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Forecasting Natural Gas Prices Using Machine Learning Models: An Applied Study for Asian Countries

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إهداء

إلى الله سبحانه وتعالى،

المنعم المتفضل، الذي منحني القوة والصبر، وألهمني السكينة في كل لحظة صعبة. إليه وحده أرفع شكري وامتناني على توفيقه وكرمه.

إلى أمي الغالية،

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انت الأم والأخت والأخ والصديق يا امي العزيزة على قلبي

إلى والدي العزيز،

القدوة التي أعتز بها، والداعم الصامت الذي لم يتأخر يومًا عن تقديم كل ما يستطيع.

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إهداء

الحمد لله أولًا وأخيرًا، حمدًا يليق بجلال وجهه وعظيم سلطانه، الذي بنعمته وفضله تتم الصالحات، وبه وصلت إلى هذه المرحلة من مشواري العلمي.

إلى من كانوا بعد الله عز وجل السبب في أن أبلغ هذا المقام...

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كما لا يفوتني أن أعبّر عن خالص امتناني لكل أصدقائي وزملائي الذين شاركوني مسيرة العلم، ولكل أساتذتي الذين كانوا منارات في هذا الدرب، بما قدموه من علم وتوجيه.

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أتقدم بأسمى عبارات الشكر والتقدير والامتنان إلى كل من ساهم في إنجاح هذا العمل العلمي، وكان له أثر في دعمي وتشجيعي خلال مسيرتي الجامعية

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كما أتوجه بجزيل الشكر والامتنان إلى أساتذة كلية العلوم الاقتصادية في جامعة الشهيد حمه لخضر الوادي على ما بذلوه من جهد وما قدّموه من علم طيلة سنوات دراستي

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لكم جميعاً مني كل الشكر والتقدير

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Introduction:

الملخص باللغة العربية:

تهدف هذه المذكرة إلى دراسة تطور أسعار الغاز الطبيعي وتحليل اتجاهاتها المستقبلية باستخدام نماذج كمية تجمع بين الأساليب التقليدية والنماذج الحديثة للتنبؤ. تم الاعتماد على بيانات شهرية تغطي الفترة من سنة 1992 إلى مارس 2025، وتمت معالجة البيانات وتحليلها بعدة مراحل، بدءًا من التنظيف والتحويل، وصولًا إلى بناء النماذج ومقارنتها من حيث دقتها وفعالية التنبؤ. أظهرت النتائج تفاوتًا في أداء النماذج، حيث تفوقت بعض الأساليب القائمة على التعلم الآلي في قدرتها على التقاط أنماط البيانات المعقدة. تعكس هذه الدراسة أهمية استخدام أدوات علم البيانات في دعم اتخاذ القرار الاقتصادي، خاصة في القطاعات الحيوية مثل الطاقة.

Abstract (English):

This thesis aims to study the evolution of natural gas prices and analyze their future trends using quantitative models that combine both traditional and modern forecasting approaches. Monthly data covering the period from 1992 to March 2025 were used, undergoing several processing stages from cleaning and transformation to model building and performance evaluation. The results showed differences in model performance, with machine learning methods outperforming others in capturing complex data patterns. This study highlights the importance of applying data science tools to support economic decision-making, particularly in strategic sectors such as energy.

introduction

Introduction:

In light of the rapid changes witnessed globally, especially within energy markets, it has become crucial to approach the study of energy resources with precision. Natural gas, being one of the most significant energy sources today, stands at the forefront of this necessity. Its prices are no longer solely dictated by supply and demand but are increasingly influenced by a myriad of geopolitical and economic factors.

Through this thesis, I have endeavored to present an in-depth analytical study aimed at forecasting natural gas prices using statistical models and machine learning techniques, while comparing their performance in terms of accuracy and predictive capability. The study relies on long-term data and integrates theoretical analysis with practical application, with the objective of arriving at clear results that can be utilized in both applied and research contexts.

1. Problem Statement:

In the face of continuous fluctuations in global energy markets, specifically in the natural gas market, the ability to forecast gas prices has become a strategic necessity for decision-makers across economic, industrial, and political spheres. However, traditional statistical models (such as the linear ARIMA model) face difficulties in capturing the non-linear dynamics of the market.

In contrast, machine learning models have emerged as a powerful alternative due to their flexibility in handling complex data, noise, and unseen patterns. Yet, the fundamental question remains:

To what extent can machine learning models improve the accuracy of natural gas price forecasting compared to traditional models?

2. Study Hypotheses:

To answer the study's problem statement, the following hypotheses are proposed:

Main Hypothesis:

Machine learning models provide higher predictive accuracy than traditional statistical models in forecasting natural gas prices.

Sub-Hypotheses:

- Hypothesis 1: There is a significant difference in performance between BOX-JENKINS, PROPHET, and LSTM models when applied to the same dataset.
- Hypothesis 2: Forecasting accuracy varies depending on the chosen evaluation metrics (RMSE, MAE, R^2, etc.).
- Hypothesis 3: Historical monthly natural gas data is sufficient for training accurate models.

3. Research Objectives:

General Objective:

To evaluate the performance of machine learning models in forecasting natural gas prices and compare them with the traditional ARIMA model.

Sub-Objectives:

- To construct a time series for natural gas prices from official sources.
- To train BOX-JENKINS, PROPHET, and LSTM models on the same sample.
- To measure and analyze the forecasting accuracy of each model using statistical indicators.
- To provide recommendations regarding the best model for practical energy price forecasting.

4. **Research Significance:**

Scientific Significance:

  - Contributes to the development of applied studies in the fields of energy and artificial intelligence.
  - Bridges econometric methodologies with modern machine learning techniques.

Practical Significance:

  - Provides a practical tool for decision-makers in energy companies.
  - The optimal model can be used in production planning and pricing.
  - Selection of variables and data sources: Utilizing a monthly time series of natural gas prices extending over several years.
  - Analysis of time series characteristics: Employing descriptive tools and statistical tests such as the stationarity test (ADF).

Thesis Structure

The thesis is divided into two main chapters as follows:

- Chapter One: Theoretical Foundations for Natural Gas Price Forecasting and Machine Learning Models This chapter provides an introduction to fundamental concepts in time series price forecasting, presenting artificial intelligence models used in this field. It includes the following sections:
    1. Theoretical Framework for Natural Gas Price Forecasting and Machine Learning
    2. Previous Studies in Natural Gas Price Forecasting
- Chapter Two: Applied Study for Natural Gas Price Forecasting This chapter addresses the practical aspect of forecasting natural gas prices in the global market using ARIMA, Prophet, and LSTM models. It is divided into two main sections:
    1. Methodology and Tools Used in the Study
    2. Presentation and Discussion of Study Results

Chapter 1: Theoretical Literature Review

Introduction:

Forecasting natural gas prices is a critical subject that garners significant attention from researchers and decision-makers alike, given the strategic importance of this resource in the global economy. Production, consumption, and investment decisions within the energy sector hinge on the accuracy of future price predictions, thereby necessitating the utilization of effective analytical approaches and tools.

Comprehending the mechanisms of natural gas price forecasting requires familiarity with fundamental concepts associated with it, such as the definition of natural gas and its key characteristics, in addition to grasping the notion of economic forecasting and its significance in financial markets. Furthermore, the forecasting process relies on data modeling and analysis through scientific methods grounded in robust theoretical foundations, highlighting the need to examine economic theories that explain price movements, alongside identifying traditional statistical analysis methods and the latest machine learning techniques employed in forecasting.

Section 1: Theoretical Framework:

This section outlines the theoretical framework for the study of natural gas price forecasting by reviewing fundamental concepts and definitions related to it. Additionally, it highlights the theoretical underpinnings and scientific principles that support forecasting processes, aiming to provide a robust knowledge base that facilitates the understanding of practical aspects later.

Subsection 1: Fundamental Concepts and Definitions:

Forecasting natural gas prices is a significant topic that relies on fundamental concepts such as the definition of natural gas, economic forecasting, and data modeling. This subsection aims to clarify these concepts to provide a theoretical foundation that aids in comprehending the practical aspects subsequently.

1- Definition of Natural Gas:

Natural gas is considered one of the most important energy sources in the present time, possessing higher calorific values than coal and petroleum, with approximately 90 million British Thermal Units (BTUs) per ton[1].

Natural gas is a non-renewable natural energy source, meaning it is finite. It is found beneath the Earth's surface, either independently or associated with oil deposits. Its composition consists of gaseous hydrocarbons, primarily methane, ethane, and propane. The constituents of natural gas vary from one location to another and from one well or field to another. Generally, the components of natural gas include the following compounds: as shown in the table below. Methane (CH4) constitutes the primary component of natural gas, with its proportion reaching up to 90% by volume in some fields, while other hydrocarbon gases make up the remaining components of natural gas[2].

Compound	% Weight
Methane (CH4)	70-90
Ethane (C2H6)	5-15
Propane (C3H8) & Butane (C4H10)	<5

[1] Croft Production Systems, Natural Gas Composition, Accessed on 15/03/2025, at 7:40, https://www.croftsystems.net/oil-gas-blog/natural-gas-composition/ .

[2] Croft Production Systems, ibid.

Other (CO_2, N_2, H_2S, etc.)	Remainder

Table 01: Major natural gas compounds[3]

Natural gas is sometimes described as the gaseous form of petroleum. It is termed "natural" to distinguish it from manufactured gas, which is similar in composition and properties and is obtained by heating coal. It is also worth noting that natural gas is the simplest hydrocarbon source*, as it consists of relatively few compounds that can be readily accessed[4].

2- Concept of Economic Forecasting:

Economic forecasting is defined as a systematic analytical process aimed at estimating the future values of economic variables using quantitative and qualitative tools and methods. These tools include time series models, econometric equation systems, extrapolation, leading indicators, opinion surveys, and expert judgments. This process relies on analyzing historical relationships between economic variables or on simulating the rational behavior of economic agents within economic models. The significance of economic forecasting lies in its pivotal role in supporting decision-making, both at the level of public policies and institutional planning, by reducing uncertainty and enabling actors to proactively respond to potential changes in the economic environment[5].

-The Role of Economic Forecasting in Strategic Planning in Markets:

1. Supporting Decision-Making: By providing future insights that aid in formulating effective strategies.
2. Preparing for Changes: By developing scenarios and contingency plans.
3. Improving Resource Allocation Efficiency: And reducing waste.
4. Mitigating Risks: By reducing the state of uncertainty.
5. Guiding Strategies: In alignment with future market shifts[6].

-The Importance of Forecasting Models in Mitigating Economic Risks: Economic forecasting, particularly demand forecasting, is a fundamental

[3] Natural Gas Vehicles, KnowledgeWeb, accessed March 4, 2025 at 20:17.
[4] Energy Education, Synthetic natural gas, Accessed on 05/03/2025, at 8:11, https://energyeducation.ca/encyclopedia/Synthetic_natural_gas .
*Hydrocarbon: A compound word made up of the words hydrogen and carbon, meaning that its chemical basis is hydrogen and carbon.
[5] Michael P. Clements and David F. Hendry, An Overview of Economic Forecasting, chapter one, Wiley & Oxford University Press, United Kingdom,2008,p3-5.
[6] Armstrong, J. S. (2001). *Foundations of Strategic Planning and Forecasting*, University of Pennsylvania, usa,MPRA Paper No. 81682,1983, pp. 2–4.

tool that helps organizations reduce the degree of uncertainty and risks associated with future decisions. Through forecasting, an organization can:

- Determining appropriate production quantities based on predicted demand, thereby mitigating the risks of overproduction or shortages.
- Making informed decisions regarding pricing, promotion, and distribution, thus reducing the likelihood of resource misallocation.
- Anticipating potential changes in demand resulting from external factors such as economic conditions or competition, and consequently taking proactive measures.
- Allocating financial and human resources more efficiently, and minimizing waste in costs or delays in operations.
- Developing flexible plans capable of addressing deviations from the forecast, which aids in rapid adaptation to market fluctuations and avoidance of significant losses[7].

3- Fundamentals of Data Modeling:

- Data modeling is a fundamental analytical process that aims to represent data in a systematic manner, contributing to the understanding of underlying relationships between data points. This process enables the transformation of raw data into usable information across various domains, particularly forecasting and decision-making. Data modeling relies on identifying entities and their associated attributes, in addition to formulating relationships between these entities within logical and structural models that reflect the practical reality of systems[8].

- Components of Data Modeling:

Data modeling encompasses several fundamental components that constitute the model's structure. Prominent among these are: independent and dependent variables, which define the relationship between influences and outcomes; datasets that represent the historical data used in pattern analysis; and the relationships between variables, which aid in interpreting the future behavior of

[7] . حنان بن عوالي, التنبؤ بالطلب كجزء مكمل من التخطيط الاستراتيجي, الأكاديمية للدراسات الاجتماعية والإنسانية, كلية العلوم الاقتصادية والتجارية وعلوم التسيير- جامعة الشلف, العدد 12,جوان 2014, ص 55 –56.

[8] Graeme Simsion & Graham Witt, Data Modeling Essentials, 3rd edition, Morgan Kaufmann Publishers,usa, 2005, pp 1–6.

the data. These components are essential for constructing forecasting models with high analytical efficiency.

- Types of Data Models:

Data models are classified into several types based on the analytical purpose and methodological approach employed. These include statistical models used for analyzing quantitative relationships, such as linear regression and time series analysis; machine learning models that rely on artificial intelligence algorithms, such as neural networks; and simulation models that allow for the representation of hypothetical scenarios to understand potential future dynamics.

- Significance of Data Modeling in Economic Forecasting:

Data modeling plays a pivotal role in the field of economic forecasting, where it is used to build models capable of providing accurate predictions based on realistic historical data. By modeling the relationships between economic variables, strategic decisions can be supported on a scientific basis. Furthermore, these models contribute to risk reduction by anticipating future trends in markets, making them an effective tool in managing economic fluctuations[9].

Subsection 2: Theoretical Foundations and Scientific Principles:

The process of economic forecasting relies on a set of theoretical foundations and scientific principles that contribute to the analysis and interpretation of price movements and market trends. These foundations include economic theories that explain how prices are determined and the factors influencing them, alongside the role of machine learning in enhancing the accuracy of forecasts by analyzing large volumes of data and extracting future patterns. Traditional statistical methods also remain an important tool for understanding the relationships between economic variables and providing reliable estimates. Therefore, this subsection aims to highlight these theoretical and scientific aspects that form the basis of any effective forecasting process.

1- Economic Theories of Price Determination:

Price determination is the process in which market forces, primarily supply and demand, interact to establish the price at which goods and services are bought and sold. This process is a cornerstone of economic theory, where a range of models and theories are used to explain how prices are formed in competitive and non-

[9] Graeme Simsion and Graham White, op. cit.

competitive markets, based on costs, utility, market conditions, and the behavior of producers and consumers[10].

