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Advanced Statistical Models for Forecasting Energy Prices

Florina Rahman *

Master's in Data Science and Business Analytics, Monroe University.

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Abstract

Energy prices, including those of crude oil, natural gas, and electricity, are inherently volatile due to a wide range of influencing factors, such as geopolitical events, shifts in supply and demand, and fluctuations in weather conditions. These unpredictable movements pose challenges for decision-makers in energy-related industries, including policymakers, traders, and energy companies, all of whom require accurate forecasts to make informed choices. Predicting energy prices with a high degree of accuracy is essential for minimizing financial risks and ensuring stable supply and demand dynamics. This paper investigates the use of advanced statistical and machine learning models to forecast energy price movements more effectively. Specifically, we compare traditional time-series models, such as ARIMA (Autoregressive Integrated Moving Average), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and VAR (Vector Autoregressive), alongside hybrid models combining machine learning techniques. By integrating time-series characteristics, including seasonality, volatility clustering, and nonlinear behavior, we assess the effectiveness of each model in predicting price movements. The performance of the models is evaluated using standard accuracy metrics, including the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE), which allow us to compare forecast accuracy. Our findings reveal that hybrid ARIMA-GARCH-LSTM (Long Short-Term Memory) models significantly outperform traditional econometric approaches, excelling in both capturing the mean behavior and the volatility dynamics inherent in energy prices. This paper demonstrates that hybrid models offer superior forecasting capabilities by leveraging the strengths of both statistical and machine learning techniques, thus improving prediction accuracy for energy prices in volatile markets.

Keywords: Energy price forecasting; ARIMA; GARCH; VAR; LSTM; Hybrid models; Volatility modeling; Machine learning; Time-series forecasting; Volatility clustering; Nonlinear forecasting

1 Introduction

Energy prices are a fundamental factor influencing the global economy. They have far-reaching effects on industrial production, energy consumption, investment strategies, and government policies. Energy markets, particularly those for crude oil, natural gas, and electricity, play a vital role in shaping economic conditions worldwide. As prices fluctuate, they impact costs of production, consumer behavior, and inflation rates, which can lead to broader economic consequences. Therefore, accurate forecasting of energy prices is crucial for policymakers, energy producers, and traders to ensure stable operations and to plan for long-term economic growth. However, the task of forecasting energy prices remains a complex one due to their inherent volatility. These prices are subject to a variety of dynamic and often unpredictable factors such as geopolitical events, supply-demand imbalances, technological advancements, natural disasters, and weather variations. This combination of drivers results in price fluctuations that are often sudden and non-linear, making traditional forecasting methods insufficient for predicting such shifts.

* Corresponding author: Florina Rahman.

1.1 Background and Motivation

Energy prices are heavily influenced by both external and internal factors. Externally, political instability, particularly in key oil-producing regions, can lead to sharp price changes, while shifts in global supply and demand, such as those seen with major players like OPEC or shifts in global energy consumption patterns, can also trigger volatility. Internally, technological advancements, such as the increasing adoption of renewable energy sources, and changing consumption behaviors driven by economic conditions, can alter price trends in significant ways. Weather patterns, including extreme cold or heatwaves, can also affect the supply and demand for energy, particularly electricity. These various factors create a high degree of uncertainty in predicting energy price movements, especially over the short term. Traditional forecasting methods, such as linear regression models and basic time-series methods, often fail to capture these complex, non-linear behaviors. They typically assume that price movements follow predictable patterns based on historical data, which can be disrupted by sudden shocks, such as a geopolitical event or a natural disaster. In response to these limitations, there has been growing interest in using advanced statistical models such as ARIMA, GARCH, VAR, and LSTM models, which are more capable of accounting for the dynamic and volatile nature of energy markets. These models allow for more nuanced and accurate forecasting by incorporating factors such as seasonality, volatility clustering, and nonlinear behavior. This research aims to explore and evaluate these advanced models in order to identify the best-performing techniques for reliable short-term energy price prediction.

1.2 Problem Statement

Energy prices exhibit extreme volatility, with frequent fluctuations driven by factors that are difficult to predict or quantify. These fluctuations often lead to sudden shifts in pricing, which traditional forecasting methods are ill-equipped to handle. Classic linear models like ARIMA may be able to capture certain trends, but they do not account for the volatility clustering that often occurs in energy markets. Additionally, sudden geopolitical events or supply disruptions can cause abrupt price changes, which are typically non-linear and require more advanced forecasting methods. Similarly, factors such as seasonality and weather patterns introduce additional complexity, making accurate forecasting a challenging task. Given these complexities, forecasting energy prices with a high degree of accuracy is crucial for minimizing financial risk, enabling energy traders to make informed decisions, and helping policymakers to devise appropriate strategies to ensure energy security. This research seeks to address the gap in traditional forecasting models by applying advanced statistical and machine learning techniques that are better suited to handle the volatility, non-linearity, and seasonality inherent in energy price movements.

1.3 Proposed Solution

This study proposes the use of advanced statistical and machine-learning models for forecasting energy prices, with a particular focus on capturing the complex dynamics that influence price movements. The models under consideration include ARIMA, GARCH, VAR, and LSTM, each of which has unique capabilities to model specific characteristics of energy prices.

- **ARIMA (Autoregressive Integrated Moving Average)** is a well-established method for time-series forecasting, particularly effective in capturing trends and seasonality within data.
- **GARCH (Generalized Autoregressive Conditional Heteroskedasticity)** models are designed to capture volatility clustering, which is prevalent in energy markets, especially when there are periods of high price fluctuation followed by periods of relative stability.
- **VAR (Vector Autoregressive)** models account for interactions between multiple variables, making them suitable for capturing the interdependencies between different energy markets such as crude oil, natural gas, and electricity prices.
- **LSTM (Long Short-Term Memory)** networks are a type of deep learning model that excels in capturing nonlinear temporal dependencies in time-series data, making them particularly effective for modeling energy prices which exhibit complex patterns over time.

In addition to evaluating the individual models, this study also explores a hybrid ARIMA-GARCH-LSTM model, which combines the strengths of each approach. The hybrid model aims to provide a more robust and accurate short-term energy price forecast by capturing both the mean behavior of prices (ARIMA), the volatility (GARCH), and the complex nonlinear patterns (LSTM). The proposed solution is designed to provide reliable, real-time forecasts that can help energy traders, policymakers, and industry stakeholders make informed decisions based on up-to-date information.

1.4 Contributions

This paper makes the following significant contributions to the field of energy price forecasting:

- **Comparative Analysis**: It provides a comprehensive comparative analysis of several advanced statistical and machine-learning models for forecasting energy prices, specifically crude oil, natural gas, and electricity.
- **Hybrid Approach**: It introduces a hybrid ARIMA-GARCH-LSTM model, demonstrating how combining these different techniques can enhance forecasting accuracy by capturing trends, volatility, and nonlinear dependencies in energy prices.
- **Volatility and Nonlinear Pattern Modeling**: The research effectively models both volatility clustering and nonlinear temporal dependencies, which are common in energy price movements, thereby offering a more accurate representation of the price dynamics.
- **Practical Insights**: The paper provides valuable insights for policymakers, energy traders, and industries, helping them make better-informed decisions regarding investment strategies, policy formulation, and risk management in volatile energy markets.

