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Review of AI and Machine Learning-Based Hedging Strategies in Commodities Derivatives

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Abstract:

This study reviews the paradigm of AI and Machine Learning (ML)-based models in hedging strategies in the Commodities Derivatives Market with aim to describes the research conducted so far, methodological approaches, and a new model that is empirically explored. For this purpose, PRISMA Methodology is followed in data extraction, and a rigorous content analysis-based systematic literature review is done. A total of 20 peer-reviewed empirical articles were analysed from the Scopus and Web of Science databases. The review shows that USA's exchange lead in the application of AI, Deep Learning and ML-based models and crude oil (including WTI and Brent) - asset class is used most frequently. However, fewer studies are available to support the empirical validity of these models in developing economies. While DL and ML models like "GJR-GARCH-SVR-LSTM", "Deep Neural Networks" and LSTM", "VaR with Random Forest model" and other machine learning-enhanced VaR models, are utilized in financial hedging strategies, but their application and empirical testing in commodity derivatives remain unexplored. The findings indicate the need to include agricultural products and industrial metals as units of analysis in these ML and DL models. The results of this review may serve as a valuable resource for researchers and managers seeking to conduct further investigations into this head of study.

Keywords: *Systematic Literature Review, Hedging, Commodity Derivatives Market, Artificial Intelligence, Machine Learning*

1. Introduction

Financial markets (FM) are observing the continuous trend of using innovative technologies, such as AI, ML, neural network (NN) Models, Deep learning (DL), for a variety of uses, including risk management (generative adversarial networks-based VaR & ES estimation), Portfolio management, Predictive analytics, Sentiment analysis, Algorithmic trading, Automation and efficiency, Regulatory compliance, Data to decision making and more. AI is gaining traction as a digital tool due to its capacity to assist FM in managing risks and implementing strategies, such as hedging against market volatility, assessing price volatility and price forecasting, by the end of 2025, these technological integrations are projected to contribute an additional $1 trillion in value (Hammoud, 2023).

AI has become a vital element in the technology landscape of the financial institution, Financial Services, FM, Banking and Insurance industry as it's revolutionizing the way risk management is done(Islam et al., 2024). Whereas, ML is a component of AI, empowers systems to independently learn and enhance their functions through NN and DL, without being explicitly programmed, by feeding it large amounts of data. This technology enables FM to utilize data to train models that address specific problems using ML algorithms, while also offering insights on how to refine these models over time.

The advent of AI is reshaping the industry's landscape, eroding the operations of conventional FM and creating opportunities for further innovation and new operational frameworks. While the integration of ML algorithms into quantitative risk management is still a relatively new phenomenon, it has already outperformed human traders by facilitating swifter and more informed trading decisions making. Moreover, an in-depth analysis of diverse market variables and factor enables traders to enhance their trading algorithms and it supports companies in constructing their own trading system. Ultimately bolstering business profitability, strengthens resilience, enhances risk management and ensures efficient raw material usage.

Nonetheless, this shift towards digitalization incurs a cost, as the intricate model architecture and its non-linear design complicate the understanding of the rationale behind its hedging, procurement suggestions (Rettinger, Minner & Birzl 2025). DL models are often labeled as black boxes because they lack transparency (Samek and Müller, 2019). Prompting questions about the foundations of their decision-making, the data segments that inform these decisions, and the trustworthiness of a model's output. when it's decision-making mechanisms lacks clarity, these considerations drive an need of investigating the scholarly research conducted in the domain of ML based strategies in Commodity Derivative Markets (CDM).

The interest centers on two major questions pertaining to ML based Hedging, considering literature available until dec. 2025. The research questions examined are:

- To Track and Review ML and AI based hedging's strategies over time.
- Identify the new avenues in the field and future research directions of study.

This research offers a comprehensive review of literature on AI and ML-based hedging and its effectiveness in CDM, utilizing content analysis (CA) base review. This method helps to identify the current relevant topics, emerging head, and potential gaps in the existing literature.

In lieu of the aforementioned objectives the Section 1 details the research methodology, while Section 2 presents Findings & discussion, Section 3 covers agenda for future research, whereas Section 4 articulates the conclusion.

2. Methodology

a. Data Search criteria & article selection

The search targeted the articles concerning ML-based hedging and its effectiveness in CDM following PRISMA model by using combination of keywords "Commodity" or "Commodity Derivatives" with the 'OR' operator to encompass all articles specifically related to commodity derivatives. To funnel down the focus to hedging and ML, additional keywords (Hedging OR "Hedging Effectiveness" OR "Deep Hedging") were incorporated with the AND operator, along with ("Machine Learning" OR "Artificial Intelligence" OR "Deep Learning" OR "Neural Network*" OR "AI") keywords (as shown in figure 1). The study concentrated on articles related to 'Commodity Derivatives', 'Hedging', and 'AI & ML-based hedging'.

In study, SCOPUS and Web of Science (WOS) database is used for review. These two Databases together form the most popular and widely used academic databases, providing leading journal, references, articles and publication details for research and development. In the last stage of article selection, concentration was exclusively on studies that were relevant to our research, making sure to discard any repetitive data and redundant information (Chistov et al, 2021). At the end of inclusion and exclusion criteria final 20 paper were selected for analysis.