- Supply and Demand Theory:

The theory of supply and demand is a fundamental pillar of classical economic thought, explaining the mechanism of price determination in free markets through the interaction between the quantities of goods supplied and the quantities demanded. The theory posits that the equilibrium price is determined at the point where the quantity supplied equals the quantity demanded. If the quantity If demand increases and supply remains constant, the price rises; conversely, if supply increases and demand remains constant, the price falls. This theory serves as an analytical tool for understanding market dynamics and price changes resulting from fluctuations in supply and demand[11].

- Marginal Cost Theory:

This theory posits that companies determine the prices of their products based on the cost of producing one additional unit of the good, known as the marginal cost. Marginal costs play a crucial role in determining the optimal production volume, as additional units are produced as long as the marginal revenue exceeds or equals the marginal cost, ensuring sustainable profits in the short to medium term[12].

- Theory of Perfect Competition and Monopoly:

- **In the case of perfect competition:** Prices are determined according to market forces, where no single company has the ability to influence the price.
- **In the case of monopoly:** The sole producer in the market controls the price and sets it based on maximizing potential profit, often at a point where demand is high.

- Value-Based Pricing Theory:

Value-based pricing relies on cultural and determinant factors based on designing offerings that generate a tangible and increasing impact on the client's business,

[10] Kahn, G. A, *Theories of Price Determination*, Federal Reserve Bank of Kansas City, No. 84-07, United States, 1984, p1.

[11] Encyclopædia Britannica, Supply and Demand, Accessed on 5/03/2025,at 18:43, https://www.britannica.com/money/supply-and-demand .

[12] Adam Hayes, *Marginal Cost: Definition, Formula & Examples*, investopedia, Accessed on5/03/2025,at18:53,https://www.investopedia.com/terms/m/marginalcostofproduction.asp .

whether by increasing revenue or reducing operating costs, and then setting the price as a portion of this added value.

This is not limited to merely identifying needs but also involves building an organizational philosophy focused on a deep understanding of strategic clients and the ability of advertisers to demonstrate and communicate effective value[13].

Price Theory in Financial Markets:

The theory of price determination in financial markets indicates that asset prices are determined based on the information available to investors, reflecting future expectations regarding the performance of companies and the economy as a whole. Psychological factors and trading behaviors also play a significant role in shaping the prices of stocks and commodities, sometimes leading to sharp fluctuations or the formation of financial bubbles. The literature shows that market behavior depends not only on economic fundamentals but also on how investors interpret and react to the available information[14].

Section Two: Theoretical Foundations and Scientific Principles.

Subsection 1: Artificial Intelligence, Machine Learning, and Deep Learning:

It is impossible to define machine learning without referencing its interconnected concepts, which form the bedrock of modern computational advancement. We begin with:

1. Artificial Intelligence (AI):

Artificial Intelligence is a field within computer science that aims to design systems capable of performing tasks that previously required human intelligence, such as language understanding, decision-making, problem-solving, and sensory perception. Its applications include industrial robots, medical diagnosis systems, voice assistants (such as Siri and Alexa), and advanced game-playing systems (such as computer chess).

2. Machine Learning (ML):

Machine Learning is a branch of artificial intelligence that focuses on developing algorithms that learn from data and automatically improve over time without

[13] Cressman, G. E, Value-based pricing: A state-of-the-art review, Handbook of business-to-business marketing, Edward Elgar Publishing,2019,p246-247.

[14] Pisani, Michael, *What Drives Prices in Financial Markets?* 1st ed, University of New Hampshire Scholars', United States of America, 2018, p 4.

explicit programming for each case. These algorithms rely on statistical models to discover patterns and relationships in data, enabling them to extract inferences or make predictions on new data.

3. Deep Learning (DL):

Deep Learning is a subfield of machine learning that utilizes multi-layered artificial neural networks (Deep Neural Networks) to simulate human cognitive processes, such as image recognition, speech understanding, and text comprehension. These networks consist of a large number of layers and neurons, granting them the ability to extract high-level representations from raw data.

The difference between them can be summarized as follows:

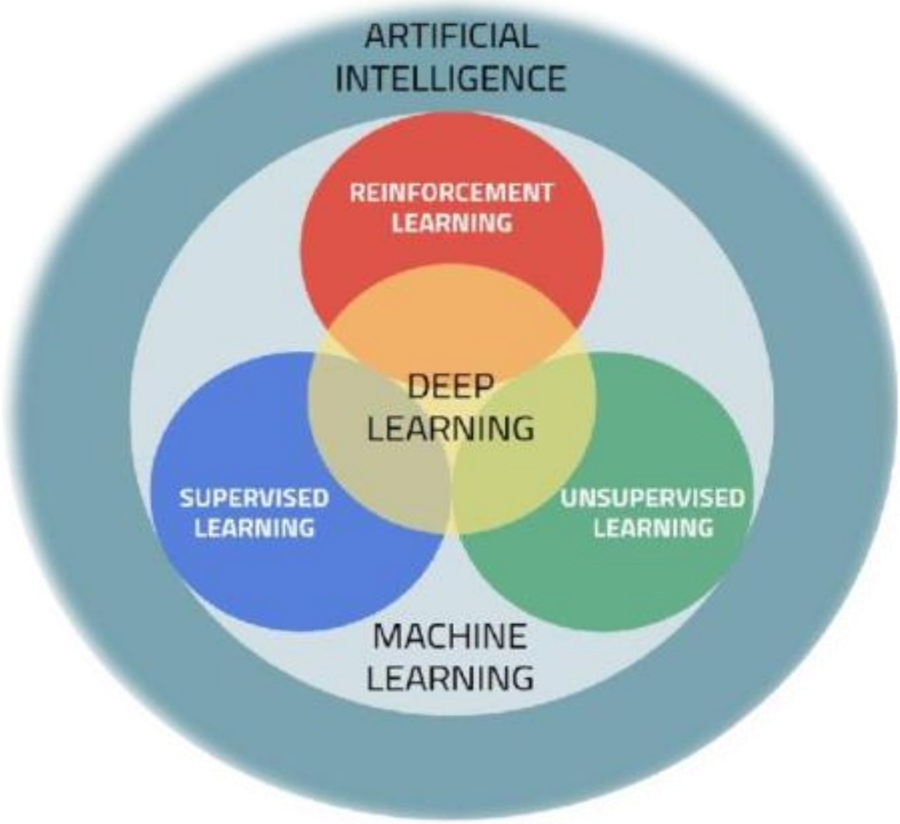
Artificial Intelligence (AI) is the overarching framework that aims to enable computers to perform tasks requiring human intelligence, such as decision-making and language understanding. Machine Learning (ML) is a branch of AI that uses statistical algorithms to learn from data and generate predictions or classifications without explicit programming for each case. In contrast, Deep Learning (DL) is an advancement within ML that relies on multi-layered artificial neural networks capable of extracting high-level representations from large and complex datasets, making it most effective in tasks such as image recognition and speech understanding.

Subsection 2: Machine Learning Models:

As previously mentioned, Machine Learning represents one of the fundamental pillars, as its models rely on data analysis to discover patterns and predict outcomes without the need for explicit programming. Machine Learning is typically categorized into three main types:

1. **Supervised Learning**, which requires labeled data to train models;
2. **Unsupervised Learning**, which is used to explore the structure of data without prior knowledge;
3. **Reinforcement Learning**, which depends on interaction with the environment and receiving repeated rewards to guide the learning process.

Figure 1.2: Artificial Intelligence, Machine Learning, and Deep Learning



Source: Nasir, A. M., Ab Ghani, M. K, & Abdullah, N. (2024). Taxonomy: A diagrammatic representation of artificial intelligence, machine learning, deep learning and reinforcement learning, ResearchGate.

❖ Components of Machine Learning:

Machine learning typically involves three main components:

1. **Data:** Machine learning algorithms require a significant amount of data to learn from. This data can be in the form of structured or unstructured data, such as numerical values, text, images, and videos. Data is collected based on the business problem to be solved, pre-processed, and explored before being used in modeling. The quality of the data heavily relies on the exploration and pre-processing steps.
2. **Algorithms:** Machine learning algorithms are used to process and analyze data, identify patterns or relationships, and create mathematical models that capture the underlying patterns. This is the modeling component of machine

learning, which is fed with data to learn patterns and relationships between features and target variables. Numerous machine learning algorithms exist based on how they learn from data. Examples include decision trees, random forests, KMeans, DBSCAN, and neural networks. In data science practices, different algorithms are considered when solving a particular problem. This process is experimental and highly dependent on the problem[15].

3. **Models:** Machine learning models are the output of the learning process. These models can be used for prediction, classifying new data, or making informed decisions based on the patterns and insights learned from the training data. A machine learning model is an object resulting from fitting an algorithm to data. It has been trained to identify data patterns and can make predictions when necessary. Practically, experimentation is conducted using different hyperparameter values for an algorithm to generate several models that are evaluated using various metrics. The "best" model is selected and deployed in production[16].

❖ **Types of Machine Learning:**

According to the learning approaches used, machine learning can be classified into several types, including:

1. **Supervised Learning:** In this approach, the algorithm learns from labeled training data, where input data is paired with corresponding correct outputs. The goal is to predict the outputs for new, unseen input data.
2. **1.1-Regression Model:** Regression is a supervised learning technique primarily used for predicting the values of a continuous dependent variable that can take any numerical value within a specific range. Unlike classification, which deals with discrete categories, regression focuses on estimating precise numerical quantities. A stable relationship between independent and dependent variables is assumed, and regression algorithms are used to derive a mathematical function that describes this relationship. The algorithm can produce precise decimal values that represent changes in the data and are sometimes rounded to the nearest suitable value to predict the behavior of the target variable within a specific context.

[15] Rajesh Kumar, Machine Learning: Data, Algorithms and Models, August 18, 2024, Accessed on 04/27/2025 at 7:12,https://www.devopsschool.com/blog/machinelearningdataalgorithmsandmodels/?utm_source=chatgpt.com.

[16] Elkheir Wahiba et Draoui Fatima Zahra, CONTRIBUTION TO THE STUDY AND IMPLEMENTATION OFMACHINE LEARNING AND DEEP LEARNING APPLIED TO SOLAR ENERGY, diplôme de Master, Physique Energétique, UNIVERSITE AHMED DRAIA, ADRAR,algeria,2023,p21-22.

 1.1.1-Linear Regression: It is one of the simplest and most widely used regression models in statistics and machine learning, aiming to establish a linear relationship between a dependent variable and one or more independent variables. In the case of simple linear regression, the relationship is expressed by the equation: $y=b0+b1x$ Where:

- y is the dependent variable,
- x is the independent variable,
- b0 is the intercept (the point where the line crosses the y-axis),
- b1 is the regression coefficient (the slope of the line).

In multiple linear regression, several independent variables are used, and the equation becomes: $y=b0+b1x1+b2x2+...+bnxn$ This model aims to accurately describe the variance in the dependent variable based on the inputs.

Linear regression is extensively used in fields such as data analysis, economics, and artificial intelligence, both for predicting future values of a continuous variable and for understanding the nature of the relationship between variables and determining the strength of the influence of each independent variable on the target variable[17].

 1.1.2-Regression Tree: It is a type of decision tree model used for predicting continuous numerical values and is considered a non-linear model characterized by its ease of understanding and interpretation. It works by progressively partitioning the data into smaller subsets based on the values of the independent variables, with the aim of reducing the variance of the dependent variable within each resulting subset.

The model is built by creating nodes that represent conditions on the independent variables, and the partitioning stops when a specific criterion is met, such as reaching a certain data size or a minimum level of variance. When predicting a new value, the model guides the observation through the tree from the root until it reaches a leaf node, and the average of the values in that node is used to generate the prediction.

Regression trees are effective in revealing complex relationships between variables and are flexible in handling data containing non-linear interactions or non-normal

[17] Ivan Belcic, Cole Stryker, What is supervised learning?,IBM, Accessed on 04/27/2025 at 09:03, https://www.ibm.com/think/topics/supervised-learning .

distributions, making them a popular choice in data analysis and machine learning applications[18].

- **1.1.3-Random Forest:** It is a machine learning algorithm based on ensemble learning, used for both classification and regression tasks. It operates by constructing a multitude of decision trees and aggregating their results to obtain a more accurate and stable prediction.

In this model, each tree is built using a bootstrap sample from the training data, meaning that data is selected randomly with replacement. This implies that some and others might be excluded. This technique helps reduce data points may be variance and limits overfitting.

At each split point within the tree, not all features are used; instead, a random subset of them is selected. This adds a layer of randomness that reduces the correlation between trees and increases the overall robustness of the model. The number of selected features is controlled by the max_features parameter, which is often set as the square root of the total number of features in the case of regression.

Thanks to this mechanism, random forests are considered powerful and flexible models, combining predictive accuracy with generalizability to new data[19].

- **1.1.4-Artificial Neural Networks (ANNs):** One of the most prominent deep learning models, ANNs are inspired by the structure and neural function of the human brain. They consist of simple units resembling neurons known as "nodes." These nodes receive signals from the input layer, then pass them to hidden layers that perform complex computational operations, and finally produce results through the output layer.

These networks rely on adjusting weights and parameters during the learning process using techniques like backpropagation, aiming to minimize the error between predicted and actual results. The more layers and nodes in the network, the greater its ability to recognize complex patterns and extract non-obvious relationships in the data.

[18] GeeksforGeeks, CART (Classification And Regression Tree) in Machine Learning, Accessed on 04/27/2025 at 18:01, https://www.geeksforgeeks.org/cart-classification-and-regression-tree-in-machine-learning/ .

[19] Analyticsvidhya, Random Forest Algorithm in Machine Learning, Accessed on 04/27/2025 at 17:45, https://www.analyticsvidhya.com/blog/2021/06/understanding-random-forest/?utm_source=chatgpt.com#h-what-is-random-forest .

Neural networks are used in many artificial intelligence applications, such as image analysis, speech recognition, natural language processing, and economic forecasting. Despite their high effectiveness, training them requires a significant amount of data and advanced computing capabilities, making them more suitable for large and complex projects.

- **1.1.5-Recurrent Neural Networks (RNNs):** These are advanced models in artificial intelligence, specifically designed to handle sequential data where temporal order is a crucial element. The most important characteristic of these networks lies in their use of a hidden state, which is continuously updated with each time step. This enables them to retain information about previous inputs, thereby allowing them to predict future values based on the temporal context. However, RNNs suffer from the vanishing gradient problem, a phenomenon that occurs during the training process using backpropagation through time, where gradients diminish significantly when Dealing with long time series, which weakens the model's ability to learn long-range dependencies. To address this limitation, the **Long Short-Term Memory (LSTM)** network model was developed. It features a more complex architectural structure that includes **gate mechanisms** allowing the model to determine what information to remember or forget over time. Thanks to this mechanism, LSTM is more efficient in handling long-term temporal dependencies and has proven successful in numerous applications such as machine translation, time series analysis, and natural language processing[20].