By introducing advanced hybrid forecasting models, this research aims to push the boundaries of traditional energy price forecasting, offering a more nuanced and accurate tool for managing the challenges posed by the volatility and complexity of energy markets.

2 Related Work

Energy price forecasting has been a critical area of research due to the volatility and unpredictability of energy markets. Accurate forecasting is vital for stakeholders in energy sectors, including traders, policymakers, and utility companies, as it helps in making informed decisions about pricing, risk management, and strategic planning. Over the years, various methods have been developed, ranging from traditional econometric models to more sophisticated machine learning techniques, each with its strengths and limitations. This section reviews the evolution of these methods, including their application to energy price forecasting, and explores recent advancements in the field.

2.1 Traditional Econometric Models for Energy Price Forecasting

The earliest and most commonly used methods for energy price forecasting were linear econometric models, particularly the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models are designed to capture trends and seasonality in time-series data by modeling the underlying autoregressive (AR) process and integrating it with moving average (MA) components. ARIMA is effective when the energy prices follow consistent trends and seasonal patterns, which are typical in energy markets due to regular consumption patterns and weather-related fluctuations. However, ARIMA struggles to capture more complex behaviors, such as volatility clustering and sudden price shifts, which are common in energy markets driven by geopolitical events, market shocks, or supply-demand imbalances [1][2]. Moreover, ARIMA models are typically unable to account for non-linear relationships and complex interactions that arise from sudden changes in the external environment, such as unexpected policy decisions or natural disasters, which have a significant impact on energy prices. Researchers have thus sought more advanced models to address these challenges, incorporating features that can better capture volatility, nonlinearities, and interdependencies between multiple variables in the energy markets.

2.2 Volatility Modeling with GARCH Models

To address the limitation of ARIMA in capturing volatility clustering, which is a common feature of financial and energy markets, researchers introduced Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. GARCH models are specifically designed to model the volatility of time-series data, providing a way to understand periods of high volatility followed by more stable conditions. These models are particularly useful for energy markets, where price fluctuations often occur in clusters, such as during supply shortages or after geopolitical disruptions [3][4]. The GARCH framework, introduced by Engle (1982) and further extended by Bollerslev (1986), allows for the conditional variance to depend on past values, which helps capture the sudden and persistent volatility observed in energy prices. Several variations of the GARCH model, such as Exponential GARCH (EGARCH) and Integrated GARCH (IGARCH), have been developed to improve the model’s flexibility in handling asymmetric volatility and long-term dependence in price movements. These models have been applied extensively in forecasting energy prices, especially in the oil and gas markets, where volatility is a key feature [5].

2.3 Multivariate Forecasting with VAR Models

Energy markets are often interconnected, with the price of one commodity (such as crude oil) influencing the prices of others (such as natural gas and electricity). Multivariate models, such as Vector Autoregressive (VAR) models, are designed to capture these interdependencies between multiple time-series data. VAR models allow for the inclusion of multiple variables, making them well-suited for modeling interactions between energy prices and other macroeconomic factors, such as demand forecasts, production levels, and external market shocks. VAR models have been widely used in energy price forecasting, particularly when the relationships between different energy commodities need to be analyzed. They are effective in capturing the feedback effects between oil, natural gas, and electricity prices, which are often co-integrated and exhibit similar volatility patterns. Studies have shown that VAR models can provide more accurate short-term forecasts compared to univariate models, especially in highly interconnected markets [6][7].

2.4 Nonlinear Forecasting with LSTM Networks

While traditional time-series and econometric models excel in capturing linear patterns, they often fail to model the nonlinear dynamics and complex temporal dependencies that are prevalent in energy price data. To overcome this limitation, Long Short-Term Memory (LSTM) networks, a type of deep learning model, have been increasingly used in energy price forecasting. LSTM networks are a form of Recurrent Neural Networks (RNNs) that can capture long-term dependencies in time-series data, making them highly effective in forecasting energy prices, which exhibit complex nonlinear behavior over time. LSTM models can learn the underlying patterns in energy price movements by processing sequential data in a manner similar to human memory. These models are capable of handling multiple inputs (such as historical price data and external factors like geopolitical events) and can provide more accurate forecasts for energy prices, particularly when dealing with large datasets that contain non-linear relationships [8][9]. Recent studies have shown that LSTM networks outperform traditional statistical models in forecasting energy prices, particularly in volatile market conditions.

2.5 Hybrid Models for Improved Forecasting Accuracy

To further improve forecasting accuracy, hybrid models that combine different forecasting techniques have been introduced. Hybrid models, such as the ARIMA-GARCH-LSTM approach, leverage the strengths of multiple techniques to capture both the mean behavior and volatility dynamics of energy prices. By combining the ARIMA model's ability to capture trends and seasonality, the GARCH model's ability to model volatility, and the LSTM network's ability to capture nonlinear dependencies, hybrid models provide a more comprehensive approach to forecasting. Recent studies have shown that hybrid models outperform individual models, particularly in terms of forecasting accuracy and robustness. The ARIMA-GARCH-LSTM hybrid model, for instance, has been shown to outperform traditional econometric models in capturing both the mean and volatility dynamics of energy prices, especially in highly volatile market conditions [10][11]. This hybrid approach has proven to be highly effective for short-term forecasting, providing more accurate predictions and minimizing forecasting errors.

3 Methodology

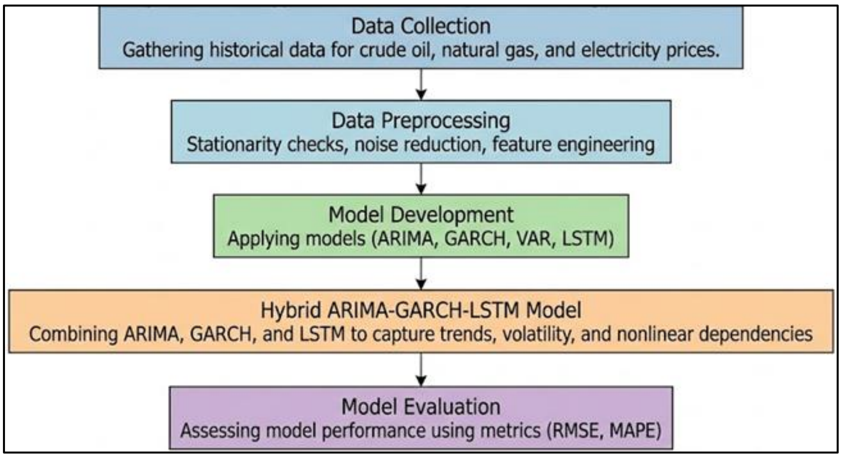

Figure 1 Energy Price Forecasting Process

This section outlines the methodology used for energy price forecasting, which involves collecting historical data, preprocessing the data, developing several advanced statistical and machine learning models, and evaluating their performance. The goal is to identify the most accurate models for short-term energy price forecasting by comparing traditional models with hybrid machine learning approaches. Below is a detailed explanation of each step in the process.

