IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 22 May 2024, accepted 17 June 2024, date of publication 21 June 2024, date of current version 28 June 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3417815

RESEARCH ARTICLE

Enhancing Trading Decision in Financial Markets: An Algorithmic Trading Framework With Continual Mean-Variance Optimization, Window Presetting, and Controlled Early-Stopping

CRISTIANA TUDOR[1] AND ROBERT SOVA[2]
[1]International Business and Economics Department, Bucharest University of Economic Studies, 010374 Bucharest, Romania
[2]Department of Management Information Systems, Bucharest University of Economic Studies, 010374 Bucharest, Romania

Corresponding author: Cristiana Tudor (cristiana.tudor@net.ase.ro)

This work was supported in part by the EU NextGenerationEU instrument through the National Recovery and Resilience Plan of Romania - Pillar III-C9-I8, and in part by the Romanian Ministry of Research, Innovation and Digitalization under Contract 760243/28.12.2023, project ID 194/31.07.2023.

ABSTRACT This study introduces a trading decision support system (DSS) enhanced by an optimized mean-variance model for algorithmic trading (AT), crucial in modern financial markets for its efficiency and error reduction. Despite AT's advantages, its limitations, including risks of losses and market instability, are notable. The proposed DSS focuses on improving trading algorithms by embedding optimized forecasting techniques to predict market movements accurately. By employing a recursive approach to refine return forecasts and trading signals, and continuously adjusting model parameters within a sliding window, the system adapts to market changes, maintaining its robustness. Key contributions include optimizing the recursive window length and addressing overfitting, significantly enhancing existing trading systems. The system is validated through backtesting in the volatile natural gas market, highlighting its relevance amid the global shift towards sustainable energy. Numerical findings show that the DSS portfolio achieved an annualized Sharpe ratio of +0.8478 compared to the buy-and-hold strategy's -0.4521, and the maximum drawdown was reduced from 90.67% to 63.59%. These results demonstrate the system's capability to create superior portfolios, even in downturns, by optimizing rolling window lengths and covariate pool sizes while mitigating model performance issues and overfitting. This has significant economic and environmental implications, facilitating a smoother energy transition, and providing trading professionals with advanced tools to enhance portfolio performance and risk management in volatile markets.

INDEX TERMS Algorithmic trading, decision support system, financial markets, trading performance, trading signals.

I. INTRODUCTION

Financial markets are complex systems influenced by economic indicators, geopolitical events, investor behavior, and technological advancements. Effective decision-making in this environment is crucial for both investors and traders. Decision Support Systems (DSSs) have become essential in providing insights and data-driven strategies, particularly through algorithmic trading.

The associate editor coordinating the review of this manuscript and approving it for publication was Wojciech Sałabun.

Algorithmic trading systems, or automated trading systems, are vital in modern financial markets [1], [2]. These systems execute orders based on predefined strategies [3], [4] and mitigate emotional biases, promoting rational trading decisions. The rise of high-performance computing and advanced communication technologies has increased the use of such systems in global markets [5], [6], [7], whereas the algorithmic trading market is projected to grow at a CAGR of 10.5% between 2022 and 2027 [8].

However, algorithmic trading systems are not without risks. Poorly designed algorithms can lead to substantial financial losses, and their impact on market stability and volatility is debated [9], [10], [11]. The effectiveness of algorithmic trading heavily depends on the quality of DSS and their ability to forecast market trends [12]. Against this backdrop, this study focuses on the natural gas market, which has gained significant financial prominence post-2008 financial crisis [13], [14] and plays an increasingly critical role due to its interconnectedness with the broader energy price ecosystem [15].

FIGURE 1. Time plot of daily prices for an ETF tracking the evolution of the US Henry Hub natural gas prices (UNG); Source: Authors' representation, data sourced from the Yahoo Finance platform.

Using the United States Natural Gas Fund LP (UNG) as a proxy for the US natural gas market enhances tradability and replicability. ETFs, known for liquidity and low transaction costs, have grown popular among investors [16], [17].

The recent volatility in natural gas prices, influenced by European market dynamics, weather patterns, and consumption shifts [18] has caused significant losses in portfolios heavily invested in natural gas (see Figure 1).

The observed volatility suggests the influence of algorithmic trading, which can amplify market instability, particularly in distressed scenarios [19]. Market participants need sophisticated trading strategies to enhance portfolio resilience and performance. This necessity is highlighted by instances of extreme volatility without pertinent news, such as the 157% increase in volatility in August 2022 with rapid price fluctuations of \$5/MWh [20], [21]. Geopolitical tensions also significantly impact the natural gas market, influencing supply routes and pricing mechanisms [22], [23].

This research aims to develop a robust DSS to enhance trading decisions in the natural gas market, addressing the unique challenges of this volatile and geopolitically sensitive sector. Key research questions include: How can algorithmic trading systems be enhanced to better predict market movements and adapt to changing conditions in the natural gas market? What impact does optimizing recursive window length and addressing overfitting have on the performance of trading algorithms? How does the proposed DSS compare to traditional trading strategies in terms of risk-adjusted returns and robustness in volatile markets?

To address these research questions comprehensively, this paper makes several key contributions. The primary contribution is the development of an enhanced DSS that incorporates dynamic and continuously optimized mean-variance specifications. Focusing on optimizing recursive window length and addressing overfitting, the proposed DSS significantly enhances the robustness of existing trading algorithms. The system, validated through backtesting in the natural gas market, demonstrates superior performance in return enhancement and risk reduction compared to traditional buy-and-hold strategies. Additionally, the research highlights the broader implications for market stability and the transition to sustainable energy sources.

In exploring the implications of our DSS within financial market efficiency, this study revisits the Efficient Market Hypothesis (EMH), a foundational concept in financial economics which posits that asset prices reflect all available information [24], [25], [26], [27], [28], [29]. The application of EMH to energy commodity markets, particularly natural gas, has yielded mixed results [30], [31], [32], [33], [34], necessitating a re-evaluation using current data. While much of the existing research focuses on price and volatility forecasting [35], [36], [37], [38], [39], [40], [41] few studies have explored the development of empirical portfolios based on these forecasts in the context of algorithmic trading [42], [43], [44], [45]. In this context, this research aims to fill that gap by providing new insights into natural gas market efficiency and introducing an enhanced DSS for algorithmic trading.

The DSS's effectiveness in generating high-performance portfolios within the natural gas market is validated in this research. These contributions offer valuable tools and insights for professionals navigating the complexities of energy commodity markets. By enhancing market predictability and resilience, the DSS supports more effective trading strategies and aids in achieving energy security and environmental sustainability goals. This research extends its impact beyond financial trading, contributing to the broader economic and environmental strategies of nations heavily invested in natural gas, particularly significant for countries like China, where natural gas plays a crucial role in energy policy [46], [47], [48].

The rest of the paper continues as follows: Section II presents the data employed in the study and explains the system architecture. Section III contains an exploratory analysis, and then reports estimation results. Next, Section IV discusses the main findings, while Section V concludes the study.

II. MATERIAL AND METHOD

A. DATA SAMPLE

This study employs daily price data of the United States Natural Gas Fund LP (UNG), the largest Exchange-Traded Fund (ETF) in terms of Assets Under Management (AUM) providing exposure to the US natural gas market. The data, spanning from 2nd January 2019 to 1st July 2023, which includes the period of the COVID-19 pandemic, were extracted from the Yahoo Finance database (finance.yahoo.com). Subsequent to data acquisition, one-period logarithmic returns were calculated as:

$$r_{UNG,t} = \log\left(\frac{P_{UNG,t}}{P_{UNG,t-1}}\right), \tag{1}$$

where $r_{UNG,t}$ is the return of the ETF on trading day t.