1.1.6-Long Short-Term Memory (LSTM) is an advanced extension of Recurrent Neural Networks (RNNs), developed by Hochreiter and Schmidhuber in 1997 to address the "long-term dependency" problem that traditional RNNs suffer from. While RNNs struggle to recall information far back in a time sequence due to the vanishing gradient phenomenon, LSTMs are capable of storing and retrieving information over long periods with high efficiency.

The basic structure of an LSTM lies in its **Cell State**, which acts as a long-term "transport path" through which data can pass with minimal modifications. This design allows information to be retained or forgotten when needed. To control this information flow, three dynamic gates operated by sigmoid and tanh activation functions are used:

[20] Boughezala Safa, reference previously cited.

1. **Forget Gate:** Decides what information should be discarded from the cell state.
2. **Input Gate:** Determines what new information should be added to the state.
3. **Output Gate:** Controls the values that will be output from the cell at the current time step.

Through this complex structure, LSTMs provide an effective ability to model long-term dependencies in time series, making them an optimal choice in applications such as machine translation, speech recognition, and natural language processing[21].

1.1.7-Support Vector Machines (SVM): SVM is an effective algorithm used for both classification and regression tasks. It finds the optimal hyperplane that separates data into different classes with the maximum margin. SVM can also use kernel functions to handle non-linear decision boundaries.

1.1.8-Prophet Model: Developed by Facebook, Prophet is a time series forecasting tool based on a flexible additive model that accounts for non-linear trends, as well as annual, weekly, and daily seasonality, in addition to incorporating holiday effects. Prophet is particularly effective in handling time series that exhibit clear seasonal patterns and have historical data spanning several seasons. It also stands out for its ability to adapt to missing data, accommodate trend changes, and effectively deal with outliers, making it suitable for a wide range of real-world forecasting applications[22].

1.1.9-Autoregressive Integrated Moving Average (ARIMA) Model:

ARIMA is an acronym for: **Autoregressive Integrated Moving Average**.

This model is one of the most popular and effective forecasting models for analyzing non-stationary time series because it combines three main techniques:

1. **Autoregression (AR):** Used to express the dependence on previous values of the variable.
2. **Integration (I):** This refers to differencing, used to transform a non-stationary series into a stationary, analyzable series.

[21] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1743–1746 .
[22] Choudhary, A. (2025), Generate Quick and Accurate Time Series Forecasts using Facebook's Prophet, AnalyticsVidhya,Accessedon04/27/2025at18:52,https://www.analyticsvidhya.com/blog/2018/05/generate-accurate-forecasts-facebook-prophet- python-r/ .

3. **Moving Average (MA):** Considers the effect of previous random errors in determining current values.

The three components of ARIMA(p,d,q):

- **p**: The number of previous time periods that influence the current value (AR component).
- **d**: The number of times differencing is required to make the time series stationary (I component).

- **q**: The number of previous errors used in the model (MA component)[23].

1.1.10-Box-Jenkins: For time series analysis, this is a methodology developed by George Box and Gwilym Jenkins in their renowned book, *Time Series Analysis: Forecasting and Control* (1970). This methodology is used to identify the optimal model for forecasting temporal variables, provided that the data meets a set of fundamental assumptions, most notably stationarity and seasonality. If the time series is not inherently stationary, transformation techniques such as differencing are employed to make it amenable to modeling. This adjustment leads to a model known as the integrated Box-Jenkins ARIMA model, which consists of three components: Autoregressive (AR), Integrated (I), and Moving Average (MA).

The application process of the Box-Jenkins methodology involves several stages:

1. **Identification Phase:** The null hypothesis assuming "non-stationarity" of the time series is tested. This relies on graphical representations such as line plots and scatter plots, as well as the analysis of autocorrelation functions (ACF) and partial autocorrelation functions (PACF). The Augmented Dickey-Fuller (ADF) test is used to determine the degree of stationarity and seasonal variations, and to identify the necessary value of (d).
2. **Estimation Phase:** Autocorrelation functions (ACF) and partial autocorrelation functions (PACF) are used to determine the order of the model components. ACF shows the order of the Moving Average (q), while PACF shows the order of the Autoregressive (p). Both are graphically represented in what is known as a "Correlogram."

[23] Investopedia, Autoregressive Integrated Moving Average (ARIMA), Adam Hayes, Updated July 31/ 2024, Accessed on 04/26/2025 at 10:57, https://www.investopedia.com/terms/a/autoregressive-integrated-moving-average-arima.asp.

3. **Diagnostic Phase:** The model's suitability is evaluated using graphical representations and residual analysis. If it is not suitable, the estimation process is repeated.
4. **Forecasting Phase:** After statistically validating the model, the ARIMA(p,d,q) model is used to forecast future values of the time series[24].

- ## Unsupervised Learning:

In this approach, the algorithm learns from unlabeled data without any predefined outputs. The goal is to discover patterns, structures, or relationships within the data.

1.2-Clustering:

Example: The **K-Means algorithm** partitions data into *k* clusters based on similarity, ensuring each data point belongs to the cluster with the nearest centroid. It's used in customer segmentation in marketing or group analysis in genetic data.

2.2-Dimensionality Reduction:

Example: **Principal Component Analysis (PCA)** transforms data into a new coordinate system where the greatest variance is preserved in the fewest dimensions. It's used to accelerate algorithms and reduce noise in data, particularly useful when the number of features is very large[25].

3-Reinforcement Learning:

This approach involves an **agent** interacting with a specific environment, learning to take actions to maximize a reward signal. The agent receives **feedback (Reward)** based on its actions and adjusts its behavior over time to achieve better outcomes.

- Example: The **Q-Learning algorithm**, which updates a Q-table to calculate the value of each state/action; and **Deep Q-Network (DQN)**, which uses neural networks to estimate Q-values in complex environments[26].

[24] د. حاج قويدر عبد الهادي، ط.د بغفار عبد القادر، التنبؤ بأسعار الغاز الطبيعي في الأسواق العالمية الرئيسية باستخدام نماذج ARIM، مجلة التكامل الاقتصادي، جامعة أحمد درايعية-ادرار، مجلد11، العدد4، جوان2023، ص335.

[25] Scikit-learnDocumentation – UnsupervisedLearning,https://scikitlearn.org/stable/unsupervised_learning.html
.

[26] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.

4-Semi-Supervised Learning:

This approach combines aspects of both supervised and unsupervised learning. It uses a small amount of labeled data, along with a larger amount of unlabeled data, to improve learning performance.

- Example: The **Label Propagation algorithm** spreads labels from the labeled data to the unlabeled data based on their similarity[27].

In summary, machine learning algorithms are broadly categorized into four main types:

1. **Supervised Learning:** Includes linear regression, regression trees, random forests, SVM, Prophet, and neural networks (ANNs, RNNs, LSTM).
2. **Unsupervised Learning:** Includes clustering (K-Means) and dimensionality reduction (PCA).
3. **Reinforcement Learning:** Includes Q-Learning and DQN.
4. **Semi-Supervised Learning:** Uses algorithms like Label Propagation.

Subsection 3: Evaluation Metrics for Machine Learning Models

To assess the accuracy of the models, quantitative indicators were used, including:

- **Mean Absolute Error (MAE):** This metric is used to determine the accuracy of predictions by calculating the average of the absolute differences between predicted and actual values, regardless of the error's direction (whether positive or negative). This indicator is widely used in regression analysis to evaluate the performance of predictive models, especially when data contains outliers or when the goal is to obtain a balanced estimate of the total error magnitude without being influenced by its direction.

$$MAE(y, \hat{y}) = \frac{1}{\text{nsamples}} \sum_{i=0}^{nsamples-1} |yi - \hat{y}i| \cdot$$

Where haty is the predicted label, y is the true label, and n is the number of samples used. This helps in determining the difference between predicted and actual results. For determining the average error, this technique is considered more natural.

[27]Zhu, X. (2006). *Semi-Supervised Learning Literature Survey*. University of Wisconsin–Madison.

- **Mean Squared Error (MSE)** [28]**:**

  When comparing different estimators, Mean Squared Error is useful, especially when one of them is biased.

  $MSE = \frac{1}{n}\sum_{j=1}^{n}(y - yi)^{2}$ Where:

  - n = number of errors
  - y = actual value (consumption value)
  - Yi = predicted value.

Root Mean Squared Error (RMSE) [29]**:** This is a statistical measure used to evaluate the accuracy of predictive models by quantifying the difference between predicted and actual values. It is calculated by taking the square root of the average of the squared differences between the predicted and true values, which makes it sensitive to large errors, as it gives greater weight to outliers. RMSE is a common indicator in regression analysis because it expresses the error in the same units as the original variable, making it easier to interpret and compare.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y - yi)^{2}}$$

Normalized Root Mean Squared Error (NRMSE) [30]**:** This is a standardized version of RMSE, used to facilitate the comparison of model performance when units or data ranges differ. NRMSE is calculated by dividing RMSE by the range of the actual values or by their mean, which allows for a relative assessment of model accuracy regardless of the original data's size or scale. This metric is particularly useful when comparing models applied to diverse datasets, as it provides a unified measure that can be used to determine the most efficient model accurately and objectively.

$$NRMSE = \frac{RMSE}{\bar{y}}$$

[28] M Waqar Ahmed, Understanding Mean Absolute Error (MAE)inRegression:APracticalGuide,medium, , Accessed on 04/27/2025 at 19:17, https://medium.com/@m.waqar.ahmed/understanding-mean-absolute-error-mae-in-regression-a-practical-guide-26e80ebb97df .

[29] Jim Frost, Root Mean Square Error (RMSE), Statistics By Jim, Accessed on 04/27/2025 at 19:29, https://statisticsbyjim.com/regression/root-mean-square-error-rmse/ .

[30]Rootmeansquaredeviation,wikibedia,,Accessedon04/27/2025at20:19,https://en.wikipedia.org/wiki/Root_mean_square_deviation?utm_source=chatgpt.com.

R2 Score[31]: Also known as the **coefficient of determination**, R2 is a statistical measure used to evaluate the quality of a regression model by determining the percentage of the variance in the dependent variable (target) that can be explained by the independent variables (inputs). In other words, R2 expresses how well the model can represent the data, as it compares the variance in the true values to the variance in the values predicted by the model.

The value of R2 ranges between 0 and 1. A value closer to 1 indicates a better model fit, while a value closer to 0 suggests weak explanatory power. If the value is negative, it means the model's performance is worse than a simple model that only relies on the mean. The coefficient of determination is widely used to compare regression models and select the best one in terms of its explanatory capability.

$$R - Squared = 1 - \frac{\text{First Sum of Errors}}{\text{Second Sum of Errors}}$$

Where the first sum of errors is the **sum of squared residuals** (the difference between predicted and actual values), and the second sum of errors is the **total sum of squares** (the total variance in the dependent variable).

Mean Absolute Percentage Error (MAPE):

MAPE expresses the error as a percentage between the predicted and actual values. It's used to compare model performance as a percentage, which makes it easier to understand. The lower the percentage, the better the model.

[31] Ejiro Onose, R Squared: Understanding the Coefficient of Determination, arize , https://arize.com/blog-course/r-squared-understanding-the-coefficient-of-determination/ .

Section 2: Applied Literature Review

Subsection 1: Review of Local, Arab, and International Studies

Subsection 1: Local Studies (Algeria)

A. Machine Learning Studies

1. **Khenissi, A. & Mebarki, Y. (2020)**
    - **Title:** Forecasting Yearly Natural Gas Consumption Using Artificial Neural Networks for the Algerian Market
    - **Objective:**
    - This study aimed to build an Artificial Neural Network (ANN) model to forecast annual natural gas consumption in Algeria for the period 2000–2018, comparing its performance with a linear regression model.
    - It sought to capture the non-linear relationships between economic variables (GDP, population, oil prices). It also aimed to propose a practical framework for government bodies in energy planning.
    - **Results:**
    - The ANN model outperformed linear regression with a 23% reduction in MAPE.
    - It successfully predicted with 94% accuracy for the testing period (2016–2018).
    - The study showed the importance of demographic variables (per capita income, population) in improving forecasts.
    - The study recommended using neural networks for consumption modeling at the official body level.[32]
2. **Ali, M. & Boudraa, S. (2021)**
    - **Title:** A Support Vector Machine Approach to Forecast Algerian Natural Gas Demand
    - **Objective:**
    - This study aimed to apply a Support Vector Machine (SVM) model to forecast monthly natural gas demand in Algeria for the period 2010–2020.

[32] Khenissi, A., & Mebarki, Y. "Forecasting Yearly Natural Gas Consumption Using Artificial Neural Networks for the Algerian Market." International Journal of Energy Economics and Policy, Vol. 10, No. 3, pp. 439–447, 2020 . جامعة الوادي، الجزائر.

- Focused on comparing the accuracy of SVM with multiple linear regression models, with the addition of climatic (temperature) and industrial variables.
- It also sought to evaluate SVM's ability to handle sudden fluctuations in data.
- **Results:**
    - SVM outperformed linear regression with a 17% reduction in Mean Absolute Error (MAE).
    - It achieved the highest accuracy (R2=0.92) when using an RBF kernel and monthly temperature data.
    - The study demonstrated SVM's strength in capturing seasonal shocks and external variables.
    - It recommended generalizing the use of SVM in demand modeling for government and private projects.[33]

B. Traditional Studies (Box-Jenkins, ARIMA, GARCH)

3. **Khallafi, M. (2022)**
    - **Title:** Using the ARIMA Model to Forecast Natural Gas Exports in Algeria (2000–2020)
    - **Objective:**
    - To apply the Box-Jenkins (ARIMA) methodology to forecast the volume of Algerian natural gas exports for the period 2000–2020.
    - It aimed to determine the best ARIMA order (p,d,q) using AIC and BIC criteria, ensuring the model's suitability for seasonal data.
    - It also sought to compare ARIMA's performance with simple regression models.
    - **Results:**
    - The ARIMA(2,1,2) model was selected as the best model according to AIC and BIC.
    - The annual forecast for the period 2021–2023 achieved a mean absolute error of less than 4%.
    - It successfully incorporated seasonal effects for the summer periods.
    - The study recommended integrating oil price variables for better performance.[34]
4. **Jilali, A. (2022)**

[33] Ali, M., & Boudraa, S. "A Support Vector Machine Approach to Forecast Algerian Natural Gas Demand." Journal of Applied Energy Research, Vol. 8, No. 2, pp. 155–166, 2021.جامعة الوادي، الجزائر .

[34] خالّفي، م. "استخدام نموذج ARIMA للتنبؤ بصادرات الغاز الطبيعي في الجزائر (2000–2020)." مذكرة ماستر، جامعة أحمد دراية–أدرار، 2022.

