2007), Pesaran *et al.* (2013), Giraitis, Kapetanios and Price (2013), and [43], and confirm that the optimization of the window length is a complementary approach that contributes to improved time series forecasting.

The restricted (minimally-optimized) rolling-over trading strategies achieve mixed results on both markets, performing better over the pandemic outbreak.

Forecasting models on the oscillated crude oil markets benefit from smaller training periods, and thus algorithmic trading strategies drawn from the novel dynamically optimized DSS with a rolling window length set to 120 days is most successful. For the Brent market, the restricted trading strategy with a wide recursive window ($l = 250$ days) is the only one that fails to over-perform the BH strategy over the analysis period. This is explained by the fact that the cumulative returns of the BH strategy benefited from the elimination of the bear market, which occurred over the second half of 2014, from the testing period. Thus, when the length of the rolling window l is set to 250 days, the training period spans January 2nd 2014 to December 26th 2014 and hence the lead time over which cumulative returns for the benchmark are estimated only starts at the very end of 2014, not being affected by the tumultuous second half of the year, when crude oil prices plunged from levels above \$110 per barrel by mid-end June 2014 to around \$50 by year end. The value of the optimization procedure for the parameters of the mean equation is even more obvious in this situation. Thus, the investment strategy based on DSS (with $l = 250$) produces an average daily return of 0.00556% over the same period, whereas the restricted trading strategy which encompasses the same window size produce a negative daily average return of -0.131%, and the BH strategy (that benefited from the aforementioned elimination of the bear market from the lead time) achieves a daily average return of 0.00189% on the Brent market over the corresponding period.

In summary, although the optimized algorithmic trading drawn from the novel DSS with a rolling window of 120 days doesn't produce portfolios with attractive Sharpe ratios (i.e., above 1) in the two crude oil markets, it does however manage to significantly improve performance without higher costs in terms of investment risks. Therefore, all portfolios based on dynamically optimized trading algorithms with $l = 120$ have higher estimated reward-to-risk Sharpe ratios (both standard and conditional) than the benchmark BH strategy. More importantly, optimized DSS-based algorithmic trading strategies can eliminate losses during turmoil and even gain significant profits in distressed markets. Our results thus deviate from the conclusions of Hongsakulvasu and Liammukda [39], Drachal [22], and Naser [61], as this research shows that it is the model selection step introduced through the fitness function (i.e. multiple recalibrations and optimal model selection at each iteration) in the rolling forecasting procedure that improves the predictive ability, and not merely the simple recalibration that produces time-varying parameters. Current findings are nonetheless in line with those of recent studies that confirm the weak-form inefficiency of the crude oil market during the outbreak of COVID-19, such as Gil-Alana and Monge [31], Qin *et al.* [68], Liu *et al.* [51], or Tudor and Anghel [82]. This result has important implications for market practitioners. For example, Mushir and Suryavanshi [59] analyze the impact of COVID-19 on the portfolio allocation decisions of individual investors and confirm that investors are moving towards conservative portfolios and away from risky-assets during the pandemic. Instead, the paper shows that over-performing strategies in terms of risk-adjusted returns can be implemented in some of the riskiest markets, such as the Brent and WTI crude oil markets. Investors thus don't need to exit crude oil markets in times of turmoil, but instead change investment strategy. Moreover, by proposing an improved recursive fixed-length window out-of-sample forecasting procedure, the study is important for policy makers that use oil price forecasts in the policymaking process, such as the European Central Bank (ECB), the IMF and the Federal Reserve Board, as Naser [61] contends.

V. CONCLUSION

In this paper, a novel decision support system (DSS) using computational intelligence and integrating a dynamically optimized forecasting procedure is designed and employed for algorithmic trading on two crude oil markets, WTI and Brent crude, respectively.

The DSS integrates seven major phases: (a) data retrieval, (b) data preprocessing and dataset generation, (c) model estimation (multiple candidates), (d) model feature selection (fitness function), (e) oil return prediction, (f) trading signal generation and trade execution, and (g) performance evaluation. The phase's c-f make up the novel forecasting procedure embedded into the DSS and are repeated recursively over the testing period.