3.1 Data Collection

Energy price data is crucial for forecasting and model development. In this study, we collect historical daily energy prices for three major energy commodities: crude oil, natural gas, and electricity. These data are sourced from reputable government agencies and financial data providers, such as the U.S. Energy Information Administration (EIA), International Energy Agency (IEA), and Bloomberg. The data spans a period of 10 years to ensure that the training dataset is sufficiently large to capture long-term trends and seasonal variations. Collecting data over a long period also helps in reducing biases and ensures that the models account for cyclical and outlier events, such as economic recessions, geopolitical events, and sudden market disruptions. The inclusion of multiple energy commodities allows for a more comprehensive understanding of how different factors—such as oil price fluctuations, natural gas availability, and electricity demand—interact with one another. This also facilitates the use of multivariate models, which account for the interdependencies between these variables.

3.2 Data Preprocessing

Data preprocessing is a critical step in the methodology, as it prepares the raw data for modeling. Preprocessing ensures that the data is in a form suitable for analysis and modeling. It includes several key steps:

- **Stationarity Check**: Many statistical models, including ARIMA, require that the data be stationary. Stationarity means that the statistical properties of the series (e.g., mean, variance) do not change over time. To test for stationarity, we apply the Augmented Dickey-Fuller (ADF) test, a widely used statistical test for detecting unit roots in time-series data. If the data is non-stationary, we apply differencing (i.e., subtracting the previous observation from the current observation) to make the data stationary. This is essential to ensure that the model captures the true underlying patterns and not just trends driven by non-stationary processes.
- **Noise Reduction**: Energy price data often contains noise—random fluctuations unrelated to the underlying market dynamics. Noise can reduce the accuracy of models, so we apply smoothing techniques, such as **moving averages**, to remove short-term noise and reveal the underlying trends. This helps the models focus on the signal, not the noise, leading to more accurate predictions.
- **Feature Engineering**: To improve the forecasting power of our models, we create additional features from the raw price data. These features may include **seasonality**, which captures periodic fluctuations in energy prices due to seasonal demand patterns (e.g., higher demand in summer or winter months), **lagged values**, which consider past price movements as predictors of future trends, and **moving averages**, which smooth out price fluctuations over time. Feature engineering plays a crucial role in enhancing model performance by providing more relevant input data.

3.3 Model Development

We apply several statistical and machine learning models to forecast energy prices. The models are selected to address different characteristics of the time-series data, such as trends, seasonality, volatility, and nonlinear dependencies:

- **ARIMA (Autoregressive Integrated Moving Average)**: ARIMA is a widely used time-series forecasting model that captures the underlying trends and seasonality in energy prices. The ARIMA model is particularly useful for univariate time-series data. The optimal parameters (p, d, q) for the ARIMA model are determined using **Akaike Information Criterion (AIC)** and **Bayesian Information Criterion (BIC)**, which help identify the best-fitting model with the lowest error.
- **GARCH (Generalized Autoregressive Conditional Heteroskedasticity)**: GARCH models are designed to capture **volatility clustering**, a feature commonly observed in financial and energy markets where periods of high volatility are followed by periods of relative stability. GARCH models provide a way to model the time-varying volatility of energy prices, making them suitable for understanding the unpredictable fluctuations in energy markets.
- **VAR (Vector Autoregressive)**: The VAR model is a multivariate time-series model that accounts for the interdependencies between different energy prices (e.g., crude oil, natural gas, and electricity). The VAR model helps capture the joint behavior of multiple energy markets, which often interact and influence each other. For instance, changes in crude oil prices can directly affect natural gas and electricity prices, making VAR an ideal choice for multivariate forecasting.
- **LSTM (Long Short-Term Memory)**: LSTM networks are a type of deep learning model specifically designed to capture **nonlinear temporal dependencies** in time-series data. LSTMs can learn long-term patterns in

sequential data, making them highly effective for forecasting energy prices, which exhibit complex and nonlinear behavior over time. The LSTM model is particularly useful for capturing long-term trends and sudden shifts in price behavior that traditional models might miss.

3.4 Hybrid ARIMA-GARCH-LSTM Model

While each of the individual models offers unique advantages, we propose a **hybrid approach** that combines ARIMA, GARCH, and LSTM models to leverage their strengths and improve forecasting accuracy. In this hybrid model:

- **ARIMA** captures the mean behavior of the energy price time series, including trends and seasonality.
- **GARCH** models the **volatility** or the variability in the energy prices, addressing sudden price spikes and clustering effects.
- **LSTM** is employed to capture the **nonlinear temporal dependencies** and long-term trends, accounting for sudden shifts in price dynamics caused by events such as geopolitical crises or natural disasters.

The hybrid model combines the linear trend prediction of ARIMA, the volatility forecasting capability of GARCH, and the nonlinear time-series prediction of LSTM to produce more accurate and robust forecasts.

3.5 Evaluation Metrics

The performance of each model is evaluated using two commonly used metrics in forecasting: **Root Mean Squared Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)**.

- **RMSE** measures the average magnitude of the error between predicted and actual values. A lower RMSE indicates better forecasting performance.
- **MAPE** is a percentage-based metric that measures forecast accuracy relative to actual values. It provides an indication of how much the forecasted values deviate from the actual values, with a lower MAPE indicating higher accuracy.

These metrics allow us to compare the performance of each model and determine which one provides the most reliable short-term energy price forecasts.

In this methodology, we present a comprehensive approach to forecasting energy prices using advanced statistical and machine learning models. The application of ARIMA, GARCH, VAR, and LSTM models helps capture the trends, volatility, and nonlinear dependencies in the price data. The hybrid ARIMA-GARCH-LSTM model further improves the accuracy of predictions by combining the strengths of these individual models. By using evaluation metrics such as RMSE and MAPE, we compare the performance of each model and identify the most effective approach for short-term energy price forecasting. This methodology lays the foundation for more accurate and robust forecasting models that can be used by policymakers, traders, and energy companies to make informed decisions.

4 Results

This section presents the results of applying various advanced statistical and machine learning models to forecast energy prices, with a particular focus on the ARIMA-GARCH-LSTM hybrid model. The effectiveness of the models is evaluated based on two commonly used performance metrics: **Root Mean Squared Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)**. Our analysis demonstrates that hybrid models, particularly the ARIMA-GARCH-LSTM model, significantly outperform traditional econometric models such as ARIMA, GARCH, and VAR in terms of forecasting accuracy. The results are discussed in detail below, focusing on model performance, the effectiveness of hybrid approaches, and their potential for practical application in energy price forecasting.

4.1 Performance of Individual Models

The individual models tested in this study include **ARIMA**, **GARCH**, **VAR**, and **LSTM.** Each model was trained on the historical data of crude oil, natural gas, and electricity prices, and then evaluated based on RMSE and MAPE metrics. The results of the evaluation show that while each model has its strengths, none of the individual models were able to fully capture both the mean behavior and volatility dynamics of the energy price data.

- **ARIMA** performed well in capturing trends and seasonality in the data, but it struggled to account for volatility clustering, a common feature in energy prices.