To ensure a comprehensive analysis, encompassing a comparison in terms of risk-return characteristics, this study also incorporates data from two additional exchange-traded funds. These include an ETF tracking the S&P 500 index, identified by its ticker SPY, representing the US equity market, and the United States Oil Fund (USO), which offers exposure to the US crude oil market. The price data for these ETFs were sourced from the same database, Yahoo Finance.

The price series for these additional ETFs were similarly converted into logarithmic returns, following the methodology applied to the UNG ETF. Each of these return series consists of 1132 daily observations. The length of these series is particularly relevant as it influences the number of iterations and optimizations undertaken by the proposed trading system.

B. THE ALGORITHMIC TRADING DECISION SUPPORT SYSTEM

In a recent development, [49] introduced an adaptable Decision Support System (DSS) for algorithmic trading, which incorporates a dynamic mean-variance optimization procedure. This DSS introduces a novel approach by implementing a fitness function that operates within a user-defined pool of covariates, optimizing the parameters of the embedded predictive model throughout the recursive window forecasting strategy. This study extends the capabilities of this DSS and backtests the new architecture on the US natural gas market, a significant energy market that has increasingly attracted financial interest since the 2008 financial crisis [13], [14].

This integrated framework encompasses several key stages, as follows.

1) DATA SEGMENTATION AND MEAN–MODEL SPECIFICATION

The implementation of the framework that develops the DSS commences by segmenting the dataset of length N (i.e, 1132) into two distinct components: a training dataset of length l, which mirrors the rolling window's duration, and a testing dataset that extends from (l+1) to N. The length of l is not preset, but instead fine-tuned, which further increases the system's capabilities. The most recent observation in the training set serves as the forecasting origin. This origin progressively shifts through the time interval spanning from l to N-1, concurrently generating one-step-ahead return forecasts, denoted as r_{i}, for each new origin.

In an extension of the work by [49] Tudor and Sova, the current DSS architecture embeds an ARMA (p, q) – GARCH(1,1) predictive model, under the assumption of a Skewed Generalized Error Distribution (SGED) for the error process.

Particularly, the mean model embedded within the DSS has the following equation form:

$$r_{i,t} = c_i + \sum_{j=1}^{p} k_{i,j} r_{i,t-j} + \sum_{j=1}^{q} \mu_{i,j} \varepsilon_{i,t-j} \tag{2}$$

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

The choice of the SGED is grounded in the research findings of [50] Lee et al. (2008), which define the probability density function for the skewed GED. Furthermore, the current selection is motivated by the work of [51], confirming the superiority of GARCH-SGED specifications compared to other common choices, highlighting the significance of skewness and tail-thickness on the conditional distribution of financial commodities returns.

In this process, a comprehensive exploration is carried out for every conceivable pair of autoregressive (p) and moving average (q) parameters, with the notable exception of the (0,0) pair. This parameter exploration is specifically focused on the mean model as specified in Equation (2) and is complemented with a GARCH (1,1) model to address the variance component of the equation, as explained later. The outcome of this exploration is a covariate pool characterized by a dimension of $[(p + 1) \times (q + 1)]-1$. The Akaike Information Criterion (AIC) is employed as a decisive criterion for selecting the best-fitting model specifications from pool of candidates within each recursive window, due to its ability to maximize "short-term predictive success" [52]. This entire process entails N-l iterations and is instrumental in generating one-step-ahead return forecasts that span the forecasting horizon from $(l + 1)$ to N.

2) MODEL SPECIFICATION FOR VOLATILITY

Subsequently, after the determination of the most appropriate (p, q) pair for the ARMA model using AIC, the {rugarch} package is leveraged to construct the variance equation, still performed in the context of each rolling window. In this model, the mean model incorporates the previously identified optimal (p, q) parameters, while a GARCH(1,1) model is applied to model the variance. Of note, the conditional variance model within the framework is based on previous studies that indicate the lack of need for higher-order ARCH and GARCH polynomials (for example [53], [54], [55], [56] and consequently is restricted to the form of a GARCH(1,1) model, given by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

which in turn provides an additional benefit in the form of increased computing efficiency.

To enhance the convergence of the model, the system introduces a "hybrid" solver in the ugarchfit() syntax. This solver sequentially tests different solvers, including "solnp," "nlminb," "gosolnp," and "nloptr," in cases where convergence is not initially achieved [57].

3) SIGNAL GENERATION AND TRADING STRATEGY

The predictions obtained through the fitted model, which dynamically optimizes forecasting, are subsequently employed as trading signals. To ensure that the system is not engaged in forward-looking practices and to preserve its practical applicability within the realm of financial markets, the system introduces a one-day lag in the series containing these trading signals. Consequently, at each forecasting origin l_i, situated within the range from l to N-1, a predetermined set of trading rules instructs the Decision Support System (DSS) to initiate buy actions at the closing price from the forecasting origin day, denoted as P_i, when the forecasted return for the next day (r_{i+1}) is positive. Conversely, the system is guided to execute sell actions when the forecasted return is negative ($r_{i+1} < 0$) and to remain inactive in the absence of market opportunities ($r_{i+1} = 0$). The DSS complies with these directives, executing transactions based on the issued trading signals, and these transactions are executed at the closing price from the previous day.

4) PORTFOLIO CREATION AND EVALUATION

The system proceeds to construct an empirical portfolio with exposure to natural gas, derived from each distinct DSS architecture, colloquially termed the DSS portfolio. In parallel, a buy-and-hold (BH) trading strategy is devised for the equivalent duration. Subsequent to the portfolio construction, the system assesses the portfolios' performance, estimating key metrics encompassing risk, return, and risk-adjusted performance.

5) TERMINOLOGY

For illustration, a specific instance is presented, highlighting a "restricted" DSS architecture that employs a fixed rolling window length of 100 days ($l = 100$). In this configuration, the ARMA autoregressive and moving average polynomials are permitted to assume values within the range of [0;1], except for the (0,0) pair. As a result, mean parameters are optimized on each rolling window by applying the fitness function after evaluating a covariate pool containing 3 covariates (i.e., [(1+1) × (1+1) – 1], hence the system is dubbed "restricted"). This specific architecture is denoted as DSS(100_1_1), specifying the rolling window length and the maximum boundaries for the two ARMA equation polynomials. Furthermore, an alternative architecture is introduced by extending the rolling window to 120 days, and concurrently expanding the covariate pool for mean parameter optimization. This more intricate DSS-based portfolio is denoted as DSS(120_p_q), where p and q establish the upper boundaries for the autoregressive and moving average polynomials within the mean equation. For the particular situation when p and q are both set to 3, the covariate pool for each rolling window serving as a training dataset comprises [(4 × 4) -1], or 15 covariates. This architecture is identified as DSS(120_3_3). Starting with the "restricted" architecture for a given window length, the upper boundary is successfully increased in increments of 1 (i.e., when l = 100, from DSS (100_1_1), DSS (100_2_2), (DSS (100_3_3), (DSS (100_4_4), ...,) until the performance of the corresponding DSS portfolios is maximized. Increasing pools of covariates are tested until the performance of the i^{th} DSS (100_p+1_q+1) portfolio is below the performance of the DSS(100_p_q).

In all systems, considering prior research findings and aiming to maintain reasonable computational efficiency, given the intricacy of the iterative mean optimization process and the comprehensive scope of the integrated architecture, including signal issuance, trading execution, portfolio construction, and backtesting, the order for both the GARCH and ARCH polynomials within the variance equation is steadfastly established at 1.

