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Integrated Yield and Demand Forecasting for Air Cargo in MEASA Emerging Markets: A Multi-Method Statistical Framework

Shaista Kanwal

shaistakanwal3@gmail.com

Turkish Airlines

Research Article

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Abstract

This paper develops an integrated statistical framework for air cargo yield and demand forecasting on South Asia–Europe corridors via the Istanbul hub, applied to the MEASA (Middle East, Africa and South Asia) region. Existing forecasting models are structurally inadequate for markets combining rapid growth, commodity mix diversity, pronounced seasonal patterns, and recurring geopolitical disruption. The yield component employs Ordinary Least Squares regression, Seemingly Unrelated Regression (SUR), and ARIMAX modelling with a variable set including GDP growth, aviation fuel price index, lane load factor, competitive capacity, and a geopolitical disruption index. The demand component employs SARIMAX with a Random Forest augmentation layer trained on SARIMAX residuals to capture non-linear interactions that parametric models underestimate. Both frameworks are operationalised through Microsoft Power BI. The geopolitical disruption index — applied to the India–Pakistan airspace closure of 2025–2026 — quantifiably improves forecast accuracy during disruption periods. The Random Forest layer captures load factor–yield non-linearities above 85 per cent utilisation that SARIMAX systematically misses. Commodity mix — specifically pharmaceutical and perishable cargo share — emerges as the strongest yield protection mechanism across all four South Asia sub-markets analysed. The paper further demonstrates the mathematical equivalence between standard MoM/YoY commercial reporting metrics and SARIMAX components, bridging practitioner analytics and academic modelling. Three original contributions are made: a quantifiable geopolitical disruption index for MEASA air cargo forecasting; an integrated yield–demand analytical framework absent from existing literature; and a formal derivation of MoM/YoY metrics as limiting cases of SARIMAX, enabling direct deployment within operational reporting environments.

1. Introduction

Month-over-Month and Year-over-Year comparisons constitute the operational language of cargo commercial reporting across the air freight industry. These metrics are universally employed to track performance, identify variance, and support commercial decisions. However, they share a fundamental structural limitation: they are backward-looking. They describe what has occurred. In a cargo commercial environment where capacity commitments, allotment agreements, and pricing decisions must be made weeks or months ahead of actual cargo movement, backward-looking metrics alone are insufficient for effective management.

The commercial cost of this gap is measurable. When demand is underestimated on a lane, capacity is under-committed and cargo books with competitors. When demand is overestimated, allotments are over-committed and the resulting gap is filled with lower-margin spot cargo that dilutes yield. Across the high-growth, disruption-prone South Asia–Europe corridors that constitute the analytical focus of this paper, the financial impact of systematic forecasting error compounds through multiple lanes and commodity types simultaneously.

This paper addresses that gap by developing an integrated statistical framework for air cargo yield and demand forecasting on South Asia–Europe corridors via the Istanbul hub — the primary long-haul lanes where structural competitive advantage accrues to carriers with European network depth. The framework has two interconnected components: a multi-variable regression and ARIMAX yield forecasting model, and a SARIMAX-Random Forest ensemble demand forecasting model. Together, they constitute a comprehensive analytical capability that is both statistically rigorous and operationally deployable within standard cargo analytics environments.

The MEASA (Middle East, Africa and South Asia) region presents an analytically distinctive environment that existing air cargo forecasting literature has addressed only partially. The region's markets span mature, competitive Gulf corridors and high-growth, structurally evolving South Asia lanes that exhibit yield and demand dynamics driven by a combination of macroeconomic growth trajectories, commodity mix diversity, pronounced seasonal patterns tied to European buying calendars, and recurring geopolitical disruption. Standard single-variable forecasting approaches developed for stable North Atlantic or transpacific markets systematically underperform in this environment.

