CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

The environment of the airline industry is a highly turbulent one since the demand is broadly cyclical, there is high operating leverage, and the industry has great exposure to financial shocks from adverse economic conditions and rising fuel prices (Chen et al., 2024). Though low-cost carriers like AirAsia have models that look cost-efficient, they are extremely vulnerable because of narrow profit margins and heavy dependence on fuel where it accounts for up to 30% of expenditure. This history proves that AirAsia can be very financially resilient it shifted from being a highly indebted company to becoming one of Asia's major low-cost airlines. However, with more rules on global carbon emissions and volatility in fuel, this will be an even bigger challenge for them to stay profitable. Sustainable aviation fuel (SAF) has been highlighted as a long-term decarbonization strategy, yet its limited commercial adoption, high production cost, and minimal penetration into global fuel markets which is less than 1% as of 2019 continue to pressure airlines financially (Chen et al., 2024). As fuel prices remain a dominant and unstable cost factor, accurately forecasting their impact on profitability becomes vital for financial planning and risk mitigation in the aviation sector.

In recent years, artificial intelligence and machine learning techniques have become very popular in big data environments as well as in the oil and gas industries because, through AI models, predictive efficiency and operational accuracy have been improved. Applications of this approach include production forecasting, optimization of drilling processes, and reservoir analysis; in all these applications, AI demonstrated strong ability to learn from nonlinear high-dimensional data. From this base, therefore, the same predictive analytical frameworks such as ARIMA for time series forecasting and XGBoost for structured data modelling, are being increasingly adopted for airline financial forecasting wherein fuel cost trends are critical. The fusion of time-series analysis with advanced ML algorithms like XGBoost offers a powerful modelling approach to capture both temporal dependencies and complex feature interactions. As such, this study adopts ARIMA and XGBoost to forecast AirAsia's profitability by examining historical fuel price patterns, addressing a critical gap in financial forecasting practices tailored to aviation dynamics.

2.1 Overview of AirAsia and the Volatile Airline Sector

This section provides an analysis of the dynamic nature of the global airline industry, highlighting its susceptibility to economic fluctuations, regulatory challenges, and environmental concerns. It discusses the essential role of sustainable aviation fuel (SAF) as a real solution to lower carbon emissions and meet long-term goals of reducing carbon impact. Also looked at are the obstacles to using SAF, like being very expensive and not able to grow easily, while stressing the importance of rules to help and new technology. This part also highlights how important it is to include better forecasting models like XGBoost to deal with business and money risks in the field leading toward greener and stronger airline services.

2.1.1 Global and Regional Airline Industry Landscape

The global airline industry is vulnerable to several factors that create a significant operational and financial environment for the business. These factors include shocks on oil prices, fluctuations in economic activities, climate risks, and media-driven investor sentiment. Regarding what pertains to the shocks of oil price volatility particularly supply and demand shocks, there is a direct relationship with profitability since fuel accounts for 20 until 50% of operating costs (Cai et al., 2025). Economic activity shocks like cyclical changes in demand are more fundamental drivers of airline stock returns while the volatility is disproportionately led by oil supply and consumption demand shocks. For example, sensitivity to oil supply shock is more pronounced in airlines such as Southwest, American Airlines while the volatility consequent upon consumption demand fluctuation is more pronounced among low-cost carriers like Ryanair. Climate risks are also a key factor, as severe weather events increase the need for route adjustments and raise maintenance expenses. This, in turn, heightens fluctuations in profitability and makes stock prices more sensitive—especially during busy travel periods (Montero et al., 2024). Climate risks further amplify operational disruptions and stock price volatility, particularly during peak travel seasons, as extreme weather events increase costs such as rerouting, maintenance in which attract media attention, led to exacerbates investor uncertainty (Jin & Cairang, 2025).

These factors vary in the different regions. For instance, Asian and European carriers like China Southern and Air France are exposed to extreme climate-related variability because of seasonal demand high plus regulatory pressure, while the North American counterparts, such as Delta and United are more susceptible to inventory demand shocks of oil. The extremes of climate risks reported in the media disproportionally affect the stock performance in markets that are more densely populated (Jin & Cairang, 2025). After the pandemic, this increased further as economic activity and stability in the oil market increased reliance on the industry; therefore, strategies need to change fuel hedging adaptive strategies with safe adoption to mitigate risks (Cai et al., 2025). These strategies underscore the need for region-specific risk management frameworks to address interconnected financial, operational and even environmental pressures.