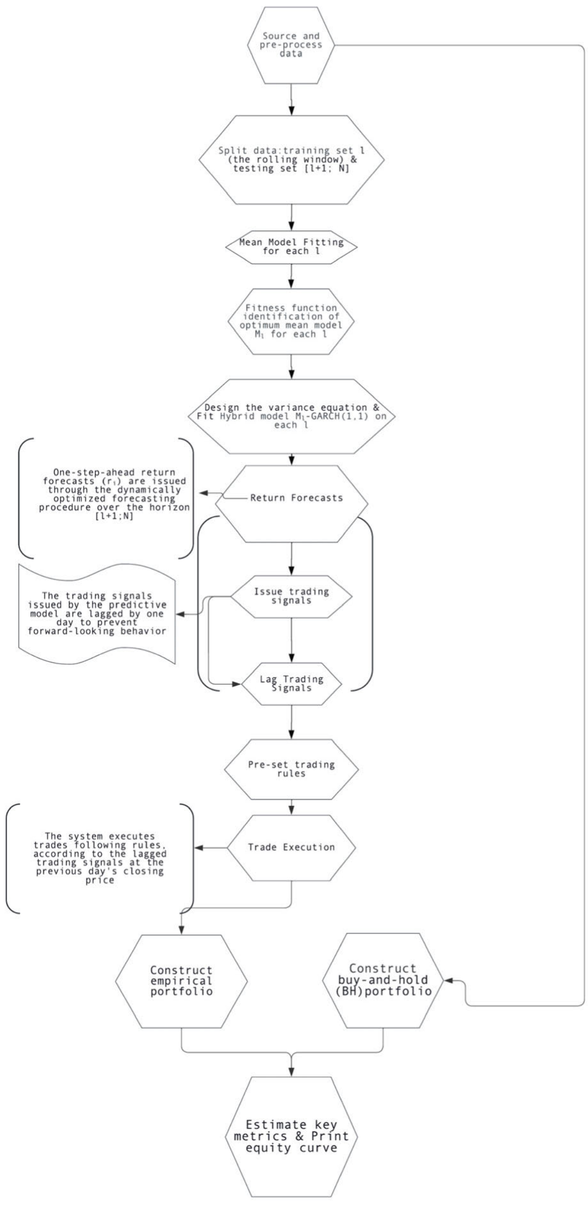

FIGURE 2. Flowchart of the proposed algorithmic trading decision-support system.

Figure 2 includes a simplified flowchart of the algorithmic trading decision-support system.

C. INNOVATION AND METHODOLOGICAL ADVANCEMENTS

The proposed methodology represents a significant deviation from traditional rolling window forecasting approaches commonly utilized in financial market analysis. Traditional methods typically involve the adaptation of model parameters through the re-estimation of a fixed-configuration model within a recursive window. The innovative approach adopted by [49] however, leads to a more refined in-sample fit and enhanced forecasting accuracy, distinguishing it from conventional practices. Going further, central to the novelty of the enhanced system proposed here, in comparison to the Decision Support System (DSS) developed by [49], is the strategic fine-tuning of the rolling window's length coupled with a focused effort to mitigate overfitting risks, particularly those that may arise from the expansion of the covariate pool. This marks a significant shift from the prior study that relies on predetermined lengths for the rolling window and mitigates the risk that such fixed lengths may not always align optimally with the dynamic nature of financial data. Consequently, the current system adopts a more dynamic, data-driven approach. It operationalizes this by integrating three distinct "restricted" DSS architectures, each characterized by different rolling window lengths ($l \in \{100, 120, 250\}$). This variation allows for an empirical evaluation of the system's performance across different temporal scales, maintaining the integrity of other core components of the DSS architecture. The subsequent assessment of these models focuses on their risk-adjusted performance, enabling the identification of the most effective rolling window length. This selection process is driven by estimation-based procedures rather than reliance on predefined, static parameters, thereby significantly boosting the predictive capabilities and overall performance of the trading system. As the complexity inherent in the DSS architectures escalates, the study strategically employs the rolling window length as a foundational parameter. This parameter serves as the cornerstone upon which the covariate pool is progressively expanded, adhering to a data-driven methodology. Such an approach ensures that the expansion of the model's complexity is closely aligned with the evolving nature of the data, thereby maintaining the relevance and effectiveness of the model. This dynamic, data-driven strategy infuses the methodology with a high degree of innovation. It notably enhances the adaptability and applicability of the system within the realm of financial market analysis. By acknowledging and responding to the fluidity of market data, the system positions itself as a versatile and robust tool, capable of delivering insightful and accurate predictions in the ever-changing landscape of financial markets. This methodological advancement not only demonstrates a significant leap in the field of algorithmic trading and financial forecasting but also sets a new benchmark for the development of decision support systems in finance.

TABLE 1. Descriptive statistics.

	US	USO	UNG
Minimum	-0.1159	-0.2919	-0.1737
Median	0.0009	0.0016	0.0000
Mean	0.0005	-0.0002	-0.0011
Maximum	0.0867	0.1542	0.1567
Standard deviation	0.0138	0.0296	0.0371
Skewness	-0.8110	-2.1052	-0.1553
Kurtosis	11.66	20.49	1.32

III. RESULTS

A. EXPLORATORY ANALYSIS

This initial phase of analysis is critical to gauge the efficacy of the buy-and-hold strategy, which serves as the comparative standard for the DSS-driven portfolios. It also provides a benchmark against significant energy markets, notably the crude oil market, and the US equity market, represented here by the S&P 500 index. Furthermore, this exploratory phase aids in identifying the factors contributing to the superior performance of portfolios generated through automated systems.

Descriptive statistics for the return series of the three ETFs, representing the target financial markets, are detailed in Table 1. Concurrently, Table 2 elucidates the metrics for risk and risk-adjusted performance of these alternative investment options, spanning from January 2019 to July 2023

During the analysis period, the natural gas fund, specifically the United States Natural Gas Fund LP, exhibited the most unfavorable price performance. This is quantitatively evidenced by a negative daily mean return of -0.11%, coupled with the highest level of risk, as delineated by a daily standard deviation of 3.71%. Conversely, the equity portfolio that tracks the S&P 500 index is characterized by the most advantageous financial performance within the same timeframe, delivering the highest return at +0.05% and maintaining the lowest risk profile, evidenced by a standard deviation of 1.38%. These observations are consistent with established empirical findings, as all examined series display negative skewness and positive excess kurtosis, indicative of heavy-tailed distributions in the data.

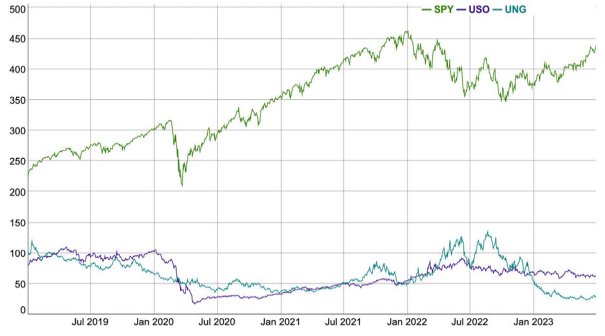

FIGURE 3. Time plot of daily ETF prices; Source: Authors' representation.

Figure 3 presents a time-series plot of the price trajectories for the three Exchange-Traded Funds (ETFs) from January 2019 to July 2023. This graphical representation effectively illustrates the underperformance in price of the natural gas portfolio in comparison to the other two ETFs.

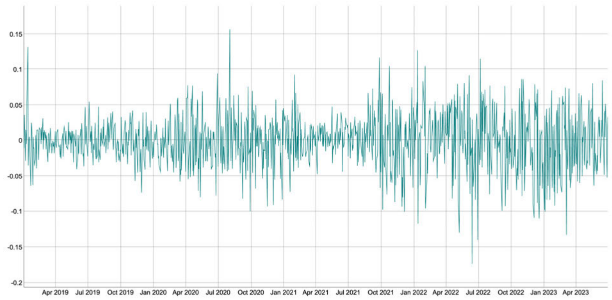

FIGURE 4. Daily UNG fund returns; Source: Authors' representation.