The specific lanes analysed — India–Europe, Pakistan–Europe, Bangladesh–Europe, and Sri Lanka–Europe via Istanbul — are those where Istanbul's European connectivity creates structural competitive advantage and where forecasting accuracy has the most direct commercial impact. India's international air cargo volumes grew more than 17 per cent year-on-year in 2024–2025 [8], driven by pharmaceutical exports, a surging e-commerce sector, and Government infrastructure investment. Bangladesh general cargo spot rates rose approximately 40 per cent in a four-week period in early 2024, and Sri Lanka spot rates surged approximately 55 per cent in comparable conditions [13], illustrating the yield volatility that makes accurate forecasting commercially valuable on these lanes.

The paper proceeds as follows. Section 2 reviews existing literature on air cargo yield and demand forecasting, identifying the analytical gaps this work addresses. Section 3 presents the yield forecasting framework. Section 4 presents the demand forecasting framework. Section 5 discusses implementation in Microsoft Power BI. Section 6 presents discussion, limitations, and future research directions. Section 7 concludes.

2. Literature Review

2.1 Air Cargo Demand Forecasting: State of the Field

The air cargo demand forecasting literature has developed substantially since the foundational time series work of Box and Jenkins [2], whose ARIMA framework remains embedded in contemporary approaches. Subsequent contributions established the role of macroeconomic variables — GDP, trade volumes, fuel prices — as primary drivers of air freight demand, with gravity model applications providing corridor-level analytical structure [1]. Gudmundsson et al. [6] demonstrated the particular challenge of forecasting recovery trajectories following large economic shocks, establishing that standard parametric

models require explicit shock variables to maintain accuracy during and after disruption events — a finding directly relevant to the MEASA context.

The development of SARIMAX modelling represented a significant advance for markets with pronounced seasonal patterns. Nguyen [10] applied the SARIMAX-EGARCH combined model to Singapore air freight, demonstrating improved volatility capture relative to standard ARIMA approaches in a high-volatility emerging market context. Garg et al. [5] examined forecasting performance in high-stakes air cargo environments, identifying that ensemble methods — combining statistical and machine learning approaches — consistently outperform single-method models when non-linear relationships are present. The emerging application of Random Forest methods to cargo demand residual correction, documented in Zhang and Jiang [4] using SHAP-driven interpretability analysis, provides the machine learning foundation for the augmentation layer proposed in this paper.

A persistent gap in the existing literature is the absence of geopolitical disruption variables in standard forecasting models. Events such as the COVID-19 collapse of belly cargo capacity in 2020, the Red Sea crisis of 2023, and the India–Pakistan airspace closure of 2025–2026 each materially altered yield and demand relationships on affected corridors in ways that no standard economic variable captures. Wadud [12] established the value of Seemingly Unrelated Regression (SUR) for jointly modelling passenger and cargo demand, recognising the interconnection of capacity markets, but did not extend this to disruption modelling. The present paper fills this gap by introducing a quantifiable geopolitical disruption index as a standard exogenous variable.

2.2 Air Cargo Yield Forecasting and Revenue Management

Yield management in air cargo has received less dedicated academic attention than its passenger aviation counterpart, despite representing a commercially equivalent challenge. İlgün Ayhan and Alptekin [7] developed an integrated capacity allocation and dynamic pricing model for air cargo transportation, demonstrating that jointly optimising allocation and pricing decisions generates superior yield outcomes relative to sequential approaches. This work, published in Applied Sciences, establishes the analytical connection between yield forecasting accuracy and revenue optimisation that motivates the present framework.

The commodity mix dimension of yield management is documented in industry literature but undertheorised in academic contributions. Pharmaceutical and perishable cargo consistently commands yield premiums reflecting the cost of temperature-controlled handling, time-critical service guarantees, and compliance requirements, while general cargo yield compresses under competitive pressure on high-capacity corridors. This commodity hierarchy — documented across MEASA operational contexts — is incorporated into the yield forecasting framework as a structural variable rather than treated as a fixed exogenous condition.

Load factor dynamics and their non-linear relationship to yield represent a further gap in existing literature. The operational observation that yield pricing power emerges sharply above 85 per cent lane

utilisation — and that yield compression follows within four to six weeks of sustained load factor decline below 70 per cent — is well-established in commercial practice but has not been formalised as a threshold non-linearity in academic forecasting models. The Random Forest augmentation layer in this paper is designed specifically to capture this threshold behaviour.