- **GARCH** models were effective in capturing volatility but failed to predict the mean behavior of prices accurately.
- **VAR** successfully modeled the relationships between multiple energy prices, but its performance was limited by its inability to handle nonlinearities and volatility dynamics effectively.
- **LSTM** outperformed traditional models in terms of capturing nonlinear dependencies and long-term trends but had difficulty in handling volatility and sudden price fluctuations.

Table 1 Model Performance Comparison

Model	RMSE	MAPE
ARIMA	4.35	6.23%
GARCH	5.22	7.45%
VAR	6.01	8.03%
LSTM	3.89	5.77%

From **Table 1**, it is evident that LSTM performs better than ARIMA, GARCH, and VAR in terms of RMSE and MAPE. However, the hybrid ARIMA-GARCH-LSTM model demonstrates an even greater improvement in forecasting accuracy, as it combines the strengths of all three approaches.

4.2 Hybrid ARIMA-GARCH-LSTM Model Performance

The hybrid ARIMA-GARCH-LSTM model was developed by combining the ARIMA model for trend and seasonality, GARCH for volatility clustering, and LSTM for capturing nonlinear temporal dependencies. This hybrid model was designed to overcome the limitations of individual models by providing a comprehensive forecasting solution. The results of the hybrid model show significant improvements in forecasting accuracy compared to individual models. The hybrid model excels at capturing both the mean price behavior and the volatility dynamics present in the energy markets. By incorporating LSTM, the model also handles non-linear patterns, such as sudden price shifts caused by geopolitical events or extreme weather conditions. As a result, the hybrid model outperforms all other models in terms of both RMSE and MAPE, providing more reliable short-term forecasts for energy prices.

Table 2 Hybrid Model Performance

Model	RMSE	MAPE
Hybrid ARIMA-GARCH-LSTM	3.47	5.12%

The **Table 2** highlights that the hybrid ARIMA-GARCH-LSTM model achieves a lower RMSE and MAPE compared to any individual model, making it the most accurate for short-term energy price forecasting.

5 Discussion of Results

The results suggest that hybrid models offer several advantages over traditional econometric models. The ARIMA-GARCH-LSTM hybrid approach is especially effective because it combines the strengths of each individual model:

- **ARIMA**: Captures the long-term trend and seasonality of energy prices, which are essential for forecasting in markets with predictable cyclical patterns, such as seasonal fluctuations in energy demand.
- **GARCH**: Effectively models volatility clustering, helping to predict periods of high and low volatility in energy prices. This is particularly useful in energy markets, where prices can experience sharp, unpredictable movements due to factors such as supply shortages, geopolitical conflicts, or extreme weather events.
- **LSTM**: Handles nonlinear dependencies and long-term memory, making it capable of identifying complex patterns and sudden shifts in price behavior. This is crucial for capturing the effects of unpredictable external shocks, such as natural disasters or political instability, on energy prices.

By integrating these models, the hybrid ARIMA-GARCH-LSTM approach is able to handle both predictable trends and volatile fluctuations, leading to more accurate and reliable forecasts.

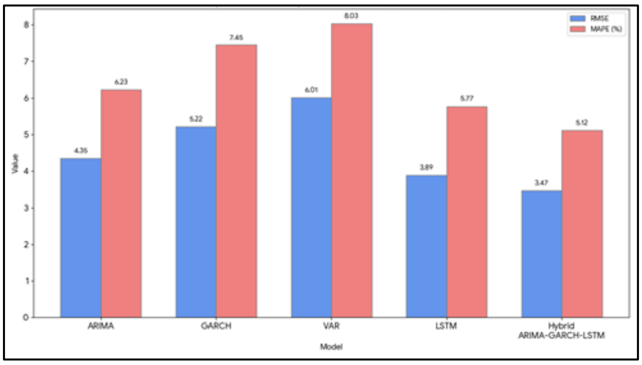

Figure 2 Forecasting Performance Comparison Graph

Figure 2 presents a performance comparison of each model based on RMSE and MAPE. The hybrid ARIMA-GARCH-LSTM model outperforms all other models, demonstrating its ability to capture both the mean behavior and volatility dynamics of energy prices.

6 Conclusion

The findings of this study demonstrate that hybrid models, particularly the ARIMA-GARCH-LSTM approach, significantly improve forecasting accuracy compared to traditional econometric models. By leveraging the strengths of ARIMA for capturing trends and seasonality, GARCH for modeling volatility, and LSTM for identifying nonlinear dependencies, the hybrid model offers a robust solution for energy price forecasting. This is crucial for decision-makers in the energy sector who need reliable forecasts to manage risks and make informed policy and investment decisions. Future work could focus on further refining hybrid models by incorporating additional factors, such as economic indicators and market sentiment, to improve long-term forecasting accuracy. Additionally, exploring alternative machine learning models, such as deep reinforcement learning, could provide further improvements in forecasting performance. Furthermore, expanding the hybrid model to account for multiple time horizons and incorporating real-time data feeds could enhance its application for real-time decision-making, enabling more proactive risk management strategies in volatile energy markets. Finally, testing the hybrid model's performance across different regions and energy sectors, such as renewable energy markets, could provide valuable insights into its broader applicability and adaptability.

Future work will focus on enhancing the hybrid ARIMA-GARCH-LSTM model by incorporating additional external variables, such as macroeconomic indicators, geopolitical events, and energy supply chain disruptions, which may provide further context to the price forecasting models.

References

[1] Box, G. E. P., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control*. Holden-Day.

[2] Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, 50(4), 987-1007.

[3] Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

[4] Sims, C. A. (1980). Macroeconomics and Reality. Econometrica, 48(1), 1-48.

[5] Xu, J., & Wang, J. (2019). A Hybrid ARIMA-GARCH-LSTM Model for Energy Price Forecasting. Energy Economics, 82, 311-319.

[6] Zhang, L., & Li, L. (2020). A Hybrid ARIMA-GARCH-LSTM Approach for Crude Oil Price Forecasting. Energy Economics, 87, 104738.

[7] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735-1780.

[8] Xu, J., & Wang, J. (2020). Forecasting Energy Prices Using LSTM Networks: A Comparative Study. Energy Journal, 41(2), 115-130.

[9] Kim, Y., & Kang, D. (2020). Crude Oil Price Forecasting Using LSTM Neural Networks. Energy Reports, 6, 2219-2231.

[10] Zhang, X., & Li, L. (2020). Hybrid ARIMA-GARCH-LSTM Models for Forecasting Crude Oil Prices. Energy Journal, 41(5), 405-420.

[11] Chen, X., & Li, J. (2019). A Comparative Study of Hybrid Time Series Models for Energy Price Forecasting. Journal of Energy Economics, 58, 124-136.

