

CHAPTER III

RESEARCH METHODOLOGY

This chapter presents the research methodology used in this study, organized into two main components. The research framework is divided into the development of appropriate models and the evaluation of model performance.

3.1 Phase I: Model Development

The model development in this study begins with the ARIMA model, which is a widely recognized linear time series model with a clear theoretical foundation. Therefore, it is used as the benchmark model for comparing the performance of the models developed in this study. Subsequently, the models were further developed to accommodate important characteristics of financial time series data discussed in Chapter 2, including mixed-frequency data, nonlinear relationships, and regime switching over time.

Under this framework, a sequence of models was developed, namely MIDAS, MIDAS-AR, MIDAS-AR-Threshold, MIDAS-AR-HMM, and MIDAS-AR-HMM-SOM. Each model was designed to reflect different characteristics of the data at varying levels, ranging from linear models to highly flexible models. The overall process of model development is illustrated in Figure 3.1.

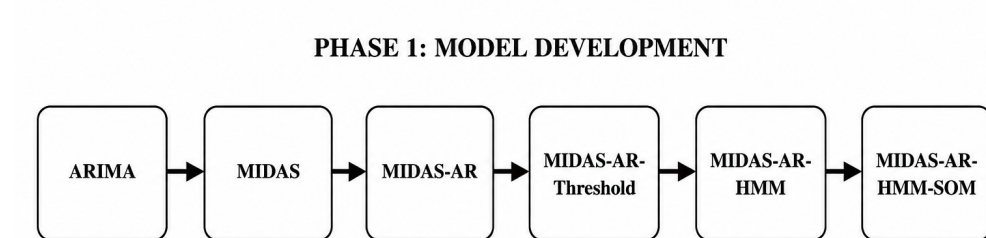


Figure 3.1 Phase I: Model Development.

3.2 Phase II: Model Performance Evaluation

The evaluation of model performance was conducted under the framework of out-of-sample forecasting in order to assess the applicability of the models to real-world data. The process in this phase consists of several important steps, including data preparation, data splitting, program development, and forecast performance evaluation.

3.2.1 Research Data

This study uses mixed-frequency time series data, in which Gold Price is used as the dependent variable in monthly form, while the independent variables, namely Oil Price and the U.S. Dollar Index, are in weekly form. The selection of these variables is based on financial economic theory. Oil prices reflect inflation conditions and production costs, while the U.S. Dollar Index has an inverse relationship with gold prices in the global market. Therefore, the use of high-frequency data together with low-frequency data is consistent with the concept of the MIDAS model, which can utilize additional information to improve forecasting performance. The data used in this study were collected from 2001 to 2025 in order to cover both normal economic periods and periods of high volatility, such as financial crises and periods of market uncertainty. This allows the models to learn the behavior of the data under different conditions.

The data sources are as follows:

- **Gold Price**

The gold price data are represented in U.S. dollars per troy ounce.

Yahoo Finance website: <https://finance.yahoo.com/quote/GC=F/history>

- **Oil Price**

The oil price data are represented in U.S. dollars per barrel.

Yahoo Finance website: <https://finance.yahoo.com/quote/CL=F/history>

- **U.S. Dollar Index**

The U.S. Dollar Index is used as an indicator of the strength of the U.S. dollar in the global financial market.

Yahoo Finance website:

<https://finance.yahoo.com/quote/DX-Y.NYB/history>

All data were examined for completeness and consistency of the time periods before being used in the analysis.

3.2.2 Data Splitting

The time series data were divided into two parts, namely the training set and the testing set, for parameter estimation and the evaluation of model performance in out-of-sample forecasting. In this study, three data splitting ratios, namely 80:20, 75:25, and 70:30, were considered in order to compare forecasting results under different data conditions.

In the in-sample estimation stage, the training set was used to estimate model parameters and learn the structure of the time series data. The use of sufficiently long historical data allows the models to capture the behavior of the data under various economic conditions, including regime switching characteristics. In the out-of-sample forecasting stage, the testing set was used to evaluate the forecasting ability of the models on unseen data, reflecting the applicability of the models to real-world situations.