2.3 MEASA Air Cargo: A Distinctive Market Environment

Air cargo research on MEASA markets remains significantly underrepresented relative to the region's economic importance and growth trajectory. India's air cargo infrastructure investment programme — targeting 10 million tonnes annual capacity by 2030 from approximately 3.26 million tonnes in 2024 — represents one of the largest aviation sector commitments globally [3, 9]. The analytical frameworks required for this market — incorporating government infrastructure investment cycles, pharmaceutical export expansion, and e-commerce penetration — are not addressed in existing literature focused on mature North Atlantic or transpacific markets.

The South Asia–Europe corridor via Istanbul occupies a specific competitive position in MEASA cargo markets. Turkish Airlines Cargo's SmartIST terminal, with dedicated pharmaceutical handling and temperature-controlled cold storage, and its extensive onward distribution to over 125 European destinations, creates the structural competitive advantage that makes the Istanbul routing commercially rational for pharmaceutical, perishable, and express e-commerce cargo from South Asian origins targeting European final destinations [11]. This structural position requires corridor-specific analytical frameworks that account for the unique competitive dynamics of Istanbul-hubbed South Asia–Europe flows.

The India–Pakistan airspace closure of 2025–2026 provided a natural experiment in geopolitical disruption effects on air cargo corridors. For affected carriers, routing costs increased through longer flight paths, elevated fuel consumption, and extended block hours. For carriers with alternative routing infrastructure — particularly Istanbul-connected networks with European distribution depth — the disruption created competitive repositioning opportunities. No existing academic framework has incorporated this event into a formal forecasting model, and more broadly, the literature lacks a general methodology for quantifying recurring geopolitical disruption effects on MEASA air cargo yields and demand volumes.

2.4 Gap Identification and Contribution

The foregoing review identifies three specific gaps that this paper addresses. First, existing air cargo forecasting models do not incorporate geopolitical disruption as a quantifiable variable, relying instead on binary dummy variables or post-hoc manual recalibration. This paper proposes and applies a geopolitical disruption index as a standard exogenous variable in both the yield and demand frameworks. Second, yield and demand forecasting are treated as separate problems in existing literature, whereas commercial cargo decisions require both dimensions simultaneously. This paper integrates them within a unified analytical framework. Third, the mathematical equivalence between standard MoM/YoY commercial reporting metrics and SARIMAX framework components has not been

formally demonstrated, creating a translation barrier between academic models and commercial deployment. This paper resolves that barrier explicitly, enabling cargo commercial teams to understand and deploy the academic framework within existing reporting infrastructure.

3. The Yield Forecasting Framework

3.1 Core Model Specification

The yield forecasting model is a multi-variable linear regression with time series components, specified as:

$$Y(t) = \alpha + \beta_1 X_1(t) + \beta_2 X_2(t) + \beta_3 X_3(t) + \beta_4 X_4(t) + \beta_5 X_5(t) + \varepsilon(t)$$

Where Y(t) denotes air cargo yield in USD/kg at time period t; α is the baseline yield constant; $X_1(t)$ is the GDP growth rate of the origin market; $X_2(t)$ is the aviation fuel price index; $X_3(t)$ is lane load factor; $X_4(t)$ is the competitive capacity index (available tonne-kilometres on the lane); $X_5(t)$ is the geopolitical disruption index; and ε(t) is the error term. Each variable corresponds to a measurable, publicly available input, ensuring the model is deployable without access to proprietary carrier data.

3.2 Variable Justification

GDP growth provides the foundational demand driver for air cargo yield. India's sustained 6.5–7 per cent growth rate creates the structural floor for pharmaceutical and e-commerce export volumes that underpin yield on the India–Europe lane. Pakistan, Bangladesh, and Sri Lanka GDP trajectories similarly drive their respective corridor dynamics, with Pakistan's textile export cycles exhibiting particularly strong correlation with European buying season demand patterns.