The most important feature of the system proposed in this study is the introduction of two new steps in the implementation of a standard fixed-length recursive window out-of-sample forecasting technique that it embeds, corresponding to phases c and d within the DSS. The DSS thus estimates multiple model candidates for each recursive window and applies a fitness function that automatically searches over the pool of covariates to select the optimal model specifications at each iteration. This is repeated recursively a total of $[\mathrm{N}-l-1]$ times. The novel DSS relies on distributional characteristics to embed an ARMA (p,q)-GARCH(1,1) as the core predictive model and performs a number of $[(p \times q - 1) \times (\mathrm{N}-l-1)]$ model estimations and $(\mathrm{N} - l - 1)$ optimizations. The specification of the system' integral elements is the prerogative of the DSS's user and should rely on an informed and assumed choice that considers the trade-off between prediction accuracy and computing efficiency. In empirical applications on two crude oil series, the base DSS designed in this study reestimates daily 35 candidate models (i.e. $p \times q - 1$), and applies the fitness function 1736 times (i.e. $N-l-1$)], for a total of 60760 model estimations (i.e. 35×1736) and 1736 daily optimizations on each market.

The DSS uses the optimized model specifications to produce one-step ahead forecasts from each recursive forecasting origin, which then trigger buy and sell signals that the algorithm follows to execute trades. As such, the proposed approach is fully tradable and is further implemented on the WTI and Brent crude oil markets.

The findings show that over-performing and resilient portfolios can be constructed via algorithmic trading strategies based on the novel DSS on the two main crude oil markets. The DSS-based algorithmic trading strategies are able to generate a long strake of winning trades and consistently outperform the BH benchmark, with a daily excess return on the WTI market of 0.254% (i.e. 89.5% annualized), while on the Brent market the DSS strategy gains a daily excess return of 0.0442% (11.8% annualized) over 2014-2021. The ongoing COVID-19 pandemic, which during its outbreak produced historical disruptions on the global crude oil markets, provides an excellent sample period that is analyzed separately. It is found that the DSS-based trading strategies are able to diminish and even eliminate losses during market downturn, including during the outbreak of the COVID-19 pandemic.

Thus, signals produced using the forecasting procedure embedded into the DSS prove to be reliable trading signals for crude oil markets, and a particularly suitable solution for algorithmic trading. Results hence contribute to improved and more accurate forecasting of oil prices, which further leads to improved policy issuance processes and more effective policies. Consequently, results of this study have important implications for policymakers, crude oil markets practitioners, and academic researchers.

Robustness checks confirm that the introduction of two additional steps in a standard fixed-length recursive window forecasting procedure has merits. When compared to an algorithmic trading strategy drawn from a DSS, which encompasses a minimally optimized recursive out-of-sample forecasting technique, results confirm the superiority of the dynamically optimized DSS in terms of predictive ability and trading performance of algorithmic trading strategies based on the system on both crude oil markets.

Additional robustness checks reveal that the forecast ability depends on the length of the rolling window, and decreases when the length of the window is increased to 250 days as compared to the initial length of 120 days. A smaller window is thus more capable of capturing the time-varying relationships that dominate the crude oil market. This also suggests that developments on the oil markets happen quickly and past movements have little influence on future evolutions, confirming previous findings.

However, as with all studies this work has several limitations. One of them is that the optimized trading algorithm can trigger very frequent signals, which theoretically might lead to the elimination of superior returns when transaction costs are considered. Nonetheless, the relatively small transaction costs involved nowadays in trading commodities and the high excess returns achieved by the strategies (as high as 9.96% per day excess return on the WTI market over the pandemic outbreak) indicate that results would still present economic value after including transaction costs, especially over (limited) turbulent periods. Further, the strategy still presents some interim inefficiency and as such the superior performance of the optimized algorithm-based trading strategy is lost on upward trading markets such us over the last half of year 2020. Also, there is room for improvement in Sharpe ratios of DSS portfolios in absolute terms. This in turn implies that a combination of methods might produce superior forecasts of oil prices during bull markets and consequently better performing oil portfolios. As this empirical research serves as an initial investigation, these would constitute good opportunities for future research.

In addition, other avenues could be followed from the current research. First of all, its generalizability characteristic makes it suitable for implementation in other financial markets, including other energy products or equities. This would in turn further contribute to assess its robustness outside of the two oil markets that constitute the base playground for the novel DSS in this study. Secondly, it should be assessed whether the optimization outcome is influenced by the fitness function introduced for model selection in the forecasting procedure. Thirdly, employing different data frequencies could also contribute to assure the robustness of the DSS. Finally, more sophisticated prediction models could be embedded into the proposed DSS.

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