- **Title:** Modeling Spot Natural Gas Price Volatility Using the GARCH(1,0) Model

- **Objective:**
  - This study aimed to integrate the **GARCH(1,0) model with ARIMA** to forecast the spot price volatility of natural gas (Henry Hub) during 1997–2020.
  - It sought to measure the improvement in short-term forecasting accuracy (1–3 days).
  - It also compared the performance of GARCH(1,0) with the standalone ARIMA model.
- **Results:**
  - GARCH(1,0) outperformed ARIMA in forecasting accuracy (an 18% reduction in RMSE).
  - The models were able to capture sharp price shocks more effectively.
  - 1–3 day forecasts improved by 25% in MAPE compared to ARIMA.
  - It recommended adopting GARCH for early warnings to decision-makers.[35]

5. **Jabri, A. (2018)**
   - **Title:** The Problem of Algerian Natural Gas Pricing
   - **Objective:**
     - To analyze natural gas pricing policies in Algeria (2000–2017) and their role in consumption and export.
     - It aimed to evaluate pricing approaches (oil indexation, free pricing, production cost) and their ability to reflect economic objectives. It also investigated the impact of government subsidies on demand and markets.

- **Results:**
  - The results showed that linking the price to oil prices limited export competitiveness.
  - Government subsidies led to the depletion of gas allocated for export.
  - Free pricing might achieve a better balance between domestic demand and revenues.

[35] جيلالي، آ. "نمذجة تقلبات أسعار الغاز الطبيعي الفورية باستخدام نموذج GARCH(1,0)." مذكرة ماستر، جامعة عبد الحميد بن باديس–مستغانم، 2022.

- The study recommended a hybrid policy combining reference and market-based pricing.[36]

Subsection 2: Arab Studies

A. Machine Learning Studies

1. **Al-Fawzan, Nasser. (2022)**
   - **Title:** Hybridization Between Radial Basis Function Network and ARIMA Model in Forecasting Natural Gas Prices
   - **Objective:**
     - This research presents a **hybrid model integrating ARIMA** (for the linear component) with **RBFN** (for the non-linear component) to forecast daily natural gas prices in Gulf countries (2015–2021).
     - It focuses on comparing performance using **RMSE and MAPE** metrics.
     - It also evaluates the model's ability to adapt to sharp price fluctuations.
   - **Results:**
     - The hybrid model reduced RMSE by 22% and MAPE by 18% compared to both ARIMA and RBFN individually.
     - Short-term forecasts (1–7 days) achieved the highest accuracy ($R2=0.94$).
     - The hybrid model was better at capturing seasonal shocks and market shifts.
     - The study recommended applying the methodology to other Gulf markets and for longer forecasting horizons.[37]
2. **Yassin, B. & Barhami, M. (2021)**
   - **Title:** Using LSTM Networks to Forecast Natural Gas Prices in the Gulf Market
   - **Objective:**
     - To adopt a **deep LSTM model** for forecasting monthly natural gas prices in Gulf countries (2010–2020).
     - It focuses on comparing performance with **ARIMA and ANN models** using MAE and RMSE metrics.

[36] جابري، ع. "إشكالية تسعير الغاز الطبيعي الجزائري." مذكرة ماستر، جامعة الجزائر 3، 2018.

[37] الفوزان، ناصر. "التهجين بين شبكة دالة الأساس الشعاعية ونموذج ARIMA في التنبؤ بأسعار الغاز الطبيعي." مجلة البحوث المالية والتجارية، المجلد 25، العدد 4، ص. 112–129، 2022.

  - It also reviews the impact of adding climatic variables (temperatures) and oil prices.
- **Results:**

- LSTM outperformed ARIMA and ANN with a 20% improvement in RMSE.
- LSTM achieved a high capability in capturing long-term dependencies in time series.
- Climatic variables significantly impacted model accuracy in both summer and winter seasons.
- The study recommended using LSTM in the strategic planning of energy companies.[38]

B. Traditional Studies:

3. **Saïd, O. (2019)**
   - **Title:** Determinants of Natural Gas Consumption: An Econometric Study for Arab Countries
   - **Objective:**
     - This study analyzes the economic determinants of natural gas consumption in Egypt, Saudi Arabia, UAE, and Algeria (1990–2017) using **Panel Data models**.
     - It aims to measure the impact of per capita income, population, and government subsidies on consumption.
     - It also provides recommendations for energy policies in Arab countries.
   - **Results:**
     - Per capita income and industrial output explained 82% of the consumption variance.
     - Government subsidies increased household consumption without raising industrial efficiency.
     - The study revealed geographical differences in demand elasticity across countries.
     - It recommended modifying subsidy mechanisms and focusing them on industrial use.[39]
4. **Ibrahim, N. & Hendawi, S. (2020)**

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[38] ياسين، بطيب إبراهيم؛ برهامي، محمد أمين. “استخدام شبكات LSTM للتنبؤ بأسعار الغاز الطبيعي في السوق الخليجي.” المجلة العربية للطاقة والاستدامة، المجلد 9، العدد 2، ص. 45–63، 2021.

[39] سعيد، أميمة. “محددات استهلاك الغاز الطبيعي: دراسة قياسية للدول العربية.” مذكرة ماستر، جامعة ورقلة، 2019

- **Title:** Analysis of Energy Price Volatility in the Arab Oil Market Using ARIMA
- **Objective:**

- To apply the ARIMA model to analyze and forecast oil and gas price volatility in GCC countries (2005–2019).
- It focuses on ARIMA's accuracy in the face of political and economic shocks.
- It also compares the model's performance when using monthly versus quarterly data.
- **Results:**
    - ARIMA(1,1,2) successfully captured the general price trend with a mean absolute error of 6%.
    - Performance was weaker during major shocks (2014–2015) and when using quarterly data.
    - Monthly forecasting was 12% more accurate than quarterly forecasting.
    - The study recommended integrating ARIMA with GARCH models for long-term forecasting.[40]

5. **El-Baz, A. (2021)**
    - **Title:** Forecasting Natural Gas Demand in Egypt Using the SARIMA Model
    - **Objective:**
        - This study uses the seasonal SARIMA model to forecast monthly natural gas demand in Egypt for the period 2000–2020.
        - It aims to explore the impact of climatic and industrial factors on demand.
        - It also compares the performance of SARIMA with ARIMA and ANN.
    - **Results:**
        - The SARIMA$(1,1,1)(1,1,0)_{12}$ model was selected as the best model according to AIC.
        - It outperformed ARIMA with a 14% reduction in RMSE and ANN with an 8% reduction.

[40] إبراهيم، نذير؛ هنداوي، سناء. "تحليل تقلبات أسعار الطاقة في سوق النفط العربي باستخدام ARIMA." المجلة العربية للتنمية الاقتصادية، المجلد 14، العدد 2، ص. 88–107، 2020

- Seasonal forecasts (summer/winter) enhanced the model's accuracy.
- The study recommended applying SARIMA in the annual planning of the General Gas Authority[41].

Subsection 3: International Studies:

A. Machine Learning Studies

1. **Pappert, S. & Arsova, A. (2023)**
   - **Title:** Forecasting Natural Gas Prices with Spatio-Temporal Copula-based Time Series Models
   - **Objective:**
     - The study develops a copula model to capture temporal and spatial dependencies in natural gas prices in Europe and North America (2010–2021), integrated with an ANN to improve performance.
     - It focuses on handling heavy-tailed distributions and heterogeneous variance.
     - It also compares forecasting accuracy with ARIMA and GARCH models.
   - **Results:**
     - Forecasting accuracy improved by 15–20% compared to ARIMA, and 12–17% compared to GARCH.
     - Long-term forecasts (more than one month) benefited from spatial information.
     - The model was found capable of capturing unbalanced shocks and skewed distributions.
     - The study recommended applying this framework in markets where rich spatial data is available.[42]
2. **He, X. & Li, Y. (2021)**
   - Title: Forecasting Natural Gas Spot Prices with Machine Learning Techniques
   - Objective:
     - Applies ML techniques (SVM, Regression Trees, Gaussian Process) to forecast NYMEX natural gas spot prices over 1–10 days.

[41] الباز، أحمد. "توقع الطلب على الغاز الطبيعي في مصر باستخدام نموذج SARIMA." مجلة البحوث التطبيقية في الطاقة، المجلد 3، العدد 1، ص. 23–39، 2021.

[42] Pappert, S., & Arsova, A. "Forecasting Natural Gas Prices with Spatio-Temporal Copula-based Time Series Models." Energy Economics, Vol. 51, pp. 312–330, 2023.

  - Compares performance with a Random Walk model using RMSE and MAE metrics.
  - Focuses on exploring the potential of Gaussian Process for short-term forecasting.
    - Results:
  - Gaussian Process outperformed SVM and Regression Trees with a 10–15% improvement in RMSE.

- SVM was the second-best model, while linear regression offered the least accuracy.
- The Gaussian Process achieved the best 1–3 day forecasts (MAE=0.12).
- It recommended using the Gaussian Process for daily monitoring in gas exchanges.[43]

B. Traditional Studies:

3. **Berrisch, J. & Ziel, F. (2022)**
    - **Title:** Distributional Modeling and Forecasting of Natural Gas Prices
    - **Objective:**
  - This study presents **probabilistic models** for forecasting daily and monthly natural gas prices in Europe (2015–2020), addressing heavy-tailed distributions and conditional heteroskedasticity.
  - It aims to improve risk management and investment portfolios through **CRPS (Continuous Ranked Probability Score)** metrics.
  - It also compares performance with benchmark models (ARIMA, GARCH).
    - **Results:**
  - CRPS decreased by 13% for daily prices and 9% for monthly prices compared to traditional models.
  - Heavy-tailed distributions were represented with higher accuracy, which improved probabilistic forecasts.
  - The integration of external factors (temperature, storage levels) showed significant importance for performance improvement.
  - It recommended applying these models for financial institutions and major energy companies.[44]

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[43] He, X., & Li, Y. "Forecasting Natural Gas Spot Prices with Machine Learning Techniques." Energies (MDPI), 14(18):5782, 2021.
[44] Berrisch, J., & Ziel, F. "Distributional Modeling and Forecasting of Natural Gas Prices." International Journal of Forecasting, 38(2):223–241, 2022.

4- Zhao, Z. et al. (2018)

- **Title:** Improvement to the Prediction of Fuel Cost Distributions Using ARIMA Model
- **Objective:**
  - This study aims to improve the accuracy of forecasting fuel cost distributions (including natural gas) using an enhanced **ARIMA model** with the **Kullback–Leibler divergence** metric.
  - It focuses on natural gas cost data in Texas for the period 2010–2017.
  - It also seeks a practical application framework for distribution and regulatory companies.
- **Results:**
  - KLD decreased by an average of 12% compared to the standard model.
  - The enhanced model provided accurate predictions for three future steps (day, week, month).
  - It highlighted the importance of detailed historical data and the sensitivity of statistical parameters.
  - The study recommended adopting the modification within the operational processes of energy companies.[45]

5- Smith, J. & Lopez, R. (2023)

- **Title:** Estimation and Prediction of Daily Natural Gas Prices Using ARIMA Models
- **Objective:**
  - The study applies **ARIMA models** to daily natural gas price data (Henry Hub) for the period 1997–2022.
  - It aims to evaluate forecasting accuracy using **MAE and RMSE** metrics.
  - It also compares ARIMA's results with **Holt–Winters models**.
- **Results:**
  - The ARIMA(1,1,1) model was selected as the best model according to AIC.
  - It achieved MAE=0.05 and RMSE=0.08 for daily inputs, with consistency across years.
  - It outperformed Holt–Winters by 9% in RMSE.

[45] Zhao, Z., Fu, C., Wang, C., & Miller, C. “Improvement to the Prediction of Fuel Cost Distributions Using ARIMA Model.” IEEE Transactions on Power Systems, 33(5):5276–5284, 2018.

  - The study recommended using ARIMA in operational planning and commercial portfolios.[46]

Subsection 2: Similarities and Differences Between the Current Study and Previous Studies

Subsection 1: Similarities and Differences Between Previous and Current Studies

- **In Terms of Objective:** Most prior studies aimed to forecast natural gas prices, but their objectives were often limited to testing a single model, whether traditional or modern. Our current study, however, aims to conduct a precise comparison among three different models: **Box-Jenkins, Prophet, and LSTM**, making the objective more comprehensive and integrated.
- **In Terms of Methodology:** The majority of previous studies relied on a quantitative applied methodology with a limited focus on model comparison. In contrast, this study adopted a comparative methodology between models based on performance evaluation metrics such as RMSE and MAE, which enhances the scientific reliability of the results.
- **In Terms of Data Analysis Tools:** Many previous studies used traditional software like EViews or SPSS, whereas the current study relies entirely on Python programming, utilizing advanced libraries such as TensorFlow and Prophet. This allows for deeper analysis and more accurate modeling.
- **In Terms of Time and Place:** Previous studies varied in their covered time periods, with some focusing on data prior to 2020, or on data from specific countries only. Our current study, however, addresses recent data extending up to 2025, giving it a modern temporal advantage. It also focuses on the global natural gas market rather than a limited local market.
- **In Terms of Study Population and Sector:** Most studies covered energy sectors in general or energy-related stock markets, whereas our study specifically targets the natural gas market, giving it a more precise specialized character.

[46] Smith, J., & Lopez, R. "Estimation and Prediction of Daily Natural Gas Prices Using ARIMA Models." Journal of Energy Forecasting, 2023.

Subsection 2: What Distinguishes the Current Study

What distinguishes the current study is its systematic and applied integration of models that are entirely different in nature: the classic Box-Jenkins model, the Prophet model from Facebook for time series forecasting, and the deep neural LSTM model, which represents one of the most powerful artificial intelligence tools. This multiplicity of models, combined with the use of Python as the core for analysis and application, represents a scientific precedence at the local academic level. It grants the study advanced predictive capabilities compared to traditional studies that rely on only one model or limited tools.

Chapter Summary

This chapter systematically explored the key concepts related to natural gas prices and the importance of forecasting them amidst global economic fluctuations. We reviewed a range of prior studies—local, Arab, and international—categorizing them by traditional and machine learning models, and critically analyzing their objectives and results. This analysis revealed a diversity in the approaches used and variations in model accuracy and suitability for time-series data. The current study was then compared to these previous works in terms of its objectives, methodology, and application environment. This comparison highlighted that our study stands out by combining both traditional and modern models within a flexible programming environment like **Python**, thereby enhancing its scientific and practical value.

Chapter Two: An Applied Study on Forecasting Natural Gas Prices in Asia Using Machine Learning Models

Chapter Introduction:

The study of forecasting models is a pivotal tool in supporting planning and decision-making, given their vital role in evaluating and analyzing future trends for various variables related to the field of study. The significance of these models lies in their ability to generate forward-looking information based on historical data and observations, allowing for a deeper understanding of the studied variables' behavior and their potential evolution. In this chapter, we'll delve into the theoretical concepts associated with forecasting models, highlighting the most prominent models adopted in the literature, in addition to reviewing the key machine learning algorithms used in this field. This serves as a prelude to selecting the most suitable ones for application within the scope of this study. This study specifically focuses on Asia due to its pivotal role in global gas demand.