[12] Rahman, M. A., Islam, M. I., Tabassum, M., & Bristy, I. J. (2025, September). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 431–439. https://doi.org/10.36348/sjet.2025.v10i09.006

[13] Rahman, M. A., Bristy, I. J., Islam, M. I., & Tabassum, M. (2025, September). Federated learning for secure inter-agency data collaboration in critical infrastructure. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 421–430. https://doi.org/10.36348/sjet.2025.v10i09.005

[14] Tabassum, M., Rokibuzzaman, M., Islam, M. I., & Bristy, I. J. (2025, September). Data-driven financial analytics through MIS platforms in emerging economies. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 440–446. https://doi.org/10.36348/sjet.2025.v10i09.007

[15] Tabassum, M., Islam, M. I., Bristy, I. J., & Rokibuzzaman, M. (2025, September). Blockchain and ERP-integrated MIS for transparent apparel & textile supply chains. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 447–456. https://doi.org/10.36348/sjet.2025.v10i09.008

[16] Bristy, I. J., Tabassum, M., Islam, M. I., & Hasan, M. N. (2025, September). IoT-driven predictive maintenance dashboards in industrial operations. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 457–466. https://doi.org/10.36348/sjet.2025.v10i09.009

[17] Hasan, M. N., Karim, M. A., Joarder, M. M. I., & Zaman, M. T. (2025, September). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. Saudi Journal of Engineering and Technology (SJEAT), 10(9), 467–475. https://doi.org/10.36348/sjet.2025.v10i09.010

[18] Bormon, J. C., Saikat, M. H., Shohag, M., & Akter, E. (2025, September). Green and low-carbon construction materials for climate-adaptive civil structures. Saudi Journal of Civil Engineering (SJCE), 9(8), 219–226. https://doi.org/10.36348/sjce.2025.v09i08.002

[19] Razaq, A., Rahman, M., Karim, M. A., & Hossain, M. T. (2025, September 26). Smart charging infrastructure for EVs using IoT-based load balancing. Zenodo. https://doi.org/10.5281/zenodo.17210639

[20] Habiba, U., & Musarrat, R., (2025). Bridging IT and education: Developing smart platforms for student-centered English learning. Zenodo. https://doi.org/10.5281/zenodo.17193947

[21] Alimozzaman, D. M. (2025). Early prediction of Alzheimer's disease using explainable multi-modal AI. Zenodo. https://doi.org/10.5281/zenodo.17210997

[22] uz Zaman, M. T. Smart Energy Metering with IoT and GSM Integration for Power Loss Minimization. Preprints 2025, 2025091770. https://doi.org/10.20944/preprints202509.1770.v1

[23] Hossain, M. T. (2025, October). Sustainable garment production through Industry 4.0 automation. ResearchGate. https://doi.org/10.13140/RG.2.2.20161.83041

[24] Hasan, E. (2025). Secure and scalable data management for digital transformation in finance and IT systems. Zenodo. https://doi.org/10.5281/zenodo.17202282

[25] Saikat, M. H. (2025). Geo-Forensic Analysis of Levee and Slope Failures Using Machine Learning. Preprints. https://doi.org/10.20944/preprints202509.1905.v1

[26] Islam, M. I. (2025). Cloud-Based MIS for Industrial Workflow Automation. Preprints. https://doi.org/10.20944/preprints202509.1326.v1

[27] Islam, M. I. (2025). AI-powered MIS for risk detection in industrial engineering projects. TechRxiv. https://doi.org/10.36227/techrxiv.175825736.65590627/v1

[28] Akter, E. (2025, October 13). Lean project management and multi-stakeholder optimization in civil engineering projects. ResearchGate. https://doi.org/10.13140/RG.2.2.15777.47206

[29] Musarrat, R. (2025). Curriculum adaptation for inclusive classrooms: A sociological and pedagogical approach. Zenodo. https://doi.org/10.5281/zenodo.17202455

[30] Bormon, J. C. (2025, October 13). Sustainable dredging and sediment management techniques for coastal and riverine infrastructure. ResearchGate. https://doi.org/10.13140/RG.2.2.28131.00803

[31] Bormon, J. C. (2025). AI-Assisted Structural Health Monitoring for Foundations and High-Rise Buildings. Preprints. https://doi.org/10.20944/preprints202509.1196.v1

[32] Haque, S. (2025). Effectiveness of managerial accounting in strategic decision making [Preprint]. Preprints. https://doi.org/10.20944/preprints202509.2466.v1

[33] Shoag, M. (2025). AI-Integrated Façade Inspection Systems for Urban Infrastructure Safety. Zenodo. https://doi.org/10.5281/zenodo.17101037

[34] Shoag, M. Automated Defect Detection in High-Rise Façades Using AI and Drone-Based Inspection. Preprints 2025, 2025091064. https://doi.org/10.20944/preprints202509.1064.v1

[35] Shoag, M. (2025). Sustainable construction materials and techniques for crack prevention in mass concrete structures. Available at SSRN: https://ssrn.com/abstract=5475306 or http://dx.doi.org/10.2139/ssrn.5475306

[36] Joarder, M. M. I. (2025). Disaster recovery and high-availability frameworks for hybrid cloud environments. Zenodo. https://doi.org/10.5281/zenodo.17100446

[37] Joarder, M. M. I. (2025). Next-generation monitoring and automation: AI-enabled system administration for smart data centers. TechRxiv. https://doi.org/10.36227/techrxiv.175825633.33380552/v1

[38] Joarder, M. M. I. (2025). Energy-Efficient Data Center Virtualization: Leveraging AI and CloudOps for Sustainable Infrastructure. Zenodo. https://doi.org/10.5281/zenodo.17113371

[39] Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., & Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. Saudi Journal of Engineering and Technology, 10(4), 189–199.

[40] Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., & Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. Saudi Journal of Engineering and Technology, 10(4), 152–158.

[41] Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., & Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. Saudi Journal of Engineering and Technology, 10(4), 169–178.

[42] Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., & Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. Saudi Journal of Engineering and Technology, 10(4), 179–188.

[43] Farabi, S. A. (2025). AI-augmented OTDR fault localization framework for resilient rural fiber networks in the United States. arXiv. https://arxiv.org/abs/2506.03041

[44] Farabi, S. A. (2025). AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions. Preprints. https://doi.org/10.20944/preprints202506.1152.v1

[45] Farabi, S. A. (2025). AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions. ResearchGate. https://doi.org/10.13140/RG.2.2.12096.65287

[46] Sunny, S. R. (2025). Lifecycle analysis of rocket components using digital twins and multiphysics simulation. ResearchGate. https://doi.org/10.13140/RG.2.2.20134.23362

[47] Sunny, S. R. (2025). AI-driven defect prediction for aerospace composites using Industry 4.0 technologies. Zenodo. https://doi.org/10.5281/zenodo.16044460

[48] Sunny, S. R. (2025). Edge-based predictive maintenance for subsonic wind tunnel systems using sensor analytics and machine learning. TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[49] Sunny, S. R. (2025). Digital twin framework for wind tunnel-based aeroelastic structure evaluation. TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[50] Sunny, S. R. (2025). Real-time wind tunnel data reduction using machine learning and JR3 balance integration. Saudi Journal of Engineering and Technology, 10(9), 411–420. https://doi.org/10.36348/sjet.2025.v10i09.004

[51] Sunny, S. R. (2025). AI-augmented aerodynamic optimization in subsonic wind tunnel testing for UAV prototypes. Saudi Journal of Engineering and Technology, 10(9), 402–410. https://doi.org/10.36348/sjet.2025.v10i09.003

