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Modeling of Container Import Port Choice in Indonesia: A Discrete Choice Approach

By

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ABSTRACT

Indonesia's fragmented and uneven port system has led to an overconcentration of container imports in a few western hubs, despite its archipelagic geography and widespread demand. This study develops a nationwide, revealed-preference model of container port choice to quantify the determinants influencing gateway selection and to provide a framework for evidence-based port investment policy. The analysis covers nine international container ports handling direct import calls, reconstructing full transport chains from Asia-Pacific origins to provincial demand centers by combining maritime and inland costs, times, and port attributes. Using a multinomial logit framework estimated from observed flows, the model identifies connectivity as the strongest positive determinant of port choice, followed by berth service effectivity, while longer maritime times and higher inland costs and times significantly reduce utility. Sensitivity analysis further shows that enhancing connectivity and reducing maritime transit times yield the largest shifts in choice probabilities, particularly where ports are closely competing. These findings demonstrate that strengthening domestic feeder connectivity, improving berth productivity, and reducing maritime times are the most effective strategies to rebalance container flows beyond Java and enhance national competitiveness. The study contributes to port choice literature by integrating sea- and land-side determinants into a nationwide, utility-based framework, offering policymakers a predictive tool to guide port development and reduce investment risks.

Keywords: Port choice, Discrete choice model, Container imports, Connectivity, Maritime transport, Hinterland logistics, Indonesia, Gravity model, Multinomial logit, Port competitiveness

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LIST OF DETERMINANTS AND ITS ABBREVIATION

Abbreviation	Determinant Name	Definition
PC	Port Cost	Port cost, including Terminal Handling Charges (THC) and port dues.
MCI	MarI Cost	Maritime shipping cost (international leg).
MTI	MarI Time	Maritime shipping time (international leg).
PRC	PDR Cost	Total cost from port to demand region including maritime and land transport (USD/TEU).
PRT	PDR Time	Inland travel time from port to demand region (hours).
TC	Total Cost	Total cost from international maritime leg to demand region.
TT	Total Time	Total transport time from international maritime leg to demand region.
EI	ET/BT-I	Effective Time to Berthing Time ratio (international leg).
ED	ET/BT-D	Effective Time to Berthing Time ratio (domestic leg).
DII	DwellI Import	Container dwell time for import cargo (international leg).
DDE	DwellD Export	Container dwell time for export cargo (domestic leg).
BSH	BSH Productivity	Berth ship-hour productivity (containers handled per ship-hour).
BN	Berth No	Number of operational container berths.
WD	Water Depth	Maximum alongside draft (meters).
CO	Connectivity	Number of demand regions connected to port through maritime services, including both direct and transit.

COD	Connectivity Direct	Number of demand regions connected to port through direct maritime services (no intermediate ports).
COT	Connectivity Total	Number of demand regions connected to port through maritime (direct and transit) and land transport services.
PCL	Port Call	Number of direct mainline calls per month.
Delta_U	Utility Difference	Utility difference compared to the reference port.
Flow	Flow	Container flow between a region–port pair.
P_ij	Choice Probability	Probability that region *i* selects port *j*.
P_ref	Reference Probability	Probability of the chosen reference port, used for comparison.

CHAPTER I

INTRODUCTION

1.1 Background

Indonesia, the world's largest archipelagic state with more than 17,000 islands, occupies a pivotal geostrategic position in global maritime trade. Located between the Indian and Pacific Oceans and adjacent to major economies such as China, Japan, India, and Singapore, the country lies along some of the world's busiest shipping routes, most notably the Malacca Strait. This chokepoint alone accounts for roughly 23.7% of global seaborne trade (UNCTAD, 2024), underscoring Indonesia's central role in international logistics.

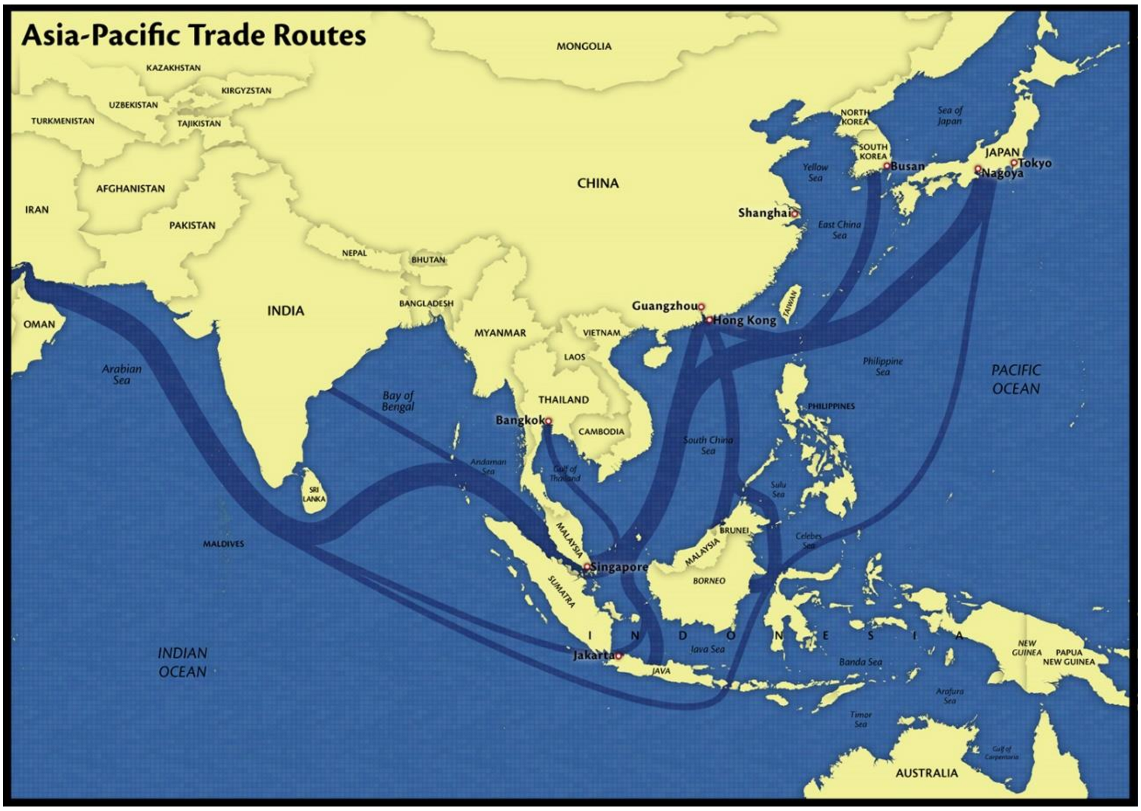


Figure 1.1 Asia Pacific Route

(source: https://www.behance.net/gallery/36884601/Asia-Pacific-Trade-Routes-%281-map%29)

Indonesia's trade figures further underscore its maritime significance. According to Badan Pusat Statistik (BPS, 2024), total imports exceeded USD 230 billion, with nonoil and gas products contributing USD 197 billion. Imports are heavily concentrated, with the top six trading partners, China (USD 71 billion), ASEAN (USD 34 billion), Japan (USD 16 billion), followed by South Korea, Taiwan, and India, accounting for nearly 70% of total imports. These figures reflect Indonesia's deep integration into East and Southeast Asian production and supply networks, reinforcing its importance as a maritime trade corridor.

Despite this strategic geography and trade intensity, Indonesia's port system remains fragmented and imbalanced. More than 600 commercial ports operate nationwide, but only a handful port which are Belawan, Palembang, Panjang, Pontianak, Tanjung Priok, Tanjung Emas, Tanjung Perak, Makassar, and Bitung handle significant international container volumes (Ministry of Transportation, 2017). In 2024, Indonesia imported over 2 million TEUs (Econdb, 2025), yet volumes were highly uneven: western ports absorbed more than 1 million TEUs annually, while eastern gateways such as Makassar and Bitung handled fewer than 50,000 TEUs (Pelindo, nd).

Figure 1.2. Location of 9 (nine) Container Ports served International Direct Import Call.

(source: google earth maps)

Geographic and infrastructural constraints intensify these disparities. Unlike continental economies linked by rail or road, Indonesia's inter-regional connectivity relies primarily on sea transport (World Bank, 2021). Inland logistics remain dominated by trucking, with rail capturing less than 1% of container volumes (BPS, 2025). Consequently, ports are not only gateways for international trade but also crucial nodes for inter-island cargo flows.

Meanwhile, global shipping dynamics are reshaping competitive pressures. Container shipping alliances, which control around 80% of global capacity, concentrate their port calls at major hubs with sufficient throughput, connectivity, and reliability (OECD, 2018). This trend benefits ports such as Tanjung Priok or Tanjung Perak but sidelines smaller eastern gateways. External shocks such as oil price volatility and emissions regulations further exacerbate cost pressures in a transport sector where 90% of energy demand still depends on oil (Sukarno et al., 2025). In such an environment, ports offering shorter inland travel distances, greater service reliability, and energy resilience gain a competitive advantage.

Despite ongoing investments in projects like Patimban and Kuala Tanjung, Indonesia still lacks a forward-looking, data-driven framework to assess port competitiveness. Infrastructure expansion alone does not guarantee integration into global liner networks or attractiveness to shippers. For example, a recent study of Makassar New Port (Palinrungi, 2023) found that physical depth and berth availability were insufficient to secure gateway status; inland cost, accessibility, and service connectivity were decisive. Without robust analytical tools, Indonesia risks both overinvesting in underperforming ports and underinvesting in emerging hubs.

This thesis responds to that gap by developing a national-scale, utility-based model of port choice. By systematically quantifying the determinants of container import gateway selection, the study aims to provide a predictive and policy-relevant framework to support Indonesia’s long-term port development strategy.

1.2 Problem Statement

Indonesian container ports serve a dual role: connecting international shipping networks to domestic hinterlands and supporting inter-island trade. However, their ability to attract and retain container flows is increasingly shaped by a combination of global shipping trends, regional economic shifts, and port-specific factors.

Current planning strategies emphasize physical capacity expansion but lack predictive tools to assess which ports are most likely to evolve as sustainable gateways. In the absence of a quantitative framework, investment risks remain high, and Indonesia may fail to align its port development with actual trade dynamics. A national-scale port choice model is therefore essential to identify the key drivers of competitiveness and to simulate how improvements in infrastructure, service, or connectivity would alter the distribution of import flows.

1.3 Objectives and Research Questions

The main objective of this thesis is to develop a nationwide port choice model for Indonesia that quantifies the relative utility of container import gateways. The model integrates the international maritime leg, port attributes, and the inland/feeder leg so that the competitiveness of each port can be systematically assessed. By doing so, the study provides a predictive framework to evaluate how improvements in determinants translate into changes in market share, supporting evidence-based policy and investment decisions.

Accordingly, this research addresses the following question:

Main Research Question:

- How can the choice of international container ports in Indonesia be modeled, and what factors significantly influence this choice?

Sub-questions:

1. What is the role of geographic location in determining port choice?
2. How significant is port connectivity—to both international container services and domestic hinterlands—in influencing port choice?
3. How do port performance and capacity affect port selection decisions?

1.4 Scope

Ports and Location

This study focuses on nine (9) international container ports in Indonesia that currently receive direct international import calls. The selected ports are:

- Port of Belawan
- Port of Palembang
- Port of Panjang
- Port of Pontianak
- Port of Tanjung Priok
- Port of Tanjung Emas
- Port of Tanjung Perak
- Port of Makassar
- Port of Bitung

These ports represent Indonesia's current international container gateway infrastructure and serve as the primary nodes for import flows in the model.

The hinterland regions in this study are defined at the provincial level, while the centroid of economic activity within each province is calculated as a GDP-weighted mean center of all 514 regencies and cities across Indonesia's 38 provinces. Using GDP as the weighting factor ensures that the centroid reflects not just geographic midpoints but also the concentration of economic demand. These centroids then serve as the representative destination points for computing inland and feeder distances and times from each port. This approach allows for a spatially representative mapping of container demand distribution across the country.

Container Flow and Transport Chain

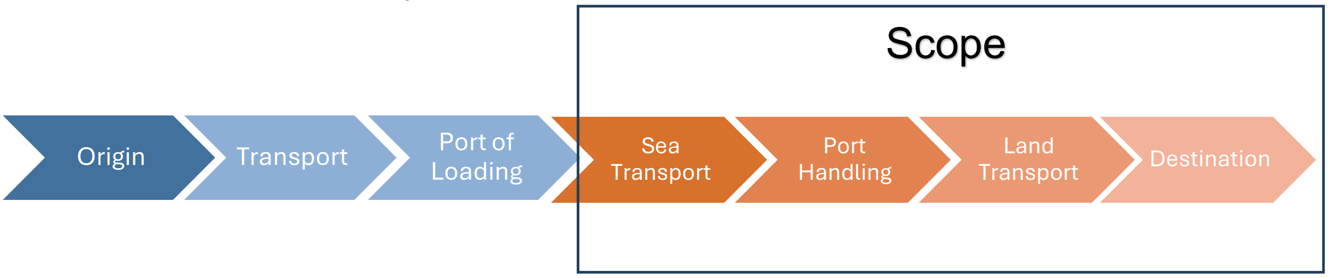


Figure 1.3. Scope in Transport Chain

(Source: Author’s illustration)

This model focuses specifically on container import flows from the Asia-Pacific region, particularly from China, ASEAN countries, Japan, South Korea, Taiwan, and India. Export flows from Indonesia are not included in the analysis. Additionally, the foreland segment—which includes container movement and decision-making processes at the port of origin—is excluded. The model begins at the point of international sea transport into Indonesian ports and traces the container movement inland.

Hinterland Mode

The inland transportation component of the model includes two sequential transport modes:

1. Feeder vessel (for inter-island movement)
2. Unimodal trucking (for final delivery to the destination regency or city)

These modes are not treated as alternatives within a mode choice framework; instead, they function sequentially based on the geographic destination of the container. For example, containers destined for other islands may be transshipped via feeder vessels, followed by last-mile delivery using trucks. This simplified logistics chain is designed to reflect the most typical import distribution pattern in Indonesia.

1.5 Thesis Structure

This thesis consists of Six chapters which are:

Chapter 1 – Introduction

This chapter introduces the research topic by outlining Indonesia's maritime significance, the current state of its port system, and the challenges of fragmentation and connectivity. It defines the research problem, objectives, and questions, specifies the scope, and explains the significance of the study for both policymakers and academia.

Chapter 2 – Literature Review

This chapter reviews existing theories and studies related to port choice, with emphasis on discrete choice modeling and its application in maritime research. It examines global and Indonesian contexts, identifies research gaps, and presents the conceptual framework that guides the study.

Chapter 3 – Methodology and Data

This chapter details the research design, model specification, and data requirements. It explains the selection of ports, the variables used, and the sources of data. It also describes the analytical approach, including estimation procedures, software tools, and model validation steps.

Chapter 4 – Results

This chapter presents the findings of the analysis. It begins with descriptive statistics of port performance and connectivity, followed by the results of the port choice model. It also includes scenario simulations to test how changes in variables affect port attractiveness.

Chapter 5 – Discussion

This chapter interprets the results in the context of Indonesia's maritime sector and compares them with previous studies. It discusses the practical implications for port development and logistics policy, as well as the strategic significance for improving Indonesia's competitiveness in global shipping networks.

Chapter 6 – Conclusions and Recommendations

This chapter summarizes the key findings, answers the research questions, and provides recommendations for policymakers, port authorities, and industry stakeholders. It also outlines the limitations of the study and suggests directions for future research.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction to Port Choice Literature

In economics, choice is the act of selecting one option from several in order to achieve the best outcome. We describe “best” using the idea of utility, which is a simple way to score how attractive each option is. Preferences are the decision maker’s ranking of options, and utility is a convenient numerical representation of that ranking. A rational decision compares benefits and costs and then chooses the option with the highest utility, meaning the greatest net gain from the decision (Mankiw, 2020).

In transport studies, this logic is formalized in the **random utility framework**. For a decision-maker *i* considering alternative *j*, total utility consists of two parts: an observable component, which can be measured through attributes of the alternative, and an unobservable component, which captures random or unmeasured factors. The general form of this is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad \ldots(1)$$

where V_{ij} capture the observable component, and ε_{ij} captures everything unobserved. The decision rule is straightforward: the chosen option is the one with the highest total utility. This approach allows researchers to connect measurable characteristics of transport options with actual observed choices in a consistent way (McFadden, 1974).

Port choice fits directly into this framework. For any given shipment or vessel call the decision is to select one port from a finite set of competing gateways, so it is naturally treated as a discrete choice. It is also an economic decision, because the selector evaluates the expected gains and costs of using each port in utility terms and chooses the port that yields the highest overall utility for moving the goods efficiently.

2.2 Port Choice Determinants

Port choice is shaped by five broad groups of determinants: geographic location and proximity, foreland and hinterland connectivity, infrastructure and capacity, operational performance, and cost. These categories provide a structured way to compare findings across different studies and form the analytical basis for this thesis. Each group captures a distinct dimension of competitiveness, and their combined effect explains why some ports emerge as dominant gateways while others remain secondary.

2.2.1 Geographic location and proximity

Location matters because it affects both the sea leg and the inland leg of a movement. A port that sits close to main liner routes requires little deviation, which reduces sailing time and fuel consumption. Reviews of container shipping identify this deviation effect as a core element of competitiveness (Notteboom, 2004). On land, distance to production and consumption centers raises haulage cost and exposure to congestion. Disaggregate analysis confirms that longer distances lower the likelihood that a port will be chosen because it raises generalized transport time and cost (Malchow and Kanafani, 2004).

Geography interacts with accessibility: even when distances are fixed, improvements in inland infrastructure can shift port market shares. Mueller (2020), using a model-based spatial interaction approach, shows how changes in hinterland travel times and access conditions can reallocate port demand, even without changes in sea-side conditions. This reinforces that “location” is not purely geographical but mediated by inland connectivity.

2.2.2 Foreland and hinterland connectivity

Connectivity is about how easily cargo reaches and leaves the port. On the foreland side, direct mainline calls, higher service frequency, and broad route coverage reduce transshipment and shorten lead times. Network studies show that ports with stronger embeddedness in carrier networks attract and retain services more easily, which improves reliability for users (Ducruet and Notteboom, 2012).

On the hinterland side, access through roads, rail links, inland depots, and intermodal facilities determines door-to-door time and cost. Stated preference evidence with Indonesian exporters and forwarders shows that inland connectivity variables such as access quality and frequency of inland services are decisive in port choice. In Indonesia, Nugroho (2016) conducted a stated-preference survey among exporters and freight forwarders, finding that inland access quality and service frequency were decisive in port choice. Complementing this, Hidayati, de Jong, & Whiteing (2022) applied a probabilistic demand model for Java, using revealed-preference data to show a strong statistical link between hinterland connectivity and port demand. Together, these studies confirm the critical role of inland access in the Indonesian context.

2.2.3 Port infrastructure and capacity

Infrastructure sets the technical ceiling for what a port can handle competitively. On the seaside, berth depth and quay length determine which ships can be accommodated. Crane outreach and availability determine ship working rates. Comparative work on port and liner integration links deeper drafts and capable equipment to stronger competitive positioning and inclusion on mainline services (Notteboom and Rodrigue, 2008).

The size of vessels matters for these requirements. Analyses of containership economies of scale show that insufficient depth or crane capability becomes a binding constraint regardless of otherwise favorable conditions, which explains why meeting threshold standards is a prerequisite for attracting or keeping direct services (Cullinane and Khanna, 2000). Design studies add a complementary perspective by showing that terminal layout and capacity choices have measurable effects on throughput and service levels. A stochastic discrete optimization model demonstrates how yard and gate configurations shape performance outcomes that users experience, which in turn influence port attractiveness in competitive settings (Zukhruf, Frazila, and Burhani, 2017).

2.2.4 Port performance

Performance is the ability to convert installed capacity into reliable service. Common indicators include vessel turnaround time, berth waiting time, crane productivity, container dwell time, gate truck turnaround, and the speed of customs clearance. Studies on liner services emphasize that time matters directly for competitiveness. Faster and more predictable operations protect schedules and reduce cascading delays across service loops, which increases a port's attractiveness even when posted charges do not change (Notteboom, 2006).

Survey based evidence supports the same conclusion from the user side. Research focused on shipping lines reports that ports combining adequate capacity with consistent operations are preferred over technically similar ports that suffer from variability or congestion (Tongzon and Sawant, 2007). At the operational level, higher effective time to berthing time ratios (ET:BT) are also found to significantly improve ship service performance, meaning ports that minimize idle time during vessel calls are more attractive than those with lower ratios (Hutauruk, Ramadhanti, & Herdian, 2023).

2.2.5 Cost

Cost is best understood as the total logistics bill rather than a single tariff item. While terminal handling charges and port dues are relevant, inland transport expenses, fuel and time costs from route deviations, and delay costs from congestion or clearance processes are often more decisive. Comparative research shows that higher port charges reduce a port's attractiveness, but differences in inland costs are frequently the determining factor in multiport regions, explaining routing shifts between otherwise similar alternatives (Tongzon, 2002). Discrete choice analyses using shipment data confirm this result: inland cost exerts a strong negative effect on the probability of selection, underscoring its weight in door-to-door decisions (Tiwari, Itoh, & Doi, 2003).

Broader trade studies also find that improvements in port efficiency lower maritime transport costs on bilateral routes, reinforcing the cost channel through which institutional and operational reforms influence port choice (Clark, Dollar, & Micco, 2004). Empirical evidence further demonstrates that composite port costs including terminal handling charges and port dues rank among the most critical determinants of port choice, often outweighing technically comparable factors when shippers face cost-based trade-offs (Teye, Asare, Frimpong, & Ackon, 2023; Chang, Lee, & Tongzon, 2000).

2.3 Methods for Assessing Port Choice Determinants

Research on port choice has employed a range of analytical methods designed to link port characteristics with the behavior of decision-makers. These methods have evolved from descriptive accounts and simple rankings to more formal, model-based approaches capable of quantifying trade-offs and forecasting outcomes. This progression has enhanced the ability of researchers not only to explain observed patterns of port use but also to simulate how changes in attributes may affect future choices. As a result, methodological developments in this field have become a crucial foundation for both academic research and policy-oriented analysis.

2.3.1 Revealed-preference evidence.

Revealed-preference (RP) studies use observed choices from customs records, freight bills, or vessel call databases. They estimate how differences in inland distance, maritime deviation, tariffs, and service frequency relate to the port that was actually chosen. A well-known RP study for the United States applied a multinomial logit model and found strong, intuitive effects of inland cost and sailing deviation on port choice, thereby validating distance and cost as core determinants in real markets (Malchow and Kanafani, 2004). RP has the advantage of realism, since it reflects genuine constraints and trade patterns. Its drawback is limited variation in some attributes and potential correlation among them, which calls for careful specification and robustness checks.

2.3.2 Stated-preference evidence.

Stated preference (SP) studies construct hypothetical choice scenarios to uncover trade-offs that may be hard to observe in RP data, for example the effect of a new direct service or a change in dwell time. Survey design follows established principles in choice experiment methodology, with attributes varied across choice tasks so that marginal effects can be identified cleanly (Louviere, Hensher, and Swait, 2000; Hensher, Rose, and Greene, 2015). SP has been used in maritime contexts to quantify the value of time and reliability and to compare price sensitivity with service sensitivity. Applications include shipping line and freight-forwarder perspectives and, in the Indonesian setting, exporters and forwarders who reveal clear preferences for better inland access and lower inland cost (Tongzon and Sawant, 2007; Nugroho, 2016).

2.3.3 Choice model families.

The workhorse is the multinomial logit model, which maps a utility function of measured attributes to a probability of choosing each port. When the decision appears hierarchical, such as route first and port second, nested logit is often used. When there is a need to relax the independence assumptions or to capture unobserved taste variation, mixed logit is appropriate. These model families are well documented in the transport economics literature, together with guidance on estimation and policy simulation (Ben-Akiva and Lerman, 1985; Train, 2009). They are widely applied in port choice because they handle multiple competing ports, convert attribute changes into changes in choice probabilities, and scale up naturally from micro decisions to aggregate market shares.

2.3.4 Complementary quantitative approaches.

Several methods complement discrete choice analysis by refining determinants or adding system context. Regression and competitiveness indices are used to rank ports and identify influential dimensions before formal choice modelling (Song and Yeo, 2004). Network analysis measures a port's position in the liner system and shows how embeddedness relates to traffic attraction, which helps operationalize "foreland connectivity" in empirical models (Ducruet and Notteboom, 2012). Mueller (2020) applied a modeling approach to show how adjustments in hinterland travel times reshape port catchments. On the terminal side, optimization and simulation studies show how yard layout, equipment, and gates affect throughput and delays, offering performance variables that can be fed back into choice models (Zukhruf, Frazila, and Burhani, 2017). These approaches do not replace discrete choice models; rather, they help build better, measurable proxies for the determinants used in them.

2.3.5 Operationalization and diagnostics.

Across methods, good practice starts with clear variable definitions: inland distance or cost, sailing deviation, direct service frequency, berth depth and cranes, turnaround and dwell times, and posted tariffs. Variables are often transformed or standardized to address scale and collinearity. Model fit is assessed with log-likelihood and pseudo-R^2, and predictive performance is checked out of sample where possible. Researchers routinely test key assumptions such as the independence of irrelevant alternatives for multinomial logit and conduct sensitivity analyses by varying the attribute set or by using alternative functional forms. This toolkit has matured to the point that it not only explains historical choices but also supports policy experiments, for example simulating how more mainline calls or faster clearance might re-rank competing ports.

2.4 Synthesis and Research Gap

2.4.1 What literature has done so far

Early work on port choice used user surveys and simple rankings to identify what matters to decision makers. These studies pointed to distance, cost, service frequency, and reliability as the main themes and provided the first structured lists of criteria, but they did not quantify causal effects or enable forecasting.

The next wave introduced revealed-preference and stated-preference discrete choice models. Using observed shipment flows, Malchow and Kanafani estimated a multinomial logit and showed that inland distance and maritime deviation have large, intuitive effects on port choice. Using survey experiments, Tiwari, Itoh, and Doi identified the trade-offs shippers make between price, time, and service when choosing ports and carriers. Shipping-line surveys by Tongzon and Sawant highlighted sensitivity to time and reliability from the carrier perspective. Together, these studies established utility-based modeling as the standard way to measure how attributes influence port choice. (Malchow & Kanafani, 2004; Tiwari, Itoh & Doi, 2003; Tongzon & Sawant, 2007).

A parallel stream studied competitiveness and network position. Comparative work linked berth depth, crane capability, and network embeddedness to a port’s ability to attract mainline calls. Network analyses showed that ports occupying central positions in the liner network tend to retain services and stabilize schedules. These studies explained why some ports become hubs while others remain feeders. (Notteboom & Rodrigue, 2008; Ducruet & Notteboom, 2012).

On Indonesia, the evidence base is thinner and often local. A stated-preference thesis with exporters and forwarders found that inland access and inland cost are decisive in port choice. A probabilistic model for Java reported a strong link between hinterland connectivity and port demand. There is also terminal-design and operations research showing how yard and gate configuration affects throughput, which points to performance variables that matter for users. These contributions are valuable, but they are typically regional, survey-based, or facility-focused rather than national and comparative. (Nugroho, 2016; Hidayati, de Jong & Whiteing, 2022; Zukhruf, Frazila & Burhani, 2017).

More recently, the literature has emphasized the effects of network shocks and schedule reliability on port attractiveness, especially after the pandemic. Reviews show that shifts in connectivity and time performance can re-rank ports even when tariffs are unchanged, which underlines the need to incorporate dynamic service variables into empirical models. (Notteboom, Pallis & Rodrigue, 2021; UNCTAD, 2023).

2.4.2 Where this fall short of your context and questions

In chapter I describes Indonesia's archipelagic geography, uneven hinterland access, and concentration of international container flows in a small set of gateways. The problem statement calls for a rigorous, system-level assessment that can identify which attributes most strongly drive port choice and that can test policy scenarios such as improving service frequency, reducing inland cost, cutting dwell and turnaround, or upgrading draft and equipment.

Set against that need, the existing research leaves four main gaps.

1. National scope

   Most Indonesian studies are corridor-specific or based on one island. There is no recent, nationwide model that compares the principal international container gateways within a single empirical framework calibrated on observed choices.

2. Integrated specification

   Prior work often treats sea-side connectivity or inland access in isolation or focuses on infrastructure without linking it to performance and cost in one utility function. On the other hand, this thesis will quantify trade-offs across foreland connectivity, hinterland access, infrastructure, performance, and cost together.

3. Method and data alignment

Indonesian evidence leans toward stated preference or local case studies. There is limited revealed-preference discrete choice estimation at national scale that uses measurable attributes for the full set of competing international ports.

This thesis will estimate a revealed-preference multinomial logit over the competing gateways, using observed flows and published or computed attributes.

4. Sensitivity Analysis

   Few Indonesian studies translate estimated effects into “what-if” scenarios at national scale. This thesis will cover what if scenario in sensitivity analysis to see what happened if there is a change in certain variable.

A practical scope issue also arises. Some new investment ports have minimal or no direct international container flows. Including them in estimation can distort inference. Your thesis addresses this by excluding such ports from the model while discussing them in the policy section as prospective cases.

2.4.3 How the thesis fills the gap

This study will estimate a nationwide, comparative discrete choice model for Indonesia’s principal international container ports. The model will integrate foreland and hinterland variables with infrastructure, performance, and cost in one utility specification, following the measurement practices established in the international literature while tailoring variables to Indonesian data availability. Estimation will be based on observed flows to ensure behavioral grounding. The results will be used to run policy simulations that speak directly to your research question and objectives, showing how specific improvements would change the relative attractiveness of competing gateways and informing investment sequencing.

2.5 Summary Port Choice Determinant

In summary, the literature on port choice highlights a consistent set of determinants that shape how shippers and carriers allocate container flows. Across different contexts, five broad groups stand out: geographic location and proximity, foreland and hinterland connectivity, infrastructure and capacity, operational performance, and cost. These factors operate through distinct but interrelated channels, influencing both the maritime leg of transport and the inland distribution of cargo.

While previous studies provide valuable insights, evidence for Indonesia remains fragmented and often limited to regional or survey-based analyses. Few works combine the full range of determinants in a nationwide, revealed-preference framework. This leaves a gap in understanding how Indonesian ports compete as a system, and how improvements in connectivity, service quality, or inland access may alter their relative attractiveness.

This thesis addresses that gap by developing a national-scale port choice model grounded in discrete choice theory. Building on the five determinant groups identified in the literature, the next chapter operationalizes them into measurable variables and outlines the methodology used to estimate their impact on port choice.

Some variables are excluded to maintain consistency and avoid double counting. Rail connectivity is not modelled explicitly because container rail is sparse and uneven; its effect is captured through inland time and inland cost. Customs or governance indices are excluded due to a lack of comparable, port-level time series; they are proxied by dwell and turnaround times. Newly invested ports without international container flows are excluded from estimation so that coefficients reflect observed behaviors. These choices keep the specification tractable and focused on measurable, high-impact levers.

Table 2.1. Summary Port Choice Determinant

(source: author's compilation)

Group	Variable	Definition & unit	Expected sign in utility	Indicative source
Location	Maritime shipping distance/time	Nautical miles or sailing hours from origin regions to each gateway	Negative	Notteboom (2004)

Location	Feeder sailing time (if cross-island)	Hours for the inter-island feeder leg when centroid ≠ gateway island	Negative	Hidayati, de Jong & Whiteing (2022)
Location	Inland travel time	Road hours from gateway to provincial demand centroid	Negative	Malchow & Kanafani (2004)
Connectivity	Direct mainline calls (Port Calls)	Number of direct mainline calls per month	Positive	Ducruet & Notteboom (2012)
Connectivity	Number Feeder Services or connection to hinterland	Sailings per week (including feeders) as a service frequency proxy	Positive	Ducruet & Notteboom (2012)
Infrastructure	Berth depth	Maximum alongside draft (meters)	Positive	Notteboom & Rodrigue (2008)
Infrastructure	Number of berths	Count of operational container berths (parallel ship-working capacity)	Positive	Notteboom & Rodrigue (2008)
Performance	BSH productivity	Boxes per ship-hour (ship-working intensity)	Positive	Zukhruf, Frazila & Burhani (2017)

Performance	Effective Time Ratios	Ratios Effective Time to Berthing Time	Negative	(Hutauruk, Ramadhanti, & Herdian, 2023)
Performance	Container dwell time	Average days from discharge to gate-out	Negative	Tongzon & Sawant (2007)
Cost	Inland trucking cost	USD/TEU computed from route length × per-km trucking rate	Negative	Tiwari, Itoh & Doi (2003)
Cost	Inter-island feeder cost	USD/TEU for feeder movement	Negative	Wilmsmeier & Sánchez (2009)
Cost	Port Cost	USD/TEU for Total Handling Cost and Port Dues	Negative	(Teye et al., 2023; Chang et al., 2000)

CHAPTER III

METHODOLOGY

The method follows the ideas in Chapter II, where port choice is a discrete choice and utility depends on observable attributes as shown in figure 3.1. First, full-chain time and cost are reconstructed for every port–province pair (international maritime leg, plus any feeder and inland legs). These are combined into a generalized cost and used, together with observed port totals and provincial demand weights (from GDP and GDP per capita), in a doubly constrained gravity model. The result is a converged Base OD Matrix that balances both margins.

From this matrix, each province's port probability is the port's share of its inbound flow. These shares are then translated into relative utility using a simple log-odds transform against a reference port: ΔU. This step connects the data to the multinomial-logit framework introduced in Chapter II and yields a province–port panel of utility differences for analysis.

Finally, literature-based port determinants are compiled—connectivity (direct calls, frequency), infrastructure and capacity (depth, berths), performance (BSH, turnaround, dwell), and corridor-specific costs (inland and feeder). To match ΔU, each determinant is expressed as a difference to the same reference port (Δ-determinants). The regression then explains ΔU with these Δ-determinants, after screening multicollinearity (correlations, VIF). Where appropriate, observations are weighted by provincial import volumes and standard errors are clustered by province. Sensitivity checks vary key assumptions (value of time, inland rate, deterrence form, demand weights) to confirm that the main results are stable.