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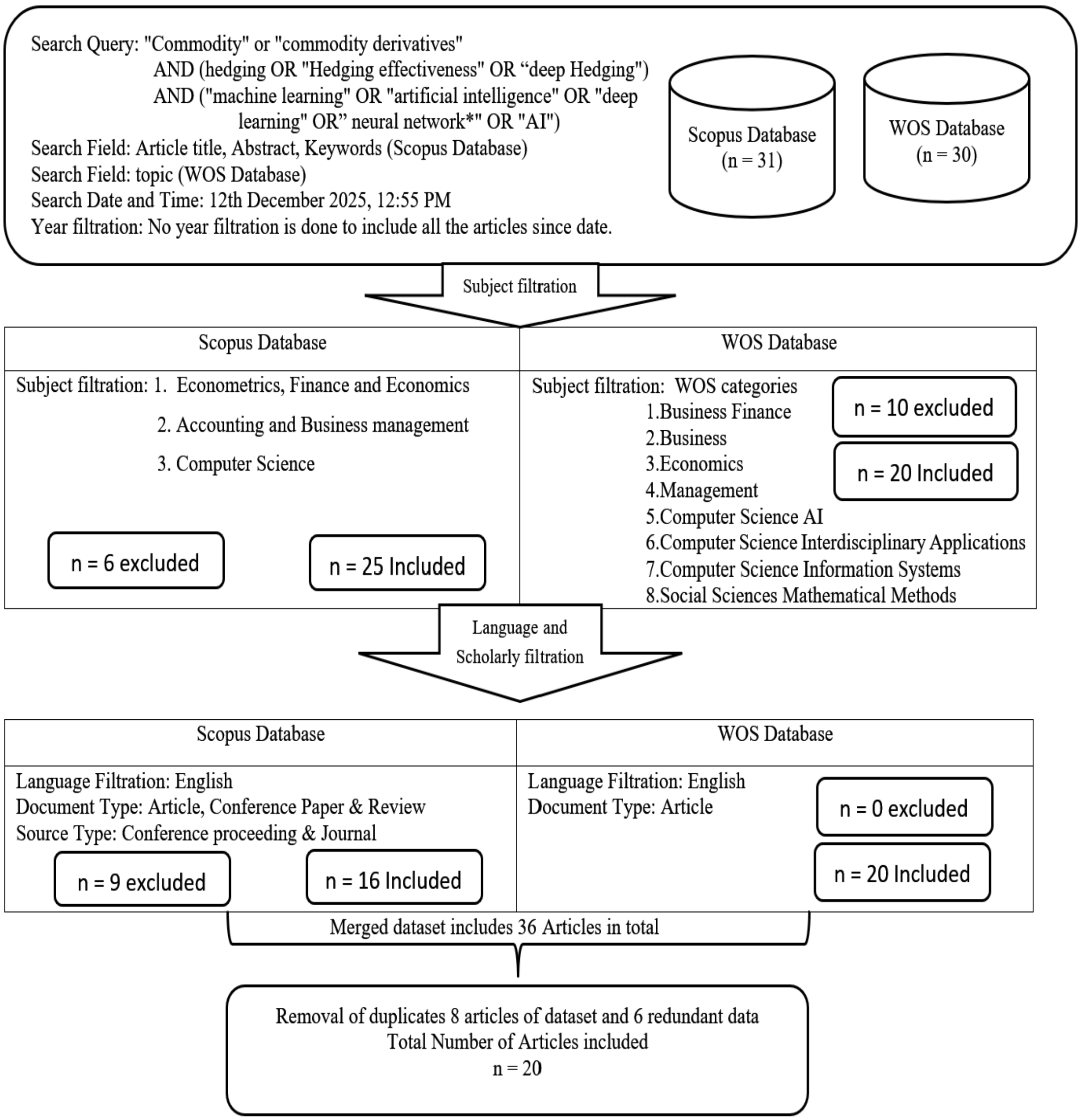

Figure 1. (Author's compilation)

b. Analysis Techniques and Rationale

In order to ensure the reliability and validity of the review, a hybrid approach combining manual, computer-assisted and AI-enabled methods have been used for the CA. AI has the potential to provide the advantages of both computer-assisted methods and manual (Lee et al., 2020). NotebookLLM, an AI-enabled platform and Bibliometrix – content analysis of RStudio were utilized.

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3. **Findings & discussion**

a. **Findings:**

I. Bedoui et al., 2023

Major theme	Advanced portfolio optimization using hybrid quantitative methods.
Country of analysis	France, Germany, UK, USA
Asset class	Bitcoin, gold, oil (WTI, BRENT), and stock indices (CAC40, DAX, FTSE100, and S&P500)
Dataset and Period	The empirical analysis uses daily prices for eight assets from August 2013 to September 2022 (2295 observations per series).
Methodology	GARCH, EGARCH, GJR-GARCH, NSGA and SPEA II -deep ML genetic algorithm
Key Contributions	• Mean CVaR optimizer, rather than relying on Gaussian or independence assumptions. • Novel optimization approach. It couples Vine Copula-GARCH-EVT risk model with an improved Non-dominated Sorting Genetic Algorithm and SPEA2 deep ML genetic algorithm to solve the multi-objective allocation problem, producing an approximated efficient frontier for downside-risk optimization.

