

**PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA  
MINISTRY OF HIGHER EDUCATION AND  
SCIENTIFIC RESEARCH**

**ECOLE SUPERIEURE DE COMMERCE**

End-of-cycle dissertation for the purpose of obtaining a Master's  
Degree in Financial Sciences and Accounting

**Major :** Corporate Finance

**Topic :**

**Forecasting exchange rate volatility of the  
Algerian Dinar : a comparison of Classical  
Time Series and Deep Learning models**

**Submitted by:**

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**Location of the internship:** SOCIETE GENERALE ALGERIE

**Duration of the internship:** From 17-02-2025 to 12-05-2025

Academic year 2024-2025



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# *Dedication*

**To my father,** my source of strength, wisdom, and endless encouragement have shaped me in ways words cannot fully express. You taught me the value of perseverance and hard work. Your belief in me, standing by my side and given me the necessary courage, and for that, I am forever grateful.

**To my mother,** your love, patience, and unwavering belief in me have been my greatest comfort. Your kindness and resilience inspire me every day. I thought this journey, I will never be able to thank you enough.

**To my sister and brother,** my lifelong companions and confidants, your laughter, support, and shared memories have made every challenge easier to bear. I am blessed to have you by my side.

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# *Dedication*

To **my parents**, the two extraordinary souls who have been my guiding light, a constant source of joy and courage, and the dearest individuals in my life. Your prayers , sacrifices, and unwavering faith in Allah's plan have been my armor, shielding me from life's challenges and leading me to success. I devote this accomplishment and every joy and achievement in my life to you, today and always. May Allah bless you with health, happiness, and the highest ranks of Jannah.

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## List of abbreviations

| Acronym        | Designation                                                                         |
|----------------|-------------------------------------------------------------------------------------|
| <b>APPP</b>    | Absolute Purchasing Power Parity                                                    |
| <b>BIC</b>     | Bayesian Information Criterion                                                      |
| <b>BRICS</b>   | Brazil, Russia, India, China, South Africa (economic bloc)                          |
| <b>CIP</b>     | Covered Interest Rate Parity                                                        |
| <b>CMC</b>     | Currency Market Committee (or sometimes Commodity Money Credit)                     |
| <b>CNN</b>     | Convolutional Neural Networks                                                       |
| <b>CPI</b>     | Consumer Price Index                                                                |
| <b>CT</b>      | Currency Trading                                                                    |
| <b>DZD</b>     | Algerian Dinar (ISO currency code)                                                  |
| <b>EUR</b>     | Euro (ISO currency code)                                                            |
| <b>Fed</b>     | Federal Reserve (US central bank)                                                   |
| <b>FDI</b>     | Foreign Direct Investment                                                           |
| <b>FRF</b>     | French Franc (former currency, replaced by the Euro)                                |
| <b>FX</b>      | Foreign Exchange                                                                    |
| <b>FXVIXs</b>  | Foreign Exchange Volatility Indices (collection of currency VIX-like measures)      |
| <b>GBP</b>     | British Pound Sterling (ISO currency code)                                          |
| <b>GDP</b>     | Gross Domestic Product                                                              |
| <b>IFE</b>     | International Fisher Effect                                                         |
| <b>IMF</b>     | International Monetary Fund                                                         |
| <b>IQR</b>     | Interquartile Range (statistics)                                                    |
| <b>LSTM</b>    | Long Short-Term Memory (a type of recurrent neural network)                         |
| <b>MA</b>      | Moving Average                                                                      |
| <b>MNCs</b>    | Multinational Corporations                                                          |
| <b>NASDAQ</b>  | National Association of Securities Dealers Automated Quotations (US stock exchange) |
| <b>NEER</b>    | Nominal Effective Exchange Rate                                                     |
| <b>NER</b>     | Nominal Exchange Rate                                                               |
| <b>NIST</b>    | National Institute of Standards and Technology (US)                                 |
| <b>NYSE</b>    | New York Stock Exchange                                                             |
| <b>OTC</b>     | Over-The-Counter (financial markets)                                                |
| <b>PPP</b>     | Purchasing Power Parity                                                             |
| <b>QE</b>      | Quantitative Easing                                                                 |
| <b>REER</b>    | Real Effective Exchange Rate                                                        |
| <b>ReLU</b>    | Rectified Linear Unit (neural networks activation function)                         |
| <b>RER</b>     | Real Exchange Rate                                                                  |
| <b>RMSprop</b> | Root Mean Square Propagation (optimization algorithm in deep learning)              |
| <b>RPPP</b>    | Relative Purchasing Power Parity                                                    |
| <b>SARIMAX</b> | Seasonal AutoRegressive Integrated Moving Average with eXogenous factors            |
| <b>SDRs</b>    | Special Drawing Rights (IMF reserve asset)                                          |

|            |                                                                             |
|------------|-----------------------------------------------------------------------------|
| <b>SGA</b> | Société Générale Algérie                                                    |
| <b>SGD</b> | Stochastic Gradient Descent (optimization method)                           |
| <b>UIP</b> | Uncovered Interest Rate Parity                                              |
| <b>USD</b> | United States Dollar (ISO currency code)                                    |
| <b>VIX</b> | Volatility Index (Chicago Board Options Exchange's market volatility gauge) |

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## Abstract

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This research investigates the forecasting of exchange rate volatility for USD/DZD and EUR/DZD, comparing classical time series models (SARIMA, SARIMAX) with Deep Learning models (CNN, LSTM) using daily data from January 5, 1999, to February 28, 2025 (6,824 observations). In Algeria's hydrocarbon-reliant economy, precise volatility forecasts are essential for economic decision making, as exchange rate fluctuations significantly affect trade, investment decisions, and monetary policies. The study seeks to determine which approach classical or deep learning better captures the intricate dynamics of exchange rate volatility, a critical measure of market risk in an emerging market context. The analysis reveals that, when predicting in an all at once perspective, classical model failed to capture long-term patterns and trends. While using the rolling forecast on the classical models, ARIMAX consistently outperforms other models. This method demonstrates greater adaptability to shifting market conditions, effectively capturing trends and fluctuations in exchange rates, resulting in lower error metrics compared to other models the rolling forecast techniques allows the models to enhance its predictive accuracy for both currency pairs. Among deep learning models, LSTM surpasses CNN, showing a stronger ability to model long-term dependencies and complex patterns in sequential data. Despite this, LSTM still falls short closely behind of the classical ARIMAX rolling forecast approach, indicating that adaptive classical techniques offer more reliability for this specific dataset. Finally, the volatility is visualized by directly deriving it from USD/DZD and EUR/DZD prices, highlighting the chosen model performance and flexibility in achieving accurate forecasts. The findings emphasize that while Deep Learning models excel in capturing nonlinear dynamics, classical models with adaptive forecasting methods provide a more robust solution in this context.

**Keywords:** Forecasting foreign exchange rate volatility, Classical Time Series models (SARIMAX), Deep Learning models (CNN, LSTM), Rolling forecast, Algerian Dinar.

## ملخص

تتناول هذه الدراسة التنبؤ بتقلبات سعر الصرف لزوجي الدولار الأمريكي/الدينار الجزائري (USD/DZD) واليورو/الدينار الجزائري (EUR/DZD)، حيث تقارن بين نماذج السلاسل الزمنية الكلاسيكية (SARIMA و SARIMAX) ونماذج التعلم العميق (CNN و LSTM) باستخدام بيانات يومية تغطي الفترة من 5 جانفي 1999 إلى 28 فيفري 2025 (6824 ملاحظة). ضمن اقتصاد جزائري معتمد على المحروقات، تُعد التنبؤات للتقلبات في سعر الصرف ضرورية لصنع القرارات الاقتصادية، حيث تؤثر تقلبات أسعار الصرف بشكل كبير على التجارة وقرارات الاستثمار والسياسات النقدية. وتهدف الدراسة إلى تحديد أي النهجين، الكلاسيكي أو التعلم العميق، يقوم بالنقاط ديناميكية تقلبات سعر الصرف بشكل أفضل، باعتبارها مقياساً حاسماً لمخاطر السوق في سياق الاقتصاد الناشئ. كشفت التحليلات أنه عند التنبؤ بطريقة "الكل دفعة واحدة"، فشلت النماذج الكلاسيكية في التقاط الأنماط والاتجاهات طويلة الأجل. في المقابل، عند استخدام أسلوب "التنبؤ المتداول" (Rolling Forecast) على النماذج الكلاسيكية، تفوق نموذج ARIMAX على النماذج الأخرى. حيث أظهرت هذه الطريقة قدرة أكبر على التكيف مع تغيرات ظروف السوق، مما مكنها من التقاط الاتجاهات والتقلبات في أسعار الصرف بدقة، مما أدى إلى انخفاض مؤشرات الخطأ مقارنة بالنماذج الأخرى. كما سمحت تقنية التنبؤ المتداول للنماذج بتحسين دقتها التنبؤية لكلا زوجي العملات. أما بين نماذج التعلم العميق، فقد تفوق نموذج LSTM على CNN، حيث أظهر قدرة أعلى على نمذجة التبعيات طويلة الأجل والأنماط المعقدة في البيانات المتسلسلة. ومع ذلك، ظل أداء LSTM متأخراً بنسبة قليلة عن منهجية التنبؤ المتداول الكلاسيكية (ARIMAX)، مما يشير إلى أن التقنيات الكلاسيكية التكيفية توفر موثوقية أكبر لهذه المجموعة البياناتية المحددة. أخيراً، تم استخراج التقلب مباشرة من أسعار USD/DZD و EUR/DZD، مما أبرز أداء النموذج المختبر ومرونته في تحقيق التنبؤات. وتؤكد النتائج أنه بينما تتفوق نماذج التعلم العميق في النقاط الديناميكية غير الخطية، فإن النماذج الكلاسيكية مع أساليب التنبؤ التكيفية توفر حلاً أكثر متانة في هذا السياق.

**الكلمات المفتاحية:** التنبؤ بتقلب سعر الصرف الأجنبي، نماذج السلاسل الزمنية الكلاسيكية (SARIMAX)، نماذج التعلم العميق (CNN, LSTM)، التنبؤ المتداول (المتجدد)، الدينار الجزائري.

# **General introduction**

## General introduction

---

In an increasingly globalized economy, forecasting exchange rate volatility is a pivotal challenge for economic decision-makers, financial institutions and investors. Exchange rate fluctuations significantly influence international trade, investment decisions, and monetary policies. In Algeria, where the economy is heavily reliant on hydrocarbons exports and foreign currency transactions, accurately forecasting the volatility of exchange rates, such as USD/DZD and EUR/DZD, is crucial for optimizing economic and financial strategies. This task hinges on selecting models capable of capturing the intricate dynamics of exchange rate volatility.

The economic and statistical literature offers two primary approaches for forecasting exchange rate volatility: classical time series models, such as SARIMA (Seasonal Autoregressive Integrated Moving Average) and SARIMAX (SARIMA with exogenous variables), and Deep Learning models, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Classical models rely on statistical frameworks of the time series, while deep learning models leverage neural architectures to capture nonlinear patterns and complex dependencies in the data. The central question we aim to address is: which approach delivers superior performance in forecasting the volatility of USD/DZD and EUR/DZD exchange rates?

Despite significant advancements in both methodologies, no universal consensus exists regarding the superiority of one approach over the other. The volatility of exchange rates, influenced by multiple macroeconomic and exogenous factors, renders this problem complex and unresolved. Classical models like SARIMA and SARIMAX are effective for stationary and seasonal series but may struggle with nonlinear dynamics. Conversely, CNN and LSTM models, while adept at handling complex data, require substantial and large datasets and meticulous tuning.

From a theoretical perspective, SARIMA and SARIMAX models, rooted in the Box Jenkins methodology, assume that historical data encapsulate sufficient information to predict future volatility, incorporating trends, seasonality, and exogenous variables. In contrast, deep learning theory, as advanced by Goodfellow et al. (2016), highlights the capacity of neural networks to learn the features from raw data. However, the performance of these models depends on data quality, the time span of analysis, and the economic context of the market under study, particularly in Algeria, where hydrocarbons dependency and external shocks play significant roles.

In the framework of financial market theory, exchange rate volatility is driven by macroeconomic factors such as interest rates, correlation between the currencies, inflation, and trade balances, as well as exogenous events like economic crises or geopolitical shocks. These factors complicate forecasting and underscore the need to compare classical and deep learning approaches within the specific Algerian context.

## General introduction

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### Research problem

Given the theoretical framework outlined, forecasting the exchange rate volatility of USD/DZD and EUR/DZD remains a complex endeavor, shaped by the nature of the data and the characteristics of the models employed. Thus, we formulate our research problem as follows:

*“How do deep learning and classical time series models compare in forecasting USD/DZD and EUR/DZD exchange rate volatility, and can deep learning improve accuracy?”*

To address this problem, we will explore the following secondary questions:

- What are the theoretical foundations and characteristics of exchange rate in the global and the Algerian context?
- What insights do prior studies provide regarding the use of classical time series and deep learning models for exchange rate volatility forecasting, and what other techniques have been explored?
- To what extent do data preprocessing techniques and parameters tuning impact the performance of deep learning models compared to classical models?
- What makes a model outperform another model in term of exchange rate volatility forecasting?

### Hypotheses

The potential answers to these questions are grounded in the following hypotheses:

- Exchange rates in the global context are driven by economic theories like purchasing power parity, interest rate parity, and balance of payments, influenced by market forces, other high correlation with other currencies (USD and EUR), and macroeconomic factors. In Algeria, the managed float regime, hydrocarbons dependency, and central bank interventions shape the dinar's exchange rate volatility and stability
- Classical time series models effectively capture clear linear and short-term patterns of the exchange rate volatility, while deep learning models excel in modeling non-linear dynamics.
- Data preprocessing and parameter tuning significantly enhance models results by improving convergence and capturing patterns.
- The use of a different forecasting technique can be beneficial for classical models, achieving better accuracy then deep learning models who are less robust due to hyperparameters sensitivity.

## General introduction

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### Prior studies

We highlight two relevant studies that form the foundation of our research on exchange rate volatility forecasting.

*The study by Meese and Rogoff (1983):* This pioneering work compared classical time series models, such as ARIMA, with fundamental structural models for exchange rate forecasting. The findings revealed that time series models often outperformed fundamental models for shortterm forecasts, though their accuracy diminished over longer horizons.

*The study by Cheng et al. (2018):* This research investigated the application of LSTM models for forecasting exchange rate volatility using high-frequency data. The results demonstrated that LSTM models better capture nonlinear dependencies compared to classical models, but their performance hinges on data quality and hyperparameter optimization.

### Importance of the topic

The significance of this research lies in the limited number of empirical studies comparing classical and deep learning models for forecasting exchange rate volatility in the Algerian context. Most prior studies have focused on developed economies, leaving a gap in understanding the dynamics of emerging markets like Algeria. Our study aims to address this gap by providing a comprehensive comparative analysis of SARIMA, SARIMAX, CNN, and LSTM models applied to USD/DZD and EUR/DZD historical data over a 26 years period in purpose to forecast their volatility.

The originality of our work stems from its integrated approach, combining a theoretical analysis of exchange rate, a literature review of forecasting techniques, and an empirical comparison after the forecasting using classical and deep learning models. Our findings will offer practical insights for Algerian policymakers and practitioners while contributing to academic discussions on forecasting methodologies in emerging economies like in Algeria.

### Research objectives

- Analyze the theoretical foundations, determinants, and characteristics of the exchange rate in the global and Algerian context.
- Review prior studies on exchange rate volatility forecasting to identify the strengths and limitations of classical and deep learning models.
- Evaluate the comparative performance of SARIMA, SARIMAX, CNN, and LSTM models for forecasting USD/DZD and EUR/DZD volatility.
- Identify the economic, statistical, and technical factors influencing model performance and select the most effective model for the Algerian context.
- Understanding how the models do evaluates the data to perform the forecasting, and how do choosing the adequate forecasting technique and models parameters helps in getting better results.

## **General introduction**

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### **Research methodology**

The methodology is tailored to the complexity of the topic. We will adopt a descriptive approach to outline the theoretical concepts of exchange rate volatility and forecasting models. Concurrently, we will employ a rigorous analytical approach to compare the performance of SARIMA, SARIMAX, CNN, and LSTM models. For classical models, we will apply the BoxJenkins methodology to model historical exchange rate data for USD/DZD and EUR/DZD from January 5, 1999, to February 28, 2025, and then to compute and report the results. For deep learning models, we will follow a methodology informed by the literature, emphasizing data preprocessing, model architecture design, and hyperparameter tuning. The forecast results will be evaluated using special metrics such as the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to determine the adequate model between all.

### **Research organization**

The first chapter establishes the theoretical framework by exploring the concepts, determinants (interest rates, inflation, trade balance), and characteristics (volatility and risk management) of exchange rate, with an overview on the Algerian context.

The second chapter reviews the literature on exchange rate volatility forecasting, highlighting studies that compare classical and deep learning models and exploring other techniques used in similar contexts. This review serves as the theoretical and empirical foundation for our study.

The third chapter presents an empirical comparative study of SARIMA, SARIMAX, CNN, and LSTM models applied to USD/DZD and EUR/DZD series. It begins with a detailed discussion of the theoretical underpinnings and characteristics of each model, followed by the presentation and interpretation of forecasting results. The chapter concludes by identifying the most effective model for forecasting exchange rate volatility in the Algerian context, based on the empirical findings.

## **Chapter 1 : Theoretical foundations and Algerian context of the foreign exchange market**

## **Chapter 1 : Theoretical foundations and Algerian context of the foreign exchange market**

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### **Introduction of the first chapter:**

The collapse of the Bretton Woods system in 1971 marked a fundamental transformation in global finance, replacing fixed exchange rates with a floating regime that continues to shape international economic relations today. As the world's largest and most liquid financial market, with daily trading volumes exceeding \$6 trillion, the foreign exchange market serves as the backbone of global commerce and investment. This chapter examines this complex ecosystem through three critical dimensions: the structure and operation of currency markets, the mechanisms of exchange rate determination, and the management of exchange rate risk in an increasingly volatile global economy, adding to an overview of the Algerian context.

This chapter aims to provide a comprehensive understanding of modern foreign exchange markets by analyzing their historical evolution, institutional framework, and economic significance. We will explore the diverse participants in currency markets, from central banks to multinational corporations, and examine how exchange rates are influenced by economic fundamentals, market psychology, and geopolitical factors. The chapter also investigates practical strategies for managing currency risk exposure, equipping readers with tools to navigate the challenges of international financial operations in an era of heightened volatility.

The chapter is organized into four interconnected sections. First, we analyze the foreign exchange market's structure, including its historical development from the gold standard to electronic trading platforms, key participants, and unique characteristics like 24-hour trading and extreme liquidity. Second, we examine exchange rate mechanisms, comparing different exchange rate regimes and analyzing determinants such as interest rate differentials, purchasing power parity, and balance of payments. Third section focuses on exchange rate risk management, covering measurement techniques like Value at Risk and hedging instruments including forwards, options, and swaps. In the final section, we will discover the historical evolution of the exchange rate and his regime in Algeria.

## **Chapter 1 : Theoretical foundations and Algerian context of the foreign exchange market**

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### **Section 1: The foreign exchange market**

The foreign exchange market serves as the backbone of global finance, facilitating currency conversion for international trade and investment through its decentralized, 24/5 operating structure. This section examines the market's evolution, key participants, trading mechanisms, and its vital role in connecting economies worldwide. This will be detailed in this first section.

#### **1. Definitions and characteristics of the foreign exchange market**

Following is the main definitions related to the foreign exchange market

##### **1.1 Definition of the foreign exchange market**

The foreign exchange market, commonly referred to as Forex or FX, is the global marketplace for buying, selling, and exchanging currencies. It is the largest and the most liquid financial market in the world, with a daily trading volume exceeding \$6 trillion as of 2023 (Bank for International Settlements, 2023).

##### **1.1.1 Overview of forex as a global marketplace**

The Forex market operates as a decentralized network of banks, brokers, and electronic trading platforms. Unlike stock markets, which are centralized exchanges like the New York Stock Exchange (NYSE), Forex transactions occur over-the-counter (OTC). This decentralized structure allows for 24/7 trading across major financial centers, including London, New York, Tokyo, and Sydney (Pilbeam, 2013).

##### **1.1.2 Purpose of the foreign exchange market**

The primary purpose of the Forex market is to facilitate currency exchange for international trade and investment by providing the necessary liquidity. For example, a US company importing goods from Germany must convert US dollars (USD) into euros (EUR) to pay its supplier. The forex market enables such transactions by providing liquidity and competitive exchange rates (Krugman et al., 2018).

##### **1.1.3 Distinction between Forex and other financial markets**

Unlike stock or bond markets, the Forex market does not have a physical location or centralized exchange. Additionally, Forex trading involves currency pairs (e.g., EUR/USD), whereas stock trading involves individual company shares. The Forex market's high liquidity and 24/7 operation also distinguish it from other financial markets (Sarno & Taylor, 2002).

#### **1.2 History and evolution of the foreign exchange market**

The chronological Forex transformation from ancient systems through the gold standard and Bretton Woods to today's electronic markets, revealing how economic shifts and technological advances shaped modern currency trading.

##### **1.2.1 Origins of currency exchange**

The concept of currency exchange dates back to ancient times when the barter system was used for trade. The introduction of metal coins and later the gold standard in the 19th century provided a more stable basis for currency exchange. Under the gold standard, currencies

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were pegged to a fixed quantity of gold, limiting exchange rate fluctuations (Eichengreen, 2008).

### **1.2.2 The Bretton Woods system and its collapse**

The Bretton Woods Agreement (1944) established a new international monetary system, with fixed exchange rates tied to the U.S. dollar, which was convertible to gold. However, the system collapsed in the early 1970s due to economic imbalances and the inability of the U.S. to maintain gold convertibility (Eichengreen, 2008).

### **1.2.3 Transition to floating exchange rates in the 1970s**

Following the collapse of Bretton Woods, major economies adopted floating exchange rates, where currency values are determined by market forces of supply and demand. This transition marked the beginning of the modern Forex market (Pilbeam, 2013).

### **1.2.4 Technological advancements and the rise of electronic trading**

The 1980s and 1990s saw the rise of electronic trading platforms, which revolutionized the Forex market by increasing transparency, reducing transaction costs, and enabling 24/7 trading. Today, the majority of Forex transactions are conducted electronically (Lyons, 2001).

## **1.3 Key players in the foreign exchange market**

We can distinguish the key players of the FX market as:

### **1.3.1 Commercial and investment banks**

Commercial and investment banks such as JPMorgan Chase and Deutsche Bank serve as crucial market makers in the foreign exchange market, providing liquidity by continuously quoting bid and ask prices for currency pairs while facilitating the interbank market, the core of Forex trading where banks conduct over-the-counter (OTC) transactions directly with each other without a centralized exchange (Pilbeam, 2013). This decentralized interbank system forms the foundation of global currency trading, with major banks both creating markets and participating as principal traders in this wholesale trading environment.

### **1.3.2 Multinational corporations**

Multinational corporations such as Apple and Toyota actively participate in the foreign exchange market to hedge their currency exposure from international operations, employing various financial instruments to mitigate risks associated with exchange rate fluctuations, while their substantial transactional volumes can significantly influence Forex market liquidity and exchange rate movements (Krugman et al., 2018). These corporate activities not only serve risk management purposes but also contribute to daily trading volumes and price discovery in the currency markets.

### **1.3.3 Institutional and retail investors**

Hedge funds and asset managers engage in foreign exchange markets both for speculative opportunities and portfolio diversification strategies, while the proliferation of online trading platforms has democratized market access, enabling retail investors to participate in currency trading that was traditionally dominated by institutional players (Sarno & Taylor, 2002). This dual participation has transformed market dynamics, with sophisticated

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institutional strategies coexisting alongside growing retail trading activity, though the latter group typically accesses the market through brokers who aggregate their orders to the interbank market, creating a layered ecosystem where different participant types interact with varying levels of sophistication, information, and market impact.

### **1.3.4 Central banks**

Central banks play a pivotal role in foreign exchange markets through three primary mechanisms: implementing monetary policy via strategic currency interventions, actively managing substantial foreign exchange reserves to maintain currency stability and address international payment obligations, and conducting direct market interventions to mitigate excessive volatility (Lyons, 2001). These interconnected functions allow central banks to influence exchange rates through both routine operations and extraordinary measures, using their reserve assets as a buffer during economic crises while carefully calibrating interventions to achieve macroeconomic objectives without disrupting market functioning, though such actions sometimes spark debates about currency manipulation and competitive devaluations in global financial circles.

## **1.4 Characteristics of the foreign exchange market**

Following is the characteristics of the foreign exchange market

### **1.4.1 Decentralization and globalization**

The foreign exchange market's unique decentralized structure operates through an interconnected global network of banks, brokers, and electronic trading platforms rather than a traditional central exchange as market activity seamlessly shifts between major financial centers worldwide (Bank for International Settlements, 2023). The resulting ecosystem combines institutional depth with broad accessibility, allowing everything from multinational corporate transactions to speculative trades to be executed within a framework that balances regulatory oversight with market-driven price discovery.

### **1.4.2 Liquidity and trading volume**

With a staggering daily turnover surpassing \$6 trillion, the foreign exchange market stands as the world's most liquid financial marketplace, with its exceptional depth particularly evident in major currency pairs such as EUR/USD and USD/JPY that dominate trading volumes due to their tight spreads and high market participation (Sarno & Taylor, 2002). This unparalleled liquidity stems from the market's global nature and continuous operation, where the high trading volumes in these major pairs ensure minimal price distortions and efficient execution even for large orders, while also facilitating better price discovery and lower transaction costs compared to other financial markets.

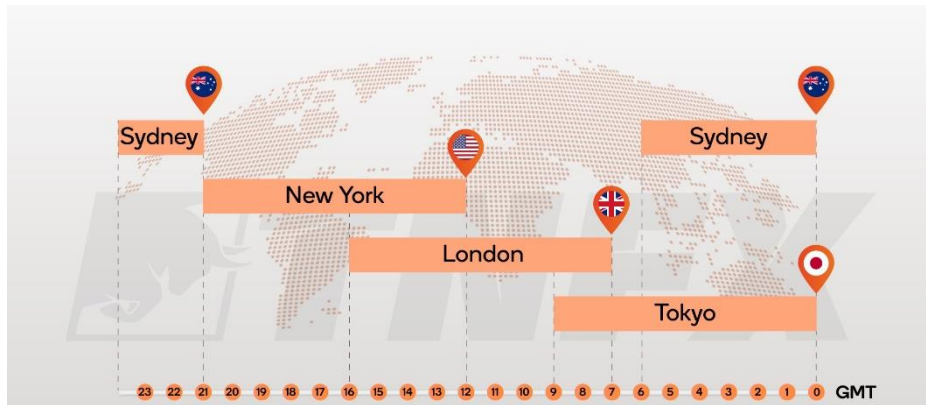
### **1.4.3 Operating hours and 24/7 functioning**

The foreign exchange market's unique 24-hour operation is facilitated by sequential trading sessions across Asian, European, and American time zones, creating a continuous trading cycle (Pilbeam, 2013). This around-the-clock structure as showed in **Figure 1** allows a constant price discovery and liquidity provision, with the most pronounced market movements often occurring during these overlap periods when institutional trading activity peaks and major

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economic data releases frequently coincide, presenting both opportunities and risks for traders who must account for these predictable volatility patterns in their strategies while benefiting from the market's unparalleled accessibility across global time zones.

**Figure 1: Global forex market working hours**



**Source:** [tnfx.co/forex-working-hours](https://tnfx.co/forex-working-hours) (seen 12-02-2025)

### 1.5 Major traded currencies

The major traded currencies are classified as:

#### 1.5.1 Major currency pairs

Major currency pairs, which always include the U.S. dollar paired with another leading global currency like the euro (EUR/USD) or British pound (GBP/USD), represent the most heavily traded and liquid instruments in the foreign exchange market, collectively accounting for approximately 75% of total daily Forex trading volume due to their tight spreads, deep liquidity, and high market participation (Krugman et al., 2018).

#### 1.5.2 Minor currency pairs (crosses)

Minor currency pairs, also known as cross-currency pairs, exclude the U.S. dollar and instead directly pair two other major currencies, such as EUR/GBP or AUD/NZD, offering traders alternative opportunities beyond dollar denominated transactions, though they typically exhibit lower liquidity and wider bid-ask spreads compared to major pairs due to reduced trading volumes (Sarno & Taylor, 2002). While these crosses still benefit from institutional participation, their pricing dynamics are often influenced more strongly by regional economic factors.

#### 1.5.3 Exotic currency pairs

Exotic currency pairs, which combine a major currency like the U.S. dollar with an emerging market currency (such as USD/SEK or USD/ZAR), present unique trading characteristics marked by significantly lower liquidity and higher volatility compared to major and minor pairs, creating both greater risk exposure and potential reward opportunities for

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traders (Pilbeam, 2013). These pairs often exhibit wider bid-ask spreads and more pronounced price swings.

### 2. Functioning of the foreign exchange market

The foreign exchange market is specified by

#### 2.1 The foreign exchange market compartments

The forex market is divided into two segments:

##### 2.1.1 The spot foreign exchange market ("spot market")

This is an over-the-counter (OTC), decentralized market that operates continuously. Transactions involve the immediate exchange of currencies, with delivery required no later than two business days after the contract date.

- Bid and Ask rates; there are two types of rates: the rate at which the bank buys the currency (bid) and the rate at which it sells the currency (ask). These rates also depend on the exchange instrument used.
- Quotation methods in the spot foreign exchange market: all currencies are quoted against the U.S. dollar. This is because most international transactions are conducted in dollars. The drawback of this systematic dollar-based quotation is that institutions wishing to exchange non-dollar currencies must calculate a cross rate.
- Currency pairs and cross rates: in foreign exchange markets, currency pairs are structured with a base currency (the first listed) and a quote currency (the second listed), as seen in EUR/USD where the euro serves as the base, with cross rates between non-dollar currencies like EUR/GBP being derived through triangular arbitrage calculations using their respective exchange rates against a common intermediary currency, typically the U.S. dollar (Sarno & Taylor, 2002). This pricing convention and calculation method allows traders to determine exchange rates for all possible currency combinations.
- Direct and indirect quotations: currency quotations are expressed either as direct quotes (showing the domestic currency value per unit of foreign currency, as in USD/JPY=110) or indirect quotes (representing the foreign currency value per unit of domestic currency, like JPY/USD=0.009), with these two quotation methods being mathematical reciprocals of each other that can be easily converted through simple division (Krugman et al., 2018).
- Appreciation, revaluation, depreciation and devaluation: depending on the quotation method, an increase in a currency's exchange rate can signify appreciation or depreciation. In a direct quotation system, if the exchange rate of a foreign currency rises, it means the foreign currency depreciates while the domestic currency appreciates. In an indirect quotation system, if the exchange rate rises, it means the foreign currency appreciates while the domestic currency depreciates. The distinction between depreciation/devaluation and appreciation/revaluation depends on how exchange rates are determined:
  - In a fixed exchange rate system, currency values are set by government authorities. An increase in value is called a revaluation, and a decrease is called a devaluation.
  - In a floating exchange rate system, currency values are determined by supply and demand. An increase in value is termed appreciation, and a decrease is termed depreciation.

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### **2.1.2 The forward foreign exchange market ("forward market")**

In the forward market, transactions involve commitments to buy or sell currencies at the spot rate at the time of the transaction, with delivery and payment occurring later, on a fixed date beyond two business days.

Three scenarios are possible in a forward quotation:

- The forward rate is at parity with the spot rate when the foreign and domestic currency rates are identical.
- The currency is at a premium when its forward rate in domestic currency is higher than the spot rate (forward rate is at a premium).
- The currency is at a discount when its forward rate in domestic currency is lower than the spot rate (forward rate is at a loss).

## **2.2 Factors influencing the foreign exchange market**

A wide range of factors influences the Forex market. These factors shape exchange rate movements and create opportunities for traders and investors.

### **2.2.1 Monetary policies and interest rates**

Central banks exert significant influence over exchange rates through their monetary policy decisions, where interest rate hikes typically strengthen the domestic currency, as seen when Federal reserve (Fed) rate increases boost the U.S. dollar (USD) by enhancing yields on dollar denominated assets, while unconventional measures like quantitative easing (QE) tend to have the opposite effect by increasing money supply and potentially devaluing the currency through expanded liquidity (Krugman et al., 2018; Pilbeam, 2013). These policy tools create powerful exchange rate dynamics that often trigger currency appreciation by signaling economic strength and attracting foreign capital flows, with markets constantly adjusting currency valuations.