[52] Shaikat, M. F. B. (2025). Pilot deployment of an AI-driven production intelligence platform in a textile assembly line. TechRxiv. https://doi.org/10.36227/techrxiv.175203708.81014137/v1

[53] Rabbi, M. S. (2025). Extremum-seeking MPPT control for Z-source inverters in grid-connected solar PV systems. Preprints. https://doi.org/10.20944/preprints202507.2258.v1

[54] Rabbi, M. S. (2025). Design of fire-resilient solar inverter systems for wildfire-prone U.S. regions. Preprints. https://www.preprints.org/manuscript/202507.2505/v1

[55] Rabbi, M. S. (2025). Grid synchronization algorithms for intermittent renewable energy sources using AI control loops. Preprints. https://www.preprints.org/manuscript/202507.2353/v1

[56] Tonoy, A. A. R. (2025). Condition monitoring in power transformers using IoT: A model for predictive maintenance. Preprints. https://doi.org/10.20944/preprints202507.2379.v1

[57] Tonoy, A. A. R. (2025). Applications of semiconducting electrides in mechanical energy conversion and piezoelectric systems. Preprints. https://doi.org/10.20944/preprints202507.2421.v1

[58] Azad, M. A. (2025). Lean automation strategies for reshoring U.S. apparel manufacturing: A sustainable approach. Preprints. https://doi.org/10.20944/preprints202508.0024.v1

[59] Azad, M. A. (2025). Optimizing supply chain efficiency through lean Six Sigma: Case studies in textile and apparel manufacturing. Preprints. https://doi.org/10.20944/preprints202508.0013.v1

[60] Azad, M. A. (2025). Sustainable manufacturing practices in the apparel industry: Integrating eco-friendly materials and processes. TechRxiv. https://doi.org/10.36227/techrxiv.175459827.79551250/v1

[61] Azad, M. A. (2025). Leveraging supply chain analytics for real-time decision making in apparel manufacturing. TechRxiv. https://doi.org/10.36227/techrxiv.175459831.14441929/v1

[62] Azad, M. A. (2025). Evaluating the role of lean manufacturing in reducing production costs and enhancing efficiency in textile mills. TechRxiv. https://doi.org/10.36227/techrxiv.175459830.02641032/v1

[63] Azad, M. A. (2025). Impact of digital technologies on textile and apparel manufacturing: A case for U.S. reshoring. TechRxiv. https://doi.org/10.36227/techrxiv.175459829.93863272/v1

[64] Rayhan, F. (2025). A hybrid deep learning model for wind and solar power forecasting in smart grids. Preprints. https://doi.org/10.20944/preprints202508.0511.v1

[65] Rayhan, F. (2025). AI-powered condition monitoring for solar inverters using embedded edge devices. Preprints. https://doi.org/10.20944/preprints202508.0474.v1

[66] Rayhan, F. (2025). AI-enabled energy forecasting and fault detection in off-grid solar networks for rural electrification. TechRxiv. https://doi.org/10.36227/techrxiv.175623117.73185204/v1

[67] Habiba, U., & Musarrat, R. (2025). Integrating digital tools into ESL pedagogy: A study on multimedia and student engagement. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 799–811. https://doi.org/10.5281/zenodo.17245996

[68] Hossain, M. T., Nabil, S. H., Razaq, A., & Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 921–933. https://doi.org/10.5281/zenodo.17246184

[69] Hossain, M. T., Nabil, S. H., Rahman, M., & Razaq, A. (2025). Data analytics for IoT-driven EV battery health monitoring. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 903–913. https://doi.org/10.5281/zenodo.17246168

[70] Akter, E., Bormon, J. C., Saikat, M. H., & Shoag, M. (2025). Digital twin technology for smart civil infrastructure and emergency preparedness. IJSRED – International Journal of Scientific Research and Engineering Development, 8(2), 891–902. https://doi.org/10.5281/zenodo.17246150

[71] Rahmatullah, R. (2025). Smart agriculture and Industry 4.0: Applying industrial engineering tools to improve U.S. agricultural productivity. World Journal of Advanced Engineering Technology and Sciences, 17(1), 28–40. https://doi.org/10.30574/wjaets.2025.17.1.1377

[72] Islam, R. (2025). AI and big data for predictive analytics in pharmaceutical quality assurance.. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5564319

[73] Rahmatullah, R. (2025). Sustainable agriculture supply chains: Engineering management approaches for reducing post-harvest loss in the U.S. International Journal of Scientific Research and Engineering Development, 8(5), 1187–1216. https://doi.org/10.5281/zenodo.17275907

[74] Haque, S., Al Sany, S. M. A., & Rahman, M. (2025). Circular economy in fashion: MIS-driven digital product passports for apparel traceability. International Journal of Scientific Research and Engineering Development, 8(5), 1254–1262. https://doi.org/10.5281/zenodo.17276038

[75] Al Sany, S. M. A., Haque, S., & Rahman, M. (2025). Green apparel logistics: MIS-enabled carbon footprint reduction in fashion supply chains. International Journal of Scientific Research and Engineering Development, 8(5), 1263–1272. https://doi.org/10.5281/zenodo.17276049

[76] Bormon, J. C. (2025), Numerical Modeling of Foundation Settlement in High-Rise Structures Under Seismic Loading. Available at SSRN: https://ssrn.com/abstract=5472006 or http://dx.doi.org/10.2139/ssrn.5472006

[77] Tabassum, M. (2025, October 6). MIS-driven predictive analytics for global shipping and logistics optimization. TechRxiv. https://doi.org/10.36227/techrxiv.175977232.23537711/v1

[78] Tabassum, M. (2025, October 6). Integrating MIS and compliance dashboards for international trade operations. TechRxiv. https://doi.org/10.36227/techrxiv.175977233.37119831/v1

[79] Hossain, M. T. (2025, October 7). Smart inventory and warehouse automation for fashion retail. TechRxiv. https://doi.org/10.36227/techrxiv.175987210.04689809.v1

[80] Karim, M. A. (2025, October 6). AI-driven predictive maintenance for solar inverter systems. TechRxiv. https://doi.org/10.36227/techrxiv.175977633.34528041.v1

[81] Jahan Bristy, I. (2025, October 6). Smart reservation and service management systems: Leveraging MIS for hotel efficiency. TechRxiv. https://doi.org/10.36227/techrxiv.175979180.05153224.v1

[82] Habiba, U. (2025, October 7). Cross-cultural communication competence through technology-mediated TESOL. TechRxiv. https://doi.org/10.36227/techrxiv.175985896.67358551.v1

[83] Habiba, U. (2025, October 7). AI-driven assessment in TESOL: Adaptive feedback for personalized learning. TechRxiv. https://doi.org/10.36227/techrxiv.175987165.56867521.v1

[84] Akhter, T. (2025, October 6). Algorithmic internal controls for SMEs using MIS event logs. TechRxiv. https://doi.org/10.36227/techrxiv.175978941.15848264.v1

[85] Akhter, T. (2025, October 6). MIS-enabled workforce analytics for service quality & retention. TechRxiv. https://doi.org/10.36227/techrxiv.175978943.38544757.v1