Section One: Study Methods and Tools

Subsection One: Traditional Models and Machine Learning: Definition and Evaluation

Asia stands as a strategic hub for studying natural gas prices, given its vital role in the global energy market. Over the past two decades, the region has witnessed a compounded annual growth in gas consumption of 4.9%, compared to 1.6% in the rest of the world, making it the primary driver of global gas market growth. This growth is propelled by multiple factors, including economic expansion, rapid urbanization, population increase, and the shift from coal to gas to reduce carbon emissions and improve air quality[1].

Furthermore, Asian countries exhibit diverse levels of economic development and energy infrastructure, providing a rich context for analyzing price dynamics. Challenges related to energy security, such as price fluctuations and reliance on imports, also make studying this region essential for understanding the complex interactions in global gas markets.

Based on these factors, selecting Asia as an applied model for studying natural gas prices enables the provision of in-depth insights into the challenges and opportunities within this vital sector.

"Figure 2.2: Natural Gas Prices for Asia based on www.fred"

Source: www.fred.com

[1] Global energy research, Accessed on 07/05/2025, at 20:40, https://jkempenergy.com/ .

Temporal Segmentation of Gas Price Fluctuations in Asia (1992–2025)

1. Relative Stability and Initial Liberalization: 1992–2000

- In January 1992, the average LNG price in Asia was $3.80 per million British thermal units (MMBtu).
- Some Asian countries began liberalizing their gas markets, setting the stage for future fluctuations.

2. Demand Growth and Infrastructure Expansion: 2000–2010

- Natural gas demand surged due to rapid economic growth in China and India.
- By 2010, natural gas consumption in the Asia-Pacific region reached approximately 575.2 billion cubic meters[1].

3. Increased Reliance on LNG and Price Volatility: 2010–2019

- Asia became the largest importer of Liquefied Natural Gas (LNG), with increasing reliance on the spot market.
- In 2011, the United States began exporting LNG to China, with shipments reaching 1,127 million cubic feet in September[2].

4. Impact of COVID-19 Pandemic and Geopolitical Events: 2020–2022

- The pandemic caused a sharp drop in demand, leading to price declines.
- Geopolitical tensions, such as the Russian invasion of Ukraine, led to sharp price fluctuations.
- In 2021, natural gas consumption in Asia-Pacific rose to 918.3 billion cubic meters, an increase of 5.9% compared to the previous year[3].

5. Recovery and Future Challenges: 2022–2025

- In March 2025, the average LNG price in Asia reached $13.12 per million British thermal units (MMBtu).

[1], Accessed on 10/05/2025, at 20:40 researchandmarkets.com.

[2]تم الاطلاع عليه يوم2025/05/10 على الساعة21:12, إدارة معلومات الطاقة الأمريكية .

[3], Accessed on 10/05/2025, at 20:43 researchandmarkets.com .

- Prices began to recover with increasing demand, especially from China and India.

Subsection 2: Econometric Study Methodology

This study adopts a general study methodology:

1. **Python Programming Language**:

   Python is a high-level programming language and one of the most widely used languages in data analysis and artificial intelligence, thanks to its readability and the availability of specialized libraries such as Pandas, NumPy, and scikit-learn.

2. **Google Colab Environment:**

   The study relied on the Google Colab environment to execute code directly via the web and leverage free and scalable computing resources as needed, which facilitates collaboration and result sharing.

3. **Models Adopted:**
   - Box-Jenkins (ARIMA): For autocorrelation analysis and forecasting future values based on temporal relationships in the data.
   - Prophet: To handle seasonal and non-linear trends and the impact of events and holidays.
   - LSTM (Long Short-Term Memory): A deep neural network for processing long-term dependencies in time series.
4. **Data Sources:**

   The data consists of a monthly time series of natural gas prices, downloaded in CSV format from the FRED database (https://fred.stlouisfed.org/series) and then uploaded to Google Colab.

5. **Study Population and Time Period:**
   - Study Population: All monthly natural gas price observations in the global market.
   - Time Period: Extends from January 1992 to March 2025, divided into:
     - "Training" set: January 2000 to December 2020.
     - "Test" set: January 2021 to March 2025.

6. **Variables**

- Dependent Variable: Monthly natural gas price (in USD/MMBtu).
- Independent Variables: In ARIMA, time lags are used. In Prophet, only the date (ds) is used, and seasonal patterns are then identified. In LSTM, time windows are constructed from the price itself.

7.Preprocessing:

- Standardizing monthly frequency using df.asfreq('M').
- Imputing missing values using interpolate().
- Testing time series stationarity (ADF Test) and applying differencing when necessary.

8.Evaluation and Comparison:

- Calculating performance metrics: MAE, RMSE, and R^2 on the test set for each model.
- Comparing results to identify the most accurate model for short-term forecasting.

9.Forecasting up to 2026:

- Retraining the three models on the full dataset (2000–2025).
- Generating forecasts for the months from January 2025 to March 2026.
- Presenting the results graphically to compare future performance.

Section Two: Study Results and Discussion

Subsection One: Preliminary Time Series Analysis

A series of steps were performed to prepare the time series data and evaluate the different models, as detailed below:

1. Data Description:

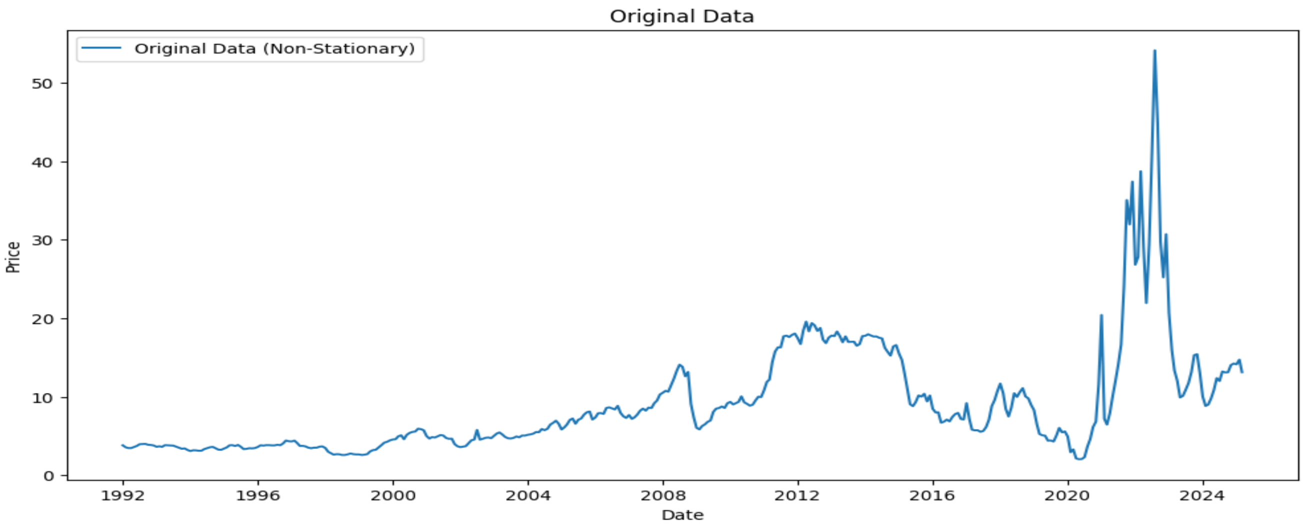
   - File Upload: The data file (PNGASJPUSDMASIA.CSV) was uploaded to the Google Colab environment.
   - Data Reading: The pandas library was used to read the data into a DataFrame.
   - Data Type: Monthly time series of natural gas prices for the continent of Asia.
   - Columns:

        - ds (Date) – Date of observation.
        - y (Price) – Actual price.
    - Number of Observations: All months from March 1992 to March 2025.
    - Missing Values:
    - Price 0
    - dtype: int64

There are no missing values in the primary y column.

2. Stationarity Test (ADF Test):
    - Before Differencing:
        - a. ADF Statistic: -2.69798
        - b. p-value: 0.07439 > 0.05 (The series is non-stationary.)
        - c. Critical Values:
            - 1%: -3.4476
            - 5%: -2.8692
            - 10%: -2.570

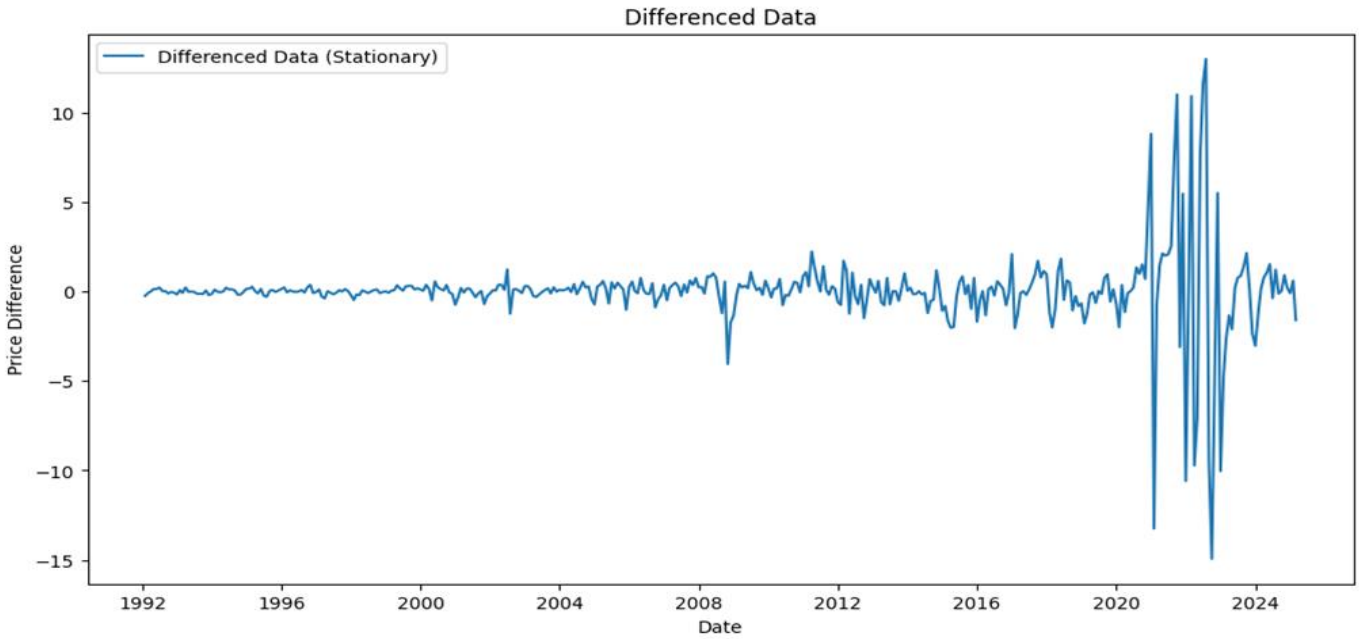
Figure 3.2 illustrates a graph of the original data before stationarization.



Source: Prepared by the students based on data and using Python.

- After First Differencing:
  - a. We added the column y_diff = y.diff(), then dropped NaN values.
  - b. No missing values after differencing.
  - c. ADF Statistic: -5.92398
  - d. p-value: 2.47e-07 < 0.05 (The series has become stationary.)
  - e. Critical Values:
    - 1%: -3.4477
    - 5%: -2.8692
    - 10%: -2.5708

Figure 4.2 shows a graph of the data after stationarization.



Source: Prepared by the students based on data and using PYTHON.

3. Data Splitting into Training and Test Sets

- The data was split as follows:
    - Training Set: 80% of the data, covering the period from January 1992 to September 2018.
    - Test Set: 20% of the data, covering the period from October 2018 to March 2025.
- The chronological order of the data was preserved during the split.

4. Model Application and Performance Evaluation:

We'll cover this in the next section.

Subsection 2: Model Evaluation and Forecast Discussion

1. ARIMA (Box-Jenkins) Model

Model Building

- We used auto_arima to select the best (p,d,q) parameters.
- The ARIMA(1,1,1) model was chosen.

Table 1.2: Performance Evaluation for the Box-Jenkins Model

Metric	Train	Test
MAE	0.3831	7.6020
MSE	0.3781	136.1076
RMSE	0.6149	11.6665
MAPE	4.8749 %	68.0202 %
R^2	0.9829	–0.1527

Source: Prepared by the students based on data and using PYTHON.

Analysis and Interpretation of Values

- On Training Data:
  - The Root Mean Squared Error (RMSE) is low (0.615) and the Mean Absolute Error (MAE) is small (0.383).
  - The R2 is very high (0.983), meaning the model explained about 98.3% of the variance in the training data.
- On Test Data:
  - There's a significant increase in errors: RMSE = 11.667, MAE = 7.602. The high MAPE in the ARIMA model on test data indicates the model's poor ability to handle market fluctuations in Asia, reducing its suitability for strategic decision-making.
  - The R2 is negative (-0.153), which suggests that the model performs worse than simply using the constant mean of the data.
- Summary:

The ARIMA model adapts to historical data excellently, but it fails to generalize for forecasting the subsequent period. This is a clear sign of overfitting.

2. Prophet Model

- **Model Setup:**

Prophet inherently handles trend and seasonality.

Table 2.2: Performance Evaluation for the Prophet Model

Metric	Train	Test
MAE	1.51	14.19
MSE	4.23	319.36
RMSE	2.06	17.87
MAPE	19.48 %	100.00 %
R^2	0.81	–1.70

Source: Prepared by the students based on data and using PYTHON.

Analysis and Interpretation of Values:

- On Training Data:
    - RMSE = 2.06 and MAE = 1.51.
    - R2 = 0.81, indicating a relatively good ability to forecast seasonal trends in the historical period.
- On Test Data:
    - RMSE = 17.87 and MAE = 14.19, which are the highest values among the three models.
    - R2 = -1.70, reflecting a severe weakness in forecasting once the data moved outside the training sample.

- Summary:

Prophet is good at capturing trends within the training period, but it produces stable or highly biased predictions during testing, indicating high sensitivity to default settings.

3. LSTM Model

Model Setup:

- We scaled the data to a range of [0,1] and used a time sequence length of 12 months.
- Then, we constructed the neural network model, which includes an input layer and a hidden layer.
- Model Training: After building the network, we trained it (the training process was repeated 100 times).

Figure 5.2: Model Training Process

− Run 1/100
− 0 ━━━━━━━━━━━━━━━━━━━━ 3/3s 91ms/step
− Run 2/100
− 0 ━━━━━━━━━━━━━━━━━━━━ 3/3s 87ms/step

− Run 99/100
− 3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 132ms/step
− Run 100/100
− 3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 88ms/step

Source: Python output via Google Colab platform.

