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Optimizing African Port Hinterland Connectivity Using Markov Processes, Max-Flow, and Traffic Flow Models: A Case Study of Dar es Salaam Port

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Abstract: Dar es Salaam Port, a crucial logistical hub in East Africa, faces significant challenges related to cargo handling efficiency, road congestion, and capacity constraints. The port's performance is pivotal for regional trade, necessitating a comprehensive analysis to identify and address operational inefficiencies. This study employed Markov processes to evaluate cargo handling and delivery times, cellular automata for simulating road traffic dynamics, and max-flow models to optimize cargo flow from the port to hinterland destinations. The analysis incorporated factors such as road and rail capacities, traffic conditions, and environmental impacts. The Markov process model indicated that cargo spends 15% of its time waiting at the port, 50% in transit, and 10% delayed, with only 25% successfully delivered. The Cellular Automata simulation revealed severe congestion for heavy trucks due to poor road conditions, with an additional 10 min delay during the rainy season. The max-flow model highlighted that while the road and rail networks generally meet demand, significant bottlenecks exist, particularly for Lubumbashi, which faces a capacity shortfall of 500 t/day. The findings offer actionable insights for stakeholders. Logistics operators can leverage the framework to predict delays, optimize resource allocation, and improve delivery reliability. Policymakers can prioritize strategic investments in infrastructure upgrades, traffic management, and road maintenance to reduce delays and congestion. Scholars can adopt the integrated methodology to analyze similar systems. Together, these efforts can enhance Dar es Salaam Port's operational efficiency, reduce transit times, and support regional trade development..

Keywords: Dar es Salaam Port; cargo handling; Markov processes; cellular automata; max-flow models; traffic flow; capacity optimization; logistical efficiency; port hinterland

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1. Introduction

Efficient hinterland connectivity is crucial for the economic vitality of a por, as it determines how seamlessly goods can move from the port to inland markets. As global trade continues to grow, ports must not only increase their capacity but also optimize the transportation networks that connect them to the hinterland [1]. Hinterland connectivity involves complex logistical challenges, including congestion, infrastructure limitations, and uncertainties such as traffic delays, making it an area ripe for optimization [2].

Dar es Salaam Port, a vital gateway to East Africa, serves as a critical hub for the movement of goods to countries like Tanzania, Zambia, Rwanda, Burundi, and the Democratic Republic of Congo [3]. However, the port faces significant challenges in efficiently connecting to its hinterland due to limitations in its transportation network, including road and rail bottlenecks, capacity constraints, and traffic congestion [3]. These issues result in delays, increased costs, and reduced throughput, all of which hinder the port's competitiveness and efficiency.

In response to these challenges, this paper proposes a novel optimization framework that integrates Markov processes, max-flow problems, and traffic flow models to enhance hinterland connectivity. Each of these models addresses specific aspects of the transportation problem. Markov processes are used to model the stochastic events and uncertainties inherent in cargo movement, such as random delays and equipment breakdowns [4,5]. Max-flow models optimize the throughput of goods from the port to inland destinations, ensuring the maximum use of available infrastructure while respecting capacity constraints [6,7]. Finally, traffic flow models simulate vehicle movement, allowing for an analysis of congestion and travel times on key routes.

The proposed framework will be applied in a case study of Dar es Salaam Port, with the goal of addressing the unique logistical challenges posed by its infrastructure and hinterland network. By integrating these models into a cohesive optimization framework, the study aims to improve the efficiency of goods movement, reduce congestion, and enhance the overall connectivity of the port.

The motivation of this study is to address the logistical challenges faced by Dar es Salaam Port, including congestion, infrastructure limitations, and delays that hinder efficient hinterland connectivity. Existing models often fail to capture the complexity of these issues. This study proposes a novel optimization framework combining Markov processes, max-flow problems, and traffic flow models to improve cargo flow, reduce delays, and enhance the port's operational efficiency. The goal is to provide a comprehensive solution for optimizing hinterland connectivity, with real-world applications for ports globally.

While previous studies have focused on optimizing specific aspects of hinterland connectivity, such as transportation routes or infrastructure capacity, they often fall short of addressing the combined and dynamic challenges faced by ports. These approaches typically neglect the stochastic nature of logistics, including random delays and unpredictable events that affect cargo flow. Moreover, most models focus on isolated components, lacking an integrated framework that combines probabilistic analysis, network flow optimization, and traffic simulation.

This study aims to fill this gap by proposing a novel optimization framework that integrates Markov processes, max-flow problems, and traffic flow models. Applying this comprehensive approach to Dar es Salaam Port will provide a more holistic solution to improving hinterland connectivity, addressing the limitations of previous models.

The primary objective of this study is to develop and apply a novel optimization framework that integrates Markov processes, max-flow problems, and traffic flow modelsto enhance hinterland connectivity. This framework aims to optimize the movement of goods from Dar es Salaam Port to inland destinations by addressing key challenges such as capacity constraints, traffic congestion, and the stochastic nature of transportation delays. By applying this model, the study seeks to improve the efficiency and reliability of port logistics, ultimately providing a more effective solution for managing port–hinterland connectivity.