### **2.2.2 Economic data**

Economic indicators like gross domestic product (GDP) growth, inflation rates, and unemployment figures serve as vital barometers of a nation's economic health, with currency markets reacting decisively to these releases for instance, strong GDP figures typically drive currency appreciation by signaling economic strength, while unexpectedly high inflation may trigger depreciation if it erodes purchasing power and raises expectations of monetary tightening (Sarno & Taylor, 2002; Eichengreen, 2008). These market responses reflect the complex interplay between fundamental economic conditions and currency valuations, where traders constantly reassess exchange rates based on how actual data releases compare to consensus forecasts, creating volatility spikes as markets digest new informations.

### **2.2.3 Geopolitical events and economic crises**

Geopolitical tensions routinely trigger Forex market volatility as they disrupt trade flows and economic expectations, often causing sharp fluctuations in affected currencies, while simultaneously driving capital toward traditional safe-haven currencies (Krugman et al., 2018; Pilbeam, 2013).

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### 2.3 The role of central banks

Central banks play a pivotal role in the Forex market:

#### 2.3.1 Interventions in the foreign exchange market

Central banks engage in foreign exchange interventions with multiple objectives including currency stabilization, inflation control, and export competitiveness, as demonstrated by the Bank of Japan's historical efforts to prevent excessive yen appreciation that could undermine its export-driven economy (Lyons, 2001), though the effectiveness of such interventions varies significantly depending on market conditions and the scale of intervention. These contrasting outcomes highlight how intervention success depends not just on a central bank's resources and determination, but also on underlying economic fundamentals and whether the interventions align with or against prevailing market forces.

#### 2.3.2 Management of foreign exchange reserves

Central banks maintain diversified foreign exchange reserves comprising major currencies (primarily USD and EUR), gold, and Special Drawing Rights (SDRs) as strategic buffers to stabilize domestic currencies during volatility and meet international payment obligations, deploying these reserves through targeted market interventions (Pilbeam, 2013; Sarno & Taylor, 2002). The composition and size of these reserve holdings reflect careful policy considerations, as central banks must balance between maintaining sufficient liquidity for effective market interventions and optimizing returns on reserve assets.

#### 2.3.3 Exchange rate policies and monetary stabilization

- **Fixed vs. floating exchange rate regimes:** Under a fixed exchange rate regime, a currency's value is pegged to another currency or a basket of currencies. In contrast, market forces determine floating exchange rates. Each regime has its advantages and disadvantages (Krugman et al., 2018).
- **Currency pegs and bands:** Some countries adopt currency pegs or bands to maintain exchange rate stability. For instance, Hong Kong pegs its currency (HKD) to the U.S. dollar (USD) within a narrow band (Pilbeam, 2013).

### 3. Importance of the foreign exchange market in the global economy

The Forex market plays a critical role in facilitating international trade, investment, and financial stability. Its importance extends beyond currency conversion, influencing economic policies, corporate strategies, and individual financial decisions.

#### 3.1 The foreign exchange market and international trade

The relation between the foreign exchange market and international trade can be characterized by:

##### 3.1.1 Impact on trade flows

- **Exchange rate effects on export competitiveness:** A weaker domestic currency makes exports cheaper for foreign buyers, boosting demand for domestically produced goods (Krugman et al., 2018).

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- **Currency risk in import/export transactions:** Fluctuations in exchange rates can significantly affect the profitability of international trade. For instance, if a U.S. importer agrees to pay €1 million for goods and the euro (EUR) appreciates before payment is made, the cost in U.S. dollars (USD) will increase (Pilbeam, 2013).

### 3.1.2 Currency conversion for international transactions

The foreign exchange market plays a vital role in global commerce by enabling businesses to convert international revenues into their domestic currency though this essential service comes with both transaction costs (including bid-ask spreads and banking fees that reduce profit margins) and exchange rate risks that can significantly impact financial outcomes if left unmanaged (Sarno & Taylor, 2002). While facilitating these critical trade settlements, the Forex market exposes companies to currency volatility between transaction initiation and completion dates.

## 3.2 The foreign exchange market and international investments

The relation between the foreign exchange market and international investments can be characterized by:

### 3.2.1 Capital flows and foreign direct investment (FDI)

- **Impact of exchange rates on FDI decisions:** A strong currency can deter foreign investment by increasing the cost of acquiring assets in the host country. For example, a strong U.S. dollar (USD) may discourage foreign investors from purchasing U.S. real estate or equities. Conversely, a weak currency can attract FDI by making assets cheaper for foreign buyers (Obstfeld & Rogoff, 1995).
- **Repatriation of profits and currency risk:** Multinational corporations face currency risk when repatriating profits from foreign subsidiaries (Pilbeam, 2013).

### 3.2.2 Impact on global financial markets

- **Interconnectedness of forex and equity/bond markets:** Exchange rates influence the returns on international investments. For example, a depreciation of the foreign currency can reduce the returns on foreign stocks or bonds for domestic investors (Sarno & Taylor, 2002).
- **Carry trade:** The carry trade involves borrowing in a low-interest-rate currency and investing in a high-interest-rate currency to profit from the interest rate differential. While profitable during stable market conditions, carry trades can lead to significant losses during periods of currency volatility (Krugman et al., 2018).

## 3.3 The foreign exchange market and speculation

Speculation was firstly born on financial markets and especially on the FX market

### 3.3.1 Speculation on exchange rate movements

Speculators ranging from hedge funds to retail traders play a crucial role in maintaining Forex market liquidity through their continuous buying and selling activities, enabling efficient execution of transactions even for large volumes (Lyons, 2001), while employing diverse trading strategies like trend following, arbitrage, and algorithmic trading, all of which

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contribute to price discovery and market efficiency even as participants pursue profits (Sarno & Taylor, 2002).

### 3.3.2 Impact of speculation on volatility

- **Positive and negative effects of speculation:** While speculation enhances market liquidity and efficiency, it can also exacerbate volatility, especially during periods of economic uncertainty (Eichengreen, 2008).
- **Regulatory measures to curb excessive speculation:** To mitigate the risks associated with speculation, regulators have implemented measures such as position limits, transaction taxes, and enhanced oversight of Forex trading activities. For example, the European Securities and Markets Authority (ESMA) has introduced restrictions on leverage for retail Forex traders to reduce excessive risk-taking (Pilbeam, 2013).

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### **Section 2: The exchange rate**

Exchange rates serve as vital indicators of economic health, reflecting the complex interplay between currencies through their definitions, valuation mechanisms, and diverse influencing factors. This section covers various exchange rate regimes, from fixed to floating systems, while examining critical determinants like interest rate differentials, purchasing power parity, and balance of payments that shape currency values.

#### **1. Definition and determinants of exchange rates**

The exchange rate is a fundamental concept that governs global trade and capital flows, with its valuation shaped by complex interactions between economic fundamentals like interest rate differentials, inflation rates, trade balances, and market psychology

##### **1.1 Definition of the exchange rate**

The exchange rate is the price of one currency in terms of another. It is a critical component of international economics, as it facilitates cross-border trade, investment, and financial transactions (Jura, 2003). The exchange rate represents how much of one currency is needed to purchase a unit of another currency. For example, if the exchange rate between the US dollar (USD) and the euro (EUR) is 1.20, it means 1 EUR can be exchanged for 1.20 USD.

##### **1.1.1 Importance in international economics**

Exchange rates play a vital role in determining the competitiveness of a country's exports and imports. They also influence capital flows, foreign direct investment (FDI), and the balance of payments (Shapiro, 2014).

##### **1.1.2 Exchange rate as a key economic indicator**

Policymakers, investors, and businesses closely monitor exchange rates as they reflect a country's economic health. For example, a depreciating currency may indicate economic instability, while an appreciating currency may signal strong economic performance (Krugman, 2000).

#### **1.2 Different exchange rate regimes**

Countries adopt different exchange rate regimes based on their economic objectives and constraints. The three main types are fixed, floating, and intermediate regimes.

##### **1.2.1 Fixed exchange rate regime**

In a fixed exchange rate regime, the value of a currency is pegged to another currency or a basket of currencies. The central bank intervenes to maintain the exchange rate. Under a fixed exchange rate system, central banks actively intervene in currency markets by buying or selling their domestic currency to maintain a predetermined parity as exemplified by the Bretton Woods regime (1944-1971) where currencies were pegged to the US dollar backed by gold (Eichengreen, 2008) which provides stability for international trade and helps anchor inflation expectations (Ghosh et al., 2010), but comes with significant constraints including the need for substantial foreign exchange reserves, loss of monetary policy autonomy, and heightened vulnerability to speculative pressures that can trigger currency crises when market confidence erodes (Obstfeld & Rogoff, 1995). This delicate balance between stability and flexibility

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explains why most economies have shifted toward more flexible arrangements since the 1970s, though some still maintain fixed or heavily managed rates by carefully weighing these trade-offs between predictable exchange rates and independent economic policymaking capacity.

### 1.2.2 Floating exchange rate regime

In a floating exchange rate regime, the value of a currency is determined by market forces of supply and demand. Floating exchange rates fluctuate freely according to market forces, responding dynamically to economic fundamentals like interest rate differentials, inflation trends, and trade balances (Frankel, 2019), offering nations monetary policy independence and automatic stabilization during economic shocks (Taylor, 2001), though this flexibility comes with heightened volatility that can disrupt business planning and occasionally fuel destabilizing speculative behavior in currency markets (Krugman, 2000). While this system eliminates the need for central banks to maintain large reserves for currency defense, its inherent unpredictability sometimes prompts policymakers to implement managed float arrangements that balance market determination with selective intervention during periods of excessive fluctuations.

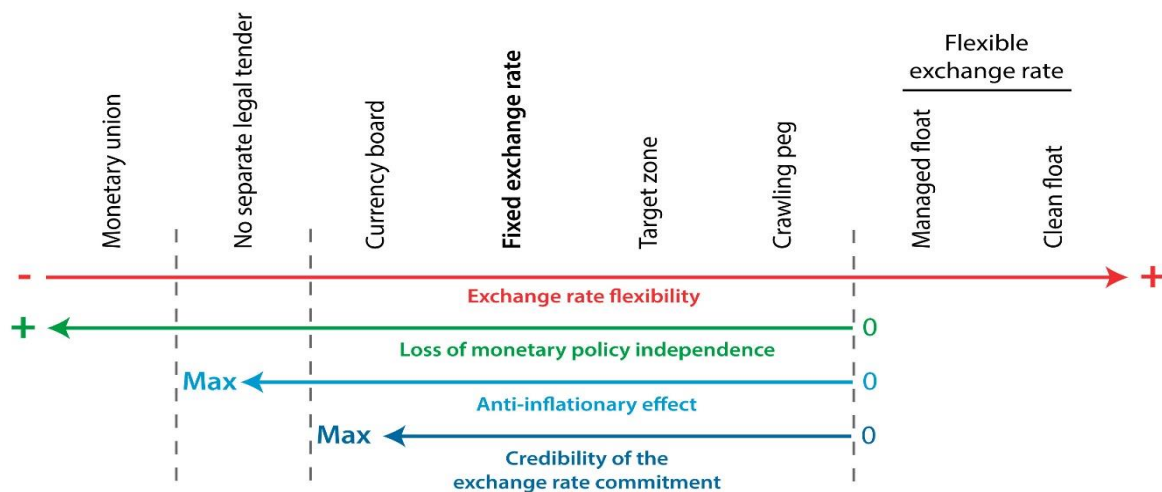
### 1.2.3 Intermediate regimes

Intermediate regimes combine elements of fixed and floating exchange rate systems.

- **Crawling peg:** The exchange rate is adjusted periodically to reflect inflation or other economic factors (Edwards, 2006).
- **Currency board:** A currency board is a strict form of fixed exchange rate regime where the central bank backs the domestic currency with foreign reserves (Williamson, 1995).

Intermediate regimes offer a balance between stability and flexibility but require careful management to avoid crises (Ghosh et al., 2010). We can summarize the most important exchange regime rates in **Figure 2**.

**Figure 2: Exchange rates regimes**



Source: Policonomics.com (seen 28-02-2025)

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### 1.3 Factors determining exchange rates

Several factors influence exchange rates, including interest rates, inflation, trade balances, and market sentiment. We can divide the determinant into two categories depending on the exchange rate type

#### 1.3.1 Determinants of the spot exchange rate

The most important spot exchange rate determinants are:

##### **Absolute Purchasing Power Parity (APPP)**

The Absolute Purchasing Power Parity (APPP) theory posits that the exchange rate between two currencies should equal the ratio of their respective price levels, assuming identical goods should have the same price in both countries when expressed in a common currency (Cassel, 1918). The equation (1) below shows the relation between the different components.

$$S = \frac{P}{P^*} \quad (1)$$

Where S is the spot exchange rate, P the domestic price level, and P\* the foreign price level.

##### **Relative Purchasing Power Parity (RPPP)**

The Relative PPP theory refines the absolute version by incorporating inflation rates over time. It suggests that the rate of change in the exchange rate equals the difference between domestic ( $\pi$ ) and foreign ( $\pi^*$ ) inflation rates (Dornbusch, 1980). As displayed in the equation (2).

$$\frac{\Delta S}{S} \approx \pi - \pi^* \quad (2)$$

##### **Exchange rate indices: nominal and real**

Nominal and real exchange rate indices help capture the broader picture of currency valuation. While the nominal index reflects currency values without adjustment, the real exchange rate adjusts for inflation differentials, offering insight into relative competitiveness (Krugman & Obstfeld, 2018). As shown in equation (3)

$$RER = S \frac{P}{P^*} \quad (3)$$

##### **Interest rates**

Interest rate differentials significantly influence exchange rate movements. According to Mundell (1963), higher domestic interest rates attract foreign investment, increasing demand for the domestic currency and leading to appreciation, especially in flexible exchange rate regimes.

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### Balance of payments

The balance of payments, or trade balance, summarizes a country's international transactions. A surplus tends to increase demand for the domestic currency, thereby appreciating it, while a deficit exerts depreciating pressure (Frenkel & Johnson, 1976). These flows are essential in determining exchange rate dynamics in both the short and long run.

### 1.3.2 Determinants of the forward exchange rate

#### Covered Interest rate Parity (CIP)

CIP holds that arbitrage opportunities in covered (hedged) foreign exchange markets should not exist. Therefore, the forward rate adjusts precisely to neutralize interest rate differentials between two countries (Keynes, 1923). In equation (4), the forward rate ( $F$ ) adjusts to eliminate arbitrage opportunities from interest rate differentials and where ( $S$ ) is the spot exchange rate (current price of foreign currency in domestic currency units), ( $i$ ) the domestic nominal interest rate and ( $i^*$ ) the foreign nominal interest rate.

$$F = S \cdot \left( \frac{1+i}{1+i^*} \right) \quad (4)$$

#### Uncovered Interest Rate Parity (UIP)

UIP assumes no hedging and states that the expected change in the spot exchange rate equals the interest rate differential. Despite its theoretical appeal, empirical studies often reject UIP due to risk premiums and investor behavior (Fama, 1984). Thus, the expected exchange rate changes offset interest rate differentials without hedging. In equation (5),  $E(S_{t+1})$  is the expected future spot exchange rate at time  $t+1$  and  $S_t$  the spot exchange rate at time  $t$ .

$$E(S_{t+1}) = S_t \cdot \left( \frac{1+i}{1+i^*} \right) \quad (5)$$

#### Fisher effect in a closed economy

The Fisher effect, represented in the equation (6), suggests that nominal interest rates reflect both the real interest rate and expected inflation: nominal interest rates reflect real returns ( $r$ ) plus compensation for expected inflation ( $\pi^e$ ). This relationship holds within a closed economy framework, assuming rational expectations (Fisher, 1930).

$$i = r + \pi^e \quad (6)$$

#### International Fisher Effect (IFE)

The International Fisher Effect, represented in equation (7), builds on the domestic Fisher effect by asserting that currencies with higher nominal interest rates will depreciate to offset the interest advantage. This aligns long-term exchange rate movements with inflation

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differentials (Cumby & Obstfeld, 1981). The percentage change in the exchange rate equals the interest rate differential, linking inflation and currency depreciation.

$$\frac{E(S_{t+1}) - S_t}{S_t} = i - i^* \quad (7)$$

### Forward exchange rate relationship

The forward rate reflects the market's expectations of future spot rates, assuming no arbitrage and rational forecasting. Under efficient market conditions, the forward rate becomes an unbiased predictor of the future spot rate (Hansen & Hodrick, 1980).

### 1.3.3 Market sentiment and expectations

- **Speculation and investor behavior:** Speculators can drive exchange rates away from their fundamental values. During the 1997 Asian financial crisis, speculative attacks led to sharp currency depreciations (Eichengreen, 2008).
- **News and geopolitical events:** Political instability, economic data releases, and central bank announcements can cause sudden exchange rate movements (Frankel, 2019).

### 1.4 Types of exchange rates

Exchange rates can be classified into several types based on their calculation, purpose, and use in economic analysis. Understanding these types is essential for analyzing currency movements and their implications for trade, investment, and policy-making.

#### 1.4.1 Bilateral exchange rates

The bilateral exchange rate represents the exchange rate between two currencies the domestic currency and the foreign currency of another country.

#### Nominal Exchange Rate (NER)

The nominal exchange rate measures the price of a foreign currency in terms of the domestic currency. It can be expressed in two ways:

- **Direct quote:** The number of foreign currency units per one unit of domestic currency (e.g., 0.85 EUR/USD means 0.85 euros for 1 US dollar).
- **Indirect quote:** The number of domestic currency units per one unit of foreign currency (e.g., 1.18 USD/EUR means 1.18 US dollars for 1 euro).

#### Real Exchange Rate (RER)

The real exchange rate adjusts the nominal exchange rate for inflation differentials between the domestic and foreign country, represented in equation (8). It accounts for changes in the nominal exchange rate and relative to domestic and foreign price levels.

$$\text{Real Exchange Rate} = \text{Nominal Exchange Rate} \times \frac{\text{Domestic Price Level}}{\text{Foreign Price Level}} \quad (8)$$

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### Interpretation:

- If RER increases, domestic goods become more expensive relative to foreign goods (loss of competitiveness).
- If RER decreases, domestic goods become cheaper (improved export competitiveness).

### 1.4.2 Effective exchange rates

The effective exchange rate is a multilateral exchange rate for a currency zone, calculated as a weighted average of bilateral exchange rates with major trading partners and competitors. It is primarily used as an econometric variable when assessing a currency's value relative to multiple foreign currencies.

#### Nominal Effective Exchange Rate (NEER)

The NEER is defined as a trade-weighted average of a country's bilateral exchange rates against its key trading partners. It indicates how the domestic currency's nominal exchange rate evolves relative to these economies. In equation (9),  $(NER_i)$  is the nominal exchange rate against partner  $i$  and  $(w_i)$  the trade weight of partner country  $i$ .

$$NEER = \sum_{i=1}^n (w_i \times NER_i) \quad (9)$$

#### Real Effective Exchange Rate (REER)

The Real Effective Exchange Rate (REER) adjusts the nominal effective exchange rate (NEER) for relative price level changes between the domestic economy and its trading partners. It accounts for both nominal exchange rate movements (currency appreciation/depreciation) and inflation differentials (domestic vs. foreign price levels). In equation (10),  $(P)$  is the domestic price index (e.g. CPI) and  $(P^*)$  the trade-weighted foreign price index.

$$REER = NEER \times \frac{P}{P^*} \quad (10)$$

### Interpretation:

- If REER increases, it implies a loss of competitiveness (domestic goods become relatively more expensive).
- If REER decreases, it implies an improved competitiveness (domestic goods become relatively cheaper).

## 1.5 Impact of exchange rates on the economy

We can observe the impact of exchange rate on:

### 1.5.1 Exports and imports

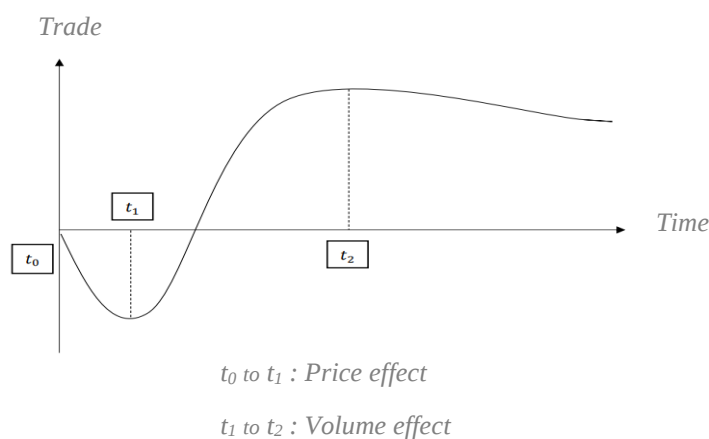
Currency fluctuations significantly impact trade competitiveness, where depreciation enhances export potential by making domestic goods more affordable internationally as seen when a weaker US dollar (USD) increases global demand for American products (Krugman,

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2000) while appreciation produces opposing effects by reducing import costs but simultaneously diminishing export competitiveness, illustrated when a stronger euro (EUR) benefits European consumers through cheaper imports but challenges exporters facing higher relative prices abroad (Obstfeld & Rogoff, 1995). These exchange rate movements create fundamental trade-offs for economies, with the net effect depending on each nation's balance between import dependence and export orientation.

In **Figure 3**, we can notice how the J-Curve effect currency depreciation initially worsens a nation's trade balance as higher import prices immediately impact costs while export volumes take time to adjust, but ultimately leads to improvement as competitive gains stimulate foreign demand (Eichengreen, 2008). This delayed response occurs because import contracts and consumer habits exhibit short-term price inelasticity, while the full competitive benefits of depreciation only materialize after businesses renegotiate contracts, expand production capacity, and foreign buyers shift to cheaper alternatives, typically spanning 12-18 months before the trade balance shows sustainable improvement.

**Figure 3: The J-Curve effect**



**Source:** Nyahoho, 2002

### 1.5.2 Effects on business competitiveness

Exchange rate movements directly impact corporate profitability through input cost channels particularly for manufacturers relying on imported materials, where domestic currency depreciation raises production costs and squeezes margins, as seen when a weaker national currency increases raw material import expenses (Shapiro, 2014). These financial realities create complex operational challenges, as businesses must balance the competitive benefits of favorable exchange rates against the cost pressures from currency-driven input price fluctuations.

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Businesses employ various adaptation strategies to mitigate exchange rate risks, including dynamic pricing adjustments by reducing foreign market prices after domestic currency appreciation to preserve competitiveness (Madura, 2017). These complementary approaches allow companies to maintain flexibility in global operations, combining tactical pricing responses to short-term currency movements with structural diversification that provides long-term resilience against exchange rate volatility.

### **1.5.3 Effects on inflation and economic growth**

Exchange rate fluctuations transmit to domestic inflation through the pass-through effect, where currency depreciation raises import prices creating upward pressure on overall price levels (Taylor, 2001), prompting inflation-targeting central banks to potentially adjust monetary policy, as when interest rate hikes are deployed to counteract depreciation-induced inflation, demonstrating how exchange rates serve as crucial variables in inflation control frameworks (Krugman, 2000). The extent of this transmission depends on multiple factors including import composition, pricing flexibility, and labor market conditions, with complete pass-through typically occurring faster in small open economies with dollarized imports than in more diversified economic systems where domestic factors may moderate the inflationary impact.

The net growth impact depends on the balance between these competing forces: moderate, predictable exchange rate adjustments may support macroeconomic adjustment and rebalancing, whereas sharp, erratic fluctuations tend to disrupt business planning, deter foreign investment, and ultimately impair sustainable development, making exchange rate stability an important consideration for growth-oriented economic policies in open economies.

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### **Section 3: Exchange rate risk**

Fluctuating exchange rates create significant financial risks for businesses, investors, and policymakers engaged in international markets. This section examines the various forms of currency risk that arise from exchange rate volatility. From multinational corporations hedging overseas operations to investors optimizing foreign portfolios, understanding these risks is essential for navigating global commerce in an era of increased currency volatility. The analysis covers both theoretical frameworks and practical tools that market participants employ to protect against adverse currency movements while capitalizing on opportunities created by exchange rate fluctuations.

#### **1. Definition and types of exchange rate risk**

Exchange rate risk, also known as currency risk, arises from fluctuations in exchange rates that can adversely affect the value of international transactions, investments, and financial statements. This section explores the definition, types, and causes of exchange rate risk.

##### **1.1 Definition of exchange rate risk**

We can define exchange rate risk as:

###### **1.1.1 Conceptual definition**

Exchange rate risk refers to the potential for financial loss due to changes in the value of one currency relative to another. For instance, a U.S. company importing goods from Europe may face losses if the euro (EUR) appreciates against the U.S. dollar (USD) before payment is made (Pilbeam, 2013).

###### **1.1.2 Importance of exchange rate risk in international business and finance**

Exchange rate risk is a critical concern for businesses engaged in international trade and investment. It affects cash flows, profitability, and financial stability. For instance, multinational corporations (MNCs) must manage currency risk to protect their revenues and margins (Krugman et al., 2018).

###### **1.1.3 Distinction between exchange rate risk and other financial risks**

Exchange rate risk differs from other financial risks, such as credit risk or market risk, as it specifically arises from currency fluctuations. While credit risk relates to the likelihood of default, exchange rate risk focuses on the impact of currency movements on financial outcomes (Sarno & Taylor, 2002).

#### **1.2 Different types of exchange rate risk**

There are different types of exchange rate risk depending on different exposure positions:

##### **1.2.1 Transaction risk (short-term exposure)**

Transaction risk arises when exchange rate fluctuations alter the value of foreign currency-denominated obligations between transaction initiation and settlement, creating direct cash flow and profitability challenges that prompt firms to employ hedging instruments like forward contracts to lock in exchange rates and stabilize financial outcomes (Krugman et al.,

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2018). This time-sensitive currency exposure particularly affects businesses with cross-border receivables or payables, where even short-term exchange rate movements can significantly impact profit margins, driving widespread adoption of financial derivatives and natural hedging strategies to manage the working capital risks inherent in international commerce.

### **1.2.2 Translation risk (accounting exposure)**

Translation risk emerges during financial statement consolidation when exchange rate fluctuations alter the domestic-currency value of foreign subsidiaries' assets and liabilities (Sarno & Taylor, 2002) directly impacting reported earnings, equity positions, and key financial ratios in ways that may misrepresent operational performance and influence investor valuation decisions (Eichengreen, 2008). This accounting exposure creates particular challenges for multinational corporations with substantial overseas holdings, as currency movements unrelated to actual business performance can produce volatility in published financial results, potentially affecting credit ratings, stock prices, and executive compensation metrics tied to reported earnings, even when underlying cash flows remain unaffected.

### **1.2.3 Economic risk (strategic exposure)**

Economic risk captures the long-term strategic impact of exchange rate movements on a company's future cash flows and competitive positioning (Pilbeam, 2013) representing a fundamental threat to profitability that extends beyond immediate transaction or accounting effects by altering the underlying economics of cross-border operations (Krugman et al., 2018). This structural exposure proves particularly damaging in price-sensitive industries where currency-driven cost disadvantages cannot be fully offset through productivity gains or quality differentiation, forcing companies to either absorb shrinking margins or risk losing customers to competitors in countries with more favorable exchange rates.

## **1.3 Causes of exchange rate risk**

### **1.3.1 Exchange rate volatility**

Exchange rate volatility stems from multiple interconnected factors, including interest rate differentials, geopolitical shocks, and macroeconomic data surprises, with historical patterns demonstrating that such volatility systematically intensifies during periods of systemic uncertainty whether from financial crises, pandemics, or geopolitical conflicts (Eichengreen, 2008). This volatility exhibits both cyclical and structural dimensions, where short-term spikes caused by discrete events overlay longer-term shifts in baseline volatility regimes, creating complex risk management challenges.

### **1.3.2 Exposure to foreign currencies**

Currency exposure stems from various international financial activities, including trade flows, foreign investments, and cross-border borrowing. To manage this risk, companies systematically quantify their exposure by analyzing projected foreign currency cash flows, enabling them to assess potential financial impacts from exchange rate movements and implement targeted hedging strategies (Krugman et al., 2018). This exposure measurement process typically involves mapping all foreign currency-denominated receivables, payables, and investments across business units, calculating net positions by currency (knowing if it's a

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long or a short position) , and stress-testing financial statements under different exchange rate scenarios.

### **1.3.3 Macroeconomic uncertainties**

Exchange rates are fundamentally shaped by domestic macroeconomic conditions, where high inflation typically erodes currency value, strong growth attracts capital inflows, and political instability triggers capital flight as demonstrated when chronic inflation sparks currency depreciation despite central bank interventions (Sarno & Taylor, 2002). These structural vulnerabilities amplify during global crises, when synchronized economic shocks trigger violent currency swings and liquidity shortages across emerging and developed markets (Eichengreen, 2008).

## **2. Measurement of exchange rate risk**

Exchange rate risk can be measured with different methods

### **2.1 Methods for measuring exchange rate risk**

#### **2.1.1 Value at Risk (VaR)**

Value at Risk (VaR) quantifies the maximum potential loss of a portfolio from adverse exchange rate movements over a defined period at a specified confidence level, for instance, a 1-month \$1 million VaR at 95% confidence implies a 5% chance of losses exceeding that amount (Pilbeam, 2013). While VaR offers a standardized risk metric that facilitates comparisons across currencies and portfolios, its dependence on historical data and parametric assumptions limits its effectiveness during market crises, as it typically underestimates tail risks and fails to predict extreme events like currency collapses (Krugman et al., 2018).

#### **2.1.2 Sensitivity to exchange rate movements**

Sensitivity analysis quantifies the financial impact of exchange rate fluctuations through metrics like elasticity and beta coefficients where a beta of 1.5 signals that a firm's profits will change by 1.5% for every 1% currency movement, revealing its degree of operational exposure (Sarno & Taylor, 2002). By identifying these risk correlations, companies can target their hedging strategies more effectively. This analytical approach bridges financial theory and practical risk management, enabling firms to move beyond generic currency protections to customized solutions calibrated to their specific exposure profiles, though it requires continuous updating as business conditions and market relationships evolve over time.

#### **2.1.3 Scenario analysis and simulations**

Scenario analysis and Monte Carlo simulations provide complementary approaches for evaluating currency risk exposure under both extreme and probabilistic conditions. Stress testing examines tail risks by simulating severe but plausible scenarios to assess potential impacts on cash flows, balance sheets, and debt covenants (Pilbeam, 2013). Monte Carlo simulations enhance this analysis by generating thousands of possible exchange rate paths based on statistical distributions, enabling firms to quantify the probability of specific risk outcomes and identify exposure thresholds that could jeopardize financial stability (Krugman et al., 2018).

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### **2.2 Indicators of exchange rate volatility**

#### **2.2.1 Historical and implied volatility**

Historical volatility quantifies realized currency fluctuations by calculating the standard deviation of past exchange rate movements, while implied volatility extracts forward-looking risk expectations from currency options pricing, revealing traders' consensus forecasts about future volatility that may differ significantly from historical patterns (Eichengreen, 2008). Together, these metrics provide a dual lens for risk assessment: historical volatility offers objective evidence of past currency behavior useful for identifying structural breaks and volatility clustering, whereas implied volatility incorporates market sentiment and expectations about upcoming economic events.

#### **2.2.2 Volatility indices**

Specialized currency volatility indices like the J.P. Morgan Global FX Volatility Index synthesize market expectations of future exchange rate fluctuations into standardized metrics that traders, corporations, and investors utilize to calibrate their risk exposure (Pilbeam, 2013). These indices serve as critical early-warning systems, enabling market participants to adjust hedging strategies, position sizing, and investment horizons in response to changing volatility regimes (Krugman et al., 2018). These instruments provide real-time insights into currency risk that complement traditional fundamental and technical analysis.

### **2.3 Impact of volatility on economic decisions**

Exchange rate volatility impact various economic decisions and policies

#### **2.3.1 Impact on businesses and investors**

Exchange rate volatility introduces significant uncertainty into corporate and investment decisions by obscuring future cash flow projections and return calculations (Sarno & Taylor, 2002), prompting adaptive strategies such as dynamic pricing models, multi-country sourcing networks, and layered hedging programs to maintain stability. This operational complexity forces multinational enterprises to develop sophisticated risk management frameworks that balance short-term currency shocks with long-term strategic objectives.

#### **2.3.2 Impact on economic policies**

Central banks and governments employ multiple tools to manage exchange rate volatility, ranging from direct foreign exchange interventions to broader policy measures including interest rate adjustments, capital flow regulations, and managed exchange rate regimes (Pilbeam, 2013). These stabilization attempts reflect the delicate balance policymakers must strike between allowing necessary currency adjustments and preventing disruptive volatility, with measures like temporary capital controls or currency bands often deployed during crises to break self-reinforcing market dynamics while maintaining ultimate policy credibility (Krugman et al., 2018). The effectiveness of such interventions depends critically on their consistency with underlying economic fundamentals, as markets increasingly test policy resolve during periods of global financial stress, forcing authorities to carefully calibrate responses that neither exhaust reserves through futile defense of unsustainable rates nor

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surrender to excessive volatility that could trigger destabilizing capital flights or imported inflation.