Conversely, Figure 4, which illustrates the daily returns of the United States Natural Gas Fund LP (UNG), substantiates the existence of volatility clustering within the natural gas market. This phenomenon is characterized by periods where high levels of market volatility are followed by similar periods, and vice versa for low volatility levels. The manifestation of such volatility clustering suggests that Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, renowned for their capacity to effectively capture and model this type of market behavior, are suitably aligned with the requirements of the Decision Support System (DSS) employed in this study. The compatibility of GARCH models with the DSS framework is thereby underscored, highlighting their utility in accurately reflecting the underlying market dynamics of the natural gas sector.

The relative underperformance of the natural gas portfolio is further accentuated by its downside risk and risk-adjusted return metrics. Analytical results presented in Table 2 reveal a pronounced negative Sharpe ratio for the natural gas-focused fund, quantified at -0.4523 as per Sharpe's methodology [58]. This metric is substantially inferior to the risk-adjusted performance of the US equity portfolio, which boasts a Sharpe ratio of 0.6576 on an annualized basis. Furthermore, it is significantly lower, by more than a factor of four, compared to the fund exposed to the crude oil market. It is noteworthy that the computation of the adjusted Sharpe ratio, as proposed by [59], which integrates a penalty for negative skewness and excess kurtosis, corroborates this finding.

Additionally, all applied risk measures consistently underscore the underperformance of the United States Natural Gas Fund LP (UNG ETF). These indicators suggest that decision support systems with the capacity to effectively mitigate risk and enhance the performance of portfolios exposed to natural gas, both in absolute and risk-adjusted terms, are of paramount importance in this sector. Such systems could play a crucial role in mitigating the substantial downturns observed in this high-risk, low-return market, where current downturns exceed 90%.

TABLE 2. Downside risk and risk-adjusted performance.

	US	USO	UNG
Semi Deviation	0.0103	0.0234	0.0267
Gain Deviation	0.0092	0.0171	0.0231
Loss Deviation	0.0116	0.0277	0.0272
Downside Deviation (MAR=0%)	0.0101	0.0235	0.0113
Sharpe ratio (annualized, scale=252, Rf=0%, p=95%)	0.6567	-0.1020	-0.4521
Adjusted Sharpe ratio (annualized,scale=252, Rf=0%, p=95%)	0.4609	-0.1048	-0.4525
Maximum Drawdown	0.3575	0.8839	0.9067
Historical VaR (95%)	-0.0219	-0.0518	-0.0638

Note: MAR stands for the minimum acceptable return; Rf is the risk-free rate; VaR is the Value-at-Risk.

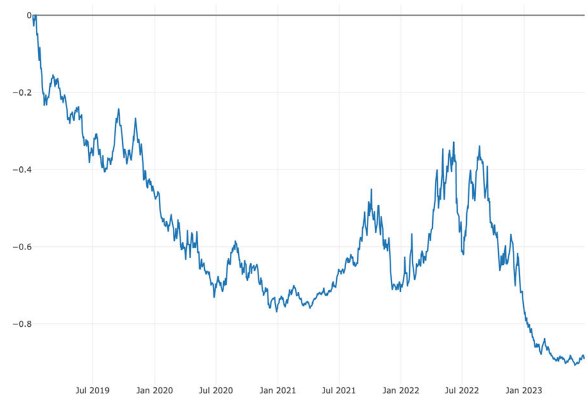

FIGURE 5. Drawdown of the UNG fund (2019-2023).

Concluding the exploratory analysis, Figure 5 presents a visual representation of the considerable drawdown experienced by this segment of the energy market in recent years. This graphical illustration provides a clear and detailed depiction of the market's challenging conditions during the specified period.

B. EMPIRICAL RESULTS

As delineated earlier, the process of determining the optimal length of the recursive window, denoted as 'l', involves an estimation-based approach. This approach assesses both the performance and the risk-adjusted performance of three distinct portfolios. These portfolios are constructed based on trading strategies derived from "restricted" Decision Support System (DSS) architectures. In these "restricted" configurations, all fundamental components remain consistent except for the variable 'l', which assumes values from the set {100, 120, 250}. Within such a "restricted" DSS framework,

FIGURE 6. The cumulative return of the restricted DSS 100_1_1 portfolio versus the buy-and-hold strategy. Annualized Sharpe ratio of the DSS(100_1_1) portfolio (Rf=0%) = −0.1388.

FIGURE 7. The cumulative return of the restricted DSS 120_1_1 portfolio versus the buy-and-hold strategy. Annualized Sharpe ratio of the DSS(120_1_1) portfolio (Rf=0%) = 0.3717.

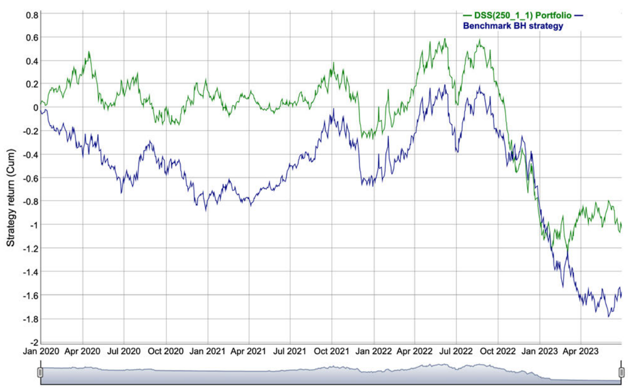

FIGURE 8. The cumulative return of the restricted DSS 250_1_1 portfolio versus the buy-and-hold strategy. Annualized Sharpe ratio of the DSS(250_1_1) portfolio (Rf=0%) = −0.1375.

the fitness function iteratively evaluates a limited pool of 3 covariates, specifically 2×2.1, across N-l-1 iterations (in this instance, 1132-l-1). Consequently, this dynamic optimization is termed ''restricted'' due to the constrained size of the covariate pool. The outcomes of these evaluations and optimizations are graphically represented in Figures 6 to 8, illustrating the resultant trading strategy performances under the varying window lengths.

The visual representations, alongside the risk-adjusted performance as indicated by the Sharpe ratios, furnish substantive evidence that portfolios generated by the Decision Support System (DSS), despite being derived from restricted system architectures, have outperformed the corresponding Buy-and-Hold (BH) strategy implemented on the UNG natural gas ETF over the designated analysis period.

FIGURE 9. The cumulative return of the optimized DSS 120_2_2 portfolio versus the buy-and-hold strategy. Annualized Sharpe ratio of the DSS(120_2_2) portfolio (Rf=0%) = +0.8478.

FIGURE 10. The cumulative return of the optimized DSS 120_3_3 portfolio versus the buy-and-hold strategy. Annualized Sharpe ratio of the DSS(120_3_3) portfolio (Rf=0%) = +0.6441.

The findings further reveal that of the three distinct ''restricted'' DSS configurations developed, the portfolio constructed using the DSS framework with a window length of $l = 120$ days for its recursive forecasting process, denoted as DSS(120_1_1), demonstrates superior risk-adjusted performance. Notably, this portfolio markedly excels over the BH strategy in both absolute returns and risk-adjusted measures, exhibiting particularly robust performance in the first half of 2023—a period marked by considerable corrections in the UNG market.

In addition, the development of increasingly optimized DSS frameworks involves the sequential expansion of the covariate pool size, which is used iteratively in the fitness function. The performance trajectories of portfolios generated using DSS architectures, which employ this dynamic and optimized recursive forecasting method with varying covariate pool sizes—8 (i.e., for p, q each within the range $\{0,1,2\}$) and 15 (i.e., for p, q each within the range $\{0,1,2,3\}$)—are delineated in Figures 9 and 10. This approach highlights the

TABLE 3. Performance metrics of DSS-based portfolios.