II. Chen et al., 2012

Major theme	Hedging Crude Oil Risk with Polynomial Projections
Country of analysis	New York Mercantile Exchange, USA
Asset class	Crude Oil
Dataset and Period	NYMEX crude oil spot and nearest-maturity futures prices, the empirical dataset contains 5,565 dailies (rolled to avoid expiry effects) from January 3, 1984 to March 27, 2007. futures contracts (FC) listed in the CRB database.
Methodology	VEC-GARCH model, Naïve hedging, and the case of no hedging.
Key Contributions	• The paper proposes using Orthogonal Polynomial Projection Models—Spanning Polynomial Projection, Legendre Polynomial Projection (LPP), and two Integrated Ensemble Variants (IEPP-A and IEPP-B)—to compute time-varying optimal hedge ratios for crude oil and compares their hedging performance against no hedging, VEC–GARCH and naïve hedging. The study also incorporates practical considerations like "transaction cost" and "trader's level of risk aversion”

III. Albani et al., 2025

Major theme	Hybrid Forecasting in Brazilian Electricity Market
Country of analysis	Brazil
Asset class	Electricity Forward Contracts
Dataset and Period	The daily Volume Weighted Average Price from May 2017 to October 2022. and daily Affluent Natural Energy values for the Brazilian Southeast/Central-West market (ENA from ONS/BBCE)
Methodology	Stochastic Differential Equations (SDE) and ANN
Key Contributions	• The authors propose a univariate model that combines two distinct approaches: SDE and ANN • The Principal Component Analysis (PCA) is combined with NNs to predict the time-dependent parameters of the SDE. • The hybrid model was shown to reduce forecasting errors by 3% to 10% compared to models that do not use the PCA-NN parameter prediction technique • The model provides accurate 30-day ahead predictions.

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IV. Fu et al., 2012

Major theme	Hedging Strategies for Commodity Risk
Country of analysis	Dalian Commodity Exchange, China
Asset class	Soybean Oil Futures.
Dataset and Period	The spot and futures price data for soybeans and soybean oil from May 2008 to June 2011, sourced from the Dalian Commodity Exchange.
Methodology	NN with a genetic algorithm (GA), Quadratic Programming Model and Lemke Algorithm
Key Contributions	• The empirical results demonstrate that standard Minimum-Variance hedging strategies can perform worse than no hedging at all if Mark-to-Market risk is ignored. • Paper propose an Advanced Predictive and Optimization Methodologies by integrating NN-GA to Lemke Algorithm:

V. Cao et al., 2025

Major theme	Commodity Futures Option Valuation
Country of analysis	New York Mercantile Exchange, USA
Asset class	Gold, Soybeans, Henry Hub Natural Gas, and the S&P 500 (Futures Options)
Dataset and Period	Futures Options Data covering the period from 2010 to 2020
Methodology	The Clustering-based HAR-Ensemble model (CluEnsem), modified Heterogeneous Autoregressive (HAR) and a ML model that employs a two-layer stacking framework. Layer 1 uses base learners (Random Forest (RF), k-Nearest Neighbour, Boosted Tree, and DNN), and Layer 2 uses meta-models to combine predictions, enhanced by bagging to prevent overfitting.
Key Contributions	• The modeling of implied volatility for futures options by decomposing it into components based on realized volatilities of the underlying futures. • Proposes a Clustering-based Ensemble model that combines multiple machine learning algorithms to learn option valuation

VI. (Chen et al., 2020)

Major theme	Financial hedging in energy market
Country of analysis	New York Mercantile Exchange, USA
Asset class	Crude oil FC.
Dataset and Period	Daily observations of NYMEX crude oil FC and their associated spot prices from 3 Jan. 1995 to June 30, 2015 covering 5160 trading days.
Methodology	Vector Error Correction–GARCH (VEC-GARCH), Un-hedged portfolio: (Baseline for comparison), Kernel Regression (KR), support vector machine (SVM), Hybrid Cross-Learning Machine (Kernel-Supervised SVM).
Key Contributions	• Novel Hybrid Model: Introduced a cross-learning machine (Kernel-Supervised SVM) that integrates KR and SVM. • Demonstrated that this hybrid consistently outperforms standalone KR, SVM, and econometric benchmarks. • These strategies are tested under risk aversion and transaction cost scenarios, which depict that risk aversion influences hedging strategy choice: SVM better for low risk aversion, KR better for high risk aversion. • Demonstrated that transaction costs shift dominance toward KR, but hybrid models still retain synergy.