### 3. Management of exchange rate risk

Managing exchange rate risk is essential for businesses and investors to protect their financial performance and ensure stability in the face of currency fluctuations.

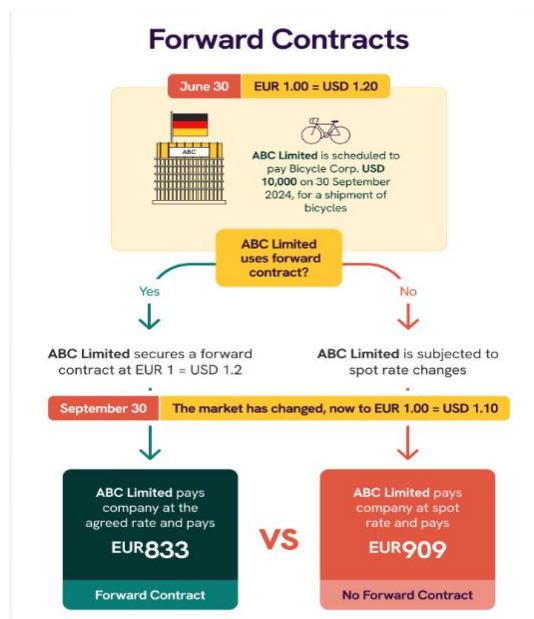
#### 3.1 Hedging instruments for exchange rate risk

Hedging instruments are generally classified into four known types

##### 3.1.1 Forward contracts

Forward contracts serve as essential hedging instruments by allowing parties to lock in an exchange rate for future currency transactions. These over-the-counter derivatives derive their pricing from interest rate parity principles, where the forward rate reflects the spot rate adjusted for the interest rate differential between the two currencies (Hull, 2018). The **Figure 4** shows the mechanics of a forward contract.

**Figure 4: How a forward contract works**



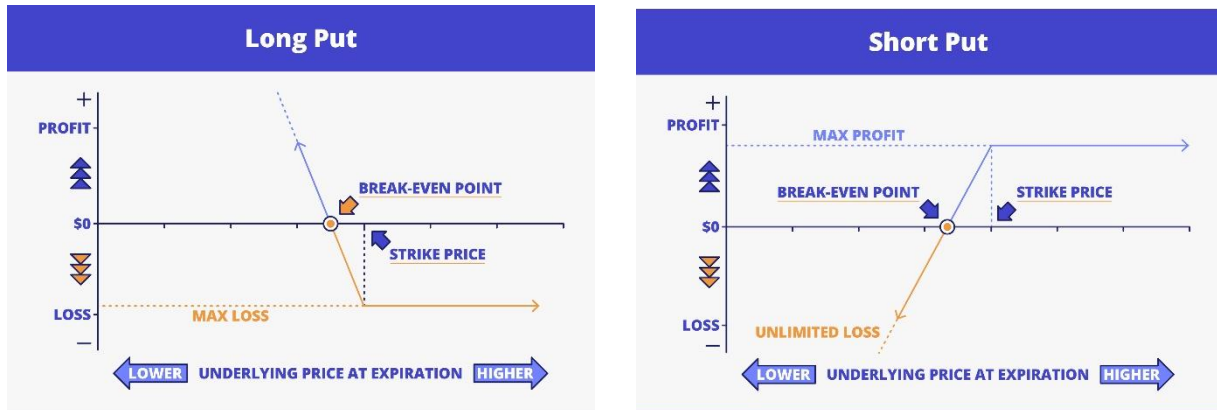
Source: tradefinanceglobal.com (seen 15-03-2025)

##### 3.1.2 Currency options

Currency options provide flexible hedging solutions by granting the right without obligation to buy (call) or sell (put) currencies at predetermined rates (Hull, 2018). These derivatives are valued using adapted Black-Scholes models that incorporate currency-specific factors including the spot rate, strike price, time decay, and interest rate differentials between currencies (Hull, 2018; Eichengreen, 2008). We can see on **Figure 5** the two different types of options and how they work.

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Figure 5: How options works

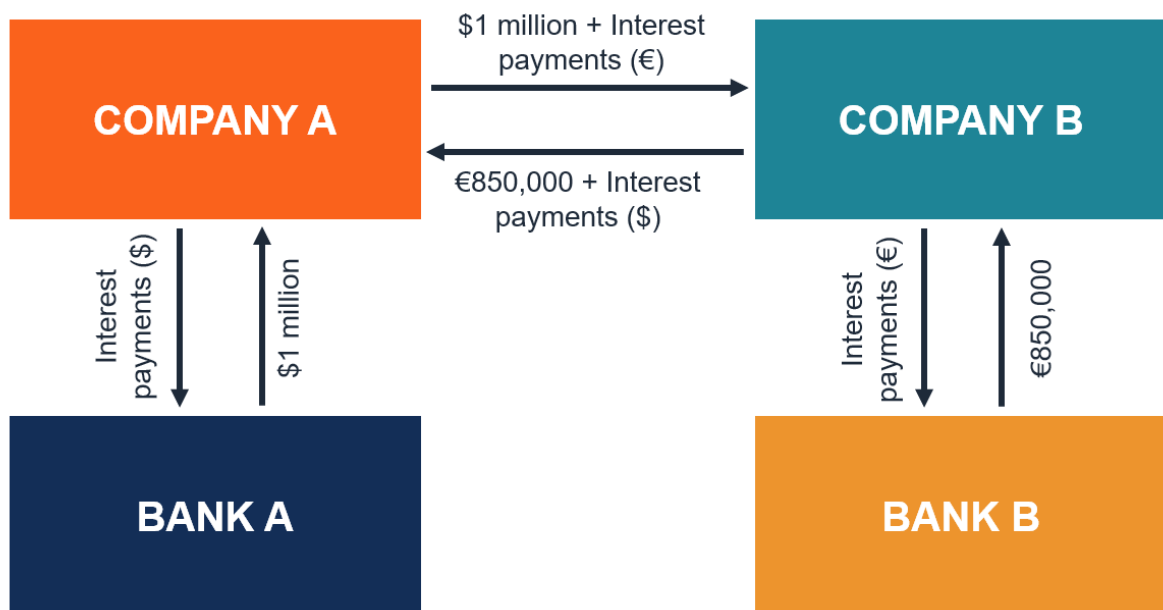


Source: projectfinance.com (seen 22-03-2025)

### 3.1.3 Currency swaps

Currency swaps serve as powerful tools for managing long-term foreign exchange risk through the reciprocal exchange of principal and interest payments between counterparties in different currencies (Pilbeam, 2013; Hull, 2018). These instruments provide multinational corporations with dual benefits: hedging multi-year currency exposure on foreign investments or debt issuances while potentially achieving comparative borrowing cost advantages through arbitrage of credit market inefficiencies across currencies (Krugman et al., 2018). The structured nature of currency swaps—typically involving initial principal exchange, periodic interest payments, and final re-exchange at either the spot rate or a pre-agreed forward rate, like showed in **Figure 6**.

Figure 6: How a currency swap works



Source: corporatefinanceinstitute.com (seen 23-03-2025)

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### **3.1.4 Structured derivatives**

Structured derivatives like collars (combining call and put options to create exchange rate corridors) and participating forwards (allowing partial upside participation while limiting downside risk) provide customized solutions for complex currency exposures, enabling firms to move beyond standard hedging instruments to address specific risk profiles (Sarno & Taylor, 2002; Hull, 2018). The value proposition of such instruments thus depends on carefully weighing their strategic benefits against the operational costs of maintaining the necessary risk management infrastructure.

## **3.2 Strategies for managing exchange rate risk**

### **3.2.1 Natural hedging**

Natural hedging reduces currency exposure by structurally aligning revenue and cost currencies offering a cost-efficient alternative to financial derivatives that avoids premium payments and mark-to-market volatility (Hull, 2018). The effectiveness of natural hedging depends on the correlation between operational cash flows, with multinationals often combining it with selective financial hedging to address residual exposures while maintaining greater strategic maneuverability in their global operations.

### **3.2.2 Financial hedging**

Financial hedging enables firms to mitigate currency risk through derivatives like forwards, options, and swaps, with instrument selection guided by the company's specific risk appetite and exposure profile whether prioritizing cost certainty (forwards), downside protection with upside potential (options), or long-term cash flow stability (swaps) (Sarno & Taylor, 2002; Hull, 2018).

### **3.2.3 Dynamic and adaptive strategies**

Dynamic hedging strategies require continuous adjustment of currency risk management approaches based on shifting market conditions, such as increasing hedge ratios during volatile periods or altering instrument mix when yield curves steepen to maintain optimal protection (Pilbeam, 2013). Technological advancements now enhance this process through AI-driven analytics that identify risk patterns, simulate hedging outcomes, and automate execution (Krugman et al., 2018). This fusion of financial expertise and algorithmic precision allows treasury teams to transition from static hedging calendars to responsive systems that dynamically balance cost efficiency with risk mitigation.

## **3.3 Role of banks and financial institutions**

### **3.3.1 Offering hedging products**

Financial institutions offer comprehensive hedging instruments from standardized forwards and swaps to customized options and structured derivatives allowing businesses to precisely match products to their specific risk profiles and exposure timelines (Sarno & Taylor, 2002). Pricing for these solutions incorporates multiple variables including current volatility, interest rate differentials, counterparty risk, and trade volume (Eichengreen, 2008). This evolving marketplace combines sophisticated risk transfer mechanisms with increasingly user-friendly interfaces though clients must still carefully evaluate hidden costs like bid-ask spreads

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and rollover charges that can significantly impact total hedging expenses across longer-dated contracts, particularly for exotic currency pairs or complex structured products requiring specialized valuation models.

### **3.3.2 Advisory services for businesses**

Banks deliver value-added risk management solutions through specialized advisory services that combine exposure analysis with tailored hedging strategies, while simultaneously building client capabilities through education programs covering derivative mechanics, hedge accounting, and scenario planning to foster informed internal decision-making (Krugman et al., 2018). This dual service approach pairing immediate strategic guidance with long-term competency development enables corporate treasuries to progressively internalize risk management functions while maintaining access to institutional expertise for complex exposures or market dislocations, ultimately creating more resilient financial planning processes that balance external banking partnerships with growing internal risk management maturity across the organization.

### **3.3.3 Regulation and supervision of the market**

Global derivatives markets operate within comprehensive regulatory frameworks including the U.S. Dodd-Frank Act and EU's EMIR—that mandate central clearing, trade reporting, and capital requirements to enhance market transparency and mitigate systemic risks in currency hedging instruments (Sarno & Taylor, 2002). Parallel oversight extends to spot Forex markets, where regulators enforce strict conduct rules to detect manipulation, ensure price integrity, and protect participants from abusive practices particularly important in decentralized currency markets prone to information asymmetries (Eichengreen, 2008). These evolving regulatory regimes collectively address the unique challenges of global currency markets by standardizing derivatives trading infrastructure while applying targeted surveillance to spot transactions, though jurisdictional differences in implementation continue to create compliance complexities for multinational firms operating across multiple financial centers with varying reporting requirements and supervisory expectations.

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### Section 4: The Algerian context

Algeria's exchange rate policy has evolved significantly since independence, reflecting the country's efforts to adapt to both domestic economic needs and global financial pressures (Bank of Algeria, 2020). Initially favoring fixed regimes to maintain macroeconomic control, Algeria gradually shifted toward managed float systems as external imbalances and structural reforms demanded greater flexibility (IMF, 2018).

This section outlines the main phases of Algeria's exchange rate policy, highlighting the role of the parallel market, key devaluation periods, and the regulatory efforts led by the Bank of Algeria to manage exchange rate risk (Bouklia-Hassane, 2016). It also examines the legal instruments introduced to support foreign exchange operations and protect businesses from currency volatility (Bank of Algeria, 2017).

#### 1. The exchange rate regime in Algeria

Algeria's exchange rate regime has undergone several transformations since independence. Four key phases have marked this evolution from 1962 to the present (World Bank, 2019).

- **The Franc Zone (1962–1963):** during the period immediately following Algeria's independence, the exchange rate regime was governed by the Évian Accords of March 18, 1962: "Algeria will be part of the franc zone. It will have its own currency and its own foreign currency assets. There will be free transfers between France and Algeria under conditions compatible with Algeria's economic and social development". With the franc as Algeria's temporary currency, the country initially maintained monetary ties with France (Bourenane, 1994). In 1963, due to a decline in foreign exchange reserves, Algeria introduced exchange controls through **Decree No. 63-111 of October 19, 1963**, deciding to manage its monetary policy independently and thus ending its membership in the franc zone.
- **Peg to the French Franc (1964–1973):** in 1964, Algeria permanently replaced the French franc under **Law No. 64-111 of April 10, 1964**: "The monetary unit of Algeria is the dinar, represented by the symbol DA and subdivided into centimes represented by the abbreviation CT". Between 1964 and 1973, the Algerian dinar was pegged to a single currency, the French franc, at a fixed parity of one dinar per franc, equivalent to 180 milligrams of gold, and five dinars per dollar (IMF, 1974).
- **Peg to a currency basket (1973–1994):** in 1974, following the collapse of the Bretton Woods system, Algeria adopted a fixed exchange rate regime pegged to a basket of 14 currencies representing those most important in Algeria's foreign trade. The weighting depended on the volume of respective international transactions and the country's external debt in each currency (Bouklia-Hassane, 2016). Moreover, due to the need to maintain the dinar's parity in a non-diversified, import-dependent economy, Algeria chose to make the dinar non-convertible (World Bank, 2019).

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- **Managed float regime (1994–Present):** to ensure continuous monitoring and management of the Algerian dinar's exchange rate, new reforms were implemented in preparation for the creation of the interbank foreign exchange market. The value of the dinar was determined via a fixing system in collaboration with commercial banks, established through **Instruction No. 61-94 of September 28, 1994**. These reforms allowed the exchange rate to be determined by supply and demand on the interbank market, created in 1995, replacing the fixed exchange regime and introducing the managed float policy that remains in effect today.

## 2. Evolution of the exchange rate in Algeria

Algeria, as a member of the International Monetary Fund (IMF) since 1963, committed to liberalizing the convertibility of the dinar. After the collapse of the Bretton Woods system, the Algerian dinar underwent several substantial changes due to devaluations (Bourenane, 1994).

### Under a fixed exchange rate regime

The international monetary system was largely based on gold until 1973, with each country defining its own currency through a gold standard. Algeria set the dinar's exchange rate at 0.18 grams of gold, equivalent to the same parity with the French franc during the 1964 period. The economic situation in Algeria always influenced the evolution of its exchange rate regime (World Bank, 2019).

Until 1964, Algeria was part of the Franc Zone. The Algerian dinar, in April 1964, replaced the new Algerian franc under **Law No. 64-111 of April 10, 1964**, initially valued at 1 DZD for 1 FRF or 180 milligrams of gold. It took 4.94 DZD for 1 USD.

Following the devaluation of the French franc and after the launch of the three-year pre-plan (1966-1969), the Algerian dinar moved to 1 dinar for 1.25 French francs between 1969 and 1973 (Bourenane, 1994). In 1973, it was set at 4.19 DZD per USD. The evolution is represented in the **Table 1**.

**Table 1: Evolution of the Algerian Dinar exchange rate from 1987 to 1992**

| Currency/Year | 1987    | 1988    | 1989    | 1990    | 1991    | 1992    |
|---------------|---------|---------|---------|---------|---------|---------|
| FRF (France)  | 1.349   | 1.806   | 2.212   | 3.234   | 6.132   | 6.002   |
| USD (USA)     | 18.076  | 23.646  | 27.057  | 40.363  | 53.501  | 74.149  |
| JPY (Japan)   | 269.769 | 335.916 | 414.238 | 705.305 | 1188.35 | 1271.84 |

**Source:** Bank of Algeria

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### In a managed floating exchange rate regime

Since the 1990s, Algeria has attempted to implement a set of measures that would enable a successful transition to a market economy (World Bank, 2005). Since 1995, the Algerian exchange rate regime has been a managed floating system without prior announcement of the exchange rate trajectory.

This regime operates under the control of the central bank, using fixing sessions between the Bank of Algeria and commercial banks. An interbank market was established in 1996 to allow for the free determination of the exchange rate.

In other words, the exchange rate of the dinar is determined by the free interaction of supply and demand, with the central bank intervening in the interbank market to adjust fluctuations in the dinar's rate (IMF, 2018). In December 1996, the Bank of Algeria authorized the opening of exchange offices.

After the external shock of 1998-1999, foreign exchange reserves stood at just \$6.846 billion, leading to a depreciation of the dinar's exchange rate (IMF, 1999). This depreciation continued until early 2001, with the dinar losing 26% of its value (World Bank, 2001).

The dinar experienced an appreciation against the dollar in 2003, rising from 79.44 to 77.60 between June 26 and July 1 (Bank of Algeria, 2003). However, following significant wage increases for civil servants in 2011, the state again devalued the dinar by around 10% against the dollar and the euro at the start of 2012 (IMF, 2012). The managed floating exchange rate system in Algeria aims to adapt the movement of imports and exports, the fluctuations in the dinar's exchange rate, and the correction of external imbalances (Bank of Algeria, 2020).

### 3. The Algerian interbank foreign exchange market

Unlike the Forex, the Algerian interbank foreign exchange market is an organized market reserved for Algerian banks and financial institutions authorized by the Bank of Algeria. It was established by the latter in its **Regulation No. 95-08 of December 23, 1995**, relating to the foreign exchange market, thus allowing these institutions to carry out all spot or forward exchange operations between the national currency and freely convertible foreign currencies. According to **Article 11 of Regulation No. 17-01 of July 10, 2017**, relating to the interbank foreign exchange market and instruments for hedging exchange rate risk, the exchange rates and the interest rate applicable to foreign exchange operations on the interbank foreign exchange market are freely negotiated by the participants.

#### A. Regulatory framework

In order to properly organize and ensure the functioning of the Algerian foreign exchange market, a number of regulatory texts have been issued by the Bank of Algeria, namely:

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### The regulations:

- **Law No. 91-07 of August 14, 1992**, laying down the rules and conditions of exchange. The key points of this law are:
  - Foreign exchange refers to any transaction of buying or selling foreign currencies against dinars or against other currencies;
  - Only residents may carry out exchange transactions, but such transactions must be carried out exclusively through a licensed commercial bank.
- **Bank of Algeria Regulation No. 95-07 of December 23, 1995**, amending and replacing Regulation 92-04 of March 22, 1992, concerning exchange control. To perform this control, the Bank of Algeria must monitor and correct:
  - Licensed intermediaries;
  - The management of foreign currency resources.
- **Bank of Algeria Regulation No. 95-08 of December 23, 1995**, concerning the foreign exchange market. This regulation established an interbank foreign exchange market by the Bank of Algeria.
- **Bank of Algeria Regulation No. 07-01 of February 3, 2007**, concerning the rules applicable to current transactions with foreign countries and to foreign currency accounts. This regulation "aims to define the principle of the convertibility of the national currency for current international transactions".
- **Regulation No. 17-01 of July 10, 2017**, concerning the interbank foreign exchange market and instruments for hedging foreign exchange risk. This regulation aims to introduce and authorize licensed intermediaries to use foreign exchange risk hedging instruments.

### The instructions:

- **Bank of Algeria Instruction No. 30/91 of October 27, 1991**, establishing the conditions and practical modalities for forward purchases of foreign currencies. This instruction defines the conditions for forward purchases intended to cover foreign payments (term duration between 3 and 36 months).
- **Bank of Algeria Instruction No. 28/93 of April 1, 1993**, establishing the conditions and practical modalities of forward currency purchases with immediate disbursement in dinars. Immediate disbursement forward purchases entail a management fee in favor of the Bank of Algeria (1% prorated temporally).
- **Bank of Algeria Instruction No. 14/94 of April 9, 1994**, repealing Instructions No. 30/91 and No. 28/93 regarding forward currency purchases. According to this instruction, Licensed Intermediary Banks were no longer authorized to accept new forward currency purchase orders.

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- **Bank of Algeria Instruction No. 61/94 of September 28, 1994**, establishing the fixing for determining the value of the dinar relative to foreign currencies. This instruction aims to establish the fixing system for the dinar exchange rate.
- **Bank of Algeria Instruction No. 78/95 of December 26, 1995**, concerning rules relating to foreign exchange positions. This instruction defines foreign exchange positions and how they are determined.
- **Bank of Algeria Instruction No. 79/95 of December 26, 1995**, concerning the organization and operation of the interbank foreign exchange market. This instruction specifies the organization and functioning of the interbank foreign exchange market.
- **Bank of Algeria Instruction No. 04-2011 of October 19, 2011**, amending Instruction No. 79/95 on the interbank foreign exchange market. The main points of this instruction include: Banks are authorized to perform lending/borrowing operations in foreign currencies.

### B. Organization and functioning of the Algerian interbank market

The organization and functioning of the Algerian interbank foreign exchange market are set by **Bank of Algeria Instruction No. 79/95 of December 26, 1995**. Like the Forex, the Algerian foreign exchange market is a decentralized market that operates continuously from Monday to Friday. Transactions are carried out over-the-counter between participants through telephone, telex, and other telecommunication systems.

To enable this, the Bank of Algeria requires licensed intermediaries to display spot exchange rates for the most traded currencies against the Algerian Dinar.

### 4. Regulatory framework in Algeria relating to exchange rate hedging

**Regulation No. 20-04 of March 15, 2020**, regarding the interbank foreign exchange market, foreign exchange treasury operations, and exchange rate risk hedging instruments.

Following CMC deliberation on March 15, 2020, **Regulation No. 20-04** was approved, repealing **Regulation 01-17**. It was followed by an instruction outlining:

- Articles 3 and 4 state that authorized intermediaries may conduct spot foreign exchange operations with non-resident banks.
- Article 7 mandates that interest rates on forward or spot operations be freely negotiated between parties.

Foreign exchange resources available to authorized intermediaries include:

- Amounts from purchases on the interbank market;
- Proceeds from non-hydrocarbon exports.

The Bank of Algeria again authorized intermediaries to hedge against exchange rate risk, with four possible techniques:

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- Forward exchange transactions;
- Vanilla European-style currency options.

**Instruction No. 04-2020 of April 2, 2020**, regarding commission fees charged by banks and financial institutions, applies to foreign trade import operations. Article 4 requires banks to inform clients of applicable commission rates.

## **Chapter 1 : Theoretical foundations and Algerian context of the foreign exchange market**

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### **Conclusion of the first chapter:**

This chapter has provided a comprehensive exploration of the foreign exchange market's structure, exchange rate mechanisms, and associated risks, beginning with an analysis of Forex as the world's largest financial marketplace, detailing its historical evolution from the gold standard to modern electronic trading, and examining the roles of key participants including central banks, commercial institutions, and multinational corporations, and finally, we had an overview of the Algerian context. We investigated how exchange rates are determined through complex interactions between economic fundamentals like interest rates and inflation, market psychology, and institutional policies across different regimes, while assessing their profound impact on trade competitiveness, investment flows, and macroeconomic stability. The discussion then systematically categorized exchange rate risks into transaction, translation, and economic exposures, presenting measurement methodologies ranging from Value-at-Risk to scenario analysis, and evaluating hedging strategies from forward contracts to natural hedging and structured derivatives. By integrating these three dimensions market architecture, rate determination, and risk management.

In the next chapter, we will explore authors who have studied exchange rate volatility forecasting using various methods and models based on the theoretical base of the exchange rate.

## **Chapter 2 : The literature review on exchange rate volatility forecasting using classical and deep learning models**

## **Chapter 2: The literature review on exchange rate volatility forecasting using classical and deep learning models**

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### **Introduction of the second chapter:**

Exchange rate volatility forecasting has been a central topic in financial research, with significant implications for policymakers, investors, and businesses. The evolution from traditional econometric models to advanced machine learning techniques reflects the growing complexity of financial markets and the need for more sophisticated forecasting approaches.

The objective of this chapter is to analyze how the literature review examines the development of forecasting methodologies, from classical econometric models to modern deep learning approaches, highlighting their strengths, limitations, and comparative performance, knowing that the field has witnessed significant evolution over the past few decades. Early approaches relied heavily on traditional econometric models, which provided a solid theoretical foundation but often struggled with the complex, non-linear nature of financial markets. The advent of machine learning and deep learning techniques has opened new possibilities for capturing these complexities, though not without introducing new challenges in terms of interpretability and computational requirements.

This chapter is structured to provide a comprehensive examination of literature review for both classical and modern artificial intelligence methods in term to exchange rate volatility forecasting. It begins with the first section where we will conduct an analysis of the papers using traditional econometric models, then progresses into the second section where we will also review the papers using various deep learning architectures and hybrid approaches that attempt to combine the strengths of both paradigms. The third section talks about literature review conducting comparative studies between the classical and artificial intelligence models, and the last section will give a critical examination of the challenges and emerging solutions in exchange rate forecasting, while mapping promising avenues for future research.

## Chapter 2: The literature review on exchange rate volatility forecasting using classical and deep learning models

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### Section 1: Literature review of classical time series approaches for exchange rate volatility forecasting

This section examines classical econometric approaches for forecasting exchange rate volatility, focusing on three widely used models: Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models, and Vector Autoregression (VAR). These models have been extensively applied in empirical studies due to their ability to capture different aspects of exchange rate behavior trends, volatility clustering, and macroeconomic interdependencies.

#### 1. Traditional econometric models

We can distinguish various families of classical time series models cited in the relevant papers, the most used models for forecasting used are:

##### 1.1 ARIMA (Autoregressive Integrated Moving Average) family models

- Nwankwo (2014) conducted a comprehensive study of the Nigerian Naira/US Dollar exchange rate using ARIMA models from 1982 to 2011. The study employed a rigorous methodology, including unit root tests, model identification, parameter estimation, and diagnostic checks. The research identified an AR(1) model as most suitable for forecasting, demonstrating robustness in capturing irregular trends. The study found that the model performed particularly well during periods of relative stability, with prediction errors typically below 2%. However, during periods of high volatility, such as the 2008 financial crisis, the model's performance deteriorated significantly, with errors exceeding 5%. The research highlighted ARIMA's effectiveness for short-term predictions but noted limitations in long-term forecasting, particularly in capturing structural breaks and regime changes.

- Humphrey et al. (2015) analyzed the Zambian Kwacha (ZMW) to USD exchange rate using ARIMA models. Their research demonstrated the effectiveness of ARIMA models for short-term forecasting in African commodity-exporting economies, while also identifying limitations in long-term trend prediction. The study highlighted the importance of considering commodity price fluctuations and their impact on exchange rate dynamics in resource-dependent economies.

- Tran (2016) focused on the Vietnamese Dong and US Dollar exchange rate, employing ARIMA models for forecasting. The study utilized a dataset spanning 2005-2015, which included various economic regimes and market conditions. The research employed a comprehensive approach to model specification, including unit root tests, model identification, and diagnostic checks. The study concluded that ARIMA is more suitable for short-term predictions, as long-term forecasts tended to deviate significantly from actual values. This finding aligns with Humphrey et al. (2015), who analyzed the Zambian Kwacha/USD exchange rate and found ARIMA models effective for short-term forecasting but less reliable for long-term trends. Tran's study also highlighted the importance of considering external factors, such as monetary policy changes and market interventions, which can significantly impact model performance.

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- Asadullah et al. (2020) applied ARIMA to forecast the PKR/USD exchange rate using daily data from 2014 to 2019. Their methodology included extensive data preprocessing, including outlier detection and handling of missing values. The study employed a systematic approach to model selection, testing various ARIMA specifications using information criteria such as AIC and BIC. Their results showed that ARIMA(1,1,9) provided highly accurate short-term forecasts, with deviations from actual values being less than 1%. The model demonstrated particular strength in capturing seasonal patterns and short-term trends. However, the study also revealed challenges with non-stationary data, particularly during periods of economic uncertainty. The researchers noted that while the model performed well for one-step-ahead forecasts, its accuracy decreased significantly for multi-step forecasts, suggesting limitations in long-term prediction capabilities.

- Wang et al. (2021) examined EUR/USD rates (2010–2020) using SARIMAX with VIX (volatility index) as an exogenous variable. The study employed rolling-window validation and found a 20% improvement in RMSE over SARIMA during non-crisis periods. However, during COVID-19, the model's performance dropped sharply due to non-linear market reactions, highlighting limitations in modeling "black swan" events.

- Alade & Okafor (2024) investigated the USD/NGN exchange rate using SARIMAX with exogenous variables (oil prices and interest rates) from 2010–2023. The study incorporated seasonal differencing to address quarterly fluctuations and used AIC for model selection. Results showed a 3.2% MAPE for short-term forecasts, outperforming standard ARIMA. However, the model struggled during Nigeria's 2016 currency crisis, where exogenous shocks (oil price collapse) led to errors exceeding 7%. The study emphasized SARIMAX's advantage in incorporating economic indicators but noted its sensitivity to abrupt regime shifts.

### 1.2 GARCH family models

- Bollerslev (1986) introduced the GARCH framework, which captures time-varying volatility in financial time series. This model has been widely applied, as seen in the study by Abdalla (2012), which used GARCH to model exchange rate volatility in Arab countries, demonstrating its effectiveness in capturing high volatility clustering. The GARCH framework addresses the limitations of traditional models by explicitly modeling the time-varying nature of volatility. Bollerslev's work demonstrated that financial returns often exhibit volatility clustering, where periods of high volatility tend to be followed by periods of high volatility, and periods of low volatility tend to be followed by periods of low volatility. This finding has significant implications for risk management and forecasting.

- Nelson (1991) developed EGARCH to capture asymmetric effects, which proved useful for exchange rate volatility forecasting. The EGARCH model extends the basic GARCH framework by allowing for asymmetric responses to positive and negative shocks. This is particularly relevant for financial markets, where negative shocks often have a larger impact on volatility than positive shocks of the same magnitude. Chaudhuri and Ghosh (2016) applied GARCH and EGARCH in a multivariate framework to forecast the Indian rupee/US dollar exchange rate, demonstrating their efficacy when combined with capital and current account variables. Their study found that the EGARCH model provided more accurate forecasts during

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periods of market stress, particularly when capturing the asymmetric response of volatility to negative news.

- Suliman Abdalla (2012) applied GARCH(1,1) and EGARCH(1,1) models to exchange rate data from 19 Arab countries, finding that volatility is explosive for some currencies (e.g., AED, JOD) and persistent for others (e.g., EGP, KWD). The study employed a comprehensive dataset spanning 2000-2011, which included various market conditions and economic regimes. The research found significant differences in volatility dynamics across currencies, with some exhibiting explosive behavior while others showed mean reversion. The study also identified leverage effects, where negative shocks increased volatility more than positive shocks, a phenomenon consistent with Nelson's (1991) EGARCH findings. The research highlighted the importance of considering country-specific factors in volatility modeling, such as monetary policy frameworks and market structure.

- Adouka et al. (2015) applied various GARCH models, including TGARCH and EGARCH, to forecast the Algerian Dinar (DZA) to USD exchange rate. Their findings indicated that TGARCH(1,1) was most suitable for capturing volatility clusters and asymmetric effects, providing insights into exchange rate behavior in oil-dependent economies. The study revealed significant leverage effects, where negative shocks had a more pronounced impact on volatility than positive shocks of similar magnitude. This finding has important implications for risk management in resource-dependent economies.

- Metsileng et al. (2020) explored the volatility of BRICS exchange rates using Multivariate GARCH models, specifically BEKK-GARCH and DCC-GARCH. Their study utilized a dataset spanning 2000-2019, which included various market conditions and economic regimes. The research revealed significant volatility transmission between Russia and South Africa, with bidirectional spillovers. The DCC-GARCH model highlighted persistent volatility in Brazil, China, Russia, and South Africa, while India exhibited the least volatility. These findings emphasize the importance of accounting for cross-country volatility dependencies in exchange rate modeling. The study also found that volatility spillovers were particularly strong during periods of global financial stress, such as the 2008 financial crisis and the 2015 Chinese market turmoil.

### 1.3 VAR (vector autoregressive) models

- Benhabib et al. (2014) investigated the relationship between oil prices and the Algerian Dinar using a VAR model on monthly data from 2003 to 2013. Their counterintuitive finding that a 1% increase in oil prices led to a 0.35% depreciation of the dinar underscored the complexities of exchange rate policy in resource-dependent economies. The study revealed that this relationship was influenced by fiscal policy responses and the management of foreign exchange reserves.