	DSS120_2_2 (l=120, pool of covariates size = 8)	DSS120_1_1(l=120, pool of covariates size = 3)	BH
Return (mean, daily)	0.002	0.0009	-0.0011
Risk (std dev, daily)	0.038	0.038	0.037
Maximum drawdown	0.6359	0.5981	0.9067
Historical VaR (95%)	-0.059	-0.062	-0.0638
Sharpe ratio (std dev, Rf=0%, p=95%)	0.0951	0.0234	-0.0284
Annualized Sharpe (Rf=0%, scale=252)	0.8478	0.3717	-0.4521

iterative refinement process and its impact on the performance of the portfolios.

Throughout the examined period, portfolios developed using the Decision Support System (DSS) consistently exhibited superior performance compared to the Buy-and-Hold (BH) benchmark. Notably, these DSS-based portfolios maintained positive returns even during phases when the BH strategy experienced negative returns. The most efficacious DSS framework was identified as the DSS_120_2_2, executing a total of 1011 optimizations (calculated as 1132-120-1) and 8088 estimations (equivalent to 8 × 1011).

The performance of the DSS(120_2_2) portfolio was particularly notable during the onset of the COVID-19 pandemic, a period characterized by a significant downturn in the natural gas market. This decline was primarily due to global lockdowns and the subsequent reduction in worldwide energy demand, disproportionately impacting the natural gas sector [60]. Moreover, this portfolio's robust outperformance was even more pronounced during recent episodes of price decreases, largely attributed to a substantial reduction in demand [18].

From these analytical results, three principal conclusions can be drawn: (i) all DSS configurations, including those with restricted system architectures, succeeded in constructing portfolios that surpassed the performance of the BH strategy; (ii) the most effective performance was achieved with a covariate pool size of 8 (i.e., p and $q \in \{0,1,2\}$); and (iii) upon expansion of the covariate pool to a size of 15 (i.e., p and $q \in \{0,1,2,3\}$), there was a noticeable decline in the DSS's predictive accuracy. Nevertheless, the overall outperformance of these portfolios remained significant, with their equity curves consistently outstripping that of the BH strategy.

Table 3 consolidates the performance metrics for the optimal DSS-derived portfolio (specifically, the DSS120_2_2 portfolio), the most effective restricted DSS architecture (namely, DSS120_1_1), and, for comparative purposes, includes the performance metrics of the corresponding BH portfolio over the analysis period. This compilation offers an extensive comparative analysis of their respective performances.

IV. DISCUSSION

Natural gas, as a pivotal component of the global energy mix, plays an essential role in a diverse range of applications, from power generation and heating to industrial processes and transportation, thus underscoring its vital place in the global energy landscape [61], [62], [63], [64]. Its significance is further accentuated as the world shifts towards more sustainable and low-carbon energy sources, with natural gas emerging as a cleaner and reliable alternative [65], [66], [67], [68]. The natural gas market, therefore, not only offers substantial investment opportunities but also plays a critical role in the transition to greener energy solutions.

This study gains particular relevance in light of the global economic implications of natural gas market trends. Recent patterns have seen a marked decline in natural gas prices, along with pronounced volatility, influenced by multiple factors including European market dynamics, warmer weather, enhanced energy efficiency, and shifting consumption patterns [18]. Such volatility has precipitated substantial losses in portfolios heavily invested in natural gas, underscoring the necessity for robust trading strategies that can adeptly improve risk-adjusted performance.

The formulation of effective trading strategies for natural gas portfolios is crucial not only for reducing investment risks but also for supporting broader goals of energy security, economic stability, and environmental sustainability. This is particularly pertinent for major economies like China, where rapid industrialization and urbanization have escalated energy demand. Natural gas plays a significant role in meeting this demand, facilitating the transition to a lower-carbon economy. Therefore, addressing the challenges posed by natural gas price volatility within financial markets through sophisticated trading strategies holds wide-ranging implications, influencing the intricacies of the global energy landscape and the economic dynamics of key players like China.

The importance of accurately predicting natural gas prices, as highlighted by [69], is a paramount concern for various stakeholders, including policymakers, whereas poorly designed algorithms can exacerbate losses [70]. However, the literature on the predictability of natural gas prices is relatively scant [71] and existing algorithmic trading strategies in this market have been limited and predominantly based on statistical arbitrage or machine-learning methods. This study addresses these gaps by proposing an advanced Decision Support System (DSS) for algorithmic trading, expanding upon the work of [49].

Thus, informed by the foundational work of [49] and guided by the characteristics of the natural gas market – high volatility, structural changes, and time-varying nature as identified by [72], [73], and [74]– the proposed system incorporates a dynamic ARMA-GARCH model. This choice is in line with previous studies [53], [54], [55] that question the value of higher-order ARCH and GARCH polynomials. Instead, a GARCH(1,1) specification for the variance equation is adopted, optimizing mean parameters within a rolling window.

The research further relies on the conclusions of [75] regarding the value of the window length in a recursive forecasting framework, enhances the Tudor-Sova DSS architecture by introducing an estimation-based selection of the rolling window length, moving away from an a priori setting. The identification of a 120-day window as most suitable for modeling and forecasting the natural gas market corroborates [49] findings for the crude oil market. Beyond previous research, the results indicate that the system's predictive performance diminishes when the pool of covariates exceeds a size of 8. This finding underscores the importance of halting the training process early to avoid overfitting and to reduce computational resources, aligning with the assertions of [76] regarding the benefits of curtailing the learning process in decision-making.

The DSS(120_2_2) architecture, with a rolling window length of 120 days and an optimized covariate pool size of 8, yields the most promising results, and manages to effectively navigate the tumultuous market conditions induced by the COVID-19 pandemic and subsequent demand shifts, delivering superior returns and risk-adjusted performance, evidenced by a high Sharpe ratio. At least as important, the proposed system managed to construct trading portfolios on the UNG natural gas market with significantly lower drawdown than passive portfolios following the BH strategy. This achievement is noteworthy, especially in light of the findings of [11], who posited that algorithmic trading could potentially destabilize markets and amplify volatility. The results from the current study provide a compelling counterargument to this perspective. Furthermore, the DSS's effectiveness challenges the idea that algorithmic trading increases volatility. Instead, it suggests that well-designed algorithmic systems, which incorporate sophisticated risk management and predictive modeling techniques, can navigate market complexities more adeptly than simpler systems or passive investment strategies. By dynamically adjusting to market conditions and employing predictive analytics, the DSS was able to sidestep substantial market downturns and maintain portfolio stability.

The findings from this study not only validate the DSS's capabilities in algorithmic trading but also demonstrate its effectiveness in generating profitable trading strategies within the natural gas market, specifically using the United States Natural Gas Fund LP (UNG). This evidence supports earlier findings by [32], [33], and [34], providing updated proof of the market's inefficiency. By leveraging dynamic and continuously optimized mean-variance specifications, the DSS can adapt to market changes and generate returns that exceed those of traditional buy-and-hold strategies.

This result has significant implications for the Efficient Market Hypothesis (EMH), which posits that asset prices fully reflect available information, making it challenging to consistently achieve higher returns than the overall market through active trading strategies [24], [25], [26], [27], [28], [29]. Specifically, our findings challenge the weak-form and semi-strong form of the EMH in the context of the natural gas market. The weak-form EMH asserts that past trading information is already reflected in stock prices, and the semi-strong form claims that all publicly available information is already accounted for in stock prices. The ability of our DSS to outperform the market by identifying and exploiting inefficiencies challenges these forms of the EMH, particularly in the context of the natural gas market. The observed inefficiencies may stem from several factors unique to the natural gas market, including its high volatility, the influence of geopolitical events, and the complexity of supply and demand dynamics [15]. These factors can create opportunities for well-designed algorithmic trading systems to capitalize on short-term price movements and anomalies that are not immediately corrected by the market.