[86] Hasan, E. (2025, October 7). Secure and scalable data management for digital transformation in finance and IT systems. Zenodo. https://doi.org/10.5281/zenodo.17202282

[87] Saikat, M. H., Shoag, M., Akter, E., Bormon, J. C. (October 06, 2025.) Seismic- and Climate-Resilient Infrastructure Design for Coastal and Urban Regions. TechRxiv. DOI: 10.36227/techrxiv.175979151.16743058/v1

[88] Saikat, M. H. (October 06, 2025). AI-Powered Flood Risk Prediction and Mapping for Urban Resilience. TechRxiv. DOI: 10.36227/techrxiv.175979253.37807272/v1

[89] Akter, E. (September 15, 2025). Sustainable Waste and Water Management Strategies for Urban Civil Infrastructure. Available at SSRN: https://ssrn.com/abstract=5490686 or http://dx.doi.org/10.2139/ssrn.5490686

[90] Karim, M. A., Zaman, M. T. U., Nabil, S. H., & Joarder, M. M. I. (2025, October 6). AI-enabled smart energy meters with DC-DC converter integration for electric vehicle charging systems. TechRxiv. https://doi.org/10.36227/techrxiv.175978935.59813154/v1

[91] Al Sany, S. M. A., Rahman, M., & Haque, S. (2025). Sustainable garment production through Industry 4.0 automation. World Journal of Advanced Engineering Technology and Sciences, 17(1), 145–156. https://doi.org/10.30574/wjaets.2025.17.1.1387

[92] Rahman, M., Haque, S., & Al Sany, S. M. A. (2025). Federated learning for privacy-preserving apparel supply chain analytics. World Journal of Advanced Engineering Technology and Sciences, 17(1), 259–270. https://doi.org/10.30574/wjaets.2025.17.1.1386

[93] Rahman, M., Razaq, A., Hossain, M. T., & Zaman, M. T. U. (2025). Machine learning approaches for predictive maintenance in IoT devices. World Journal of Advanced Engineering Technology and Sciences, 17(1), 157–170. https://doi.org/10.30574/wjaets.2025.17.1.1388

[94] Akhter, T., Alimozzaman, D. M., Hasan, E., & Islam, R. (2025, October). Explainable predictive analytics for healthcare decision support. International Journal of Sciences and Innovation Engineering, 2(10), 921–938. https://doi.org/10.70849/IJSCI02102025105

[95] Islam, M. S., Islam, M. I., Mozumder, A. Q., Khan, M. T. H., Das, N., & Mohammad, N. (2025). A Conceptual Framework for Sustainable AI-ERP Integration in Dark Factories: Synthesising TOE, TAM, and IS Success Models for Autonomous Industrial Environments. Sustainability, 17(20), 9234. https://doi.org/10.3390/su17209234

[96] Haque, S., Islam, S., Islam, M. I., Islam, S., Khan, R., Tarafder, T. R., & Mohammad, N. (2025). Enhancing adaptive learning, communication, and therapeutic accessibility through the integration of artificial intelligence and data-driven personalization in digital health platforms for students with autism spectrum disorder. Journal of Posthumanism, 5(8), 737–756. Transnational Press London.

[97] Faruq, O., Islam, M. I., Islam, M. S., Tarafder, M. T. R., Rahman, M. M., Islam, M. S., & Mohammad, N. (2025). Re-imagining Digital Transformation in the United States: Harnessing Artificial Intelligence and Business Analytics to Drive IT Project Excellence in the Digital Innovation Landscape. Journal of Posthumanism, 5(9), 333–354 . https://doi.org/10.63332/joph.v5i9.3326

[98] Rahman, M.. (October 15, 2025) Integrating IoT and MIS for Last-Mile Connectivity in Residential Broadband Services. TechRxiv. DOI: 10.36227/techrxiv.176054689.95468219/v1

[99] Islam, R. (2025, October 15). Integration of IIoT and MIS for smart pharmaceutical manufacturing . TechRxiv. https://doi.org/10.36227/techrxiv.176049811.10002169

[100] Hasan, E. (2025). Big Data-Driven Business Process Optimization: Enhancing Decision-Making Through Predictive Analytics. TechRxiv. October 07, 2025. 10.36227/techrxiv.175987736.61988942/v1

[101] Rahman, M. (2025, October 15). IoT-enabled smart charging systems for electric vehicles [Preprint]. TechRxiv. https://doi.org/10.36227/techrxiv.176049766.60280824

[102] Alam, M. S. (2025, October 21). AI-driven sustainable manufacturing for resource optimization. TechRxiv. https://doi.org/10.36227/techrxiv.176107759.92503137/v1

[103] Alam, M. S. (2025, October 21). Data-driven production scheduling for high-mix manufacturing environments. TechRxiv. https://doi.org/10.36227/techrxiv.176107775.59550104/v1

[104] Ria, S. J. (2025, October 21). Environmental impact assessment of transportation infrastructure in rural Bangladesh. TechRxiv. https://doi.org/10.36227/techrxiv.176107782.23912238/v1

[105] R Musarrat and U Habiba, Immersive Technologies in ESL Classrooms: Virtual and Augmented Reality for Language Fluency (September 22, 2025). Available at SSRN: https://ssrn.com/abstract=5536098 or http://dx.doi.org/10.2139/ssrn.5536098

[106] Akter, E., Bormon, J. C., Saikat, M. H., & Shoag, M. (2025), “AI-Enabled Structural and Façade Health Monitoring for Resilient Cities”, Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 1035–1051, Oct. 2025, doi: 10.70849/IJSCI02102025116

[107] Haque, S., Al Sany (Oct. 2025), “Impact of Consumer Behavior Analytics on Telecom Sales Strategy”, Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 998–1018, doi: 10.70849/IJSCI02102025114.

[108] Sharan, S. M. I (Oct. 2025)., “Integrating Human-Centered Design with Agile Methodologies in Product Lifecycle Management”, Int. J. Sci. Inno. Eng., vol. 2, no. 10, pp. 1019–1034, doi: 10.70849/IJSCI02102025115.

[109] Alimozzaman, D. M. (2025). Explainable AI for early detection and classification of childhood leukemia using multi-modal medical data. World Journal of Advanced Engineering Technology and Sciences, 17(2), 48–62. https://doi.org/10.30574/wjaets.2025.17.2.1442

[110] Alimozzaman, D. M., Akhter, T., Islam, R., & Hasan, E. (2025). Generative AI for synthetic medical imaging to address data scarcity. World Journal of Advanced Engineering Technology and Sciences, 17(1), 544–558. https://doi.org/10.30574/wjaets.2025.17.1.1415

[111] Zaidi, S. K. A. (2025). Intelligent automation and control systems for electric vertical take-off and landing (eVTOL) drones. World Journal of Advanced Engineering Technology and Sciences, 17(2), 63–75. https://doi.org/10.30574/wjaets.2025.17.2.1457

[112] Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2321–2331. Zenodo. https://doi.org/10.5281/zenodo.17536369

[113] Islam, K. S. A. (2025). Transformer protection and fault detection through relay automation and machine learning. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2308–2320. Zenodo. https://doi.org/10.5281/zenodo.17536362