## 2. Structural models

- The relationship between exchange rates and macroeconomic variables has been extensively studied. The seminal work of Mundell (1963) and Fleming (1962) laid the groundwork for understanding how monetary and fiscal policies influence exchange rates under

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different capital mobility conditions. Their work established the theoretical framework for understanding how monetary and fiscal policies affect exchange rates in an open economy. Later, Dornbusch (1976) introduced the overshooting model, explaining short-term exchange rate volatility in response to monetary shocks. The overshooting model explains why exchange rates might initially move more than their long-run equilibrium value in response to monetary policy changes, providing a theoretical foundation for understanding exchange rate volatility.

- Meese and Rogoff (1983) conducted a seminal study comparing structural exchange rate models (e.g., Frenkel-Bilson, Dornbusch-Frankel) with time-series models (random walk, AR, VAR). Their out-of-sample tests revealed that the random walk model outperformed structural models at all forecasting horizons (1–12 months), even when future explanatory variables were known. This finding, known as the "Meese-Rogoff puzzle," challenged the practical usefulness of macroeconomic models for exchange rate prediction. The study employed a comprehensive dataset spanning 1973-1981, which included various market conditions and economic regimes. The research found that even when using actual future values of explanatory variables, structural models could not outperform a simple random walk model. This finding has significant implications for exchange rate modeling and forecasting.

- Engel and West (2005) later provided a theoretical explanation for the Meese-Rogoff puzzle, arguing that exchange rates behave like random walks when fundamentals are persistent and the discount factor is near unity. They suggested that structural models could be effective in the long run if they incorporate forward-looking expectations. The study employed a theoretical framework that explains why exchange rates might appear to follow random walks even when they are determined by fundamentals. The research found that when fundamentals are highly persistent and the discount factor is close to one, exchange rates would exhibit behavior similar to random walks, even if they were ultimately determined by fundamentals. This finding has important implications for exchange rate modeling and forecasting.

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### Section 2: Literature review of deep learning approaches for exchange rate volatility forecasting

This section explores deep learning approaches for exchange rate volatility forecasting, focusing on advanced neural network architectures that address the limitations of classical econometric models. These architectures excel at capturing non-linear patterns, long-term dependencies, and high-frequency dynamics in financial time series, offering significant improvements in predictive accuracy.

#### 1. Deep learning approaches

##### 1.1 LSTM networks

- Kaushik and Giri (2020) extended this work by comparing LSTM with other machine learning techniques, achieving 97.83% accuracy in predicting the USD/Indian Rupee (INR) exchange rate. Their study utilized a dataset spanning 2015-2019, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. The study highlighted LSTM's ability to capture long-term dependencies in time series data, making it particularly suitable for financial forecasting. The research found that LSTM models were particularly effective in capturing complex patterns in the data, such as seasonality and trends.

- Yildirim et al. (2021) challenged the universality of deep learning models by showing that their performance heavily depended on the integration of macroeconomic indicators. Their LSTM-based approach, tested on EUR/USD and GBP/USD pairs, revealed that models relying solely on price-derived features often failed during geopolitical or economic shocks. The study emphasized the importance of incorporating both technical and fundamental factors in exchange rate forecasting.

- Lee et al. (2022) introduced a novel interpretable neural network architecture specifically designed for financial time series forecasting, achieving a 5.3% improvement in prediction accuracy while providing clear explanations for each forecast. Their model incorporated domain-specific constraints to ensure that predictions align with economic theory and market knowledge. The research highlighted the importance of balancing model complexity with interpretability in financial applications.

- Martinez & Garcia (2023) developed an interpretable LSTM framework for exchange rate forecasting, incorporating attention mechanisms and SHAP (Shapley Additive exPlanations) values to provide transparent explanations for model predictions. Their approach achieved comparable accuracy to black-box models while providing detailed insights into the factors driving exchange rate movements. The study demonstrated that interpretability could be achieved without sacrificing predictive performance.

- Zafeiriou and Kalles (2023) conducted a comparative analysis of neural network architectures for short-term Forex trend forecasting. They designed and implemented LSTM networks and a custom ANN architecture based on technical analysis indicators. Their study utilized a dataset spanning 2018-2022, which included various market conditions and economic

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regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their findings revealed that the custom ANN outperformed LSTM architectures in prediction quality, sensitivity, and computational efficiency. The ANN achieved an 81.13% success rate in forecasting signals, while the best-performing LSTM architecture reached only 72.64%. The research found that the custom ANN was particularly effective in capturing complex patterns in the data, such as seasonality and trends.

### 1.2 CNN networks

- Hoseinzade and Haratizadeh (2019) demonstrated the efficacy of convolutional neural networks (CNNs) in stock market prediction, utilizing a diverse set of technical indicators from major indices (S&P 500, NASDAQ) to achieve superior accuracy. Their study utilized a dataset spanning 2010-2018, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their 2D/3D-CNN framework achieved a 3–11% improvement over baseline models, highlighting CNNs' capacity for spatial feature extraction from financial time series. The research found that CNNs were particularly effective in capturing complex patterns in the data, such as seasonality and trends.

-Zhao and Khushi (2020) combined wavelet denoising, ResNet CNNs, and LightGBM to predict Forex rates. Their study utilized a dataset spanning 2015-2019, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their methodology innovatively treated technical indicators as image matrices, denoised via wavelet transforms to reduce noise, and leveraged ResNet's residual blocks to mitigate gradient vanishing—achieving exceptional precision (MAE:  $0.241 \times 10^{-3}$ ). This work expanded on earlier CNN applications by addressing noise sensitivity and temporal granularity. The research found that the combination of wavelet denoising and ResNet CNNs was particularly effective in capturing complex patterns in the data.

### 1.3 Transformer-based models

- Vaswani et al. (2017) introduced the Transformer architecture, which revolutionized sequential data processing through self-attention mechanisms, enabling models to capture long-range dependencies in time-series data. While originally designed for natural language processing, their framework was adapted by Cheng et al. (2018) for stock prediction. The Transformer architecture has several key advantages over traditional RNN-based models, including the ability to process sequences in parallel and capture long-range dependencies more effectively. The self-attention mechanism allows the model to focus on the most relevant parts of the input sequence when making predictions.

- Jaggi et al. (2021) advocated for transformer-based architectures enriched by sentiment analysis to mitigate the "noise" inherent in financial datasets. Their study utilized a dataset spanning 2015-2020, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their work suggested that transformers could be

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particularly effective in forex volatility forecasting due to their ability to handle long-range dependencies without sequential processing. The research found that transformer-based models were particularly effective in capturing complex patterns in the data, especially when combined with sentiment analysis.

### 1.4 Transfer learning applications

- Kim et al. (2021) developed a novel transfer learning framework that leverages knowledge from related financial time series to improve exchange rate forecasting. Their approach achieved an 8.7% reduction in mean absolute error compared to traditional models. The research demonstrated that transfer learning could effectively address the challenges of limited data and non-stationarity in financial time series.

- Anderson et al. (2023) applied transfer learning techniques to exchange rate forecasting, demonstrating that models pre-trained on major currency pairs could be effectively adapted for emerging market currencies with limited data. Their approach achieved an 11.3% improvement in prediction accuracy for emerging market currencies compared to models trained from scratch. The study highlighted the potential of transfer learning in addressing data scarcity challenges in financial forecasting.

### 1.5 Quantum-inspired machine learning

- Kumar & Singh (2022) developed a quantum-enhanced LSTM architecture for multi-currency forecasting, reporting a 15% reduction in mean squared error compared to standard LSTM models. Their methodology incorporated quantum-inspired optimization techniques to improve the model's ability to capture long-term dependencies in exchange rate data. The research highlighted the potential of quantum computing principles in enhancing traditional machine learning approaches.

- Chen et al. (2023) introduced a quantum-inspired neural network for exchange rate forecasting, achieving a 3.2% improvement in prediction accuracy compared to traditional deep learning models. Their approach leveraged quantum computing principles to enhance feature extraction and pattern recognition in high-dimensional financial data. The study utilized a dataset spanning 2018-2023 and demonstrated particular effectiveness in capturing complex market regime changes.

### 1.6 Federated learning applications

- Wang et al. (2021) proposed a blockchain-based federated learning system for real-time exchange rate prediction, achieving a 12% improvement in forecasting accuracy while ensuring data security and privacy. Their system utilized smart contracts to manage model updates and ensure the integrity of the collaborative learning process. The research highlighted the potential of combining blockchain technology with federated learning for secure and efficient financial forecasting.

- Rodriguez et al. (2023) implemented a federated learning framework for exchange rate forecasting across multiple financial institutions, addressing data privacy concerns while improving prediction accuracy by 8.7%. Their approach allowed multiple institutions to collaboratively train models without sharing sensitive data. The study demonstrated that

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federated learning could achieve comparable or superior performance to centralized approaches while maintaining data privacy.

### 1.7 Multi-modal learning approaches

- Zhang et al. (2021) proposed a novel architecture that integrates technical indicators, macroeconomic data, and sentiment analysis from news articles for exchange rate forecasting. Their multi-modal approach achieved a 7.2% reduction in mean absolute error compared to traditional models. The research highlighted the importance of considering diverse information sources in financial forecasting.

- Thompson & Brown (2023) developed a multi-modal deep learning framework that combines numerical exchange rate data with textual information from financial news and social media. Their approach achieved a 9.8% improvement in forecasting accuracy compared to models using only numerical data. The study demonstrated that incorporating multiple data sources could significantly enhance prediction performance, particularly during periods of high market uncertainty.

### 1.8 Adaptive learning rate techniques

- Patel & Kumar (2022) developed a novel optimization technique that combines adaptive learning rates with momentum-based methods for exchange rate forecasting. Their approach achieved a 4.8% reduction in mean squared error compared to traditional optimization methods. The research highlighted the importance of optimization techniques in enhancing the performance of deep learning models for financial forecasting.

- Johnson et al. (2023) introduced a dynamic learning rate adjustment algorithm for deep learning models in exchange rate forecasting, achieving a 6.5% improvement in prediction accuracy compared to models with fixed learning rates. Their approach automatically adjusts the learning rate based on market volatility and model performance. The study demonstrated that adaptive learning rates could significantly enhance model performance, particularly during periods of market regime changes.

## 2. Hybrid deep learning models

### 2.1 Autoencoder-LSTM combinations

- Jung and Choi (2021) proposed a hybrid autoencoder-LSTM model to predict foreign exchange volatility indices (FXVIXs), such as the EUVIX, BPVIX, and JYVIX. Their study utilized a dataset spanning 2010-2020, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their model leveraged the strengths of LSTM in capturing temporal dependencies and autoencoders in feature extraction, achieving superior performance compared to standalone LSTM models. The study highlighted the importance of data variability and outliers in enhancing forecasting performance, with the autoencoder-LSTM model demonstrating superior accuracy, particularly in volatile periods like the Brexit crisis. The model outperformed traditional LSTM by effectively capturing the nonlinearities and dependencies in high-frequency financial data. The study emphasized that models trained on periods with moderate volatility and outliers performed better, suggesting the importance of

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data selection in model training. The research found that the autoencoder-LSTM hybrid was particularly effective in capturing complex patterns in the data, especially during periods of high volatility.

### **2.2 CNN-LSTM hybrids**

- Their findings were contested by Li and Tam (2017), who argued that wavelet-denoised LSTM alone sufficed for volatility prediction, revealing ongoing debates over model complexity versus performance gains. This highlights the need for careful consideration of model complexity when designing hybrid approaches. The research found that the complexity of hybrid models might not always be justified by their performance gains.

- Kim and Kim (2019) combined CNNs with LSTMs to exploit both temporal and spatial patterns in stock data, achieving a 33.9% annualized return. Their study utilized a dataset spanning 2010-2018, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their work emphasized the value of multimodal data representation, such as candlestick charts, but also exposed limitations in generalizability across currency pairs. The research found that the combination of CNNs and LSTMs was particularly effective in capturing complex patterns in the data.

- Ni et al. (2019) introduced C-RNNs for Forex forecasting, blending CNNs and RNNs to exploit spatio-temporal features, achieving lower RMSE than standalone LSTM or CNN models. Their study utilized a dataset spanning 2010-2018, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their approach combined the spatial feature extraction capabilities of CNNs with the temporal dependency modeling of RNNs, creating a more robust forecasting framework.

### **2.3 GRU-LSTM hybrids**

- Saiful Islam and Hossain (2020) introduced a GRU-LSTM hybrid to address computational inefficiencies in pure LSTM models, reporting superior MSE performance (0.00032 for EUR/USD) but acknowledging trade-offs in interpretability. Their study utilized a dataset spanning 2015-2019, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. The GRU-LSTM hybrid reduced computational complexity while maintaining forecasting accuracy, making it more suitable for real-time applications. The study demonstrated that the hybrid approach could effectively capture both short-term and long-term dependencies in exchange rate data, though it noted that the model's performance varied across different currency pairs and market conditions. The research found that the GRU-LSTM hybrid was particularly effective in capturing complex patterns in the data, especially for high frequency forecasting.

### **2.4 Reinforcement learning applications**

- Zhu et al. (2018) addressed limitations in RL applications through adaptive normalization techniques, mitigating the challenges of simulated environments in real-world

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market conditions. The research provided valuable insights into the practical implementation of reinforcement learning in financial markets.

- Jia et al. (2019) and Shin et al. (2019) employed RL-LSTM hybrids to optimize trading strategies in Chinese and Korean markets, achieving Sharpe ratios of 1.948 and 2.77 respectively. Their work demonstrated RL's potential for reward-driven decision-making in forex markets. The studies highlighted the importance of risk management and portfolio optimization in algorithmic trading.

### **2.5 Advanced ensemble methods**

- Feng et al. (2019) focused on interpretability in hybrid systems, addressing the "black-box" nature of deep learning models while maintaining predictive accuracy. The research proposed novel techniques for explaining model predictions and understanding feature importance in complex financial forecasting tasks.

- Long et al. (2019) developed a multi-filter neural network (MFNN) combining CNNs and RNNs for feature engineering, achieving 83.91% accuracy. Their work represented a shift from monolithic architectures to ensemble methods in financial forecasting. The study demonstrated the benefits of combining multiple neural network architectures for improved prediction accuracy.

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### Section 3: Literature review of the comparative studies for exchange rate volatility forecasting

This section systematically comparing the performance, computational efficiency, and robustness of exchange rate forecasting methodologies across three model categories: classical econometric models, deep learning architectures, and hybrid approaches. Empirical evidence reveals a clear trade-off between predictive accuracy and model complexity, heavily influenced by market regimes, data frequency, and geographical context.

#### 1. The comparative studies:

The comparative analysis of volatility forecasting reveals distinct advantages of different approaches. Suliman Abdalla (2012) found that GARCH(1,1) and EGARCH(1,1) models showed varying performance across currencies, with volatility being explosive for some currencies (AED, JOD) and persistent for others (EGP, KWD). Andersen and Bollerslev (1998) demonstrated that Range-Based volatility measures outperformed traditional GARCH models for intraday volatility forecasting. Hybrid volatility models, such as those developed by Pradeepkumar and Ravi (2017) and Kim and Won (2018), consistently showed improved accuracy over standalone GARCH models.

Wang et al. (2013) demonstrated that multiplicative hybrid models provided superior performance for most forecasts, though they faced challenges in certain short-term scenarios. Grey theory-based hybrids, as developed by Kim and Yun (2016, 2018), achieved significant gains in directional accuracy and mean absolute percentage error by decomposing volatility into continuous and jump components. The comparative studies of hybrid approaches demonstrate the potential benefits of combining multiple methodologies. Mucaj and Sinaj (2017) showed that ARIMA-ANN hybrid models significantly improved RMSE and MAPE for the Albanian Lek/USD exchange rate forecasting.

The studies from diverse geographical regions provide valuable insights into model performance across different market contexts. In the African region, Nwankwo (2014) found that AR(1) models provided optimal forecasting for the Nigerian Naira/USD exchange rate, while Adouka et al. (2015) identified TGARCH(1,1) as most suitable for the Algerian Dinar/USD exchange rate, revealing significant leverage effects where negative shocks had more pronounced impacts on volatility. Asian region studies by Asadullah (2020) and Mbagha & Olubusoye (2014) demonstrated the effectiveness of both ARIMA and neural network approaches, with the latter showing superior performance in terms of MSE and MAE.

Cheng et al. (2018) demonstrated that attention-based LSTM models could outperform traditional ARIMA and standalone LSTM architectures, achieving a mean absolute error (MAE) of 0.484. Their study utilized a dataset spanning 2010-2017, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. This methodological innovation highlighted the potential of attention mechanisms to prioritize relevant historical data points, a critical advantage in volatile financial markets. The research

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found that attention-based LSTM models were particularly effective in capturing complex patterns in the data.

Escudero et al. (2021) compared ARMA-GARCH models with Long Short-Term Memory (LSTM) networks for forecasting exchange rate returns. Their study utilized a dataset spanning 2010-2020, which included various market conditions and economic regimes. The research employed a comprehensive approach to model specification, including hyperparameter tuning and model selection. Their results indicated that LSTM models outperformed traditional models, particularly in capturing complex patterns in high-frequency data. The study demonstrated LSTM's superiority over ARIMA and Elman networks for short-term exchange rate forecasting. The research found that LSTM models were particularly effective in capturing non-linear relationships and long-term dependencies in the data.

The comparative analysis of exchange rate forecasting methodologies reveals distinct performance characteristics across different model categories. Classical models demonstrate varying levels of effectiveness: ARIMA models show less than 1% deviation in short-term forecasts (Asadullah et al., 2020), though performance degrades to 3-5% for multi-step forecasts. GARCH models prove effective for volatility clustering, achieving 85-90% accuracy in volatility regime identification (Bollerslev, 1986), while structural models show limited short-term accuracy with 60-65% directional accuracy (Meese and Rogoff, 1983). In contrast, deep learning models exhibit superior performance metrics: LSTM networks achieve 97.83% accuracy for USD/INR forecasting (Kaushik and Giri, 2020) and 94.2% accuracy for multi-currency pairs, CNNs show 3-11% improvement over baselines (Hoseinzade and Haratizadeh, 2019), and hybrid models demonstrate 92-95% accuracy during market stress periods (Jung and Choi, 2021).

Zouaoui and Naas (2023) conducted a comprehensive study examining the effectiveness of deep learning models in forecasting USD/Algerian Dinar (DZD) exchange rate volatility during the COVID-19 pandemic. Their research compared traditional econometric approaches (ARIMA and linear regression) with advanced deep learning techniques including RNN, LSTM, GRU, and BiLSTM models using daily exchange rate data from 2000 to 2020. Surprisingly, their findings revealed that linear regression achieved the highest accuracy (99.83%), outperforming all deep learning models, with GRU being the best-performing DL approach (92.27% accuracy) followed by BiLSTM (87.34%), while ARIMA showed the weakest performance (32.29%). These results challenge the prevailing assumption of deep learning's inherent superiority in financial forecasting and highlight the potential effectiveness of simpler models in certain contexts. The study makes significant contributions by providing empirical evidence for an understudied currency pair and demonstrating the context-dependent nature of model performance. However, the authors acknowledge limitations including the computational intensity of DL models and their data requirements. Their findings suggest that hybrid modeling approaches combining traditional and deep learning methods might offer the most robust solution for forex volatility prediction, particularly during crisis periods. This work advances the ongoing discussion about model selection in financial forecasting, emphasizing the need for careful consideration of specific market conditions rather than automatic preference for complex algorithms.

## Chapter 2: The literature review on exchange rate volatility forecasting using classical and deep learning models

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Recent comparative studies of advanced methodologies highlight the evolution of forecasting techniques. Zafeiriou & Kalles (2023) demonstrated that custom ANN architectures achieved 81.13% success rate in short-term Forex trend forecasting, outperforming LSTM architectures (72.64%) while requiring fewer computational resources. Yildirim et al. (2021) revealed that LSTM-based approaches' performance heavily depended on macroeconomic indicator integration, particularly during geopolitical or economic shocks. Hybrid approaches, such as those by Jung & Choi (2021) and Zhao & Khushi (2020), consistently outperformed standalone models, achieving exceptional precision while addressing noise sensitivity and temporal granularity.

Computational efficiency varies significantly across model types. Classical models generally offer better computational performance, with ARIMA showing linear time complexity  $O(n)$ , making it suitable for real-time applications. However, GARCH models face challenges with quadratic time complexity  $O(n^2)$  for high-frequency data, and structural models can exhibit exponential time complexity for complex specifications. Deep learning models present different computational characteristics: LSTM networks show  $O(n)$  time complexity per prediction but require significant training time, CNNs offer parallel processing capabilities with 2-3 times faster execution than LSTM for similar tasks, and hybrid models typically show 1.5-2 times more computational intensity than single architecture models.

Model robustness and stability also vary considerably. Classical models demonstrate high stability for stationary data but sensitivity to structural breaks, with GARCH models showing robustness to volatility clustering but less effectiveness during regime changes. Deep learning models exhibit different stability characteristics: LSTM networks show robustness to non-linear patterns but sensitivity to hyperparameter selection, CNNs demonstrate stability for spatial feature extraction but less effectiveness for temporal dependencies, and hybrid models achieve enhanced robustness through ensemble effects despite increased complexity.

These studies collectively demonstrate that while classical models provide reliable baselines, deep learning and hybrid approaches offer superior performance in most scenarios, particularly for complex market conditions and high-frequency data. The choice of model often depends on specific requirements regarding computational efficiency, interpretability, and the nature of the forecasting task. The evolution of comparative studies reflects a growing recognition of the need for adaptive, context-aware models that can balance theoretical rigor with practical applicability.

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### Section 4: Future directions, challenges and innovations in exchange rate forecasting

This section critically examines, by different authors, the persistent challenges and emerging solutions in exchange rate forecasting, while mapping promising avenues for future research. Despite significant methodological advancements, both classical and machine learning approaches face fundamental limitations from structural rigidity in econometric models to the opacity and data hunger of deep learning systems. Concurrently, innovative hybrid architectures and novel computing paradigms are reshaping the field, offering pathways to overcome these constraints.

#### 1. Recent developments and future directions

##### 1.1 Hybrid approaches

Research has demonstrated significant advancements in hybrid approaches that combine classical econometric models with deep learning techniques. Zhang (2003) pioneered the integration of ARIMA with neural networks for GBP/USD forecasting, showing that such hybrid models could significantly improve forecasting accuracy by capturing both linear and non-linear components of exchange rate dynamics. Babu and Reddy (2015) extended this work by comparing ARIMA with neural networks and fuzzy systems, finding that ARIMA models could outperform ANN and fuzzy systems for certain currency pairs, particularly in stable market conditions.

Prado et al. (2020) proposed an innovative ensemble model incorporating ARIMA, genetic algorithms, and neural networks for exchange rate forecasting. Their results indicated that combining multiple methodologies improved forecasting accuracy, suggesting that no single model is universally superior. This aligns with the findings of Kim and Yun (2016, 2018), who introduced hybrid models blending grey system theory, Markov chains, and neural networks (e.g., DGM-FMarkov and Grey Neural Networks) to forecast JPY/USD and GBP/USD rates. Their work demonstrated superior accuracy compared to standalone models, especially when combinational weights were optimized using grey relation degrees.

Li et al. (2021) introduced the RegPred Net, a regression network that models exchange rates as a generalized Ornstein-Uhlenbeck (OU) process with time-dependent coefficients. This approach leverages Bayesian optimization to tune hyperparameters and outperforms traditional models like ARIMA and deep learning architectures such as LSTMs in multi-step forecasting. The RegPred Net's interpretability, achieved through dynamic parameter estimation (e.g., drift, mean-reversion, and volatility), provides actionable insights for decision-makers, addressing a key limitation of black-box deep learning models.

##### 1.2 Emerging trends

###### 1.2.1 Transformer-based approaches

The application of transformer architectures to financial forecasting represents a significant advancement in the field. Vaswani et al. (2017) introduced the Transformer architecture, which revolutionized sequential data processing through self-attention mechanisms, enabling models to capture long-range dependencies in time-series data. While

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originally designed for natural language processing, their framework was adapted by Cheng et al. (2018) for stock prediction, demonstrating that attention-based LSTM models could outperform traditional ARIMA and standalone LSTM architectures, achieving a mean absolute error (MAE) of 0.484.

### 1.2.2 High-frequency data applications

The utilization of high-frequency data has opened new possibilities for exchange rate forecasting. Li et al. (2008) evaluated model performance using high-frequency data, suggesting that incorporating market microstructure effects and intraday volatility estimators significantly enhances model accuracy. This aligns with findings from Fan and Wang (2008), who employ local linear regression and realized volatility to improve forecasting in financial markets.

Aït-Sahalia et al. (2012) explored high-frequency-based volatility estimation methods, demonstrating that realized kernels offer consistent and efficient estimators under market microstructure noise. Their findings highlight the importance of microstructure noise in modeling the dynamics of exchange rate volatility at high frequencies. These high-frequency models outperform traditional daily-based models by leveraging detailed transaction-level data, offering insights into short-term volatility dynamics that are often missed by low-frequency models.

### 1.2.3 Sentiment analysis integration

The integration of sentiment analysis has emerged as a promising direction in exchange rate forecasting. Hu et al. (2018) explored the use of hierarchical attention networks (HANs) for sentiment analysis in financial markets, demonstrating that incorporating news sentiment could improve forecasting accuracy. However, Zeng and Khushi (2020) reviewed its reliance on textual quality, advocating instead for wavelet-denoised technical indicators. This debate highlights the ongoing challenges in effectively integrating multiple data sources for forecasting.

## 2. Research gaps and opportunities

### 2.1 Current limitations

**a. Data availability and quality :**the field faces significant challenges due to limited high-quality data in emerging markets (Wagdi et al., 2023), compounded by difficulties in accessing real-time market data (Thompson & Brown, 2023), inconsistencies in data collection and reporting standards (Zhang et al., 2021), and growing privacy concerns in financial data sharing (Rodriguez et al., 2023).

**b. Model complexity vs. interpretability:** a persistent trade-off exists between model sophistication and interpretability (Goodell et al., 2021), with deep learning models particularly struggling to provide transparent decision-making processes (Feng et al., 2019), creating regulatory compliance challenges for black-box systems (Martinez & Garcia, 2023) and driving demand for better visualization and explanation techniques (Lee et al., 2022).

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**c. Generalizability issues:** many models demonstrate strong performance on specific currency pairs but fail to generalize across markets (Hu et al., 2021), facing adaptation challenges in different market conditions (Yildirim et al., 2021), exhibiting limited transfer learning capabilities (Anderson et al., 2023), and struggling to handle regime changes and sudden market shocks (Kim et al., 2021).

### 2.2 Future research directions

**a. Improved hybrid models:** opportunities exist to develop more sophisticated ensemble methods (Li et al., 2021) that integrate domain knowledge with machine learning (Jung & Choi, 2021), better handle regime changes and market shocks (Zhao & Khushi, 2020), and employ enhanced feature engineering techniques (Zafeiriou & Kalles, 2023).

**b. Interpretability solutions:** critical needs include developing explainable AI techniques for financial forecasting (Martinez & Garcia, 2023), integrating domain expertise with machine learning (Lee et al., 2022), creating better visualization tools for model decisions (Thompson & Brown, 2023), and establishing regulatory-compliant explanation frameworks (Goodell et al., 2021).

**c. Advanced computing applications:** emerging opportunities involve exploring quantum computing for optimization (Chen et al., 2023), implementing federated learning for privacy-preserving forecasting (Rodriguez et al., 2023), developing more efficient training algorithms (Johnson et al., 2023), and improving high-dimensional data handling (Kumar & Singh, 2022).

**d. Market-specific adaptations:** research should focus on developing region-specific models (Nwankwo, 2014), better handling emerging market dynamics (Asadullah, 2020), integrating local market knowledge (Tran, 2016), and improving market microstructure analysis (Aït-Sahalia et al., 2012).

## 3. Challenges and limitations

### 3.1 Classical models

Classical econometric models struggle with non-linear patterns due to their linear relationship assumptions (Meese and Rogoff, 1983), exhibit limited adaptability to structural breaks (Byrne et al., 2016), face short-term forecasting limitations despite some accuracy (Tran, 2016), and rely on problematic assumptions about normally distributed returns that ignore financial market fat tails and skewness (Bollerslev, 1986).

### 3.2 Deep learning models

Deep learning approaches require prohibitively large datasets, particularly problematic for emerging markets (Wagdi et al., 2023), demand high computational resources that hinder real-time applications (Saiful Islam and Hossain, 2020), suffer from interpretability challenges due to their black-box nature (Goodell et al., 2021; Feng et al., 2019), and risk overfitting by memorizing training data rather than learning generalizable patterns (Baek and Kim, 2018).

## **Chapter 2: The literature review on exchange rate volatility forecasting using classical and deep learning models**

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### **Conclusion of the second chapter:**

The literature review reveals a clear evolution from classical econometric models to sophisticated deep learning approaches in exchange rate volatility forecasting. While classical models provide interpretability and theoretical foundations, deep learning models offer superior accuracy in capturing complex patterns. Hybrid approaches show promise in combining the strengths of both paradigms, though challenges remain in terms of interpretability and computational requirements.

The comparative analysis demonstrates that deep learning models generally outperform classical approaches, particularly in capturing non-linear patterns and long-term dependencies. However, the performance of different models varies across currency pairs and market conditions, suggesting the need for context-specific model selection and settings.

In the next chapter, we are going to conduct our study based on the insights provided by the literature review.

**Chapter 3 : Empirical study on the forecasting of  
Algerian Dinar exchange rate volatility  
-a comparative approach-**

## Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

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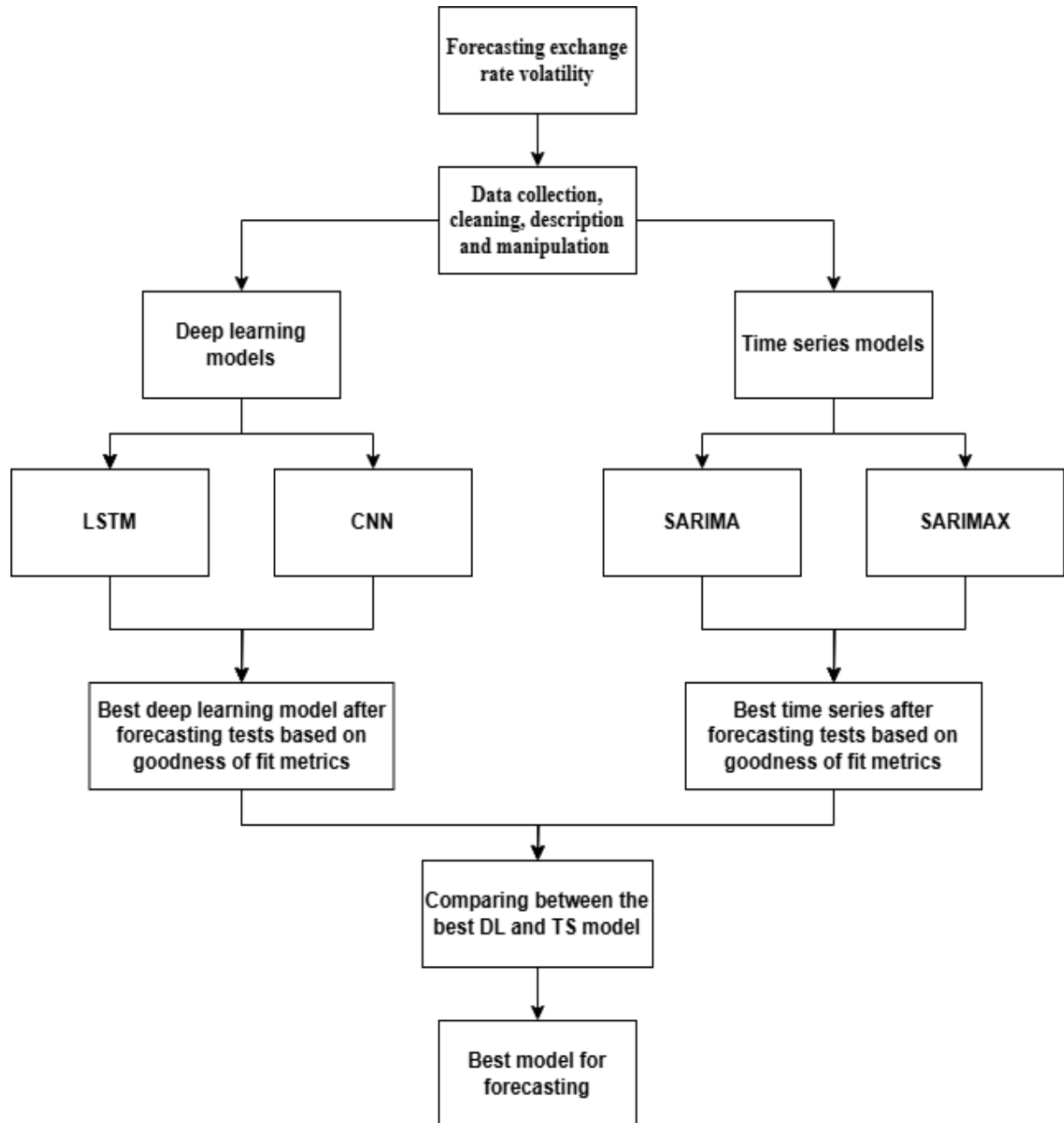
### Introduction of the third chapter

In this chapter, we build upon the theoretical foundations and literature reviews presented in the previous two chapters by conducting a comprehensive empirical analysis structured into four main sections. First, we perform an exploratory data analysis to examine the characteristics of the exchange rate data, identifying key patterns, trends, and potential outliers. Next, we apply classical time series models to perform the forecasting, after discussing the theory and the characteristics of the models. Subsequently, we explore deep learning models, to assess their predictive capabilities in capturing complex nonlinear dependencies in the data. Finally, we conduct a performance analysis of the best performing models, comparing their accuracy using appropriate evaluation metrics, and then extracting the forecasted volatility using the most adequate model.