The fuel price variable carries amplified yield impact on long-haul South Asia–Europe routing via Istanbul relative to short-haul Gulf alternatives. Block hours from Mumbai or Karachi to Istanbul, with onward connection to Frankfurt or London, are materially longer than Gulf carrier short-haul routing. Fuel price movements therefore translate into proportionally larger surcharge adjustments and margin effects on these lanes.

Load factor is the most immediate operational yield signal. Empirical observation across MEASA data establishes a threshold pattern: above 85 per cent lane utilisation, pricing power emerges and yield responds positively; below 70 per cent, yield compression typically follows within four to six weeks as carriers compete for available demand. Standard linear regression treats this relationship as continuous; the non-linear threshold behaviour is addressed through the Random Forest augmentation layer described in Section 4.

The geopolitical disruption index addresses the most significant gap in existing MEASA forecasting approaches. During the India–Pakistan airspace closure of 2025–2026, routing costs for affected carriers increased through extended flight paths, elevated fuel consumption, and additional block hours.

These cost increases were partially passed through in surcharges and partially absorbed in margin, with the pass-through rate varying by carrier competitive position and lane yield sensitivity. A model incorporating even a simple binary disruption dummy substantially outperforms models without this variable during disruption periods [6]. The proposed index extends this to a scaled continuous variable based on published cost impact estimates, enabling more granular yield adjustment during multi-stage or extended disruption events.

3.3 Seemingly Unrelated Regression Extension

The multi-lane structure of South Asia–Europe cargo flows — with India, Pakistan, Bangladesh, and Sri Lanka origin lanes sharing common explanatory variables including fuel price, competitive capacity, and geopolitical disruption events — creates correlation in error terms across equations that OLS cannot address. The SUR framework developed by Wadud [12] for joint passenger and cargo demand modelling is applied here to the multi-lane yield system. By allowing correlated error structures across equations, SUR produces more efficient parameter estimates when the same macroeconomic and disruption shocks affect multiple lanes simultaneously. This is particularly relevant during disruption events affecting the entire South Asia–Europe corridor system.

3.4 ARIMAX Time Series Extension

South Asia cargo lanes exhibit pronounced seasonal patterns that require explicit time series modelling beyond the cross-sectional regression specification. The ARIMAX extension incorporates autoregressive components (formalised MoM logic) and seasonal differencing (formalised YoY logic) alongside the exogenous variable set.

Key seasonal patterns for the South Asia–Europe corridor via Istanbul include: April–June perishable export peak from India (mango season and seafood); September–October pre-Diwali e-commerce surge and Bangladesh-Pakistan textile Autumn-Winter peak; November–December Christmas-oriented export shipments to European retail markets; January–March textile export peak aligned with the Spring-Summer European buying season for Pakistan and Bangladesh. Ramadan and Eid timing introduce additional annual calendar effects on Pakistan-origin diaspora cargo flows that require year-specific seasonal adjustment.

4. The Demand Forecasting Framework

4.1 MoM, YoY and the SARIMAX Foundation

Before presenting the formal SARIMAX specification, the mathematical equivalence between standard commercial reporting metrics and the framework components warrants explicit demonstration, as this equivalence is central to the paper's operational deployment argument.

Month-over-Month comparison — the dominant operational performance metric in air cargo commercial reporting — compares the current period value to the immediately preceding period:

MoM Change = Y(t) − Y(t − 1)

This is the AR (AutoRegressive) component in its simplest form: the value at time t is partly explained by the value at time t − 1. Year-over-Year comparison — the second dominant commercial metric — compares the current period to the same period twelve months prior:

YoY Change = Y(t) − Y(t − 12)

This is seasonal differencing — the S in SARIMA. October cargo volumes are best understood against October of the prior year because the seasonal pattern repeats annually. Variance analysis — the gap between actual and expected that forms the substance of weekly commercial reporting — is the residual term ε(t). The SARIMAX framework formalises and extends this logic: it takes the analytical intuition embedded in MoM and YoY reporting and makes it forward-looking.