The remainder of this paper is structured as follows: The next section reviews the existing literature on hinterland connectivity and optimization models. The methodology section presents the framework in detail, describing the specific roles of Markov Processes, Max-Flow Problems, and Traffic Flow Models. Following that, the case study of Dar es Salaam Port is presented, where the proposed framework is applied, and results are discussed. Finally, the paper concludes with key findings, implications for the port's operations, and suggestions for future research.

In this study, "cargo flow" refers to the movement of goods through the port and transport network, from arrival at the port to delivery at inland destinations [8,9]. "Traffic congestion" is the condition where the volume of vehicles exceeds the capacity of the roads, leading to delays and inefficiencies in the transportation network [10,11]. "Capacity optimization" involves adjusting the use of available infrastructure such as roadways, railways, and port facilities to maximize the throughput of goods while minimizing delays, congestion, and resource underutilization [12,13]. These terms are central to understanding the dynamics of port operations and hinterland connectivity.

2. Literature Review

In this section, we delve into the literature surrounding optimization techniques in port logistics, with a particular emphasis on methodologies such as Markov processes, Cellular Automata models, and the Max-Flow problem. We explore how these approaches have been applied to enhance efficiency and address challenges in port management. By examining foundational works and recent advancements, we aim to provide a comprehensive understanding of current practices and identify opportunities for future research in optimizing port operations.

2.1. Introduction to Hinterland Connectivity

In this section, we explore the critical concept of hinterland connectivity, focusing on how efficiently ports connect with their surrounding regions to facilitate cargo movement. Hinterland connectivity encompasses the transportation infrastructure and logistical systems that link ports to inland destinations, including roads, railways, and other transport modes [14,15]. Effective connectivity is essential for optimizing cargo flow, reducing transit times, and ensuring timely delivery of goods [16,17].

The study on hinterland transport connectivity [18] underscores its pivotal role in port competitiveness, placing it just behind port costs. The review traces the evolution of port–hinterland relationships from early 20th-century models to the transformative effects of containerization in the late 1960s. It highlights a shift from distance-decay to functional approaches in analyzing these relationships, emphasizing the growing importance of hinterland network dynamics over individual port performance. As business trends and technological advancements accelerate, the study advocates for leveraging enhanced regional network intelligence to better understand and adapt to these changes.

The study [19] examines the impact of international land–sea transport corridors on port competition between neighboring countries using the Hoteling model. It highlights that while these corridors improve transport efficiency, trade integration, and inland access to markets, they also intensify competition among ports. The findings show that high cross-border transportation costs reduce the market share of overseas ports, while high maritime transportation costs offset the land transport advantages of these corridors, favoring domestic ports. This research emphasizes the need for balanced cross-border and maritime transport costs to maximize the benefits of transport corridors and supports strategic decision-making in port development and policy planning.

Another study [14] highlights the critical role of hinterland connectivity in port competitiveness, emphasizing its evolution from local to multimodal perspectives. Traditionally, hinterland connectivity was assessed based on direct service connections, but with increasing intramodality, this local view is inadequate. By applying complex network science, the study expands the definition of connectivity to include non-local and multimodal elements. It finds that multimodal routes and transfer connections greatly enhance overall connectivity, showing that ports with limited local connections can still be well-positioned within a broader network. Multimodal integration benefits all ports, though some, particularly multimodal hubs, gain more than others.

Also, the study [20] investigates how seaports and their hinterlands shape national spatial structures, focusing on Iran over the past two decades. Using social network analysis, the research examines the intensity, direction, and concentration of commodity flows between ports and hinterlands. The findings reveal that southern Iranian ports have bolstered the centrality of key inland cities, particularly Tehran, Bandar Abbas, and Mahshahr Port. Tehran, as the primary hub, plays a pivotal role in commodity production, consumption, processing, and distribution, influencing regional and local logistics. This pattern, characterized by strong core-port connectivity, represents a distinct phase in the evolution of port–hinterland relationships.

2.2. Existing Optimization Models for Hinterland Connectivity

This section reviews optimization models for enhancing hinterland connectivity. It highlights various strategies and tools used to improve transport efficiency between ports and their hinterlands, focusing on addressing connectivity and capacity challenges.

The study [21] examines the use of automated ground vehicles (AGVs) to improve port hinterland connectivity. It proposes a robust optimization approach to evaluating the time and cost efficiency of AGV platoons in container pickup and delivery tasks. The research introduces a bi-objective mixed-integer programming model to minimize time, cost, and emissions, addressing uncertainties in vehicle availability. Case studies of the Port of Rotterdam and Port of Valparaíso show that AGV platoons offer significant benefits, including reduced dwell times (56% on average) and lower carbon emissions (10% on average), with increased cost savings as travel distance grows.

This study [22] explores the development of a dedicated corridor system to enhance the connectivity between hinterlands and seaports in the Bohai Rim region of China. It employs the shortest path model and forecasting techniques to evaluate and select optimal routes for multimodal transport systems. By assessing various transport modes and their performance, the study aims to identify cost-effective strategies to improve regional development. The results highlight that an efficient multimodal transport network can significantly strengthen the connection between hinterlands and seaports, contributing to the overall growth of the Bohai Rim region.