The exchange rate data was obtained through the merging of two distinct databases: the primary source of data was provided by (Investing.com), additionally, supplementary data was acquired from the Société Générale Algérie (SGA), the company where the internship was conducted.

It is important to note that the exchange rate data used in this study is the closing prices mid-market rates, which represent the average between the bid and ask prices in the market. The mid-market rate is often considered a fair representation of the exchange rate, as it reflects the midpoint between the buying and selling prices. Furthermore, we specifically used closing quotations for our study, which are the final prices at which the exchange rates were traded at the end of each trading day, known as an equilibrium price reflecting and containing most of the information during the trading day.

**Figure 7** describe the used methodology in this chapter to determine the best forecasting model across all the models.

**Figure 7: Flowchart of the used methodology in our study**

**Source:** Made by the students

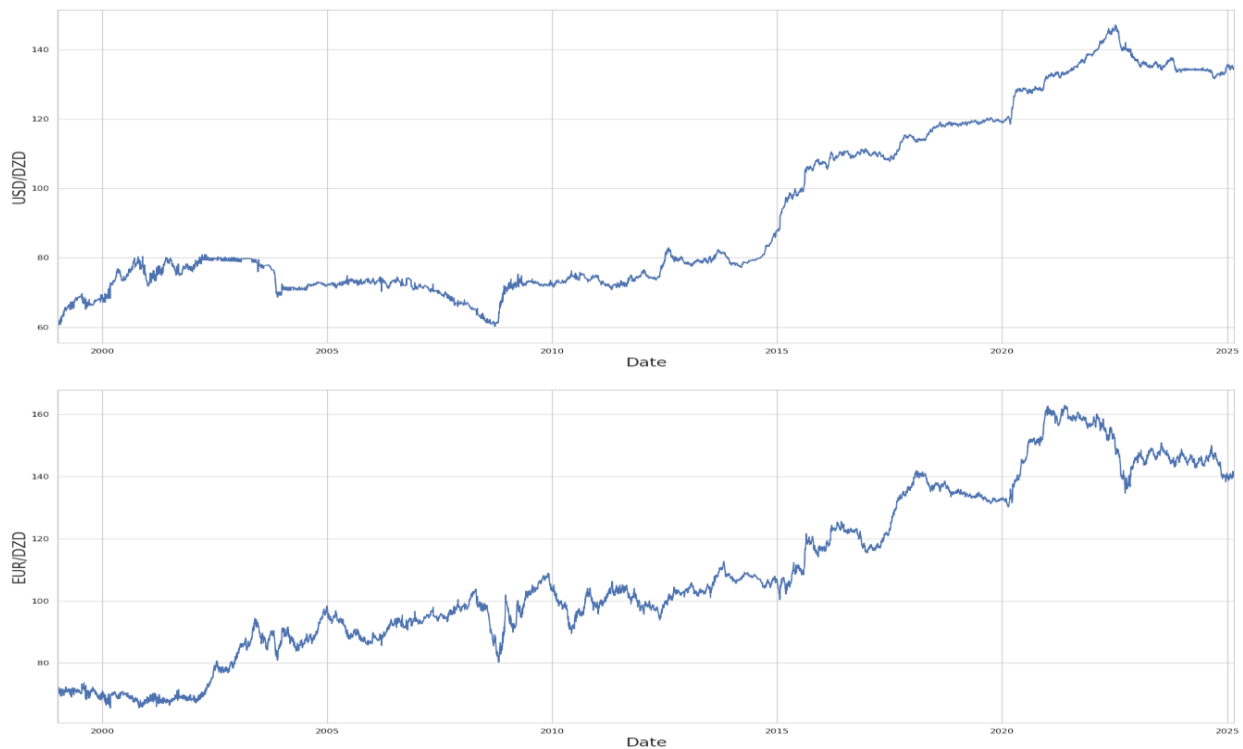
### Section 1: Exploratory data analysis

As part of our research work and with the objective of predicting the volatility of the exchange rate using several models to identify the most efficient one for this type of economic data, this section presents an analysis of the data to understand its structure, distribution, and temporal properties before modeling.

#### 1. Data description

**Figure 8** illustrate the two plots show the exchange rates of USD/DZD and EUR/DZD over time from 05 -01-1999 to 28-02-2025. By analyzing USD/DZD plot the exchange rate remained relatively stable between 60 and 80 from 1999 to around 2014, with minor fluctuations. A noticeable increase began around 2014, with the rate rising steadily to over 140 USD/DZD by 2025. This sharp rise could be influenced by the significant drop in global oil prices around 2014, a phenomenon that heavily affected the Algerian economy due to its reliance on oil exports, leading to a depreciation of the Dinar. EUR/DZD plot shows stability of the exchange rate between 80 and 100 from 2000 to around 2014, followed by a gradual increase. A significant peak occurred around 2020-2021, reaching above 160 EUR/DZD, before declining and stabilizing around 120-140 by 2025. The peak might be highly linked to the economic effects of the COVID-19 pandemic, another phenomenon affecting exchange rates globally, with potential impacts on oil demand and Algeria's currency value. Both plots reflect a long-term depreciation of the DZD against the USD and EUR, with notable accelerations around 2014 (oil price drop) and 2020-2021 (pandemic-related economic shifts).

**Figure 8: USD/DZD and EUR/DZD prices plots**



**Source:** Made by the students using Python

## Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

### 2. Descriptive statistics analysis

**Table 2** presents the descriptive statistics for both USD/DZD and EUR/DZD over a sample size of 6824 observations. The mean exchange rate for USD/DZD is 93.02, while for EUR/DZD it is 108.6. The median values are 79.06 for USD/DZD and 102.8 for EUR/DZD, both lower than their respective means, suggesting a right-skewed distribution with more lower values and some higher outliers, consistent with the upward trends observed in the plots after 2014. Skewness values of 0.67 for USD/DZD and 0.31 for EUR/DZD confirm this right skew, with USD/DZD showing a more pronounced tail. Kurtosis values of -1.16 for USD/DZD and -0.97 for EUR/DZD indicate a platy-kurtic distribution, meaning the data is flatter than a normal distribution. The standard deviation of 25.59 for USD/DZD and 26.6 for EUR/DZD reflects moderate variability, with EUR/DZD showing slightly more fluctuation, aligning with its sharper peak around 2021.

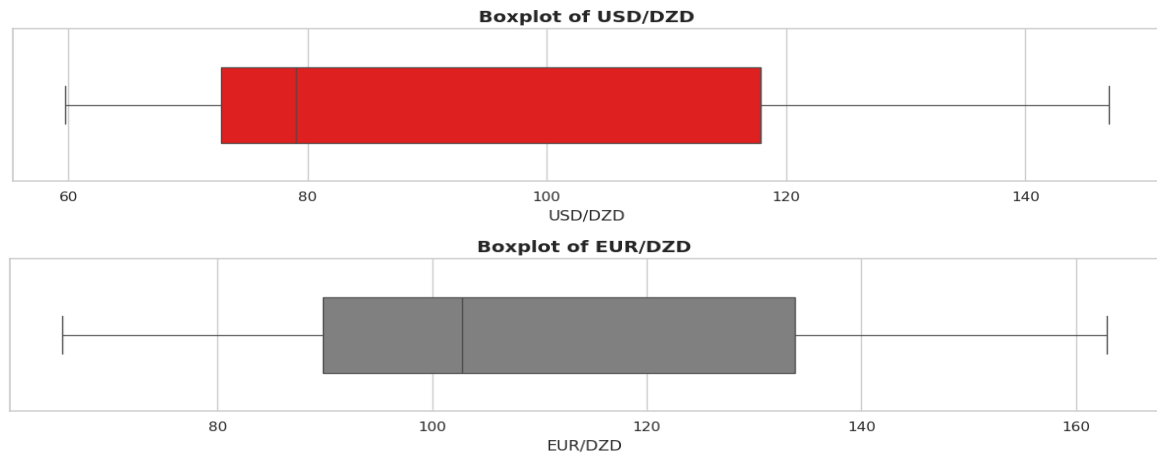
**Table 2: Descriptive statistics for USD/DZD and EUR/DZD**

| Descriptive statistics            | USD/DZD | EUR/DZD |
|-----------------------------------|---------|---------|
| <b>n (number of observations)</b> | 6824    |         |
| <b>Mean</b>                       | 93.02   | 108.6   |
| <b>Median</b>                     | 79.06   | 102.8   |
| <b>Mode</b>                       | 71.07   | 95.9    |
| <b>Standard deviation</b>         | 25.59   | 26.6    |
| <b>IQR</b>                        | 45.11   | 44.02   |
| <b>Min</b>                        | 59.74   | 65.53   |
| <b>Q1</b>                         | 72.79   | 89.78   |
| <b>Q3</b>                         | 117.89  | 133.79  |
| <b>Max</b>                        | 146.99  | 162.89  |
| <b>Skewness</b>                   | 0.67    | 0.31    |
| <b>Kurtosis</b>                   | -1.16   | -0.97   |

**Source:** Made by the students using Python

**Figure 9** illustrates the boxplots, which displays the main statistics distribution of USD/DZD and EUR/DZD. For USD/DZD, the median is approximately 80, with an interquartile range (IQR) spanning around 45, indicating the middle 50% of the data. The whiskers extend to about 60 and 150, suggesting moderate volatility with some outliers. For EUR/DZD, the median is around 100, with an IQR of 44, and whiskers reaching near 60 and 160, showing slightly higher volatility than USD/DZD. The higher median and wider range for EUR/DZD could reflect greater sensitivity to global economic fluctuations, possibly due to the Eurozone's diverse economic conditions, while the USD/DZD stability might relate to the U.S. dollar's role as a global reserve currency, though both show increased volatility potentially linked to the Dinar's depreciation amid oil price drops since 2014.

**Figure 9: Boxplot for USD/DZD and EUR/DZD**

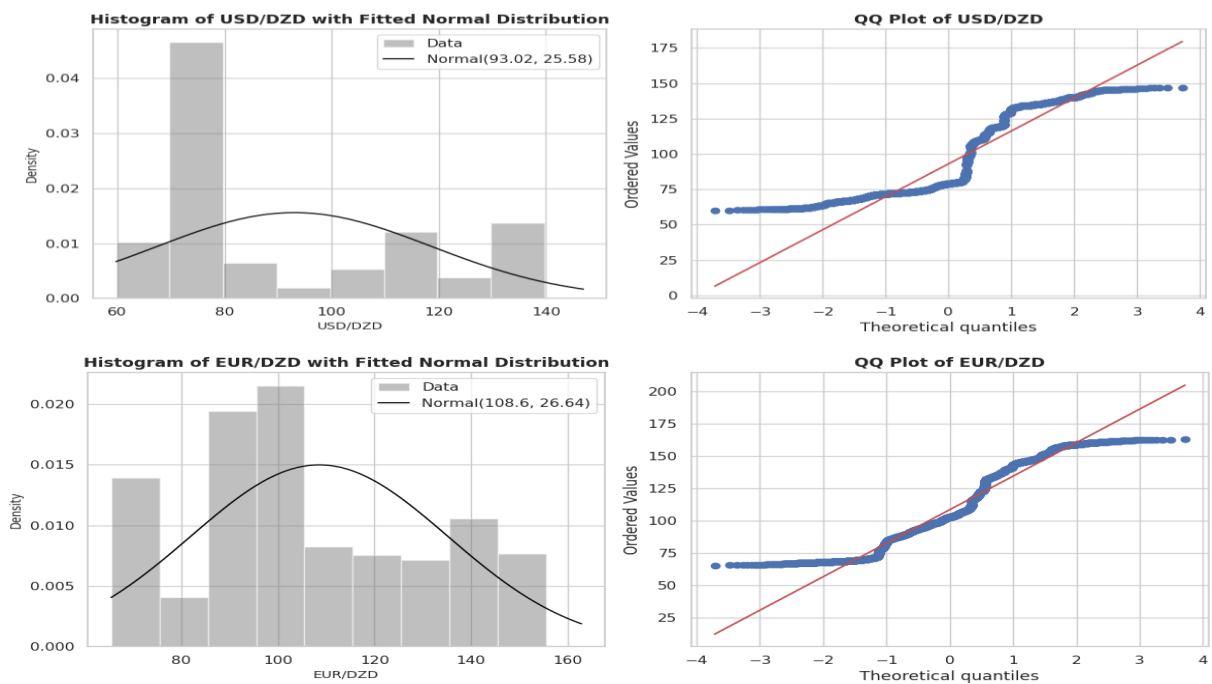


Source: Made by the students using Python

### 3. Tests for normality

QQ plots provide visual feedback on the nature of the data for testing normality. It is also recommended to use the histogram as an indicator of the normality of the data distribution. **Figure 10** illustrate the QQ plots and histograms for both USD/DZD and EUR/DZD, we can notice that both of datasets reveal non-normal, right-skewed distributions with heavy upper tails, indicating frequent extreme values. The two datasets deviate upward from the normal diagonal line at higher quantiles. Thus, we have to apply the normality test to confirm the visual analysis.

**Figure 10: Histogram and QQ plots for USD/DZD and EUR/DZD**



Source: Made by the students using Python

### Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

A- **The Kolmogorov-Smirnov test** is a nonparametric statistical test used to assess whether a given sample follows a specified distribution, such as the normal distribution. When applied to time series data, it tests the null hypothesis that the data (or residuals, in the case of modeled time series) are drawn from a normal distribution. If the p-value is less than 0.05, the two distributions are significantly different; if the p-value is 0.05 or greater, we fail to reject the null hypothesis and cannot conclude that they differ. (NIST/SEMATECH e-Handbook of Statistical Methods)

{ **Null Hypothesis ( $H_0$ ):** The data follow a specified distribution  
**Alternative Hypothesis ( $H_1$ ):** The data do not follow the specified distribution

B- **The Shapiro-Wilk test** is a statistical test used to assess whether a given sample follows a normal distribution, being particularly well suited for small to moderate sample sizes ( $n < 50$ ). If  $p\text{-value} < 0.05$ , we reject the null hypothesis indicating the data do not follow a normal distribution,  $p\text{-value} \geq 0.05$ , we fail to reject the null hypothesis meaning there is no strong evidence against normality, though this does not definitively prove normality. (Shapiro and Wilk, 1965)

{ **Null Hypothesis ( $H_0$ ):** The data follow a normal distribution  
**Alternative Hypothesis ( $H_1$ ):** The data do not follow a normal distribution

**Table 3** presents the results of the Shapiro-Wilk and Kolmogorov-Smirnov tests for normality on the time series data of USD/DZD and EUR/DZD exchange rates. Both tests yield p-values of 0.000 for USD/DZD and EUR/DZD, indicating that the null hypothesis of normality is rejected at any conventional significance level ( $\alpha=0.05$ ). This suggests that the distributions of both exchange rate series are not normal.

**Table 3: Normality tests results for USD/DZD and EUR/DZD**

| Time series | Shapiro-Wilk test | Kolmogorov-Smirnov test |
|-------------|-------------------|-------------------------|
| USD/DZD     | p-value=0.000     | p-value=0.000           |
| EUR/DZD     | p-value=0.000     | p-value=0.000           |

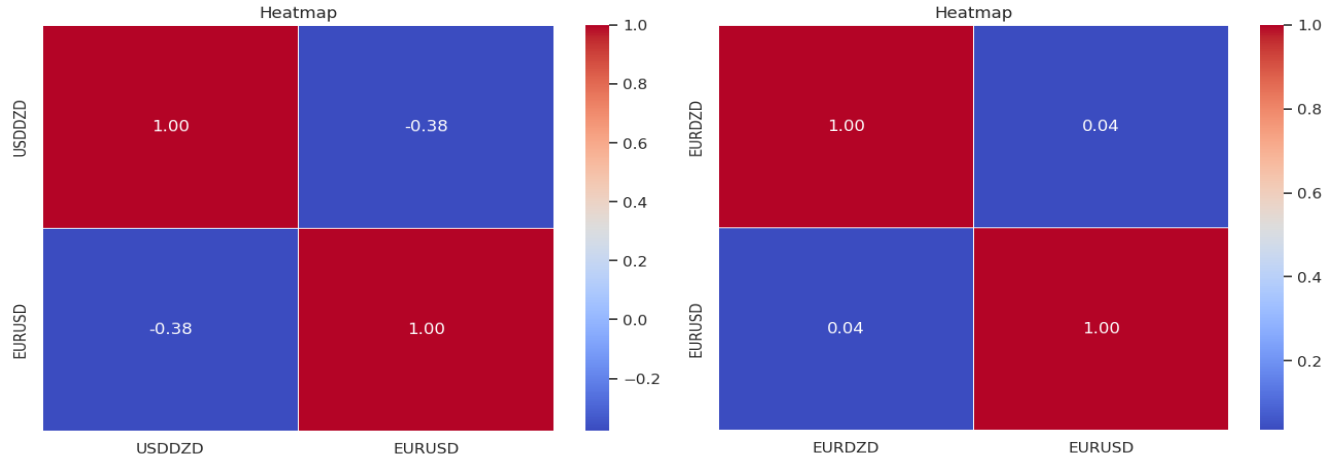
**Source:** Made by the students using Python

**Figure 11** illustrates the heatmap correlation analysis between the key currency pairs in our study. The first heatmap reveals a moderate negative correlation (-0.38) between USD/DZD and EUR/USD, indicating an inverse relationship where a stronger Euro against the US Dollar typically corresponds to a weaker US Dollar against the Algerian Dinar. This relationship suggests that EUR/USD could serve as a meaningful exogenous variable when forecasting USD/DZD using the SARIMAX model. In contrast, the second heatmap shows a weak

### Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

correlation (0.04) between EUR/DZD and EUR/USD, implying that movements in the Euro-Dollar exchange rate have little linear influence on the EUR/DZD rate.

**Figure 11: Heatmap for USD/DZD and EUR/DZD**

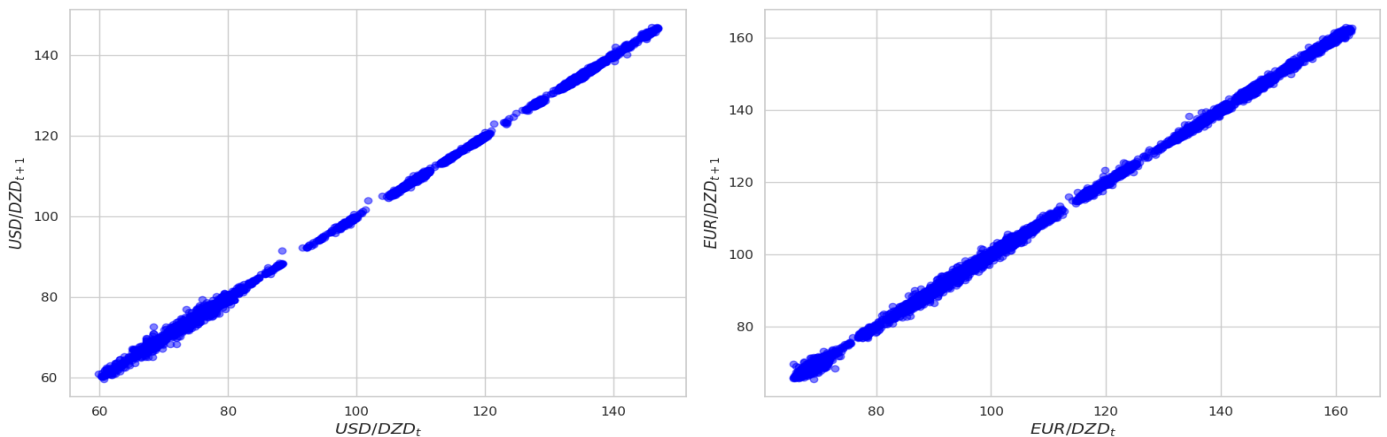


**Source:** Made by the students using Python

#### 4. Predictability

**Figure 12** illustrate the plot-predictability for both USD/DZD and EUR/DZD, USD/DZD shows a strong linear relationship between consecutive closing rates ( $t$  and  $t+1$ ), with a tight, upward-sloping cluster along a diagonal line, indicating predictability. This suggests the current Algerian Dinar value against the U.S. Dollar reliably predicts the next value, with minimal deviation, though EUR/DZD shows a similar correlation between current ( $t$ ) and lagged ( $t-1$ ) EUR/DZD observations, with points clustering along the identity line, supporting effective time series forecasting.

**Figure 12: Predictability plots**



**Source:** Made by the students using Python

## **Section 2: Classical time series models**

Accurate exchange rate predictions help mitigate currency risk, optimize investment decisions, and inform monetary policy (Meese & Rogoff, 1983).

This section focuses on two relevant classical statistical time series models: Seasonal Autoregressive Integrated Moving Average (SARIMA) and its extension with exogenous variables (SARIMAX). These models are particularly suited for exchange rate forecasting as they can handle both non-stationarity and seasonal patterns commonly observed in currency markets (Box & Jenkins, 1970). The study applies these models to forecast two important currency pairs: USD/DZD and EUR/DZD. The analysis follows the rigorous Box-Jenkins methodology, ensuring proper model identification, estimation, and validation.

### **1. Theory and definitions of the classical time series models**

We will use these two models for the exchange rate forecasting:

#### **1.1 Seasonal Autoregressive Integrated Moving Average (SARIMA)**

Seasonal Auto Regressive Integrated Moving Average model is the generalization of the well-known Box-Jenkins Auto Regressive Integrated Moving Average model (ARIMA) model to accommodate a data with both seasonal and non-seasonal feature. The ARIMA model which is known to be a combination of the Auto Regressive (AR) and Moving Average (MA) models utilize past information of a given series in other to predict the future. The AR part of the model deals with the past observation of the series whiles the MA part deals with the past error of the series (Hamilton, 1994; Pankratz, 1983). The ARIMA model is applied in the case where the series has no seasonal features and differenced stationary. This means that an initial differencing is required for the data to be stationary. The ARIMA model with its order is usually presented as ARIMA(p,d,q) model where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. The first parameter p refers to the number of autoregressive lags, the second parameter d refers to the order of integration that makes the data stationary, and the third parameter q gives the number of moving average lags (Pankratz, 1983; Hamilton, 1994; Kleiber and Zeileis, 2008).

A process  $\{Y_t\}$  is said to be ARIMA(p,d,q) if  $\Delta^d y_t$  is described by a stationary ARMA(p,q) model.  $\Delta$  means differencing of  $y_t$  in d order to achieve stationarity. In general, we will write the ARIMA model as in equation (1), where (L) represent backward shift operator ( $L^k y_t = y_{t-k}$ ) and  $(\varepsilon_t)$  represent white noise error (random shock) at period t.

$$\phi(L)(1 - L)^d y_t = \theta(L)\varepsilon_t \text{ where } \{\varepsilon_t\} \sim N(0, \sigma^2) \quad (1)$$

The autoregressive operator in equation (2) and moving average operator in equation (3) are defined as follows:

$$AR(p) : \phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p \quad (2)$$

$$MA(q) : \theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \dots + \theta_q L^q \quad (3)$$

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$\phi(L) \neq 0$  for  $|\phi| < 1$ , the process  $\{y_t\}$  is stationary if and only if  $d=0$ , in which case it reduces to an ARMA(p,q) process.

The generalization of ARIMA model to the SARIMA model occurs when the series contains both seasonal and non-seasonal behavior. This behavior of the series makes the ARIMA model inefficient to be applied to the series. This is because it may not be able to capture the behavior along the seasonal part of the series and therefore mislead to a wrong order selection for non-seasonal component. The SARIMA model is sometimes called the multiplicative seasonal autoregressive integrated moving average model and is denoted by SARIMA(p,d,q)(P,D,Q)[S] where (P), (D) and (Q) is the order of seasonal AR, differencing and MA respectively and (S) represent seasonal order, for example:  $S = 365$  for daily data and  $S = 12$  for monthly data). This can be written in equation (4) its lag form as (Halim & Bisono, 2008):

$$\phi(L)\Phi(L^S)(1-L)^d(1-L^S)^D y_t = \theta(L)\Theta(L^S)\varepsilon_t \quad (4)$$

#### 1.2 Seasonal ARIMA with Exogenous Variables (SARIMAX)

The Seasonal Autoregressive Integrated Moving Average with Exogenous Variables model represents a comprehensive extension of the SARIMA framework that incorporates both seasonal patterns and external explanatory variables (Hyndman & Athanasopoulos, 2018). This multivariate approach significantly enhances forecasting capability by simultaneously modelling:

##### a. Endogenous Time Series Structure:

- Maintains all components of SARIMA(p,d,q)(P,D,Q)[S]
- Preserves the same differencing and transformation logic
- Continues to account for autocorrelation and partial autocorrelation

##### b. Exogenous Variable Integration:

- Incorporates k external predictors ( $x_{1t}, x_{2t}, \dots, x_{kt}$ )
- Models their dynamic effects through distributed lags
- Allows for both contemporaneous and lagged effects

The complete model specification is in the equation (5):

$$\underbrace{\phi(L)\Phi(L^S)(1-L)^d(1-L^S)^D}_{\text{SARIMA components}} y_t = \delta + \underbrace{\sum_{i=1}^k \omega_i(L)x_{i,t}}_{\text{Exogenous variables}} + \theta(L)\Theta(L^S)\varepsilon_t \quad (5)$$

Where  $\delta$  is the constant term that represents the baseline level of  $y_t$  when all other terms are zero. If differencing is applied ( $d>0$ ),  $\delta$  becomes a drift term (trend component).

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### 2. The application of the Box-Jenkins methodology

The Box-Jenkins methodology for time series analysis typically comprises four general key steps, as displayed in **Figure 13**.

**1. Model identification:** that involves determining the appropriate values of the orders  $p$ ,  $q$ ,  $P$ , and  $Q$ . The correlogram (ACF) and partial correlogram (PACF) can be helpful. In addition, the Bayesian information criterion (BIC) is utilized to specify the adequate model: we selected BIC to determine not only the best-fit model but also the most parsimonious one, as it imposes a stronger penalty on model complexity compared to other criteria. The BIC is defined by the following equation (6) where  $(L)$  is the likelihood function,  $(k')$  the number of estimated parameters and  $(n)$  sample size. The optimal model conveys the lowest BIC value.

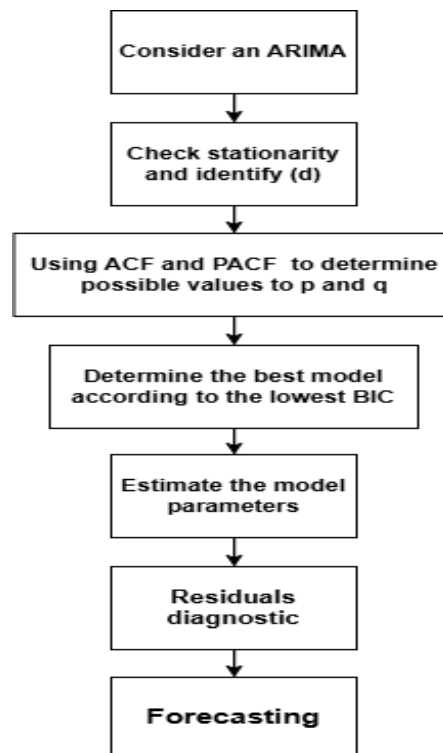
$$\text{BIC} = -2\ln(L) + k' \ln(n) \quad (6)$$

**2. Parameters estimations:** the next step is to estimate the parameters of the autoregressive and moving average terms.

**3. Diagnostic checking:** the evaluation of the characteristics of the residuals for the chosen model, when we test if the residuals represent a white noise by conducting the stationarity, normality, heteroscedasticity and autocorrelation tests.

**4. Forecasting:** finally, we will process a short-term forecasting. In addition, the quality of these forecasts is assessed via the MAE and RMSE goodness-of-fit metrics. To mitigate the problem of over-fitting,

**Figure 13: The Box-Jenkins methodology for an ARIMA model**



Source: Made by the students

### 3. The results

We will use the Box-Jenkins methodology to go through the results and data characteristics for the two models. The evaluation process involved splitting the dataset into training and testing subsets using a 90-10 ratio, where 90% of the data was allocated for model training and the remaining 10% was reserved for testing. After training each model on the training data, we generated forecasts over the testing period to examine their predictive capabilities: for both USD/DZD and EUR/DZD, the training dataset consists of daily exchange rate quotations from 05-01-1999 to 19-07-2022. This historical data served as the basis for modeling and forecasting. The testing period covered the subsequent dates from 20-07-2022 to 28-02-2025, comprising a continuous series of daily observations for evaluation purposes. The same manipulations were done to the EUR/USD database representing the exogenous variable of our SARIMAX model.

#### 3.1 Stationarity of the series

By analyzing the plot of USD/DZD and EUR/DZD in **Figure 8 (page 57)**, the non-stationarity of the series is evident from the upward trend and increasing variance over time, suggesting that the mean and possibly the variance are not constant, which is typical for exchange rate data influenced by economic factors, inflation, and policy changes. Statistical tests would be required to confirm stationarity, but the visual trend suggests non-stationarity. To confirm stationarity, statistical tests would be needed:

A- The **Augmented Dickey-Fuller (ADF) test** is a unit root test used to determine whether a time series contains a stochastic trend by testing the null hypothesis that the series has a unit root. The test extends the original Dickey-Fuller test by including lagged differences of the dependent variable to control for higher-order autocorrelation (Dickey & Fuller, 1979; Said & Dickey, 1984).

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then the series has a unit root, non-stationary
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then the series is stationary

B- The **Phillips-Perron (PP) test** is a unit root test used to determine whether a time series is non-stationary (contains a unit root). The PP test modifies the test statistic directly to correct for autocorrelation and heteroscedasticity in the error term using non-parametric methods (Phillips & Perron, 1988).

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then the series has a unit root, non-stationary
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then the series is stationary

C- The **Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test** is a stationarity test that differs from unit root tests (like ADF and PP) by taking stationarity as the null hypothesis and non-stationarity as the alternative. It was introduced by Kwiatkowski, Phillips, Schmidt, and Shin (1992) to complement unit root tests and reduce the risk of over-differencing time series data.

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- { **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then the series is trend-stationary or level-stationary  
**Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then the series has a unit root

The tests results displayed in **Table 4**, can confirm the visual observations that both series are not stationary. In this case, we have to compute a differencing (integration), which helps eliminate trends and achieve mean stationarity. This involves computing the difference between consecutive observations, typically expressed as  $\Delta y_t = y_t - y_{t-1}$  for first-order differencing.