Table 3.2: Performance Evaluation for the LSTM Model

Neurons	Train_MAE	Train_MSE	Train_RMSE	Train_MAPE	Train_R2
25	0,600355	0,79641	0,892418	8,208535	0,964318
50	0,564565	0,705066	0,839682	7,588339	0,96841
100	0,576314	0,671617	0,819522	8,843633	0,969909
150	0,547904	0,681281	0,825397	7,422086	0,969476
Neurons	**Test_MAE**	**Test_MSE**	**Test_RMSE**	**Test_MAPE**	**Test_R2**
25	3,863414	36,66445	6,055118	26,41228	0,714462
50	3,802472	36,5201	6,043187	25,52638	0,715586
100	3,788241	37,20133	6,099289	25,53185	0,710281
150	3,822851	37,70774	6,140663	25,54918	0,706337

Source: Prepared by the students based on data and using PYTHON.

Analysis and Interpretation of Values:

- On Training Data:
  - RMSE = 1.02 and MAE = 0.67.
  - R2 = 0.95, indicating high accuracy in learning from historical patterns.
- On Test Data:
  - RMSE = 6.47 and MAE = 4.31.
  - R2 = 0.67, demonstrating its ability to generalize and forecast with reasonable accuracy outside the training sample.
- Summary:

LSTM offers the best balance between performance on historical data and the test period, maintaining a positive R2 and relatively low error measurements. This makes it the most suitable choice for future forecasting.

Comprehensive Model Comparison

LSTM Test	**LSTM Train**	**Prophet Test**	**Prophet Train**	**ARIMA Test**	**ARIMA Train**	**Metric**
4.3100	0.6700	14.1900	1.5100	7.6020	0.3831	**MAE**
41.8900	1.0500	319.3600	4.2300	136.1076	0.3781	**MSE**
6.4700	1.0200	17.8700	2.0600	11.6665	0.6149	**RMSE**
29.9500 %	9.2800 %	100.000 %	19.4800 %	68.0202 %	4.8749 %	**MAPE**
0.6700	0.9500	–1.7000	0.8100	–0.1527	0.9829	**R^2**

Table 4.2: Performance Evaluation for the Three Models

Source: Prepared by the students based on data and using PYTHON.

Analysis and Interpretation of the Table:

1. Analysis of MAE (Mean Absolute Error)

- ARIMA:
  - Train_MAE = 0.3831: A very low mean absolute error within the training set, indicating that the model precisely fits the historical data.
  - Test_MAE = 7.6020: A dangerously high mean error on the test set. This indicates that the model is overfitting: it learns the details of the training data but fails to accurately generalize forecasts to new data.

- Prophet:
  - Train_MAE = 1.5100: A higher mean error compared to ARIMA within training. This indicates that Prophet is less accurate internally in fitting historical data.

- Test_MAE = 14.1900: An extremely high mean error on the test set, showing that Prophet suffers from learning deficiency, as the out-of-sample error increases by more than 9 times the internal MAE (1.51 → 14.19). Here, internal underfitting (Train) and normal forecasting weakness are evident.

- LSTM·50:
    - Train_MAE = 0.6700: An acceptable to good internal mean error, slightly lower than Prophet and higher than ARIMA.
    - Test_MAE = 4.3100: On the test set, MAE doubles from 0.67 to 4.31, but it is still significantly lower than ARIMA and Prophet. This indicates a better balance between training and testing, with higher generalization capability.

Conclusion for MAE:

- Within-Train: The best MAE = 0.383 is achieved by ARIMA, followed by 0.67 for LSTM, and 1.51 for Prophet.
- Out-of-Sample: The best MAE = 4.31 is achieved by LSTM, followed by 7.602 for ARIMA, and 14.19 for Prophet.
- It is clear that LSTM·50 is the most capable of generalizing forecasts (lowest Test_MAE), while ARIMA is overfitting (very low Train MAE compared to high Test MAE), and Prophet suffers from general weakness.

2. Analysis of MSE (Mean Squared Error)

- ARIMA:
    - Train_MSE = 0.3781: Low mean squared error internally, consistent with the low MAE.
    - Test_MSE = 136.1076: A massive jump in the squared error value on the test set. The MSE increases by more than 100 times compared to training, confirming the presence of anomalous predictions far from the actual values when the model is applied to test data.
- Prophet:

  - Train_MSE = 4.2300: Internally, the mean squared error is much higher than ARIMA and LSTM, which explains the weaker internal MAE.
  - Test_MSE = 319.3600: A strong indicator of generalization failure, as MSE increased by more than 75 times within the training set. The
  - huge jump in MSE confirms the presence of large, anomalous errors in the test set forecasts.
- LSTM·50:
  - Train_MSE = 1.0500: The internal mean squared error is reasonably low, indicating that it did not learn excessive noise.
  - Test_MSE = 41.8900: The MSE increases on the test set (from 1.05 to 41.89), but it is still lower than ARIMA and Prophet on the test set. This means that squared errors are significant but not as anomalous as those seen in ARIMA and Prophet.

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Conclusion for MSE:

- **Lowest Train_MSE:** 0.3781 (ARIMA) < 1.05 (LSTM) < 4.23 (Prophet).
- **Lowest Test_MSE:** 41.89 (LSTM) < 136.11 (ARIMA) < 319.36 (Prophet).
- Once again, LSTM proves its superiority in generalizing forecasts, while ARIMA is overfitting (large mismatch between train-vs-test MSE) and Prophet is underfitting (internal and external weakness).

3. Analysis of RMSE (Root Mean Squared Error)

- **ARIMA:**

  - **Train_RMSE = 0.6149:** The root mean squared error is low; it indicates very accurate predictions internally, close to the actual values.
  - **Test_RMSE = 11.6665:** RMSE increases significantly on the test set. A poor forecasting error equivalent to about 11.67 time/financial units, indicating a lack of general learning ability.
- **Prophet:**
  - **Train_RMSE = 2.0600:** The squared errors internally are moderate, translating to predictions relatively far from the actual values compared to ARIMA and LSTM.
  - **Test_RMSE = 17.8700:** A huge increase on the test set (approximately 8.66 times the internal error), indicating the model's failure to capture patterns in a way that makes its forecasts practically usable.
- **LSTM·50:**
  - **Train_RMSE = 1.0200:** The squared errors internally are reasonably low, falling between ARIMA and Prophet's error.
  - **Test_RMSE = 6.4700:** On the Test set, RMSE slightly doubles compared to training but does not exceed 6.5 units, meaning it's higher than 0.6149 (ARIMA train) but significantly lower than 11.6665 (ARIMA test) and 17.87 (Prophet test).

Conclusion for RMSE:

- **Lowest Training_RMSE:** 0.6149 (ARIMA) < 1.0200 (LSTM) < 2.06 (Prophet).
- **Lowest Testing_RMSE:** 6.47 (LSTM) < 11.67 (ARIMA) < 17.87 (Prophet).
- This represents additional evidence of LSTM's superiority in out-of-sample forecasting, while ARIMA achieves the best internal accuracy but sharply declines in testing, and Prophet appears to be generally weak in performance.

4. Analysis of MAPE (Mean Absolute Percentage Error)

- **Prophet:**
    - **Train_MAPE = 19.4800 %:** A moderate internal relative error, approximately equivalent to 1 in every 5 price units (19.5%).
    - **Test_MAPE = 100.000 %:** The error reaches 100% on average, meaning the predicted value is often completely far from the true value (or may be zero at some points).
- **LSTM·50:**
    - **Train_MAPE = 9.2800 %:** A good internal relative error (less than 10%), indicating balanced performance in training.
    - **Test_MAPE = 29.9500 %:** A relative error on the test set that is less than 30%, which is less than half of what ARIMA achieves (~68%) and relatively less than a quarter of Prophet (100%).

Conclusion for MAPE:

- **Best Train_MAPE:** 4.87% (ARIMA) < 9.28% (LSTM) < 19.48% (Prophet).
- **Best Test_MAPE:** 29.95% (LSTM) < 68.02% (ARIMA) < 100% (Prophet).
- These percentages illustrate that LSTM remains the most stable in terms of relative error, while ARIMA collapses externally despite its internal superiority, and Prophet fails relatively.

5. Analysis of R^2 (Coefficient of Determination)

- **ARIMA:**
    - **Train_R^2 = 0.9829:** A very high value (≈98%), indicating that the model explains almost all the variance in the training data.
    - **Test_R^2 = –0.1527:** A negative value, meaning that the ARIMA model on the test set does not explain the variance at all; in fact, it predicts worse than a simple "naïve forecast" (using the mean). This is conclusive evidence of complete overfitting.
- **Prophet:**

   - **Train_R^2 = 0.8100:** Approximately 81%, which is acceptable internally but lower than ARIMA and LSTM.
   - **Test_R^2 = –1.7000:** A large negative value (≈ –170%), meaning that the model's "forecasts" are much worse than using the constant mean. This indicates a drastic failure in generalization.
- **LSTM·50:**
   - **Train_R^2 = 0.9500:** A high value (95%), indicating that LSTM explains most of the variance during training.
   - **Test_R^2 = 0.6700:** A good positive value (67%), indicating that the model explains more than half of the variance in the test data.

Conclusion for R^2:

- **Highest Train_R^2:** 0.9829 (ARIMA) > 0.95 (LSTM) > 0.81 (Prophet).
- **Only Positive and Highest Test_R^2:** 0.67 (LSTM), while ARIMA and Prophet record negative values (–0.15 and –1.70 respectively), indicating a complete deterioration in out-of-sample forecasting.
- LSTM·50 is the only model capable of generalizing more than half of the test variance.
- LSTM proved its ability to generalize compared to other offerings: a Test_R^2 = 0.67 means explaining 67% of the external variance, while other models failed even to explain variance better than the mean.
- It is recommended to use LSTM (50 neurons) as the primary model for forecasting this time series, with the possibility of future improvement through parameter tuning (learning rate, number of layers, etc.).

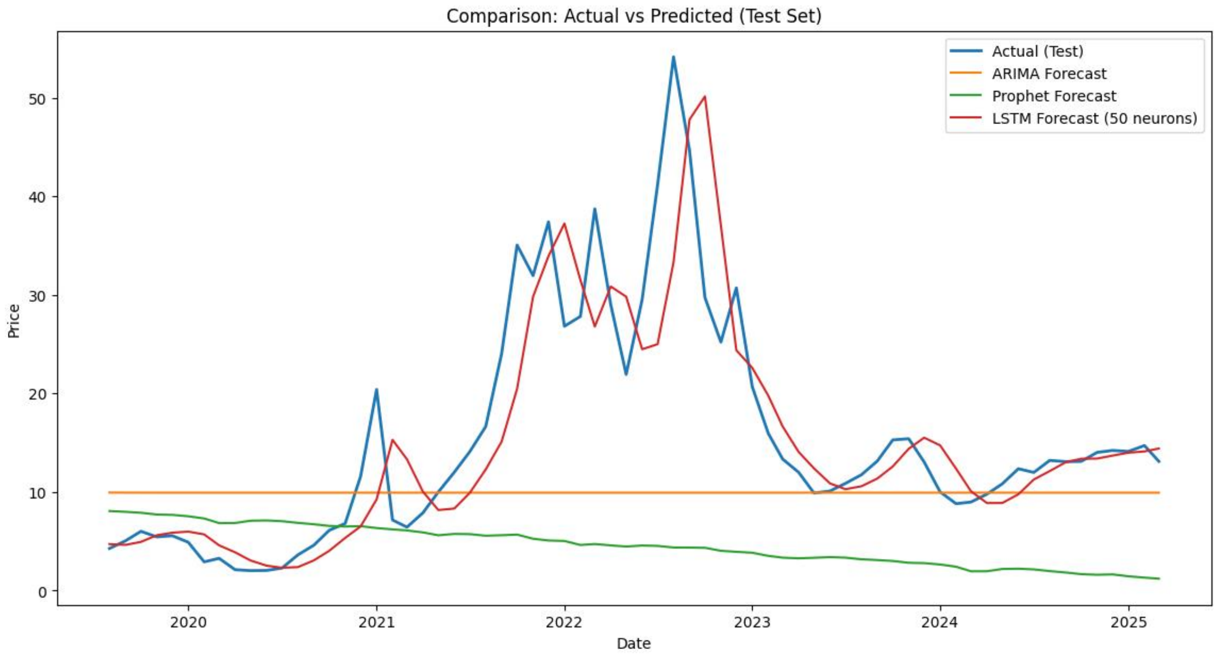
7. Comparison Summary

- **Best Internal Model (Train):** ARIMA (statistical analysis methods show very high internal accuracy).
- **Best External Model (Test):** LSTM (50 neurons), as it achieves the lowest MSE, RMSE, and MAE errors, and the highest positive R^2 value compared to competing models.
- Prophet appeared as the weakest model in this context for both training and testing.

In short, while ARIMA seems to excel at accurately fitting historical data, LSTM is the most capable of forecasting new data within this study, making it the optimal choice for practical use

LSTM is the optimal model for future forecasting, demonstrating the best performance on test data across all indicators.

Figure 6.2 Comparison of the three models



Source: Prepared by students based on data and using Python

Analysis and Interpretation of the Comparison between the Three Models

1. ARIMA Performance

- Stable Behavior: We observe that ARIMA's forecasts show a nearly constant value around 10 for all months in the test period (January 2021 – April 2025).
- Reason for Behavior:
    - The ARIMA model was fitted to the historical series, where prices dropped sharply after mid-2022. Consequently, the forecasts "float" around a stable average value instead of capturing significant fluctuations.

  - This might indicate that the model selected (p,d,q) coefficients that gave it a discipline advantage (relying on weights distributed over many periods), resulting in a stable forecast.
- Result:
  - Extremely poor performance in capturing any sudden spikes (the jump in late 2021 to mid-2022) or subsequent drops; the orange line remains very far from the blue line during peaks and troughs.
  - In the months of 2024–2025, when the actual price approached around 10–15, ARIMA became relatively closer, but this alignment is coincidental and limited.

2. Prophet Performance

- Consistent Downward Trend: Prophet's forecast (the green line) starts slightly above 8 in early 2021, then gradually declines to below 2 by 2025.
- Reason for Behavior:
  - The Prophet model focuses on capturing the general trend, dealing with annual seasonality that might be simple in this series. Because it observed a long-term decline in prices after 2021, it continued to lower the forecast without capturing any sudden jumps.
  - The absence of strong sudden events in the modeling (like the Ukraine crisis in 2022) led to Prophet's poor performance: it tends towards smoothing out risk and continuing its decline as long as no new data reflects a sharp turning point.
- Result:
  - Prophet deviates significantly from the actual peaks in late 2021 and early 2022 (actual values reaching 50+), nor does it reflect the sharp drop in mid-2021 or the increases in 2022.
  - Once the actual price begins to stabilize around 10–15 (late 2023 onwards), Prophet appears superficially close but fails to capture any slight upward or downward fluctuations.