Another study [23] addresses the intermodal routing problem for regional freight transportation in the ECOWAS region of West Africa, focusing on optimizing freight flow quantities and transportation modes across transit corridors in countries like Mali, Burkina Faso, and Niger. Using a linear programming model solved with Lingo Mathematic Application, the research aims to minimize inland transportation costs. The results indicate that current freight logistics often do not follow the most efficient paths, leading to longer transit times and higher costs than geographically necessary.

Also, the study [24] focuses on coordinated scheduling in Yangtze River ports, aiming to reduce berth deviation costs, shorten ship scheduling times, and maximize berth utilization in river–sea intermodal transportation. By introducing factors like berth preferences, seagoing ship inspections, and planning cycles, the research applies an optimized non-dominated sorting genetic algorithm III (NSGA-III). Using a seven-day dataset, the model improved objective values by 30.81%, 13.73%, and 12.11%, outperforming traditional NSGA-III and NSGA-II methods. The findings demonstrate the model's ability to lower operational costs, enhance ship and berth scheduling, and improve clearance efficiency for port authorities.

2.3. Markov Processes in Logistics and Transportation

This section examines the use of Markov processes in logistics and transportation. These processes help model the probabilistic transitions and behaviors within these systems, offering insights for optimizing and predicting performance.

The study [25] explores the application of Markov models in analyzing transportation processes within logistics systems. By using discrete and continuous time Markov models, the research examines how changes in supplier selection impact vehicle readiness and overall system efficiency. Initially, the system faced random and chaotic supplier choices. However, after a detailed analysis and selection of optimal suppliers, the study demonstrated improved system readiness through Markov processes. The proposed models offer a robust framework for diagnosing and forecasting operational indicators in various logistics contexts, including military, emergency services, and civil transport. These models are particularly effective for systems where readiness is crucial and data on task completion are accurately recorded. The study highlights the practical value of Markov models in optimizing logistic operations, ensuring reliable supply, and facilitating system evaluation and improvement.

Another paper [26] addresses the modeling of light utility vehicle operations within military transport systems. Effective system performance hinges on maintaining vehicles at optimal technical readiness, which involves efficient fuel refilling, maintenance, and repair processes. Failures significantly impact transport capacity and hinder task execution. To manage and optimize vehicle operations, the paper proposes using advanced mathematical methods, particularly Markov processes. It introduces three key performance indicators: functional readiness, technical efficiency, and airworthiness. A stochastic exploitation model, incorporating a nine-state phase space and a semi-Markov model, is used to assess these indicators based on empirical data. Sensitivity analysis indicates that reducing vehicle repair wait times by 50% could improve performance metrics from 0.91 to 0.95, demonstrating the potential for significant operational enhancements.

The research [27] focuses on the operational analysis of Honker 2000 light utility vehicles within the Polish Armed Forces. The study identifies four key operational states: task execution, awaiting a task, periodic maintenance, and repair. Functional readiness and technical suitability are used as performance metrics. A Monte Carlo simulation model, developed in MATLAB, was used to analyze these states. The model accounted for periodic maintenance as a deterministic process, while other states were modeled as stochastic. The simulation, validated against 16 models with different cumulative distribution functions (CDFs), showed that the results aligned within 6% of those from a semi-Markov model. Sensitivity analysis revealed that the Monte Carlo model is effective for forecasting vehicle performance and can be a valuable tool for analyzing and predicting operational outcomes.

2.4. Max-Flow Problems in Network Optimization

This section addresses max-flow problems in network optimization, focusing on maximizing flow through a network from source to sink under capacity constraints. We review key models and algorithms, such as the Ford–Fulkerson method, and their applications in optimizing network performance across various domains.

The paper [28] develops a method for finding the maximum flow between source and target nodes in a network using the "max-flow, min-cut" theorem from graph theory. This theorem identifies a set of links that limits the flow of commodities from a given source to the target node. By applying this approach to transportation networks, the study effectively separates the network into source and target domains and directs commodity flow to its maximum capacity using the minimum number of edges. The results are applicable to transportation problems, particularly in minimizing the capacity of cuts and the cost of sensor placement for traffic data collection.

The study [29] explores the maximum flow problem, a fundamental challenge in optimization theory that seeks to determine the highest feasible flow from a source to a sink in a network. It highlights various techniques developed for handling maximum flow, including the Ford–Fulkerson algorithm, Dinic's algorithm, and methods such as the max-flow min-cut theorem, scaling algorithm, and push–relabel algorithm. This research presents a new approach for calculating maximum flow between source and target nodes and introduces an innovative algorithmic method for addressing transportation problems by minimizing costs. The proposed method is noted for requiring fewer iterations to reach optimal solutions compared to established meta-heuristic algorithms.

The study [30] focuses on maximizing flow in wireless sensor networks (WSNs) by addressing bottleneck nodes with poor energy. It explores using mobile chargers (MCs) to improve sensor node energy in an energy-harvesting environment. By modeling the problem with linear programming (LP) and employing a heuristic approach to optimal MC deployment and scheduling, the study demonstrates that its method, bottleneck, effectively increases maximum flow. Simulation results confirm significant flow improvements through this approach.

2.5. Traffic Flow Models in Transportation Planning

Traffic flow models are crucial for understanding and managing vehicle movement on road networks. They help address congestion, optimize routes, and improve mobility. Incorporating dynamic assignments, real-time data, and communication technologies, these models support the development of efficient and adaptive transportation systems.