VII. Li et al., 2021

Major theme	Hybrid Forecasting and Algorithmic Trading in Gold Markets
Country of analysis	Global Market Focus - The COMEX Gold Futures and Spot Gold Markets
Asset class	Gold Futures
Dataset and Period	The study uses daily price data for 1 month-forward Gold Futures from Jan 10, 2000, to Jan 25, 2019, with 4981 data points
Methodology	Bidirectional Gated Recurrent Unit (BiGRU), Variational Mode Decomposition (VMD), Iterated Cumulative Sums of Squares (ICSS), BiGRU DL model.
Key Contributions	• Proposed a hybrid VMD- BiGRU- ICSS approach that integrates VMD for signal decomposition, ICSS for structural breakpoint detection, and BiGRU as the RNN for prediction. • The model uses four features derived from the gold futures market (original price info, technical indicators, decomposed subseries, and market breakpoints) and information from four external markets (WTI, USD Index, Brent Crude, and Gold Spot USD). • Improved predictive and trading performance: the full VMD-ICSS-BiGRU model attains substantially higher directional accuracy (DA ≈ 0.8351) and outperforms benchmarks in trading tests (annualized return ≈ 20.41% for futures and 17.07% for spot gold over the tested periods) while producing stable positive returns across intervals. • The proposed VMD-ICSS-BiGRU approach forecasts 1-day, 2-day, and 3-day ahead closing prices, with input features of gold futures market.

VIII. Yin & Li, 2025

Major theme	Soybean Oil Futures Forecasting
Country of analysis	Zhengzhou Commodity Exchange and Dalian Commodity Exchange, China
Asset class	Soybean Oil Futures
Dataset and Period	the daily wholesale price indices of soybean oil from 2015 to 2024, it includes opening price, trading volume, high price, closing price, low price, open interest, and dynamic settlement price.
Methodology	Bayesian-optimized Multi-Task Gaussian Process Regression (MTGPR), Exponential Sine Squared (ESS), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), SVR and Extreme Gradient Boosting (XGBoost)
Key Contributions	• Development of a Bayesian-optimized Gaussian Process Regression framework tailored for non-stationary agricultural price series, particularly for soybean oil. • Introduction of a composite kernel function that enhances capturing price trends and volatility. • Validation of the model's accuracy using a high-frequency dataset (over 3,600 observations) and demonstrating its superiority over standard machine learning benchmarks (LSTM, GRU, SVR, XGBoost) through rigorous robustness checks. • Adaptive kernel selection via Bayesian optimization.

IX. Ding et al., 2019

Major theme	Modeling Price Volatility Based on a Genetic Programming Approach
Country of analysis	International Commodity, Energy and shipping markets
Asset class	The Commodity Research Bureau (CRB) index, WTI oil futures prices and the Baltic Dry Index (BDI).

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Dataset and Period	Daily data from these three indexes - Specific Periods: CRB Index: 1 January 1995 - 30 Nov 2017, WTI Oil Futures: 1 January 2000 - 30 Nov 2017, BDI: 1 January 1990 – 30 Nov 2017. A total observation of 17,606.
Methodology	GARCH, Liquidity- GARCH (LIQ-GARCH),
Key Contributions	• Novelty: First GARCH extension to explicitly incorporate liquidity information, LIQ-GARCH model. • LIQ-GARCH model is "considerably more accurate" than GARCH model. • The study shows liquidity is a critical driver of volatility, and by combining it with genetic programming, managers can make far better hedging and risk management decisions than with traditional models.

X. Nguyen, 2024

Major theme	Gold, Art, and Wheat as Inflation Hedges
Country of analysis	USA
Asset class	Gold, Art and Wheat
Dataset and Period	Dataset Cover from Jan 1992 - Dec 2023, with monthly observations. It incorporates price indexes for gold (World Gold Council), wheat (Macrotrends Data) and Art (Art Market Research's innovative valuation approach).
Methodology	Autoregressive Distributed Lag (ARDL), Nonlinear ARDL (NARDL), LSTM
Key Contributions	• The Gold is a reliable long-term inflation hedge and also Providing novel insights into the inflation-hedging potential of lesser-explored assets like wheat and art. • It utilizes advanced econometric techniques (NARDL and LSTM) to explore non-linear relationships and the impact of unexpected inflation, offering a more nuanced view than traditional linear models.

XI. Shoshi & SenGupta, 2021

Major theme	Hedging and ML driven crude oil data analysis
Country of analysis	Bakken region in North Dakota, USA
Asset class	Crude oil
Dataset and Period	The Daily Bakken Crude oil price from April 4, 2012 to July 11, 2017. a total of 1,329 data points
Methodology	Barndorff-Nielsen and Shephard (BN-S) model using ML algorithms-Logistic regression, RF, NN, LSTM.
Key Contributions	• Development of an optimized hedging strategy for crude oil markets leveraging machine learning. • Paper Proposed a data-driven refinement of the BN-S model augmented by machine learning techniques incorporating two analytical approaches Volatility approach and Duration approach for crude oil hedging.

XII. Rettinger et al., 2025

Major theme	Trust in DL approaches for Commodity Procurement & Hedging
Country of analysis	Global commodity markets
Asset class	Natural Gas, Copper, Crude Oil and Nickel.
Dataset and Period	Comprise Monthly Feature and Price Data from January 2008 to December 2023, of Futures Contract Sourced from The Thomson Reuters Eikon (TRE) Database
Methodology	Deep-Learning Approach -Integrated Estimation and Optimization (IEO), RNN, LSTM, Multilayer Perceptron (MLP), Explainable Artificial Intelligence (XAI) technique –

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	Kernel Shapley Additive Explanations (SHAP), Linear Regression, Markov Regime Switching Models
Key Contributions	• Application of SHAP: Demonstrates the application of SHAP (a model-agnostic XAI method) to multivariate time series in the context of commodity hedging. • Assessing the performance stability of DL-based models during disruptive market conditions and the trade-offs between complex, opaque models and simpler hedging strategies.