Moreover, the study's findings highlight the importance of advanced trading strategies that can dynamically adjust to changing market conditions. This adaptability is crucial for maintaining robustness and avoiding the pitfalls of overfitting, which can plague less sophisticated models. The DSS's success in this volatile market underscores the potential for similar systems to be applied to other energy commodities or volatile financial markets, further questioning the universality of the weak-form and semi-strong forms of the EMH.

Consequently, the enhanced DSS not only serves as a powerful tool for improving trading performance but also provides empirical evidence that markets, particularly commodity markets like natural gas, may not always be efficient. This challenges the weak-form and semi-strong forms of the EMH and suggests that there are still opportunities for active trading strategies to generate excess returns. Future research should continue to explore these inefficiencies and develop more advanced models to better understand and exploit them.

In conclusion, the findings of this research add a nuanced perspective to the debate on algorithmic trading's impact on market dynamics. By demonstrating the ability of a well-structured algorithmic trading system to reduce drawdowns and manage risks effectively, the study provides evidence that algorithmic trading, when implemented judiciously, can indeed contribute to portfolio stability and contradict assertions of inherent market destabilization. This enhanced DSS provides traders in the natural gas markets with essential tools for informed decision-making and strategy optimization, thereby gaining a competitive advantage in a complex market environment [9], [10]; [77], [78], [79].

V. CONCLUSION

With the development of information technology, intelligent algorithms have demonstrated powerful decision-making capabilities and have been widely utilized [80], [81], [82]. Algorithmic trading in financial markets has expanded rapidly, yet its application in natural gas markets faces significant challenges due to high volatility driven by geopolitical events and supply-demand imbalances, necessitating advanced strategies to improve performance and manage risk.

This study addresses this gap by developing a robust trading decision-support system (DSS) that enhances trading algorithms through optimized forecasting techniques and adaptive model parameter adjustments. Validated through backtesting from January 2019 to July 2023, the proposed DSS incorporates dynamic mean-variance specifications. The system's adaptability to evolving market dynamics has shielded the DSS-issued natural gas portfolios from significant downturns. Performance metrics demonstrated consistent outperformance in both return enhancement and risk reduction compared to the buy-and-hold strategy, highlighting the system's capability to create superior portfolios even in volatile conditions.

Despite these promising results, the research acknowledges limitations. The historical market conditions and back-testing period may not fully capture future market dynamics. Future research could extend the system's application to other volatile markets and explore ensemble or machine-learning methods to enhance the DSS's potential. This study enriches the literature on algorithmic trading in the natural gas market and significantly contributes to optimizing returns while managing risk effectively.

REFERENCES

[1] U.S. Securities Exchange Commission. (2020). *Staff Report on Algorithmic Trading in U.S. Capital Markets*. Accessed: May 17, 2024. [Online]. Available: https://www.sec.gov/files/Algo_Trading_Report_2020.pdf

[2] B. M. Weller, "Does algorithmic trading reduce information acquisition?" *Rev. Financial Stud.*, vol. 31, no. 6, pp. 2184–2226, Jun. 2018.

[3] M. Mathur, S. Mhadalekar, S. Mhatre, and V. Mane, "Algorithmic trading bot," in *Proc. ITM Web Conf.*, vol. 40, 2021, p. 03041.

[4] A. Srinivas Murthy, A. Akshay, and B. R. Hanji, "Cryptocurrency trading bot with sentimental analysis and backtracking using predictive ML," in *Proc. Innovations in Computer Science and Engineering*. Cham, Switzerland: Springer, 2022, pp. 501–512.

[5] R. Kissell, *Algorithmic Trading Methods: Applications Using Advanced Statistics, Optimization, and Machine Learning Techniques*. New York, NY, USA: Academic, 2020.

[6] Y. Liang, A. Thavaneswaran, and Md. E. Hoque, "A novel algorithmic trading strategy using data-driven innovation volatility," in *Proc. IEEE Symp. Ser. Comput. Intell.*, Dec. 2020, pp. 1107–1114.

[7] R. K. Dubey, "Algorithmic trading: The intelligent trading systems and its impact on trade size," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117279.

[8] (2022). *Algorithmic Trading Market—Growth, Trends, COVID-19 Impact, and Forecasts (2022–2027)*. Accessed: May 15, 2024. [Online]. Available: https://www.reportlinker.com/p06246232/Algorithmic-Trading-Market-Growth-Trends-COVID-19-Impact-and-Forecasts.html.

[9] R. K. Dubey, A. S. Babu, R. R. Jha, and U. Varma, "Algorithmic trading efficiency and its impact on market-quality," *Asia–Pacific Financial Markets*, vol. 29, no. 3, pp. 381–409, Sep. 2022.

[10] S. Nawn and A. Banerjee, "Do the limit orders of proprietary and agency algorithmic traders discover or obscure security prices?" *J. Empirical Finance*, vol. 53, pp. 109–125, Sep. 2019.

[11] D. Arumugam, P. K. Prasanna, and R. R. Marathe, "Do algorithmic traders exploit volatility?" *J. Behav. Experim. Finance*, vol. 37, Mar. 2023, Art. no. 100778.

[12] B. Huang, Y. Huan, L. D. Xu, L. Zheng, and Z. Zou, "Automated trading systems statistical and machine learning methods and hardware implementation: A survey," *Enterprise Inf. Syst.*, vol. 13, no. 1, pp. 132–144, Jan. 2019.

[13] D. Zhang, "Oil shocks and stock markets revisited: Measuring connectedness from a global perspective," *Energy Econ.*, vol. 62, pp. 323–333, Feb. 2017, doi: 10.1016/j.eneco.2017.01.009.

[14] D. Zhang, T. Wang, X. Shi, and J. Liu, "Is hub-based pricing a better choice than oil indexation for natural gas? Evidence from a multiple bubble test," *Energy Econ.*, vol. 76, pp. 495–503, Oct. 2018.

[15] P. Ferreira, D. Almeida, A. Dionísio, E. Bouri, and D. Quintino, "Energy markets—Who are the influencers?" *Energy*, vol. 239, Jan. 2022, Art. no. 121962.

[16] C. P. Clifford, J. A. Fulkerson, and B. D. Jordan, "What drives ETF flows?" *Financial Rev.*, vol. 49, no. 3, pp. 619–642, Aug. 2014.

[17] I. Ben-David, F. Franzoni, and R. Moussawi, "Exchange-traded funds," *Annu. Rev. Financial Econ.*, vol. 9, pp. 169–189, Jul. 2017.

[18] (2023). *Bubble Trouble: What's Behind the Highs and Lows of Natural Gas Markets?*. Accessed: May 20, 2024. [Online]. Available: https://blogs.worldbank.org/opendata/bubble-trouble-whats-behind-highs-and-lows-natural-gas-markets

[19] P. Treleaven, M. Galas, and V. Lalchand, "Algorithmic trading review," *Commun. ACM*, vol. 56, no. 11, pp. 76–85, 2013.