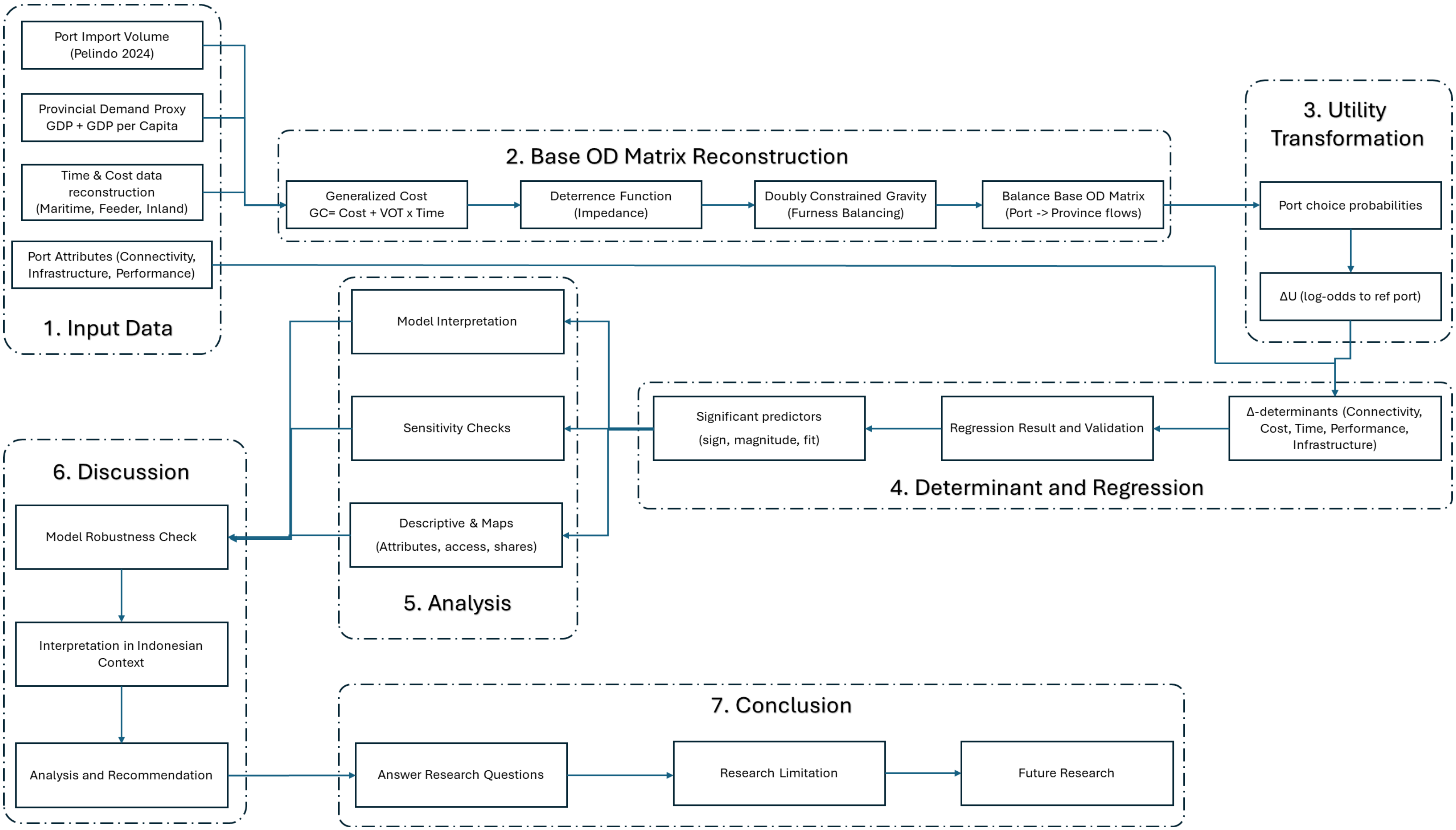


Figure 3.1. Research Design

(source: author's illustration)

3.1 Supply and Demand Data

The supply container data from asia pacific to every port with international call in Indonesia in year of 2024 is get from Pelindo. The number of containers for each port is presented on the table below:

Table 3.1. Total Container Import in 2024

(source: Throughput Data POD POL Pelindo 2024)

No	Container Imported	Total Import (TEU)
1	Tanjung Priok	1,326,880
2	Tanjung Mas	549,984
3	Tanjung Perak	958,439
4	Belawan	227,366
5	Makassar	22,211
6	Bitung	4,706
7	Pontianak	35,792
8	Panjang	10,162
9	Palembang	58,349
	Total	**3,193,889**

The demand data is reconstructed using proxy of GDP and GDP per capita. The approach is based on earlier studies by Groot et al. (2004) and Hausman et al. (2005), which examined how a country's economic size and income level influence its imports. These studies measure this relationship using *elasticities* numbers that show how much imports change when GDP or GDP per capita changes. In Groot et al. (2004) Log of importers GDP is 0.86 and log of importers GDP per capita 0.11 with R squared is 0.65. On the other hand, Hausman et al. (2005) found that Log of importers GDP is 0.915 and log of importers GDP per capita is 0.358 with R squared is 0.69. GDP reflects the total size of the economy, while GDP per capita shows the average income and purchasing power of the population. Together, they provide a good picture of a region's ability to generate demand for containerized goods.

The average elasticities from the two studies: 0.89 for GDP which means that if GDP grows by 1%, imports will grow by about 0.89%and 0.23 for GDP per capita. It can be converted into *weights*—79% for GDP and 21% for GDP per capita—so the two factors can be combined into one measure. This combined measure is called a container demand index, which serves as a proxy for the actual demand for containerized trade. It does not directly measure container volumes but gives a relative score that can be compared across regions.

The formula for the weighted container demand index for region i is:

$$D_j = (GDP_j)^{0.79} x (GDP\ PC_j)^{0.21} \qquad \ldots(2)$$

Here, GDP_j is the region's total GDP, $GDP\ PC_j$ is its GDP per capita, and D_j is the index value. To calculate the total flow to each region based on total imported in Indonesia 2024 using GDP and GDP per capita from BPS, 2024 is as follows:

$$O_j = \frac{D_j}{\sum D_j} x\ Total\ Import\ (TEU) \qquad \ldots(3)$$

The demand region centroid is defined to reflect economic mass rather than geography. A GDP-weighted mean center of regions is calculated for each province using ArcGIS (Weighted Mean Center tool) in an equal-area projection; coordinates $(\bar{x}, \bar{y})$ are given by:

$$\bar{x} = \frac{\sum w_i x_i}{\sum w_i}, \bar{y} = \frac{\sum w_i y_i}{\sum w_i} \qquad \ldots(4)$$

with weights w_i equal to region GDP. This centroid provides a consistent destination for computing feeder and road distances and times.

3.2 Time and Cost Data (overview)

This section compiles the time and cost inputs used to build full-chain impedance as in in the equation (6) for every port–province pair. Two segments are considered: the international maritime leg from Asia–Pacific loading regions to each Indonesian import gateway, and the domestic transport leg from the gateway to the provincial demand centroid. All times are expressed in hours and all monetary values in USD/TEU (with local-currency items converted in the Appendix 1). A value of time (VOT) is applied later to combine hours and money into generalized cost.

3.2.1 International Maritime Leg

Distances from representative Asia–Pacific origins to Indonesia's hubs differ by gateway, so shipping time to Tanjung Priok, Tanjung Perak, Belawan, Makassar, and other ports is not the same. In addition, Pelindo statistics show that the average calling ship size varies by port (see in Appendix 1.1). Because service speed depends on vessel class, average speeds by ship size are taken from Clarksons Research (2024) vessel benchmarks; shipping time to every port is then computed as route distance divided by the class speed.

The maritime cost framework is based on Stopford's (2009) cost structure and is presented in the Appendix 1.1. Four components are considered: (i) capital & maintenance (depreciation/financing and technical upkeep allocated by time and carried TEUs); (ii) operating (crewing, insurance/administration, stores); (iii) voyage (fuel consumption at sea and in port multiplied by the bunker price, plus port/canal charges); and (iv) cargo handling at the call (THC/stevedoring). Voyage fuel is the main distance- and time-sensitive term. Where THC is uniform across Indonesian terminals, it provides no cross-port variation and is treated as a constant in generalized cost. Key references include Stopford (2009) for cost taxonomy, Clarksons Research for speed by vessel class, and Notteboom (2006) and Cariou (2011) for the link between speed, fuel, and schedule time.

3.2.2 Domestic Transport

After discharge at the import gateway, containers move to the provincial demand centroid through one of four routing patterns, determined by island geography and feeder availability:

1. Inland transport only: gateway and province are on the same island; road haul from gateway to centroid.
2. Direct-call feeder + inland: a feeder vessel sails directly from the gateway to a secondary port on the province's island, followed by road haul.
3. Feeder with transit + inland: a feeder leg with one intermediate stop (transit) before reaching the secondary port, then road haul.
4. Feeder with vessel change + inland: a feeder to a transshipment node where cargo shifts to another feeder serving the province, then road haul.

For the feeder segment, maritime time and cost are calculated analogously to the international leg: sailing time equals corridor distance divided by representative feeder speed (by vessel size), with a waiting allowance based on published headways; cost is derived from fuel and port-charge parameters or, where available, from observed feeder tariffs per TEU. For the inland segment, cost is computed from corridor distance and a benchmark per-kilometre trucking rate from Indonesian studies (≈ Rp 8,000 per km, adjusted to the study's price year), and time is taken from Google Maps travel-time estimates on the most plausible trucking corridor, augmented by a gate-access allowance (Sudjana, 2011; Nariendra & Taufiq, 2020).

3.3 Base OD Matrix Reconstruction

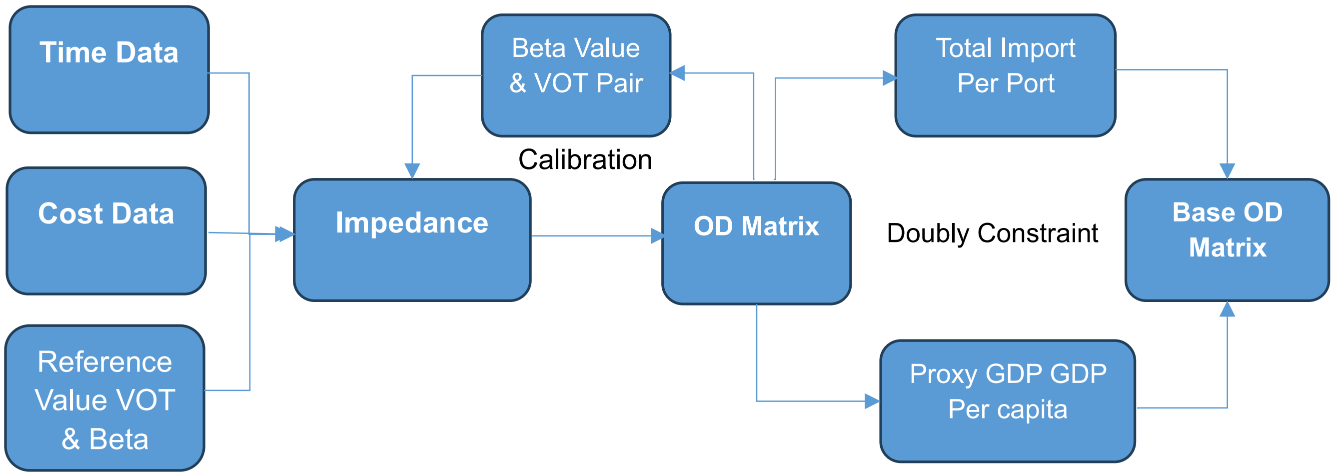


Figure 3.2. Base OD Matrix Reconstruction Diagram

(source: author's illustration)

This section converts the time–cost inputs from 3.1 into a port→province Origin–Destination matrix. The procedure has two stages. First, an impedance matrix is built by combining total transport time and money for each port–province pair into a generalized cost and mapping that cost into a deterrence/impedance weight. A set Value of Time (VOT) and Beta Value from the freight literature anchors the time–money conversion, and the pair of VOT and decay parameter β is calibrated to match observed port totals. Second, the calibrated deterrence enters a doubly constrained gravity model, solved with the Furness method, to obtain a Base OD Matrix that satisfies both the observed port totals and the constructed provincial demand totals.

3.3.1 Construction of the Impedance Matrix

For port i and province j, the full chain generalized cost is:

$$GC_{ij} = \underbrace{(Maritime + Feeder + Inland)}_{\text{Total}}\ Cost + (VOT x\ Total\ Time) \qquad \ldots(5)$$

Impedance is translated into a deterrence weight using the exponential form:

$$f(GC_{ij}) = e^{-\beta GC_{ij}} \quad \text{...(6)}$$

which is the standard specification in spatial-interaction and transport modelling, capturing the smooth decrease of flows with increasing generalized “cost” and arising from the entropy-maximizing derivation of gravity models (Wilson, 1971; Ortúzar & Willumsen, 2011; Cascetta, 2009).

The Value of Time converts hours to money. A range of 0.53–3.00 USD/TEU/hour from recent freight applications is adopted (Binsuwadan et al., 2022), with supporting evidence using 1.46 USD/TEU/hour in maritime cost analysis (Triantoro, 2020). VOT and the decay parameter β paired is calibrated by constructing a preliminary, unbalanced allocation where:

$$\hat{T}_{ij} = O_j x \frac{f(GC_{ij})}{\sum_j f(GC_{ij})} \quad \text{...(7)}$$

Where $\hat{T}_{ij}$is container flow from port i to deman region j O_j is the demand at a provincial level and $f(GC_{ij})$ is the impedance for certain ports to demand regional flow. The chosen β and VOT pair minimizes an error measure between actual port import data and modelled port.

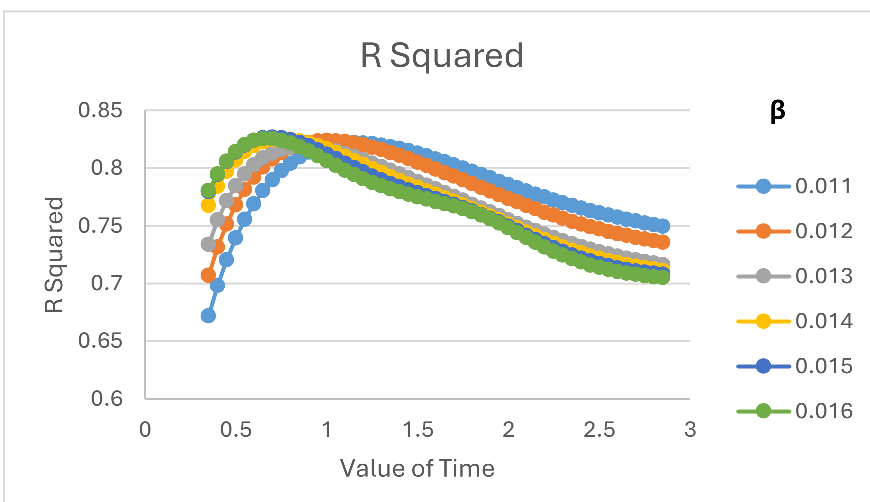


Figure 3.3. R squared modelled Port Import to Actual

(source: author’s calculations)

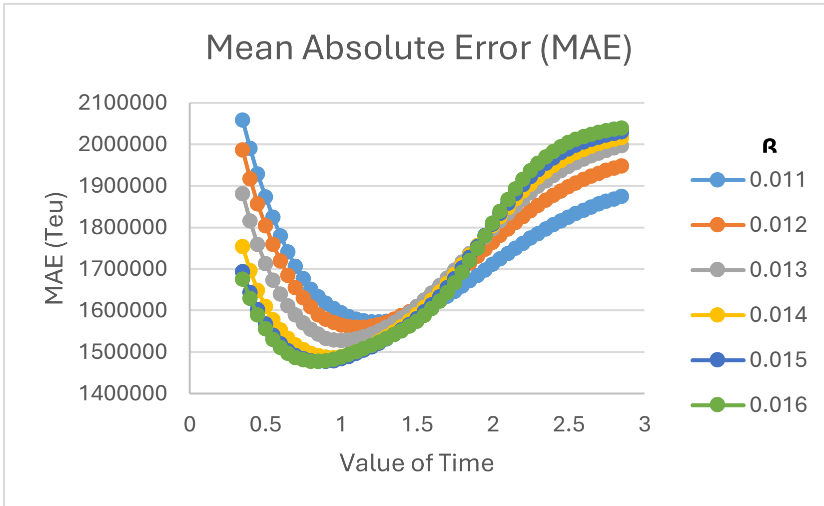


Figure 3.4. MAE modelled Port Import to Actual

(source: author's calculations)

Based on the graph above, the value of beta which is minimizing error is when VOT is 0.7 and β =0.015. So, the final equation of impedance function is as follows:

$$f(GC_{ij}) = e^{-0.015(Total\ Cost+0.7*Total\ Time)} \quad \ldots(8)$$

3.3.2 Construction of the Base OD Matrix (Doubly Constrained; Furness)

Under the entropy-maximizing formulation of spatial interaction, a Doubly Constrained Gravity Model allocates flows so that the known margins are matched exactly while allocation declines with a measure of generalized impedance (Wilson, 1971). Transport modelling texts recommend this specification precisely for cases with known productions and attractions, because singly constrained or unconstrained variants would either violate one margin or fail to conserve flows (Ortúzar & Willumsen, 2011; Cascetta, 2009). In freight and interregional trade applications, the same logic is used to recover OD matrices from sparse observations by combining a deterrence function with bi-proportional balancing, yielding stable, policy-useful estimates when detailed shipment data are missing; under ideal conditions, an unknown OD matrix can even be recovered exactly by scaling a prior impedance matrix to the marginals (Cai, 2021: shows the DCGM/RAS "plain vanilla" estimator and its properties) . In container-port work, Mueller, Wiegmans, and van Duin (2020) implement precisely this approach: they generate an OD matrix using a “double constraint distribution model,” also known as bi-proportional fitting or a gravity-based distribution model, and then iteratively balance it by equalizing the row and column constraints before estimating port-choice relations.

With $f(GC_{ij})$ fixed by VOT and β, flows are determined by the doubly constrained gravity model:

$$T_{ij} = A_i x P_i x B_j x O_j x f(GC_{ij}) \quad \ldots(9)$$

subject to the row constraints $\sum_i T_{ij} = P_i$ (observed TEUs handled by port i) and column constraints $\sum_j T_{ij} = O_j$ (province demand totals scaled to the national import). The A_i and B_j are the balancing factors (the Lagrange multipliers in the entropy formulation) that rescale the deterrence-weighted matrix so that both margins hold (Wilson, 1971).

In practice, the balancing step is carried out by the Furness method, also known as bi-proportional fitting or iterative proportional fitting (IPF). The procedure alternately adjusts row and column totals of a seed matrix until both sets of margins converge to the target values. This algorithm is mathematically equivalent to the RAS method in input–output economics and is guaranteed to converge under standard positivity conditions (Ortúzar & Willumsen, 2011; Cascetta, 2009). Its advantage lies in simplicity and robustness: starting from any non-negative prior matrix, it preserves the relative distribution given by the impedance function while ensuring exact reproduction of the observed supply (import per port) and demand (demand per region). For this reason, the Furness/IPF method has become the standard computational tool for implementing doubly constrained gravity models in transport planning and trade flow reconstruction (Wilson, 1971; Mueller, Wiegmans, & van Duin, 2020).

Balancing is performed by the Furness (iterative proportional fitting) method. Starting from $A_i = B_j = 1$, the factors are updated alternately as

$$A_i = \frac{1}{\sum_j B_j x O_j x f(GC_{ij})} \quad \text{...(10)}$$

$$B_j = \frac{1}{\sum_i A_i x P_i x f(GC_{ij})} \quad \text{...(11)}$$

and the updates continue until the maximum relative deviation from the target row and column totals falls below a pre-set tolerance. Under standard positivity conditions on $f(GC_{ij})$, the procedure converges to a unique solution for the matrix T_{ij} (Ortúzar & Willumsen, 2011; Cascetta, 2009).

The converged result is the Base OD Matrix. It provides the complete set of flows from each port to each province, consistent with observed port totals and with provincial demand totals, and serves as the quantitative foundation for subsequent probability, utility, and econometric analyses. Convergence was monitored using the maximum relative margin error, defined for rows as:

$$Error = \left| \frac{\sum_i T_{ij} - P_i}{P_i} \right| \quad \text{...(12)}$$

with an analogous measure for columns. The procedure converged in 61 iterations, at which point the maximum error fell to 7.3898×10^{-5} (e <0.001%). The resulting matrix is taken as the Base OD Matrix, which matches observed port totals and scaled provincial demand totals to within the specified tolerance.

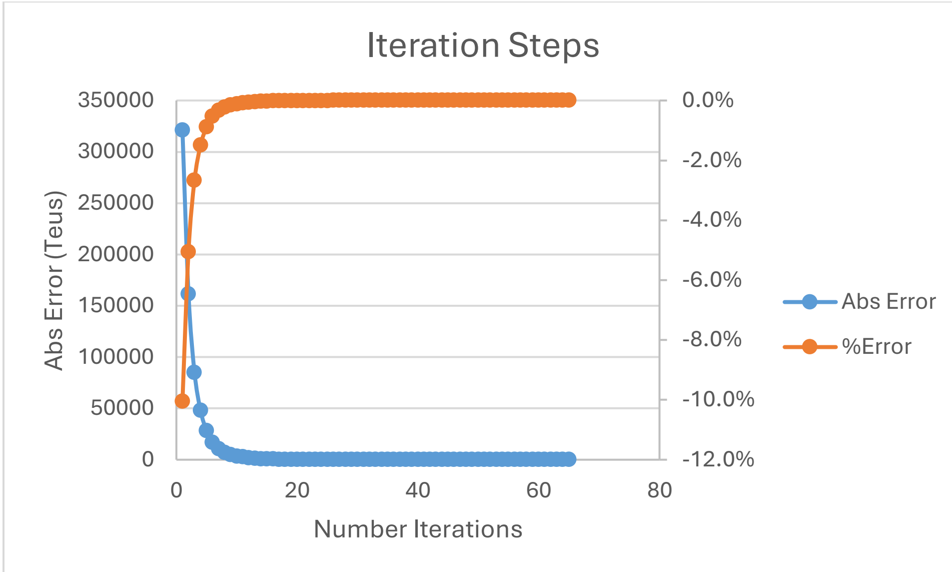


Figure 3.5. Iterations step during Furness balancing.

(source: author's calculations)

The chart plots the maximum relative row error against iteration count. Error declines rapidly during the first iterations and reaches 9.33415×10^{-5} by iteration 84, meeting the tolerance for convergence and confirming that the Base OD Matrix is properly balanced.

3.4 Δ Utility from the Multinomial Logit

Following Chapter II, port choice is modelled with a multinomial logit (MNL)

From the Base OD Matrix, let T_{ij} be the balanced flow from port i to region j. The probability that region j uses port i is defined as that port's share of the region's inbound flow:

$$P_{ij} = \frac{T_{ij}}{\sum_i T_{ij}} \quad \ldots(13)$$

(the denominator sums over all available ports for region j).

In the random-utility framework with i.i.d. Gumbel errors, the multinomial logit (MNL) gives:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_i e^{V_{ij}}} \quad \dots(14)$$

where V_{ij} the systematic (observable) utility for port i as seen by region j. The Multinomial Logit (MNL) model is the most popular, widely applied, and practical form of discrete choice model in transportation studies. As emphasized by Ortúzar and Willumsen (2011), the MNL model's widespread use stems from its relative simplicity, analytical tractability, and the ability to estimate it with standard statistical techniques. It offers a closed-form expression for the probability of choosing each alternative, making it computationally efficient and suitable for large-scale applications in travel demand forecasting. Despite some limitations, such as the assumption of the Independence of Irrelevant Alternatives (IIA), the MNL model remains a cornerstone in transportation modeling due to its flexibility in incorporating various explanatory variables and its proven empirical performance across numerous case studies. Its practicality makes it an essential tool for evaluating the impacts of transport policy interventions, infrastructure projects, pricing strategies, and service improvements on traveler behavior. (McFadden, 1974; Ben-Akiva & Lerman, 1985; Train, 2009; Ortúzar & Willumsen, 2011).

A core identity of the MNL links probability ratios to utility differences. Fix a reference port r (one of the available ports). Then:

$$\ln\left(\frac{P_{ij}}{P_{ref}}\right) = V_{ij} - V_{ref} \quad \dots(15)$$

Using probabilities built from the Base OD Matrix, this yields the empirical log-odds (also called log-share or utility-difference) transform:

$$\Delta U_{ij} = ln\, P_{ij} - \ln P_{ref} = \ln\left(\frac{P_{ij}}{P_{ref}}\right) \quad \dots(16)$$

This transformation is standard when only aggregate outcomes (shares) are observed: it maps observed probabilities to relative utility and cancels alternative-specific constants, allowing ΔU_{ij} to be related directly to differences in attributes (Ben-Akiva & Lerman, 1985;

Train, 2009; cf. Berry, 1994 for log-share transforms in demand). The resulting panel ΔU_{ij} is the dependent variable where:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \qquad \ldots(17)$$

Whereas:

$$V_{ij} = \alpha_1 X_{1(ij)} + \cdots + \alpha_n X_{n(ij)} \qquad \ldots(18)$$

U_{ij}: Utility of choosing route from port I to hinterland region j

V_{ij}: Observed variable component for route ij

ε_{ij}: Unobserved variable component

α_n: Coefficient n

$X_{n(ij)}$=factor/determinant n for route ij

The sign and magnitude of each α (alpha) reflect the relative importance of the variable. For example, we expect:

$\alpha_1, \alpha_2, \alpha_n$<0 higher factor determinant reduce utility,

$\alpha_1, \alpha_2, \alpha_n$> higher factor determinant increase utility.

This construction has two advantages. First, ΔU_{ij} measures each port's utility relative to a fixed reference within region j, so alternative-specific constants and common factors cancel out. Second, because ΔU_{ij} is linear in$V_{ij} - V_{ref}$, it can be analysed with standard regression tools using differences in attributes as covariates, providing a transparent way to test which determinants significantly explain port choice.

When the Multinomial Logit (MNL) model is applied to two competing routes, Route 1 and Route 2, each with its own utility value (U_1 and U_2), a probability curve can be drawn as shown in Figure 3-4. The likelihood of selecting Route 2 (denoted as P_2) depends not just on its own utility (U_2), but on the difference between the utilities of both routes. When both routes offer equal utility ($\Delta U = U_2 - U_1 = 0$), the probability of choosing Route 2 is exactly 50%.

If Route 2 has a higher utility than Route 1 ($U_2 > U_1$), the utility difference (ΔU) becomes positive, resulting in a probability greater than 50% for choosing Route 2. Conversely, if Route 2's utility is lower than that of Route 1 ($U_2 < U_1$), the probability drops below 50%. In this context, Route 1 serves as the reference or base option, meaning that the probability of selecting Route 2 is driven by the utility difference relative to this base. The actual (absolute) value of U_2 does not directly determine choice probability—only the difference between U_2 and the base utility (Ubasic) does.

3.4.2 Independent Variables: Determinants of Port Choice (Δ–form)

The explanatory side of the model mirrors the literature reviewed in Chapter II and is expressed in differences to a reference port so that the right-hand side lines up with the dependent variable ΔU_{ij}. For each determinant X, the covariate is:

$$\Delta X_{ij} = X_{ij} - X_{ref} \qquad \ldots(19)$$

where i is the port under evaluation, j is the demand region, and r is the fixed reference gateway. This Δ–form cancels common factors and alternative-specific constants, letting the regression speak directly to relative advantages.

CHAPTER IV

RESULT

4.1 Descriptive of the Datasets

This section describes the data used in Chapter IV, organised along the logistics chain: the international maritime leg, port-side attributes, and domestic transport from port to demand regions. All variables are period-matched; time is recorded in hours (or days where conventional), monetary values in USD/TEU.

4.1.1 International Maritime Leg

This subsection summarizes the ocean-side conditions faced by each gateway. Four descriptors are shown: (i) great-circle distance from representative Asia–Pacific loading areas, (ii) average vessel size calling at each port, (iii) the vessel cost structure per TEU following Stopford's taxonomy (voyage, capital, operating), and (iv) modeled sailing time using class-specific service speeds. Together, these variables explain why generalized maritime cost and time differ by gateway and why they matter for the impedance used later in the gravity step.

Port Distance (nm)

Distances cluster between roughly 1,300 and 1,800 nautical miles, but there is meaningful spread across gateways. Eastern ports such as Makassar and Bitung sit near the upper end, while Pontianak, Palembang, and Belawan are shorter. This geometry is the first-order driver of maritime time and, via fuel consumption, of voyage cost.

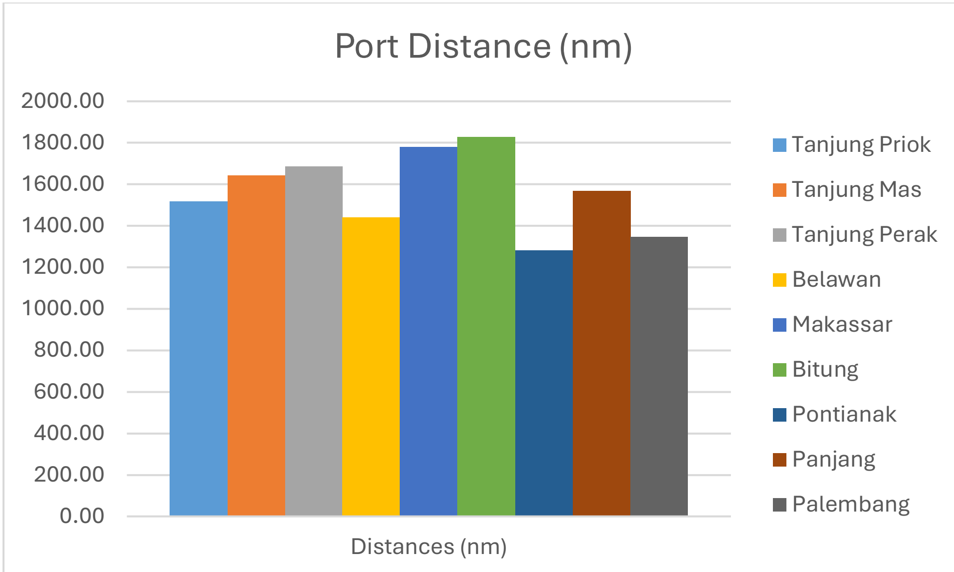


Figure 4.1. Port Distance of each port
(source: author's calculations based on sea-distances.org)

Average Vessel Size (TEU/call)

Call sizes vary strongly. Panjang and Palembang handle the largest vessels (≈3,5k–3,6k TEU/call), Tanjung Priok and Tanjung Perak are mid-range (≈2,5k–3,0k), while Belawan, Makassar, and Bitung see smaller classes (≈1,3k–2,0k). Because service speed depends on ship class, larger average vessels imply higher reference speeds and better economies of scale, which tends to reduce time per mile and cost per TEU.

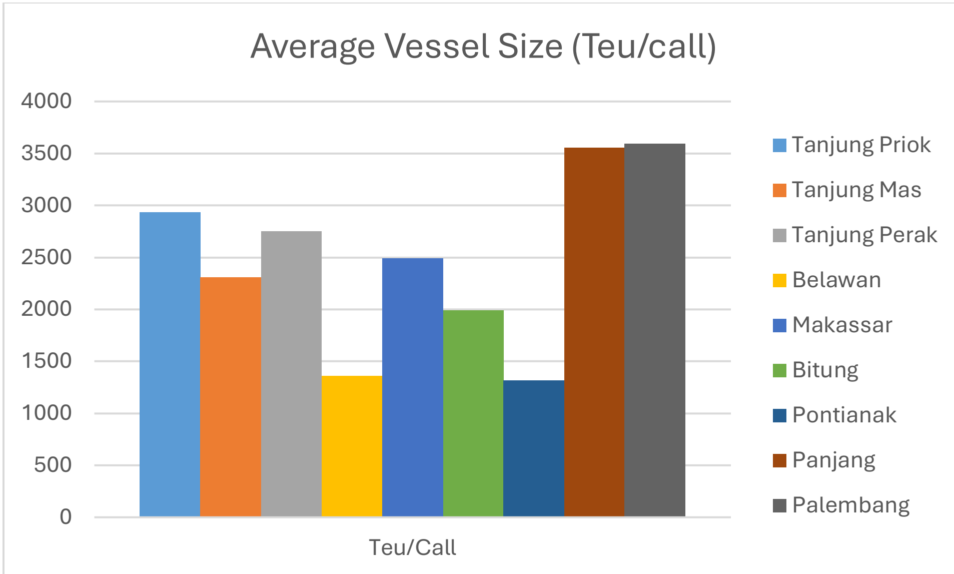


Figure 4.2. Average Vessel Size in TEU/Call in each port location

(source: author's calculation based on Pelindo Raports Data)

Vessel Cost Structure (USD/TEU)

Total maritime cost per TEU ranges roughly from USD 60 to 100 across ports. Voyage cost (fuel at sea/port plus port charges) is the dominant block everywhere, followed by capital (depreciation/financing) and a smaller operating component (crewing, insurance, stores). Ports with longer routes and/or smaller, slower ships— notably Makassar and Bitung—sit at the high end; gateways with shorter routes and larger ships—such as Palembang and Panjang—sit lower. This cost structure is not include terminal charges which will be different for every port location due to different dwelling time.

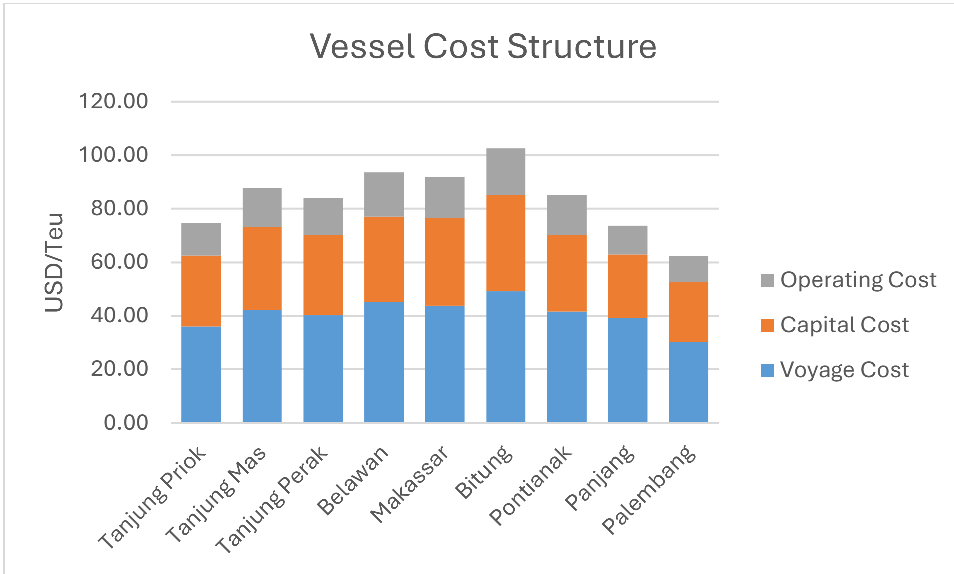


Figure 4.3. Vessel Cost Structure for International Maritime Transport to Indonesian Port

(source: author's calculations)

Maritime Sailing Time (days/hours)

Modeled steaming time falls between ~4 and ~6 days. The longest times occur at Bitung and Makassar (≈6 days), reflecting both distance and smaller vessel classes. Pontianak and Palembang are closer to 4–4½ days; Tanjung Priok and Tanjung Perak lie in the middle. The time picture aligns with the distance and ship-size patterns above and feeds directly into generalized cost once the value of time is applied.

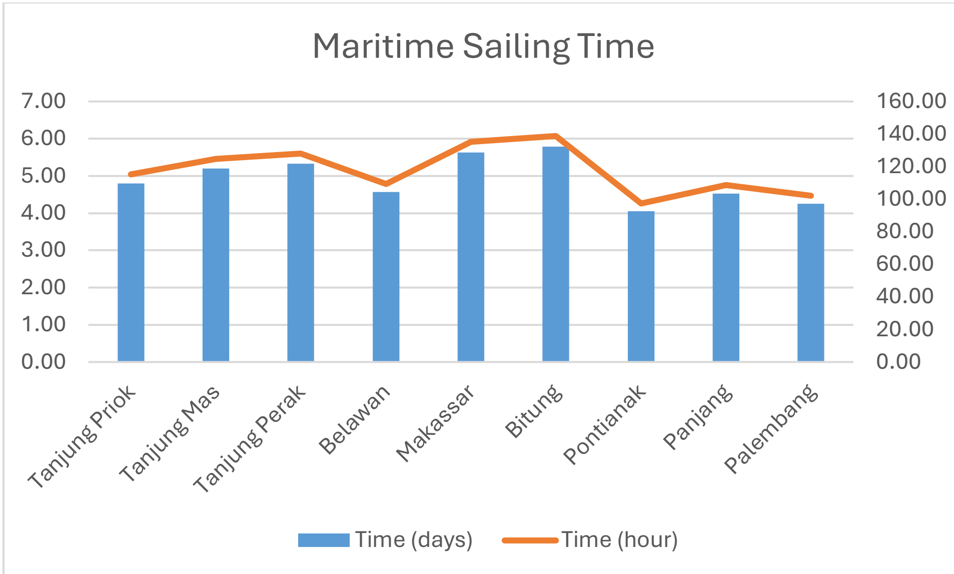


Figure 4.4. Maritime time transport to Indonesian Port

(source:author's calculations)

4.1.2 Port Attributes (connectivity, infrastructure/capacity, performance)

Port-side determinants are compiled at the port–period level. Connectivity to International shipping includes is presented by number of calls from international shipping activities. From the figure 4.5 can be seen that the unbalance port calls where java ports dominated following by other western Indonesia's Port. Port of Bitung and Port of Makassar representing eastern port of Indonesia have insignificance port call compared to others.