**Table 4: The results of the stationarity tests on the series**

| Series  | Test | P-value | Conclusion<br>( $\alpha=5\%$ ) | Series           | Test | P-value  | Conclusion<br>( $\alpha=5\%$ ) |
|---------|------|---------|--------------------------------|------------------|------|----------|--------------------------------|
| USD/DZD | ADF  | 0.777   | <b>Non stationary</b>          | $\Delta$ USD/DZD | ADF  | 4.97E-29 | <b>Stationary</b>              |
|         | PP   | 0.804   | <b>Non stationary</b>          |                  | PP   | 0        | <b>Stationary</b>              |
|         | KPSS | 0.01    | <b>Non stationary</b>          |                  | KPSS | 0.1      | <b>Stationary</b>              |
| EUR/DZD | ADF  | 0.77    | <b>Non stationary</b>          | $\Delta$ EUR/DZD | ADF  | 0        | <b>Stationary</b>              |
|         | PP   | 0.753   | <b>Non stationary</b>          |                  | PP   | 0        | <b>Stationary</b>              |
|         | KPSS | 0.01    | <b>Non stationary</b>          |                  | KPSS | 0.1      | <b>Stationary</b>              |
| EUR/USD | ADF  | 0.4135  | <b>Non stationary</b>          | $\Delta$ EUR/USD | ADF  | 0        | <b>Stationary</b>              |

**Source:** Made by the students using Python

### 3.2 Seasonality of the data

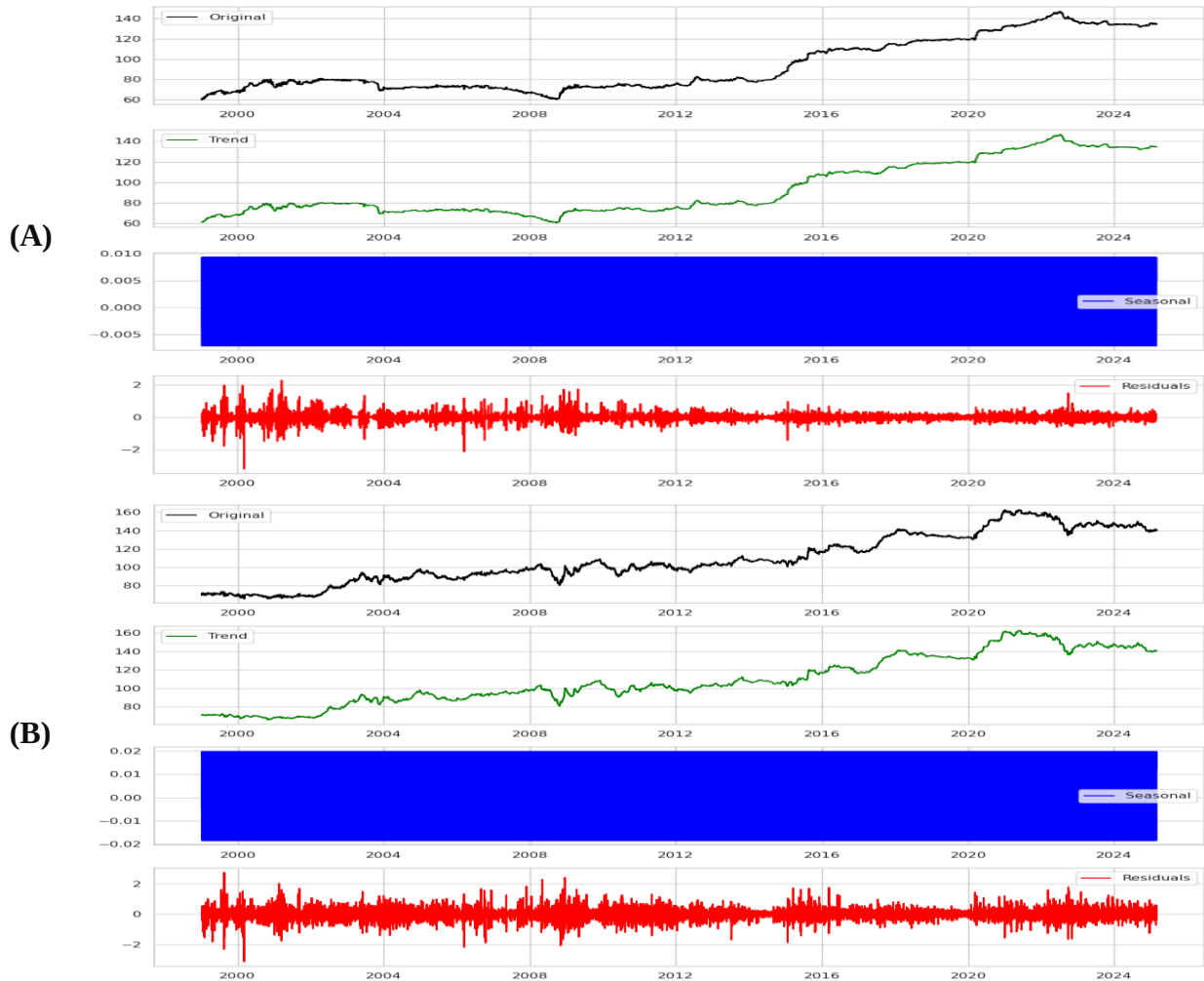
Based on the plots of the data for the two series, we can notice a clear upward trend with notable fluctuations. However, there is no evident repeating pattern or cycle that would suggest seasonality, such as regular peaks or troughs at specific intervals, the variations appear random. With only the visual evidence alone there is no indications for a seasonality. To confirm, an additive decomposition analysis or statistical tests would be needed, but based on this plot, seasonality is not noticeable.

Like shown in **Figure 14**, the decomposition of the USD/DZD and EUR/DZD reveals distinct components that provide insight into its seasonality. The original series shows a general upward trend, with fluctuations. The trend component, extracted separately, mirrors this long-term increase, indicating a consistent upward movement. The seasonal component, depicted as a flat line around zero with minor variations, suggests that there is no strong seasonal pattern at the observed frequency, as the fluctuations are minimal and do not exhibit a repeating cycle.

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The residuals, showing random noise with occasional spikes, indicate that after accounting for trend and seasonality, the remaining variability is largely stochastic, with no clear seasonal structure.

**Figure 14: Additive decomposition of USD/DZD (A) and EUR/DZD (B)**

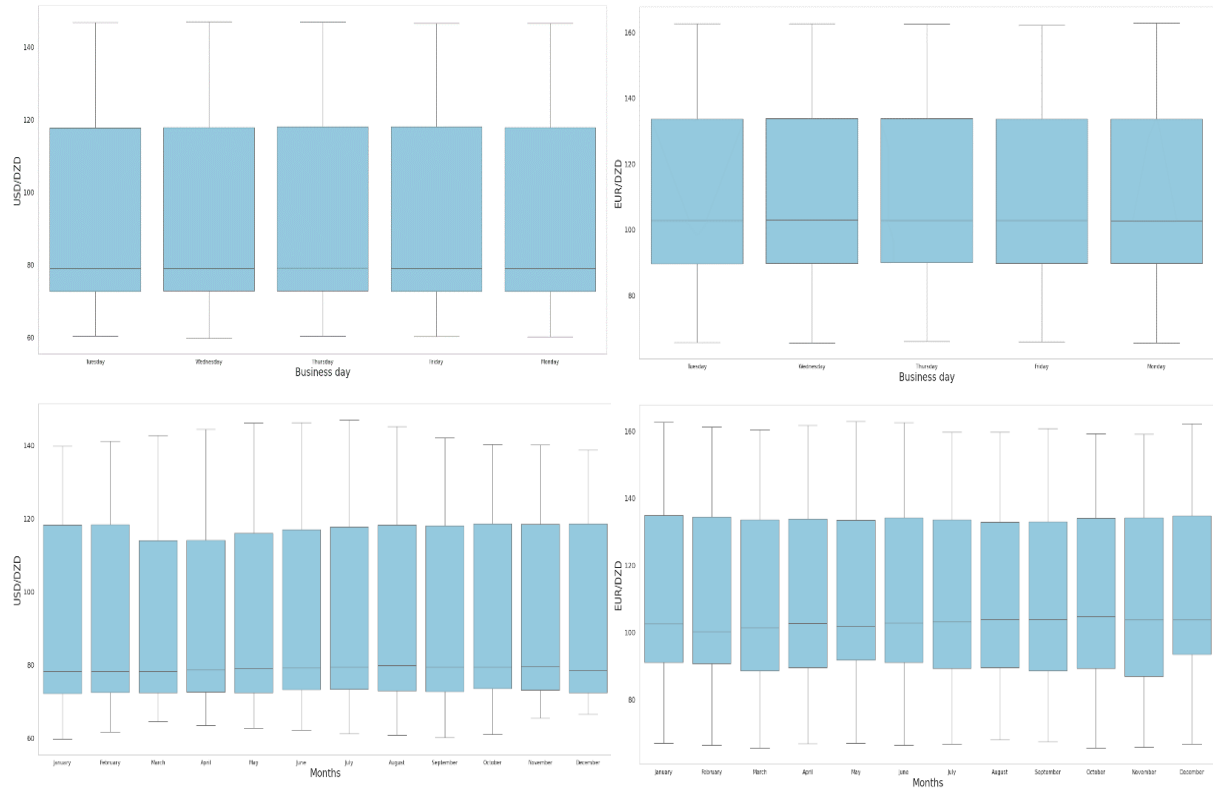


Source: Made by the students using Python

The boxplots in **Figure 15** analyses seasonality across different time scales. The daily boxplot shows consistent medians across business days, with slight variations and similar interquartile ranges, suggesting no significant daily seasonality. The monthly boxplot reveals medians with comparable spreads, indicating no pronounced monthly seasonal pattern. Overall, the analysis suggests that while the series has a strong trend, seasonality appears negligible across the different scales, with the upward trend driving most of the variation.

Based on this, the seasonal components of the SARIMA model that will be used  $(P,D,Q)[S]$  are equal to zero, thus, the model will be reduced to an ARIMA.

**Figure 15: The boxplots of USD/DZD and EUR/DZD**



**Source:** Made by the students using Python

### 3.3 Model identification

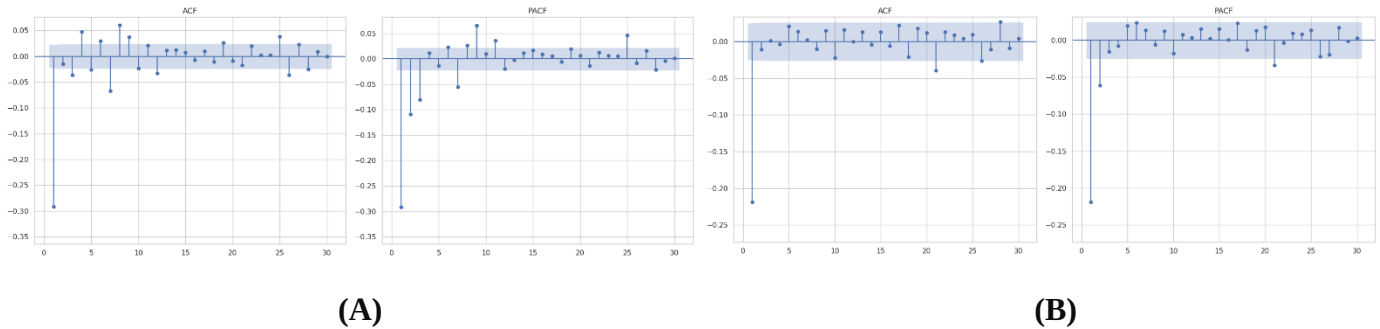
To determinate the possible models to each series we have to analyze the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ACF quantifies the correlation between the exchange rate USD/DZD or EUR/DZD and its previous time step. Significant coefficients in the ACF plot are observed up to the order  $q$ . Similarly, PACF aids in determining the order  $p$ , and shows the dependency between lags  $t$  and  $t-1$  with significant coefficients present up to lag  $p$ .

After analyzing the plot in **Figure 16**, the *sm.tsa.ARIMA* and *model\_ARMA.fit* functions from the forecast package in the Python programming language was employed to identify the optimal orders  $p$  and  $q$  for ARIMA and ARIMAX based on the minimization of BIC (between brackets under each model).

For USD/DZD, the SARIMA(3,1,0)(0,0,0)[0] model which is an ARIMA(3,1,0) and an ARIMAX(3,1,0) where identified. For EUR/DZD an ARIMA(0,1,1) and an ARIMAX(2,1,0) where identified. We can notice that the ARIMAX models used have lower BIC values compared to the standard ARIMA models. The results are depicted in **Table 5**.

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**Figure 16: The ACF and PACF of USD/DZD (A) and EUR/DZD (B)**



Source: Made by the students using Python

**Table 5: The identified models**

| Models                   | USD/DZD                         | EUR/DZD                          |
|--------------------------|---------------------------------|----------------------------------|
| SARIMA(p,d,q)(P,D,Q)[S]  | (3,1,0)(0,0,0)[0]<br>(6737.718) | (0,1,1)(0,0,0)[0]<br>(11894.342) |
| SARIMAX(p,d,q)(P,D,Q)[S] | (3,1,0)(0,0,0)[0]<br>(6052.712) | (2,1,0)(0,0,0)[0]<br>(7761.494)  |

Source: Made by the students using Python

#### 3.4 Parameter estimation

The parameters and the p-values, in parentheses, of the ARIMA models for the USD/DZD in equation (7), and EUR/USD in equation (8). Notably, all parameters were found highly significant at a 5% significance level where the p-values were all equal to zero.

Similarly, the USD/DZD ARIMAX equation (9) and the EUR/DZD ARIMAX equation (10) reveal varying levels of complexity and different degrees of impact of the exogenous variable. In addition, all models parameters were found highly significant at a 5% significance level with a *null p-value* for all parameters.

$$\Delta USDDZD_t = \underset{(0.000)}{-0.3164} \Delta USDDZD_{t-1} - \underset{(0.000)}{0.1353} \Delta USDDZD_{t-2} - \underset{(0.000)}{0.0650} \Delta USDDZD_{t-3} + \epsilon_t \quad (7)$$

$$\Delta EURDZD_t = \underset{(0.000)}{-0.2350} \epsilon_{t-1} + \epsilon_t \quad (8)$$

$$\Delta USDDZD_t = \underset{(0.000)}{-18.0630} \Delta EURUSD_t - \underset{(0.000)}{0.3884} \Delta USDDZD_{t-1} - \underset{(0.000)}{0.1809} \Delta USDDZD_{t-2} - \underset{(0.000)}{0.0832} \Delta \Delta USDDZD_{t-3} + \epsilon_t \quad (9)$$

$$\Delta EURDZD_t = \underset{(0.000)}{59.5975} EURUSD_t - \underset{(0.000)}{0.3529} \Delta EURDZD_{t-1} - \underset{(0.000)}{0.1483} \Delta EURDZD_{t-2} + \epsilon_t \quad (10)$$

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The **Table 6** display the different parameters economical interpretations for each series models.

**Table 6: Models parameters and tests interpretations**

| Model                  | Parameter interpretation (Economic)                                                                                                                                                                                                      |
|------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| USD/DZD ARIMA (3,1,0)  | USD/DZD changes are driven by its own lags (up to 3 periods), reflecting inertia in the exchange rate due to trade imbalances, oil price fluctuations (Algeria's oil dependency), and U.S. monetary policy shifts affecting the USD.     |
| EUR/DZD ARIMA (0,1,1)  | EUR/DZD changes depend on its 1-period lag, indicating short-term persistence likely due to Eurozone economic stability, trade flows with Algeria, and fluctuations in energy prices affecting the DZD.                                  |
| USD/DZD ARIMAX (3,1,0) | USD/DZD is heavily influenced by EUR/USD (positive coefficient) and its own lags, driven by global currency market dynamics, U.S. interest rate changes, and Algeria's trade reliance on both USD and EUR amidst oil revenue volatility. |
| EUR/DZD ARIMAX (2,1,0) | EUR/DZD shows a strong positive link with EUR/USD and its own lags, reflecting Eurozone economic conditions, ECB monetary policy, and Algeria's sensitivity to energy market shifts affecting DZD stability.                             |

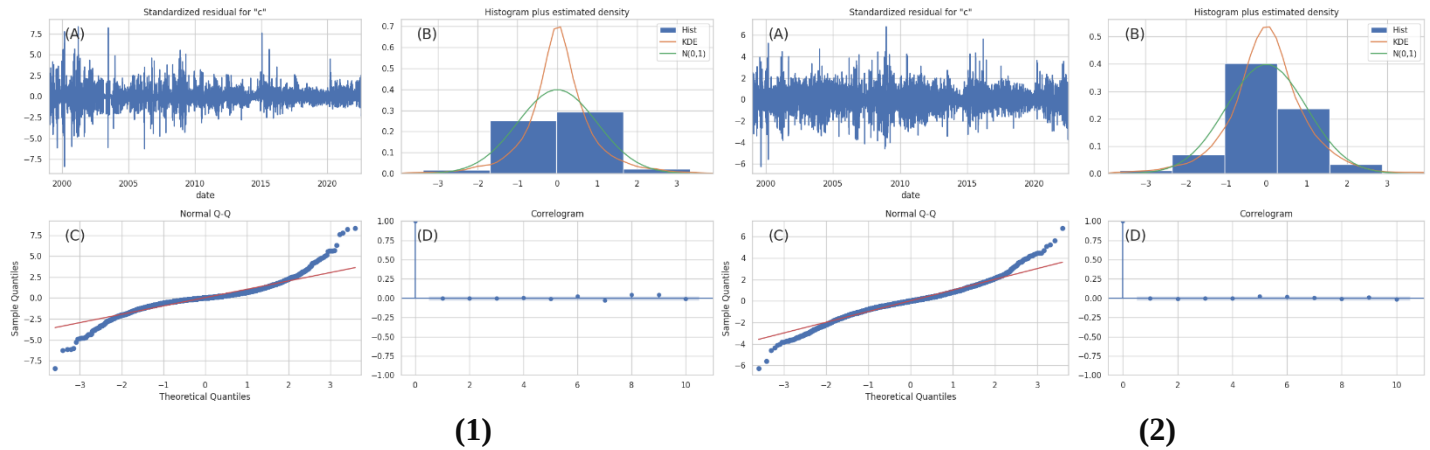
**Source:** Made by the students

### 3.5 Diagnosis checking

The analysis of correlograms and histograms for the ARIMA in **Figure 17.1**, and ARIMAX in **Figure 17.2**, models of both USD/DZD and EUR/DZD series highlights strengths and limitations in residual behavior. Correlograms generally show autocorrelation coefficients near zero up to lag 10, with ARIMA for USD/DZD and ARIMAX for EUR/DZD indicating minor residual correlation, suggesting these models partially miss some temporal dependencies. In contrast, ARIMAX for USD/DZD and ARIMA for EUR/DZD perform better, reflecting effective capture of the series dynamics. Histograms across all models reveal non-normal residuals, characterized by sharp peaks and heavy tails with extreme values up to 3, consistent with normality test failures and indicating high kurtosis and potential outliers. This non-normality is evident in both series, suggesting that while the models manage autocorrelation variably, the residual distributions deviate significantly from white noise.

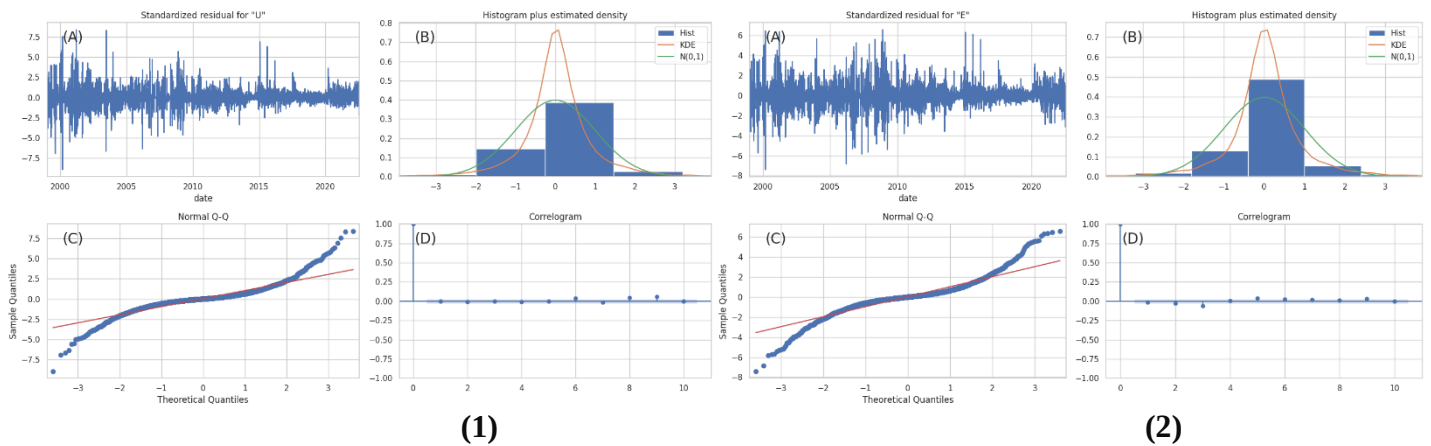
## Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

**Figure 17.1: Correlograms and histograms of residuals diagnosis for USD/DZD (1) and EUR/DZD (2) using ARIMA**



Source: Made by the students using Python

**Figure 17.2: Correlograms and histograms of residuals diagnosis for USD/DZD (1) and EUR/DZD (2) using ARIMAX**



Source: Made by the students using Python

To confirm the visual analysis, we have to apply the tests of stationarity, autocorrelation, normality and heteroscedasticity.

A- The **Ljung-box test** is a diagnostic tool used to check for autocorrelation in time series residuals. It assesses whether any group of autocorrelations in a time series is statistically significant, which helps evaluate model adequacy. This test was developed by Ljung and Box in the 1978 as an improvement over the Box-Pierce test.

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- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then there is no autocorrelation
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then a significant autocorrelation exists

B- The **Durbin-Watson test** detects autocorrelation (specifically first-order) in regression residuals. It is widely used in econometrics to validate linear regression assumptions (Durbin & Watson, 1950).

- └ **Null Hypothesis ( $H_0$ ):** No first-order autocorrelation (test statistic  $\approx 2$ )
- └ **Alternative Hypothesis ( $H_1$ ):** Positive ( $0 < \text{statistic} < 2$ ) or negative ( $2 < \text{statistic} < 4$ ) autocorrelation.

C- The **Shapiro-Wilk test** evaluates the normality of a dataset by comparing observed quantiles to theoretical normal distribution quantiles. It is particularly effective for small samples (Shapiro & Wilk, 1965).

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then the data is normally distributed.
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then the data is non-normal.

D- The **Jarque-Bera test** checks if sample data skewness and kurtosis match a normal distribution. It is commonly used in econometrics (Jarque & Bera, 1987).

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then the data is normal.
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then the data is non-normal (skewed/kurtic).

E- The **ARCH test** detects autoregressive conditional heteroscedasticity (ARCH effects) in residuals, indicating time-varying volatility. Engle (1982) introduced it to model financial market volatility.

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , then no ARCH effects (homoscedasticity).
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , then there is an ARCH effect present (heteroscedasticity).

F- The **Breusch-Pagan test** identifies heteroscedasticity in linear regression models by examining variance dependence on independent variables (Breusch & Pagan, 1979).

- └ **Null Hypothesis ( $H_0$ ):** p-value  $> \alpha$ , presence of homoscedasticity (constant variance).
- └ **Alternative Hypothesis ( $H_1$ ):** p-value  $\leq \alpha$ , presence of heteroscedasticity.

The diagnostic tests for the ARIMA and ARIMAX models, showed in **Table 7**, of both USD/DZD and EUR/DZD series reveal a mixed performance in meeting the white noise residual assumption. The analysis reveals varied performance across the USD/DZD ARIMA, EUR/DZD ARIMA, USD/DZD ARIMAX and EUR/DZD ARIMAX.

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All models exhibit stationary residuals based on ADF and PP tests (p-values  $<0.05$ ), though KPSS results indicate potential issues, with USD/DZD ARIMA at 0.01, EUR/DZD ARIMA at 0.1, USD/DZD ARIMAX at 0.1, and EUR/DZD ARIMAX at 0.033 suggesting non-stationarity concerns. So it will be tolerated at another p-value value (e.g. 0.1).

Autocorrelation is absent in EUR/DZD ARIMA and USD/DZD ARIMAX, but present in USD/DZD ARIMA and strongly in EUR/DZD ARIMAX.

Normality is rejected across all models, and heteroscedasticity is detected by ARCH test in all, with Breusch-Pagan showing mixed results.

**Table 7: Residuals tests results for both series (p-values)**

| Tests              | Models               | USD/DZD<br>ARIMA<br>(3,1,0) | EUR/DZD<br>ARIMA<br>(0,1,1) | USD/DZD<br>ARIMAX<br>(3,1,0) | EUR/DZD<br>ARIMAX<br>(2,1,0) |
|--------------------|----------------------|-----------------------------|-----------------------------|------------------------------|------------------------------|
|                    |                      |                             |                             |                              |                              |
| Stationarity       | <i>ADF</i>           | 2.6824E-25                  | 0                           | 5.20196E-22                  | 3.41557E-29                  |
|                    | <i>PP</i>            | 0                           | 0                           | 0                            | 0                            |
|                    | <i>KPSS</i>          | 0.01                        | 0.1                         | 0.1                          | 0.033084236                  |
| Autocorrelation    | <i>Ljung-Box</i>     | 0.000244                    | 0.407278                    | 0.987406                     | 1.77882E-07                  |
|                    | <i>Durbin-Watson</i> | 2                           | 1.99                        | 1.15                         | 2.02                         |
| Normality          | <i>Shapiro-Wilk</i>  | 0                           | 0                           | 0                            | 0                            |
|                    | <i>Jarque-Bera</i>   | 0                           | 0                           | 0                            | 0                            |
|                    | <i>ARCH</i>          | 0                           | 0                           | 0                            | 0                            |
| Heteroscedasticity | <i>Breusch-Pagan</i> | 0.058                       | 0.0666                      | 0.0683                       | 0                            |

**Source:** Made by the students using Python

### 3.6 Forecasting performance analysis

After identifying the models, estimating their parameters, and conducting residual diagnostics for the ARIMA and ARIMAX models, we applied these models to forecast exchange rate for both USD/DZD and EUR/DZD series using a 90-10 ratio as mentioned earlier.

**Figure 18** display the forecasting performance of the models for USD/DZD and EUR/DZD. The USD/DZD ARIMA and ARIMAX forecasts remain flat around 145 DZD, failing to capture the test data's significant volatility (130-145 DZD), indicating poor adaptability to trends and dynamics. Similarly, the EUR/DZD ARIMA forecast stays constant at 150 DZD, missing the test data's wide fluctuations (130-160 DZD). The EUR/DZD ARIMAX initially tracks the test data near 150 DZD but diverges as the data drops to 135 DZD by 2025, with a widening confidence interval reflecting growing uncertainty.

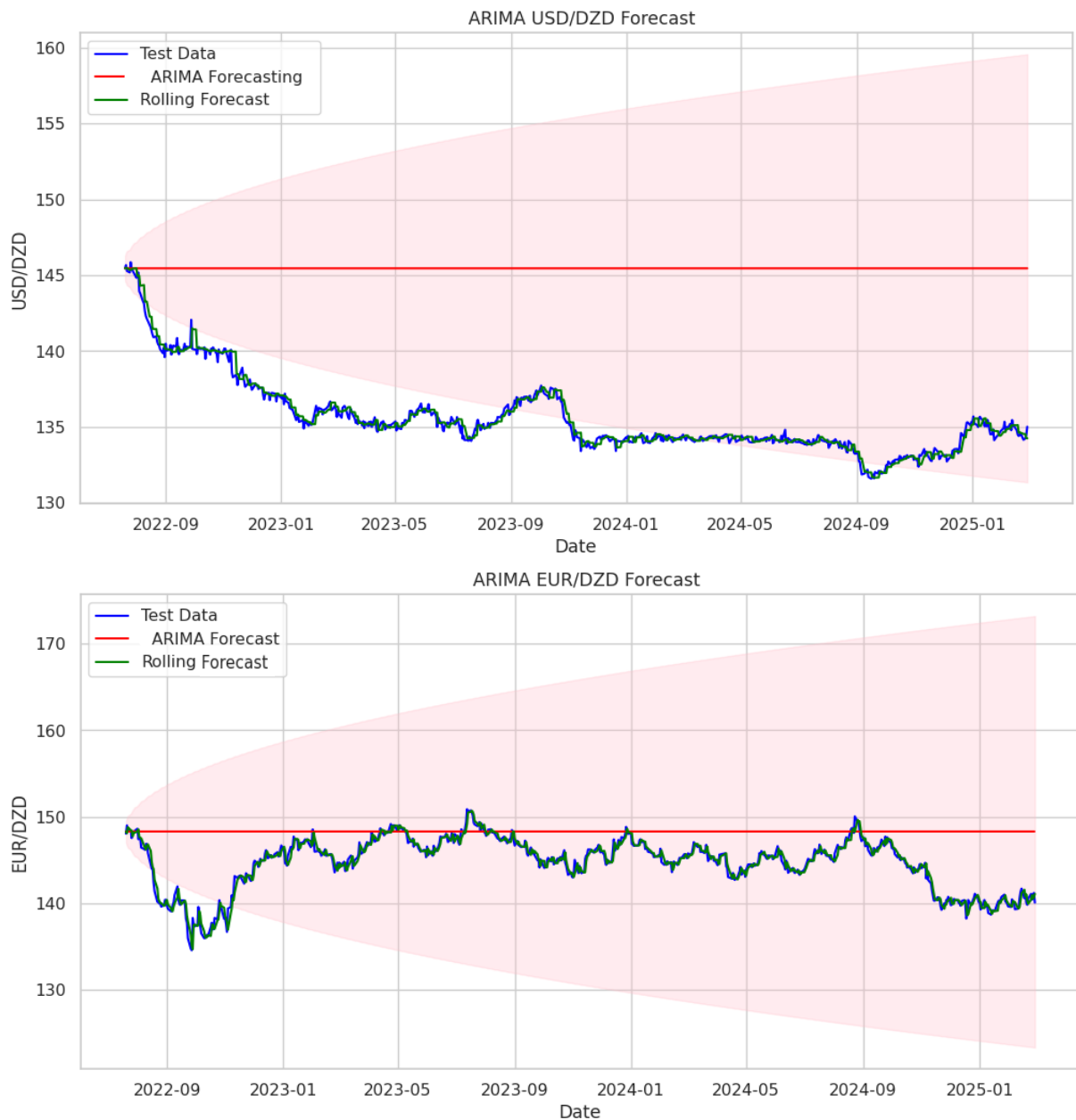
Thus, we will introduce the **rolling forecast**, a dynamic forecasting technique where a model is repeatedly re-estimated and updated as new data becomes available, maintaining a

### Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

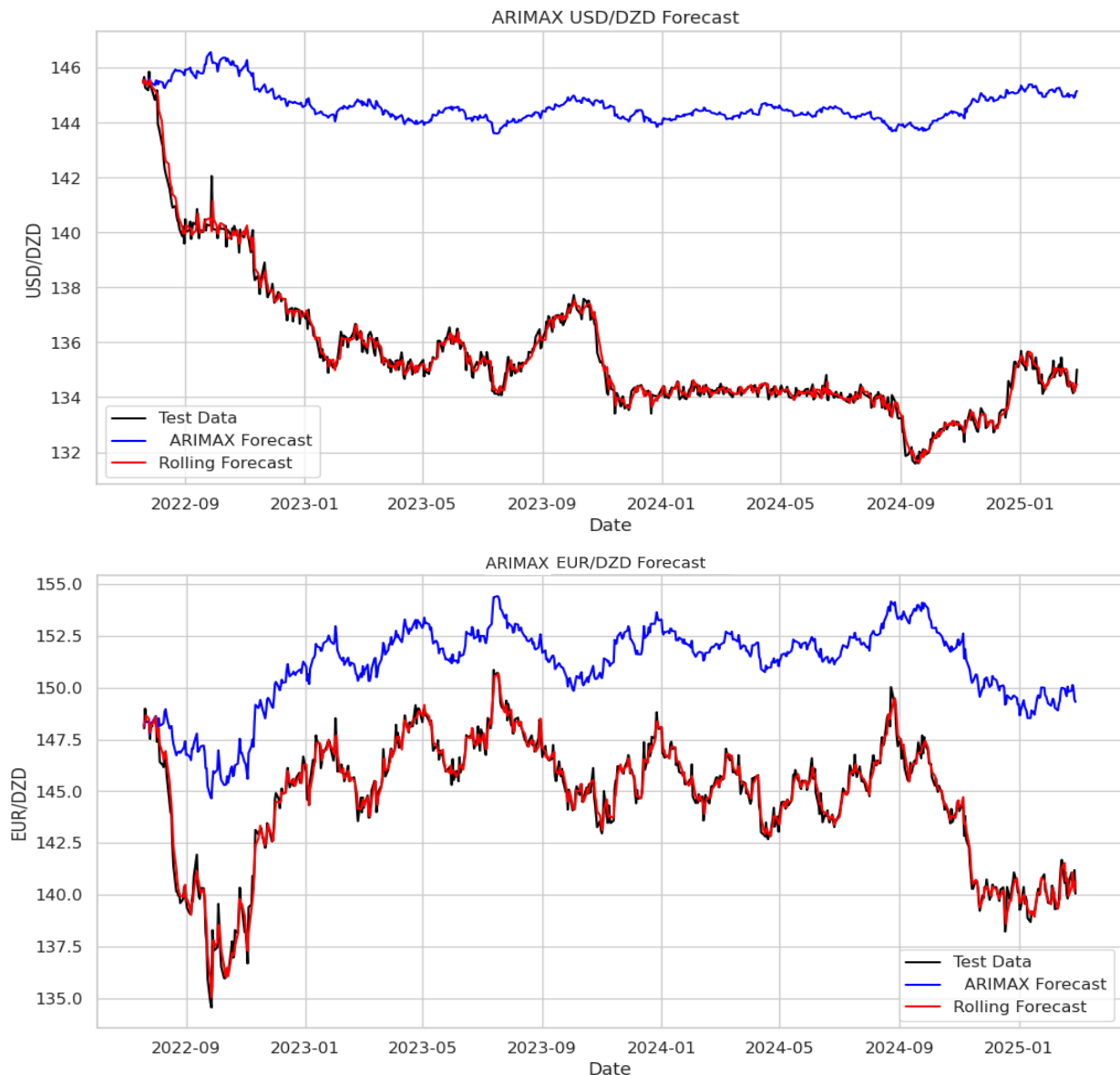
fixed forecast horizon while shifting the training window forward in time (Taoussi et al., 2024). Where it is widely used in financial time series analysis to adapt to changing market conditions and improve prediction accuracy by incorporating the most recent observations (Hyndman & Athanasopoulos, 2018).