The study [31] uses traffic flow models to analyze and predict vehicle movements within urban environments, employing various approaches, like macroscopic, mesoscopic, and microscopic simulations. These models are instrumental in optimizing traffic patterns, mitigating congestion, and enhancing the efficiency of transportation networks, making them essential for urban planning and smart city initiatives.

The study [32] uses an integrated modeling framework to address the dynamic interconnections between traffic and power systems, particularly in the context of electric vehicle penetration. By employing a dynamic traffic assignment model, the study captures time-varying travel demand and flow dynamics, which are crucial for real-time operations. An accelerated diagonalization algorithm is introduced to compute traffic flows efficiently, while a fixed-point problem formulation enables a decentralized approach to determining equilibrium flow patterns. Numerical results highlight the differences between dynamic, semi-dynamic, and static network models, emphasizing the practical benefits of dynamic modeling for coupled power and transportation systems.

The study [11] uses traffic flow models to address the challenges posed by increasing vehicle density and congestion. It explores various communication technologies, such as vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X), to enhance traffic efficiency and safety. By utilizing simulations based on symmetry models, the research aims to streamline vehicle density, reduce congestion, and improve traffic flow through enhanced communication and prioritization strategies between vehicles and infrastructure.

2.6. Integrated Optimization Approaches for Hinterland Connectivity

This paper [33] uses integrated optimization approaches for hinterland connectivity to address the complexities of port–hinterland freight transportation. By incorporating intermodal transport and considering uncertain transportation demand, the study integrates economic and environmental objectives to develop green flow distribution solutions. A robust optimization model is employed, leveraging chance constraints to handle demand uncertainties and ensure that transportation needs are met even under worst-case scenarios. The approach, applied to the Yangtze River Economic Belt, reveals the benefits of promoting railway–road intermodal transport, balancing network costs, and emissions, thus providing strategic guidance for sustainable port–hinterland connectivity in dynamic and stochastic conditions.

The study [1] investigates mathematical models for optimizing container transport in port areas by integrating inter-terminal transport (ITT) and rail freight operations. Using an integer linear programming model, it addresses the challenges of container movements within ports and their subsequent transport to hinterland areas. A tabu search algorithm is proposed to solve the complex optimization problem, tested across realistic infrastructure and demand scenarios. The findings demonstrate significant improvements in operational efficiency when ITT and railway processes are integrated, showing a 20% reduction in ITT costs and a 44% decrease in railway operational costs, compared to a 17% ITT cost reduction but a 93% increase in railway costs when ITT is optimized independently.

Another study [34] explores the use of computer simulations to analyze the correlation effects in tourism space systems, focusing on Mohan port and the Yunnan economic hinterland. Using gray correlation analysis from 2006 to 2020, the study quantifies the relationship between the port and hinterland, highlighting trends influenced by administrative actions, port competition, and other factors. Key findings include a rising and falling correlation trend, significant fluctuations in the port–city relationship, and spatial evolution patterns. Factors such as location, policies, and infrastructure are identified as major drivers. This research contributes to theoretical advancements in economic buildings and supports decision-making in tourism spatial optimization.

2.7. Summary and Identification of Gaps

The reviewed studies emphasize various approaches to optimizing hinterland connectivity, such as enhancing transportation routes, integrating intermodal systems, and applying advanced optimization techniques. For instance, optimization frameworks that combine Markov processes, max-flow problems, and traffic flow models offer a comprehensive approach to improving connectivity and managing transportation challenges. Markov processes address operational uncertainties and delays, max-flow problems optimize cargo throughput through the network, and traffic flow models simulate vehicle congestion and travel times. This tri-stage framework highlights the benefits of a holistic approach, integrating uncertainty modeling, network optimization, and traffic simulation to improve port–hinterland connectivity.

Despite these advancements, current research often falls short of integrating these models into a cohesive framework that addresses the full complexity of transportation systems. Many studies tend to focus on isolated aspects of connectivity, such as specific network components or operational strategies, without accounting for the dynamic and stochastic nature of real-world scenarios. For instance, while max-flow problems effectively optimize cargo flow, they may not fully consider the impact of random delays or equipment failures modeled by Markov processes. Similarly, traffic flow models provide valuable insights into congestion but may not integrate seamlessly with network optimization models to offer a comprehensive solution.

There is a notable gap in developing integrated frameworks that combine probabilistic analysis, real-time traffic simulation, and network flow optimization. Expanding research to include these elements in a unified model could address the challenges posed [13] by unpredictable events and operational uncertainties. By bridging these gaps, future studies can provide more robust and adaptable solutions, enhancing the resilience and efficiency of transportation systems. This approach would better align with the dynamic nature of modern logistics, leading to more effective management of port–hinterland connectivity.

3. Methodology and Data Description

3.1. Overview of the Optimization Framework

The methodology of this study adopts an integrated approach combining data analysis and optimization models to improve hinterland connectivity at Dar es Salaam Port. The proposed framework utilizes three interconnected methods—Markov processes, max-flow problems, and traffic flow models —each selected for its ability to address specific challenges in transportation and port logistics.