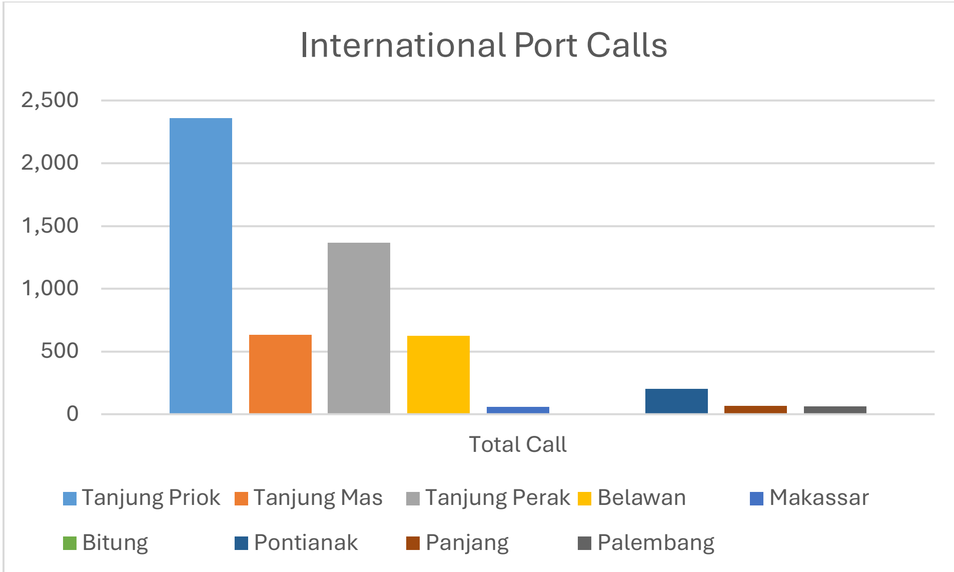


Figure 4.5. Total International Shipping Port Calls for each Port in Indonesia

(source: Pelindo Raports Data)

Connectivity Port to the demand region represent by three kind of connectivity type: 1) Connectivity represents number of vessel service from port to the demand region direct and transit, 2) Connectivity Direct just count the number of vessel service from port to the demand region for direct call without transit, 3) Connectivity total represent total connectivity from vessel service (direct and transit) and land connectivity. Figure 4.6. shows a hub-and-feeder pattern in Indonesia's port network. Tanjung Perak (Surabaya) and Tanjung Priok (Jakarta) act as national gateways, with the highest number of service options and the broadest reach to demand regions which many of them served directly, so shippers can access most markets without transhipment. Tanjung Emas (Semarang) has plenty of services but fewer direct links, indicating more reliance on one-stop connections via the main hubs. Makassar functions as an eastern Indonesia node with balanced direct and total reach. In contrast, Palembang, Panjang, and Pontianak are feeder/river ports: they have very few direct connections but can still reach many regions after a hub transfer.

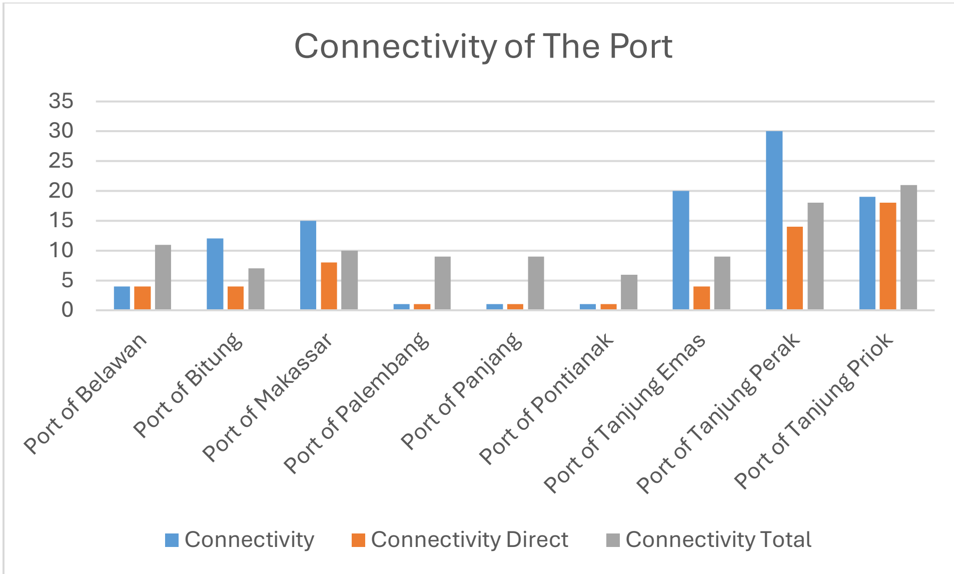


Figure 4.6. Connectivity of each Port to the Hinterland or Demand Region

(source: authors calculation)

Infrastructure and capacity are represented by berth depth (metres alongside) and the number of container berths. Operational performance records boxes per ship hour (BSH), vessel turnaround time (hours in port, including waiting and service), and container dwell time (days). The performance plot reports the Effective Time / Berthing Time ratio for imports (ET/BT–I) and exports (ET/BT–D), alongside Boxes per Ship Hour (BSH). ET/BT measures the share of time at berth that is spent productively under the cranes; BSH captures the intensity of ship working. Most ports show ET/BT ratios in the 70–90% range, but BSH varies more widely, dipping in several outer-island ports and rising steadily for Tanjung Perak and Tanjung Priok, which approach 50–60 boxes/hour. Higher BSH and higher ET/BT both indicate faster, more reliable vessel handling. This kind of attributes that protect liner schedules and are typically rewarded in port choice.

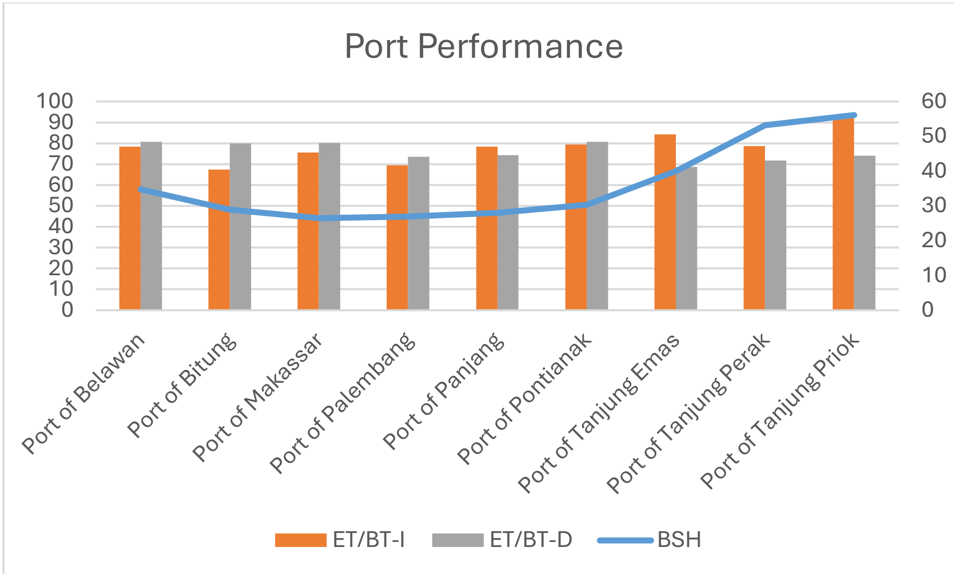


Figure 4.7. Performance each Port Effectivity and Productivity

(source: Pelindo Raports Data)

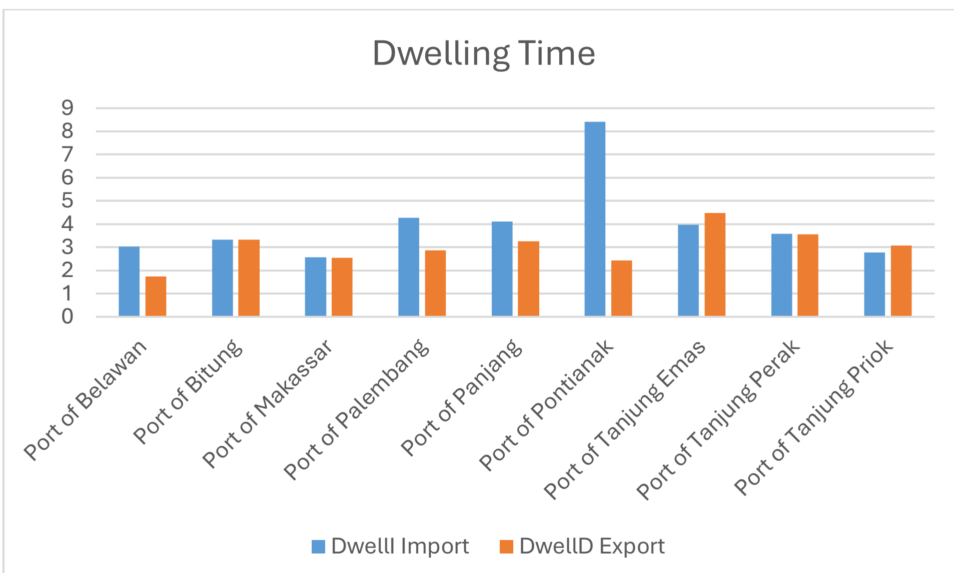


Figure 4.8. Port Dwelling time for International Import Activity and Domestic Export

(source: Pelindo Raports Data)

Import dwell is generally longer than export dwell, reflecting clearance processes and inland coordination. The spread is meaningful: Pontianak shows the longest import dwell (around eight days), while Makassar and Tanjung Emas are shorter. Tanjung Perak and Belawan sit in a mid–upper band. These differences translate directly into inventory and buffer costs for users and help explain variations in relative utility if other factors are held constant.

In sum, the figures reveal a consistent story: connectivity is concentrated in the main Java hubs; operational intensity and berth-time effectivity peak at Tanjung Perak and Tanjung Priok; and dwell performance is heterogeneous, with some outer-island gateways facing longer import clearance. These dimensions form the determinants used later in Δ-form to explain the observed differences in provincial port choice.

4.1.3 Domestic Transport from Port to Demand Region

Domestic access is measured along the feasible chain from gateway port i to the GDP-weighted centroid of region j. Four routing patterns are distinguished in the data: (1) inland trucking only (same island), (2) direct-call feeder plus inland, (3) feeder with one transit stop plus inland, and (4) feeder with vessel change plus inland. Not all transportation in the same island using inland transportation. If there are two kinds of possibility route by road or sea with the available direct call (without transit), the cost and time is compared and choose the minimum one.

This heatmap compares, for every Indonesian province (rows), how suitable each major gateway port (columns) is as a serving node; the shade shows the relative cost/access score, and the white dot marks the best port for that province. A clear West–Java–Sumatra pattern emerges: Belawan anchors North/West Sumatra and often Aceh; Palembang and Panjang pick up South Sumatra, Jambi, Bengkulu and Lampung; Pontianak naturally serves West Kalimantan. On Java, hinterlands align tightly with their home gateways, Tanjung Priok for DKI Jakarta/Banten/West Java, Tanjung Emas for Central Java (and often Yogyakarta), and Tanjung Perak for East Java, showing less need for transshipment to reach these dense markets.

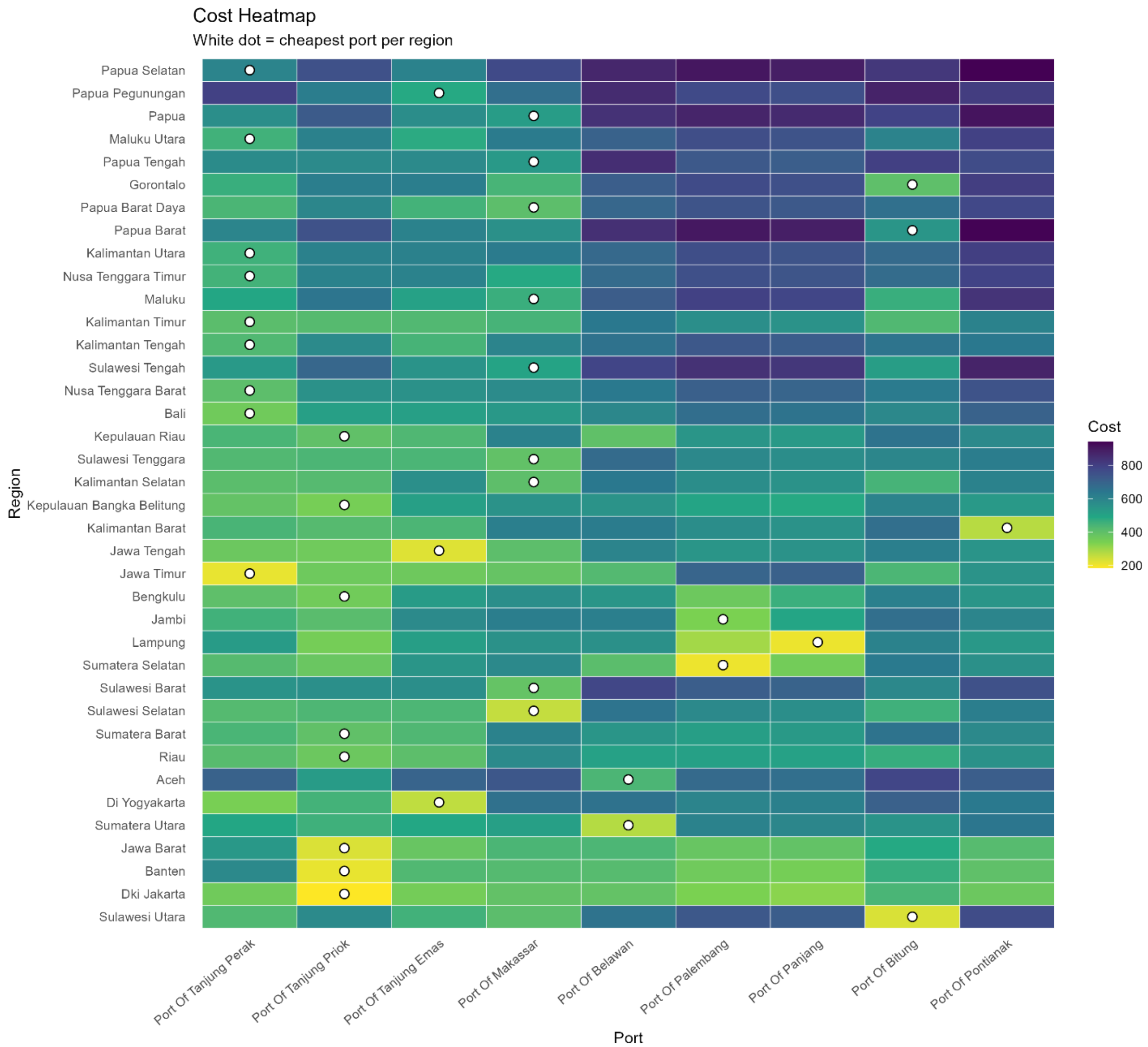


Figure 4.9. Cost Heatmap from Port to Demand Region Area

(source: author's calculations)

East of Java, the network becomes more polycentric. Makassar dominates much of Sulawesi and frequently parts of Nusa Tenggara and Maluku, while Bitung captures the far-north (e.g., North Sulawesi, Gorontalo). For Nusa Tenggara, Maluku and Papua provinces, dots often fall under Tanjung Perak or Makassar, reflecting their role as primary hubs feeding the eastern archipelago; a few areas split between two gateways, indicating overlapping, competitive catchments. Overall, the dots trace a hub-and-feeder system with five main gateways which are Priok, Perak, Emas, Makassar and Belawan, while Bitung, Pontianak, Palembang and Panjang play targeted regional roles where proximity or direct coastal access lowers the door-to-door cost.

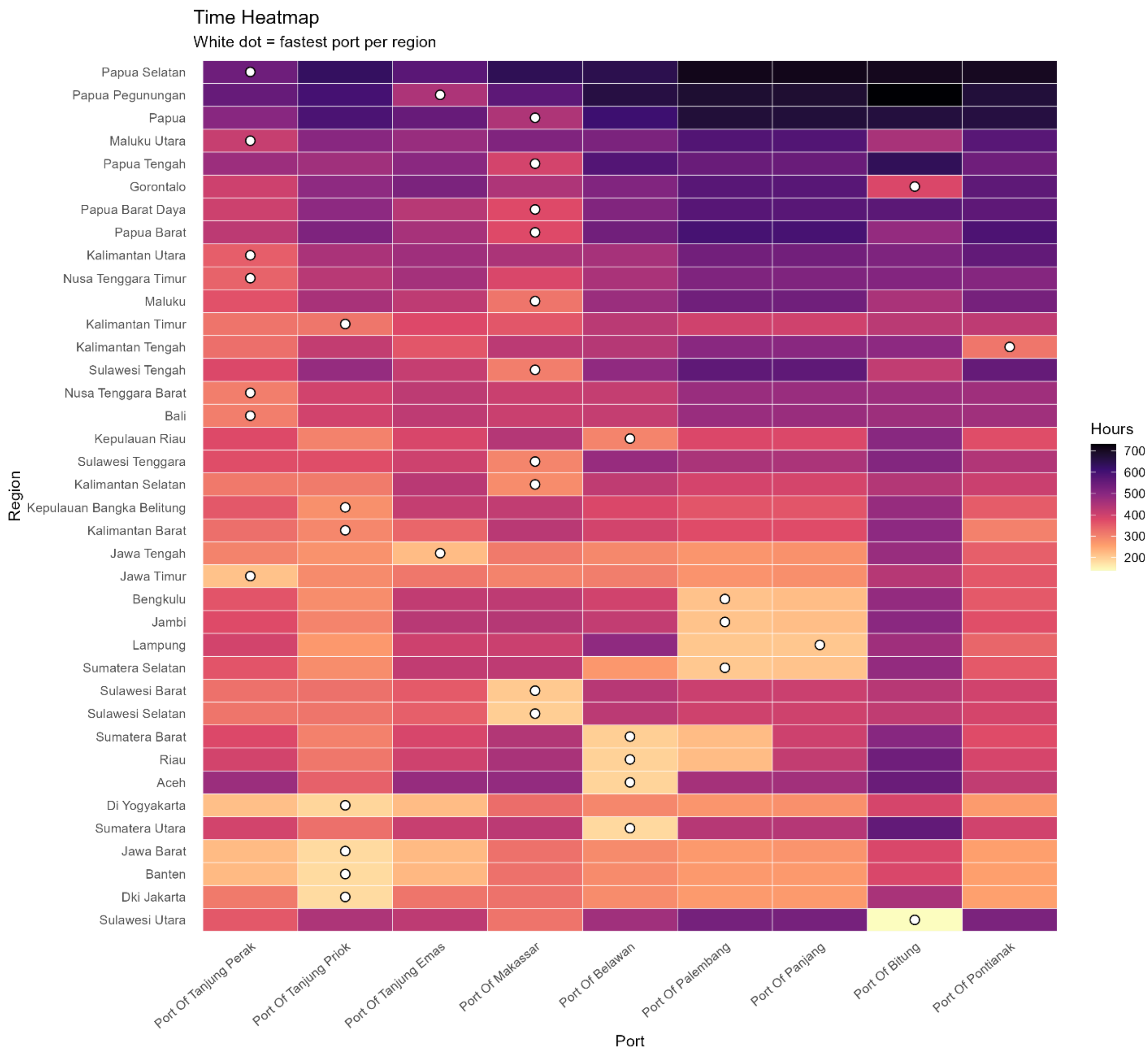


Figure 4.10. Time Heatmap from Port to Demand Region Area

(source: author's calculations)

This heatmap shows the travel time from each province (rows) to each gateway port (columns): light colors mean shorter time, dark colors mean longer time, and the white dot marks the fastest gateway for that province. The pattern is clear and matches the earlier cost heatmap: in the west, Tanjung Priok is fastest for DKI, Banten, and West Java; Tanjung Emas for Central Java (often DI Yogyakarta); Tanjung Perak for East Java; Belawan for the north of Sumatra; Palembang and Panjang for the south of Sumatra; Pontianak for West Kalimantan. In the east, Makassar is the natural fast hub for most of Sulawesi and parts of Nusa Tenggara/Maluku, while Bitung serves the far north; for Maluku and Papua, Perak or Makassar often minimize time because feeder distances are shorter than routing via Jakarta.

Comparing the cost and time heatmaps shows a broadly consistent picture of gateway choice across Indonesia: both maps point to Tanjung Priok for DKI, Banten, and West Java; Tanjung Emas for Central Java (often DI Yogyakarta); Tanjung Perak for East Java and much of the eastern archipelago; Belawan for North/West Sumatra; Palembang and Panjang for the southern Sumatran belt; Pontianak for West Kalimantan; Makassar for most of Sulawesi and parts of Nusa Tenggara/Maluku; and Bitung for the far north. Differences appear mainly at the edges of these catchments: some provinces in Nusa Tenggara, Maluku, and Papua select Perak on the cost map but Makassar on the time map; in central–southern Sumatra, a few rows prefer Palembang/Panjang by cost but Belawan by time; and within Kalimantan, the least-cost and least-time dots alternate among Pontianak, Makassar, and Perak. Where both maps show similar light tones and the dot in the same column, the gateway is a clear leader; where tones are mid and dots move between columns, the choice is mixed and more than one gateway is competitive.

4.2 Correlation and Collinearity Diagnostics

This subsection examines relationships among the candidate determinants of port choice to avoid redundancy and ensure stable estimation in Chapter V. Two diagnostics are applied. First, a pairwise correlation analysis identifies variables that carry the same signal (e.g., direct mainline calls vs. weekly sailing frequency; boxes per ship-hour vs. turnaround time; berth depth vs. typical vessel size; inland cost vs. inland time; feeder cost vs. feeder time). Second, a multicollinearity screen based on Variance Inflation Factors (VIF) is run on the final Δ–form covariates (differences to the reference port), which are the regressors used with ΔUij.

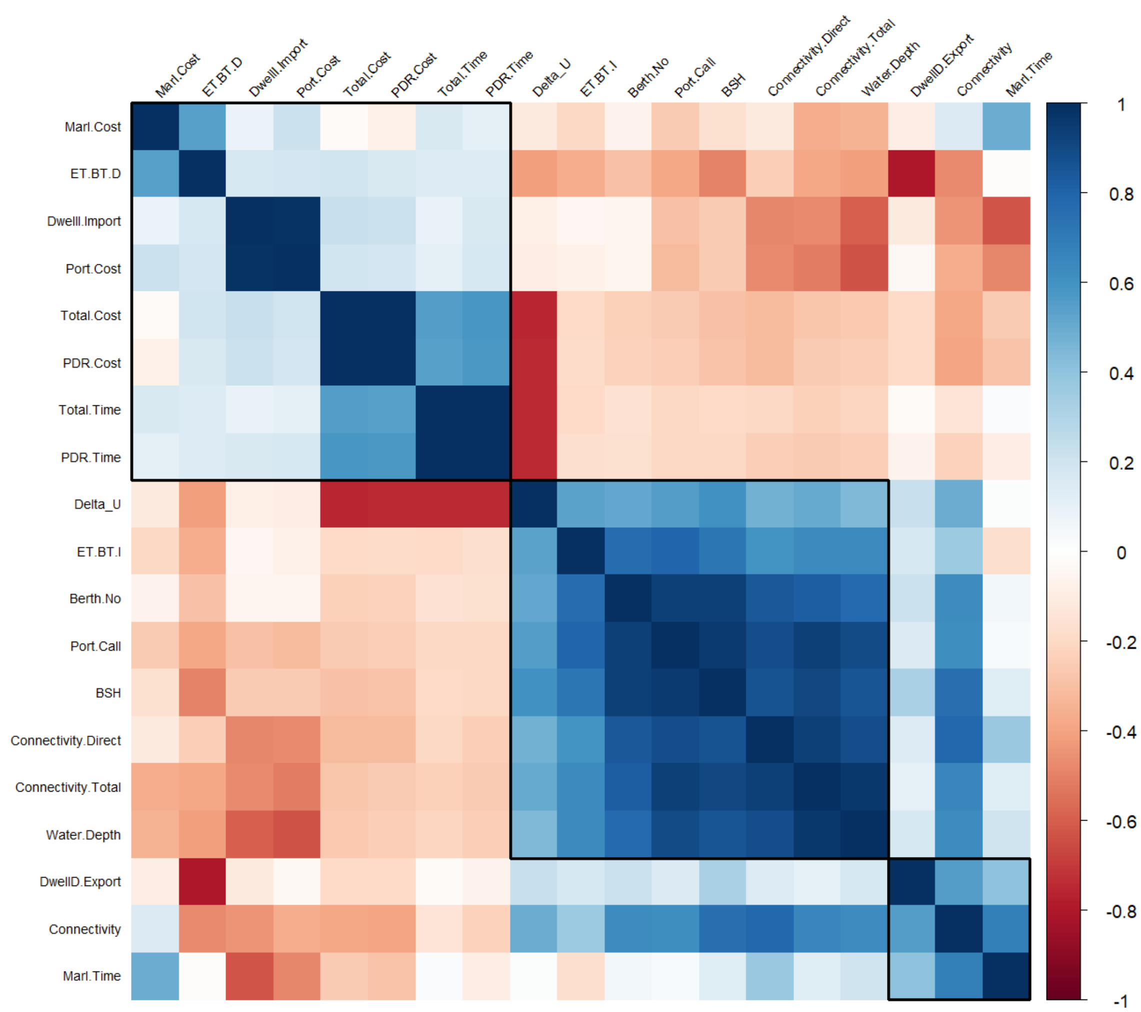


Figure 4.11. Pearson Correlation matrix between variables

(source: author's calculations)

The correlation map is a quick way to see which variables move together. Blue squares mean two variables that increase or decrease at the same time; red means when one goes up the other tends to go down; white is little or no link. Three patterns stand out. First, the “performance” measures—total cost, route cost, maritime cost and their time versions—are dark blue with each other, showing that time and cost largely tell the same story. Second, the “port scale/connectivity” measures—port calls, number of berths, productivity (BSH), connectivity (direct/total) and water depth—also cluster tightly together, meaning big, busy, well-connected ports share the same signal. Third, a few variables bridge the two groups: on-port delays (e.g., entry-to-berth time, import dwell) relate to performance, while the utility gap (Delta_U) is negative against cost/time, as expected.

Because many variables inside each group are saying almost the same thing, using too many of them at once will create collinearity which the model cannot tell which one deserves the credit, coefficients become unstable, and standard errors inflate. The remedy is simple and practical: pick one or two representatives from each highly related set (e.g., keep Total Time or Total Cost, not both; keep Port Calls or Connectivity Total, not all connectivity proxies), or combine them into a single index/factor for “performance,” “port scale/connectivity,” and “delay.”

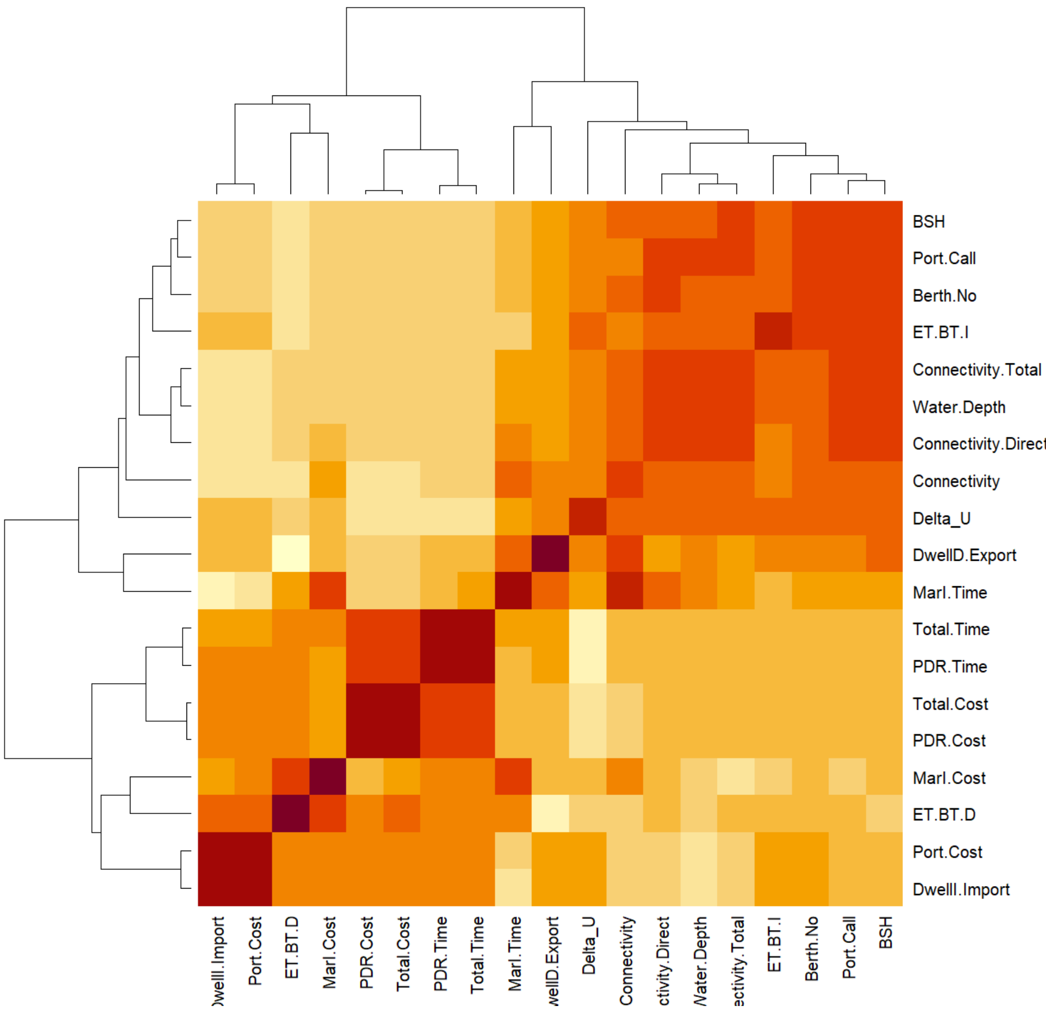


Figure 4.12. Pairwise correlation heatmap between variables Port Choice

(source: author's calculations)

This is a pairwise correlation heatmap with hierarchical clustering. Darker orange/red squares mean a stronger positive association between two variables: pale/yellow means weak or negative association. The dendrograms group variables that move together.

What stands out is three clear clusters:

1. Cost–time cluster — *Total.Cost, PDR.Cost (port→demand-region), Marl.Cost (maritime), Port.Cost* and their time counterparts (*Total.Time, PDR.Time, Marl.Time*) are tightly linked (deep red among them), and each cost variable aligns strongly with its matching time variable (e.g., Marl.Cost ↔ Marl.Time).

2. Port-operations cluster — *DwellI.Import, DwellD.Export, ET.BT.D/I (entry-to-berth times), Port.Cost* sit together; longer dwell/berth times co-vary with higher total time and, to a lesser degree, higher total cost.

3. Scale/connectivity cluster — *BSH (berth/ship-hour productivity), Port.Call, Berth.No, Connectivity, Connectivity.Direct, Connectivity.Total, Water.Depth* correlate strongly with one another (busy, deeper ports tend to have more links and calls) but only mildly with the dwell/berth delays and the cost–time block, indicating that network scale and nautical capacity are a different dimension from door-to-door performance.

A bridging metric, Delta_U (utility gap/advantage of the chosen gateway), shows moderate ties to *Total.Time/Cost* and weaker ties to the connectivity block, consistent with it summarizing overall door-to-door attractiveness rather than infrastructure scale. Overall, the map says: costs and times move together, operational delays are the main on-port drivers of those times, and large, well-connected ports cluster together but are not automatically the least-time/least-cost options to every region.

4.3 Regression Results

This section reports the linear ΔU regression used as a cross-check before the discrete-choice estimation. The dependent variable is the relative utility of port i for region j constructed from the Base OD Matrix probabilities. The right-hand side contains the Δ-determinants, which is the differences in attributes of port i versus the reference port r for the same region j. The estimated specification is:

$$\begin{aligned}\Delta U_{ij} = {} & \beta_1 \Delta PC_{ij} + \beta_2 \Delta MCI_{ij} + \beta_3 \Delta MTI_{ij} + \beta_4 \Delta PRC_{ij} + \beta_5 \Delta PRT_{ij} \\ & + \beta_6 \Delta TC_{ij} + \beta_7 \Delta TT_{ij} + \beta_8 \Delta EI_i + \beta_9 \Delta ED_i + \beta_{10} \Delta DII_i \\ & + \beta_{11} \Delta DDE_i + \beta_{12} \Delta BSH_i + \beta_{13} \Delta BN_i + \beta_{14} \Delta WD_i \\ & + \beta_{15} \Delta CO_i + \beta_{16} \Delta COD_i + \beta_{17} COT_i + \beta_{18} \Delta PC_i + \varepsilon_{ij}\end{aligned} \quad \ldots(20)$$

Where:

Abbreviations	Determinants compared to reference port
ΔPC	$PortCost$
ΔMCI	$MarICost$
ΔMTI	$MarITime$
ΔPRC	$PDRCost$
ΔPRT	$PDRTime$
ΔTC	$TotalCost$
ΔTT	$TotalTime$
ΔEI	ET/BTI
ΔED	ET/BTD
ΔDII	$DwellIImport$
ΔDDE	$DwellDExport$
ΔBSH	BSH
ΔBN	$BerthNo$
ΔWD	$WaterDepth$
ΔCO	$Connectivity$
ΔCOD	$Connectivity.Direct$
ΔCOT	$Connectivity.Total$
ΔPCL	$PortCall$

In this study, the Port of Bitung is selected as the reference category in the port choice model. As one of the smallest international container gateways among the nine observed ports, Bitung currently handles limited import flows and offers relatively weaker connectivity compared to major hubs such as Tanjung Priok or Tanjung Perak. Using Bitung as the reference provides a neutral baseline that anchors the utility scale at a low-competitiveness port, allowing the coefficients of other ports to be interpreted as relative improvements in utility compared to this benchmark. This approach not only ensures statistical stability in the estimation but also offers policy relevance by highlighting the extent to which other Indonesian ports outperform Bitung in terms of connectivity, maritime access, and operational performance, thereby illustrating the structural gap that must be addressed for eastern gateways to become more competitive.

We use hierarchical (blockwise) multiple regression, in which conceptually related predictors are entered in pre-planned steps so we can see each block's incremental value over the previous model; the order is chosen by theory rather than by an automatic algorithm. In reporting, we focus on each coefficient's sign (direction of effect), its t-value and significance, and the model's (adjusted) R^2, which are standard outputs for interpreting contribution and overall fit. We then compare the steps to identify a best variable pair: two predictors that (i) keep a stable, sensible sign across specifications, (ii) remain statistically meaningful (t-values) when controls are added, and (iii) yield a noticeable improvement in R^2 with minimal redundancy.