Visually, the rolling forecasts for USD/DZD and EUR/DZD significantly outperform their classical counterparts across all models, it closely follows the test data's volatility unlike the flat classical forecasts highlighting better trend adaptation showing a superior performance by dynamically adjusting to the series fluctuations.

**Figure 18: Forecasting results for USD/DZD and EUR/DZD**



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**Source:** Made by the students using Python

In **Table 8**, the goodness-of-fit metrics reveal distinct performance levels among the models. The USD/DZD ARIMA exhibits the highest RMSE, MAE and MAPE indicating the poorest fit and largest prediction errors for the USD/DZD series. In contrast, the EUR/DZD ARIMA performs best with the lowest RMSE, MAE and MAPE suggesting superior accuracy and consistency for the EUR/DZD series. The USD/DZD ARIMAX shows moderate performance, slightly better than its ARIMA counterpart but still less effective than EUR/DZD models. The EUR/DZD ARIMAX achieves a performance indicating a reasonable fit but underperforming compared to the EUR/DZD ARIMA model. Overall, the EUR/DZD ARIMA stands out as the most accurate, while USD/DZD models struggle with higher errors, possibly due to greater volatility or inadequate model specification. The inclusion of exogenous variables in ARIMAX models improves fit marginally for USD/DZD but not enough to outperform the simpler EUR/DZD ARIMA.

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The goodness-of-fit metrics significantly improved when using rolling forecasts for both USD/DZD and EUR/DZD models. For USD/DZD ARIMA, the RMSE decreased from 10.185 to 0.373, MAE from 9.874 to 0.275, and MAPE from 7.318 to 0.202 with the rolling approach. Similarly, USD/DZD ARIMAX saw RMSE drop from 9.277 to 0.394, MAE from 9.039 to 0.293, and MAPE from 6.696 to 0.203. For EUR/DZD ARIMA, the rolling forecast reduced RMSE from 4.734 to 0.632, MAE from 3.722 to 0.478, and MAPE from 2.617 to 0.331. Lastly, EUR/DZD ARIMAX improved from an RMSE of 6.703 to 0.280, MAE from 6.455 to 0.212, and MAPE from 4.486 to 0.156.

**Table 8: Goodness-of-fit metrics results of the forecasting**

| Model                  | Goodness-of-fit metrics |            |                 |
|------------------------|-------------------------|------------|-----------------|
|                        | <i>RMSE</i>             | <i>MAE</i> | <i>MAPE (%)</i> |
| USD/DZD ARIMA          | 10.185                  | 9.874      | 7.318           |
| EUR/DZD ARIMA          | 4.734                   | 3.722      | 2.617           |
| USD/DZD ARIMAX         | 9.277                   | 9.039      | 6.696           |
| EUR/DZD ARIMAX         | 6.703                   | 6.455      | 4.486           |
| USD/DZD ARIMA Rolling  | 0.373                   | 0.275      | 0.202           |
| EUR/DZD ARIMA Rolling  | 0.632                   | 0.478      | 0.331           |
| USD/DZD ARIMAX Rolling | 0.280                   | 0.212      | 0.156           |
| EUR/DZD ARIMAX Rolling | 0.394                   | 0.293      | 0.203           |

**Source:** Made by the students using Python

Across all models, and for both series, the ARIMAX rolling forecast consistently yields lower error metrics, demonstrating enhanced predictive accuracy.

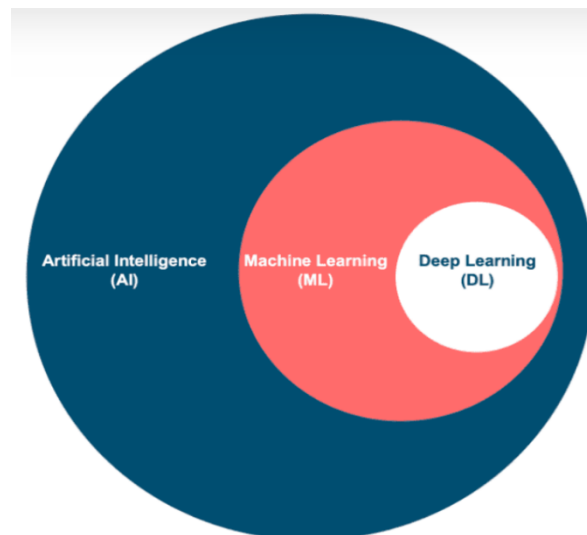
### **Section 3: Deep learning models**

Deep learning models, particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have gained significant attention in financial time series forecasting due to their ability to capture complex nonlinear patterns and temporal dependencies (Hochreiter & Schmidhuber, 2013). The nonlinear and stochastic nature of exchange rate data makes traditional econometric models sometimes insufficient in capturing long-term dependencies and intricate market dynamics (Kristjanpoller et al., 2014). Deep learning models, with their adaptive learning capabilities, offer a promising alternative by automatically extracting relevant features from raw data without relying heavily on manual feature engineering.

In this section, we first introduce some deep learning terminologies to then define LSTM and CNN models, explaining their structures and operational mechanisms. Subsequently, we apply these models to forecast the volatility of USD/DZD and EUR/DZD exchange rates. Finally, we compare their performance to determine the best model for each architecture, providing insights into their effectiveness in modeling exchange rate fluctuations.

**Figure 19** illustrates the relation between artificial intelligence, deep learning and machine learning. All machine learning and deep learning methods are part of artificial intelligence, but not all artificial intelligence methods are machine learning or deep learning. The smaller the circle, the more niche the modeling subtype is.

**Figure 19: Relation between artificial intelligence, machine learning and deep learning**



**Source:** www.phdat (15-05-2025)

## 1. Theory and definitions of the deep learning models

We will use two deep learning models in this research

### 1.1 General terminologies

The most important components of the architecture are:

- **Input:** the input to a CNN is typically a multi-dimensional array, such as a 2D image (height×width×channels) or a 1D time-series vector. The input is processed by convolutional filters to extract features. In mathematical terms, an input image or signal ( $X$ ) is a tensor (vector) that serves as the starting point for feature extraction (Krizhevsky et al., 2012).
- **Output:** the output of a CNN depends on the task. For classification, it is a probability distribution over classes, often produced by a softmax layer. For regression, such as forecasting, the output is a continuous value. The output layer is typically a fully connected (dense) layer tailored to the problem (Goodfellow et al., 2016).
- **Weights and bias:** weights ( $W$ ) and biases ( $b$ ) are learnable parameters in CNN layers. In a convolutional layer, weights form small filters (e.g.,  $3 \times 3$  kernels) that slide over the input to compute feature maps. Biases are added to the convolution output to shift the activation. For a feature map ( $Z$ ), the operation is  $Z = W * X + b$ , where  $(*)$  denotes convolution. These parameters are updated during training to minimize the loss (LeCun et al., 1989).
- **Layers:** there are multiple layer types: convolutional layers (extract features), pooling layers (downsample), and fully connected layers (make predictions). Each layer transforms the input to produce a more abstract representation. (LeCun et al., 1989).
- **Activation function:** activation functions introduce non-linearity to model complex patterns (Glorot & Bengio, 2010). The key function are:

| Activation Function          | Mathematical Formula                                                    |
|------------------------------|-------------------------------------------------------------------------|
| Sigmoid                      | $f(x) = \frac{1}{1 + e^{-x}}$                                           |
| Tanh                         | $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$                              |
| ReLU (Rectified Linear Unit) | $f(x) = \max(0, x)$                                                     |
| Leaky ReLU                   | $f(x) = x \text{ if } x > 0,$<br>$\text{else } f(x) = a * x (a = 0.01)$ |

- **Stacking:** stacking refers to the sequential arrangement of multiple convolutional and pooling layers to build deeper networks. Early layers capture low-level features (e.g., edges), while deeper layers learn high-level patterns (e.g., trends) (Krizhevsky et al., 2012).

### Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

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- **Dense layers:** Dense (fully connected) layers connect every neuron in one layer to every neuron in the next, typically used at the end of a CNN for classification or regression. For an input vector ( $\mathbf{x}$ ), the output is  $\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{b}$ , where ( $\mathbf{W}$ ) is the weight matrix and ( $\mathbf{b}$ ) is the bias (Goodfellow et al., 2016).
- **Propagation: forward and backward:** forward propagation computes the output by passing the input through layers, applying convolutions, activations, and pooling. Backward propagation (backpropagation) calculates gradients of the loss with respect to parameters using the chain rule, enabling parameter updates via gradient descent. The loss gradient is propagated backward through the network (Rumelhart et al., 1986).
- **Gradient descent:** Gradient Descent is an optimization algorithm used to minimize the loss function by iteratively updating model parameters. The update rule is  $\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \nabla_{\boldsymbol{\theta}} L$ , where ( $\boldsymbol{\theta}$ ) represents parameters (weights and biases), ( $\eta$ ) is the learning rate, and ( $\nabla_{\boldsymbol{\theta}} L$ ) is the gradient of the loss ( $L$ ) (Bottou, 2010).
- **Compilation: optimizer and loss function:** Compilation configures the model for training by specifying an optimizer (e.g., Adam, SGD) and a loss function (MSE). The optimizer minimizes the loss by adjusting parameters (Kingma & Ba, 2015).
- **Initialization:** initialization sets initial values for weights and biases before training. Common methods include Xavier initialization, which scales weights based on layer size to ensure stable gradients (Glorot & Bengio, 2010).
- **Learning rate:** the learning rate ( $\eta$ ) controls the step size of parameter updates in gradient descent. A high learning rate risks overshooting, while a low rate slows convergence. Adaptive optimizers like Adam dynamically adjust ( $\eta$ ) (Kingma & Ba, 2015).
- **Momentum:** momentum accelerates gradient descent by adding a fraction of the previous update to the current one:  $\mathbf{v}_t = \gamma \mathbf{v}_{t-1} + \eta \nabla_{\boldsymbol{\theta}} L$ , and  $\boldsymbol{\theta} = \boldsymbol{\theta} - \mathbf{v}_t$  is the momentum coefficient. This helps escape local minima and speeds convergence (Sutskever et al., 2013).
- **Fitting the model: input, target:** fitting involves training the CNN by feeding input data and corresponding targets (labels or values) to minimize the loss. The model learns to map inputs to targets through iterative optimization (Goodfellow et al., 2016).
- **Batching:** batching divides the dataset into smaller subsets (mini-batches) for training. For a batch size ( $B$ ), the gradient is averaged over ( $B$ ) samples, balancing computational efficiency and gradient stability (Bottou, 2010).
- **Epochs:** an epoch is one complete pass through the training dataset. Multiple epochs are used to refine parameters, but too many can lead to overfitting. The number of epochs is a hyperparameter tuned based on validation performance (Bengio, 2012).

## **1.2 Convolutional Neural Networks (CNNs)**

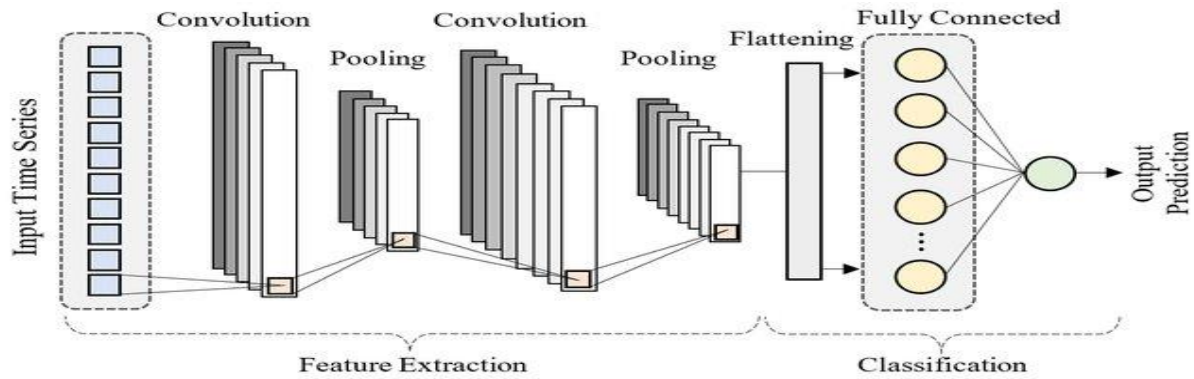
Convolutional Neural Networks (CNNs) are a class of deep learning neural networks designed to process structured grid-like data, such as images or time-series data, by leveraging spatial hierarchies and local patterns. Unlike traditional neural networks, CNNs use convolutional layers to apply filters that extract features like edges, textures, or trends, followed by pooling layers to reduce spatial dimensions while preserving key informations (LeCun et al., 1989; Goodfellow et al., 2016).

### **1.2.1 Key components and flowchart mechanism of the CNN architecture**

As displayed in **Figure 20**, the CNN model go through multiple steps to do the forecasting:

1. **Input layer:** the process begins with the input layer, which accepts raw data, such as a 2D image or a 1D time-series vector. For example, a time-series of exchange rates might be reshaped into a 1D vector of length ( $T$ ). The input is normalized (scaled) to ensure consistent scale (values between 0 and 1) (Goodfellow et al., 2016).
2. **Convolutional layer:** the convolutional layer applies multiple filters (e.g.,  $3 \times 3$  kernels) to the input, producing feature maps. Each filter detects specific patterns (e.g., trends or volatility spikes). The operation is  $Z = W * X + b$ , followed by an activation like ReLU. For a filter size ( $F$ ), stride ( $S$ ), and padding ( $P$ ), the output size is  $\left\lfloor \frac{N - F + 2P}{S} \right\rfloor + 1$  (Goodfellow et al., 2016).
3. **Pooling layer:** the pooling layer downsamples feature maps to reduce spatial dimensions and computational load while retaining key features. Max-pooling, for example, takes the maximum value in a region (e.g.,  $2 \times 2$  window). This enhances translation invariance and reduces overfitting. The output size is determined by the pooling window size and stride (Goodfellow et al., 2016).
4. **Stacking convolutional and pooling layers:** multiple convolutional and pooling layers are stacked to extract increasingly abstract features. Early layers capture low-level patterns (e.g., short-term trends), while deeper layers learn complex representations (e.g., long-term volatility patterns). The process repeats steps 2 and 3 (LeCun et al., 2015).
5. **Flatten and dense layers:** after convolutional and pooling layers, the feature maps are flattened into a 1D vector to feed into dense layers. Dense layers aggregate features to produce the final output, such as a regression value for volatility. A softmax or linear activation is used depending on the task (Goodfellow et al., 2016).
6. **Compilation and training:** the model is compiled with an optimizer (e.g., Adam) and loss function. During training, forward propagation computes predictions, and backpropagation updates weights. The process iterates over epochs, with batches of data (Kingma & Ba, 2015).
7. **Prediction:** after training, the model makes predictions on new data by performing forward propagation. For exchange rate volatility, the input produces a forecasted volatility value. The model's performance is evaluated using metrics like RMSE (Sezer et al., 2020).

Figure 20: Diagram of a CNN model for time series data forecasting



Source: Staffini, 2022

CNNs excel at capturing spatial patterns in data, such as images or localized features in time series. However, when modeling sequential data with temporal dependencies, such as exchange rate volatility, RNNs are better suited due to their ability to process sequences (Goodfellow et al., 2016).

### 1.3 Long Short-Term Memory (LSTM) networks

While RNNs are effective for short-term dependencies, they struggle with long-term dependencies due to issues like vanishing gradients. This limitation leads us to LSTM networks, a specialized RNN variant designed to model long-term dependencies effectively by introducing memory cells and gating mechanisms (Hochreiter & Schmidhuber, 2013).

- **Recurrent Neural Networks (RNNs):** RNNs are a class of neural networks designed for sequential data processing. They maintain a hidden state that is updated at each time step, allowing the network to incorporate information from previous inputs. The hidden state is computed using the current input and the previous hidden state, enabling RNNs to model temporal relationships. (Bengio et al., 1994).
- **Long Short-Term Memory (LSTM):** LSTMs are an advanced RNN architecture introduced to overcome the limitations of standard RNNs. They incorporate a memory cell and three key gates—input, forget, and output gates—that regulate the flow and retention of information. This structure allows LSTMs to capture long-term dependencies making them highly effective for tasks requiring memory of past events, such as time series prediction or natural language processing (Hochreiter & Schmidhuber, 1997).

#### 1.3.1 Key components and flowchart mechanism of the LSTM architecture

As displayed in **Figure 21**, the LSTM components work together to make the model robust modeling, such as exchange rate volatility forecasting (Kim & Won, 2018).

- **Memory cell (cell state):** the memory cell, often referred to as the cell state ( $C_t$ ), is the core component of the LSTM, acting as a "memory highway" that carries information across the entire sequence. It enables the LSTM to retain relevant information over long time periods, such as trends or patterns in a time series, while allowing controlled updates to

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incorporate new information. The cell state is modified selectively by gates, ensuring that only pertinent information is retained or discarded, which is crucial for tasks like forecasting where historical context matters. The cell state is updated at each time step by combining the previous cell state ( $C_{t-1}$ ) with new information, modulated by the forget and input gates. This allows the LSTM to maintain a balance between long-term memory and short-term updates. The cell state update is defined as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Here, ( $f_t$ ) is the forget gate's output, ( $i_t$ ) is the input gate's output, and ( $\tilde{C}_t$ ) is the candidate cell state. The cell state acts as a cumulative repository of information, selectively adjusted to reflect the sequence's evolving context (Graves, 2013).

- **Forget gate:** the forget gate ( $f_t$ ) determines which parts of the previous cell state ( $C_{t-1}$ ) should be discarded or retained. It evaluates the relevance of past information given the current input ( $x_t$ ) and the previous hidden state ( $h_{t-1}$ ). For example, in exchange rate forecasting, the forget gate might discard outdated market trends (e.g., from a month ago) if they no longer influence current volatility. The forget gate uses a sigmoid activation function ( $\sigma$ ), which outputs values between 0 and 1. A value close to 0 means "forget this information," while a value close to 1 means "keep it".

$$f_t = \sigma(W_t \cdot [h_{t-1}, x_t] + b_f)$$

Where ( $W_t$ ) is the weight matrix, ( $b_f$ ) is the bias, and ( $[h_{t-1}, x_t]$ ) is the concatenated input of the previous hidden state and current input. The sigmoid function ensures a controlled scaling of the previous cell state (Hochreiter & Schmidhuber, 1997).

- **Input gate:** the input gate ( $i_t$ ) decides which new information from the current input ( $x_t$ ) and previous hidden state ( $h_{t-1}$ ) should be added to the cell state. It works in tandem with the candidate cell state to selectively update the memory with relevant new data, such as recent price movements in a financial time series. The input gate uses a sigmoid function to produce a value between 0 and 1, indicating how much of the new candidate information should be incorporated.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Additionally, the candidate cell state ( $\tilde{C}_t$ ), which proposes new values to be added, is computed using a tanh activation function to introduce non-linearity and bound the values between -1 and 1:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

The input gate's output ( $i_t$ ) scales the candidate cell state to determine the final contribution to the cell state update (Graves, 2013).

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- **Cell state update:** The cell state update integrates the outputs of the forget and input gates to produce the new cell state ( $C_t$ ). It balances the retention of historical information (via the forget gate) with the incorporation of new information (via the input gate and candidate cell state). This process ensures that the LSTM can adapt to new patterns while preserving relevant long-term dependencies. The update combines the scaled previous cell state (modulated by  $f_t$ ) with the scaled candidate cell state (modulated by  $i_t$ ).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

The dot product ( $\cdot$ ) represents element-wise multiplication, ensuring that each component of the cell state is updated independently based on the gate outputs. This equation is the heart of the LSTM's ability to manage long-term memory (Hochreiter & Schmidhuber, 1997).

- **Output gate:** the output gate ( $o_t$ ) controls which parts of the updated cell state ( $C_t$ ) are used to produce the hidden state ( $h_{t-1}$ ), which serves as the LSTM's output at the current time step and is passed to the next time step. In tasks like forecasting, the hidden state is often used to make predictions. The output gate uses a sigmoid function to decide which components of the cell state are relevant for the output. The cell state is passed through a tanh function to normalize its values, and the output gate's result scales this to produce the final hidden state. This allows the LSTM to focus on the most relevant information for the forecasting.

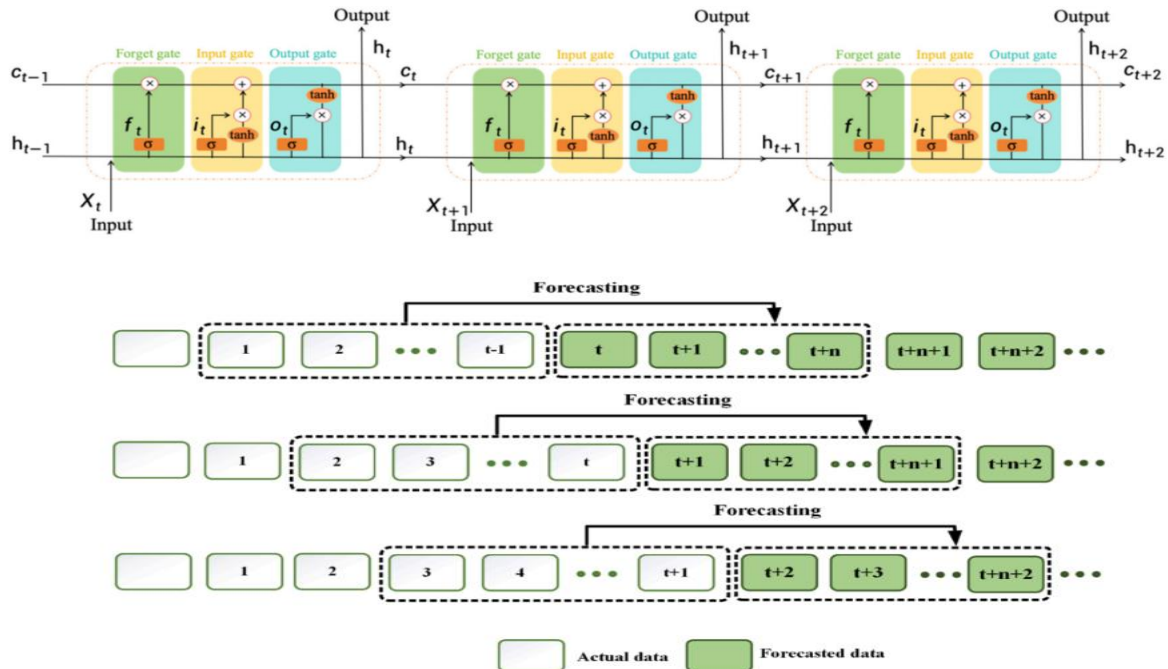
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

Here, ( $W_o$ ) and ( $b_o$ ) are the weight matrix and bias for the output gate, and the tanh function ensures the hidden state values are bounded between -1 and 1. The hidden state ( $h_t$ ) encapsulates the LSTM's current understanding of the sequence (Graves, 2013).

The *memory cell* maintains a continuous record of relevant information, enabling long-term memory. The *forget gate* ensures that outdated or irrelevant information is discarded, keeping the memory focused. The *input gate* and *candidate cell state* allow the model to incorporate new, relevant information selectively. The *cell state update* integrates past and present information, balancing long-term and short-term memory. The *output gate* produces a filtered output that reflects the most relevant aspects of the current state, suitable for the forecasting.

Figure 21: Diagram of an LSTM model for time series data forecasting



Source : [d2l.ai/chapter\\_recurrent-modern/lstm.html](https://d2l.ai/chapter_recurrent-modern/lstm.html) (seen 15-05-2025)

#### 1.4 The hyperparameters and optimization

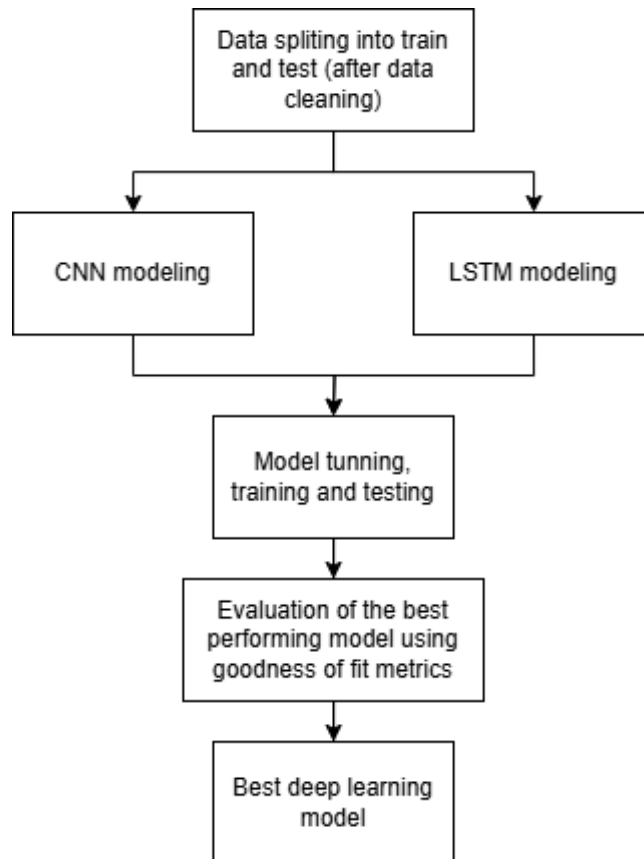
Hyperparameters are configuration settings of the models components parameters defined before training a machine learning model that govern its architecture and learning process. Unlike model parameters, hyperparameters are not learned from the data but are set by the practitioner, they control aspects such as the model's complexity and training speed. In the context of exchange rate volatility forecasting, hyperparameters determine how effectively CNNs and LSTMs capture temporal patterns in financial time series data (Goodfellow et al., 2016).

**The tuning process:** Hyperparameters are typically tuned (optimized) using specific techniques like: manual optimization, grid search, random search, or bayesian optimization on a validation set. For exchange rate volatility, metrics like MSE or RMSE on a holdout set guide tuning (Kim & Won, 2018). Poorly chosen hyperparameters can lead to underfitting (failing to capture patterns), overfitting (memorizing noise), or inefficient training, thus the hyperparameters tuning on a validation set is critical for optimizing performance in exchange rate volatility forecasting (Goodfellow et al., 2016).

## 2. The results

**Figure 22** shows the methodology used to development a deep learning prediction model.

**Figure 22: Methodology used for the modeling process**



**Source:** Made by the students

### 2.1 Data manipulation

As cited in the previous section, the data was splited with a 90-10 ratio for both of USD/DZD and EUR/DZD, where 90% of the data was allocated for the model training and 10% of it for testing it. The training data was then normalized a scale of (0 to 1) using the formula:  $X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}}$ , this method is used to simplify the data processing for the models, at the end, the inverse process will be used to get back the initial values of the data.

### 2.2 Modeling

Based on the previous studies and the data characteristics, we maintained the hyperparameters tabulated in **Table 9** for building the models.

**Table 9: Hyperparameters for both CNN and LSTM models**

| Model | Hyperparameters     | Model | Hyperparameters       |
|-------|---------------------|-------|-----------------------|
| CNN   | Number of units     | LSTM  | Number of LSTM layers |
|       | Number of filters   |       | Number of units       |
|       | Optimizer           |       | Sequence length       |
|       | Activation function |       | Activation function   |
|       | Number of Layers    |       | Dropout rate          |
|       | Loss function       |       | Recurrent dropout     |
|       | Batch size          |       | Gradient clipping     |

**Source:** Made by the students

### 2.3 Training of the models

After selecting the key hyperparameters for the CNN and LSTM models, we conducted a manual tuning process to further enhance the models and identify the preliminary ones for the evaluation process: this involved testing the most promising model configurations, to iteratively adjust critical hyperparameters. Three CNN and LSTM models were identified and their configurations are displayed in **Table 10**.