Markov processes are employed to model uncertainties in port operations, a crucial aspect of port logistics where fluctuations in cargo handling times, operational disruptions, and delays are common. The advantage of Markov processes lies in their ability to represent state transitions over time, allowing us to capture the dynamic nature of port operations. Using historical port data, including cargo arrival/departure times, delays due to equipment breakdowns, adverse weather, and congestion, we construct transition matrices. These matrices quantify the probabilities of moving between states, such as "Waiting at Port", "In Transit" and "Delivered", providing a realistic and adaptable model for the inherent uncertainties in port operations.

Max-flow problems are applied to optimize the movement of cargo through the transportation network. This method is particularly effective in scenarios where resources, such as road and rail capacity, are constrained. Max-flow problems excel at identifying the most efficient flow paths, ensuring the optimal allocation of resources, and maximizing cargo throughput. The method relies on detailed maps of road and rail infrastructure, capacity data, and cargo demand information. Demand variations, including delivery time windows and peak period surges, are incorporated to ensure efficient resource allocation and to optimize the flow of cargo across the transport network. The application of this model addresses the challenge of efficiently managing the large volumes of cargo typical of port operations.

Traffic flow models are integrated to simulate vehicle congestion and travel times along the routes connecting the port to hinterland destinations. Traffic congestion is a major challenge in many ports, and understanding its dynamics is critical for improving transportation efficiency. Traffic flow models, particularly those using real-time traffic volume data, road characteristics, and historical travel time information, help us analyze congestion patterns and identify optimal travel routes. The ability to simulate varying traffic conditions enhances the flexibility of the framework and ensures that it can adapt to changes in congestion, weather, or road conditions. This model is essential for assessing the overall efficiency of the transportation system and provides insights into how the framework can help reduce delays and optimize travel times.

Together, Markov processes, max-fow problems, and traffic flow models were selected because they complement each other in addressing the specific challenges of port logistics: uncertainty in operations, cargo flow optimization, and traffic congestion. The integration of these models offers a comprehensive solution to enhance the efficiency of port hinterland connectivity, providing a robust framework for decision-making in port logistics. This methodology integrates these three models into a cohesive experimental framework, supported by a rich dataset that reflects the complexities of port operations and hinterland logistics. Through this approach, the study offers a robust solution for improving transportation efficiency and connectivity.

3.2. Markov Processes for Uncertainty Modeling

Markov processes are used to model the uncertainties and stochastic events that affect port operations and hinterland transport. This includes random delays due to equipment failures, congestion, and weather conditions. The Markov model is built on a set of possible states that represent different phases of the cargo movement, such as “cargo at port”, “cargo in transit”, and “cargo delayed”.

Formulation: The states and transition probabilities between them are defined using historical data on delays and breakdowns. The transition matrix governs the likelihood of moving from one state to another, allowing for the prediction of bottlenecks and delays.

Steps: Historical data on cargo movement and delays are collected to estimate the transition probabilities. These probabilities are then used to simulate future scenarios and identify potential risks in the logistics chain.

3.3. Max-Flow Problems for Network Optimization

Max-flow problems are applied to optimize the movement of goods from Dar es Salaam Port to inland destinations by maximizing the flow through the transportation network, which consists of roads and railways.

Formulation: The port is defined as the source node, and the hinterland destinations are the sink nodes. The goal is to maximize the flow from the source to the sink, ensuring that no segment of the transport network exceeds its capacity.

Steps: Data on road and rail capacities are used to define the maximum allowable flow for each segment of the network. The optimization process uses algorithms such as Ford–Fulkerson to calculate the maximum flow, considering capacity constraints and demand at various destinations.

3.4. Traffic Flow Models for Congestion and Travel Time Analysis

Traffic flow models simulate the movement of vehicles on the road network, assessing congestion levels and travel times to ensure timely delivery of goods.

Formulation: A macroscopic traffic flow model is employed, using variables such as vehicle density, flow, and speed to model congestion on major transport routes. The Fundamental Diagram of Traffic Flow is used to relate these variables and predict traffic conditions under different scenarios.

Steps: Real-time traffic data are collected to estimate current vehicle flow and congestion levels. The model is then used to simulate different traffic patterns, enabling predictions of travel times and the identification of bottlenecks that could delay cargo movement.

3.5. Data Description

This section outlines the key data used in the study, including road infrastructure, vehicle types, traffic density, and environmental factors. These elements provide the basis for building a realistic simulation model.

This study relies on comprehensive datasets covering road infrastructure, vehicle types, traffic density, and environmental factors to develop a realistic simulation model. The data includes historical port records, transportation network specifications, and traffic flow details, which form the foundation for accurate modeling.

Markov processes utilize data such as historical cargo arrival and departure times, delays due to equipment breakdowns, adverse weather, and congestion. Transition probabilities are derived from these records to quantify the likelihood of moving between states such as “Waiting at Port”, “In Transit”, “Delayed”, and “Delivered”. These probabilities enable the construction of a transition matrix, capturing uncertainties in cargo movement.