4.3.1 Regression Results

The regression is started by using Total Time and Total Cost as predictors. This combination is taken by recognizing that the Base OD Matrix is constructed using these predictors. Both variables showed strong negative and highly significant coefficients. This means that longer door-to-door transport times and higher overall costs reduce the relative utility of a port, exactly as expected. The intercept was positive and significant, which suggests that even when time and cost differences are zero, there remains some baseline advantage in utility that is not yet explained by these variables. The adjusted R^2

of 0.72 shows that these two variables alone already explain most of the variation in the choice of ports, forming the backbone of the model.

The second step replaced the totals with maritime time, port-to-demand-region time, and inland costs—and added service quality variables such as connectivity, ship productivity (BSH), berth effectivity (ET.BT.I), and water depth. Connectivity, BSH, and ET.BT.I all had positive and significant coefficients, indicating that better network integration and faster ship working increase a port's attractiveness. Maritime and inland times and costs were negative and significant, consistent with theory. Interestingly, water depth came in as negative and significant, which is counter intuitive. This most likely reflects collinearity, since large, deep ports are also the ones with higher connectivity and productivity, making the depth variable flip in sign when entered together. The intercept remained significant but was smaller than in the first step. The adjusted R^2 rose sharply to 0.94, showing a major improvement in explanatory power.

In the third step, the model kept maritime and inland time and cost variables, berth effectivity (ET.BT.I), connectivity, and water depth, but dropped BSH. Connectivity remained strongly positive and significant, and ET.BT.I was also positive and significant, while maritime time, inland time, and inland cost continued to be negative and highly significant. Water depth, however, stayed negative and significant, which is inconsistent with theory: deeper ports should be more attractive, not less. This unexpected sign is likely the result of multicollinearity, because water depth overlaps with connectivity and productivity characteristics of large ports. Dropping BSH may have pushed water depth to absorb some of the same explanatory power, producing the unlogic negative coefficient. Even so, the adjusted R^2 rose to about 0.95, the highest across all steps, showing that statistically the model explains the most variation here, even if one coefficient contradicts expectations.

In the fourth step, water depth was dropped from the model and export dwell time (DwellD.Export) was added. The inland and maritime cost and time variables kept their expected negative and significant signs, while connectivity and berth effectivity (ET.BT.I) continued to be positive and significant. Export dwell time entered with a negative sign, suggesting that longer export dwell reduces utility, which is consistent with intuition. However, the variable for port calls appeared with a negative and significant coefficient, which is not logical. Normally, more calls should make a port more attractive by improving service options. This unexpected sign indicates that port calls are highly correlated with the composite connectivity variable, so once connectivity is already in the model, the residual effect of port calls may capture congestion or collinearity rather than genuine attractiveness. The adjusted R^2 remained very high at around 0.94, showing that the model still explains most of the variation in port choice despite the odd behaviour of the port call variable.

The fifth step shifted focus towards infrastructure and the sea leg by including the number of berths and maritime cost more explicitly. The results showed that the number of berths was negative and weakly significant, which again reflects collinearity with other port size and connectivity indicators. Maritime time remained strongly negative, and maritime cost was also negative and significant. Overall, the model explained less of the variation, with an adjusted R^2 of 0.88, indicating that this combination of variables is less effective than earlier steps.

In the sixth step, the model includes connectivity, ET.BT.I (berth-time effectivity), maritime time, maritime cost, and import dwell (DwellI.Import). Maritime time and maritime cost keep the expected negative and significant signs, showing that longer sea passage or higher sea-leg cost lowers a port's relative utility. ET.BT.I remains positive and significant, meaning that a higher share of productive berth time raises utility. However, DwellI.Import enters with a positive coefficient, which is not logical because longer import dwell should reduce utility. This sign inversion is a common symptom of overlap among time/performance variables: once connectivity and ET.BT.I (and sea-leg time/cost) are in the model, import dwell can become a residual proxy for "big busy ports" rather than pure delay, flipping its partial effect. The very low adjusted R^2 (≈ 0.42) confirms that this specification is unstable and explains little of ΔU compared with earlier models.

The seventh step focused on import dwell time rather than export dwell. Import dwell showed inconsistent signs across different versions, sometimes positive and sometimes strongly negative, which means it is not a robust determinant once other indicators of time, cost, and performance are controlled. Other time and cost variables remained correctly signed, but the adjusted R^2 was only 0.48, confirming that this specification is unstable and not reliable.

In step eight, connectivity and ET.BT.I are positive and highly significant, so stronger network links and more productive berth time both increase a port's relative utility. MarI.Time, PDR.Time, and PDR.Cost are negative and highly significant, confirming that more time or inland cost reduces the chance a port is chosen. Port.Call is negative and significant, which is odd and economically illogic. The intercept is positive and significant, and adjusted $R^2 \approx 0.909$, meaning this compact specification explains most variation.

Step 9 keeps the same backbone: Connectivity (positive, highly significant), ET.BT.I (positive, significant), Maritime Time (negative, highly significant), PDR.Time (negative, highly significant), and PDR.Cost (negative, highly significant). It also includes Port.Call, which again has a negative and significant coefficient for the same overlap reason as in Step 8. Importantly, Maritime Cost is not included in this step, so there is no sign issue to interpret for that variable here. The intercept is not significant, which is desirable in a Δ-utility setting because it indicates no remaining baseline bias. The adjusted R^2 rises to about 0.939, showing very strong explanatory power with a clean behavioural story: better connectivity and berth effectivity increase utility, whereas longer times and higher inland costs reduce it.

The final step maintains the core variables: Connectivity and ET.BT.I remain positive and significant; Maritime Time, PDR.Time, and PDR.Cost remain negative and highly significant; and Port.Call stays negative and significant due to its overlap with the Connectivity index. The intercept is again not significant, which fits the Δ-utility framework. The adjusted R^2 is about 0.935, just below Step 9, but with the same stable and intuitive interpretation.

Table 4.1. Regression Result for 10 Step Model

(source: author's calculations)

Variable	Step_1	Step_2	Step_3	Step_4	Step_5	Step_6	Step_7	Step_8	Step_9	Step_10
(Intercept)	3.524*** (21.7)	0.839*** (4.8)	0.110 (0.8)	-0.189 (-1.1)	1.528*** (7.4)	1.143* (2.1)	0.811. (1.8)	1.454*** (9.2)	-0.114 (-0.7)	0.174 (1.0)
Berth.No					-0.024* (-2.2)		0.020 (0.5)			
BSH		0.115*** (4.9)						0.376*** (11.9)		
Connectivity		0.229*** (9.2)	0.296*** (24.0)	0.307*** (18.6)	0.128*** (7.1)	0.288*** (6.6)	0.613*** (11.4)		0.301*** (20.1)	0.260*** (19.9)
Connectivity. Total							-0.383* (-2.0)			
DwellD.Export					-0.456** (-2.8)	-1.054** (-2.7)		0.014 (0.1)		
DwellI.Import						0.477*** (3.4)	-1.269*** (-3.9)			
ET.BT.I			0.113*** (8.8)	0.117*** (7.5)	0.255*** (12.1)	0.256*** (5.1)			0.114*** (7.4)	0.069*** (5.5)
Marl.Cost						-0.073*** (-3.3)	0.080** (2.8)			

Marl.Time		-0.158*** (-13.2)	-0.170*** (-22.5)	-0.188*** (-17.9)			-0.405*** (-9.3)	-0.084*** (-13.4)	-0.182*** (-21.2)	-0.167*** (-20.3)
PDR.Cost		-0.010*** (-23.1)	-0.010*** (-24.4)	-0.010*** (-23.9)	-0.009*** (-15.2)			-0.010*** (-20.5)	-0.010*** (-23.9)	-0.010*** (-23.3)
PDR.Time		-0.017*** (-25.1)	-0.017*** (-26.8)	-0.016*** (-24.3)	-0.018*** (-19.1)			-0.017*** (-21.1)	-0.016*** (-24.8)	-0.016*** (-23.8)
Port.Call				-0.001*** (-4.6)		-0.001 (-0.9)		-0.003*** (-6.6)	-0.001*** (-4.8)	
Port.Cost				-0.033 (-1.0)	0.321*** (7.6)					
Total.Cost	-0.012*** (-14.3)									
Total.Time	-0.019*** (-13.6)									
Water.Depth		-0.354*** (-6.4)	-0.282*** (-7.8)							
Adjusted R2	**0.719**	**0.937**	**0.945**	**0.939**	**0.876**	**0.42**	**0.482**	**0.909**	**0.939**	**0.935**

Across the ten-step regression, the combination of PDR Time, PDR Cost, Connectivity, Marl time and ET.BT.I predictors give the best fit to the model with consistent logical sign. Regression step_3 gives the highest R Squared result, but water depth variable is not showing consistent sign since the more water depth the utility to choose certain port should be increased (not decreased as the regression result).

4.3.2 Model Validation

Model validation is started by finding another the best pair of variables to explain the delta U. One way to do this is by doing constrained best-subsets regression for every candidate subset of predictors you (i) fit an OLS model for ΔU, (ii) filter it out if multicollinearity is high (VIF > 5), (iii) filter it out if any coefficient violates your theory-driven sign constraints (e.g., delays ≤ 0, connectivity ≥ 0), and (iv) among the models that pass both screens, rank by our objective find the best fit model which is have maximize R Squared. The result will give a feasible set of models that are statistically clean (low collinearity) and behaviorally consistent (right signs). The top 15 highest R-Squared from this method is as follows:

Table 4.2. Top 15 Highest R-Squared constrained best-subsets regression

(source: author's calculations)

No.	k	Variable predictors Pair	R Squared	Adj R Squared
1	6	Connectivity, DwellD.Export, Total.Cost, PDR.Time, Marl.Time, ET.BT.I	0.931551	0.930325
2	5	Connectivity, Total.Cost, PDR.Time, Marl.Time, ET.BT.I	0.931333	0.930312
3	5	Connectivity, Total.Time, Total.Cost, Marl.Time, ET.BT.D	0.925787	0.924683
4	5	Connectivity, DwellD.Export, Total.Time, Total.Cost, Marl.Time	0.925435	0.924326

5	4	Connectivity, Total.Time, Total.Cost, MarI.Time	0.925168	0.924279
6	5	BSH, Total.Time, Total.Cost, MarI.Time, ET.BT.I	0.895576	0.894022
7	4	BSH, Total.Cost, PDR.Time, MarI.Time	0.890352	0.88905
8	4	BSH, Total.Time, Total.Cost, ET.BT.I	0.886721	0.885376
9	5	DwellD.Export, BSH, Total.Cost, PDR.Time, ET.BT.I	0.876359	0.874519
10	6	Connectivity, DwellD.Export, Port.Call, Total.Time, Total.Cost, ET.BT.I	0.874621	0.872376
11	7	Connectivity, Berth.No, DwellD.Export, Total.Time, Total.Cost, MarI.Cost, ET.BT.I	0.874273	0.871638
12	6	Connectivity, Berth.No, DwellD.Export, Total.Time, Total.Cost, ET.BT.I	0.874148	0.871894
13	6	Connectivity, Berth.No, Total.Time, Total.Cost, MarI.Cost, ET.BT.I	0.87397	0.871712
14	4	Connectivity, Total.Time, Total.Cost, ET.BT.I	0.873888	0.872391
15	3	BSH, Total.Time, Total.Cost	0.872676	0.871546

From the result, the series of predictors that gives the highest R squared are Connectivity, DwellD Export, Total Cost, PDR Time, Maritime Time for International shipping, ET/BT for International Vessel. It's like from the best pair predictors from ten step method before unless there is one more addition of predictors, DwellD Export. If these predictors are regressed, the result is as follows:

Table 4.3. Regression result predictors with highest R Squared

(source: author's calculations)

Variable	Estimate	Std. Error	t value	p-value	Sig
(Intercept)	0.0995435	0.1571203	0.634	0.527	
Connectivity	0.2572087	0.0135350	19.003	<2e-16	***
DwellD.Export	-0.1131027	0.1096457	-1.032	0.303	
PDR.Time	-0.0160609	0.0007006	-22.923	<2e-16	***
Total.Cost	-0.0098145	0.0004462	-21.997	<2e-16	***
Marl.Time	-0.1433750	0.0085538	-16.762	<2e-16	***
ET.BT.I	0.0710858	0.0129934	5.471	8.78e-08	***
Residual standard error: 1.225 on 335 degrees of freedom Multiple R-squared: 0.9316, Adjusted R-squared: 0.9303 F-statistic: 759.9 on 6 and 335 DF, p-value: < 2.2e-16					

The result showed that Domestic Export Dwelling time doesn't give significant contribution to the model, thus we can neglect it to focus on 5 other significant predictors. To verify the best model whether using Total Cost and Total Time or PDR Cost and PDR Time, the compared table is shown below:

Table 4.4. Model Compared Table between Model A and Model B

(source: author's calculations)

Metric	Model A: ΔU ~ Connectivity + Total.Time + Total.Cost + Marl.Time + ET.BT.I	Model B: ΔU ~ Connectivity + PDR.Time + PDR.Cost + Marl.Time + ET.BT.I
ResidualStd. Error	1.225	1.183
R^2	0.9313	0.9360
Adjusted R^2	0.9303	0.9350
#Predictors (excl. intercept)	5	5
Coefficient signs	Conn(+) Time(–) Cost(–) Marl.Time(–) ET.BT.I(+)	Conn(+) PDR.Time(–) PDR.Cost(–) Marl.Time(–) ET.BT.I(+)

Both models have corrected signs and highly significant coefficients, but Model B (with PDR.Time and PDR.Cost) fits better: higher R^2/Adj-R^2 and lower residual error with the same complexity, so its AIC/BIC would also be lower. Interpretation-wise, the route-specific PDR measures carry more useful information than the aggregate Total measures. I'd report Model B as the main specification and keep Model A as a robustness check.

The next validation is by checking the collinearity of the model with the result as below:

Table 4.5. VIF Test for several variables

(source: author's calculations)

Variable	VIF
Connectivity	3.562472
PDR.Time	1.519807
PDR.Cost	1.698309
Marl.Time	3.134939
ET.BT.I	1.917163

These VIFs look healthy which show **all variables VIF < 5** (and well below the stricter "problematic" >10 rule), so multicollinearity is **not** a concern in this specification. Connectivity and International Shipping Maritime Time share some overlap with the rest (as expected given network scale vs. time/cost), but still within comfort. With VIFs in this range, coefficient signs and t-values should be stable; all variables are acceptable for collinearity reasons.

CHAPTER V

ANALYSIS AND DISCUSSION

5.1. Port-Choice Probabilities

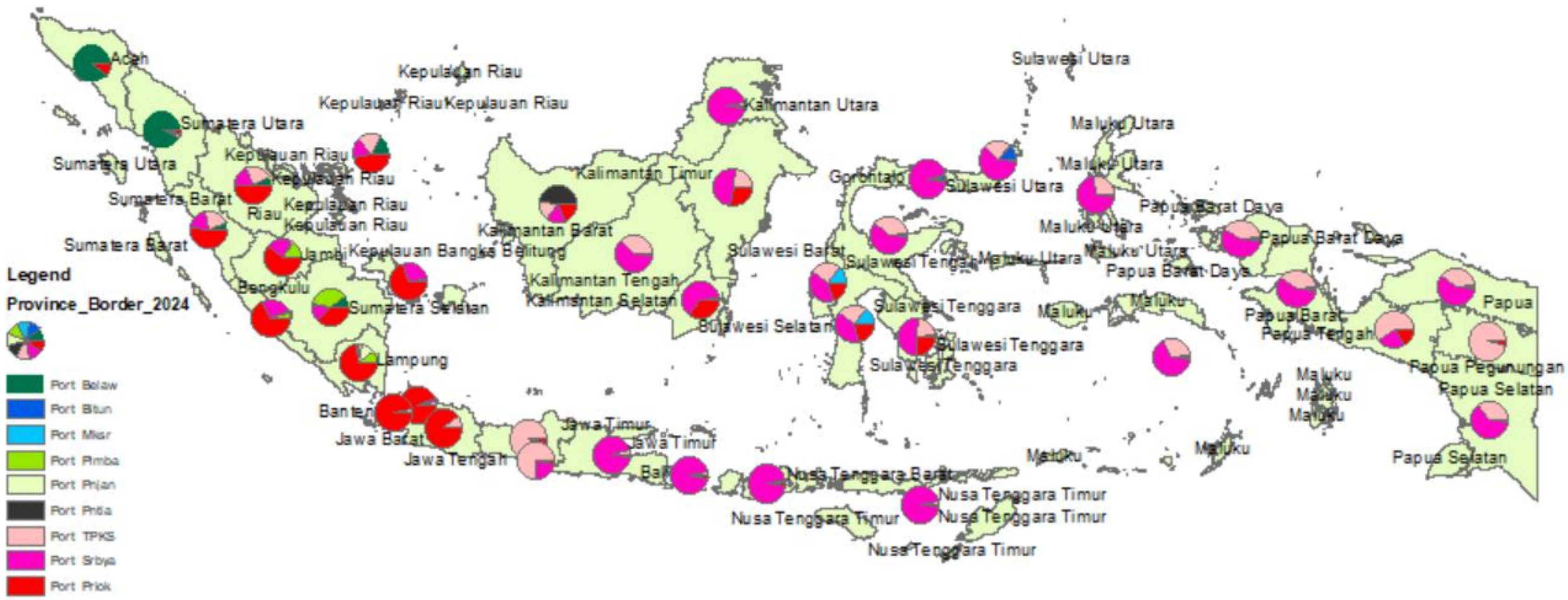


Figure 5.1. Port Choice Probability in Indonesia

(source: author's calculations)

The figure presents the market share distribution of Indonesian container ports across different provinces. Each pie chart represents the division of container flows handled by major national ports, while the color coding reflects individual ports such as Tanjung Priok (red), Tanjung Perak (orange), Belawan (dark green), Makassar (light green), and others. By visualizing port market shares at the regional level, the map provides a clear picture of how container flows are distributed across the archipelago and highlights the degree of concentration in specific ports based on Base OD Matrix.

A key observation is the dominant position of Tanjung Priok (red) in Java and across the nation. Its market share extends well beyond its immediate hinterland in West Java, influencing flows from provinces in Sumatra, Kalimantan, and eastern Indonesia. This reflects the central role of Tanjung Priok as Indonesia's main international gateway, reinforced by its extensive service connectivity and proximity to the Malacca Strait. The visualization confirms the empirical finding that connectivity and maritime access remain the strongest determinants of port choice.

The map also shows significant shares for Tanjung Perak in East Java (orange), which emerges as the secondary hub serving both eastern Indonesia and some parts of central Java. Its influence reaches Bali, Nusa Tenggara, and Sulawesi, underscoring its role as the primary eastern gateway. However, while Tanjung Perak captures a large hinterland, it remains secondary to Tanjung Priok in total market share, reflecting the continued concentration of flows in the western part of the country.

Regional ports such as Belawan in North Sumatra and Makassar in South Sulawesi also capture visible shares within their respective territories. Belawan serves the northern Sumatra region but competes with Tanjung Priok for long-haul international flows, while Makassar consolidates much of the inter-island trade in eastern Indonesia. Their shares illustrate the dual role of Indonesian ports: serving as both gateways to international networks and facilitators of domestic inter-island connectivity. Yet, compared to Java-based hubs, their reach across provinces is more limited.

Finally, the overall pattern highlights the high centralization of Indonesian container trade, with a few large ports controlling most flows while many provincial ports play only marginal roles. This imbalance reflects structural issues in Indonesia's maritime system: uneven distribution of connectivity, reliance on feedering to major hubs, and infrastructure disparities. Policymakers aiming to achieve more balanced port development must address these gaps by improving connectivity for emerging ports like Patimban or Kuala Tanjung, which could redistribute flows and reduce overdependence on Tanjung Priok. The map thus not only visualizes current market shares but also underscores strategic challenges for Indonesia's long-term port planning.

5.2 Port Choice Model Interpretation

To understand the Port Choice model, we already developed Port Choice Model in table 4.1 in chapter 4 which are:

$$\Delta U_{ij} = 0.260\Delta CO + 0.069\Delta EI - 0.167\Delta MTI - 0.010\Delta PRC - 0.016\Delta PRT \quad \text{...(21)}$$

Where:

$\Delta U_{ij} = Relative\ Utility\ to\ Port\ Reference$

$\Delta CO = Relative\ connectivity\ to\ Port\ reference$

$\Delta EI = Relative\ Berth\ Service\ effectivity\ of\ International\ Vessel\ to\ Port\ reference$

$\Delta MTI = Relative\ International\ Maritime\ Time\ to\ Port\ reference$

$\Delta PRC = Relative\ Port\ to\ Demand\ Region\ Cost\ to\ Port\ reference$

$\Delta PRT = Relative\ Port\ to\ Demand\ Region\ Time\ to\ Port\ reference$

The estimated utility model highlights the relative influence of connectivity, service effectiveness, and transport impedances on port choice in Indonesia. The positive coefficient for feeder connectivity (ΔCO, β=0.260) indicates that stronger network connections to a port significantly increase its attractiveness compared to the reference port. Similarly, berth service effectiveness of international vessels (ΔEI, β=0.069) has a positive but smaller effect, suggesting that higher operational effectivity at the quay improves the port's relative competitive position. In contrast, international maritime time

(ΔMTI, β=–0.167) reduces port attractiveness: longer sailing distances or voyage times make a port relatively less preferred.

On the hinterland side, both port–region transport cost (ΔPRC, β=–0.010) and transport time (ΔPRT, β=–0.016) negatively influence relative utility, confirming that higher inland expenses and delays weaken a port's competitiveness. Among the determinants, connectivity and maritime time stand out as the most influential, meaning that shipping lines and shippers weigh network accessibility and voyage duration more heavily than hinterland costs when making routing or port choice decisions. Overall, the results confirm that port choice in the Indonesian context is shaped by a combination of maritime accessibility and inland logistics performance, but the maritime leg exerts relatively stronger explanatory power.

5.3 Sensitivity Analysis

In this sensitivity analysis, we will see the effect of each determinant to the change of port choice. To assess the sensitivity of each determinant in a port choice model, the change in relative utility from a marginal variation of an explanatory factor can be translated into a change in choice probability. Discrete choice theory treats the probability of selecting alternative i over a reference j as a bounded outcome, constrained between 0 and 1. This is achieved through the logistic transformation of the latent utility difference, such that:

$$\Delta U_{ij} = ln\ P_{ij} - \ln P_{ref} = \ln\left(\frac{P_{ij}}{P_{ref}}\right) \quad \ldots(22)$$

$$P_{ij} = \frac{1}{1 + \exp\left(-U_{ij}\right)} \quad \ldots(23)$$

where ΔU_{ij} is the relative utility difference. Because the probability is a nonlinear S-shaped function of utility, the marginal effect of any determinant depends not only on its coefficient but also on the current level of probability. Formally, the derivative is:

$$\frac{\partial P_{ij}}{\partial x_k} = P_{ij}(1 - P_{ij})\,\beta_k \quad \text{...(24)}$$

where β_k is the estimated coefficient of determinant X_k. This derivative provides the marginal sensitivity: the probability impact of a small change in a determinant.

The S-shape of the logistic function has a clear economic interpretation. When utility levels are balanced across alternatives (ΔU≈0), probabilities are near 0.5 and the slope is steep, meaning small changes in determinants strongly shift choice shares. At the extremes (ΔU≪0 or ΔU≫0), probabilities approach 0 or 1, and the slope flattens, implying diminishing marginal effects. In economic terms, once a port is already very unattractive or very dominant, incremental changes in attributes contribute little to shifting actual choice probabilities.

Therefore, sensitivity analysis in discrete choice models involves translating the coefficients of determinants into probability changes, and then into market share changes. When multiplied by total demand volumes, these probability shifts lead to quantified changes in container flows. This chain—utility → probability → market share → flow—is grounded in random utility maximization theory, ensuring that the assessment respects the bounded nature of probabilities and the nonlinear response embedded in the logistic function.

To find out the change of probability, we assume if there is determinant change as follows:

Tabel 5.1. Determinant Change Scenario

(source: author's calculations)

Po (Initial Probability)	Δ P				
	Connectivity (Beta=0.260)	PRT (Beta= -0.016)	EI (Beta = 0.069)	PRC (Beta = -0.010)	MTI (Beta = -0.167)
0.1	0.0234	0.00144	0.00621	0.0009	0.01503
0.2	0.0416	0.00256	0.01104	0.0016	0.02672

0.3	0.0546	0.00336	0.01449	0.0021	0.03507
0.4	0.0624	0.00384	0.01656	0.0024	0.04008
0.5	0.065	0.004	0.01725	0.0025	0.04175
0.6	0.0624	0.00384	0.01656	0.0024	0.04008
0.7	0.0546	0.00336	0.01449	0.0021	0.03507
0.8	0.0416	0.00256	0.01104	0.0016	0.02672
0.9	0.0234	0.00144	0.00621	0.0009	0.01503
Determinant Change	+1 connection	-1 hour travel time	+1% of ET/BT	-1 USD/teu Cost	-1 hour maritime time

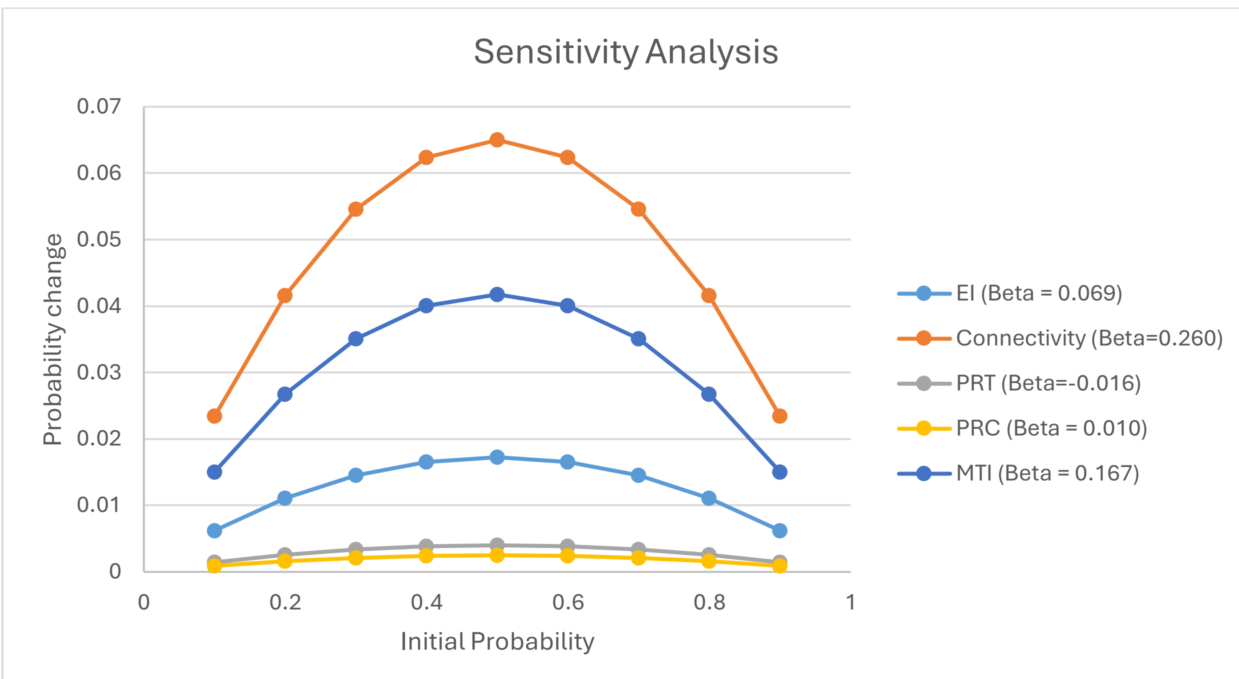


Figure 5.2. Sensitivity analysis results

(source: author's calculations)

The sensitivity analysis illustrates how changes in each determinant translate into probability shifts across different baseline levels of port choice probability (Po). The logistic function ensures that these effects are nonlinear, with the strongest impacts occurring at intermediate probabilities and diminishing at the extremes. This explains the arch-shaped curves observed in the figure: probability changes are largest around an initial probability of 0.5, and gradually decline when the initial probability approaches 0 or 1.

Across determinants, the magnitude of change reflects the estimated coefficients. Connectivity has the highest coefficient ($\beta = 0.260$) and therefore generates the largest probability response, reaching a maximum shift of more than six percentage points at mid-range probabilities. Maritime time ($\beta = -0.167$) and berth service effectiveness ($\beta = 0.069$) also show meaningful impacts, though with smaller magnitudes. By contrast, port-to-region cost ($\beta = -0.010$) and port-to-region time ($\beta = -0.016$) have very modest effects, producing only fractional changes in probability even at their peak.

From an economic interpretation, this result highlights that improvements in network connectivity and reductions in maritime time have the greatest leverage in shifting port choice, particularly when shippers are undecided between ports (probabilities around 50%). When a port is already dominant or unattractive, incremental changes in determinants exert only limited influence on market share and resulting container flows, consistent with the bounded and S-shaped nature of the logistic choice model.

5.4. Regression Model using another Port as reference

To verify the robustness of the model, regressions were also performed using a range of alternative ports as reference, with the detailed outcomes reported in Appendix 1.5. These specifications, based on Belawan, Tanjung Priok, Tanjung Emas, Panjang, Tanjung Perak, Makassar, Palembang, and Pontianak as base ports, produce results that are highly consistent with those obtained when Bitung is used as the reference. While the intercept and the overall fit statistics vary slightly depending on the choice of baseline, the coefficients for the main determinants remain stable in both sign and significance. Connectivity consistently raises port utility, while higher costs and longer times on the maritime and inland segments reduce it, and berth-time effectivity continues to exert a positive effect.

The consistency of these results confirms that the determinants of port choice are not dependent on which port serves as the base. In discrete choice modelling, one alternative must be normalized as the reference to avoid indeterminacy, which inevitably shifts the intercept but leaves the relative impacts of explanatory variables unaffected. The Indonesian regressions clearly reflect this property: although the zero point of utility shifts with the chosen reference, the coefficients describing the effects of cost, time, connectivity, and effectivity remain robust.

This stability carries methodological importance. It demonstrates that the model's explanatory power is anchored in genuine structural relationships rather than artefacts of specification. The consistently high explanatory fit across all versions, with R^2 values exceeding 0.92, indicates that the chosen variables capture most of the systematic variation in utility differences. Such robustness reinforces confidence that the estimates represent meaningful behavioral responses.

Overall, the additional regressions validate the reliability of the modelling framework. The determinants of port choice behave consistently across a variety of reference points, supporting the conclusion that the model captures stable and interpretable relationships. This outcome is in line with the conventions of discrete choice analysis, where coefficient stability across normalisations is taken as evidence that the specification reflects underlying decision processes rather than statistical coincidence (Train, K. (2009)).

5.5. Model Relevancies in Maritime Transportation and Indonesia's Context

The results of this study contribute directly to the literature on port choice and maritime logistics, which emphasizes how shippers and carriers allocate flows based on a combination of cost, time, service quality, and connectivity. The model confirms established findings in discrete choice research: probabilities are bounded, marginal effects depend on baseline conditions, and determinants such as connectivity, maritime time, and operational effectivity carry the greatest weight. By quantifying the probability shifts from improvements in these factors, the model provides an empirical bridge between theoretical port choice frameworks and policy applications. This is highly relevant to maritime transportation studies, where decision-making processes are often abstracted and require concrete quantification to inform infrastructure and service planning.

The sensitivity analysis further reinforces the economic logic of maritime competition. It shows that improvements matter most when ports are in direct competition with similar attributes, aligning with global evidence that competition among container gateways is most intense where services, costs, and times are closely matched. This finding is not only consistent with the S-shaped response of the logit model but also highlights practical implications for policymakers and operators in maritime systems worldwide: marginal investments are most effective in contested markets rather than at ports that are already dominant or marginal.

For Indonesia, the results are particularly significant because of the country's archipelagic geography and uneven demand distribution. With over 17,000 islands and a container demand structure heavily concentrated in Java and parts of Sumatra, the model reveals why domestic connectivity emerges as the most influential factor. Unlike continental economies where rail and road networks integrate hinterlands, Indonesia relies primarily on sea transport for inter-regional trade. This structural condition makes inter-island linkages decisive in shaping port competitiveness, confirming that strengthening feeder and coastal connections is critical to rebalancing flows beyond Java.

The strong role of maritime time also reflects Indonesia's position in global trade networks. Ports located closer to international shipping routes, such as Tanjung Priok and Belawan, are naturally advantaged compared to more peripheral eastern gateways. This aligns with Indonesia's reliance on the Malacca Strait as a conduit for imports from China, ASEAN, Japan, and South Korea, which together account for nearly 70% of its import volumes. Investments that reduce sailing times through more direct services or improved nautical operations therefore directly enhance port attractiveness.

Finally, the significance of berth effectivity underscores the operational challenges of Indonesian ports. Congestion and low productivity have long been identified as bottlenecks, particularly at high-volume hubs like Tanjung Priok and Tanjung Perak. The model confirms that improving vessel turnaround times is not just a matter of operational effectivity but a determinant of market share, with direct implications for national logistics costs. While inland transport cost and time are also significant, their lower marginal effect reflects the dominance of maritime accessibility in an archipelagic economic country.

Taken together, the model's results are highly relevant because they integrate global maritime transport theory with Indonesia's unique structural realities. They show that improving connectivity, maritime time, and berth effectivity are the most effective levers for shifting container flows and building a more balanced port system. For policymakers, the framework provides a predictive, evidence-based approach to prioritize investments, helping Indonesia avoid the risks of overbuilding underperforming ports or neglecting critical gateways. In this way, the model not only advances academic understanding of port choice but also delivers actionable insights for one of the world's most strategically positioned maritime nations.

5.6 Analysis and Recommendation

The port choice model provides Indonesian policymakers with a data-driven framework to prioritize investments in the nine ports that currently handle international import flows. The results demonstrate that the most effective levers for increasing market share are domestic connectivity, maritime time, and berth effectivity, while inland cost and time are significant but less decisive. This suggests that investment strategies should move beyond physical capacity expansion and instead focus on targeted measures that strengthen network integration and operational reliability.

First, strengthening domestic and feeder connectivity should be the top priority. Investments in coastal shipping routes, inter-island feeder services, and multimodal hinterland links will allow regional ports such as Belawan, Makassar, Pontianak, and Panjang to capture a greater share of demand from their surrounding provinces. This would help reduce Indonesia's overdependence on Tanjung Priok and Tanjung Perak, creating a more balanced and resilient port system.

Second, reducing international maritime time through direct services and improved nautical access offers a high impact. By securing additional mainline calls for Belawan and Makassar, and by reducing waiting times at major hubs, Indonesia can make peripheral ports more competitive in global liner networks. For ports in Sumatra and Kalimantan, geographic proximity to Singapore and Malaysia alone has not translated into competitiveness. In the absence of sufficient volume concentration, international connectivity, and operational reliability, these ports have historically been bypassed in favor of larger Java hubs such as Tanjung Priok or Tanjung Perak, despite being geographically closer to global shipping lanes.

Third, improving berth effectivity at high-volume hubs such as Port of Tanjung Priok, Port of Tanjung Perak, and Port of Tanjung Emas will generate immediate throughput gains without necessarily requiring new infrastructure. Digitalization, optimized berth allocation, modern equipment, and improved scheduling can reduce vessel turnaround times and enhance service reliability, directly influencing shippers' port choice.

By investing in these priority areas, Indonesia can achieve several outcomes. National logistics costs will decline, as shorter maritime times and more efficient port operations reduce total transport costs for shippers. Systemic risks will be reduced by distributing flows more evenly across multiple gateways, thereby avoiding overconcentration at Port of Tanjung Priok. Regional economic development will be strengthened, as improved connectivity allows provincial ports to handle a larger share of trade, stimulating local supply chains and reducing dependence on Java-based hubs. Finally, investment effectivity will improve, as funds are directed toward factors with the greatest marginal effect on market share and flow, minimizing the risk of overbuilding underutilized infrastructure.