The forecasting results obtained from each data splitting ratio were compared to examine the consistency and stability of the models under different data conditions. If the forecasting results show similar patterns across different data splitting ratios, this indicates the reliability and practical applicability of the models. On the other hand, differences in forecasting performance were used to discuss the limitations and sensitivity of the models to data splitting conditions.

3.2.3 Program Development

For this study, the development and estimation of the models were conducted using the Python programming language, with Jupyter Notebook employed as the computational environment under the Windows 11 operating system and an Intel Core i5-13500H processor.

3.2.4 Forecast Performance Evaluation

The performance of the models was evaluated using forecasting error measures, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), which reflect the magnitude of the differences between the actual values and the forecasted values.

In addition, information criteria, including the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), were used to evaluate the structural suitability of the models by considering both forecasting accuracy and model complexity.

From a statistical perspective, the comparison of forecasting accuracy among the models was further examined using the Diebold–Mariano (DM) test in order to determine whether the differences in forecasting errors between the models were statistically significant.

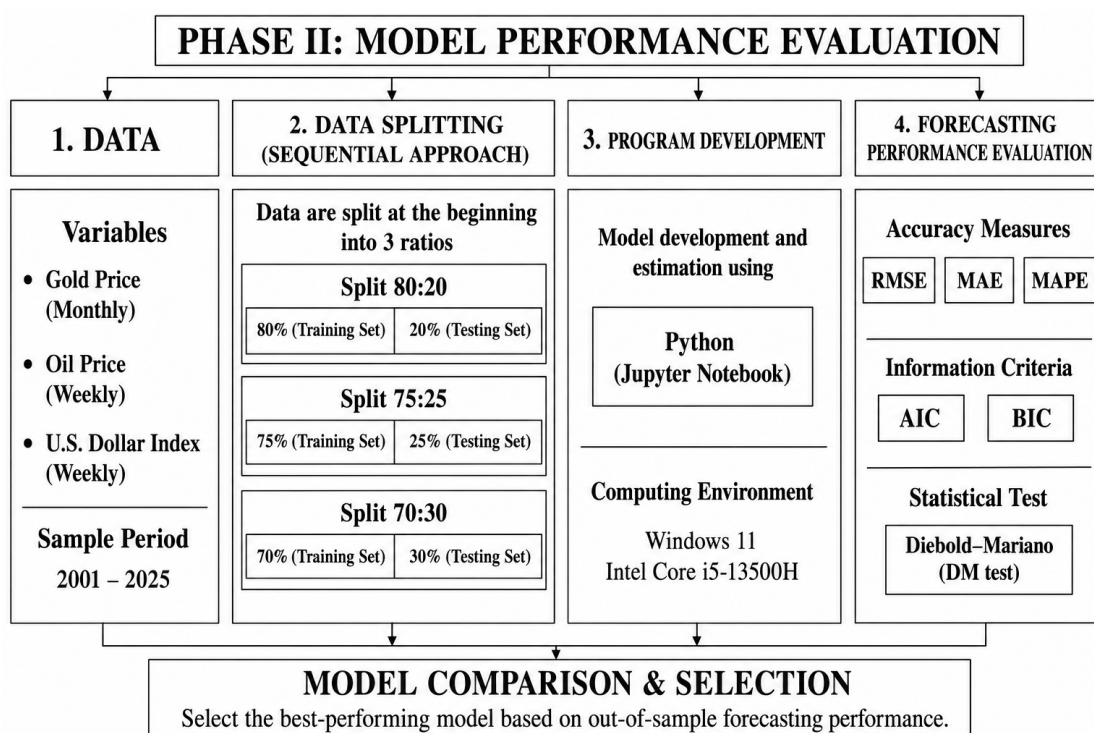


Figure 3.2 Phase II: Model Performance Evaluation.