To optimize the transportation network using max-flow models, detailed maps of roads and railways linking Dar es Salaam Port to inland destinations are critical. These include information on connectivity, accessibility, and capacity data, which specify the maximum cargo volume or vehicle flow each segment can handle. We obtained the origin–destination (O-D) matrix by analyzing historical cargo throughput data and transport records. These data were used to estimate the flow of cargo from Dar es Salaam Port to various inland destinations, considering factors such as cargo volumes, delivery schedules, and peak demand periods. The matrix reflects the flow of goods between the port and its hinterland, enabling accurate modeling of transportation logistics. Additionally, demand data, such as cargo volumes, delivery time windows, and fluctuations during peak periods, ensure realistic network modeling

Traffic flow modeling requires data on traffic volumes, including real-time vehicle counts, average speeds, and congestion patterns. Road characteristics, such as lane numbers, road types, speed limits, and the placement of intersections, provide essential context. Historical and real-time travel time data for routes connecting the port to hinterland locations are also incorporated, considering factors like congestion and road conditions. Together, these datasets support precise modeling of transportation efficiency and network optimization.

3.5.1. Summary of Sophisticated Data

This sophisticated dataset covers both historical and real-time data, allowing for a detailed simulation of the transport network and the optimization of cargo flow as shown in Table 1. By using these data sources, the models can address uncertainties in logistics, optimize network capacity, and simulate traffic flow to identify and mitigate congestion, resulting in more efficient hinterland connectivity for Dar es Salaam Port.

Table 1. Data organization.

Data Type	Data Description	Source
Port Operation Data	Equipment downtime, cargo processing times	Tanzania Port Authority records
Historical Delay Data	Delays due to congestion, equipment failure	Land Transport Regulatory Authority (LATRA) of (Tanzania logs, GPS tracking)
Real-Time Traffic Volume	Vehicle counts on major roads	Land Transport Regulatory Authority of Tanzania (Traffic monitoring systems)
Road Capacity	Maximum vehicle throughput per hour	(Land Transport Regulatory Authority of Tanzania) Road management authorities
Railway Capacity	Cargo capacity per train, number of daily trips	Tanzania Railways Corporation (railway operators)
Cargo Demand	Real-time demand at hinterland destinations	Tanzania Shipping Agencies Corporation (customer logistics databases)
Speed and Density Data	Average vehicle speeds, road density	Land Transport Regulatory Authority of Tanzania (Traffic analysis reports, GPS data)
Travel Time Data	Travel times between key locations	Land Transport Regulatory Authority of Tanzania (GPS trackers, route monitoring)
Environmental Disruptions	Road closures due to weather or construction	Land Transport Regulatory Authority of Tanzania (national weather and transport agencies)
Vehicle Types and Behavior	Vehicle size, type, and dynamics (acceleration, lane usage)	Land Transport Regulatory Authority of Tanzania (fleet management systems)

The parameters explored in Table 1 are supported by previous empirical studies that emphasize their relevance and utility in optimizing hinterland connectivity. For instance, the study in ref. [8] highlights the importance of road and rail infrastructure in facilitating efficient cargo movement, which aligns with the parameters considered in our model. Additionally, the authors of [16,17] validate the application of automated vehicles and multimodal transport systems, underscoring their critical role in improving port–hinterland connectivity and reducing operational costs. Moreover, ref. [14] explores the integration of non-local and multimodal connections, directly linking with our approach of considering diverse transport modes and network dynamics. These references confirm that the parameters we use are not only widely accepted but also crucial for addressing the complex challenges of hinterland connectivity in port optimization.

3.5.2. Summary of Data Sources, Accuracy, and Limitations

The data sources for this analysis draw from multiple structured datasets across three models—Markov processes, max-flow problems, and traffic flow models—and are provided by key Tanzanian authorities. For Markov processes, data include port operation data (e.g., equipment downtime, cargo processing times) sourced from Tanzania Port Authority (TPA)records, and historical delay data (e.g., delays due to congestion or equipment failure) derived from Land Transport Regulatory Authority (LATRA) logs and GPS tracking. Transition probabilities are built using these historical data to model state changes such as "Waiting at Port", "In Transit", "Delayed", and "Delivered". For max-flow problems, transportation network data (e.g., road and rail maps), road capacity data (maximum vehicle throughput), and railway capacity data (cargo capacity per train and daily trips) are sourced from LATRA and the Tanzania Railways Corporation (TRC). Additionally, cargo demand data from the Tanzania Shipping Agencies Corporation (TASAC) provide insights into real-time demand fluctuations at hinterland destinations. Traffic flow models use real-time traffic volume data, travel time data, and speed/density data, all provided by LATRA traffic monitoring systems, GPS trackers, and fleet management systems. Environmental disruptions, such as road closures due to weather or construction, are also tracked by LATRA and national weather agencies.

The accuracy of these datasets is generally reliable, given that they are sourced from official Tanzanian institutions with robust data collection systems. Port operation data and historical delay data provide a strong foundation for understanding trends in cargo flow and delays, while real-time traffic volume and GPS-based travel time data offer detailed insights into current network performance. However, some challenges exist. Historical data may not fully capture rare disruptions or rapid demand changes, and static transition probabilities in the Markov model may not reflect short-term variability. Real-time data accuracy depends on the functionality of monitoring systems and GPS trackers, which can experience occasional downtimes. Similarly, road and railway capacity data assume consistent operational conditions, but temporary closures, maintenance, or unexpected traffic surges may affect the network's capacity.