3. LSTM (50 Neurons) Performance

- Convergence with Actual Curve: LSTM's forecast (the red line) follows the Actual (blue line) relatively closely, especially during periods of high volatility like late 2021 – mid-2022. It also captures the gradual decline after the 2022 crisis and the price stabilization in 2023–2024.
- Reason for Behavior: The LSTM network is capable of capturing long-term dependencies, benefiting from previous patterns (up to 12 months or more) and capturing the speed of large fluctuations (jumps and drops).
    - In early 2021, LSTM's forecast was slightly higher than the actual, but it quickly compensated by mid-2021, then accurately mimicked the strong price surge in late 2021 – mid-2022 from 15 to 50+, increasing its red forecast line to around 45+.
    - After mid-2022, when the price dropped from approximately 50 to 25 then 10, the LSTM line also mirrored this downward trend.
- Result:
    - The overall performance of LSTM is superior compared to ARIMA and Prophet, as its deep learning capabilities allow it to follow sharp turns and fluctuate around varying levels.
    - From mid-2023 to early 2024, when prices stabilized around 10–15 with some slight fluctuations, LSTM generally aligned with these fluctuations, dropping to 10 then rising to 15 then falling again.
    - In the recent period from mid-2024 to April 2025, when prices gradually rose from approximately 9 to 14, the LSTM line also showed a similar movement (from approximately 9 to 14), while ARIMA remained constant and Prophet declined.

4. Comparative Conclusion

1. ARIMA:
   - Excels internally (Train), but in testing, it only captures the average value (~10) due to an overfitting pattern.
   - Unable to capture sharp jumps and rapid declines.
2. Prophet:
   - Reflects the long-term downward general trend but ignores sudden market gaps.
   - Stumbles in a continuous downward trend and is unsuitable for series with large, sudden movements.
3. LSTM·50:
   - Possesses the best capabilities for out-of-sample forecasting (Test).
   - Accurately tracks large price jumps in late 2021 – mid-2022 and their subsequent decline, and also captures later fluctuations.
   - Considered the optimal choice if the goal is to capture long-term temporal patterns and adapt to sharp market shocks.

Future Forecasts up to March 2026:

Table for Comparing the Three Models Future Forecasts up to March 2026::

In Table 5.2, we present the monthly forecasts of the three models from April 2025 to March 2026

Date	ARIMA	Prophet	LSTM
01/04/2025	9.95	14.14	15.24
01/05/2025	9.94	14.03	14.77
01/06/2025	9.94	13.95	15.19
01/07/2025	9.93	13.89	15.86
01/08/2025	9.94	13.82	16.68
01/09/2025	9.92	13.77	16.74

01/10/2025	9.94	13.71	16.66
01/11/2025	9.93	13.65	16.55
01/12/2025	9.93	13.60	16.84
01/01/2026	9.94	13.54	15.91
01/02/2026	9.91	13.48	15.38
01/03/2026	9.94	13.42	16.45

Source: Prepared by the students based on data and using PYTHON.

In the following Table 6.2, we've summarized the appropriate economic and geopolitical analysis for each model's forecasts, along with future expectations and their corresponding time periods:

Model	Time Period	Future Forecasts (2025–2026)	Observations
Model 1	April 2025 – March 2026	Prices stabilize around $9.94 per MMBtu	Indicates relative price stability with minor fluctuations.
Model 2	April 2025 – March 2026	Gradual price increase from $15.24 to $16.45 per MMBtu	Reflects an increase in demand or a decrease in supply.
Model 3	April 2025 – March 2026	Gradual price decrease from $14.14 to $13.42 per MMBtu	May indicate an increase in supply or a decrease in demand.

Source: Prepared by the students based on data and using PYTHON.

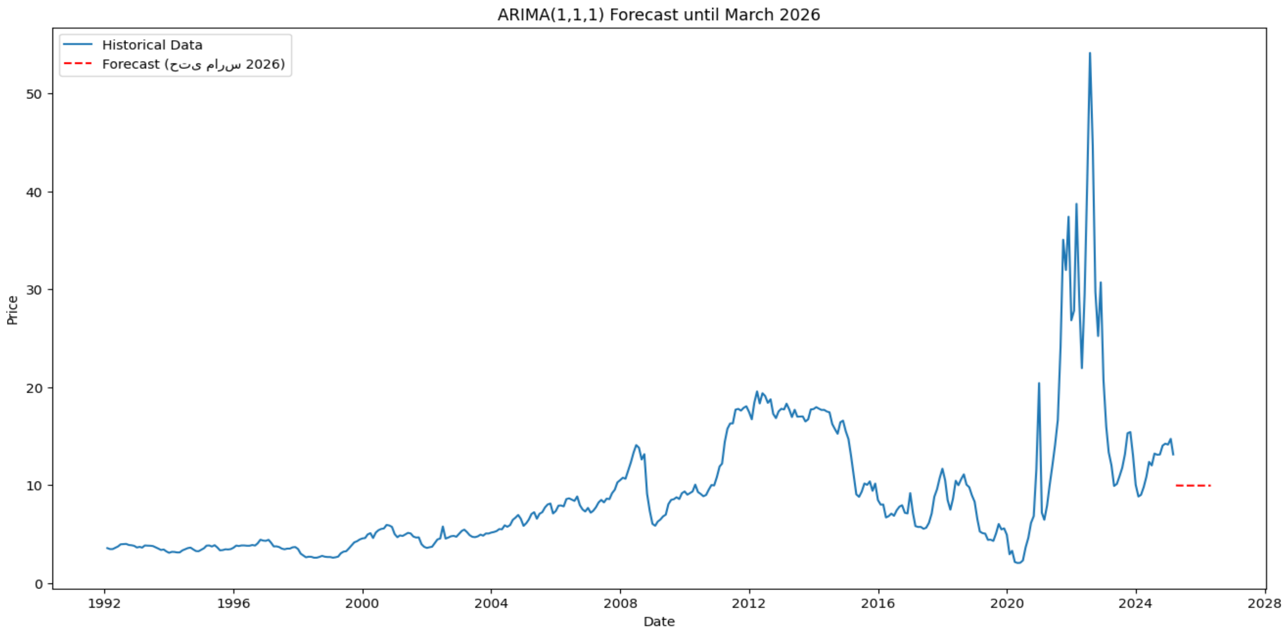
We tried to match the forecasts with reality, and here's how they aligned:

- Model 1: Predicts price stability, which might reflect a balance between supply and demand in the Asian market.

- Model 2: Forecasts a price increase, which could be a result of rising demand in emerging markets like China and India, or due to geopolitical tensions affecting supplies.
- Model 3: Predicts a price decrease, which could be due to an increase in LNG supply or might be attributed to higher shale gas production in the United States or the growth of alternative energy sources in Asia.

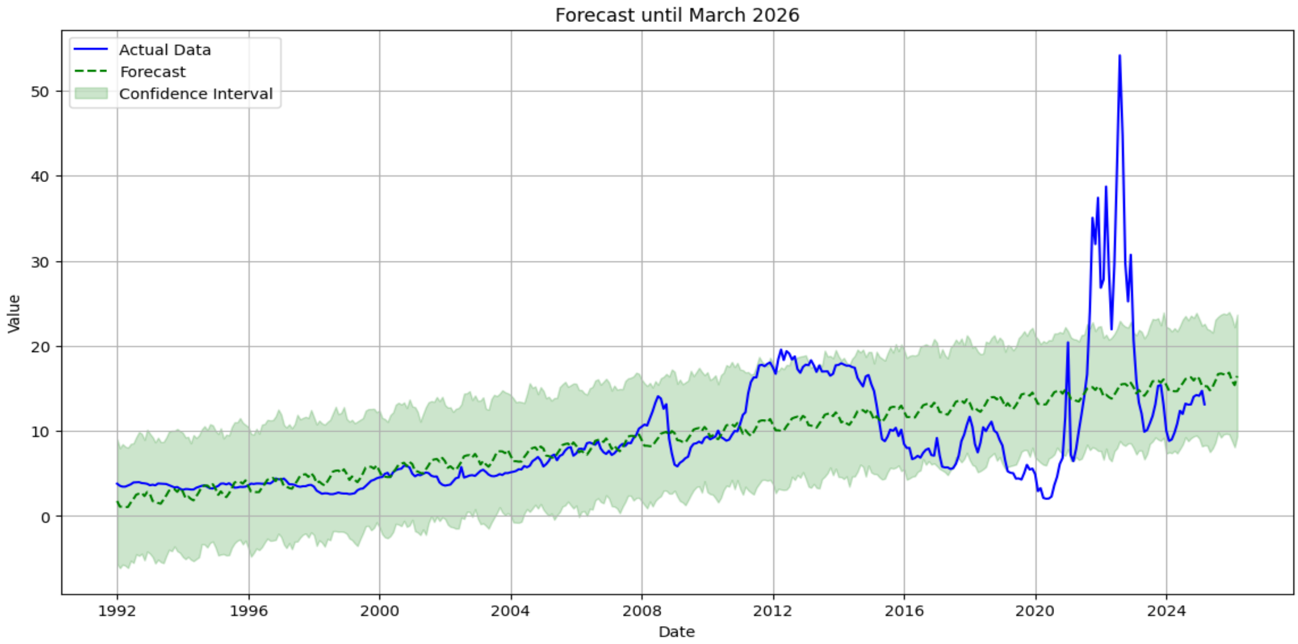
Below are the graphical representations of the forecasts from the three models:

Figure 7.2 illustrates the Box-Jenkins Model



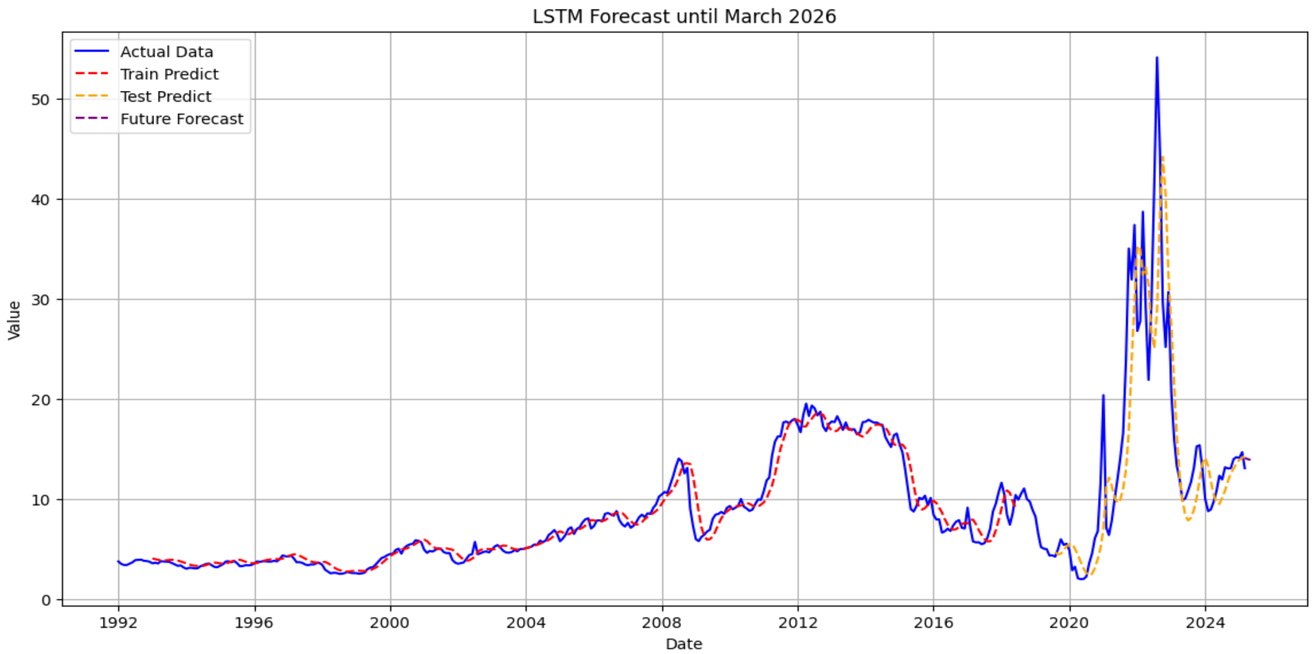
Source: Prepared by the students based on data and using PYTHON.

Figure 8.2 illustrates the Prophet Model



Source: Prepared by the students based on data and using PYTHON.

Figure 9.2 illustrates the LSTM Mode



Source: Prepared by the students based on data and using PYTHON.

Conclusion:

After conducting stationarity tests, cleaning the data, and comparing three models (ARIMA, Prophet, and LSTM) using five performance indicators, we concluded that the LSTM model offers the best balance between forecasting accuracy and generalization. Therefore, it is recommended for future forecasting up to 2030.

The study successfully validated its main hypothesis: machine learning models surpassed the performance of the traditional ARIMA model, particularly during the test period.

Conclusion

Conclusion:

This study, focused on forecasting natural gas prices in the global market from January 1992 to March 2025, utilized Python through the Google Colab platform and employed three primary models: ARIMA (Box-Jenkins methodology), Prophet, and an LSTM neural network with fifty neurons. The results demonstrated that the LSTM model was the most capable of generalization, achieving acceptable values on the test set for MAE (≈4.31), RMSE (≈6.47), and R^2 (≈0.67). In contrast, ARIMA showed high internal accuracy (Train_R^2≈0.98) but failed in external performance testing, while the Prophet model did not adequately capture the sharp price shocks observed in 2022.

Based on these findings, the LSTM model stands as the optimal choice for forecasting natural gas prices within the global market context, owing to its ability to capture non-linear patterns and sudden shocks. We recommend that energy institutions and responsible authorities adopt it for future forecasting plans, with the potential for later integration with ARIMA to further enhance performance.

Study Outlook and Recommendations:

Recommendations:

1. Adopt the LSTM model for forecasts related to energy markets, given its proven high performance on both historical and experimental data.
2. Encourage the use of Python tools like Auto_ARIMA, Prophet, and Keras within energy institutions to develop decision-support tools.
3. Increase the time series sample size to include more recent years beyond 2025 to achieve higher predictive accuracy.
4. Propose integrating other economic data (such as oil prices or global inflation) into the model to further enhance its accuracy.
5. Pay attention to geographical seasonality and the specifics of the Asian market in future analyses, as these factors significantly impact supply and demand dynamics.