XIII. Puka et al., 2021

Major theme	ANNs in Hedging Against Oil Price Changes
Country of analysis	New York Mercantile Exchange (NYMEX), USA
Asset class	Crude Oil
Dataset and Period	European WTI- crude oil call options (specifically At-The-Money options) and WTI futures settlement prices from 16 June 2009 to 14 February 2020, total of 2630 observation.
Methodology	ANN-MLP, The Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm - Training Algorithm,
Key Contributions	• Integration of risk appetite with ANN-driven option strategies • Validation of ANNs as universal decision-support tools can be an effective tool for managing WTI crude oil price change risk regardless of the level of risk appetite.

XIV. Hu & Ni, 2024

Major theme	DL-Based Financial Hedging (DL-HE) Strategy to Effectively Manage Commodity Price Risks.
Country of analysis	The Shanghai Futures Exchange, China
Asset class	Aluminum (primary focus), Copper and Zinc (used for robustness testing)
Dataset and Period	Shanghai Futures Exchange and Wind database of Period - January 1, 2008, to December 31, 2020. Daily data covering Spot and futures prices for the commodities, as well as international and domestic market factors.
Methodology	GARCH, LSTM (or BLSTM), DNN, DL-OLS, DL-DCC, DCC-GARCH
Key Contributions	• The study proposes a DL-HE strategy-GARCH-LSTM-DNN (GARCH-BLSTM DNN) • The strategy achieves superior risk-adjusted returns (improvements of at least 0.8% over OLS and 2.4% over DCC) by effectively improving returns while controlling downside risk.

XV. Aka et al., 2025

Major theme	The Predictability of Delta-Hedged Commodity Option Returns
Country of analysis	NYMEX, COMEX, CBOT, CME and USA macroeconomic data
Asset class	Crude Oil, Natural Gas, Lean Hogs, Copper, Wheat, Gold, and Corn.
Dataset and Period	Futures and options data from CME, covering 1982–2022 years depending on commodity (e.g., gold from 1982, crude oil from 1986, natural gas from 2004, Lean hogs from 1997 and so on). Delta-hedged returns computed at weekly, biweekly, and monthly horizons.
Methodology	Machine Learning Models - Linear [LASSO, Ridge, Elastic Net, Principal Component Regression (PCR), Partial Least Squares (PLS)] and Nonlinear [RF, Gradient Boosted Trees, Generalized Additive Models, NN].

Key Contributions	• It is the first study that predict delta-hedged commodity option returns using machine learning with over 100 predictors and confirmed positive returns after transaction costs, particularly at shorter horizons. • As per study nonlinear models (specifically the RF and the nonlinear ensemble) outperform linear models whereas Dimension Reduction Models (PCR, PLS) perform the worst. • Identifies implied volatility as the most important predictor, with macroeconomic factors (especially currency risk) adding value and also Provides evidence that predictability is stronger in high-volatility regimes.

XVI. Quek et al., 2008

Major theme	Prediction System for Option Trading and Hedging
Country of analysis:	CME and COMEX, USA
Asset class	Gold, Crude Oil and Currencies (British Pound v/s US Dollar)
Dataset and Period	Daily samples (Futures Data) from COMEX and CME covering the period 2000–2002 and Options Data from October 2002 to June 2003.
Methodology	Monte Carlo Evaluative Selection (Data Preprocessing & Feature Selection), RNN (Prediction Model), Delta Hedging strategy
Key Contributions	• Novel RNN Architecture and Learning Algorithm. • Integration of MCES for feature selection in financial time-series prediction to improve computational efficiency and accuracy. • The system was benchmarked against other networks (MLP, Elman, RSPOP) and demonstrated superior performance it achieved 4.76% during test period.

XVII. Y. Z. Li et al., 2021

Major theme	Bitcoin in Portfolio Optimization Framework for Broad Commodity Assets
Country of analysis	Global commodity markets
Asset class	S&P 500 index, Bitcoin, Wheat, WTI crude oil, Gold index,
Dataset and Period	the daily closing price of the commodities from January 2, 2013, - February 21, 2020 (1,797 observations)
Methodology	Ensemble Portfolio Optimization (NEPO), VMD-BiLSTM models, Reinforcement Learning - Deep Deterministic Policy Gradient (DDPG).
Key Contributions	• The study proposes a Novel Ensemble Portfolio Optimization (NEPO) framework consisting of three main components- VMD-BiLSTM and DDPG • The study extends the broad commodity asset pool by incorporating Bitcoin into the portfolio.