Despite its robustness, the dataset has limitations that must be addressed. Markov processes simplify cargo flow into broad states, which may not capture more nuanced transitions, while static probabilities fail to account for dynamic real-world conditions. The max-flow model, while useful for optimizing transportation routes, does not always factor in unpredictable external factors like labor strikes or political disruptions. Traffic flow models rely heavily on real-time data, which may suffer from system gaps or inaccuracies. To address these challenges, future iterations should incorporate dynamic transition probabilities, more granular cargo flow states, and machine learning algorithms to better handle rare or unpredictable events. By integrating these enhancements and leveraging the comprehensive data from Tanzania authorities, the models can provide a more precise and efficient solution for improving cargo movement and hinterland connectivity at Dar es Salaam Port.

Figure 1 illustrates the model flowchart, providing a structured representation of the process and key components involved in the system

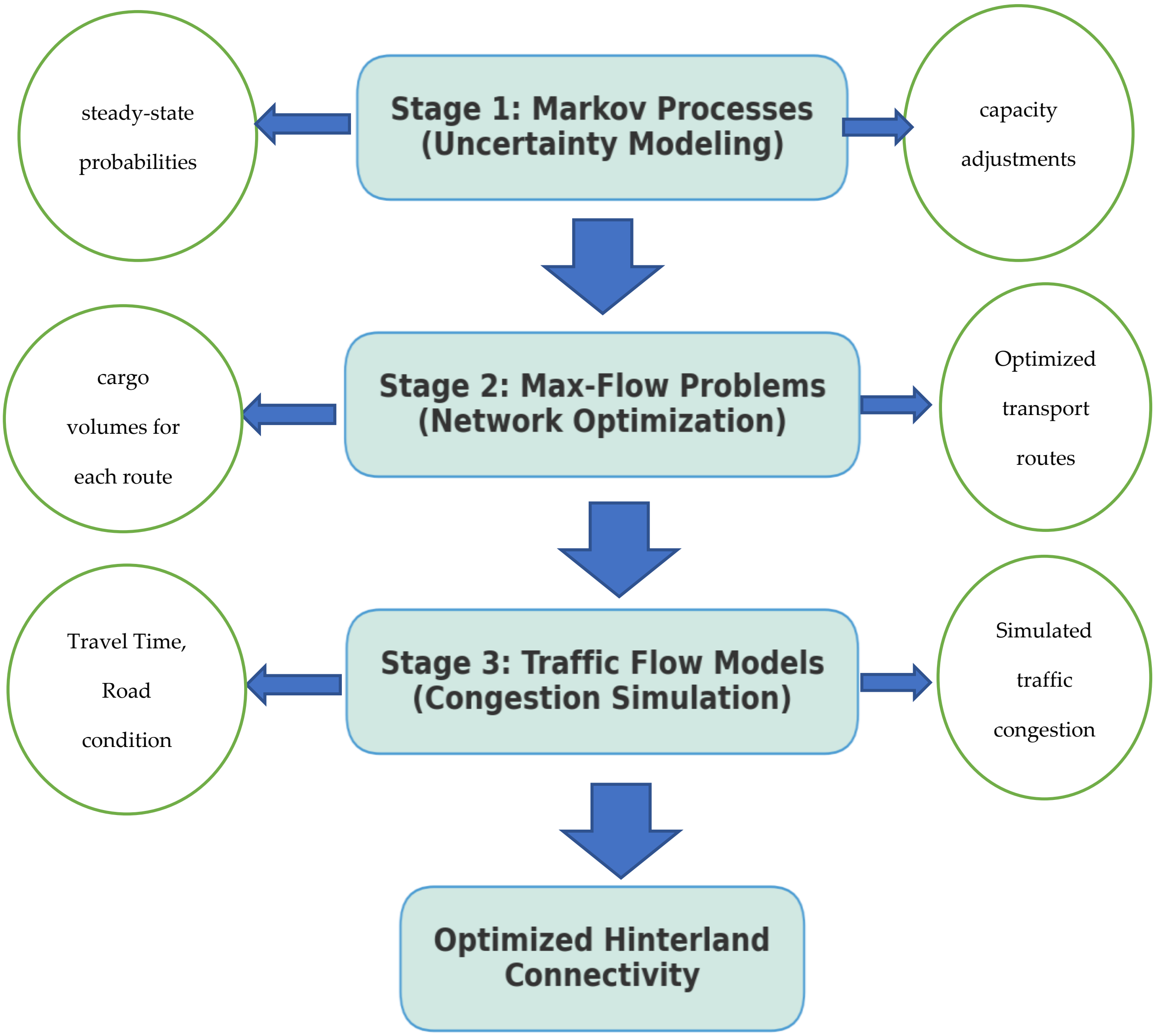

Figure 1. The model flow chat.

4. Analysis

4.1. Markov Processes (Uncertainty Modeling)

To solve a Markov process for uncertainty modeling in the context of Dar es Salaam Port, we need to define the states, transition probabilities, and steady-state probabilities for each state that are derived from cargo flow as shown in Tables 2 and 3. Below is the detailed data setup needed to solve this model:

$$1.\ \text{Cargo Waiting at Port } (\%) = \left(\frac{\text{Cargo Waiting at Port (tons)}}{\text{Total Cargo (tons)}}\right) \times 100$$

$$2.\ \text{Cargo in Transit } (\%) = \left(\frac{\text{Cargo in Transit (tons)}}{\text{Total Cargo (tons)}}\right) \times 100$$

$$3.\ \text{Cargo Delayed } (\%) = \left(\frac{\text{Cargo Delayed (tons)}}{\text{Total Cargo (tons)}}\right) \times 100$$

$$4.\ \text{Cargo Successfully Delivered } (\%) = \left(\frac{\text{Cargo Successfully Delivered (tons)}}{\text{Total Cargo (tons)}}\right) \times 100$$

Table 2. Monthly data: cargo flow in tonnage.