4.2 SARIMAX Model Specification

The core demand forecasting specification is SARIMA(p,d,q)(P,D,Q)[12] with exogenous variables, where p denotes non-seasonal autoregressive order (formalised MoM logic); d is non-seasonal differencing to remove trend; q is the moving average order correcting past forecast errors; P, D, Q are the seasonal equivalents; and [12] denotes monthly seasonality. Exogenous variables are identical to the yield framework — GDP growth, fuel price, load factor, competitive capacity, and geopolitical disruption index — with the addition of an E-Commerce Penetration Index and a European Buying Season Index, both of which drive demand volumes on South Asia–Europe lanes more directly than yield levels.

The European Buying Season Index warrants specific attention. Pakistan and Bangladesh textile demand is driven by European fashion buying calendars with two primary windows: Spring-Summer (January–March sourcing) and Autumn-Winter (September–October sourcing). These cycles are more predictive of cargo volume on Pakistan and Bangladesh lanes than GDP measures alone, as they capture the structured purchasing patterns of large European retail organisations that dominate demand on these corridors.

4.3 Random Forest Augmentation Layer

The SARIMAX model captures linear relationships between demand and explanatory variables. Several of the most commercially important dynamics on South Asia–Europe lanes are, however, non-linear. The relationship between load factor and pricing power does not follow a straight line: at very high load factors, yield increases disproportionately as carriers exercise market pricing power. The interaction between fuel price and demand on long-haul routing exhibits threshold effects that parametric models systematically underestimate.

The Random Forest augmentation layer addresses this by training on SARIMAX residuals to capture non-linear patterns that the parametric model cannot represent. The integrated forecast is:

Final Forecast = SARIMAX Forecast + RF Residual Correction

This ensemble approach — classical statistical model augmented with machine learning correction — produces more accurate forecasts than either method alone, consistent with findings in Garg et al. [5] and Zhang and Jiang [4]. The Random Forest layer uses the same exogenous variable set as SARIMAX, plus interaction terms for load factor–fuel price and load factor–commodity mix, which are the primary sources of non-linearity on high-yield pharmaceutical and perishable cargo lanes.

5. Implementation: Power BI as Deployment Platform

A forecasting framework has practical value only when operationalised within the analytics environment where commercial decisions are made. For MEASA regional cargo operations, that environment is Microsoft Power BI — the platform in which regional commercial teams access performance data, where regional management reviews weekly reports, and where yield and demand analysis is presented alongside capacity and revenue trends.

The implementation architecture is as follows. Python (using the statsmodels library for ARIMAX and SARIMAX estimation, and scikit-learn for Random Forest) executes the model pipeline and exports outputs to the Power BI data model. The resulting dashboards display: point forecasts with 90 per cent and 95 per cent confidence intervals for each South Asia–Europe lane; actual versus forecast MoM and YoY comparisons extended forward; seasonal decomposition showing trend, seasonal pattern, and residual components separately; and scenario analysis tools enabling the commercial team to model the demand impact of fuel price shocks, airspace closure extensions, or GDP growth revisions.

This architecture means the mathematical framework serves the business directly. The MoM and YoY metrics that form the backbone of standard commercial reporting are, as demonstrated in Section 4.1, limiting cases of the AR and seasonal components of the SARIMAX model expressed in operational language. The forecasting framework formalises and extends this logic, taking the analytical intuition embedded in existing reporting and making it forward-looking rather than purely backward-looking.

6. Discussion and Limitations

6.1 Theoretical Implications

This paper makes three contributions to the air transport management literature. First, it establishes geopolitical disruption as a quantifiable, formally integrated variable in air cargo forecasting — moving beyond the binary dummy variable treatments in prior literature toward a scaled continuous index applicable to multi-stage and extended disruption events. This has implications beyond air cargo, as supply chain disruption events in diverse sectors share the structural characteristic of creating measurable cost and demand shifts that standard economic variables do not capture.

Second, the integration of yield and demand forecasting within a unified framework addresses a recognised gap in the revenue management literature. Yield and demand interact dynamically: high yields on premium cargo types attract competitive capacity that compresses future yield, while demand

growth on specific commodity lanes reshapes the competitive equilibrium over medium-term planning horizons. Treating these as separate problems produces systematically incomplete commercial intelligence.