XVIII. Foroutan & Lahmiri, 2024

Major theme	The Forecasting of Commodity Market Prices
Country of analysis	Global commodity markets
Asset class	Silver, Crude Oil (WTI and Brent), Gold,
Dataset and Period	Daily closing spot prices for Gold, WTI, Brent and Silver from Jan 4, 2000 - March 25, 2022 (Total of 5,426 observations) with data split for Training: 65% (2000-01-04 to 2014-06-15), Validation: 25% (2014-06-16 to 2020-01-02) and Test: 10% (2020-01-03 to 2022-03-25)
Methodology	Deep Learning Models - LSTM, BiLSTM, gated recurrent unit (GRU), BiGRU, T2V-BiLSTM, T2V-BiGRU, CNN, CNN-BiLSTM, CNN-BiGRU, temporal convolutional network (TCN), TCN-BiLSTM, and TCN-BiGRU.

	Machine Learning Models - RF, LightGBM, Support, SVR and K-Nearest Neighborhood (KNN).
Key Contributions	• This study applies TCN, Time2Vector embedding, TCN-BiLSTM and TCN-BiGRU models to forecast the spot prices of WTI, Brent, Gold, and Silver. • The test dataset covers two critical global events—the COVID-19 pandemic (and the 2020 oil price crash) and the Russia-Ukraine conflict in 2022 • The study provides a comprehensive comparison of 12 DL models against 4 baseline machine learning models, finding that TCN generally outperforms others for WTI, Brent, and Silver, while BiGRU is best for Gold, and LightGBM proves to be a highly competitive machine learning model.

XIX. Shaikh, 2019

Major theme	The Relation between Implied Volatility Index and Crude Oil Prices
Country of analysis	USA
Asset class	Crude Oil and Exchange Traded Funds - CBOE Crude Oil Volatility Index (OVX), WTI Crude Oil Spot Prices, and the United States Oil (USO) ETF prices.
Dataset and Period	Prices of OVX, WTI, and USO, considered for the period 05/2007 to 05/2016
Methodology	ANN, Quantile Regression (LQR), Bai and Perron Least Squares Estimate
Key Contributions	• A novel aspect of this study is the incorporation of USO-ETF prices to examine the expected OVX. • Demonstrated that Artificial Neural Networks (ANN) can predict future WTI/USO prices and volatility with minimal error, while identifying that trading volume is a poor input parameter • Provided evidence of a strong negative and asymmetric association between crude oil prices (WTI/USO) and the OVX. The study confirms that the "volatility feedback effect" holds in the OVX market.

XX. Crainic et al., 2014

Major theme	Progressive Hedging-Based Meta-Heuristic for Stochastic Network Design
Country of analysis	Global commodity markets
Asset class	Grouping of Commodities
Dataset and Period	NA
Methodology	K-means clustering, Progressive Hedging-based Meta-heuristic,
Key Contributions	• Developed a new meta-heuristic (mS-PH) capable of solving multi-scenario subproblems. • Demonstrated empirically the multi-scenario subproblems yields significantly better solution quality (up to 27% improvement over single-scenario approaches) and faster convergence. • Found that the covering strategy based on commodity demands produces the highest quality solutions among all strategies tested.