In sum, the port choice model enables policymakers to move from reactive capacity expansion toward evidence-based, demand-driven investment planning. By aligning future port development with the determinants that most strongly shape port choice, Indonesia can build a port system that is not only larger, but also more efficient, resilient, and regionally inclusive.

CHAPTER VI

CONCLUSSION

6.1 Conclusion

This study applied a port choice model to identify the main factors shaping container flow distribution across Indonesia. The findings show that domestic connectivity exerts the strongest influence on port choice, confirming the critical role of inter-island linkages in reinforcing a port's attractiveness. Maritime time, defined as the duration of international vessel travel from origin to port, and berth effectivity in handling international vessels also emerge as significant determinants, emphasizing the importance of reliable access to global shipping lanes and efficient port operations. Transport cost and time from port to demand regions are likewise significant, but their marginal effects are smaller in comparison, suggesting that shippers place greater weight on maritime accessibility and port integration than on hinterland logistics alone.

These results highlight important implications for Indonesia's port development strategy. The analysis demonstrates that competitiveness depends not only on expanding capacity, but also on strengthening domestic connectivity, reducing maritime transit times, and improving operational effectivity at the berth. At the same time, inland transport cost and time remain relevant, particularly where hinterland access is a constraint, but they are unlikely to decisively alter port choice without corresponding improvements in seaborne connections. The non-linear nature of the logit framework further indicates that competitive shifts are greatest when ports are closely matched in attributes, offering policymakers clear guidance on where targeted interventions can achieve the most impact. In this way, the model provides a quantitative tool to align national port development with actual trade dynamics and reduce investment risks in Indonesia's evolving maritime system.

Having established the overall model and its main results, the chapter now turns to the sub-research questions to provide more specific insights into the role of location, connectivity, and performance in shaping port choice.

1. What is the role of geographic location in determining port choice?

Geographic location establishes the fundamental structure of port choice by shaping both the **international maritime leg** and the **domestic port-to-region leg** of container transport. On the international side, ports located closer to major Asia–Pacific origins and the Malacca Strait enjoy shorter sailing times and lower voyage costs. In the model, this effect is captured through **MarI.Time (β ≈ –0.167)**, which is negative and highly significant: longer maritime distances reduce a port's relative attractiveness. This structural advantage explains why **Tanjung Priok and Belawan** dominate, while more peripheral eastern ports face higher transport times and costs.

On the domestic side, geographic location matters through the **PDR.Time and PDR.Cost variables**, which measure the total time and cost from each port to provincial demand centers. These values integrate both feeder shipping and inland trucking, depending on whether the destination province is located on the same island or requires inter-island movement. Both coefficients are negative and highly significant, confirming that longer or more expensive port-to-region connections reduce a port's utility. The cost and time heatmaps in Chapter IV illustrate this pattern: provinces overwhelmingly align with the geographically nearest efficient gateway when port-to-region costs and times are minimized.

In sum, location determines the baseline competitiveness of ports. Proximity to international shipping lanes provides enduring advantages for western hubs, while port to demand area impedances explain regional catchment areas. However, the results also show that location effects are not absolute: ports such as **Makassar**, though more distant from international origins, capture demand through their role as efficient regional connectors, underscoring how location interacts with connectivity and performance in shaping port choice.

2. How significant is port connectivity—to both international container services and domestic hinterlands—in influencing port choice?

Port connectivity emerges as the **most significant positive determinant** of port choice in the Indonesian context, but its influence operates differently for international and domestic dimensions.

On the **domestic side**, the results show that connectivity—defined as the number of demand regions a port is linked to through maritime services—is highly significant and consistently positive. With an estimated coefficient of about **β ≈ +0.26**, connectivity has the strongest marginal effect in the model, larger than berth efficiency (β ≈ +0.07) and far outweighing inland cost or time (β ≈ –0.010 and –0.016). Sensitivity analysis further confirms that connectivity improvements generate the largest probability shifts, reaching over six percentage points when ports are closely competing. This demonstrates that in an archipelagic system, the breadth of hinterland coverage is decisive: ports that connect to more provinces become markedly more attractive, regardless of call frequency.

On the **international side**, total port calls show a high raw correlation with relative utility but do not remain significant in the final model once connectivity is included. This is because port calls measure intensity of service at the port, while connectivity captures the effective reach of those services to demand regions. In Indonesia's setting, a single maritime connection between a port and a province can be sufficient to secure access, so the breadth of coverage matters more than the sheer number of ship arrivals. As a result, the explanatory power of international port calls is largely absorbed into the connectivity variable.

In sum, the model demonstrates that connectivity is the most influential driver of port choice in Indonesia. Domestic hinterland connectivity, measured as the range of regions served, exerts the strongest statistical and economic effect, while international connectivity through port calls is important but secondary once network coverage is accounted for. This finding reflects Indonesia's geography: in an archipelago, *being connected at all* is more decisive than *how often* a service runs, making connectivity the primary lever for shifting container flows across competing gateways.

3. How do port performance and capacity affect port choice decisions?

Port performance and capacity affect port choice by determining how effectively a port can handle vessel calls and container flows once connectivity and location bring cargo to its gates. In the model, this effect is captured by **berth service efficiency (ET/BT-**

I), which enters as positive and significant (β ≈ +0.07). This shows that a higher share of productive time at berth raises a port's relative utility by reducing delays and ensuring smoother ship operations. Efficient performance protects liner schedules and reduces cascading delays, making such ports more attractive to carriers and shippers.

Other performance variables, such as container dwell time, were tested but produced inconsistent signs due to overlap with connectivity and time variables. Nonetheless, descriptive analysis in Chapter IV confirms that long import dwell times (e.g., Pontianak, Priok) increase logistics costs, while ports with shorter clearance times (e.g., Makassar, Tanjung Emas) offer competitive advantages.

Capacity, measured by berth depth and the number of operational container berths, also shapes port choice by setting the ceiling for vessel accommodation and parallel ship-working. Although these variables were collinear with connectivity and port size and thus did not remain stable in the regression, their importance is supported by the literature and by descriptive comparisons: deeper drafts and greater berth capacity are prerequisites for attracting mainline services and preventing congestion at high-volume hubs.

In sum, port performance and capacity influence port choice by determining how reliably a port can turn physical infrastructure into effective service. Performance effects are visible in the positive impact of berth-time efficiency, while capacity factors act more as enabling conditions, ensuring that connectivity and location advantages can be realized without bottlenecks. For Indonesia, this means that operational improvements—such as higher berth productivity and reduced dwell times—are critical for established hubs like Tanjung Priok and Tanjung Perak, while new ports must combine sufficient capacity with efficient operations to translate investments into actual competitiveness.

6.2. Research Limitation

This thesis has been designed as a nationwide, revealed-preference study of port choice in Indonesia. In line with this scope, several boundaries define the analysis.

First, the model is calibrated on secondary data sources, which ensures consistency and comparability across ports. While this approach focuses on measurable variables, it necessarily leaves out qualitative aspects such as institutional arrangements or governance conditions. These dimensions, although relevant, fall outside the remit of a data-driven framework and can be pursued in complementary research.

Second, the specification concentrates on a well-established set of determinants: maritime and inland time and cost, connectivity, infrastructure, and operational performance. These factors capture the core trade-offs documented in the literature and provide a robust foundation for statistical estimation. Other aspects of port competitiveness such as digitalization, intermodal integration, or environmental performance are recognized as important but require a different type of dataset and methodology and are therefore better addressed in future studies.

Third, the model provides a cross-sectional snapshot of port choice under current conditions. This design is suited to identifying the structural drivers of competitiveness and to running scenario-based simulations. Longer-term dynamics, such as network reconfigurations or trade shifts, would require a panel or time-series approach, which could be developed as a follow-up to this work.

Finally, the framework follows the established principles of random utility theory, where port users are assumed to make rational, utility-maximizing choices. This assumption enables transparent estimation and interpretation, consistent with international transport modeling practice. At the same time, it is acknowledged that real-world decisions may also be shaped by political or strategic considerations, which extend beyond the scope of this analysis.

6.3 Future Research

This study establishes a national-scale, revealed-preference framework for analyzing container port choice in Indonesia. Building on this foundation, several avenues for future research can be pursued.

First, primary data collection from shippers, forwarders, and carriers could complement the present model. Survey-based evidence would capture perceptions of service quality, reliability, or institutional effectiveness that are difficult to observe in secondary data. Combining revealed and stated preferences would provide a richer understanding of decision-making processes.

Second, additional determinants can be integrated as data availability improves. Factors such as customs performance, digitalization, intermodal integration, and environmental standards are increasingly relevant in global port competition. Incorporating these dimensions would broaden the model's explanatory power and reflect emerging priorities in sustainable and smart logistics.

Third, future work could adopt dynamic or longitudinal approaches. Time-series estimation or panel-data models would allow analysis of how port choice evolves in response to shifting trade flows, service networks, or infrastructure investments. Scenario-based forecasting could then test the resilience of Indonesian ports under different policy and market conditions.

Finally, applying the framework in a comparative regional setting would provide valuable benchmarks. Extending the analysis to other Southeast Asian economies would highlight Indonesia's relative position in regional port competition and strengthen the generalizability of the findings.

Together, these directions show how the present framework can be expanded to address new questions, adapt to emerging trends, and inform broader debates on maritime connectivity and port development.

REFERENCE

Bappenas. (2020). Indonesia National Logistics Strategy (Sislognas). Jakarta: Ministry of National Development Planning.

Ben-Akiva, M., & Lerman, S. R. (1985). Discrete choice analysis: Theory and application to travel demand. MIT Press.

Brooks, M. R., & Cullinane, K. (2007). Devolution, port governance and port performance. Elsevier.

Cai, M. (2021). Doubly constrained gravity models for interregional trade estimation. Papers in Regional Science, 100, 455–474.

Cariou, P. (2011). Is slow steaming a sustainable means of reducing CO_2 emissions from container shipping? Transportation Research Part D, 16(3), 260–264.

Cascetta, E. (2009). Transportation systems analysis: Models and applications (2nd ed.). Springer.

Chang, Y.-T., Lee, S.-Y., & Tongzon, J. (2000). Port selection factors for shipping lines: A model of port logistics cost comparison between Kaohsiung and Hong Kong. In *Ports 2000: Conference Proceedings* (pp. 1–10). WIT Press. https://www.witpress.com/Secure/elibrary/papers/PORTS00/PORTS00003FU.pdf

Clark, X., Dollar, D., & Micco, A. (2004). Port efficiency, maritime transport costs, and bilateral trade. Journal of Development Economics, 75(2), 417–450.

Clarksons Research. (2024). *Containership speed dataset* [Data set]. Shipping Intelligence Network (SIN).

Cullinane, K., & Khanna, M. (2000). Economies of scale in large containerships: Optimal size and geographical implications. Transportation Research Part E: Logistics and Transportation Review, 36(3), 195–217.

Cullinane, K., & Toy, N. (2000). Identifying criteria for port selection using a stated preference approach. Transportation Planning and Technology, 23(3), 263–278.

de Jong, G., Vierth, I., Tavasszy, L., & Ben-Akiva, M. (2012). Recent developments in national and international freight transport models within Europe. Transportation, 39(6), 1029–1053.

de Groot, H. L. F., Linders, G. J. M., Rietveld, P., & Subramanian, U. (2004). The institutional determinants of bilateral trade patterns. *Kyklos, 57*(1), 103–123. https://doi.org/10.1111/j.0023-5962.2004.00245.x

Ducruet, C., & Notteboom, T. (2012). The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks, 12(3), 395–423.

Esri. (n.d.). Weighted mean center (Spatial Statistics). ArcGIS Pro documentation.

Hausman, W. H., Lee, H. L., & Subramanian, U. (2005). *Global logistics indicators, supply chain metrics, and bilateral trade patterns* (Policy Research Working Paper No. 3773). World Bank. https://doi.org/10.1596/1813-9450-3773

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). Applied choice analysis (2nd ed.). Cambridge University Press.

Hidayati, L. N. N., de Jong, G., & Whiteing, A. (2022). A probabilistic model of container port demand in Java concerning the port hinterland connectivity. In Lecture Notes in Civil Engineering (Vol. 281, pp. 781–789). Springer.

Hutauruk, O. G., Ramadhanti, S. S., & Herdian, T. (2023). The role of effective time in relation to equipment utilization on ship service performance. *Advances in Transportation and Logistics Research, 5*, 526–540. Global Research on Sustainable Transport & Logistics (GROSTLOG 2023). Institut Transportasi dan Logistik Trisakti.

Louviere, J., Hensher, D., & Swait, J. (2000). Stated choice methods: Analysis and applications. Cambridge University Press.

Lu, C.-S., & Nguyen, V. T. (2014). The impact of port service quality on customer satisfaction: The case of Vietnamese exporters. The Asian Journal of Shipping and Logistics, 30(1), 87–104.

Malchow, M., & Kanafani, A. (2004). A disaggregate analysis of port selection. Maritime Policy & Management, 31(4), 285–303.

Malchow, M. B., & Kanafani, A. (2004). A disaggregate analysis of port selection. Transportation Research Part E: Logistics and Transportation Review, 40(4), 317–337.

Mankiw, N. G. (2020). Principles of economics (9th ed.). Cengage.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), Frontiers in econometrics (pp. 105–142). Academic Press.

Ministry of Transportation. (2023). National port development plan update. Jakarta.

Mueller, M. A. (2014). Container port development: A port choice model for the European mainland (Master's thesis). Delft University of Technology.

Mueller, M. A., Wiegmans, B., & van Duin, J. H. R. (2020). The geography of container port choice: Modelling the impact of hinterland changes on port choice. Maritime Economics & Logistics, 22, 26–52.

Nariendra, N., & Taufiq, A. (2020). Road freight unit-cost evidence for Indonesia (benchmark ≈ Rp 8,000 per km).

Notteboom, T. (2004). Container shipping and ports: An overview. Review of Network Economics, 3(2), 86–106.

Notteboom, T. (2006). The time factor in liner shipping services. Maritime Economics & Logistics, 8(1), 19–39.

Notteboom, T., Pallis, A. A., & Rodrigue, J.-P. (2021). Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic and beyond. Maritime Economics & Logistics, 23(2), 295–308.

Notteboom, T., & Rodrigue, J.-P. (2008). Containerisation, box logistics and global supply chains: The integration of ports and liner shipping networks. Maritime Economics & Logistics, 10(1–2), 152–174.

Notteboom, T. E., & Rodrigue, J.-P. (2008). Port regionalization: Towards a new phase in port development. Maritime Policy & Management, 32(3), 297–313.

Nugroho, S. (2016). Exporters' and forwarders' preferences in port choice: Evidence from Indonesia (Master's thesis). University repository.

OECD. (2021). Logistics performance and transport connectivity in Southeast Asia. OECD Publishing.

Ortúzar, J. de D., & Willumsen, L. G. (2011). Modelling transport (4th ed.). Wiley.

Pelindo. (2022). Annual logistics and port infrastructure report. Jakarta.

Pelindo. (n.d.). *Monitoring per bulan* [Excel spreadsheet]. RAPORTS (Pelindo Operational Reporting System). Retrieved July 20, 2025, from https://raports.pelindo.co.id/ExcelReport/MonitoringPerbulan?height=551

Robinson, R. (2002). Ports as elements in value-driven chain systems: The new paradigm. Maritime Policy & Management, 29(3), 241–255.

Song, D.-W., & Yeo, K.-T. (2004). A competitive analysis of Chinese container ports. Maritime Policy & Management, 31(4), 335–351.

Stopford, M. (2009). Maritime economics (3rd ed.). Routledge.

Sudjana. (2011). Estimation of Indonesian road-freight costs (rate benchmark).

Tavasszy, L. A., & de Jong, G. (2014). Modelling freight transport. Elsevier.

Teye, C., Asare, S., Frimpong, S., & Ackon, R. (2023). Economic assessment of transporting refrigerated cargo between West-Africa and Europe. *Journal of Shipping and Trade, 8*(1), 1–24. https://doi.org/10.1186/s41072-023-00136-x

Tiwari, P., Itoh, H., & Doi, M. (2003). Shippers' port and carrier selection behaviour in China: A discrete choice analysis. Maritime Economics & Logistics, 5(1), 23–39.

Tongzon, J. L. (2002). Port choice determinants in a competitive environment. In Proceedings of the International Association of Maritime Economists (IAME) Conference.

Tongzon, J. L., & Sawant, L. (2007). Port choice in a competitive environment: From the shipping lines' perspective. Applied Economics, 39(4), 477–492.

Train, K. (2009). Discrete choice methods with simulation (2nd ed.). Cambridge University Press.

UNCTAD. (2023). Review of maritime transport 2023. United Nations Conference on Trade and Development.

Wang, J. J., & Slack, B. (2000). The evolution of a regional container port system: The Pearl River Delta. Journal of Transport Geography, 8(4), 263–275.

Wilmsmeier, G., & Sánchez, R. J. (2009). The relevance of liner shipping connectivity to shipping costs. Maritime Economics & Logistics, 11(1), 1–18.

Wilson, A. G. (1971). A family of spatial interaction models, and associated developments. Environment and Planning, 3(1), 1–32.

World Bank. (2021). Indonesia: Strengthening maritime logistics. World Bank Group.

World Bank. (2021). Indonesia logistics sector review: Connecting for competitiveness and inclusion.

Zukhruf, F., Frazila, R., & Burhani, J. (2017). A stochastic discrete optimization model for designing container terminal facilities. AIP Conference Proceedings, 1903(1), 060007.

APPENDIX I

DATASETS BUILDING

1.1 Maritime Leg

a. Import Location and Distance

Based on Pelindo 2024 Port of Loading and Port Destination Container Data, there nine ports have international throughput as follows:

No	Container Imported	Total Import (TEU)
1	Tanjung Priok	1,326,880
2	Tanjung Mas	549,984
3	Tanjung Perak	958,439
4	Belawan	227,366
5	Makassar	22,211
6	Bitung	4,706
7	Pontianak	35,792
8	Panjang	10,162
9	Palembang	58,349
	Total	**3,193,889**

The detail of the throughput is majority comes from asia pacific region with top three biggest origin container thourghput is China, Singapore and Malaysia.

Container Imported	China	Taiwan	Korea	Japan	Viet/Thai
Tanjung Priok	325,767	22,782	77,599	76,712	169,621
Tanjung Mas	225,594	21,626	1,718	30	10,675
Tanjung Perak	353,031	35,250	61,258	6,198	22,468
Belawan	1,472	2,826	0	202	4,366
Makassar	22,211	0	0	0	0

Bitung	4,316	2	0	17	0
Pontianak	0	0	0	0	0
Panjang	3,039	0	0	0	962
Palembang	0	0	0	0	0

Container Imported	Philippine	India	Malaysia	Singapura	Hongkong
Tanjung Priok	0	61,707	385,606	177,507	29,579
Tanjung Mas	0	251	86,458	189,653	13,979
Tanjung Perak	0	11,746	170,050	279,591	18,847
Belawan	0	1,522	115,316	99,610	2,052
Makassar	0	0	0	0	0
Bitung	371	0		0	0
Pontianak	0	0	0	35,792	0
Panjang	0	0	4,579	1,582	0
Palembang	0	0	0	58,349	0

The distance between port to International Origin of Container is taking from https://sea-distances.org/, we use popular port as a reference of each country.

Distance (nm)	**China**	**Taiwan**	**Korea**	**Japan**	**Viet/Thai**
Tanjung Priok	2799	1957	2839	3221	1032
Tanjung Mas	2923	2059	2956	3218	1119
Tanjung Perak	2909	2042	2884	3103	1203
Belawan	2838	1996	2878	3267	1021
Makassar	2631	1764	2711	2819	1506
Bitung	2251	1346	2113	2213	1460

Pontianak	2511	1647	2515	2863	708
Panjang	2863	2021	2903	3286	1096
Palembang	2683	1841	2723	3112	866

Distance (nm)	**Philippine**	**India**	**Malaysia**	**Singapura**	**Hongkong**
Tanjung Priok	1562	2710	554	527	1789
Tanjung Mas	1625	2928	677	670	1877
Tanjung Perak	1567	3086	766	759	1940
Belawan	1716	2104	400	375	1835
Makassar	1289	3462	1106	1102	1822
Bitung	877	3928	1565	1493	1423
Pontianak	1217	2787	356	352	1465
Panjang	1626	2693	587	574	1852
Palembang	1497	2697	330	301	1680

To determine the distance between origin to destination port, weighted average formulation is done where the weighted is represented by the number of cargo of each origin country.

$$\bar{x} = \frac{\sum w_i x_i}{\sum w_i}$$

	Distances (nm)
Tanjung Priok	1517.61
Tanjung Mas	1641.27
Tanjung Perak	1685.72
Belawan	1442.09

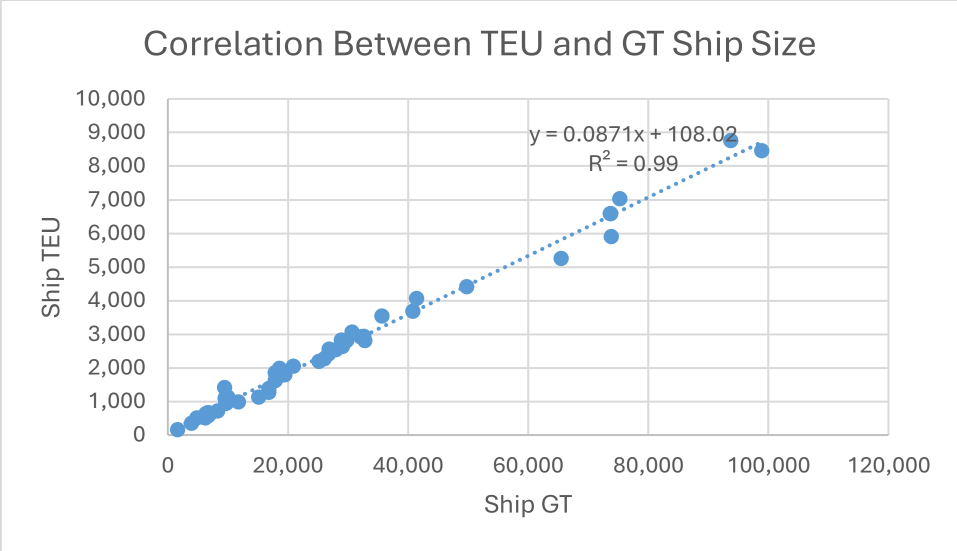
Makassar	1779.85
Bitung	1828.14
Pontianak	1282.42
Panjang	1567.83
Palembang	1346.34

b. Ship Size

Ship Size and Total Call data is gotten from Pelindo Raports 2024, to get the average ship size per call that is entered every port.

Ship Size (Average)	**Total GT**	**Total Call**	**GT/Call**
Tanjung Priok	76,514,611	2,357	32,463
Tanjung Mas	15,944,820	631	25,269
Tanjung Perak	41,432,190	1,367	30,309
Belawan	9,009,438	628	14,346
Makassar	1,587,599	58	27,372
Bitung	129,424	6	21,571
Pontianak	2771939	200	13,860
Panjang	2533056	64	39,579
Palembang	2401270	60	40,021

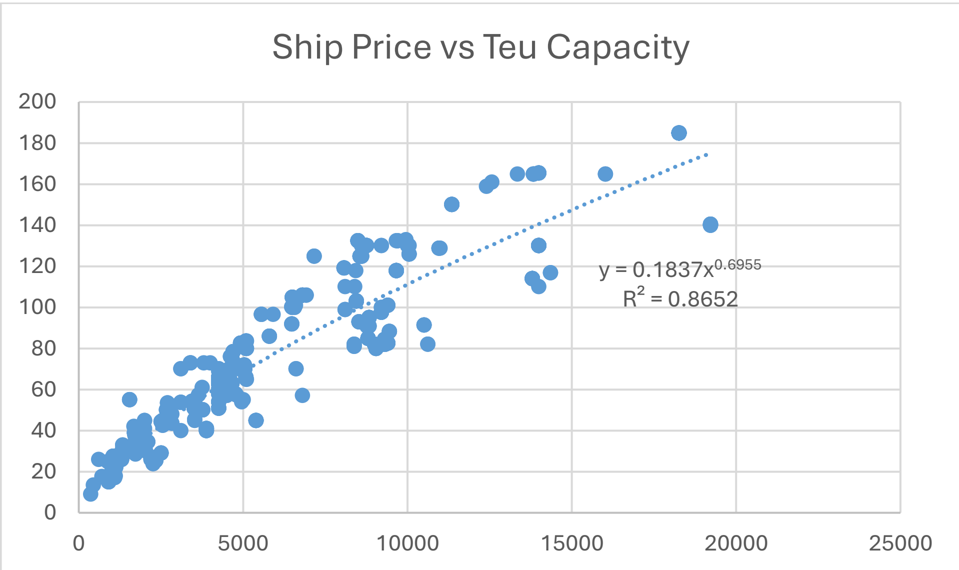
This ship size (GT) data is then converted to TEU. Based on Clarkson ship database 2025, we can find the correlation between ship size in TEU and GT.



Source: Clarkson

c. Capital Cost

As this report specifically looked at the 2024 ship data, by assuming average ship age around 9 to 17 years old, we searched for contract new building container vessel data from September 2005 to September 2015 in Container Intelligent Quarterly in Clarkson. Using the Data, the correlation between Ship price and TEU vessel capacity as follows:



Source: Clarkson Container Intelligent Quarterly

Using the data, the formulation of capital cost by assuming that depreciation is 10% per year, the total capital cost per day is as follows:

$$Capital\ Cost = \frac{\left((Ci) * \frac{183700}{365} * C^{0.6955} * (sailing\ time)\right)}{C * U}$$

$$Capital\ Cost = \frac{\left((Ci) * \frac{183700}{365} * C^{0.6955} * \left(\frac{di}{24 * v}\right)\right)}{C * U}$$

$$MC = Maritime\ Cost\ \left(\frac{\$}{teu}\right)$$
$$di = Distance\ (nmiles)$$
$$v = Speed\ (Knot)$$
$$Ci = Capital\ Cost\ (\%)$$
$$C = Ship\ Capacity\ (Teu)$$
$$U = Utilization$$
$$E = Currency\ Exchange\ (euro\ to\ dollar)$$

For the maintenance and capital cost we assume that it is 3% of total ship price per year.

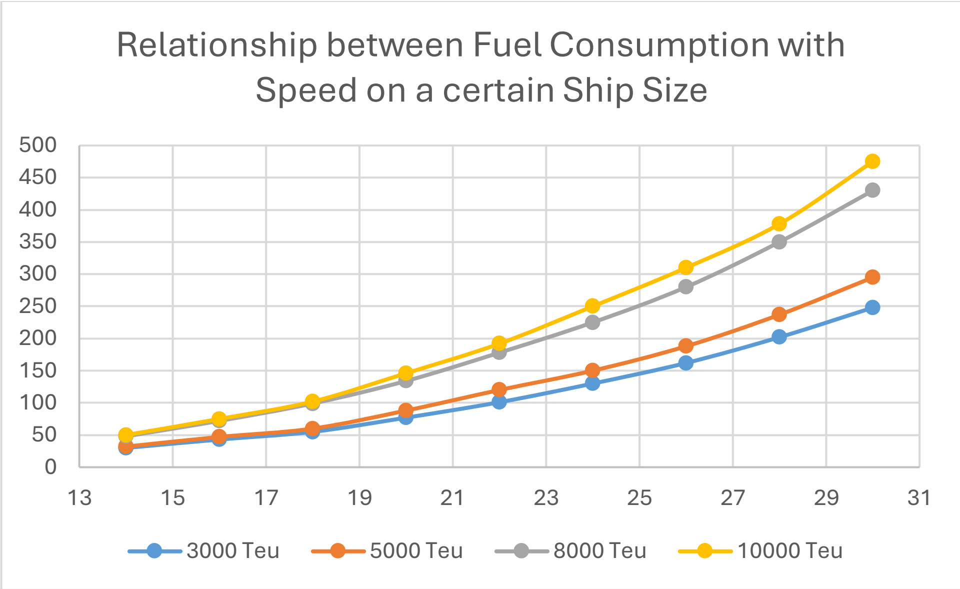
d. Voyage Cost

Voyage cost consists of Fuel Cost and Port Dues with the equation:

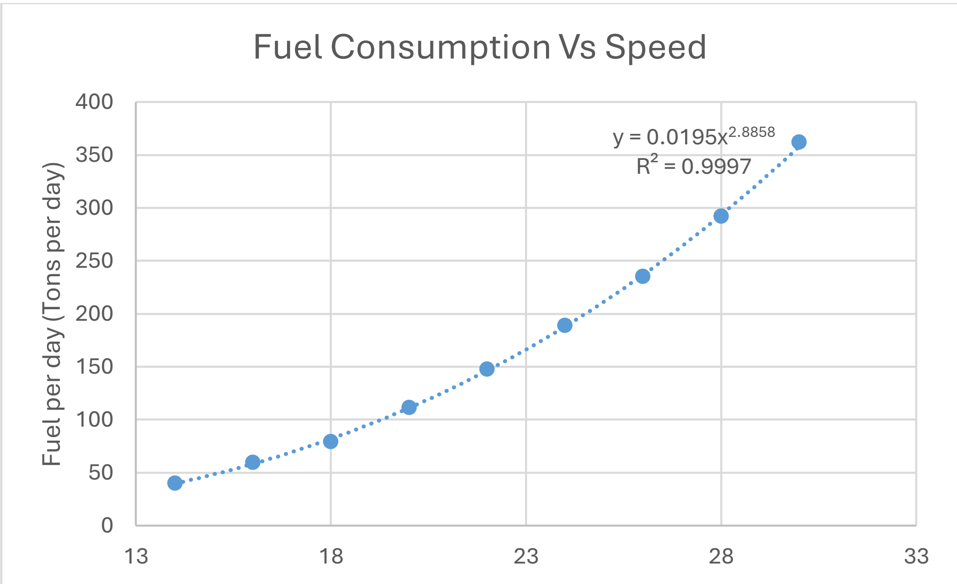
$$Voyage\ Cost = Fuel\ Cost + Port\ Dues$$

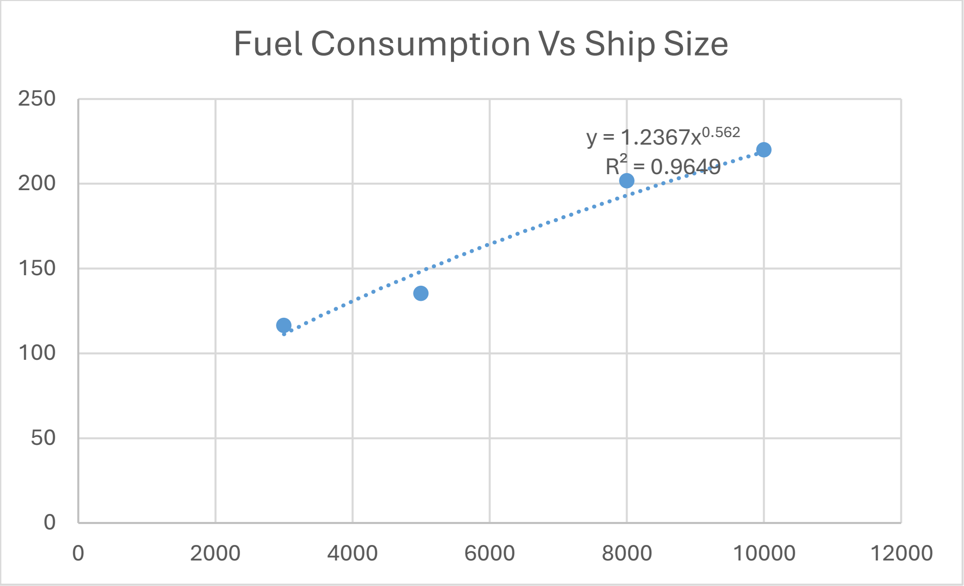
- Fuel Cost

To determine the fuel cost, we used data from Notteboom and Vernimmen, 2009.



By knowing this, we can formulate vessel speed, fuel consumption and ship size as follows:





To formulate the relation between fuel consumption, ship size, and speed in one equation, new regression is performing to know the elasticity of each variable.

Thus,

$$Fuel\ Consumption = 0.00015 * v^{2.89} * C^{0.56}$$

Where:

$v = Speed\ (Knot)$

$C = Ship\ Capacity\ (Teu)$

For Fuel Price data, we used average data from January to December 2024 in Clarkson Research. VLSFO used as Indonesian shipping majority rely on VLSFO as a source of power.

	542456
	VLSFO Bunker Prices (0.5% Sulphur), Singapore
Date	$/Tonne
Jan-2024	611.75
Feb-2024	643.81
Mar-2024	640.15
Apr-2024	647.63
May-2024	616.65
Jun-2024	604.31
Jul-2024	625.44
Aug-2024	611.55
Sep-2024	596.06
Oct-2024	599.88
Nov-2024	575.65
Dec-2024	551.25

For the shipping velocity, we used average data for vessel with size 100-2,999 TEU and 3,000 to 5,999 from Clarkson Research.