[20] (2022). *Energy Markets Need Urgent Debate About Role of Algorithmic Trading in Volatility*. Accessed: May 22, 2024. [Online]. Available: https://www.icis.com/explore/resources/news/2022/08/01/10790863/energy-markets-need-urgent-debate-about-role-of-algorithmic-trading-in-volatility/

[21] (2022). *Energy Markets and Algo Trading*. Accessed: May 20, 2024. [Online]. Available: https://www.eventus.com/cat-validus-in-practice/energy-markets-and-algorithmic-trading/

[22] (2023). *Outlook 2023: The Return of Geopolitical Risk in the Energy Market*. Accessed: May 20, 2024. [Online]. Available: https://pemedianetwork.com/petroleum-economist/articles/geopolitics/2022/outlook-2023-the-return-of-geopolitical-risk-in-the-energy-market/

[23] (2023). *How Geopolitics Have Reshaped Natural Gas Markets*. Accessed: May 21, 2024. [Online]. Available: https://www.forbes.com/sites/cme-group/2023/07/13/how-geopolitics-have-reshaped-natural-gas-markets/

[24] E. F. Fama, "The behavior of stock-market prices," *J. Bus.*, vol. 38, no. 1, p. 34, Jan. 1965.

[25] E. F. Fama, "Efficient capital markets: A review of theory and empirical work," *J. Finance*, vol. 25, no. 2, p. 383, May 1970.

[26] E. F. Fama, "Efficient capital markets: II," *J. Finance*, vol. 46, no. 5, p. 1575, Dec. 1991.

[27] P. Samuelson, "Proof that properly anticipated prices fluctuate randomly," *Industrial Management Review*, vol. 6, pp. 41–50, Aug. 1965.

[28] P. A. Samuelson, "Proof that properly anticipated prices fluctuate randomly," in *The World Scientific Handbook Futures Markets*. Singapore: World Scientific, 2016, pp. 25–38.

[29] B. G. Malkiel, "Efficient market hypothesis," in *Finance*. London, U.K.: Palgrave Macmillan, 1989, pp. 127–134.

[30] Y. K. Gebre-Mariam, "Testing for unit roots, causality, cointegration, and efficiency: The case of the northwest U.S. Natural gas market," *Energy*, vol. 36, no. 5, pp. 3489–3500, May 2011.

[31] W. W. David, "An econometric analysis of the market for natural gas futures," *Energy J.*, vol. 16, no. 1, pp. 71–83, Jan. 1995.

[32] J. H. Herbert and E. Kreil, "U.S. Natural gas markets: How efficient are they?" *Energy policy*, vol. 24, no. 1, pp. 1–5, 1996.

[33] D. Lien and T. H. Root, "Convergence to the long-run equilibrium: The case of natural gas markets," *Energy Econ.*, vol. 21, no. 2, pp. 95–110, Apr. 1999.

[34] A. E. H. Mazighi, "The efficiency of natural gas futures markets," *OPEC Rev.*, vol. 27, no. 2, pp. 143–158, Jun. 2003.

[35] S. Borovkova and D. Mahakena, "News, volatility and jumps: The case of natural gas futures," *Quant. Finance*, vol. 15, no. 7, pp. 1217–1242, Jul. 2015.

[36] E. Ceperic, S. Žikovic, and V. Ceperic, "Short-term forecasting of natural gas prices using machine learning and feature selection algorithms," *Energy*, vol. 140, pp. 893–900, Dec. 2017.

[37] G. P. Herrera, M. Constantino, B. M. Tabak, H. Pistori, J.-J. Su, and A. Naranpanawa, "Long-term forecast of energy commodities price using machine learning," *Energy*, vol. 179, pp. 214–221, Jul. 2019.

[38] M. Su, Z. Zhang, Y. Zhu, D. Zha, and W. Wen, "Data driven natural gas spot price prediction models using machine learning methods," *Energies*, vol. 12, no. 9, p. 1680, May 2019.

[39] I. E. Livieris, E. Pintelas, N. Kiriakidou, and S. Stavroyiannis, "An advanced deep learning model for short-term forecasting U.S. Natural gas price and movement," in *Proc. Artificial Intelligence Applications and Innovations*. Cham, Switzerland: Springer, 2020, pp. 165–176.

[40] D. Mouchtaris, E. Sofianos, P. Gogas, and T. Papadimitriou, "Forecasting natural gas spot prices with machine learning," *Energies*, vol. 14, no. 18, p. 5782, Sep. 2021.

[41] R. K. Jana and I. Ghosh, "A residual driven ensemble machine learning approach for forecasting natural gas prices: Analyses for pre-and during-COVID-19 phases," *Ann. Oper. Res.*, vol. 1, pp. 1–22, Jan. 2022.

[42] K. Driaunys, S. Masteika, V. Sakalauskas, and M. Vaitonis, "An algorithm-based statistical arbitrage high frequency trading system to forecast prices of natural gas futures," *Transformations Bus. Econ.*, vol. 13, no. 3, pp. 1–12, 2014.

[43] S. Masteika and M. Vaitonis, "Quantitative research in high frequency trading for natural gas futures market," in *Business Information Systems Workshops*. Cham, Switzerland: Springer, 2015, pp. 29–35.

[44] T. Nakajima, "Expectations for statistical arbitrage in energy futures markets," *J. Risk Financial Manage.*, vol. 12, no. 1, p. 14, Jan. 2019.

[45] Z. Huang, W. Gong, and J. Duan, "TBDQN: A novel two-branch deep Q-network for crude oil and natural gas futures trading," *Appl. Energy*, vol. 347, Oct. 2023, Art. no. 121321.

[46] (2022). *Natural Gas Use Contributed to Cleaner Air and Lower Emissions in China but is Slated to Take Second Seat to Renewables in Future Plans*. Accessed: Jan. 4, 2024. [Online]. Available: https://www.climatescorecard.org/2022/06/natural-gas-use-contributed-to-cleaner-air-and-lower-emissions-in-china-but-is-slated-to-take-second-seat-to-renewables-in-future-plans/

[47] S. Zhao, J. Lu, J. Yan, H. Wu, and C. Guan, "Energy transition in China: It is necessary to increase natural gas utilization," *Energy Rep.*, vol. 10, pp. 2439–2447, Nov. 2023.

[48] (2023). *A Rising China is Reshaping Global Energy Markets*. Accessed: Jan. 4, 2024. [Online]. Available: https://www.gisreportsonline.com/r/china-energy-markets/

[49] C. Tudor and R. Sova, "Flexible decision support system for algorithmic trading: Empirical application on crude oil markets," *IEEE Access*, vol. 10, pp. 9628–9644, 2022.

[50] M. C. Lee, J. B. Su, and H. C. Liu, "Value-at-risk in U.S. Stock indices with skewed generalized error distribution," *Applied Financial Economics Letters*, vol. 4, no. 6, pp. 425–431, 2008.

[51] Y.-H. Lee and T.-Y. Pai, "REIT volatility prediction for skew-GED distribution of the GARCH model," *Expert Syst. Appl.*, vol. 37, no. 7, pp. 4737–4741, Jul. 2010.

[52] M. Kéry and J. A. Royle, "What are hierarchical models and how do we analyze them?" in *Applied Hierarchical Modeling in Ecology*, M. Kéry and J. A. Royle, Eds. London, U.K.: Academic, 2016, pp. 19–78, doi: 10.1016/B978-0-12-801378-6.00002-3.

[53] R. Bali and H. Guirguis, "Extreme observations and non-normality in ARCH and GARCH," *Int. Rev. Econ. Finance*, vol. 16, no. 3, pp. 332–346, Jan. 2007.

[54] P. Agnolucci, "Volatility in crude oil futures: A comparison of the predictive ability of GARCH and implied volatility models," *Energy Econ.*, vol. 31, no. 2, pp. 316–321, Mar. 2009.

[55] Y. Fan, Y.-J. Zhang, H.-T. Tsai, and Y.-M. Wei, "Estimating 'value at risk' of crude oil price and its spillover effect using the GED-GARCH approach," *Energy Econ.*, vol. 30, no. 6, pp. 3156–3171, Nov. 2008.

[56] M. Manera, M. Nicolini, and I. Vignati, "Modelling futures price volatility in energy markets: Is there a role for financial speculation?" *Energy Econ.*, vol. 53, pp. 220–229, Jan. 2016.