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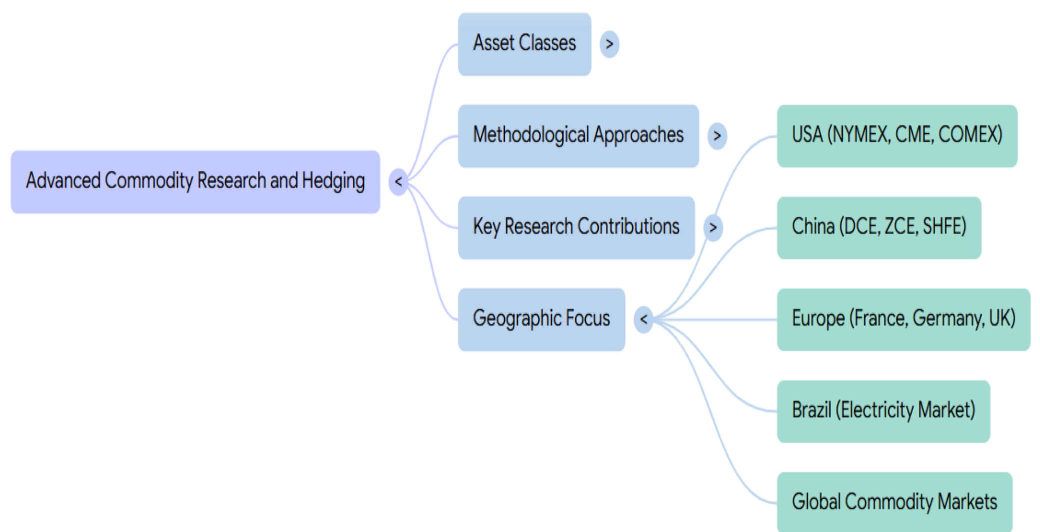
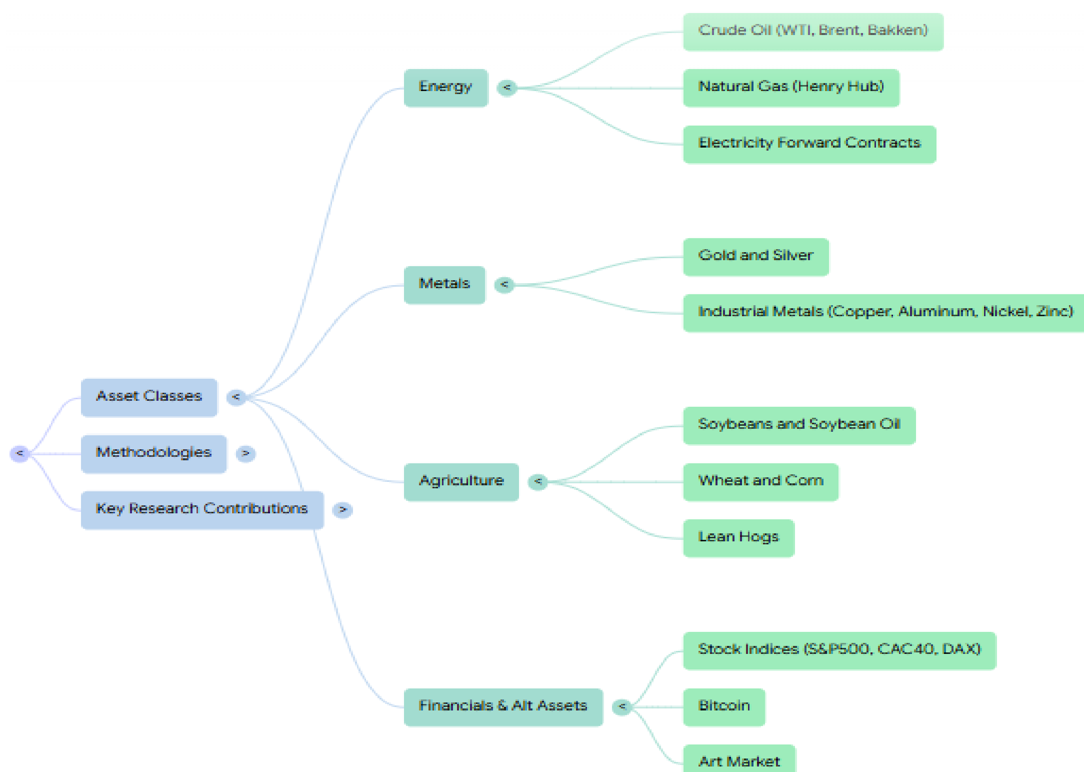
b. Summary of Finding





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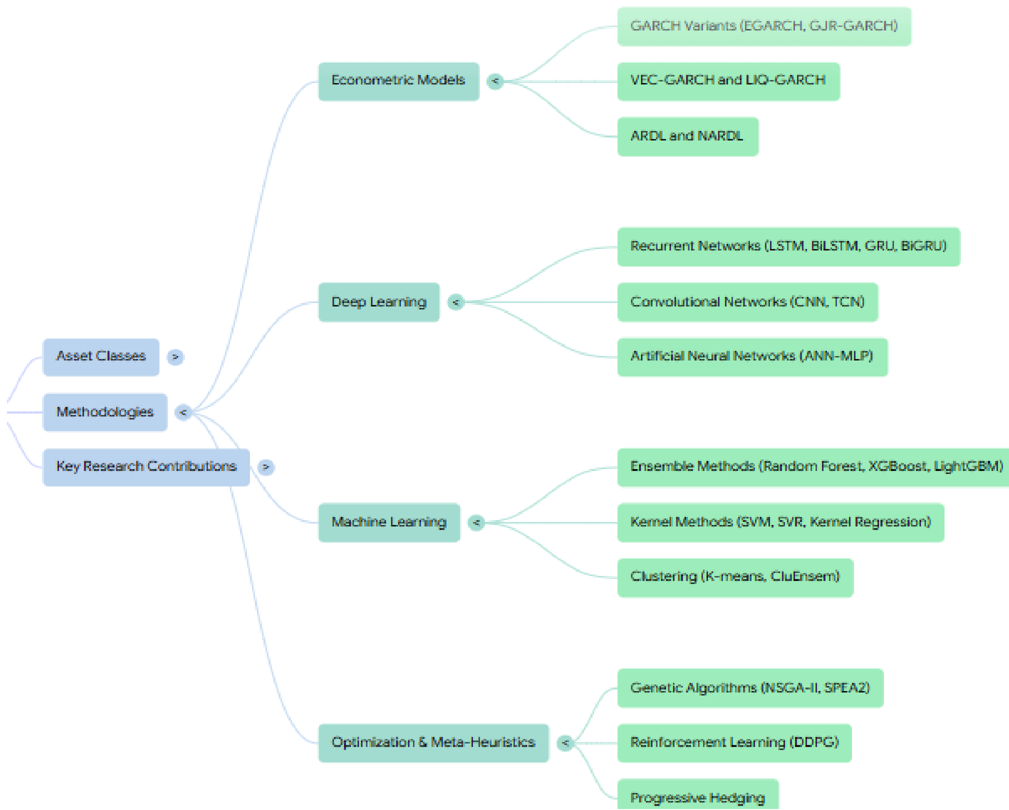