	8851996	8852100
	Feeder Containership 100-2,999 TEU Average Speed	Intermediate Containership 3,000-5,999 TEU Average Speed
Date	Knots	Knots
Jan-2024	13.15	14.33
Feb-2024	13.18	14.25
Mar-2024	13.15	14.29
Apr-2024	13.25	14.37
May-2024	13.21	14.38
Jun-2024	13.23	14.49
Jul-2024	13.20	14.49
Aug-2024	13.23	14.57
Sep-2024	13.15	14.48
Oct-2024	13.10	14.45
Nov-2024	13.11	14.43
Dec-2024	13.08	14.44

So, as the fuel cost is the multiplication of fuel price, duration, and fuel consumption, the final fuel cost equation as follows:

$$Fuel\ Cost = \frac{\left(Fp * \left(\frac{di}{24 * v}\right) * (0.00015 * v^{2.89} * C^{0.56})\right)}{C * U}$$

$$Fp = Fuel\ Price \left(\frac{\$}{tonne}\right)$$
$$di = Distance\ (nmiles)$$
$$v = Speed\ (Knot)$$
$$C = Ship\ Capacity\ (Teu)$$
$$U = Utilization$$
$$E = Currency\ Exchange\ (euro\ to\ dollar)$$

- Port Dues

Port Dues consists of Anchorage Cost, Pilotage Cost, Tug Cost, and Berthing Cost. The data is generated from Port of Tanjung Priok ship service tariff 2016 and converted it to USD. The total Port dues for each port as follows:

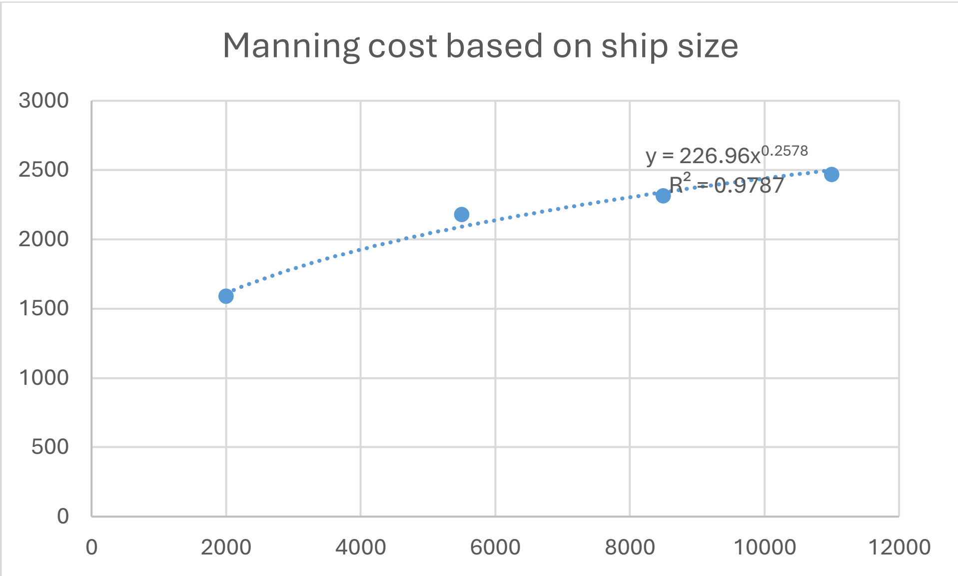
Port Name	**Anchorage**	**Pilot**	**Tug**	**Berthing**	**Total**	**Cost/ Teu**
Tanjung Priok	2986.57	1428.36	6139.25	7920.90	18475.08	7.87
Tanjung Mas	2324.76	1111.84	5995.38	6165.67	15597.65	8.44
Tanjung Perak	2788.41	1333.59	6096.18	7395.36	17613.54	8.01
Belawan	1319.85	631.23	2851.92	3500.48	8303.50	7.65
Makassar	2518.26	1204.39	6037.45	6678.86	16438.96	8.25
Bitung	1984.50	949.11	5921.41	5263.24	14118.27	8.88
Pontianak	1275.09	609.83	2842.19	3381.77	8108.88	7.71
Panjang	3641.27	1741.48	6281.58	9657.28	21321.60	7.50
Palembang	3681.95	1760.93	6290.42	9765.16	21498.47	7.48

e. Operating Cost

Total Operating cost can be formulated:

$$Operating\ Cost = Maintenance\ and\ Admin\ Cost + Manning\ Cost$$

For the maintenance and administrative cost, we assume that it is 3% of total ship price per year. While for the manning cost, we too reference from Compass Report, 2010, the correlation between ship size data and manning cost per day represented by graph below:



As the data is euro unit, the conversion to USD unit is needed. Based on the graph, the calculation formula for manning cost is:

$$Manning\ Cost = \frac{\left((226.968 * E * \left(\frac{di}{24 * v}\right) * C^{0.2587})\right)}{C * U}$$

So, the total cost for operating costs is:

$$Operating\ Cost = \frac{\left((mi) * \frac{183700}{365} * C^{0.6955} * \left(\frac{di}{24 * v}\right)\right) + (226.968 * E * \left(\frac{di}{24 * v}\right) * C^{0.2587})\Big)}{C * U}$$

$$di = Distance\ (nmiles)$$

$$v = Speed\ (Knot)$$

$$mi = Maintenance\ Cost\ (\%)$$

$$Ci = Capital\ Cost\ (\%)$$

$$C = Ship\ Capacity\ (Teu)$$

$$U = Utilization$$

$$E = Currency\ Exchange\ (euro\ to\ dollar)$$

f. Terminal Dues

Terminal dues consist of container handling at the sea side and lift on lift off and Storage container in terminal yard. We assume that the duration of container in the yard is same with total dwelling time import of the container in the terminal. The Data is taken from Pelindo 2024 Raports.

Port Name	**THC Cost**	**Dwell Time Import**	**Storage+Lolo**	**Total Terminal**
Tanjung Priok	86	2.78	17.08	103.08
Tanjung Mas	86	3.97	18.93	104.93
Tanjung Perak	86	3.59	18.34	104.34
Belawan	86	3.03	17.47	103.47
Makassar	86	2.56	16.73	102.73
Bitung	86	3.34	17.95	103.95
Pontianak	86	8.42	25.89	111.89
Panjang	86	4.1	19.14	105.14
Palembang	86	4.28	19.42	105.42

g. Total Maritime Cost

Total maritime costs consist of shipping costs and terminal costs in the maritime transport process. These include Capital cost of the ship, Voyage Cost, Operating Cost, and Terminal Handling Cost with the details below:

$$MC = Capital\ Cost + Voyage\ Cost + Operating\ Cost + Terminal\ Cost$$

$$MC = Capital\ Cost + (Fuel\ Cost + Port\ Dues) + (Manning\ Cost + Maintenance) + Terminal\ Cost$$

Port Name	**Voyage Cost**	**Capital Cost**	**Operating Cost**	**THC & Storage**	**Cost**
Tanjung Priok	36.04	26.56	12.07	103.08	177.74
Tanjung Mas	42.30	30.90	14.57	104.93	192.70
Tanjung Perak	40.22	30.10	13.81	104.34	188.48
Belawan	45.23	31.92	16.48	103.47	197.08
Makassar	43.75	32.74	15.25	102.73	194.47
Bitung	49.17	36.03	17.41	103.95	206.56
Pontianak	41.60	28.66	14.88	111.89	197.02
Panjang	39.22	23.65	10.77	105.14	178.77
Palembang	30.34	22.15	9.78	105.42	167.69

h. Total Maritime Time

To obtain Maritime time, simply by dividing distance from origin to destination port and divided by vessel speed according to average vessel speed in the port.

$$Maritime\ Time\ (Hour) = \frac{Distance\ (nm)}{Vessel\ Speed\ (knot)}$$

Port Name	Time (days)	Time (hour)
Tanjung Priok	4.80	115.23
Tanjung Mas	5.19	124.62
Tanjung Perak	5.33	128.00
Belawan	4.56	109.50
Makassar	5.63	135.14
Bitung	5.78	138.81
Pontianak	4.06	97.37
Panjang	4.53	108.77
Palembang	4.26	102.23

1.2 Port Attributes Data

The first group concerns the foreland and feeder connectivity. Several measures use are Port Call and Connectivity. Port Call represents the number International call in the port showed the connectivity from the port to the international route. Connectivity is the number of connection from port to demand region. It can separated into three main category which are connectivity call the number of feeder vessel call that connect port to the port direct and transit, connectivity direct is the number of feeder vessel connect port to port direct without transit, and connectivity total is the number of feeder vessel direct call (without transit) and inland transport that connect to the port via trucking where the connection between port and demand region cannot be count 2 (two) times if it is connected via land and sea. This connectivity segmented type important to mapping the importance of feeder port connection from sea transport as well as using inland transport as an geographic advantage. Below is the table shows number connectivity using Pelindo 2024 Port of Loading and Port of Destination data to know connectivity each of the Ports as well as compile with another geographic from google map to determine land connectivity.

No	Port Name	Connectivity	Connectivity Direct	Connectivity Total
1	Port of Belawan	4	4	11
2	Port of Bitung	12	4	7
3	Port of Makassar	15	8	10
4	Port of Palembang	1	1	9
5	Port of Panjang	1	1	9
6	Port of Pontianak	1	1	6

7	Port of Tanjung Emas	20	4	9
8	Port of Tanjung Perak	30	14	18
9	Port of Tanjung Priok	19	18	21

The second group captures infrastructure and capacity through berth depth and the number of container berths getting from Clarkson Research database. Depth determines whether larger vessels can call without tidal constraints; the number of berths governs how much parallel ship-working is feasible. Both features underpin a port's technical capability to host bigger ships and avoid berth queues.

No	Port Name	Berth Depth	Number of Berth
1	Port of Belawan	14.9	26
2	Port of Bitung	13.31	25
3	Port of Makassar	14.9	18
4	Port of Palembang	18.32	11
5	Port of Panjang	18.6	23
6	Port of Pontianak	10.8	36
7	Port of Tanjung Emas	14.25	32
8	Port of Tanjung Perak	15	55
9	Port of Tanjung Priok	18.32	70

The third group measures operational performance taken from Pelindo 2024 Raports. Three indicators are taken in Δ–form: boxes per ship hour (BSH) as a direct measure of ship-working intensity, vessel turnaround time, and container dwell time. Faster and more predictable operations protect network schedules and curb inventory buffers;

both shippers and carriers rank time reliability highly in port choice stated-preference and revealed-preference work (Notteboom, 2006; Tongzon & Sawant, 2007). Hence, Δ\DeltaΔBSH should be positive, while longer Δ\DeltaΔTurnaround and Δ\DeltaΔDwell should be negative.

No	Port	BTI	ET/BT-I	BTD	ET/BT-D	TRTI	TRTD
1	Port of Belawan	23.53	78.4	25.82	80.6	2.43	2.55
2	Port of Bitung	8.54	67.35	21.38	80	1.59	0.99
3	Port of Makassar	14.68	75.57	14.87	80.17	1.9	1.27
4	Port of Palembang	15.19	69.32	14.15	73.48	9.06	9.44
5	Port of Panjang	25.05	78.39	13.93	74.19	1.25	0.91
6	Port of Pontianak	10.32	79.41	18.01	80.67	6.15	5.15
7	Port of Tanjung Emas	19.58	84.21	11.69	68.63	1.15	1.02
8	Port of Tanjung Perak	24.5	78.53	18.8	71.77	10.94	9.24
9	Port of Tanjung Priok	36.15	92.58	19.27	74.04	2.5	2.22

No	Port	DwellI Import	DwellD Export
1	Port of Belawan	3.03	1.75
2	Port of Bitung	3.34	3.33
3	Port of Makassar	2.56	2.55
4	Port of Palembang	4.28	2.87
5	Port of Panjang	4.1	3.27
6	Port of Pontianak	8.42	2.42
7	Port of Tanjung Emas	3.97	4.48
8	Port of Tanjung Perak	3.59	3.56
9	Port of Tanjung Priok	2.78	3.07

1.3 Transportation to Demand Region

Transportation to demand region is calculated using four time of connectivity criteria:

5. Inland transport only: gateway and province are on the same island; road haul from gateway to centroid (blue).
6. Direct-call feeder + inland: a feeder vessel sails directly from the gateway to a secondary port on the province’s island, followed by road haul (yellow).
7. Feeder with transit + inland: a feeder leg with one intermediate stop (transit) before reaching the secondary port, then road haul (green).
8. Feeder with vessel change + inland: a feeder to a transshipment node where cargo shifts to another feeder serving the province, then road haul (no color).

The distance data to the demand region centroid for the inland transportation is taken from google map services. On the other hand, for maritime distance is taking from https://sea-distances.org/.

No	Demand Region	Port of Belawan								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.4	10.2	241.4	509.0	72.7	0.0	0.0	82.9	241.4
2	Sumatera Utara	0.1	3.0	79.7	168.0	72.7	0.0	0.0	75.7	79.7
3	Sumatera Barat	0.7	16.7	350.0	738.0	72.7	0.0	0.0	89.4	350.0
4	Riau	0.5	12.5	312.1	658.0	72.7	0.0	0.0	85.2	312.1
5	Jambi	0.9	22.4	62.6	132.0	287.3	358.4	0.0	309.7	421.0
6	Sumatera Selatan	0.1	2.1	39.8	84.0	159.5	172.8	637.0	161.6	212.6
7	Bengkulu	1.2	29.0	20.8	43.8	259.2	330.2	0.0	288.2	351.0
8	Lampung	1.4	33.0	29.9	63.1	349.2	337.8	0.0	382.2	367.7
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	272.7	343.8	0.0	273.4	357.9
10	Kepulauan Riau	2.0	48.7	45.4	95.8	139.4	157.3	373.0	188.2	202.7
11	DKI Jakarta	0.0	0.7	8.6	18.2	176.6	186.1	863.0	177.4	194.7
12	Jawa Barat	0.1	1.9	54.1	114.0	176.6	186.1	0.0	178.6	240.2
13	Jawa Tengah	0.1	7.0	219.1	462.0	176.6	186.1	0.0	183.6	405.2
14	DI Yogyakarta	0.3	8.0	273.6	577.0	176.6	186.1	0.0	184.7	459.8
15	Jawa Timur	0.0	1.1	25.8	54.5	196.9	201.8	1130.0	198.0	227.7
16	Banten	0.1	1.5	36.1	76.1	176.6	186.1	0.0	178.2	222.2
17	Bali	0.1	1.5	16.4	34.5	304.7	378.7	0.0	306.2	395.1
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	302.6	376.7	0.0	306.7	438.8

19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	339.5	413.5	0.0	343.8	482.3
20	Kalimantan Barat	0.2	3.6	75.9	160.0	282.2	353.3	0.0	285.8	429.2
21	Kalimantan Tengah	0.1	3.0	60.7	128.0	325.0	399.1	0.0	328.1	459.8
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	310.4	384.4	0.0	313.6	442.7
23	Kalimantan Timur	0.1	2.5	49.3	104.0	318.9	392.9	0.0	321.4	442.2
24	Kalimantan Utara	0.2	5.7	67.3	142.0	344.7	418.7	0.0	350.4	486.1
25	Sulawesi Utara	0.0	1.0	26.2	55.2	357.6	431.6	0.0	358.6	457.8
26	Sulawesi Tengah	0.3	7.3	142.3	300.0	373.7	447.7	0.0	381.0	590.0
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	315.5	389.6	0.0	318.9	453.6
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	369.2	443.3	0.0	371.5	480.7
29	Sulawesi Barat	0.4	9.7	194.9	411.0	315.5	389.6	0.0	325.3	584.5
30	Gorontalo	0.1	2.5	44.1	93.0	400.0	474.0	0.0	402.5	518.1
31	Maluku	0.4	10.1	92.5	195.0	356.8	430.8	0.0	366.8	523.3
32	Maluku Utara	0.8	19.2	40.5	85.5	392.8	466.8	0.0	412.0	507.4
33	Papua	0.1	3.4	69.7	147.0	498.7	572.7	0.0	502.0	642.4
34	Papua Barat	0.3	8.0	155.6	328.0	419.5	493.5	0.0	427.5	649.1
35	Papua Selatan	0.1	3.5	60.2	127.0	537.3	611.3	0.0	540.7	671.5
36	Papua Tengah	0.3	6.1	111.4	235.0	466.6	540.6	0.0	472.7	652.1
37	Papua Pegunungan	0.1	3.0	35.6	75.0	549.9	624.0	0.0	552.9	659.6
38	Papua Barat Daya	0.0	0.9	14.8	31.2	402.7	476.8	0.0	403.6	491.5

No	Demand Region	Port of Palembang								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	1.6	39.0	860.8	1815.0	102.7	0.0	0.0	141.7	860.8
2	Sumatera Utara	1.3	31.0	650.7	1372.0	102.7	0.0	0.0	133.7	650.7
3	Sumatera Barat	0.7	17.3	352.4	743.0	102.7	0.0	0.0	120.0	352.4
4	Riau	0.7	17.5	344.3	726.0	102.7	0.0	0.0	120.2	344.3
5	Jambi	0.4	9.0	170.3	359.0	102.7	0.0	0.0	111.7	170.3

6	Sumatera Selatan	0.1	2.0	40.2	84.7	102.7	0.0	0.0	104.7	40.2
7	Bengkulu	0.4	9.4	202.5	427.0	102.7	0.0	0.0	112.1	202.5
8	Lampung	0.2	4.1	128.0	270.0	102.7	0.0	0.0	106.8	128.0
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	259.5	318.3	0.0	260.1	332.5
10	Kepulauan Riau	0.1	2.7	45.4	95.8	277.0	335.9	0.0	279.7	381.3
11	DKI Jakarta	0.0	0.7	9.3	19.7	163.4	160.7	0.0	164.1	170.0
12	Jawa Barat	0.1	1.9	54.1	114.0	163.4	160.7	0.0	165.4	214.8
13	Jawa Tengah	0.1	7.0	219.1	462.0	163.4	160.7	0.0	170.4	379.8
14	DI Yogyakarta	0.3	8.0	273.6	577.0	163.4	160.7	0.0	171.4	434.3
15	Jawa Timur	0.0	10.0	367.1	774.0	163.4	160.7	0.0	173.4	527.8
16	Banten	0.1	1.5	36.1	76.1	163.4	160.7	0.0	165.0	196.8
17	Bali	0.1	1.5	16.4	34.5	374.0	483.8	0.0	375.5	500.2
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	372.0	481.7	0.0	376.1	543.8
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	408.8	520.3	0.0	413.2	589.1
20	Kalimantan Barat	0.2	3.6	75.9	160.0	269.0	327.9	0.0	272.6	403.7
21	Kalimantan Tengah	0.1	3.0	441.5	931.0	269.0	327.9	0.0	272.0	769.4
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	286.7	345.6	0.0	289.9	403.9
23	Kalimantan Timur	0.1	2.5	49.3	104.0	295.2	354.1	0.0	297.7	403.4
24	Kalimantan Utara	0.2	19.0	381.8	805.0	414.1	525.8	0.0	433.1	907.6
25	Sulawesi Utara	0.0	1.0	26.2	55.2	427.0	539.4	0.0	428.0	565.5
26	Sulawesi Tengah	0.8	19.2	402.2	848.0	295.0	353.9	0.0	314.2	756.1
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	295.0	353.9	0.0	298.4	417.9
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	348.7	383.7	0.0	350.9	421.1
29	Sulawesi Barat	0.4	9.7	194.9	411.0	295.0	353.9	0.0	304.7	548.8
30	Gorontalo	0.1	2.5	44.1	93.0	469.3	558.7	0.0	471.9	602.8
31	Maluku	0.4	10.1	92.5	195.0	426.1	538.9	0.0	436.2	631.4
32	Maluku Utara	0.8	19.2	40.5	85.5	462.1	554.1	0.0	481.3	594.6
33	Papua	0.1	3.4	69.7	147.0	568.1	637.1	0.0	571.4	706.8
34	Papua Barat	0.3	8.0	155.6	328.0	488.8	579.1	0.0	496.8	734.7
35	Papua Selatan	0.1	3.5	60.2	127.0	606.6	677.6	0.0	610.1	737.8

36	Papua Tengah	0.3	6.1	111.4	235.0	441.5	452.7	0.0	447.7	564.1
37	Papua Pegunungan	0.1	3.0	35.6	75.0	576.9	570.7	0.0	579.9	606.3
38	Papua Barat Daya	0.0	0.9	14.8	31.2	472.1	561.5	0.0	473.0	576.3

No	Demand Region	Port of Panjang								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	1.8	43.0	1009.7	2129.0	98.4	0.0	0.0	141.4	1009.7
2	Sumatera Utara	1.4	34.0	799.1	1685.0	98.4	0.0	0.0	132.4	799.1
3	Sumatera Barat	0.9	21.5	501.8	1058.0	98.4	0.0	0.0	119.9	501.8
4	Riau	0.9	21.5	493.2	1040.0	98.4	0.0	0.0	119.9	493.2
5	Jambi	0.5	12.8	319.2	673.0	98.4	0.0	0.0	111.2	319.2
6	Sumatera Selatan	0.2	5.9	177.8	375.0	98.4	0.0	0.0	104.3	177.8
7	Bengkulu	0.6	13.7	285.0	601.0	98.4	0.0	0.0	112.1	285.0
8	Lampung	0.1	1.2	29.9	63.1	98.4	0.0	0.0	99.6	29.9
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	252.6	292.6	0.0	253.2	306.8
10	Kepulauan Riau	0.1	2.7	45.4	95.8	270.0	310.2	0.0	272.7	355.6
11	DKI Jakarta	0.0	0.7	8.6	18.2	156.5	135.0	117.0	157.2	143.6
12	Jawa Barat	0.1	1.9	54.1	114.0	163.4	160.7	0.0	165.4	214.8
13	Jawa Tengah	0.1	7.0	219.1	462.0	163.4	160.7	0.0	170.4	379.8
14	DI Yogyakarta	0.3	8.0	273.6	577.0	163.4	160.7	0.0	171.4	434.3
15	Jawa Timur	0.0	10.0	367.1	774.0	163.4	160.7	0.0	173.4	527.8
16	Banten	0.1	1.5	36.1	76.1	156.5	135.0	0.0	158.0	171.1
17	Bali	0.1	1.5	16.4	34.5	367.1	458.1	0.0	368.6	474.5
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	365.0	456.0	0.0	369.1	518.1
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	401.9	494.6	0.0	406.2	563.4
20	Kalimantan Barat	0.2	3.6	75.9	160.0	262.1	302.2	0.0	265.7	378.0
21	Kalimantan Tengah	0.1	3.0	441.5	931.0	262.1	302.2	0.0	265.1	743.7
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	279.7	319.9	0.0	283.0	378.2

23	Kalimantan Timur	0.1	2.5	49.3	104.0	288.3	328.4	0.0	290.8	377.7
24	Kalimantan Utara	0.2	19.0	381.8	805.0	407.1	500.1	0.0	426.1	881.9
25	Sulawesi Utara	0.0	1.0	26.2	55.2	420.0	513.7	0.0	421.0	539.8
26	Sulawesi Tengah	0.8	19.2	402.2	848.0	288.0	328.2	0.0	307.2	730.4
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	288.0	328.2	0.0	291.4	392.2
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	341.7	357.9	0.0	344.0	395.4
29	Sulawesi Barat	0.4	9.7	194.9	411.0	288.0	328.2	0.0	297.8	523.1
30	Gorontalo	0.1	2.5	44.1	93.0	462.4	533.0	0.0	464.9	577.1
31	Maluku	0.4	10.1	92.5	195.0	419.2	513.2	0.0	429.2	605.7
32	Maluku Utara	0.8	19.2	40.5	85.5	455.2	528.4	0.0	474.4	568.9
33	Papua	0.1	3.4	69.7	147.0	561.1	611.4	0.0	564.4	681.1
34	Papua Barat	0.3	8.0	155.6	328.0	481.9	553.4	0.0	489.9	709.0
35	Papua Selatan	0.1	3.5	60.2	127.0	599.7	651.9	0.0	603.1	712.1
36	Papua Tengah	0.3	6.1	111.4	235.0	434.6	427.0	0.0	440.7	538.4
37	Papua Pegunungan	0.1	3.0	35.6	75.0	569.9	545.0	0.0	572.9	580.6
38	Papua Barat Daya	0.0	0.9	14.8	31.2	465.1	535.8	0.0	466.0	550.6

No	Demand Region	Port of Pontianak								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.3	6.5	132.8	280.0	315.8	385.6	0.0	322.3	518.3
2	Sumatera Utara	0.1	3.0	79.7	168.0	298.3	368.0	0.0	301.3	447.7
3	Sumatera Barat	0.1	2.6	43.0	90.7	275.0	344.7	0.0	277.5	387.7
4	Riau	0.0	0.1	1.9	4.0	291.2	361.0	0.0	291.4	362.9
5	Jambi	0.1	3.5	62.6	132.0	269.7	339.4	0.0	273.3	402.0
6	Sumatera Selatan	0.1	2.1	39.8	84.0	258.2	327.9	0.0	260.3	367.7
7	Bengkulu	0.0	1.0	20.8	43.8	259.3	329.0	0.0	260.3	349.8
8	Lampung	0.1	1.3	29.9	63.1	241.7	311.3	0.0	242.9	341.2
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	255.2	324.8	0.0	255.8	338.9

10	Kepulauan Riau	0.1	2.7	45.4	95.8	272.6	342.3	0.0	275.4	387.8
11	DKI Jakarta	0.0	0.7	9.3	19.7	159.1	167.2	0.0	159.8	176.5
12	Jawa Barat	0.1	1.9	54.1	114.0	159.1	167.2	0.0	161.0	221.2
13	Jawa Tengah	0.1	2.4	33.3	70.3	250.5	320.2	0.0	252.9	353.5
14	DI Yogyakarta	0.3	8.0	273.6	577.0	159.1	167.2	0.0	167.1	440.8
15	Jawa Timur	0.0	1.1	25.8	54.5	261.9	331.6	0.0	263.0	357.4
16	Banten	0.1	1.5	36.1	76.1	159.1	167.2	0.0	160.6	203.3
17	Bali	0.1	1.5	16.4	34.5	369.7	490.3	0.0	371.2	506.6
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	367.6	488.1	0.0	371.7	550.2
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	404.5	526.8	0.0	408.8	595.5
20	Kalimantan Barat	0.2	3.6	75.9	160.0	202.1	0.0	0.0	205.7	75.9
21	Kalimantan Tengah	0.8	18.5	441.5	931.0	202.1	0.0	0.0	220.6	441.5
22	Kalimantan Selatan	1.1	27.0	624.6	1317.0	202.1	0.0	0.0	229.1	624.6
23	Kalimantan Timur	1.5	37.0	49.3	104.0	290.9	360.6	0.0	327.9	409.9
24	Kalimantan Utara	2.2	52.0	381.8	805.0	402.2	539.8	0.0	454.2	921.6
25	Sulawesi Utara	0.0	1.0	26.2	55.2	422.6	545.8	0.0	423.6	572.0
26	Sulawesi Tengah	0.8	19.2	402.2	848.0	290.6	360.4	0.0	309.8	762.5
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	290.6	360.4	0.0	294.0	424.4
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	344.3	390.1	0.0	346.6	427.6
29	Sulawesi Barat	0.4	9.7	194.9	411.0	290.6	360.4	0.0	300.4	555.3
30	Gorontalo	0.1	2.5	44.1	93.0	465.0	565.1	0.0	467.5	609.2
31	Maluku	0.4	10.1	92.5	195.0	421.8	545.4	0.0	431.8	637.9
32	Maluku Utara	0.8	19.2	40.5	85.5	457.8	560.6	0.0	477.0	601.1
33	Papua	0.1	3.4	69.7	147.0	563.7	643.6	0.0	567.1	713.3
34	Papua Barat	0.3	8.0	155.6	328.0	484.5	585.6	0.0	492.5	741.2
35	Papua Selatan	0.1	3.5	60.2	127.0	602.3	684.1	0.0	605.7	744.3
36	Papua Tengah	0.3	6.1	111.4	235.0	437.2	459.2	0.0	443.3	570.6
37	Papua Pegunungan	0.1	3.0	35.6	75.0	572.5	577.2	0.0	575.5	612.8

38	Papua Barat Daya	0.0	0.9	14.8	31.2	467.7	568.0	0.0	468.6	582.8

No	Demand Region	Port of Tanjung Priok								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.3	6.5	132.8	280.0	225.8	218.4	1093.0	232.3	351.2
2	Sumatera Utara	0.1	3.0	79.7	168.0	208.3	200.9	863.0	211.3	280.6
3	Sumatera Barat	0.1	2.6	43.0	90.7	185.0	177.5	556.0	187.6	220.5
4	Riau	0.0	0.1	1.9	4.0	201.3	193.8	770.0	201.4	195.7
5	Jambi	0.1	3.5	62.6	132.0	179.8	172.3	487.0	183.3	234.9
6	Sumatera Selatan	0.1	2.1	39.8	84.0	168.2	160.7	335.0	170.3	200.5
7	Bengkulu	0.0	1.0	20.8	43.8	169.4	161.8	350.0	170.4	182.6
8	Lampung	0.1	1.3	29.9	63.1	151.7	144.1	117.0	152.9	174.0
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	165.2	157.7	295.0	165.8	171.8
10	Kepulauan Riau	0.1	2.7	45.4	95.8	182.7	175.2	525.0	185.4	220.6
11	DKI Jakarta	0.0	0.7	9.3	19.7	66.7	0.0	0.0	67.4	9.3
12	Jawa Barat	0.1	1.9	54.1	114.0	66.7	0.0	0.0	68.7	54.1
13	Jawa Tengah	0.1	2.4	33.3	70.3	160.6	153.0	234.0	163.0	186.3
14	DI Yogyakarta	0.3	8.0	273.6	577.0	66.7	0.0	0.0	74.7	273.6
15	Jawa Timur	0.0	1.1	25.8	54.5	172.0	164.4	384.0	173.0	190.3
16	Banten	0.1	1.5	36.1	76.1	66.7	0.0	0.0	68.2	36.1
17	Bali	0.1	1.5	16.4	34.5	279.7	323.1	0.0	281.2	339.5
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	277.7	321.0	0.0	281.7	383.1
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	314.5	359.6	0.0	318.9	428.4
20	Kalimantan Barat	0.2	3.6	75.9	160.0	174.7	167.2	420.0	178.3	243.0
21	Kalimantan Tengah	0.1	3.0	441.5	931.0	174.7	167.2	0.0	177.7	608.7
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	192.4	184.9	653.0	195.6	243.2
23	Kalimantan Timur	0.1	2.5	49.3	104.0	200.9	193.4	765.0	203.4	242.7
24	Kalimantan Utara	0.2	19.0	381.8	805.0	200.9	193.4	0.0	219.9	575.2

25	Sulawesi Utara	0.0	1.0	26.2	55.2	332.6	378.7	0.0	333.7	404.8
26	Sulawesi Tengah	0.8	19.2	402.2	848.0	200.7	193.2	0.0	219.9	595.4
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	200.7	193.2	762.0	204.1	257.2
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	254.3	223.0	1153.0	256.6	260.4
29	Sulawesi Barat	0.4	9.7	194.9	411.0	200.7	193.2	0.0	210.4	388.1
30	Gorontalo	0.1	2.5	44.1	93.0	375.0	398.0	0.0	377.5	442.1
31	Maluku	0.4	10.1	92.5	195.0	331.8	378.2	0.0	341.9	470.7
32	Maluku Utara	0.8	19.2	40.5	85.5	367.8	393.4	0.0	387.0	433.9
33	Papua	0.1	3.4	69.7	147.0	473.7	476.4	0.0	477.1	546.1
34	Papua Barat	0.3	8.0	155.6	328.0	394.5	418.4	0.0	402.5	574.0
35	Papua Selatan	0.1	3.5	60.2	127.0	512.3	516.9	0.0	515.8	577.1
36	Papua Tengah	0.3	6.1	111.4	235.0	347.2	292.0	2060.0	353.3	403.4
37	Papua Pegunungan	0.1	3.0	35.6	75.0	482.5	410.0	0.0	485.5	445.6
38	Papua Barat Daya	0.0	0.9	14.8	31.2	377.8	400.8	0.0	378.6	415.6

No	Demand Region	Port of Tanjung Emas								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time	Cost
1	Aceh	0.3	6.5	132.8	280.0	351.1	371.6	0.0	357.6	504.4
2	Sumatera Utara	0.1	3.0	79.7	168.0	283.9	218.9	1097.0	286.9	298.6
3	Sumatera Barat	0.1	2.6	43.0	90.7	260.6	195.5	790.0	263.2	238.5
4	Riau	0.0	0.1	1.9	4.0	276.9	211.8	1004.0	277.0	213.7
5	Jambi	0.1	3.5	62.6	132.0	305.1	325.5	0.0	308.6	388.1
6	Sumatera Selatan	0.1	2.1	39.8	84.0	293.5	313.9	0.0	295.6	353.7
7	Bengkulu	0.0	1.0	20.8	43.8	294.7	315.1	0.0	295.6	335.8
8	Lampung	0.1	1.3	29.9	63.1	277.0	297.3	0.0	278.2	327.2
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	290.5	310.9	0.0	291.1	325.0
10	Kepulauan Riau	0.1	2.7	45.4	95.8	258.3	193.2	759.0	261.0	238.6
11	DKI Jakarta	0.0	0.7	8.6	18.2	194.4	153.2	234.0	195.1	161.8
12	Jawa Barat	0.2	5.6	188.8	398.0	95.3	0.0	0.0	100.9	188.8
13	Jawa Tengah	0.1	2.4	33.3	70.3	95.3	0.0	0.0	97.7	33.3

14	DI Yogyakarta	0.1	2.5	70.7	149.0	95.3	0.0	0.0	97.7	70.7
15	Jawa Timur	0.0	1.1	25.8	54.5	191.4	150.2	194.0	192.4	176.0
16	Banten	0.3	7.0	236.2	498.0	95.3	0.0	0.0	102.3	236.2
17	Bali	0.1	1.5	16.4	34.5	299.1	308.9	0.0	300.6	325.2
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	297.1	306.7	0.0	301.2	368.8
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	333.9	345.4	0.0	338.3	414.1
20	Kalimantan Barat	0.2	3.6	75.9	160.0	211.7	170.6	462.0	215.3	246.4
21	Kalimantan Tengah	0.1	3.0	60.7	128.0	234.0	192.9	756.0	237.1	253.6
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	304.8	314.8	0.0	308.1	373.2
23	Kalimantan Timur	0.1	2.5	49.3	104.0	251.9	186.8	675.0	254.4	236.1
24	Kalimantan Utara	0.2	5.7	67.3	142.0	339.1	350.9	0.0	344.8	418.2
25	Sulawesi Utara	0.0	1.0	26.2	55.2	300.6	235.6	1317.0	301.7	261.8
26	Sulawesi Tengah	0.3	7.3	142.3	300.0	282.7	217.7	1081.0	290.1	360.0
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	221.7	180.5	593.0	225.1	244.6
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	275.4	210.3	984.0	277.6	247.8
29	Sulawesi Barat	0.4	9.7	194.9	411.0	221.7	180.5	0.0	231.4	375.5
30	Gorontalo	0.1	2.5	44.1	93.0	394.4	383.7	0.0	396.9	427.8
31	Maluku	0.4	10.1	92.5	195.0	290.2	225.2	1180.0	300.3	317.7
32	Maluku Utara	0.8	19.2	40.5	85.5	335.8	246.8	1464.0	355.0	287.4
33	Papua	0.1	3.4	69.7	147.0	424.3	311.5	2314.0	427.7	381.2
34	Papua Barat	0.3	8.0	155.6	328.0	325.6	260.7	1646.0	333.6	416.2
35	Papua Selatan	0.1	3.5	60.2	127.0	443.4	354.7	2881.0	446.9	414.9
36	Papua Tengah	0.3	6.1	111.4	235.0	368.2	279.3	1891.0	374.4	390.8
37	Papua Pegunungan	0.1	3.0	35.6	75.0	322.0	257.0	1598.0	325.0	292.6
38	Papua Barat Daya	0.0	0.9	14.8	31.2	308.8	243.9	1425.0	309.7	258.7

No	Demand Region	Port of Tanjung Perak		
		Land Transport	Sea Transport	TOTAL

		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.3	6.5	132.8	280.0	340.4	384.2	0.0	346.9	517.0
2	Sumatera Utara	0.1	3.0	79.7	168.0	264.4	225.3	1130.0	267.4	305.0
3	Sumatera Barat	0.1	2.6	43.0	90.7	249.9	210.2	940.0	252.5	253.2
4	Riau	0.0	0.1	1.9	4.0	266.2	227.2	1154.0	266.3	229.1
5	Jambi	0.1	3.5	62.6	132.0	244.7	204.7	871.0	248.2	267.3
6	Sumatera Selatan	0.1	2.1	39.8	84.0	233.2	192.6	719.0	235.2	232.4
7	Bengkulu	0.0	1.0	20.8	43.8	234.3	193.8	734.0	235.3	214.5
8	Lampung	0.1	1.3	29.9	63.1	266.3	310.0	0.0	267.5	339.9
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	230.1	189.4	679.0	230.7	203.5
10	Kepulauan Riau	0.1	2.7	45.4	95.8	247.6	207.7	909.0	250.3	253.1
11	DKI Jakarta	0.0	0.7	8.6	18.2	183.7	165.9	384.0	184.5	174.5
12	Jawa Barat	0.4	9.5	350.9	740.0	86.2	0.0	0.0	95.6	350.9
13	Jawa Tengah	0.1	2.4	33.3	70.3	169.3	150.7	194.0	171.7	184.1
14	DI Yogyakarta	0.2	4.2	155.6	328.0	86.2	0.0	0.0	90.4	155.6
15	Jawa Timur	0.0	1.1	25.8	54.5	86.2	0.0	0.0	87.2	25.8
16	Banten	0.5	11.1	397.9	839.0	86.2	0.0	0.0	97.2	397.9
17	Bali	0.1	1.5	16.4	34.5	176.9	158.7	294.0	178.4	175.0
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	174.8	156.5	267.0	178.9	218.7
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	211.7	195.2	752.0	216.0	264.0
20	Kalimantan Barat	0.2	3.6	75.9	160.0	196.0	178.8	546.0	199.6	254.7
21	Kalimantan Tengah	0.1	3.0	60.7	128.0	197.2	180.0	562.0	200.2	240.8
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	182.6	164.7	369.0	185.8	223.0
23	Kalimantan Timur	0.1	2.5	49.3	104.0	191.1	173.6	481.0	193.6	222.9
24	Kalimantan Utara	0.2	5.7	67.3	142.0	216.9	200.7	821.0	222.6	268.0
25	Sulawesi Utara	0.0	1.0	26.2	55.2	229.8	214.2	991.0	230.8	240.4
26	Sulawesi Tengah	0.3	7.3	142.3	300.0	245.9	206.0	887.0	253.2	348.2
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	187.7	170.1	437.0	191.1	234.1