2.1.2 AirAsia’s Business Model and Sensitivity to Fuel Prices

AirAsia, a pioneer in the Asian low-cost carrier (LCC) market, adopts a business model which is highly efficient and low-cost with aggressive fleet expansion characterized by high aircraft utilization and ancillary revenue streams. This allows AirAsia to use secondary airports, optimize its route network, and minimize operational frills scaling the company to more than 60 destinations in 16 countries with 84 aircraft by 2009 (Chen et al., 2024). For AirAsia, the dominance of fuel as a cost driver is made worse by its short-haul high-frequency flights which augment fuel consumption relative to revenue generation.

As a result of external economic fluctuations and fuel price volatility, AirAsia's profitability risks are heightened significantly. LCCs are adversely affected by oil price shocks because their profit margins are thin and hedging capacity is limited (Cai et al., 2025). It is estimated that a 10% increase in fuel prices can result in a loss of up to 15% of an LCC's net profit, owing to their inability to quickly pass on costs to price-sensitive customers (Cai et al., 2025). Further, AirAsia's financial performance is dependent upon macroeconomic conditions during recessions, as seen in its 2001 debt restructuring in the context of rising oil prices (Chen et al., 2024). Therefore, this underscored the airline’s vulnerability to exogenous shocks, necessitating adaptive strategies like fuel hedging and fleet modernization to mitigate risks.

2.2 Fuel Price Volatility and Its Impact on Airline Profitability

This section explores how fuel price fluctuations significantly affect airline profitability. It begins by examining fuel price trends in Malaysia and the key factors that drive volatility, such as taxes, global oil supply, and geopolitical events. It also explains how hybrid forecasting models like ARIMA and XGBoost to help improve prediction accuracy. This section also highlights how jet fuel is the largest operating cost for airlines and how rising prices can reduce profit margins, even with strategies like fuel hedging and fleet upgrades. Finally, it looks at how climate-related disruptions increase costs through rerouting and maintenance, adding more financial uncertainty.

2.2.1 Fuel Pricing Trends in Malaysia and Global Drivers

Several factors influence fuel pricing trends, including taxation policies, global oil supply and demand dynamics, and geopolitical risk factors. Prices are volatile due to these factors, which are critical for industries that rely on fuel, such as aviation. It has been shown by Pin Li and Jin-Suo Zhang (2018) that advanced hybrid forecasting models such as ARIMA and XGBoost are highly accurate in predicting the security of energy supplies and fuel prices in China, thereby providing valuable insight into how similar methodologies could be applied to analysis of Ron97 pricing trends in Malaysia. Several factors influence retail fuel prices, including supply-demand imbalances, geopolitical tensions, and taxation, making it essential for stakeholders to utilize robust predictive tools to anticipate and mitigate risks.

The interconnected nature of global energy markets means that disruptions in one region can ripple across the globe, influencing fuel costs and availability. For instance, geopolitical events such as trade disputes or sanctions often lead to sudden spikes in oil prices, affecting airlines' operational budgets and profitability. In their study, Pin Li and Jin-Suo Zhang (2018) highlight the importance of integrating multiple indicators—such as energy dependence, production diversity, and clean energy adoption—to assess and forecast energy supply security comprehensively. This approach aligns with the need to understand Ron97 pricing trends within the broader context of global drivers, emphasizing the necessity of adopting advanced predictive models to enhance decision-making in volatile environments. By leveraging such methodologies, policymakers and industry players can better anticipate fuel price movements and implement strategies to manage financial risks effectively.

2.2.2 Fuel as a Primary Operational Cost

Globally, jet fuel is the largest operating cost for airlines, accounting for approximately 24% of total expenses (Zhang et al., 2021). In 2019 alone, the industry spent $188 billion on jet fuel. Although airlines have attempted to reduce costs by utilizing fuel-efficient aircraft and implementing predictive maintenance, rising fuel prices continue to erode profit margins (Wu, 2024). AirAsia, for example, utilizes analytics and IoT to enhance efficiency, yet remains vulnerable to fluctuations in fuel prices (Wu, 2024). Machine learning models, such as those in Baumann et al. (2021), help improve fuel monitoring; however, external factors—such as global oil markets and taxes—remain significant challenges (Sokkalingam et al., 2021).

Malaysia's fuel prices are shaped by factors including MOPS, operational costs, and government subsidies (Sokkalingam et al., 2021). However, airlines still struggle to manage the financial risks associated with volatile fuel prices, even with advanced models such as gray box systems and random forests (Baumann et al., 2021). The situation is particularly acute for low-cost carriers like AirAsia, where even a 10% increase in fuel prices could result in a 15% drop in profits because of limited hedging options and price-sensitive customers (Cai et al., 2025).