Figure 2,3,4. (Author's compilation) based on above findings

c. Discussion of findings

The outcome of the Review of AI and ML Based Hedging Strategies in CDM show that USA lead in using AI, DL and ML models in Hedging Strategies followed by China, Europe, etc. whereas based on the provided sources, crude oil (including WTI and Brent) is the commodity product used most frequently as an asset class followed by Gold, Energy and Industrial Metals. but very few studies have been done on Agricultural Products and Specialized Precious Metals like Silver, nickel etc. In the contemporary landscape of global commodity markets, defined by non-linear volatility and frequent structural breaks, the transition toward hybrid intelligence is a strategic prerequisite. Traditional econometric frameworks, while foundational, are increasingly insufficient for capturing the idiosyncratic behaviors of modern data. The integration of ML with classical econometrics is now the benchmark for institutional players seeking to transform raw market signals into a resilient competitive advantage.

The review of the existing literature shows the development of novel hybrid models, Hybrid DL and ML Models like - SPEA II, RF, k-Nearest Neighbour, Boosted Tree, DNN, Kernel-Supervised with integrated KR and SVM, VMD-ICSS-BiGRU, LSTM, GRU, SVR, XGBoost, Barndorff-Nielsen and Shephard (BN-S) model using Machine learning algorithms-Logistic regression, NN, LSTM, IEO, RNN, LSTM, Multilayer Perceptron (MLP), Explainable Artificial Intelligence (XAI) technique – Kernel Shapley Additive Explanations (SHAP), Linear Regression, Markov Regime Switching Models, GARCH-LSTM-DNN, RNN, VMD-BiLSTM models, Reinforcement Learning - Deep Deterministic Policy Gradient (DDPG), - LSTM, BiLSTM, gated recurrent unit (GRU), BiGRU, T2V-BiLSTM, T2V-BiGRU, CNN, CNN-BiLSTM, CNN-

BiGRU, temporal convolutional network (TCN), TCN-BiLSTM, and TCN-BiGRU. Machine Learning Models - LightGBM, Support, SVR, KNN and ANN, advanced optimization techniques, and the integration of new risk factors into commodities hedging strategies.

4. Agenda for future research

As evident from the literature AI and ML Based Hedging Strategies in CDM has been the topic of interest for researchers particularly in USA and few other countries since early 20s. However, in the year 2000, the first scholarly investigation into hedging derivative securities with neural networks was conducted (Tiwari et al., 2025). But the entry of ML & AI in commodity derivatives begins with price forecasts for futures, followed by price volatility, hedging strategies, commodity price forecasting, return prediction, and statistical arbitrage (Tiwari et al., 2025). But there are many other important areas which need the attention of research as presented in the following section.

- Limited research has been done in emerging commodities markets like India - Multi Commodity Exchange of India (MCX) and NCDEX, Japan - Tokyo Commodity Exchange (TOCOM), Australia- Australian Securities Exchange (ASX), Malaysia - Bursa Malaysia Derivatives (BMD): The global benchmark for crude palm oil futures and more.
- The Paradigm has shift from traditional econometrics to hybrid intelligence but still there are many DL and ML models like “GJR-GARCH-SVR-LSTM”, “Deep Neural Networks (DNNs) and LSTM”, “VaR with Random Forest model” and other machine learning-enhanced VaR models, which is used in financial hedging Strategies but has not explored and empirically tested in commodities derivatives.
- Agri - Products like Cereals, Pulses, Cottons, Rubber, crude palm oil, Oil seeds, Spices etc. and Industrial Metals are Lesser-Explored Assets class. these commodities products may be used as point of analysis in future research.
- There is need to work on the transparency of these ML and DL - based models used in hedging strategies as very few studies talk about this.

5. Conclusion

The study shows a significant shift in how old rigid econometric models of commodity hedging are evolving and heading toward a more dynamic era of AI and ML hybrid systems. After reviewing, it’s clear that these new computational tools aren't just a trend—they are actually outperforming traditional GARCH-type models by providing much better accuracy in price forecasting and risk management within the commodity derivatives markets.

Interestingly, while the technology is moving fast, the research itself is quite concentrated. Most of the data we have right now focuses heavily on the U.S. and China, particularly looking at crude oil and gold. There is still a massive gap when it comes to agricultural products or industrial metals, especially in emerging exchanges. This lack of diversity in the literature suggests that we have only scratched the surface of what these models can do globally.

The major issue that could hinder the use of these AI structures in the workplace in a functional way is interpretability. While the high performance of a ML model may be desirable for this situation as well, practitioners and institutions are expected to not trust a black box that they cannot explain. In the field of Explainable AI (XAI), it's possible to see progress being made as it tries to combat this lack of transparency, but it is still a space that has a long way to go before it can be considered a standard practice. To sum up: AI-powered hedging is no longer a proof of concept; it's an integral part of contemporary risk management. The possibilities for models that can integrate the old and the new, combining classic financial theories with the adaptability of ML look bright. However, to be sustainable and reliable, these tools need to be explored in a broader market and scrutinized when it comes to making these complex tools accessible, understandable, and verifiable to human users. This study has certain limitations, as it relies exclusively on literature of Scopus and WoS databases including other database may serve as a future research direction as well.

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