28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	241.4	201.3	828.0	243.7	238.7
29	Sulawesi Barat	0.4	9.7	194.9	411.0	187.7	170.1	0.0	197.5	365.0
30	Gorontalo	0.1	2.5	44.1	93.0	272.2	233.5	1233.0	274.7	277.6
31	Maluku	0.4	10.1	92.5	195.0	229.0	213.4	980.0	239.0	305.8
32	Maluku Utara	0.8	19.2	40.5	85.5	265.0	226.0	1138.0	284.2	266.5
33	Papua	0.1	3.4	69.7	147.0	370.9	312.0	2217.0	374.2	381.7
34	Papua Barat	0.3	8.0	155.6	328.0	291.7	254.0	1490.0	299.7	409.6
35	Papua Selatan	0.1	3.5	60.2	127.0	409.5	352.5	2725.0	412.9	412.7
36	Papua Tengah	0.3	6.1	111.4	235.0	338.8	278.3	1794.0	344.9	389.7
37	Papua Pegunungan	0.1	3.0	35.6	75.0	422.1	575.9	0.0	425.1	611.5
38	Papua Barat Daya	0.0	0.9	14.8	31.2	274.9	236.4	1269.0	275.8	251.2

No	Demand Region	Port of Makassar								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.3	6.5	132.8	280.0	344.9	409.8	0.0	351.4	542.5
2	Sumatera Utara	0.1	3.0	79.7	168.0	290.5	243.8	1477.0	293.5	323.5
3	Sumatera Barat	0.1	2.6	43.0	90.7	304.1	368.9	0.0	306.6	411.9
4	Riau	0.0	0.1	1.9	4.0	320.3	385.2	0.0	320.4	387.1
5	Jambi	0.1	3.5	62.6	132.0	298.8	363.6	0.0	302.4	426.2
6	Sumatera Selatan	0.1	2.1	39.8	84.0	287.3	352.1	0.0	289.4	391.9
7	Bengkulu	0.0	1.0	20.8	43.8	288.4	353.2	0.0	289.4	374.0
8	Lampung	0.1	1.3	29.9	63.1	270.7	335.5	0.0	272.0	365.4
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	284.3	349.0	0.0	284.9	363.2
10	Kepulauan Riau	0.1	2.7	45.4	95.8	301.7	366.5	0.0	304.4	412.0
11	DKI Jakarta	0.0	0.7	8.6	18.2	188.2	191.4	762.0	188.9	200.0
12	Jawa Barat	0.1	1.9	54.1	114.0	188.2	191.4	0.0	190.1	245.4
13	Jawa Tengah	0.1	2.4	33.3	70.3	175.3	179.0	593.0	177.7	212.3
14	DI Yogyakarta	0.3	8.0	273.6	577.0	188.2	191.4	0.0	196.2	465.0
15	Jawa Timur	0.0	1.1	25.8	54.5	163.5	167.5	437.0	164.6	193.4
16	Banten	0.1	1.5	36.1	76.1	188.2	191.4	0.0	189.7	227.5
17	Bali	0.1	1.5	16.4	34.5	271.3	326.2	0.0	272.7	342.6
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	269.2	324.1	0.0	273.3	386.2

19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	202.5	182.1	635.0	206.9	250.8
20	Kalimantan Barat	0.2	3.6	75.9	160.0	293.7	346.3	0.0	297.3	422.2
21	Kalimantan Tengah	0.1	3.0	60.7	128.0	291.6	347.6	0.0	294.6	408.3
22	Kalimantan Selatan	0.1	3.3	58.3	123.0	147.8	152.3	230.0	151.0	210.7
23	Kalimantan Timur	0.1	2.5	49.3	104.0	176.5	156.9	292.0	179.0	206.2
24	Kalimantan Utara	0.2	5.7	67.3	142.0	311.3	368.2	0.0	317.0	435.6
25	Sulawesi Utara	0.0	1.0	26.2	55.2	185.3	188.6	724.0	186.3	214.8
26	Sulawesi Tengah	0.3	7.3	142.3	300.0	164.5	168.5	450.0	171.8	310.7
27	Sulawesi Selatan	0.1	3.4	64.0	135.0	61.4	0.0	0.0	64.8	64.0
28	Sulawesi Tenggara	0.1	2.3	37.5	79.0	160.0	164.1	391.0	162.3	201.6
29	Sulawesi Barat	0.4	9.7	194.9	411.0	61.4	0.0	0.0	71.2	194.9
30	Gorontalo	1.3	30.0	44.1	93.0	283.6	205.8	0.0	313.6	249.9
31	Maluku	0.4	10.1	92.5	195.0	174.9	178.5	587.0	185.0	271.0
32	Maluku Utara	0.8	19.2	40.5	85.5	359.3	393.5	0.0	378.5	434.0
33	Papua	0.1	3.4	69.7	147.0	309.0	261.7	1721.0	312.3	331.5
34	Papua Barat	0.3	8.0	155.6	328.0	234.3	212.7	1053.0	242.3	368.3
35	Papua Selatan	0.1	3.5	60.2	127.0	503.9	520.0	0.0	507.3	580.2
36	Papua Tengah	0.3	6.1	111.4	235.0	167.7	230.7	1298.0	173.8	342.2
37	Papua Pegunungan	0.1	3.0	35.6	75.0	428.2	436.0	0.0	431.2	471.6
38	Papua Barat Daya	0.0	0.9	14.8	31.2	241.5	196.5	832.0	242.4	211.3

No	Demand Region	Port of Bitung								
		Land Transport				Sea Transport			TOTAL	
		Time (hour)		Cost	Distance (km)	Time (hour)	Cost	Distance (km)	Time (hour)	Cost
1	Aceh	0.3	6.5	132.8	280.0	402.8	444.2	0.0	409.4	577.0
2	Sumatera Utara	0.1	81.9	79.7	168.0	338.9	267.5	1868.0	420.8	347.1
3	Sumatera Barat	0.1	2.6	43.0	90.7	362.1	403.3	0.0	364.6	446.4
4	Riau	0.0	69.4	1.9	4.0	331.5	260.6	1771.0	400.9	262.5
5	Jambi	0.1	3.5	62.6	132.0	356.8	398.1	0.0	360.3	460.7

6	Sumatera Selatan	0.1	2.1	39.8	84.0	345.3	386.5	0.0	347.3	426.4
7	Bengkulu	0.0	1.0	20.8	43.8	346.4	387.7	0.0	347.4	408.4
8	Lampung	0.1	1.3	29.9	63.1	328.7	369.9	0.0	330.0	399.9
9	Kepulauan Bangka Belitung	0.0	0.6	14.1	29.8	342.2	383.5	0.0	342.9	397.6
10	Kepulauan Riau	0.1	2.7	45.4	95.8	359.7	401.0	0.0	362.4	446.4
11	DKI Jakarta	0.0	70.5	8.6	18.2	246.2	225.8	1279.0	316.7	234.5
12	Jawa Barat	0.1	1.9	54.1	114.0	243.8	225.8	0.0	245.7	279.9
13	Jawa Tengah	0.1	2.4	33.3	70.3	337.6	378.8	0.0	340.0	412.2
14	DI Yogyakarta	0.3	8.0	273.6	577.0	243.8	225.8	0.0	251.8	499.5
15	Jawa Timur	0.0	73.3	25.8	54.5	224.3	205.5	991.0	297.5	231.3
16	Banten	0.1	1.5	36.1	76.1	243.8	225.8	0.0	245.3	261.9
17	Bali	0.1	1.5	16.4	34.5	332.1	364.1	0.0	333.5	380.5
18	Nusa Tenggara Barat	0.2	4.1	62.1	131.0	330.0	362.0	0.0	334.1	424.1
19	Nusa Tenggara Timur	0.2	4.4	68.8	145.0	366.8	400.7	0.0	371.2	469.4
20	Kalimantan Barat	0.2	3.6	75.9	160.0	351.7	384.2	0.0	355.3	460.1
21	Kalimantan Tengah	0.1	3.0	60.7	128.0	352.4	385.5	0.0	355.4	446.2
22	Kalimantan Selatan	0.1	78.5	58.3	123.0	222.9	181.8	657.0	301.4	240.2
23	Kalimantan Timur	0.1	77.0	49.3	104.0	214.4	173.9	545.0	291.4	223.2
24	Kalimantan Utara	0.2	5.7	67.3	142.0	372.1	406.2	0.0	377.7	473.5
25	Sulawesi Utara	0.0	1.0	26.2	55.2	0.0	0.0	0.0	1.0	26.2
26	Sulawesi Tengah	0.3	91.9	142.3	300.0	189.0	172.6	526.0	280.9	314.9
27	Sulawesi Selatan	0.1	79.4	64.0	135.0	204.0	186.6	724.0	283.4	250.6
28	Sulawesi Tenggara	1.6	198.0	805.3	1698.0	80.2	0.0	0.0	278.2	805.3
29	Sulawesi Barat	1.3	175.0	661.6	1395.0	80.2	0.0	0.0	255.2	661.6
30	Gorontalo	0.1	76.2	44.1	93.0	167.4	152.5	242.0	243.6	196.6
31	Maluku	0.4	83.9	92.5	195.0	230.7	166.7	443.0	314.6	259.2
32	Maluku Utara	0.8	109.4	251.4	530.0	208.2	145.8	147.0	317.6	397.1
33	Papua	0.1	3.4	69.7	147.0	526.1	517.4	0.0	529.4	587.1
34	Papua Barat	0.3	94.0	155.6	328.0	252.3	186.9	728.0	346.3	342.4
35	Papua Selatan	0.1	3.5	60.2	127.0	564.6	557.9	0.0	568.1	618.2

36	Papua Tengah	0.3	6.1	111.4	235.0	493.9	483.7	0.0	500.1	595.2
37	Papua Pegunungan	0.1	3.0	35.6	75.0	590.5	635.9	0.0	593.5	671.4
38	Papua Barat Daya	0.0	0.9	14.8	31.2	430.1	441.9	0.0	431.0	456.7

1.4 Impedance and OD Matrix

- OD Matrix

Teu Modelled based on Fij	Aceh	Sumatera Utara	Sumatera Barat	Riau	Jambi	Sumatera Selatan	Bengkulu	Lampung	Kepulauan Bangka Belitung	Kepulauan Riau	DKI Jakarta	Jawa Barat	Jawa Tengah	DI Yogyakarta	Jawa Timur	Banten	Bali	Nusa Tenggara Barat	Nusa Tenggara Timur	Kalimantan Barat	Kalimantan Tengah	Kalimantan Selatan	Kalimantan Timur	Kalimantan Utara	Sulawesi Utara	Sulawesi Tengah	Sulawesi Selatan	Sulawesi Tenggara	Sulawesi Barat	Gorontalo	Maluku	Maluku Utara	Papua	Papua Barat	Papua Selatan	Papua Tengah	Papua Pegunungan	Papua Barat Daya	Modelled	Actual
Port of Belawan	38,690	151,385	7,835	35,356	81	2,140	111	13	265	27,679	7,038	3,802	297	32	4,980	1,615	486	282	163	76	269	144	523	361	2	89	25	45	3	19	30	110	23	28	30	30	2	19	284,079	227,366
Port of Palembang	62	75	9,193	25,310	46,914	86,691	11,001	14,684	747	1,219	19,654	10,728	838	91	120	4,556	81	47	27	215	44	553	2,013	51	0	18	88	229	12	4	5	24	7	6	9	243	6	4	235,572	58,349
Port of Panjang	74	90	1,117	3,341	3,992	8,730	2,523	54,524	934	1,524	24,831	8,481	663	72	95	5,697	102	59	33	268	56	691	2,517	64	0	23	111	286	15	5	6	30	9	8	11	304	8	6	121,304	10,162
Port of Pontianak	56	64	702	2,153	180	84	173	97	481	785	12,652	6,906	354	59	409	2,933	52	30	17	40,136	1,245	277	902	21	0	12	57	147	8	3	3	16	4	4	6	157	4	3	71,192	35,792
Port of Tanjung Priok	1,954	2,254	24,519	75,256	6,295	2,947	6,033	3,405	16,812	27,426	453,478	247,531	12,385	2,106	14,279	105,130	1,831	1,063	600	4,827	1,000	12,438	45,290	1,147	7	412	1,989	5,154	270	95	109	542	157	140	204	5,478	145	99	1,084,807	1,326,880
Port of Tanjung Emas	38	563	6,124	18,796	123	57	118	66	328	6,850	8,717	16,938	176,624	25,148	10,440	2,646	1,339	777	439	2,251	14,050	394	21,202	964	64	6,683	1,396	3,618	190	70	1,216	4,950	2,258	2,234	3,468	3,845	5,620	1,556	352,161	549,984
Port of Tanjung Perak	36	646	5,656	17,161	1,458	688	1,407	63	3,933	6,337	8,296	1,616	8,708	7,820	308,247	254	47,282	27,447	15,493	2,413	25,805	13,903	50,320	34,048	191	12,060	2,399	6,085	326	2,465	2,842	14,646	4,043	3,625	5,265	5,475	17	2,555	651,032	958,439
Port of Makassar	20	315	251	771	65	30	62	35	172	281	4,578	2,473	4,535	21	9,403	1,050	1,206	700	6,152	59	658	20,439	19,475	868	379	42,183	98,239	21,165	13,338	2,105	7,170	374	13,949	10,434	134	23,346	110	5,599	312,147	22,211
Port of Bitung	5	47	65	1,722	17	8	16	9	45	73	573	661	33	6	1,057	281	289	168	95	15	158	2,173	12,195	208	36,048	10,130	484	117	61	7,841	1,761	989	25	4,138	32	34	1	16	81,596	4,710
Modelled	40,936	155,439	55,461	179,867	59,124	101,375	21,445	72,897	23,717	72,174	539,816	299,136	204,437	35,355	349,030	124,163	52,670	30,574	23,020	50,259	43,285	51,011	154,436	37,732	36,693	71,610	104,788	36,847	14,223	12,608	13,143	21,681	20,475	20,617	9,160	38,913	5,913	9,857	3,193,889	354,877
Actual	40,936	155,439	55,461	179,867	59,125	101,375	21,445	72,897	23,717	72,174	539,817	299,136	204,438	35,355	349,030	124,163	52,670	30,574	23,020	50,260	43,285	51,011	154,436	37,732	36,693	71,611	104,788	36,847	14,223	12,608	13,143	21,681	20,475	20,617	9,160	38,913	5,913	9,857		

Error Calc	Demand Re	Port Import
	100.00%	82.66%

- Base OD Matrix

i/j	Aceh	Sumatera Utara	Sumatera Barat	Riau	Jambi	Sumatera Selatan	Bengkulu	Lampung	Kepulauan Bangka Belitung	Kepulauan Riau	DKI Jakarta	Jawa Barat	Jawa Tengah	DI Yogyakarta	Jawa Timur	Banten	Bali	Nusa Tenggara Barat	Nusa Tenggara Timur
Port of Belawan	35602	143987	3261	15174	163	9755	95	75	94	11951	2812	1449	63	7	1157	649	112	65	50
Port of Palembang	5	7	364	1034	8977	37615	898	7860	25	50	747	389	17	2	3	174	2	1	1
Port of Panjang	2	2	13	39	216	1071	58	8251	9	18	267	87	4	0	1	62	1	0	0
Port of Pontianak	43	51	245	775	304	322	124	460	144	284	4241	2209	64	10	80	990	10	6	4
Port of Tanjung Priok	4955	5907	28121	88995	34873	37010	14261	52759	16483	32631	499188	259931	7295	1228	9144	116493	1167	677	508
Port of Tanjung Emas	175	2673	12725	40272	1233	1308	504	1865	583	14766	17385	32226	188475	26567	12113	5313	1546	897	673
Port of Tanjung Perak	152	2799	10728	33561	13353	14289	5501	1620	6377	12469	15102	2806	8481	7540	326443	465	49821	28920	21706
Port of Makassar	1	12	4	13	5	6	2	8	2	5	74	38	39	0	88	17	11	7	76
Port of Bitung	0	0	0	4	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0
Model	40936	155439	55461	179867	59125	101375	21445	72897	23717	72174	539817	299136	204438	35355	349030	124163	52670	30574	23020
Actual	40936	155439	55461	179867	59125	101375	21445	72897	23717	72174	539817	299136	204438	35355	349030	124163	52670	30574	23020

i/j	Kalimantan Barat	Kalimantan Tengah	Kalimantan Selatan	Kalimantan Timur	Kalimantan Utara	Sulawesi Utara	Sulawesi Tengah	Sulawesi Selatan	Sulawesi Tenggara	Sulawesi Barat	Gorontalo	Maluku	Maluku Utara	Papua	Papua Barat	Papua Selatan	Papua Tengah	Papua Pegunungan	Papua Barat Daya	Model	Actual
Port of Belawan	55	61	73	175	83	53	70	95	27	13	20	20	26	15	20	7	19	0	10	227366	227366
Port of Palembang	15	1	27	64	1	1	1	32	13	4	0	0	1	0	0	0	15	0	0	58349	58349
Port of Panjang	5	0	9	23	0	0	0	11	5	2	0	0	0	0	0	0	5	0	0	10162	10162
Port of Pontianak	24420	236	118	253	4	5	8	182	75	25	2	2	3	3	2	1	85	1	1	35792	35792
Port of Tanjung Priok	9643	621	17331	41687	729	533	891	20941	8572	2842	277	202	348	288	280	123	9729	83	135	1326880	1326880
Port of Tanjung Emas	8146	15827	994	35357	1111	8365	26166	26634	10903	3615	367	4060	5755	7514	8059	3784	12373	5812	3841	549984	549984
Port of Tanjung Perak	7973	26533	32037	76595	35795	22770	43102	41760	16737	5668	11813	8661	15543	12280	11937	5244	16081	16	5758	958439	958439
Port of Makassar	2	6	416	262	8	400	1333	15123	515	2053	89	193	4	375	304	1	606	1	112	22211	22211
Port of Bitung	0	0	5	20	0	4565	38	9	0	1	40	6	1	0	14	0	0	0	0	4710	4710
Model	50260	43285	51011	154436	37732	36693	71611	104788	36847	14223	12608	13143	21681	20475	20617	9160	38913	5913	9857		
Actual	50260	43285	51011	154436	37732	36693	71611	104788	36847	14223	12608	13143	21681	20475	20617	9160	38913	5913	9857		

1.5 Regression Result for other Port Reference

- Port Belawan as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1607 -0.6485 -0.2197  0.5222  3.6380

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.4131444  0.0708093 -19.957  < 2e-16 ***
Connectivity  0.2537827  0.0104145  24.368  < 2e-16 ***
PDR.Time     -0.0126251  0.0007106 -17.766  < 2e-16 ***
PDR.Cost     -0.0122484  0.0004654 -26.319  < 2e-16 ***
MarI.Time    -0.1716281  0.0069683 -24.630  < 2e-16 ***
ET.BT.I       0.0674097  0.0106132   6.351 6.93e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9992 on 336 degrees of freedom
Multiple R-squared:  0.9487,    Adjusted R-squared:  0.948
F-statistic:  1243 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I
    3.592423     1.867100     2.168425     3.159378     1.920869
```

- Port Tanjung Priok as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-1.9559 -0.6995 -0.2518  0.6769  3.5179

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.9013139  0.1237404   7.284 2.32e-12 ***
Connectivity  0.2529117  0.0105100  24.064  < 2e-16 ***
PDR.Time     -0.0125961  0.0007835 -16.077  < 2e-16 ***
PDR.Cost     -0.0124196  0.0004738 -26.212  < 2e-16 ***
MarI.Time    -0.1719032  0.0069667 -24.675  < 2e-16 ***
ET.BT.I       0.0669845  0.0106330   6.300 9.35e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.999 on 336 degrees of freedom
Multiple R-squared:  0.9396,    Adjusted R-squared:  0.9387
F-statistic:  1046 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity      PDR.Time      PDR.Cost     MarI.Time       ET.BT.I
    3.659964      1.493146      1.780024      3.159199      1.928750
```

- Port Tanjung Emas as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-2.2317 -0.6369 -0.2142  0.5624  3.9138

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.3730320  0.0832793 -16.487  < 2e-16 ***
Connectivity  0.2502149  0.0105854  23.638  < 2e-16 ***
PDR.Time     -0.0132913  0.0007678 -17.311  < 2e-16 ***
PDR.Cost     -0.0125606  0.0004765 -26.361  < 2e-16 ***
MarI.Time    -0.1718081  0.0070597 -24.336  < 2e-16 ***
ET.BT.I       0.0657036  0.0107582   6.107  2.8e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.012 on 336 degrees of freedom
Multiple R-squared:  0.9445,    Adjusted R-squared:  0.9437
F-statistic:  1144 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I
    3.617357     1.706884     1.998192     3.160768     1.923756
```

- Port of Panjang as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-4.4087 -0.8758 -0.1225  0.7386  3.1330

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.1369302  0.1025447  11.087  < 2e-16 ***
Connectivity  0.2588512  0.0121886  21.237  < 2e-16 ***
PDR.Time     -0.0151708  0.0006445 -23.537  < 2e-16 ***
PDR.Cost     -0.0100751  0.0003957 -25.460  < 2e-16 ***
MarI.Time    -0.1671596  0.0081079 -20.617  < 2e-16 ***
ET.BT.I       0.0699923  0.0124137   5.638 3.64e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.169 on 336 degrees of freedom
Multiple R-squared:  0.9265,    Adjusted R-squared:  0.9254
F-statistic:   847 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I
    3.597360     1.187203     1.336087     3.127087     1.921220
```

- Tanjung Perak as reference

```
Residuals:
    Min      1Q  Median      3Q     Max 
-2.1578 -0.5665 -0.2451  0.6446  3.8287 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)   0.3083636  0.1487351   2.073   0.0389 *  
Connectivity  0.2506063  0.0106051  23.631  < 2e-16 ***
PDR.Time     -0.0125569  0.0007215 -17.403  < 2e-16 ***
PDR.Cost     -0.0128539  0.0004307 -29.842  < 2e-16 ***
MarI.Time    -0.1725862  0.0070643 -24.431  < 2e-16 ***
ET.BT.I       0.0658607  0.0107838   6.107  2.8e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.015 on 336 degrees of freedom
Multiple R-squared:  0.9445,	Adjusted R-squared:  0.9437 
F-statistic:  1144 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I 
    3.612303     1.519517     1.745692     3.148718     1.923056 
```

- Port of Makassar as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-2.3472 -0.6143 -0.1869  0.8635  3.6925

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.1619791  0.1022356   1.584    0.114
Connectivity  0.2526724  0.0106990  23.616  < 2e-16 ***
PDR.Time     -0.0128892  0.0007189 -17.930  < 2e-16 ***
PDR.Cost     -0.0123174  0.0005071 -24.292  < 2e-16 ***
MarI.Time    -0.1716156  0.0071806 -23.900  < 2e-16 ***
ET.BT.I       0.0668814  0.0109203   6.124 2.54e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.029 on 336 degrees of freedom
Multiple R-squared:  0.951,	Adjusted R-squared:  0.9503
F-statistic:  1305 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I
    3.578298     2.263305     2.623004     3.166345     1.919332
```

- Port of Palembang as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time + 
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.4391 -0.7703 -0.1921  0.5280  3.2817 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)   0.1997031  0.1332323   1.499    0.135    
Connectivity  0.2539116  0.0112851  22.500  < 2e-16 ***
PDR.Time     -0.0134716  0.0006542 -20.592  < 2e-16 ***
PDR.Cost     -0.0118059  0.0004147 -28.468  < 2e-16 ***
MarI.Time    -0.1705714  0.0075363 -22.633  < 2e-16 ***
ET.BT.I       0.0675110  0.0115130   5.864 1.08e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.084 on 336 degrees of freedom
Multiple R-squared:  0.9415,	Adjusted R-squared:  0.9407 
F-statistic:  1082 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I 
    3.581988     1.461550     1.658265     3.138201     1.919483 
```

- Port of Pontianak as reference

```
Call:
lm(formula = Delta_U ~ Connectivity + PDR.Time + PDR.Cost + MarI.Time +
    ET.BT.I, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-4.3483 -0.7715 -0.1393  0.3674  3.0609

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.0972512  0.1077008  -0.903    0.367
Connectivity  0.2554527  0.0113831  22.441  < 2e-16 ***
PDR.Time     -0.0139393  0.0008627 -16.158  < 2e-16 ***
PDR.Cost     -0.0112969  0.0004745 -23.810  < 2e-16 ***
MarI.Time    -0.1695822  0.0075795 -22.374  < 2e-16 ***
ET.BT.I       0.0682823  0.0115627   5.905 8.61e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.088 on 336 degrees of freedom
Multiple R-squared:  0.933,     Adjusted R-squared:  0.932
F-statistic: 935.8 on 5 and 336 DF,  p-value: < 2.2e-16

> vif(model_filtered)
Connectivity     PDR.Time     PDR.Cost    MarI.Time      ET.BT.I
    3.621928     1.603862     1.815827     3.154645     1.924109
```

APPENDIX 2

SOFTWARE PROGRAM

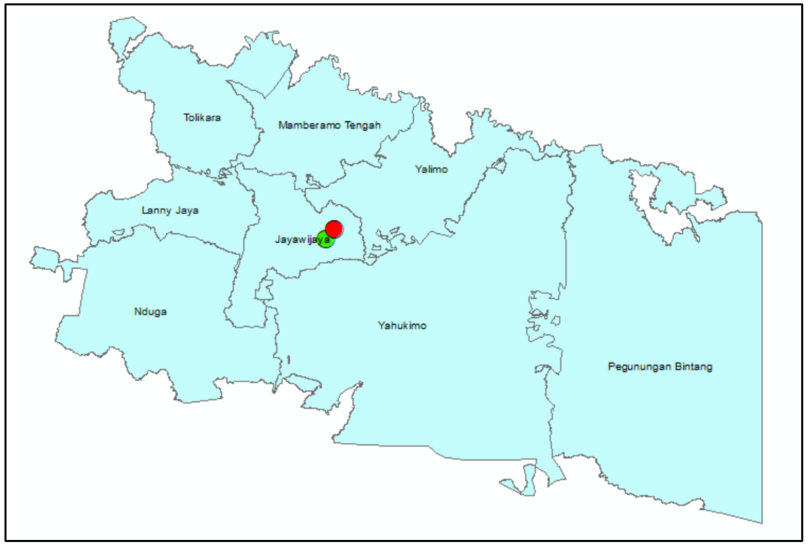
2.1 Demand Region ARCGIS

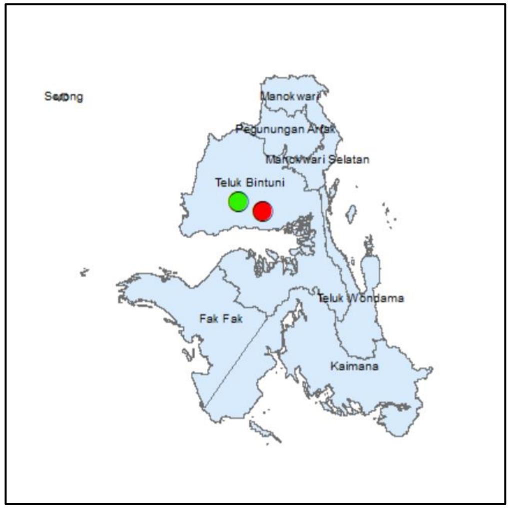
No	**Province**	**Provincial Capital**	**Mean Center**		**Weighted Mean Center**		**Delta**	
			Latitude	Longitude	Latitude	Longitude	Latitude	Longitude
1	Aceh	Banda Aceh	4.362401	96.799086	4.727685	96.622817	0.365284	-0.176269
2	Sumatera Utara	Medan	2.264720	98.868507	3.000033	98.935900	0.735313	0.067393
3	Sumatera Barat	Padang	-0.683614	100.477129	-0.646860	100.477378	0.036754	0.000249
4	Riau	Pekanbaru	0.634186	101.709829	0.698689	101.653505	0.064503	-0.056324
5	Jambi	Jambi	-1.710946	102.668792	-1.603286	102.924330	0.107660	0.255538
6	Sumatera Selatan	Palembang	-3.448835	103.906494	-3.192947	104.269786	0.255888	0.363292
7	Bengkulu	Bengkulu	-3.679670	102.488361	-3.684980	102.412456	-0.005310	-0.075905
8	Lampung	Bandar Lampung	-4.987191	105.035852	-5.060629	105.222783	-0.073438	0.186931
9	Kepulauan Bangka Belitung	Pangkal Pinang	-2.413013	106.551698	-2.322678	106.409778	0.090335	-0.141920
10	Kepulauan Riau	Tanjung Pinang	1.480523	105.091049	1.227361	104.500130	-0.253162	-0.590919
11	DKI Jakarta	Jakarta	-6.116942	106.789954	-6.194763	106.827253	-0.077821	0.037299
12	Jawa Barat	Bandung	-6.867453	107.693607	-6.661736	107.418768	0.205717	-0.274839
13	Jawa Tengah	Semarang	-7.242490	110.214751	-7.220008	110.216468	0.022482	0.001717
14	DI Yogyakarta	Yogyakarta	-7.846743	110.378273	-7.820885	110.388280	0.025858	0.010007
15	Jawa Timur	Surabaya	-7.651498	112.559908	-7.557805	112.643550	0.093693	0.083642
16	Banten	Serang	-6.269646	106.270627	-6.196411	106.393204	0.073235	0.122577

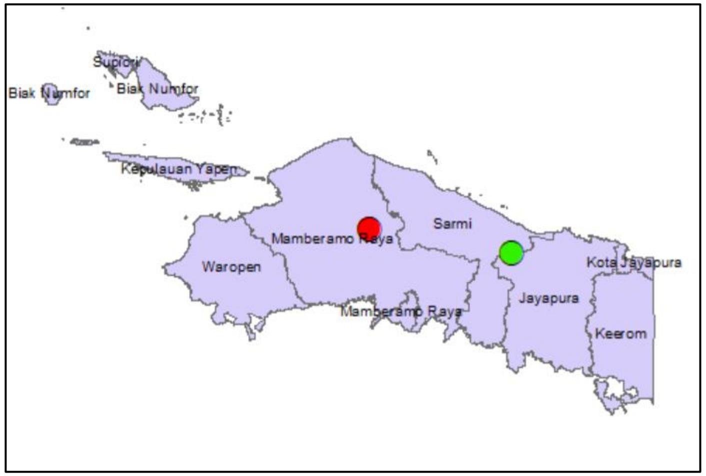
17	Bali	Denpasar	-8.445647	115.198844	-8.488894	115.175100	-0.043247	-0.023744
18	Nusa Tenggara Barat	Mataram	-8.572098	117.108867	-8.615270	116.881370	-0.043172	-0.227497
19	Nusa Tenggara Timur	Kupang	-9.240898	122.190490	-9.427307	122.638244	-0.186409	0.447754
20	Kalimantan Barat	Pontianak	0.041313	110.232287	0.251031	110.304599	0.209718	0.072312
21	Kalimantan Tengah	Palangka Raya	-1.798604	113.384842	-1.875085	113.304187	-0.076481	-0.080655
22	Kalimantan Selatan	Banjarmasin	-2.949114	115.208627	-3.000127	115.262576	-0.051013	0.053949
23	Kalimantan Timur	Samarinda	-0.211330	116.593675	-0.163012	116.659633	0.048318	0.065958
24	Kalimantan Utara	Tanjung Selor	3.249903	116.833505	3.348903	116.989918	0.099000	0.156413
25	Sulawesi Utara	Manado	1.478626	124.773203	1.411563	124.813608	-0.067063	0.040405
26	Sulawesi Tengah	Palu	-0.944184	121.305487	-1.709160	121.461239	-0.764976	0.155752
27	Sulawesi Selatan	Makassar	-4.372107	119.972166	-4.578171	119.807591	-0.206064	-0.164575
28	Sulawesi Tenggara	Kendari	-4.525513	122.391303	-4.233033	122.093897	0.292480	-0.297406
29	Sulawesi Barat	Mamuju	-2.573511	119.290581	-2.543016	119.296467	0.030495	0.005886
30	Gorontalo	Gorontalo	0.637956	122.473031	0.628666	122.488121	-0.009290	0.015090
31	Maluku	Ambon	-4.892534	129.629248	-4.380601	129.572642	0.511933	-0.056606
32	Maluku Utara	Ternate	0.368558	127.515626	0.262960	127.743294	-0.105598	0.227668
33	Papua	Jayapura	-2.330275	138.128785	-2.567637	139.572784	-0.237362	1.443999

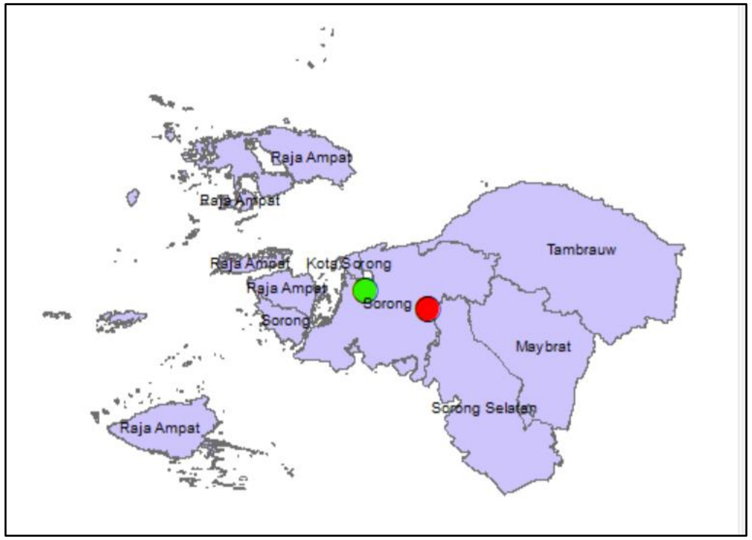
34	Papua Barat	Manokwari	-2.050661	133.460526	-1.949742	133.216119	0.100919	-0.244407
35	Papua Selatan	Salor (Merauke)	-6.429869	139.529873	-7.108773	139.673512	-0.678904	0.143639
36	Papua Tengah	Wanggar (Nabire)	-3.806115	136.496179	-4.289649	136.626297	-0.483534	0.130118
37	Papua Pegunungan	Wamena (Jayawijaya)	-4.044147	139.081021	-4.089441	139.045182	-0.045294	-0.035839
38	Papua Barat Daya	Sorong	-1.133547	131.819315	-1.022083	131.410325	0.111464	-0.408990