2.3 Forecasting Models ARIMA and XGBoost

Accurate forecasting models are essential for anticipating fuel price trends and managing cost-related risks in the aviation industry. Two widely used approaches are the ARIMA model, known for its effectiveness in capturing linear and time-dependent patterns, and XGBoost, a powerful machine learning algorithm that excels in modelling complex, nonlinear relationships. This section explores the strengths and limitations of each model and highlights the benefits of combining them into a hybrid approach for more reliable and robust forecasting. By combining both ARIMA and XGBoost, a hybrid forecasting model can be developed to better navigate the uncertainties of the global fuel market and improve the reliability of airline profitability predictions.

2.3.1 ARIMA in Fuel Price Forecasting

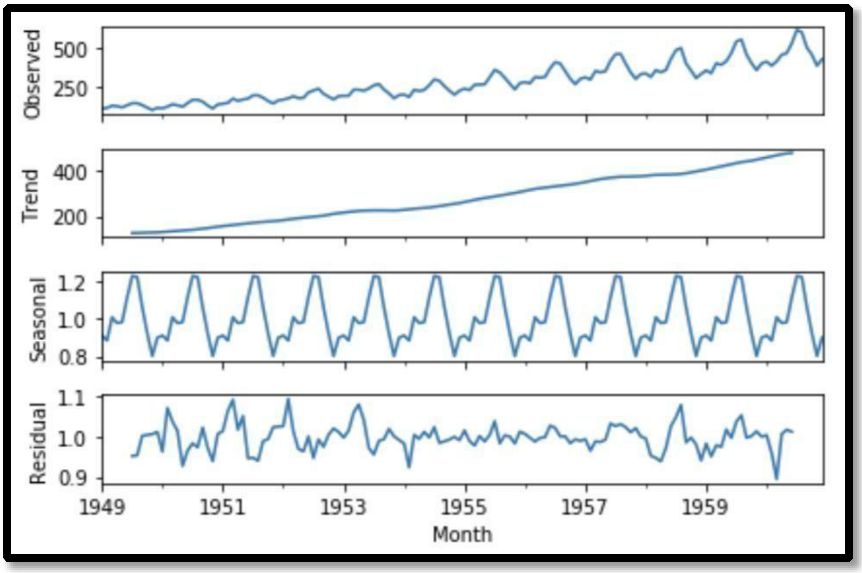

Figure 5.1 ARIMA Model for Time Series Forecasting

Autoregressive Integrated Moving Average (ARIMA) models are commonly used to forecast time series data, especially in the fields of energy and fuel prices. As a result of its ability to handle non-stationary data through differencing, ARIMA excels at capturing linear trends and has been used to forecast petroleum fuel prices (Li & Zhang, 2018). According to Okkalingam et al., 2024, ARIMA performed well when it was applied to Malaysian Ron97 fuel prices, where it effectively modelled price fluctuations over the week based on historical data. A stationary or nearly stationary dataset is particularly suitable for this model since it requires fewer assumptions than more complex models.

Furthermore, ARIMA has been utilized beyond individual fuel commodities to broader energy security assessments. This study proposes a hybrid approach by combining ARIMA and XGBoost for forecasting China's energy supply security, demonstrating the model's adaptability and reliability (Li & Zhang, 2018). The study emphasized that ARIMA serves as a reliable baseline for predictive accuracy, particularly when combined with machine learning techniques to improve long-term forecasts. This finding aligns with research on unconventional oil and gas development, where ARIMA has also been used for production forecasting, highlighting its versatility across various energy sectors (Chen et al., 2025). Therefore, ARIMA continues to be a fundamental tool in forecasting fuel prices and energy markets due to its interpretability and proven effectiveness in real-world applications.

2.3.2 Limitations of ARIMA for Nonlinear Events

Although ARIMA models are effective for analysing linear trends and forecasting stationary time series, they face notable limitations in capturing nonlinear events. These shortcomings are especially apparent when dealing with residuals caused by unexpected shocks, such as abrupt changes in demand or disruptions related to climate variability (Li & Zhang, 2018). For instance, ARIMA models frequently leave behind residual patterns that display nonlinear characteristics, which the model alone cannot effectively capture, resulting in reduced forecasting accuracy in complex or dynamic conditions (Su, 2021). This limitation underscores the importance of combining ARIMA with more advanced methods, such as XGBoost. These machine learning techniques can model the nonlinear aspects of the data that ARIMA overlooks. When integrated into hybrid systems, they improve forecasting precision, especially in high-volatility sectors like energy and aviation.