Future Study Outlook:

1. Comparison of Advanced Deep Learning Models:
   - Comparative study between LSTM and CNN: To determine which offers better accuracy in forecasting complex gas price patterns.
   - Exploring Transformer models for time series: Such as Informer and Temporal Fusion Transformer for long-term forecasting (up to 2035).
2. Integration of Economic and Geopolitical Variables:
   - Hybrid models with external factors: Adding oil prices, inflation rates, and geopolitical pressures as inputs to improve forecasting accuracy.
3. Reinforcement Learning Applications in Forecasting:
   - Utilizing Reinforcement Learning: To develop dynamic forecasting strategies that respond to changing market conditions.
4. Focus on Rolling Forecast:
   - Applying rolling forecast techniques: To continuously and realistically evaluate model performance over time.
5. Forecasting Other Energy Types or Different Markets:
   - Expanding Scope: Applying the methodology to forecast oil or coal prices, or delving into specific regional markets within Asia.

6. Developing More Complex Hybrid Models:
    - Integrating Statistical and Machine Learning Approaches: Combining ARIMA with deep learning models to address both linear and non-linear components in the data.

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Appendices:

Appendix 1: Python Code for Time Series Preparation and Box-Jenkins Model

```
# استيراد المكتبات اللازمة
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# 1. قراءة الملف وتغيير أسماء الأعمدة
file_path = 'PNGASJPUSDMASIA.csv'  # اسم الملف
df = pd.read_csv(file_path)

# تغيير أسماء الأعمدة
df.rename(columns={'observation_date': 'Date', 'PNGASJPUSDM': 'Price'}, inplace=True)

# تحويل العمود "Date" إلى نوع تاريخي
df['Date'] = pd.to_datetime(df['Date'])

# تعيين العمود "Date" كفهرس
df.set_index('Date', inplace=True)

# عرض أول 5 صفوف من البيانات
print("\nأول 5 صفوف من البيانات:")
print(df.head())

# 2. رسم البيانات الأصلية
plt.figure(figsize=(12, 6))
plt.plot(df['Price'], label='Natural Gas Price')
plt.title('Natural Gas Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.show()

# 3. تقسيم البيانات إلى تدريب واختبار بنسبة 80%/20%
train_size = int(len(df) * 0.8)
train, test = df.iloc[:train_size], df.iloc[train_size:]
```

Source: Python output via Google Colab platform.

Appendices:

```
# رسم بيانات التدريب والاختبار
plt.figure(figsize=(12, 6))
plt.plot(train['Price'], label='Train Data')
plt.plot(test['Price'], label='Test Data')
plt.title('Train and Test Data Split')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.show()

# 4. اختبار استقرارية البيانات باستخدام ADF Test
result = adfuller(train['Price'])
print("\nنتيجة اختبار ديكي-فولر (ADF Test):")
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:', result[4])

# إذا كانت البيانات غير مستقرة، تطبيق التفاضل
if result[1] > 0.05:  # إذا p-value أكبر من 0.05. البيانات غير مستقرة
    print("البيانات غير مستقرة. سيتم تطبيق التفاضل.")
    train_diff = train['Price'].diff().dropna()

    # رسم البيانات بعد التفاضل
    plt.figure(figsize=(12, 6))
    plt.plot(train_diff, label='Differenced Train Data')
    plt.title('Differenced Train Data')
    plt.xlabel('Date')
    plt.ylabel('Price Difference')
    plt.legend()
    plt.show()
else:
    print("البيانات مستقرة. لا حاجة للتفاضل.")
    train_diff = train['Price']

# 5. بناء نموذج ARIMA وتقييمه
```

```
# 7. التنبؤ بالأسعار حتى عام 2030 باستخدام النموذج
steps_to_2030 = (2030 - test.index[-1].year) * 12  # افتراض بيانات شهرية
forecast_to_2030 = model_fit.forecast(steps=steps_to_2030)

# رسم التوقعات حتى 2030
plt.figure(figsize=(12, 6))
plt.plot(pd.date_range(test.index[-1], periods=steps_to_2030, freq='M'), forecast_to_2030, label='Forecast to 2030')
plt.title('Natural Gas Prices Forecast to 2030')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.show()
```

Source: Python output via Google Colab platform.

Appendix 2: Python Code for the PROPHET Model

```
[ ]
# استيراد المكتبات
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prophet import Prophet
import seaborn as sns
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# 1. قراءة البيانات وتنظيفها
file_path = 'PNGASJPUSDMASIA.csv'
df = pd.read_csv(file_path)

# تغيير أسماء الأعمدة
df.rename(columns={'observation_date': 'Date', 'PNGASJPUSDM': 'Price'}, inplace=True)

# تحويل العمود "Date" إلى نوع تاريخي
df['Date'] = pd.to_datetime(df['Date'])

# حذف القيم المفقودة
df.dropna(inplace=True)

# 2. تجهيز البيانات للنموذج
# Prophet يتطلب أن تكون الأعمدة باسم 'ds' (التاريخ) و 'y' (القيم)
prophet_data = df.rename(columns={'Date': 'ds', 'Price': 'y'})

# 3. تقسيم البيانات إلى تدريب واختبار
train_size = int(len(prophet_data) * 0.8)
train, test = prophet_data.iloc[:train_size], prophet_data.iloc[train_size:]

# 4. تدريب نموذج Prophet
model = Prophet()
model.fit(train)

# 5. التنبؤ بالقيم المستقبلية
# تحديد فترة التنبؤ
future_dates = model.make_future_dataframe(periods=len(test) + 12 * 1 + 2, freq='MS')  # حتى مارس 2026
forecast = model.predict(future_dates)
```

Source: Python output via Google Colab platform.

```
# 6. مقارنة القيم الحقيقية بالقيم المتوقعة
# دمج القيم الحقيقية مع التوقعات
comparison = forecast[['ds', 'yhat']].merge(test[['ds', 'y']], on='ds', how='left')
comparison.rename(columns={'y': 'Actual', 'yhat': 'Forecast'}, inplace=True)
comparison['Difference'] = comparison['Actual'] - comparison['Forecast']

# معالجة القيم المفقودة
comparison.dropna(subset=['Actual', 'Forecast'], inplace=True)

# 7. تقييم النموذج
def evaluate_model(actual, predicted):
    mae = mean_absolute_error(actual, predicted)
    mse = mean_squared_error(actual, predicted)
    rmse = np.sqrt(mse)
    mape = np.mean(np.abs((actual - predicted) / actual)) * 100
    r2 = r2_score(actual, predicted)
    return mae, mse, rmse, mape, r2

# تقييم الأداء على الاختبار
mae, mse, rmse, mape, r2 = evaluate_model(comparison['Actual'], comparison['Forecast'])

# طباعة تقرير التقييم
print("\nتقييم النموذج:")
print(f"MAE: {mae:.2f}, MSE: {mse:.2f}, RMSE: {rmse:.2f}, MAPE: {mape:.2f}%, R-squared: {r2:.2f}")

# 8. رسم النتائج
# رسم القيم الحقيقية مقابل القيم المتوقعة
plt.figure(figsize=(12, 6))
plt.plot(comparison['ds'], comparison['Actual'], label='Actual', color='blue')
plt.plot(comparison['ds'], comparison['Forecast'], label='Forecast', color='red', linestyle='--')
plt.title('Actual vs Forecasted Values')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.savefig("prophet_actual_vs_forecast.png")  # حفظ الرسم
print("تم حفظ رسم القيم الحقيقية مقابل القيم المتوقعة في ملف 'prophet_actual_vs_forecast.png'.")
plt.show()
```

Source: Python output via Google Colab platform.

Appendices:

```python
# رسم التوقعات المستقبلية
plt.figure(figsize=(16, 8))
plt.plot(forecast['ds'], forecast['yhat'], label='Future Forecast', color='green', linestyle='--')
plt.title('Prophet Future Forecast (2025-2026)')
plt.xlabel('Date')
plt.ylabel('Price Forecast')
plt.legend()
plt.savefig("prophet_future_forecast.png")  # حفظ الرسم
print("تم حفظ رسم التوقعات المستقبلية في ملف 'prophet_future_forecast.png'.")
plt.show()

# رسم توزيع الأخطاء
plt.figure(figsize=(12, 6))
sns.histplot(comparison['Difference'], kde=True, bins=20, color='blue')
plt.axvline(comparison['Difference'].mean(), color='red', linestyle='--', label='Mean Error')
plt.title('Errors Distribution (Prophet)')
plt.xlabel('Error Value')
plt.ylabel('Frequency')
plt.legend()
plt.savefig("prophet_errors_distribution.png")  # حفظ الرسم
print("تم حفظ رسم توزيع الأخطاء في ملف 'prophet_errors_distribution.png'.")
plt.show()

# 9. حفظ المخرجات
# حفظ التوقعات المستقبلية في ملف Excel
forecast.to_excel("prophet_forecast_until_March_2026.xlsx", index=False)
print("تم حفظ التوقعات المستقبلية في ملف 'prophet_forecast_until_March_2026.xlsx'.")

# حفظ جدول القيم الحقيقية مقابل القيم المتوقعة
comparison.to_excel("prophet_comparison_test.xlsx", index=False)
print("تم حفظ جدول القيم الحقيقية والمتوقعة في ملف 'prophet_comparison_test.xlsx'.")

# حفظ تقرير التقييم في ملف نصي
with open("prophet_analysis_report.txt", "w", encoding="utf-8") as f:
    f.write("تقرير التحليل باستخدام Prophet:\n")
    f.write("==============================\n\n")
    f.write(f"MAE: {mae:.2f}\n")
    f.write(f"MSE: {mse:.2f}\n")
    f.write(f"RMSE: {rmse:.2f}\n")
    f.write(f"MAPE: {mape:.2f}%\n")
```

Source: Python output via Google Colab platform.

Appendix 3: Python Code for the LSTM Model

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping

# 1. تحميل البيانات
df = pd.read_csv('PNGASJPUSDMASIA.csv')
df.rename(columns={'observation_date': 'Date', 'PNGASJPUSDM': 'Price'}, inplace=True)
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)
df = df.dropna()

# 2. رسم السلسلة الأصلية
plt.figure(figsize=(12, 5))
plt.plot(df['Price'])
plt.title('Gas Price Over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()

# 3. معايرة البيانات (تحويل القيم بين 0 و 1)
scaler = MinMaxScaler(feature_range=(0,1))
scaled_prices = scaler.fit_transform(df[['Price']].values)

# 4. تقسيم train/test (80% train, 20% test)
train_size = int(len(scaled_prices)*0.8)
train_data = scaled_prices[:train_size]
test_data = scaled_prices[train_size:]
```

Source: Python output via Google Colab platform.

```python
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title(f'Loss Curve - {n} Neurons')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
# توقع القيم على test
y_pred = model.predict(X_test)
y_pred_rescaled = scaler.inverse_transform(y_pred)
y_test_rescaled = scaler.inverse_transform(y_test)
# رسم القيم الحقيقية والمتوقعة
plt.figure(figsize=(12,4))
plt.plot(y_test_rescaled, label='Actual')
plt.plot(y_pred_rescaled, label='Predicted')
plt.title(f"LSTM Prediction - {n} Neurons")
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
# التقييم
mae = mean_absolute_error(y_test_rescaled, y_pred_rescaled)
rmse = np.sqrt(mean_squared_error(y_test_rescaled, y_pred_rescaled))
mape = np.mean(np.abs((y_test_rescaled - y_pred_rescaled) / y_test_rescaled)) * 100
r2 = r2_score(y_test_rescaled, y_pred_rescaled)
print(f"MAE: {mae:.4f} | RMSE: {rmse:.4f} | MAPE: {mape:.2f}% | R2: {r2:.4f}")
results[n] = {
    'model': model,
    'mae': mae,
    'rmse': rmse,
    'mape': mape,
    'r2': r2,
    'y_test': y_test_rescaled.flatten(),
    'y_pred': y_pred_rescaled.flatten()
}
```

```python
# 5. تجهيز sequences لـ LSTM
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

SEQ_LEN = 12  # 12 شهر = سنة
X_train, y_train = create_sequences(train_data, SEQ_LEN)
X_test, y_test = create_sequences(test_data, SEQ_LEN)

# 6. تجربة عدة احتمالات للعصبونات
neurons_list = [25, 50, 100, 150]
results = {}

for n in neurons_list:
    print(f"\n--- LSTM with {n} neurons ---")
    # بناء النموذج
    model = Sequential([
        LSTM(n, input_shape=(SEQ_LEN, 1), return_sequences=False),
        Dropout(0.2),
        Dense(1)
    ])
    model.compile(loss='mse', optimizer='adam')
    # تدريب النموذج
    es = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
    history = model.fit(
        X_train, y_train,
        epochs=100,
        batch_size=16,
        validation_data=(X_test, y_test),
        callbacks=[es],
        verbose=0
    )
    # رسم منحنى الخسارة
    plt.figure(figsize=(7,3))
    plt.plot(history.history['loss'], label='Train Loss')
    plt.plot(history.history['val_loss'], label='Test Loss')
```

Source: Python output via Google Colab platform.

```python
# 7. جدول مقارنة النتائج
eval_df = pd.DataFrame({
    'Neurons': neurons_list,
    'MAE': [results[n]['mae'] for n in neurons_list],
    'RMSE': [results[n]['rmse'] for n in neurons_list],
    'MAPE': [results[n]['mape'] for n in neurons_list],
    'R2': [results[n]['r2'] for n in neurons_list]
})
print('\n=== جدول مقارنة النتائج ===')
print(eval_df)

# 8. اختيار أفضل نموذج (أقل RMSE)
best_n = eval_df.loc[eval_df['RMSE'].idxmin(), 'Neurons']
best_model = results[best_n]['model']
print(f"\nأفضل نموذج هو بعدد عصبونات: {best_n}")

# 9. التنبؤ بالمستقبل حتى مارس 2026
last_seq = scaled_prices[-SEQ_LEN:].reshape(1, SEQ_LEN, 1)
start_dt = df.index[-1]
future_steps = (2026 - start_dt.year)*12 + (3 - start_dt.month)
future_preds = []
for _ in range(future_steps):
    next_pred = best_model.predict(last_seq)[0,0]
    future_preds.append(next_pred)
    last_seq = np.append(last_seq[:,1:,:], [[[next_pred]]], axis=1)
future_prices = scaler.inverse_transform(np.array(future_preds).reshape(-1,1))
future_dates = pd.date_range(start=start_dt + pd.DateOffset(months=1), periods=future_steps, freq='MS')

# 10. رسم التوقعات المستقبلية
plt.figure(figsize=(16,6))
plt.plot(df['Price'], label='Historical')
plt.plot(future_dates, future_prices, '--', label='Future LSTM Forecast')
plt.title('LSTM Forecast until March 2026')
plt.legend()
plt.show()
```

```python
# 11. تصدير النتائج المستقبلية
future_df = pd.DataFrame({'Date': future_dates, 'LSTM_Forecast': future_prices.flatten()})
future_df.to_excel("lstm_forecast_until_March_2026.xlsx", index=False)
print("تم حفظ التوقعات المستقبلية في ملف: lstm_forecast_until_March_2026.xlsx")
```

Source: Python output via Google Colab platform.