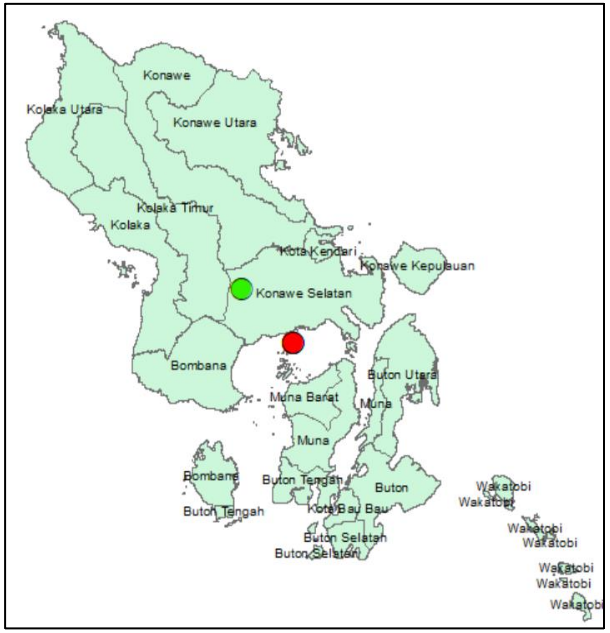
Picture location of centeriod, Mean Center (Red) and Weighted Mean Center (Green)

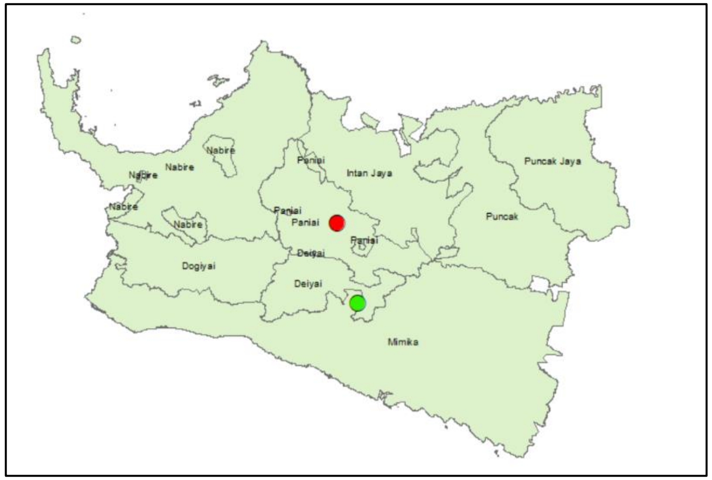


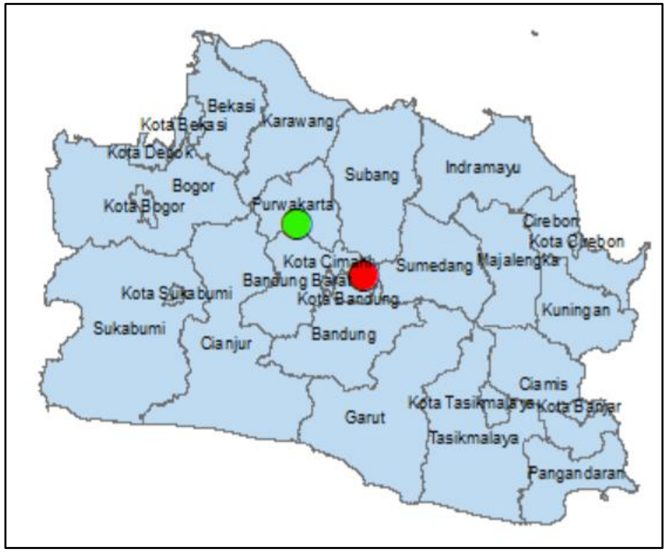


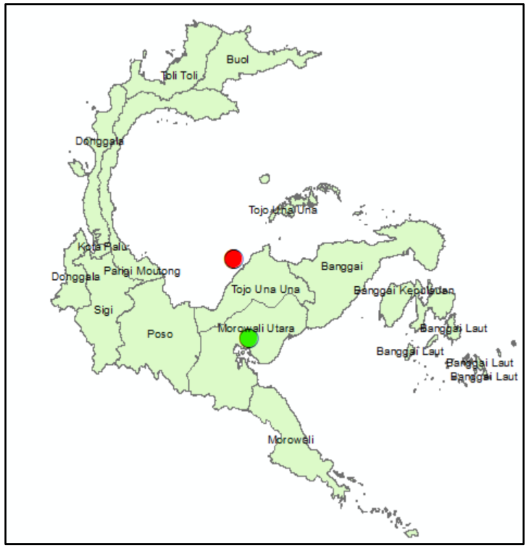

Supiori
Biak Numfor
Biak Numfor
Kepulauan Yapen
Mamberamo Raya
Sarmi
Waropen
Kota Jayapura
Mamberamo Raya
Jayapura
Keerom

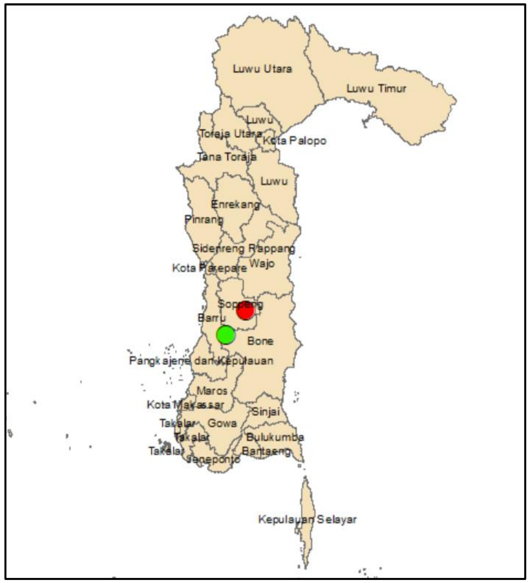

Raja Ampat
Raja Ampat
Raja Ampat
Kota Sorong
Tambrauw
Raja Ampat
Sorong
Sorong
Maybrat
Sorong Selatan
Raja Ampat

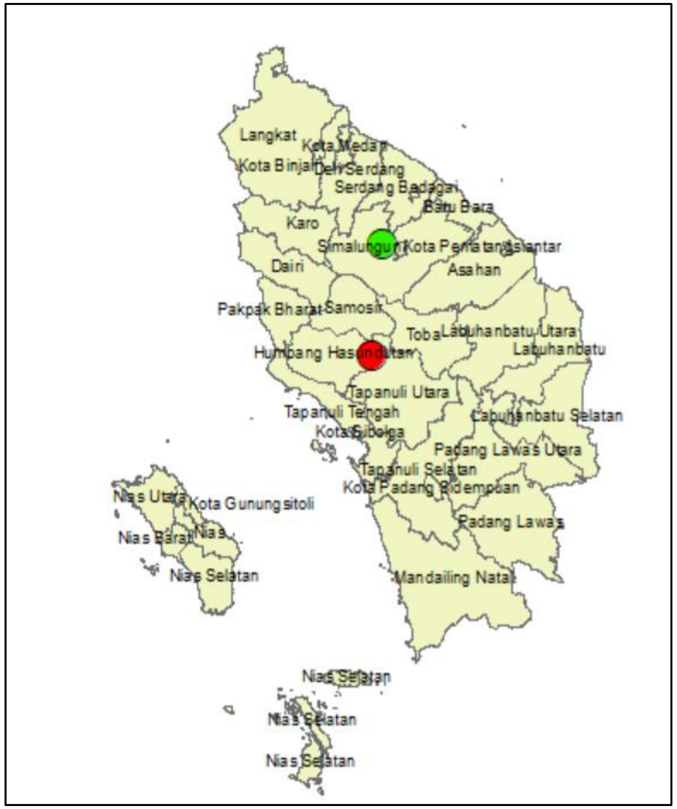

Konawe
Kolaka Utara
Konawe Utara
Kolaka Timur
Kolaka
Kota Kendari
Konawe Kepulauan
Konawe Selatan
Bombana
Buton Utara
Muna Barat
Muna
Muna
Bombana
Buton Tengah
Buton
Wakatobi
Wakatobi
Buton Tengah
Kota Bau Bau
Wakatobi
Wakatobi
Buton Selatan
Buton Selatan
Wakatobi
Wakatobi
Wakatobi

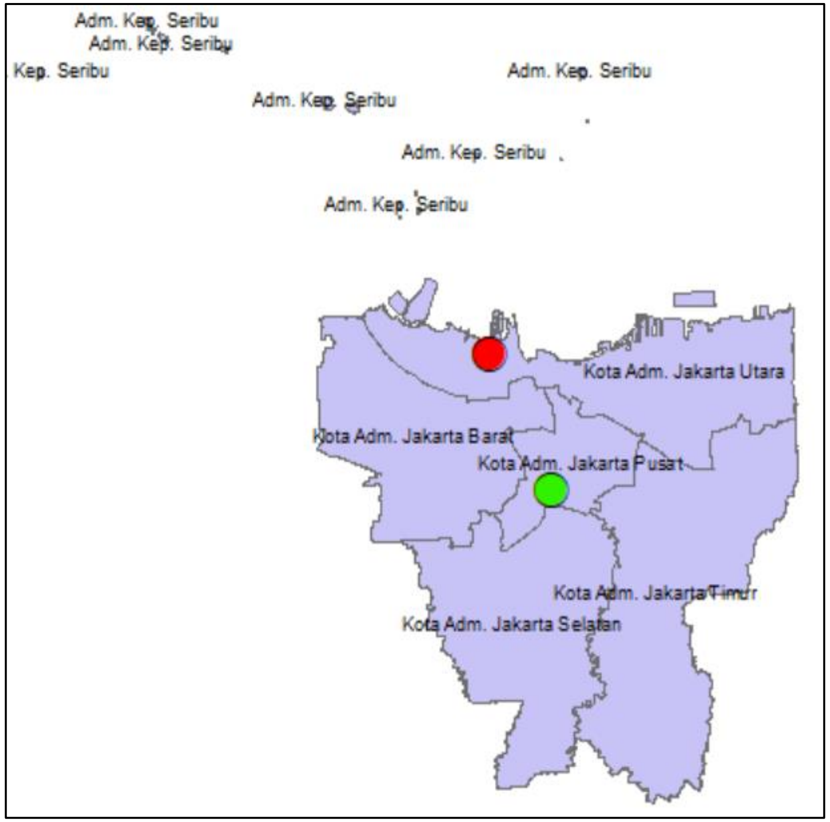

Nabire
Nabire
Paniai
Intan Jaya
Puncak Jaya
Paniai
Paniai
Puncak
Dogiyai
Deiyai
Mimika


Bekasi
Kota Bekasi
Karawang
Kota Depok
Bogor
Kota Bogor
Subang
Indramayu
Purwakarta
Cirebon
Kota Cirebon
Kota Cimahi
Sumedang
Majalengka
Bandung Barat
Kota Bandung
Kota Sukabumi
Kuningan
Sukabumi
Cianjur
Bandung
Ciamis
Kota Tasikmalaya
Kota Banjar
Garut
Tasikmalaya
Pangandaran


Buol
Toli Toli
Donggala
Tojo Una Una
Kota Palu
Parigi Moutong
Banggai
Donggala
Tojo Una Una
Banggai Kepulauan
Sigi
Banggai Laut
Poso
Morowali Utara
Banggai Laut
Banggai Laut
Banggai Laut
Morowali


Luwu Utara
Luwu Timur
Luwu
Toraja Utara
Kota Palopo
Tana Toraja
Luwu
Enrekang
Pinrang
Sidenreng Rappang
Kota Parepare
Wajo
Soppeng
Barru
Bone
Pangkajene dan Kepulauan
Maros
Kota Makassar
Sinjai
Takalar
Gowa
Takalar
Bulukumba
Takalar
Jeneponto
Bantaeng
Kepulauan Selayar


Langkat
Kota Medan
Kota Binjai
Deli Serdang
Serdang Bedagai
Batu Bara
Karo
Simalungun
Kota Pematangsiantar
Dairi
Asahan
Pakpak Bharat
Samosir
Toba
Labuhanbatu Utara
Humbang Hasundutan
Labuhanbatu
Tapanuli Utara
Tapanuli Tengah
Labuhanbatu Selatan
Kota Sibolga
Padang Lawas Utara
Tapanuli Selatan
Kota Padang Sidempuan
Nias Utara
Kota Gunungsitoli
Nias Barat
Nias
Padang Lawas
Nias Selatan
Mandailing Natal
Nias Selatan
Nias Selatan
Nias Selatan


Adm. Kep. Seribu
Adm. Kep. Seribu
Kep. Seribu
Adm. Kep. Seribu
Adm. Kep. Seribu
Adm. Kep. Seribu
Adm. Kep. Seribu
Kota Adm. Jakarta Utara
Kota Adm. Jakarta Barat
Kota Adm. Jakarta Pusat
Kota Adm. Jakarta Timur
Kota Adm. Jakarta Selatan

2.2 Developing Base OD Matrix and Regression using R

- **Minimized Error – Paired Beta and VOT Value**

```
# Clear and set up

remove(list=ls())

cat("\f")

while (dev.cur() > 1) dev.off()


library(readxl)

library(writexl)


# === 1. Load Data ===

cost_data <- read_excel("D:/Cost Optimization Port Choice Java/Data/Cost_Data14.xlsx", sheet = "Cost Data")

time_data <- read_excel("D:/Cost Optimization Port Choice Java/Data/Cost_Data14.xlsx", sheet = "Time Data")

demand_data <- read_excel("D:/Cost Optimization Port Choice Java/Data/Cost_Data14.xlsx", sheet = "Port Demand")

port_actual <- read_excel("D:/Cost Optimization Port Choice Java/Data/Cost_Data14.xlsx", sheet = "Port Supply")


# === 2. Prepare Matrices ===

cost_matrix <- as.matrix(cost_data[,-1])

time_matrix <- as.matrix(time_data[,-1])

rownames(cost_matrix) <- rownames(time_matrix) <- cost_data[[1]]

colnames(cost_matrix) <- colnames(time_matrix) <- colnames(cost_data)[-1]
```

```
# === 3. Demand Data (Already Scaled TEUs per Region) ===
Dj <- setNames(as.numeric(demand_data[1, -1]), colnames(demand_data)[-1])

# === 4. Actual Port Import (TEUs) ===
P_actual <- setNames(port_actual[[2]], port_actual[[1]])

# === 5. Parameter Grid ===
beta_vals <- seq(0.0005, 0.015, by = 0.0005)
vot_vals <- seq(0.5, 2, by = 0.05)
results <- data.frame()

# === 6. Iterate Over Beta and VOT ===
for (beta in beta_vals) {
  for (vot in vot_vals) {

    # Step 1: Generalized Cost
    GC <- cost_matrix + vot * time_matrix
    GC[is.na(GC) | GC == 9999] <- Inf

    # Step 2: Accessibility (Impedance)
    fij <- exp(-beta * GC)
    fij[is.infinite(fij)] <- 0
```

```
# Step 3: Destination-Constrained Flow Allocation
Tij <- matrix(0, nrow = nrow(fij), ncol = ncol(fij),
              dimnames = list(rownames(fij), colnames(fij)))

for (j in colnames(fij)) {
  denom <- sum(fij[, j])
  if (denom > 0) {
    Tij[, j] <- Dj[j] * fij[, j] / denom
  }
}

# Step 4: Aggregate Modeled Port TEUs
P_model <- rowSums(Tij)

# Step 5: Compare to Actual
common_ports <- intersect(names(P_actual), names(P_model))
actual <- P_actual[common_ports]
model <- P_model[common_ports]

ss_res <- sum((actual - model)^2)
ss_tot <- sum((actual - mean(actual))^2)
r_squared <- 1 - (ss_res / ss_tot)
```

```
    lse <- ss_res
    mae <- sum(abs(actual - model))

    results <- rbind(results, data.frame(
      Beta = beta,
      VOT = vot,
      R_squared = r_squared,
      LSE = lse,
      MAE = mae
    ))
  }
}

# === 7. Export Results ===
write_xlsx(results, "D:/Cost Optimization Port Choice Java/Beta_VOT_DemandModel_Evaluation143.xlsx")
```

- **OD Matrix Convergence**

```
# Clear and set up

remove(list=ls())

cat("\f")

while (dev.cur() > 1) dev.off()


# --- Load required libraries ---

library(readxl)

library(writexl)

library(dplyr)


# --- Step 1: Read from Excel file ---

file_path <- "D:/Cost Optimization Port Choice Java/Data/OD Matrix1 0.7 0.015.xlsx"


# Read full production-attraction table

prod_attr <- read_excel(file_path, sheet = "Production Attraction")


# Extract port names

origin_names <- prod_attr$`i\\j`[-nrow(prod_attr)]

dest_names <- colnames(prod_attr)[-c(1, ncol(prod_attr))]  # exclude port name and
Production column


# Extract production vector (last column excluding last row)

P <- prod_attr$Production[-nrow(prod_attr)]
```

```r
names(P) <- trimws(origin_names)

# Extract attraction vector (last row, excluding 1st col)
A <- as.numeric(prod_attr[nrow(prod_attr), -c(1, ncol(prod_attr))])
names(A) <- trimws(dest_names)

# --- Step 2: Read impedance matrix ---
impedance <- read_excel(file_path, sheet = "Impedance")
fij <- as.matrix(impedance[, -1])
rownames(fij) <- trimws(impedance[[1]])
colnames(fij) <- trimws(colnames(impedance)[-1])

# --- Step 3: Align impedance matrix with production and attraction names ---
names(P) <- trimws(names(P))
names(A) <- trimws(names(A))
fij <- fij[names(P), names(A)]

# --- Step 4: Initialize parameters ---
n_origin <- length(P)
n_dest <- length(A)
alpha <- rep(1, n_origin)
beta <- rep(1, n_dest)
names(alpha) <- names(P)
```

```
names(beta) <- names(A)


tolerance <- 1e-4

max_iter <- 500

converged <- FALSE

error_log <- data.frame(iteration = integer(), max_row_error = double(), max_col_error =
double())


# --- Step 5: Iterative balancing ---

for (iter in 1:max_iter) {

 # Update alpha

 for (i in 1:n_origin) {

  denom <- sum(beta * A * fij[i, ])

  alpha[i] <- ifelse(denom == 0, 0, 1 / denom)

 }


 # Update beta

 for (j in 1:n_dest) {

  denom <- sum(alpha * P * fij[, j])

  beta[j] <- ifelse(denom == 0, 0, 1 / denom)

 }


 # Calculate T_ij

 Tij <- matrix(0, nrow = n_origin, ncol = n_dest)
```

```
  for (i in 1:n_origin) {
    for (j in 1:n_dest) {
      Tij[i, j] <- alpha[i] * P[i] * beta[j] * A[j] * fij[i, j]
    }
  }

  rownames(Tij) <- names(P)
  colnames(Tij) <- names(A)

  # Compute error
  max_row_error <- max(abs(rowSums(Tij) - P))
  max_col_error <- max(abs(colSums(Tij) - A))
  error_log <- rbind(error_log, data.frame(iteration = iter,
                                           max_row_error = max_row_error,
                                           max_col_error = max_col_error))

  if (max_row_error < tolerance && max_col_error < tolerance) {
    cat("✅ Converged at iteration", iter, "\n")
    converged <- TRUE
    break
  }
}
```

```r
if (!converged) cat("❌ Not converged after", max_iter, "iterations.\n")


# --- Step 6: Output results ---

output_path <- "D:/Cost Optimization Port Choice Java/Output/OD_Results1 0.7 0.015.xlsx"

dir.create(dirname(output_path), showWarnings = FALSE)


write_xlsx(list(

  "Final_OD_Matrix" = as.data.frame(Tij),

  "Convergence_Log" = error_log

), path = output_path)
```

- **OD Matrix Datasets Formed Pij and Delta Utility**

```
# Clear and set up

remove(list=ls())

cat("\f")

while (dev.cur() > 1) dev.off()


library(readxl)

library(dplyr)

library(tidyr)


# === Load the OD Flow Matrix ===

flow_data <- read_excel("D:/Cost Optimization Port Choice Java/Data/OD Matrix Dataset14.xlsx")


# Convert to long format

flow_long <- flow_data %>%

  pivot_longer(

    cols = -1,

    names_to = "Region",

    values_to = "Flow"

  ) %>%

  rename(Port = 1)  # Ensure the first column is named "Port"
```

```
# Remove zero flows (optional)
flow_long <- flow_long %>% filter(Flow > 0)

# === Step: Create P_ij (probability for each region) ===
flow_long <- flow_long %>%
  group_by(Region) %>%
  mutate(P_ij = Flow / sum(Flow)) %>%
  ungroup()

# === Step: Get reference probabilities (Tanjung Priok) ===
ref_port <- "Port of Bitung"

ref_probs <- flow_long %>%
  filter(Port == ref_port) %>%
  select(Region, P_ref = P_ij)

# === Step: Join back and compute log-odds (Delta U) ===
flow_long <- flow_long %>%
  left_join(ref_probs, by = "Region") %>%
  mutate(Delta_U = log(P_ij / P_ref))  # ln for natural log

# === Step: Construct Route column and keep needed data ===
result <- flow_long %>%
```

```
  mutate(Route = paste(Port, Region, sep = "–")) %>%
  select(Route, Port, Region, Flow, P_ij, P_ref, Delta_U)


# === Save to Excel ===
library(writexl)
write_xlsx(result, "D:/Cost Optimization Port Choice Java/Route_LogOdds_Dataset14-
2.xlsx")
```

- **Multivariable Regression 10 Steps**

```
# ==================================================

# 10-Step Multivariable Regression Table (with Intercept)

# Cells show: beta + stars + (t-value)

# ==================================================


suppressPackageStartupMessages({

  library(readxl)

  library(dplyr)

  library(tidyr)

  library(broom)

  library(purrr)

  library(stringr)

})


# ---------- SETTINGS ----------

data_path <- "D:/Cost Optimization Port Choice Java/Route_LogOdds_Dataset14-1.xlsx"

sheet     <- "Sheet2"

dep_var   <- "Delta_U"   # dependent variable name after make.names()


# ---------- LOAD DATA ----------

dat <- read_excel(data_path, sheet = sheet) |> as.data.frame()
```

```
names(dat) <- make.names(names(dat))        # standardize names (dots instead of
spaces, etc.)

stopifnot(dep_var %in% names(dat))


# ---------- DEFINE STEP MODELS ----------

models <- list(

  # Step 1

  c("Total.Cost","Total.Time"),

  # Step 2

  c("PDR.Cost","PDR.Time","Connectivity","Marl.Time","BSH","Water.Depth"),

  # Step 3

  c("PDR.Cost","PDR.Time","Connectivity","Marl.Time","ET.BT.I","Water.Depth"),

  # Step 4

  c("Port.Cost","PDR.Cost","PDR.Time","Connectivity","Marl.Time","ET.BT.I","Port.Call"),

  # Step 5


c("Port.Cost","PDR.Cost","PDR.Time","Connectivity","DwellD.Export","ET.BT.I","Berth.N
o"),

  # Step 6

  c("Marl.Cost","DwellI.Import","DwellD.Export","Connectivity","ET.BT.I","Port.Call"),

  # Step 7


c("Marl.Cost","DwellI.Import","Connectivity","Marl.Time","Berth.No","Connectivity.Total"),

  # Step 8

  c("PDR.Cost","PDR.Time","DwellD.Export","Marl.Time","Port.Call","BSH"),
```

```
  # Step 9
  c("PDR.Cost","PDR.Time","Connectivity","Marl.Time","Port.Call","ET.BT.I"),
  # Step 10 (example adds Water.Depth)
  c("PDR.Cost","PDR.Time","Connectivity","Marl.Time","ET.BT.I")
)
# ---------- HELPERS ----------
pstars <- function(p){
  ifelse(is.na(p), "",
         ifelse(p < 0.001, "***",
                ifelse(p < 0.01 , "**",
                       ifelse(p < 0.05 , "*",
                              ifelse(p < 0.10 , ".", "")))))
}

fmt_cell <- function(beta, p, tval, digits_beta=3, digits_t=1){
  paste0(format(round(beta, digits_beta), nsmall = digits_beta),
         pstars(p),
         "\n(",
         format(round(tval, digits_t), nsmall = digits_t),
         ")")
}

# Fit one step and return a column for the output table
```

```r
fit_step <- function(xvars, data, dep){
  fml <- as.formula(paste(dep, "~", paste(xvars, collapse = " + ")))
  df  <- data |>
    dplyr::select(dplyr::all_of(c(dep, xvars))) |>
    tidyr::drop_na()

  mod <- stats::lm(fml, data = df)
  sm  <- summary(mod)

  # tidy coefficients (keep intercept now)
  td <- broom::tidy(mod) |>
    dplyr::mutate(cell = fmt_cell(estimate, p.value, statistic)) |>
    dplyr::select(term, cell)

  # adjusted R2
  adjr <- sm$adj.r.squared

  list(coef_table = td, adjr = adjr)
}

# ---------- RUN ALL STEPS ----------
all_vars <- c("(Intercept)", unique(unlist(models))) |> sort()
steps    <- paste0("Step_", seq_along(models))
```

```
cols <- vector("list", length(models))
adjr_vec <- numeric(length(models))

for(i in seq_along(models)){
  res_i <- fit_step(models[[i]], dat, dep_var)
  td    <- res_i$coef_table
  adjr_vec[i] <- res_i$adjr

  # align to all_vars; show blank for vars not in the step
  col_i <- tibble(Variable = all_vars) |>
    left_join(td, by = c("Variable" = "term")) |>
    mutate(cell = ifelse(is.na(cell), "", cell)) |>
    pull(cell)

  cols[[i]] <- col_i
}

# Build final table + Adjusted R2 row
report <- tibble(Variable = all_vars) |>
  bind_cols(setNames(cols, steps)) |>
  bind_rows(tibble(
    Variable = "Adjusted R2",
```

```
    !!!setNames(as.list(sprintf("%.3f", adjr_vec)), steps)
  ))

# ---------- SAVE & PRINT ----------
out_csv <- "D:/Cost Optimization Port Choice Java/regression_steps_table-14-1.csv"
write.csv(report, out_csv, row.names = FALSE)

cat("Saved regression table to:\n", out_csv, "\n\n")
print(report, n = nrow(report))
```

- **Optimized R squared constraint multivariable regression**

```
# ============================================================
# Constrained Subset Selection with Sign + VIF Constraints
# Objective: maximize R^2 (default), optional adjR2/AIC/BIC
# ============================================================

# Clear and set up
remove(list=ls())
cat("\f")
while (dev.cur() > 1) dev.off()

# ---- Packages ----
install.packages("leaps")
suppressPackageStartupMessages({
  library(readxl)
  library(car)
  library(leaps)
  library(dplyr)
  library(tidyr)
  library(purrr)
  library(stringr)
  library(broom)
})
```

```
# ---- SETTINGS ----

data_path    <- "D:/Cost Optimization Port Choice Java/Route_LogOdds_Dataset14-
1.xlsx"

sheet        <- "Sheet2"

dep_var      <- "Delta_U"


# Variables to drop from the numeric set (as you had)

drop_vars    <- c("P_ij", "P_ref", "Flow")


# Multicollinearity control

vif_threshold <- 5        # e.g., 5 or 10


# Objective for model ranking: "rsq", "adjr2", "aic", or "bic"

objective    <- "rsq"     # per your request: highest R^2


# Optional: restrict subset size (set to NA to allow all)

k_min <- 1

k_max <- NA  # set to a number to cap model size, e.g., 10


# ---- SIGN CONSTRAINTS ----

# Specify desired coefficient signs:  1 = must be positive, -1 = must be negative, 0 = free
(no constraint).

# Leave variables out if you don't want to constrain them.
```

```
# Example constraints for your common variables (EDIT as needed):
sign_constraints <- c(
  "DwellD.Export" = -1,
  "Connectivity.Direct" = 1,
  "Connectivity.Total" = 1,
  "Berth.No" = 1,
  "Port.Call" = 1,
  "BSH" = 1,
  "Connectivity" =1,
  "ET.BT.I" = 1,
  "MarI.Time" = -1,
  "MarI.Cost" = -1,
  "DwellI.Import" = -1,
  "Port.Cost" = -1,
  "PDR.Time" = -1,
  "Total.Time" = -1,
  "Total.Cost" = -1,
  "PDR.Cost" = 1,
  "ET.BT.D" = 1,
  "Water.Depth" = 1)

# ============================================================
# 1) Load + prep data
```

```
# ============================================================
data <- read_excel(path = data_path, sheet = sheet)
colnames(data) <- make.names(colnames(data)) # keep your cleaning step

# keep strictly numeric columns, drop specified vars
num <- data[, sapply(data, is.numeric), drop = FALSE]
num <- num %>% select(-any_of(drop_vars))

stopifnot(dep_var %in% names(num))
predictors_all <- setdiff(names(num), dep_var)

# If you want to inspect names:
# print(names(num))

# ============================================================
# 2) Correlation visualization (your original section)
# ============================================================
M <- cor(num, use = "pairwise.complete.obs", method = "pearson")
print(round(M, 3))

heatmap(M)

suppressPackageStartupMessages(library(corrplot))
```

```
M <- cor(num, use="pairwise.complete.obs")
corrplot(
  M,
  order = "hclust",
  method = "color",
  addrect = 3,
  diag = TRUE,
  tl.col = "black",
  tl.cex = 0.6,
  tl.srt = 45,
  mar = c(1,1,1,1)
)

# ============================================================
# 3) Helper functions
# ============================================================
safe_vif <- function(model) {
  # car::vif() fails if perfect collinearity; we trap and return Inf
  out <- tryCatch({
    v <- car::vif(model)
    # vif() returns named vector; handle factor terms if any (shouldn't be in numeric-only)
    as.numeric(v)
  }, error = function(e) rep(Inf, length(coef(model)) - 1))
```

```
  out
}

sign_ok <- function(model, sign_constraints) {
  if (length(sign_constraints) == 0) return(TRUE)
  co <- coef(model)
  # co includes "(Intercept)"; drop it
  co <- co[setdiff(names(co), "(Intercept)")]
  # only check constraints for vars that are in the model
  constrained_vars_in_model <- intersect(names(sign_constraints), names(co))
  if (length(constrained_vars_in_model) == 0) return(TRUE)
  for (v in constrained_vars_in_model) {
    s <- sign_constraints[[v]]
    if (s == 1 && co[[v]] <= 0) return(FALSE)
    if (s == -1 && co[[v]] >= 0) return(FALSE)
  }
  TRUE
}

metric_value <- function(model, objective = "rsq") {
  sm <- summary(model)
  if (objective == "rsq")    return(unname(sm$r.squared))
  if (objective == "adjr2")  return(unname(sm$adj.r.squared))
```

```r
  if (objective == "aic")    return(-AIC(model))  # negate so higher is better
  if (objective == "bic")    return(-BIC(model))  # negate so higher is better
  stop("Unknown objective. Use one of: 'rsq','adjr2','aic','bic'.")
}

# Build formula from a vector of predictors
form_from <- function(dep, preds) {
  as.formula(paste(dep, "~", paste(preds, collapse = " + ")))
}

# ============================================================
# 4) Candidate subset generation (leaps::regsubsets)
#    (Faster than brute-force for moderate/high p)
# ============================================================
# ============================================================
# 4) Candidate subset generation (base R, robust)
# ============================================================
p <- length(predictors_all)
if (is.na(k_max)) k_max <- min(p, 7)       # hard cap size
k_min <- max(1, k_min); k_max <- min(k_max, p)

max_per_k  <- 30000                        # evaluate at most 30000 models per size
cand_list <- list()
```

```
set.seed(1)
for (k in k_min:k_max) {
  all_combos <- combn(predictors_all, k, simplify = FALSE)
  if (length(all_combos) > max_per_k) {
    # sample a subset to bound runtime
    all_combos <- sample(all_combos, max_per_k)
  }
  cand_list <- c(cand_list, all_combos)
}
message(sprintf("Total candidate models to test: %d", length(cand_list)))



# ============================================================
# 5) Evaluate candidates under constraints  (FIXED)
# ============================================================
suppressPackageStartupMessages(library(tibble))

results <- purrr::map_dfr(cand_list, function(vars) {
  fml <- form_from(dep_var, vars)
  df_fit <- num %>% dplyr::select(dplyr::all_of(c(dep_var, vars))) %>% tidyr::drop_na()
```

```
  if (nrow(df_fit) < length(vars) + 2) {
    return(tibble(
      predictors = list(vars), k = length(vars),
      feasible = FALSE, reason = "Too few rows after NA drop",
      rsq = NA_real_, adjr2 = NA_real_, aic = NA_real_, bic = NA_real_, metric =
NA_real_
    ))
  }

  mod <- tryCatch(stats::lm(fml, data = df_fit), error = function(e) NULL)
  if (is.null(mod)) {
    return(tibble(
      predictors = list(vars), k = length(vars),
      feasible = FALSE, reason = "LM failed",
      rsq = NA_real_, adjr2 = NA_real_, aic = NA_real_, bic = NA_real_, metric =
NA_real_
    ))
  }

  # VIF constraint
  v <- safe_vif(mod)
  if (any(is.infinite(v)) || any(v > vif_threshold, na.rm = TRUE)) {
    return(tibble(
      predictors = list(vars), k = length(vars),
```

```
    feasible = FALSE, reason = sprintf("VIF>%.2f", vif_threshold),
    rsq = summary(mod)$r.squared,
    adjr2 = summary(mod)$adj.r.squared,
    aic = AIC(mod), bic = BIC(mod),
    metric = metric_value(mod, objective)
  ))
}

# Sign constraints
if (!sign_ok(mod, sign_constraints)) {
  return(tibble(
    predictors = list(vars), k = length(vars),
    feasible = FALSE, reason = "Sign constraint violated",
    rsq = summary(mod)$r.squared,
    adjr2 = summary(mod)$adj.r.squared,
    aic = AIC(mod), bic = BIC(mod),
    metric = metric_value(mod, objective)
  ))
}

tibble(
  predictors = list(vars), k = length(vars),
  feasible = TRUE, reason = NA_character_,
```

```
    rsq = summary(mod)$r.squared,

    adjr2 = summary(mod)$adj.r.squared,

    aic = AIC(mod), bic = BIC(mod),

    metric = metric_value(mod, objective)

  )

})


# Rank feasible models

feasible <- results %>%

  dplyr::filter(feasible) %>%

  dplyr::arrange(dplyr::desc(metric))


dim(results)           # should be (#candidates, many columns)

table(results$feasible) # counts

head(feasible, 3)


if (nrow(feasible) == 0) {

  warning("No feasible model found under current VIF/sign constraints. Consider
relaxing constraints.")

  print(results %>% arrange(desc(rsq)) %>% head(10))

} else {

  # Best model

  best_vars <- feasible$predictors[[1]]

  best_fml  <- form_from(dep_var, best_vars)
```

```r
best_df   <- num %>% select(all_of(c(dep_var, best_vars))) %>% drop_na()
best_mod  <- lm(best_fml, data = best_df)

cat("\n================ BEST MODEL ================\n")
cat("Objective      :", toupper(objective), "(higher is better)\n")
cat("Dependent var  :", dep_var, "\n")
cat("Predictors     :", paste(best_vars, collapse = ", "), "\n")
cat("Formula        :", deparse(best_fml), "\n\n")

print(summary(best_mod))

cat("\n--- VIFs ---\n")
vif_vals <- car::vif(best_mod)
print(round(vif_vals, 3))

cat("\n--- Metrics ---\n")
cat(sprintf("R^2   = %.5f\n", summary(best_mod)$r.squared))
cat(sprintf("AdjR2 = %.5f\n", summary(best_mod)$adj.r.squared))
cat(sprintf("AIC   = %.3f\n", AIC(best_mod)))
cat(sprintf("BIC   = %.3f\n", BIC(best_mod)))

# Save a ranked table of feasible candidates
out_tbl <- feasible %>%
```

```
    mutate(predictors = sapply(predictors, function(v) paste(v, collapse = ", "))) %>%
    select(k, predictors, rsq, adjr2, aic, bic) %>%
    arrange(desc(rsq))

  write.csv(out_tbl,
            "D:/Cost Optimization Port Choice Java/feasible_models_ranked-141.csv",
            row.names = FALSE)
}
```