2.3.3 Applications of XGBoost in Energy and Aviation Forecasting

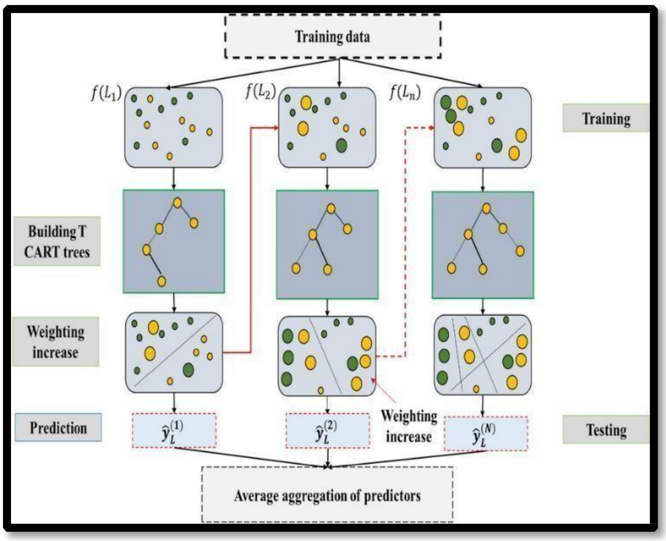

Figure 5.2 Graphical scheme of XGBoost Model

XGBoost has emerged as a powerful tool in energy and aviation forecasting due to its scalability, speed, and accuracy in handling complex nonlinear relationships. In the aviation sector, XGBoost has been applied to predict operational costs, delays, and profitability, particularly in volatile markets where traditional models like ARIMA struggle to capture nonlinear patterns (Li & Zhang, 2018). For instance, hybrid models combining ARIMA and XGBoost have demonstrated superior performance in forecasting energy supply security, with applications extending to airline fuel price predictions and operational efficiency metrics. These advancements enable airlines to better anticipate cost fluctuations, optimize resource allocation, and mitigate risks associated with fuel price volatility and climate-related disruptions (Wu, 2024). By leveraging machine learning techniques like XGBoost, airlines can enhance decision-making processes and improve resilience in dynamic operational environments.

2.4 Overview of Hybrid Models

Hybrid models have gained significant attention in forecasting complex systems, particularly in industries like aviation and energy, where linear and nonlinear patterns coexist. The integration of traditional statistical methods, such as ARIMA, with advanced machine learning techniques like XGBoost has proven effective in addressing the limitations of standalone models. For instance, ARIMA is adept at capturing linear trends but struggles with nonlinear residuals, which often arise from unexpected shocks in fuel prices or climate-related disruptions (Li & Zhang, 2018). To overcome this limitation, hybrid models combine ARIMA's strength in modelling linear components with XGBoost's ability to capture nonlinear relationships, as demonstrated in energy supply security forecasts for China (Li & Zhang, 2018). Similarly, studies on aircraft fuel economy have highlighted the importance of advanced statistical approaches, such as decision forests and grey box modelling, to evaluate fuel consumption metrics and account for measurement errors (Baumann et al., 2021). These hybrid methodologies enhance predictive accuracy and provide a robust framework for addressing volatility in fuel costs and operational efficiency in aviation.

In addition to their application in energy forecasting, hybrid models have been successfully employed in other domains, such as electricity market price prediction and wind speed forecasting. For example, Kavousi-Fard and Kavousi-Fard (2013) developed a hybrid model combining ARIMA, Support Vector Regression (SVR), and the cuckoo search algorithm to improve short-term load forecasting accuracy. Yan and Chowdhury (2014) further demonstrated the effectiveness of hybrid models by integrating SVM and ARMAX for mid-term electricity market clearing price predictions. In the context of aviation, these advancements offer promising opportunities to address challenges such as fuel price volatility and operational cost management. By leveraging hybrid approaches, airlines can better anticipate market fluctuations, optimize resource allocation, and mitigate risks associated with external factors like geopolitical tensions and climate change (Sokkalingam et al., 2021). Such models underscore the growing importance of integrating diverse analytical tools to tackle the multifaceted challenges faced by the aviation industry.

2.5 Summary

The airline industry operates in a highly volatile environment due to cyclical demand, high operating leverage, and exposure to financial shocks from economic downturns and fluctuating fuel prices. Low-cost carriers like AirAsia, despite their cost-efficient models, face significant challenges due to narrow profit margins and heavy reliance on fuel, which accounts for up to 30% of expenses. While AirAsia has demonstrated financial resilience by transitioning from debt to becoming a major low-cost airline, rising global carbon emission regulations and fuel price volatility pose ongoing challenges to profitability. Accurate forecasting of fuel price impacts is crucial for effective financial planning and risk management. To address this, advanced predictive models like ARIMA and XGBoost are increasingly being adopted to analyse fuel cost trends and forecast profitability. These hybrid approaches, which combine time-series analysis with machine learning, provide a powerful tool for capturing complex patterns and improving decision-making in the aviation sector. By integrating such techniques, airlines can better anticipate market fluctuations, optimize resources, and mitigate risks from external factors like geopolitical tensions and climate change.