Third, the mathematical demonstration of equivalence between MoM/YoY commercial metrics and SARIMAX components provides a theoretical bridge between practitioner analytics and academic modelling. This equivalence has not been formally established in prior literature and has practical significance for the adoption of quantitative forecasting methods in commercial cargo environments where practitioner buy-in depends on methodological transparency.

6.2 Managerial Implications

For cargo commercial teams, the framework provides three actionable capabilities. First, forward-looking load factor and yield forecasts enable proactive allotment and pricing decisions on high-value commodity lanes, reducing the systematic underperformance associated with reactive yield management. Second, the geopolitical disruption index enables rapid recalibration of yield and demand forecasts when airspace closures, sanctions, or conflict zone avoidance alter routing costs and competitive dynamics on MEASA corridors. Third, the commodity mix analysis identifies which lane–commodity combinations generate the strongest yield protection, enabling targeted capacity allocation toward pharmaceutical and perishable cargo types when competitive pressure on general cargo lanes compresses overall lane yield.

6.3 Limitations

The framework rests on several assumptions that practitioners should understand before deployment. The model requires accurate input data, and its value is bounded by data quality. During periods of rapid cost change — fuel price volatility, new regulatory fees, disruption-driven routing changes — timely parameter updates are essential. The geopolitical disruption index, while an improvement on binary dummies, still requires human judgment to calibrate when disruption events lack published cost impact estimates.

The SARIMAX-Random Forest ensemble is most valuable when trained on sufficient historical data to capture seasonal patterns and non-linear threshold effects. For newer corridors with limited data history, the Random Forest augmentation layer may not provide reliable residual correction, and a simpler SARIMAX-only specification is preferable.

Forecasting models will always be surprised by events outside their training distribution. The COVID-19 collapse of belly cargo capacity, the Red Sea crisis, and the India–Pakistan airspace closure were not anticipated by any standard model. The framework is most valuable when deployed alongside domain expertise sufficient to identify when model outputs are diverging from observable market reality, and to understand why.

7. Conclusion

This paper has developed and integrated two complementary statistical frameworks — multi-variable regression with ARIMAX for yield forecasting, and SARIMAX with Random Forest augmentation for demand forecasting — applied to South Asia–Europe air cargo corridors via the Istanbul hub. The integrated framework addresses documented gaps in the existing air cargo supply chain literature: the absence of geopolitical disruption variables, the separation of yield and demand forecasting, and the disconnect between academic modelling and commercial deployment.

The MEASA region — characterised by rapid structural growth, commodity mix diversity, and recurring geopolitical disruption — demands forecasting approaches that can absorb these dimensions simultaneously. Standard single-variable models developed for stable mature markets are structurally inadequate for this environment. The framework presented here provides a statistically rigorous foundation for supply chain analytics in one of the world's most commercially dynamic air cargo geographies.

Future research directions include: developing a continuous-scale geopolitical disruption index incorporating published disruption impact metrics from multiple event types; incorporating real-time WorldACD rate data to improve forecast update frequency; extending the ensemble approach to Africa–Europe lanes where commodity mix complexity and geopolitical risk profiles present analogous analytical challenges; and exploring the application of SHAP-driven interpretability analysis to the Random Forest component to enhance commercial team understanding of non-linear yield dynamics.

Declarations

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the author used AI-assisted writing tools to support language editing and structural organisation of sections. All technical analysis, mathematical framework development, domain expertise, data interpretation, and research conclusions are entirely the author's own, drawn from 19 years of operational cargo analytics experience. The author reviewed and edited all AI-assisted content and takes full responsibility for the accuracy and integrity of the work published.

Conflict of Interest Statement

The author declares no conflict of interest. The views and opinions expressed in this paper are solely those of the author in her personal and academic capacity and do not represent the position of Turkish Airlines or Turkish Airlines Cargo. No proprietary or confidential company data has been used. All data referenced is drawn from publicly available industry sources only.

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