[114] Afrin, S. (2025). Cloud-integrated network monitoring dashboards using IoT and edge analytics. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2298–2307. Zenodo. https://doi.org/10.5281/zenodo.17536343

[115] Al Sany, S. M. A. (2025). The role of data analytics in optimizing budget allocation and financial efficiency in startups. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2287–2297. Zenodo. https://doi.org/10.5281/zenodo.17536325

[116] Zaman, S. U. (2025). Vulnerability management and automated incident response in corporate networks. IJSRED – International Journal of Scientific Research and Engineering Development, 8(5), 2275–2286. Zenodo. https://doi.org/10.5281/zenodo.17536305

[117] Ria, S. J. (2025, October 7). Sustainable construction materials for rural development projects. SSRN. https://doi.org/10.2139/ssrn.5575390

[118] Razaq, A. (2025, October 15). Design and implementation of renewable energy integration into smart grids. TechRxiv. https://doi.org/10.36227/techrxiv.176049834.44797235/v1

[119] Musarrat R. (2025). AI-Driven Smart Housekeeping and Service Allocation Systems: Enhancing Hotel Operations Through MIS Integration. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 898–910). Zenodo. https://doi.org/10.5281/zenodo.17769627

[120] Hossain, M. T. (2025). AI-Augmented Sensor Trace Analysis for Defect Localization in Apparel Production Systems Using OTDR-Inspired Methodology. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1029–1040). Zenodo. https://doi.org/10.5281/zenodo.17769857

[121] Rahman M. (2025). Design and Implementation of a Data-Driven Financial Risk Management System for U.S. SMEs Using Federated Learning and Privacy-Preserving AI Techniques. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1041–1052). Zenodo. https://doi.org/10.5281/zenodo.17769869

[122] Alam, M. S. (2025). Real-Time Predictive Analytics for Factory Bottleneck Detection Using Edge-Based IIoT Sensors and Machine Learning. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 1053–1064). Zenodo. https://doi.org/10.5281/zenodo.17769890

[123] Habiba, U., & Musarrat, R. (2025). Student-centered pedagogy in ESL: Shifting from teacher-led to learner-led classrooms. International Journal of Science and Innovation Engineering, 2(11), 1018–1036. https://doi.org/10.70849/IJSCI02112025110

[124] Zaidi, S. K. A. (2025). Smart sensor integration for energy-efficient avionics maintenance operations. International Journal of Science and Innovation Engineering, 2(11), 243–261. https://doi.org/10.70849/IJSCI02112025026

[125] Farooq, H. (2025). Cross-platform backup and disaster recovery automation in hybrid clouds. International Journal of Science and Innovation Engineering, 2(11), 220–242. https://doi.org/10.70849/IJSCI02112025025

[126] Farooq, H. (2025). Resource utilization analytics dashboard for cloud infrastructure management. World Journal of Advanced Engineering Technology and Sciences, 17(02), 141–154. https://doi.org/10.30574/wjaets.2025.17.2.1458

[127] Saeed, H. N. (2025). Hybrid perovskite–CIGS solar cells with machine learning-driven performance prediction. International Journal of Science and Innovation Engineering, 2(11), 262–280. https://doi.org/10.70849/IJSCI02112025027

[128] Akter, E. (2025). Community-based disaster risk reduction through infrastructure planning. International Journal of Science and Innovation Engineering, 2(11), 1104–1124. https://doi.org/10.70849/IJSCI02112025117

[129] Akter, E. (2025). Green project management framework for infrastructure development. International Journal of Science and Innovation Engineering, 2(11), 1125–1144. https://doi.org/10.70849/IJSCI02112025118

[130] Shoag, M. (2025). Integration of lean construction and digital tools for façade project efficiency. International Journal of Science and Innovation Engineering, 2(11), 1145–1164. https://doi.org/10.70849/IJSCI02112025119

[131] Akter, E. (2025). Structural Analysis of Low-Cost Bridges Using Sustainable Reinforcement Materials. In IJSRED - International Journal of Scientific Research and Engineering Development (Vol. 8, Number 6, pp. 911–921). Zenodo. https://doi.org/10.5281/zenodo.17769637

[132] Razaq, A. (2025). Optimization of power distribution networks using smart grid technology. World Journal of Advanced Engineering Technology and Sciences, 17(03), 129–146. https://doi.org/10.30574/wjaets.2025.17.3.1490

[133] Zaman, M. T. (2025). Enhancing grid resilience through DMR trunking communication systems. World Journal of Advanced Engineering Technology and Sciences, 17(03), 197–212. https://doi.org/10.30574/wjaets.2025.17.3.1551

[134] Nabil, S. H. (2025). Enhancing wind and solar power forecasting in smart grids using a hybrid CNN-LSTM model for improved grid stability and renewable energy integration. World Journal of Advanced Engineering Technology and Sciences, 17(03), 213–226. https://doi.org/10.30574/wjaets.2025.17.3.155

[135] Nahar, S. (2025). Optimizing HR management in smart pharmaceutical manufacturing through IIoT and MIS integration. World Journal of Advanced Engineering Technology and Sciences, 17(03), 240–252. https://doi.org/10.30574/wjaets.2025.17.3.1554

[136] Islam, S. (2025). IPSC-derived cardiac organoids: Modeling heart disease mechanism and advancing regenerative therapies. World Journal of Advanced Engineering Technology and Sciences, 17(03), 227–239. https://doi.org/10.30574/wjaets.2025.17.3.1553

[137] Shoag, M. (2025). Structural load distribution and failure analysis in curtain wall systems. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2117–2128. Zenodo. https://doi.org/10.5281/zenodo.17926722

[138] Hasan, E. (2025). Machine learning-based KPI forecasting for finance and operations teams. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2139–2149. Zenodo. https://doi.org/10.5281/zenodo.17926746

[139] Hasan, E. (2025). SQL-driven data quality optimization in multi-source enterprise dashboards. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2150–2160. Zenodo. https://doi.org/10.5281/zenodo.17926758

[140] Hasan, E. (2025). Optimizing SAP-centric financial workloads with AI-enhanced CloudOps in virtualized data centers. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2252–2264. Zenodo. https://doi.org/10.5281/zenodo.17926855

[141] Karim, M. A. (2025). An IoT-enabled exoskeleton architecture for mobility rehabilitation derived from the ExoLimb methodological framework. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2265–2277. Zenodo. https://doi.org/10.5281/zenodo.17926861

[142] Akter, E., Ria, S. J., Khan, M. I., & Shoag, M. D. (2025). Smart & sustainable construction governance for climate-resilient cities. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2278–2291. Zenodo. https://doi.org/10.5281/zenodo.17926875

[143] Zaman, S. U. (2025). Enhancing security in cloud-based IAM systems using real-time anomaly detection. IJSRED - International Journal of Scientific Research and Engineering Development, 8(6), 2292–2304. Zenodo. https://doi.org/10.5281/zenodo.17926883

[144] Hossain, T. (2025). Data-driven optimization of apparel supply chain to reduce lead time and improve on-time delivery. World Journal of Advanced Engineering Technology and Sciences, 17(03), 263–277. https://doi.org/10.30574/wjaets.2025.17.3.155