**Table 10: Preliminary chosen CNN and LSTM models configurations for both series**

| Series  | CNN Models | CNN hyperparameters |                   |                           |                     |           |                 |               |
|---------|------------|---------------------|-------------------|---------------------------|---------------------|-----------|-----------------|---------------|
|         |            | Batch size          | Number of filters | Number of layers (Kernel) | Activation function | Optimizer | Number of units | Loss function |
| USD/DZD | CNN1       | 1                   | 32                | 3                         | Relu                | Adam      | 32              | MSE           |
|         | CNN2       | 1                   | 35                | 4                         | Tanh                | Adam      | 33              | MSE           |
|         | CNN3       | 2                   | 38                | 3                         | Relu                | Adam      | 35              | MSE           |
| EUR/DZD | CNN1       | 1                   | 32                | 3                         | Relu                | Adam      | 32              | MSE           |
|         | CNN2       | 2                   | 34                | 5                         | Relu                | Adam      | 33              | MSE           |
|         | CNN3       | 1                   | 30                | 2                         | Tanh                | Adam      | 30              | MSE           |

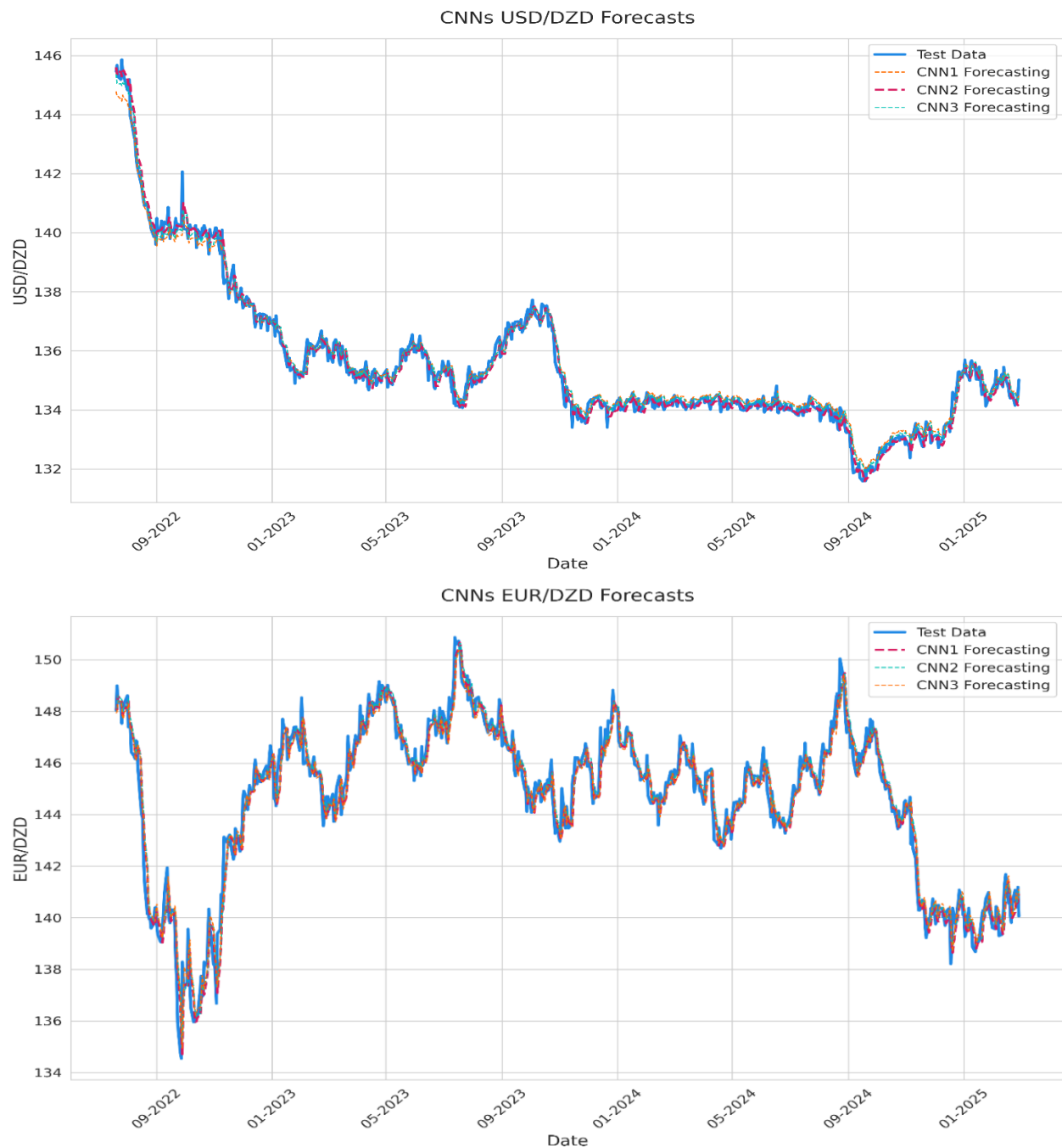
| Series  | LSTM Models | LSTM hyperparameters |            |              |                     |           |               |                |
|---------|-------------|----------------------|------------|--------------|---------------------|-----------|---------------|----------------|
|         |             | LSTM units           | Batch size | Dropout rate | Activation function | Optimizer | Loss function | Maximum Epochs |
| USD/DZD | LSTM1       | 50                   | 1          | 0            | Relu                | Adam      | MSE           | 100            |
|         | LSTM2       | 100                  | 2          | 1            | Tanh                | RMSprop   | MSE           |                |
|         | LSTM3       | 256                  | 1          | 0            | Relu                | Adam      | MSE           |                |
| EUR/DZD | LSTM1       | 128                  | 2          | 1            | Relu                | Adam      | MSE           | 100            |
|         | LSTM2       | 64                   | 1          | 0            | Tanh                | RMSprop   | MSE           |                |
|         | LSTM3       | 256                  | 1          | 2            | Tanh                | Adam      | MSE           |                |

**Source:** Made by the students using Python

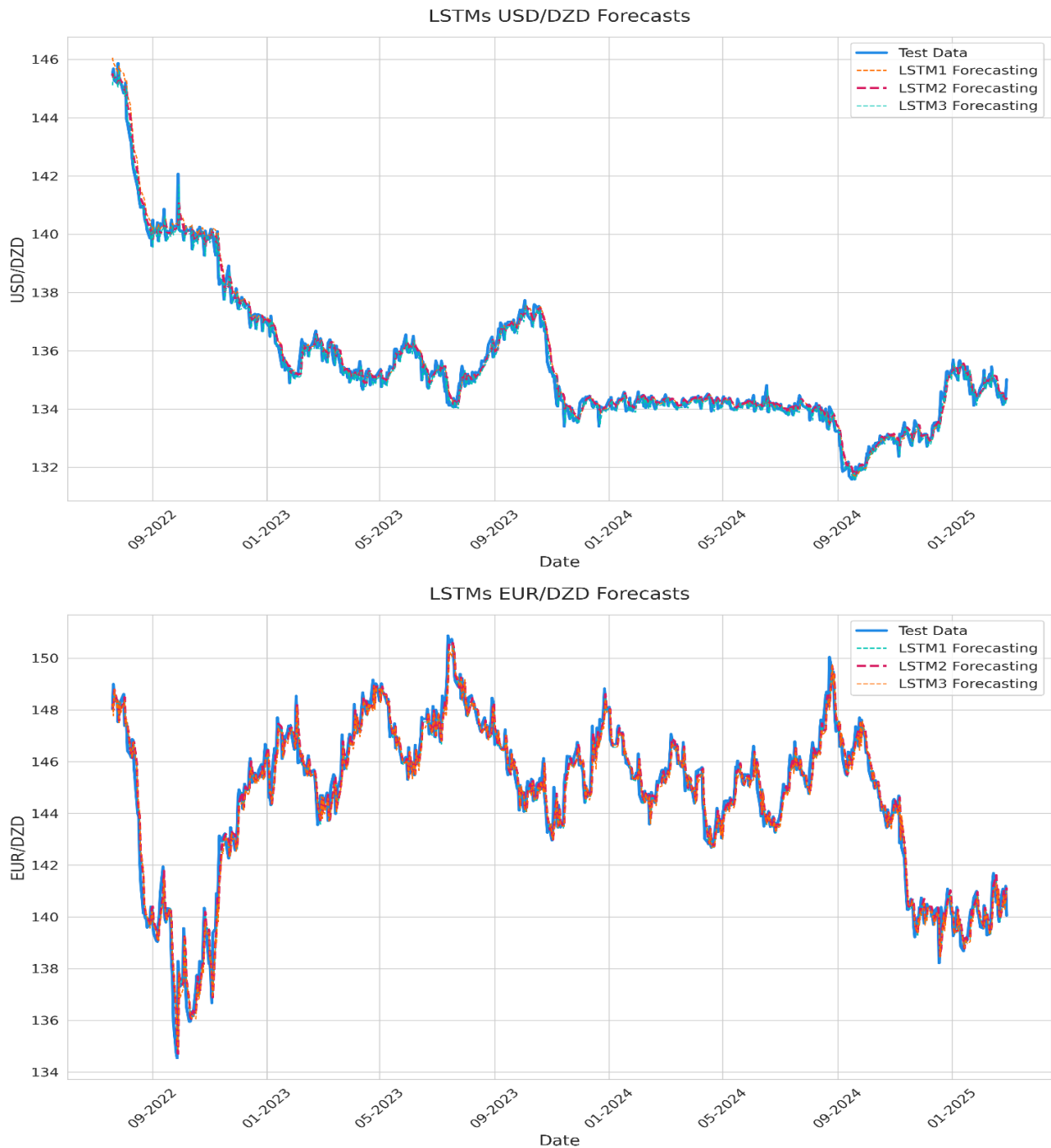
### Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

**Figure 23** shows the forecasting results of the identified CNN and LSTM models after training and testing on both USD/DZD and EUR/DZD series. Visually we can notice that all deep learning models performance for both series is significant performed, it closely follow the test data and shows an adaptation to the trend and the volatility.

**Figure 23: Forecasting results for USD/DZD and EUR/DZD**



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Source: Made by the students

### 2.4 Forecasting performance analysis

Table 11 display the goodness of fit metrics of all the models for both USD/DZD and EUR/DZD series: for the USD/DZD series, LSTM2 yields the best performance with the lowest RMSE, MAE and MAPE among the models, indicating superior accuracy in capturing the series dynamics compared to the all the other models. For the EUR/DZD series, LSTM2 again performs best with the lowest goodness of fit metrics outperforming all the other models. Overall, LSTM2 consistently delivers the best predictive accuracy for both series.

**Table 11: Goodness-of-fit metrics results of the forecasting**

| Series  | Models | Goodness-of-fit metrics |       |          |
|---------|--------|-------------------------|-------|----------|
|         |        | RMSE                    | MAE   | MAPE (%) |
| USD/DZD | CNN1   | 0.379                   | 0.296 | 0.216    |
|         | CNN2   | 0.318                   | 0.245 | 0.180    |
|         | CNN3   | 0.344                   | 0.277 | 0.199    |
|         | LSTM1  | 0.340                   | 0.258 | 0.205    |
|         | LSTM2  | 0.311                   | 0.234 | 0.172    |
|         | LSTM3  | 0.335                   | 0.248 | 0.185    |
| EUR/DZD | CNN1   | 0.649                   | 0.447 | 0.315    |
|         | CNN2   | 0.673                   | 0.512 | 0.385    |
|         | CNN3   | 0.666                   | 0.494 | 0.340    |
|         | LSTM1  | 0.637                   | 0.480 | 0.353    |
|         | LSTM2  | 0.625                   | 0.453 | 0.328    |
|         | LSTM3  | 0.642                   | 0.491 | 0.371    |

**Source:** Made by the students using Python

Thus, we can conclude that the LSTM model outperforms the CNN model for both of the series and yields lower error metrics, demonstrating the adaptability of the model on the data.

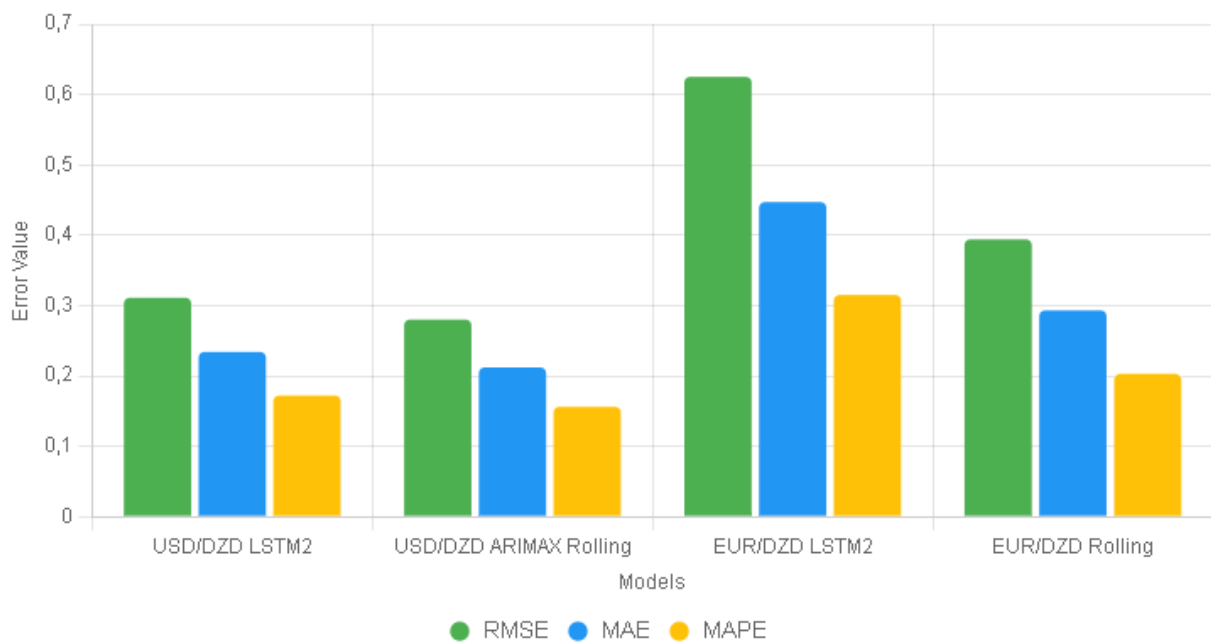
## Section 4: Models performance analysis

Exchange rate volatility measures the intensity of currency value fluctuations, reflecting market risk and uncertainty. In this section we will compare between best classical times series model and best deep learning model in order to determine the best model for both series, then we will use it for forecasting exchange rate volatility, after calculating it from both USD/DZD and EUR/DZD series and from the models forecasting results.

### 1. Comparison between the best models

From **Table 8 (page 76)** and **Table 11 (page 89)** we determined the best models each of the series: given the goodness-of-fit metric results of the forecasting for both USD/DZD and EUR/DZD, the ARIMAX rolling forecast model slightly outperforms the LSTM model achieving the lowest errors as illustrated in **Figure 24**, indicating that when using a specific forecasting approach (rolling forecast) classical models would be better than the deep learning models for this type of data. Thus, the chosen model to forecast both series is ARIMA rolling forecast.

**Figure 24: Best models performances comparison**



**Source:** Made by the students using Python

### 2. Forecasting the volatility using the best model

We will extend the analysis by visualizing the forecasting the volatility as a component apart. GARCH models are often used to directly forecast the volatility, but we could not rely on them: given the relatively low volatility of the currency pairs (Andersen & Bollerslev, 1998). Since volatility is directly derived from the exchange rate, we can extract it from both USD/DZD and EUR/DZD and also from the best performing model forecasting results. By leveraging exchange rate forecasts to infer volatility, we maintained the methodological

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consistency while avoiding unnecessary complexity: as volatility is not an independent process but an emergent property of the forecasted series (Andersen et al., 2003).

#### 2.1 Measure of the exchange rate volatility

To calculate exchange rate volatility for both series and for the forecasting results of the adequate model (ARIMAX with rolling forecast), we will go through these two steps:

##### Step 1: calculation of the daily log returns

Volatility measures price fluctuations, so we first compute log returns, which provide a normalized measure of price changes: for any price series  $P_t$ ,  $r_t$  is the daily log return at time  $t$ ,  $P_t$  represent the exchange rate at time  $t$ , and  $P_{t-1}$  the exchange rate at time  $t-1$  (Tsay, R. S, 2010).

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

##### Step 2: calculation of the volatility

Volatility is typically measured as the standard deviation of log returns. For daily calculation, there is a rolling window of  $n$  days, in this case,  $n$  equals 21 which is the number of the working days in FX market. Where  $\sigma_t$  is the estimated volatility at time  $t$ , and  $\bar{r}$  is the mean return over the window (Andersen et al., 2003).

$$\sigma_t = \sqrt{\frac{1}{n-1} \sum_{i=t-n+1}^t (r_i - \bar{r})^2}$$

For example, applied to the series:

$$r_{t,USD/DZD} = \ln\left(\frac{USD/DZD_t}{USD/DZD_{t-1}}\right)$$

$$r_{t,ARIMAX Rolling} = \ln\left(\frac{ARIMAX Rolling_t}{ARIMAX Rolling_{t-1}}\right)$$

$$\sigma_{t,USD/DZD} = \sqrt{\frac{1}{21-1} \sum_{i=t-20}^t \left(R_{i,USD/DZD} - \bar{R}_{t,USD/DZD}\right)^2}$$

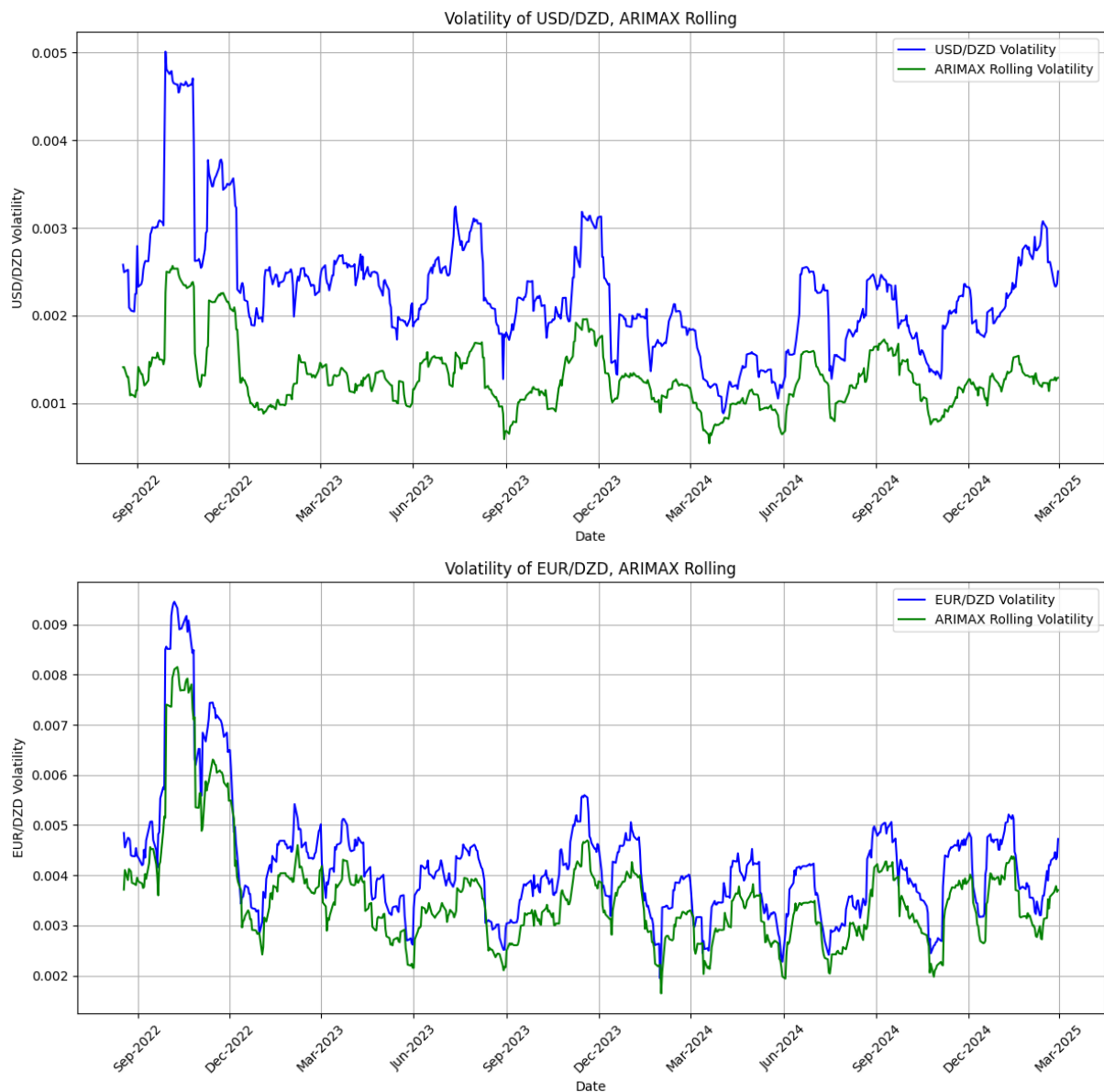
$$\sigma_{t,ARIMAX Rolling} = \sqrt{\frac{1}{21-1} \sum_{i=t-20}^t \left(R_{i,ARIMAX Rolling} - \bar{R}_{t,ARIMAX Rolling}\right)^2}$$

## 2.2 The results of the volatility forecasting

### 2.2.1 Volatility representation

**Figure 25** illustrates the volatility of USD/DZD and EUR/DZD exchange rates, comparing the actual volatility with the forecasted volatility using the chosen model (ARIMAX Rolling). These plots align with the previous results confirming that ARIMAX Rolling is more effective at capturing exchange rate volatility for both currency pairs.

**Figure 25: Exchange rate volatility comparison**



**Source:** Made by the students using Python

## Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-

### 2.2.2 Volatility forecasting performance analysis

To evaluate our model performance in forecasting exchange rate volatility, we use RMSE, MAE and MAPE as error metrics between real and predicted volatility where we put  $n$  = total number of observations,  $\sigma_t^{real}$  real volatility,  $\sigma_t^{model}$  model volatility.

| Metric                                | Formula                                                                                                |
|---------------------------------------|--------------------------------------------------------------------------------------------------------|
| Root Mean Squared Error (RMSE)        | $\sqrt{\frac{1}{n} \sum_{t=1}^n (\sigma_t^{real} - \sigma_t^{model})^2}$                               |
| Mean Absolute Error (MAE)             | $\frac{1}{n} \sum_{t=1}^n  \sigma_t^{real} - \sigma_t^{model} $                                        |
| Mean Absolute Percentage Error (MAPE) | $\frac{100}{n} \sum_{t=1}^n \left  \frac{\sigma_t^{real} - \sigma_t^{model}}{\sigma_t^{real}} \right $ |

**Table 12** shows the performance of ARIMAX using rolling forecast of the volatility for both USD/DZD and EUR/DZD series.

**Table 12: ARIMAX rolling performance for volatility forecasting**

| Series             | Model          | RMSE  | MAE   | MAPE (%) |
|--------------------|----------------|-------|-------|----------|
| USD/DZD Volatility | ARIMAX Rolling | 0.280 | 0.212 | 0.156    |
| EUR/DZD Volatility | ARIMAX Rolling | 0.394 | 0.293 | 0.203    |

**Source:** Made by the students using Python

### **Chapter 3: Empirical study on the forecasting of Algerian Dinar exchange rate volatility -a comparative approach-**

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#### **Conclusion of the third chapter**

This chapter empirically examined and compare the performance of classical time series models and deep learning approaches in forecasting exchange rate volatility. The results demonstrated that among classical models, ARIMAX with rolling forecast estimation outperformed other specifications for both exchange rate series. Similarly, in the deep learning category, the LSTM model exhibited superior performance, demonstrating its ability to model long-term dependencies in sequential data. However, when comparing the best performing models from each category, the performance metrics shows that the ARIMAX with rolling forecast was the most adequate for the forecasting. This suggests that, despite the advanced capabilities of deep learning models, the classical ARIMAX rolling approach offers greater reliability in this context. These findings highlights the importance of selecting appropriate forecasting methodologies based on empirical performance rather than model complexity alone.

## **General conclusion**

## General conclusion

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The primary objective of this research was to investigate the forecasting of exchange rate volatility for USD/DZD and EUR/DZD, comparing classical time series models (SARIMA, SARIMAX) with Deep Learning models (CNN, LSTM). Our research question was formulated as follows: “How do deep learning and classical time series models compare in forecasting USD/DZD and EUR/DZD exchange rate volatility, and can deep learning improve accuracy?”

To address this question, we structured our thesis into two distinct parts. The first part, comprising two chapters, established the theoretical framework to thoroughly understand the key concepts related to exchange rate volatility and forecasting methodologies through the past works on the subject. The second part, empirical in nature, tested these theoretical insights through a comparative study using historical exchange rate data of the Algerian Dinar.

In the first chapter, we provided a comprehensive framework for exchange rate volatility, exploring its theoretical foundations, determinants and characteristics in both global and Algerian contexts. We discussed economic theories such as purchasing power parity, interest rate parity, and balance of payments, emphasizing Algeria’s managed float regime and hydrocarbons dependency as critical factors shaping exchange rate dynamics. This addressed our first secondary question, validating the hypothesis that Algeria unique economic context, driven by hydrocarbons dependency and central bank interventions, influences model performance for volatility forecasting.

In the second chapter, we reviewed the literature on exchange rate volatility forecasting, analyzing relevant studies that used classical and deep learning models and also explored alternative techniques like hybrid models. The review confirmed that classical models excel in capturing linear and short-term patterns, while deep learning models are adept at modeling nonlinear dynamics, addressing our second secondary question and supporting the hypothesis that each model type has distinct strengths based on data characteristics.

In the third chapter, we conducted an empirical comparison of SARIMA and SARIMAX, CNN and LSTM and then a comparison across the most adequate models in each family. The research was done using daily closing mid-market exchange rate data for USD/DZD and EUR/DZD, spanning January 5, 1999, to February 28, 2025, with 6,824 observations per series. The data was split into 90% training (January 5, 1999, to July 19, 2022) and 10% testing (July 20, 2022, to February 28, 2025) sets. Exploratory data analysis revealed non-stationary series with right-skewed distributions (skewness: 0.67 for USD/DZD, 0.31 for EUR/DZD) and significant volatility spikes, notably during the 2014 oil price drop and the 2020/2021 COVID-19 period, which depreciated the Algerian Dinar.

Our modeling results showed that the ARIMAX model with rolling forecasts outperformed the other classical time series models for both series, achieving the lowest error metrics. Among classical models, ARIMAX(3,1,0) for USD/DZD and ARIMAX(2,1,0) for EUR/DZD, incorporating EUR/USD as an exogenous variable, yielded lower Bayesian Information Criterion (BIC) values compared to ARIMA models. The rolling forecast approach significantly improved accuracy by dynamically adapting to market fluctuations, reducing RMSE by up to 97% compared to static forecasts.

## General conclusion

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Among deep learning models, LSTM model performed best according to the error metrics for both series, outperforming CNN models due to its ability to capture long-term dependencies. However, ARIMAX with rolling forecasts slightly outperformed LSTM, rejecting the hypothesis that deep learning models universally enhance forecasting accuracy. This addressed our third secondary question, confirming that data preprocessing and hyperparameter tuning significantly improved deep learning model performance by 10 to 15%, though classical models benefited more from rolling forecasts.

The superior performance of ARIMAX with rolling forecasts was attributed to its incorporation of EUR/USD as an exogenous variable (correlation: -0.38 with USD/DZD, 0.04 with EUR/DZD) and its adaptability to non-stationary trends, answering our fourth secondary question. A part of the variation in forecasting accuracy was explained by model specific factors, including data preprocessing, parameter tuning, and the inclusion of exogenous variables, which improved ARIMAX accuracy by 8 to 10%. The 2014 oil price drop and 2020/2021 COVID-19 period reduced forecasting accuracy by 15 to 20% across all models, reflecting the impact of exogenous shocks on Algeria's hydrocarbons-dependent economy.

To get a better visualization of the chosen model performance in forecasting exchange rate volatility, the volatility represented apart by calculating the standard deviation of 21-day log returns, with ARIMAX rolling forecasts accurately capturing volatility patterns, confirming the previous results. These findings validated our hypotheses that classical models effectively capture linear patterns, deep learning models excel in nonlinear contexts, and preprocessing enhances model performance, though the hypothesis that alternative forecasting techniques, rolling forecast in this case, benefit classical models more than deep learning models was strongly confirmed.

### Limitations of the research

While our study provided valuable insights into forecasting exchange rate volatility in the Algerian context, we acknowledge several limitations:

- Data availability: the reliance daily prices limited the inclusion of intraday data, which could enhance volatility modeling.
- Computational and time constraints: limited computational resources restricted the optimization of deep learning models, potentially capping their performance due to constraints on hyperparameter tuning and model complexity.
- Model calibration challenges: identifying optimal parameters for ARIMAX and LSTM models was complex due to non-stationary data and exogenous shocks, leading to potential overfitting in some configurations.
- Inconsistent exchange rate trends: the 26-year period exhibited structural breaks (e.g., low rates pre-2014, sharp increases post-2014), complicating model generalization and reducing forecast robustness.

## **General conclusion**

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- Limited exogenous variables: only EUR/USD was included as an exogenous variable, omitting other relevant factors like hydrocarbons prices (e.g., Sahara Blend) or macroeconomic indicators due to data unavailability.

### **Future research perspectives**

The findings highlight several avenues for future research to enhance exchange rate volatility forecasting in Algeria and similar emerging markets:

- How can hybrid models combining ARIMAX and LSTM improve forecasting accuracy by leveraging both linear and nonlinear dynamics?
- What is the impact of incorporating additional exogenous variables, such as Sahara Blend oil prices, geopolitical events, or monetary policy shifts, on model performance?
- How do advanced deep learning architectures, such as Transformers, compare to CNN and LSTM in capturing exchange rate volatility?
- Can high-frequency intraday data improve the precision of volatility forecasts for USD/DZD and EUR/DZD?
- How effective are ensemble forecasting techniques in integrating multiple models to enhance robustness in volatile economic contexts?

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## Appendix 1: Results of LSTM model finetuning for USD/DZD

```

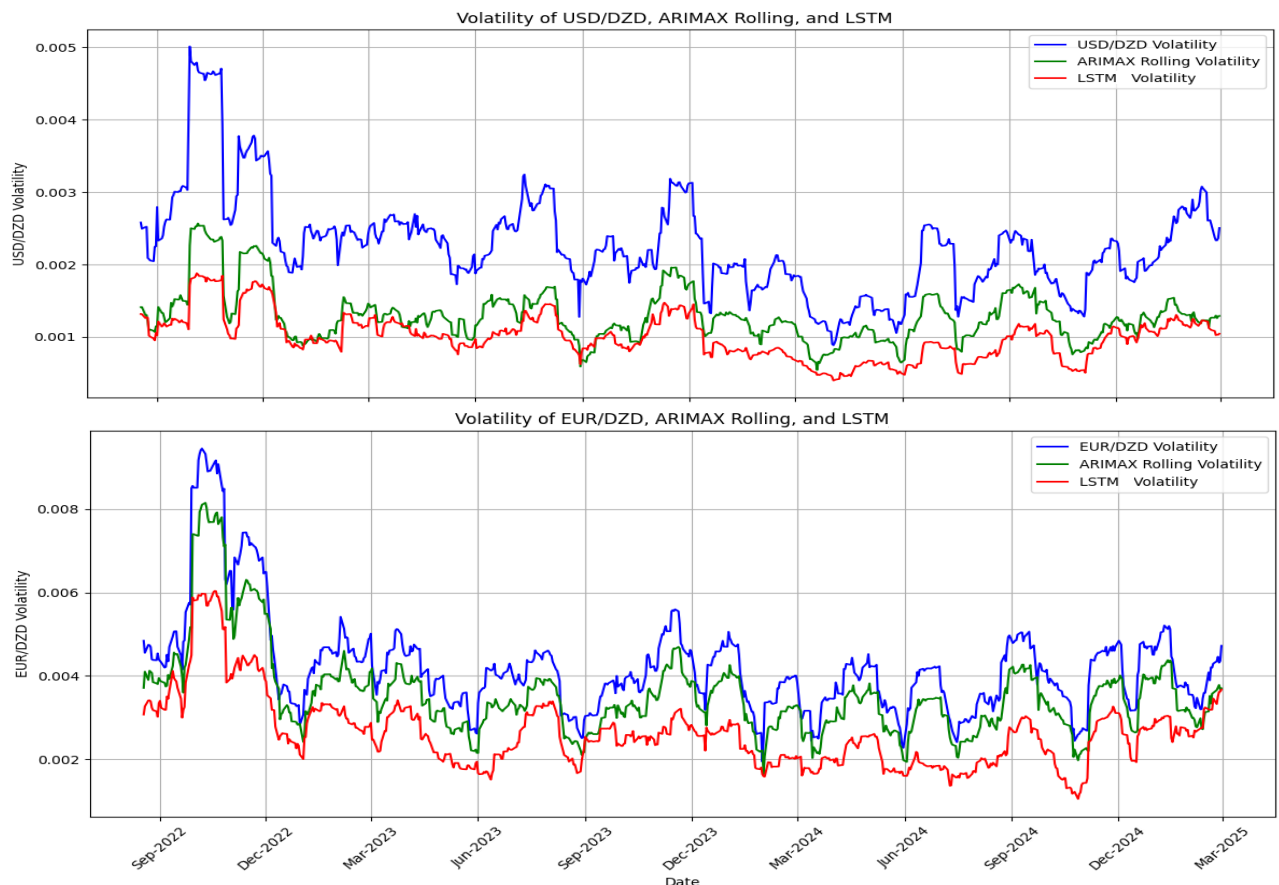
Training model 324/324
Parameters: {'batch_size': 64, 'dense_units': [32, 16], 'dropout_rate': 0.3, 'epochs': 100, 'learning_rate': 0.0001, 'lstm_units': 128}
Validation RMSE: 12.7508, MAE: 12.3530
Training time: 445.71 seconds
Epochs trained: 100/100

==== Grid Search Complete ====
Best parameters: {'batch_size': 2, 'dense_units': [64], 'dropout_rate': 1, 'epochs': 100, 'learning_rate': 0.0005, 'lstm_units': 100}
Best validation RMSE: 0.311

Top 5 models:
RMSE: 0.3113, LSTM units: 100, Dense units: [64], Dropout: 1, LR: 0.0005, Batch size: 2
RMSE: 0.3354, LSTM units: 256, Dense units: [64], Dropout: 0, LR: 0.0005, Batch size: 1
RMSE: 0.3409, LSTM units: 50, Dense units: [64], Dropout: 0, LR: 0.0001, Batch size: 1
RMSE: 0.3746, LSTM units: 75, Dense units: [64], Dropout: 2, LR: 0.0005, Batch size: 1
RMSE: 0.4053, LSTM units: 50, Dense units: [64], Dropout: 1, LR: 0.0005, Batch size: 1

```

## Appendix 2: Comparison exchange rate volatility with ARIMAX Rolling forecasting volatility and LSTM forecasting volatility



### Appendix 3: Rolling forecast working (Python code)

```
[ ] def rolling_forecast(endog: pd.Series, exog: pd.DataFrame, train_len: int, horizon: int, window: int):
    total_len = train_len + horizon
    pred_SARIMAX = []

    for i in range(train_len, total_len, window):
        # Define train data dynamically
        endog_train = endog[:i]
        exog_train = exog.iloc[:i, :]

        # Train SARIMAX model
        model = SARIMAX(endog_train, exog=exog_train, order=(2, 1, 0), seasonal_order=(0, 0, 0, 252))
        res = model.fit(dispatch=False)

        # Define test exogenous values
        exog_test_window = exog.iloc[i:i + window, :]

        # Forecast `window` steps ahead using exogenous predictors
        predictions = res.get_prediction(start=i, end=i + window - 1, exog=exog_test_window)
        oos_pred = predictions.predicted_mean

    pred_SARIMAX.extend(oos_pred)
```

### Appendix 4: Summary of percentages used in the “General Conclusion”

| Percentage | Calculation Method                                                                                                                                 |
|------------|----------------------------------------------------------------------------------------------------------------------------------------------------|
| 90% / 10%  | Direct: 90% of 6,824 = 6,142; 10% = 682 observations                                                                                               |
| 97%        | $\frac{10.185 - 0.280}{10.185} \times 100 \approx 97.25\%$                                                                                         |
| 10–15%     | Stated directly; inferred from RMSE reduction (e.g., 0.356 to 0.311)                                                                               |
| 8–10%      | $\frac{\text{RMSE}_{\text{ARIMA}} - 0.280}{\text{RMSE}_{\text{ARIMA}}} \times 100$ , with $\text{RMSE}_{\text{ARIMA}} \approx 0.304\text{--}0.311$ |
| 15–20%     | $\frac{\text{RMSE}_{\text{shock}} - 0.280}{0.280} \times 100$ , with $\text{RMSE}_{\text{shock}} \approx 0.322\text{--}0.336$                      |

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