[57] A. Ghalanos. (2022). *Package 'Rugarch', Ver. 1.4-1*. Accessed: May 17, 2024. [Online]. Available: https://cran.r-project.org/web/packages/rugarch/index.html

[58] W. F. Sharpe, "The Sharpe ratio," *J. Portfolio Manage.*, vol. 21, no. 1, pp. 49–58, Oct. 1994, doi: 10.3905/jpm.1994.409501.

[59] J. Pezier and A. White, *The Relative Merits of Investable Hedge Fund Indices and of Funds of Hedge Funds in Optimal Passive Portfolios*. England, U.K.: University of Reading, 2006.

[60] (2021). *COVID-19 Dents Demand for Gas and Undermines its Role as a Bridge Fuel in the Energy Transition*. Accessed: May 14, 2024. [Online]. Available: https://www.spglobal.com/en/research-insights/featured/covid-19-dents-demand-for-gas-and-undermines-its-role-as-a-bridge-fuel-in-the-energy-transition

[61] M. J. Economides and D. A. Wood, "The state of natural gas," *J. Natural Gas Sci. Eng.*, vol. 1, nos. 1–2, pp. 1–13, Jul. 2009.

[62] M. Melikoglu, "Shale gas: Analysis of its role in the global energy market," *Renew. Sustain. Energy Rev.*, vol. 37, pp. 460–468, Sep. 2014.

[63] R. Egging and F. Holz, "Risks in global natural gas markets: Investment, hedging and trade," *Energy Policy*, vol. 94, pp. 468–479, Jul. 2016.

[64] F. Belaïd, A. Al-Sarihi, and R. Al-Mestneer, "Balancing climate mitigation and energy security goals amid converging global energy crises: The role of green investments," *Renew. Energy*, vol. 205, pp. 534–542, Mar. 2023.

[65] Y. Chen, C. Wang, and Z. Zhu, "Toward the integration of European gas futures market under COVID-19 shock: A quantile connectedness approach," *Energy Econ.*, vol. 114, Oct. 2022, Art. no. 106288.

[66] S. K. A. Rizvi, B. Naqvi, S. Boubaker, and N. Mirza, "The power play of natural gas and crude oil in the move towards the financialization of the energy market," *Energy Econ.*, vol. 112, Aug. 2022, Art. no. 106131.

[67] S. Shakya, B. Li, and X. Etienne, "Shale revolution, oil and gas prices, and drilling activities in the United States," *Energy Econ.*, vol. 108, Apr. 2022, Art. no. 105877.

[68] J. Zeng, R. Bao, and M. McFarland, "Clean energy substitution: The effect of transitioning from coal to gas on air pollution," *Energy Econ.*, vol. 107, Mar. 2022, Art. no. 105816.

[69] J. Wang, C. Lei, and M. Guo, "Daily natural gas price forecasting by a weighted hybrid data-driven model," *J. Petroleum Sci. Eng.*, vol. 192, Sep. 2020, Art. no. 107240.

[70] M. A. Goldstein, P. K. Kumar, and F. C. Graves, "Computerized and high-frequency trading," *SSRN Electron. J.*, vol. 49, no. 2, pp. 177–202, Aug. 2014.

[71] K. Luo, Q. Guo, and X. Li, "Can the return connectedness indices from grey energy to natural gas help to forecast the natural gas returns?" *Energy Econ.*, vol. 109, May 2022, Art. no. 105947.

[72] B. Li, "Pricing dynamics of natural gas futures," *Energy Econ.*, vol. 78, pp. 91–108, Feb. 2019.

[73] A. Hailemariam and R. Smyth, "What drives volatility in natural gas prices?" *Energy Econ.*, vol. 80, pp. 731–742, May 2019.

[74] L. Kristoufek and M. Vosvrda, "Commodity futures and market efficiency," *Energy Econ.*, vol. 42, pp. 50–57, Mar. 2014.

[75] A. Inoue, L. Jin, and B. Rossi, "Rolling window selection for out-of-sample forecasting with time-varying parameters," *J. Econometrics*, vol. 196, no. 1, pp. 55–67, Jan. 2017.

[76] M. V. Ferro, Y. D. Mosquera, F. J. R. Pena, and V. M. D. Bilbao, "Early stopping by correlating online indicators in neural networks," *Neural Netw.*, vol. 159, pp. 109–124, Feb. 2023.

[77] T. Saito, T. Adachi, T. Nakatsuma, A. Takahashi, H. Tsuda, and N. Yoshino, "Trading and ordering patterns of market participants in high frequency trading environment: Empirical study in the Japanese stock market," *Asia–Pacific Financial Markets*, vol. 25, no. 3, pp. 179–220, Sep. 2018.

[78] S. R. Syamala and K. Wadhwa, "Trading performance and market efficiency: Evidence from algorithmic trading," *Res. Int. Bus. Finance*, vol. 54, Dec. 2020, Art. no. 101283.

[79] M. E. Aloud and N. Alkhamees, "Intelligent algorithmic trading strategy using reinforcement learning and directional change," *IEEE Access*, vol. 9, pp. 114659–114671, 2021.

[80] S. Yang, C. Guo, D. Meng, Y. Guo, Y. Guo, L. Pan, and S. Zhu, "MECSBO: Multi-strategy enhanced circulatory system based optimisation algorithm for global optimisation and reliability-based design optimisation problems," *IET Collaborative Intell. Manuf.*, vol. 6, no. 2, Jun. 2024, Art. no. e12097, doi: 10.1049/cim2.12097.

[81] D. Meng, H. Yang, S. Yang, Y. Zhang, A. M. P. D. Jesus, J. Correia, T. Fazeres-Ferradosa, W. Macek, R. Branco, and S.-P. Zhu, "Kriging-assisted hybrid reliability design and optimization of offshore wind turbine support structure based on a portfolio allocation strategy," *Ocean Eng.*, vol. 295, Mar. 2024, Art. no. 116842, doi: 10.1016/j.oceaneng.2024.116842.

[82] D. Meng, S. Yang, A. M. P. De Jesus, T. Fazeres-Ferradosa, and S.-P. Zhu, "A novel hybrid adaptive Kriging and water cycle algorithm for reliability-based design and optimization strategy: Application in offshore wind turbine monopile," *Comput. Methods Appl. Mech. Eng.*, vol. 412, Jul. 2023, Art. no. 116083, doi: 10.1016/j.cma.2023.116083.

CRISTIANA TUDOR received the Ph.D. degree. She has an academic career in the field of economics, which spans over 20 years. She has acquired extensive experience as a Visiting Professor at international universities and research centers. She has been actively involved in the CFA program development, as a member of the Education Advisory Committee Working Body and a member of the Practice Analysis Working Body. She has also acquired relevant experience in policy-making at the national/international level as the first President of the Romanian Statutory Audit Oversight Body (ASPAAS), established in the subordination of the Ministry of Public Finances. She is a Chartered Financial Analyst (CFA), a member of the CFA Institute, and an Expert Accountant (CPA). She contributed to the setup of two public research centers, such as the Research Centre in International Business and Economics and the Research Centre in Applied Mathematics, Bucharest University of Economic Studies. Since 2013, she has been a Board Member of the Research Centre in Applied Mathematics.

ROBERT SOVA received the Ph.D. degree. He is an Economics Professor with an academic career that spans 27 years. He has acted as a Vice-Rector of Bucharest University of Economic Studies, from 2012 to 2016. He is also a Certified Accountant (CPA) and the Prime Vice-President of a Romanian professional body that represents all accountants and accounting companies, namely the Body of Expert and Licensed Accountants of Romania (CECCAR). He acts as the Editor-in-Chief of the body's magazine, *CECCAR Business Review*.