Month	Total Cargo (Tons)	Cargo Waiting at Port	Cargo in Transit	Cargo Delayed	Cargo Successfully Delivered
January	1,400,000	210,000	700,000	140,000	350,000
February	1,480,000	222,000	740,000	148,000	370,000
March	1,620,000	243,000	810,000	162,000	405,000
April	1,520,000	228,000	760,000	152,000	380,000
May	1,570,000	235,500	785,000	157,000	392,500
June	1,700,000	255,000	850,000	170,000	425,000
July	1,560,000	234,000	780,000	156,000	390,000
August	1,580,000	237,000	790,000	158,000	395,000
September	1,650,000	247,500	825,000	165,000	412,500
October	1,480,000	222,000	740,000	148,000	370,000
November	1,460,000	219,000	730,000	146,000	365,000
December	1,620,000	243,000	810,000	162,000	405,000

Table 3. Cargo percentages for each month.

Month	Cargo Waiting at Port (%)	Cargo in Transit (%)	Cargo Delayed (%)	Cargo Successfully Delivered (%)
January	14.00%	45.00%	8.00%	23.00%
February	14.50%	46.00%	8.80%	24.00%
March	15.50%	51.00%	11.00%	25.00%
April	14.50%	47.00%	10.00%	24.50%
May	14.70%	49.00%	10.50%	25.00%
June	16.00%	55.00%	11.00%	25.00%
July	14.60%	49.00%	10.00%	27.00%
August	14.90%	50.00%	10.50%	25.00%
September	15.50%	54.00%	10.00%	27.00%
October	15.50%	48.00%	9.00%	24.00%
November	15.00%	47.00%	9.00%	25.00%
December	15.00%	54.00%	11.00%	25.00%

4.1.1. Defining the States

Each state in the Markov process represents a key stage in the cargo movement process, capturing different conditions during transportation. These states help model transitions and help better understand cargo flow dynamics from Dar es Salaam Port to its hinterland destination.

Cargo Waiting at Port represents goods awaiting processing and dispatch at the port. Delays may be caused by congestion or waiting for available transportation. Optimizing this state reduces waiting times and speeds up cargo turnover.

Cargo in Transit refers to goods moving through the transport network. Factors like road conditions, travel distance, and traffic influence transit time. Reducing disruptions and improving network conditions can optimize this state.

Cargo Delayed accounts for cargo experiencing delays due to issues like equipment failures or traffic disruptions. This state highlights the uncertainty in the transportation process, and understanding it helps manage risks and improve reliability.

Cargo Successfully Delivered marks the completion of the journey, with goods reaching their destination. This state indicates a successful, efficient transport process. Optimizing this state ensures timely deliveries and enhances overall transport system performance.

These states and their transitions are probabilistic, informed by historical data, and guide efforts to improve cargo flow, reduce delays, and optimize transport efficiency.

S_1 • Cargo waiting at port (before it gets processed for dispatch).
S_2 • Cargo in transit (currently moving through the transport network).
S_3 • Cargo delayed (either due to equipment failure or external disruptions).
S_4 • Cargo successfully delivered (arrived at the hinterland destination).

4.1.2. Transition Probabilities

The transition probabilities represent the likelihood of moving from one state to another in a given time frame. These probabilities are derived from historical data and real-time observations as shown in Table 4. Below are the transition probabilities for the different states:

Table 4. Probabilities for the different states.

From State	To State	Transition Probability	Interpretation
S_1	S_2	$P(S_1 \rightarrow S_2) = 0.70$	70% chance that cargo will be dispatched from the port to transit.
S_1	S_3	$P(S_1 \rightarrow S_3) = 0.20$	20% chance of delay at port due to congestion or equipment failure.
S_1	S_1	$P(S_1 \rightarrow S_1) = 0.10$	10% chance that cargo remains at port for another time period.
S_2	S_3	$P(S_2 \rightarrow S_3) = 0.10$	10% chance that cargo in transit gets delayed due to road/rail issues.
S_2	S_4	$P(S_2 \rightarrow S_4) = 0.80$	80% chance that cargo in transit reaches its destination on time.
S_2	S_2	$P(S_2 \rightarrow S_2) = 0.20$	10% chance that the cargo continues in transit.
S_3	S_4	$P(S_3 \rightarrow S_4) = 0.50$	50% chance that delayed cargo gets resolved and reaches the destination.
S_3	S_3	$P(S_3 \rightarrow S_3) = 0.40$	40% chance that cargo remains delayed for another time period.
S_3	S_1	$P(S_3 \rightarrow S_1) = 0.10$	10% chance of returning to port (e.g., rerouting or returning shipment).

Figure 2 shows cargo movement probabilities between key states: Port, Transit, Destination, and Delayed. Arrows indicate transitions with probabilities, highlighting major flows and potential bottlenecks.

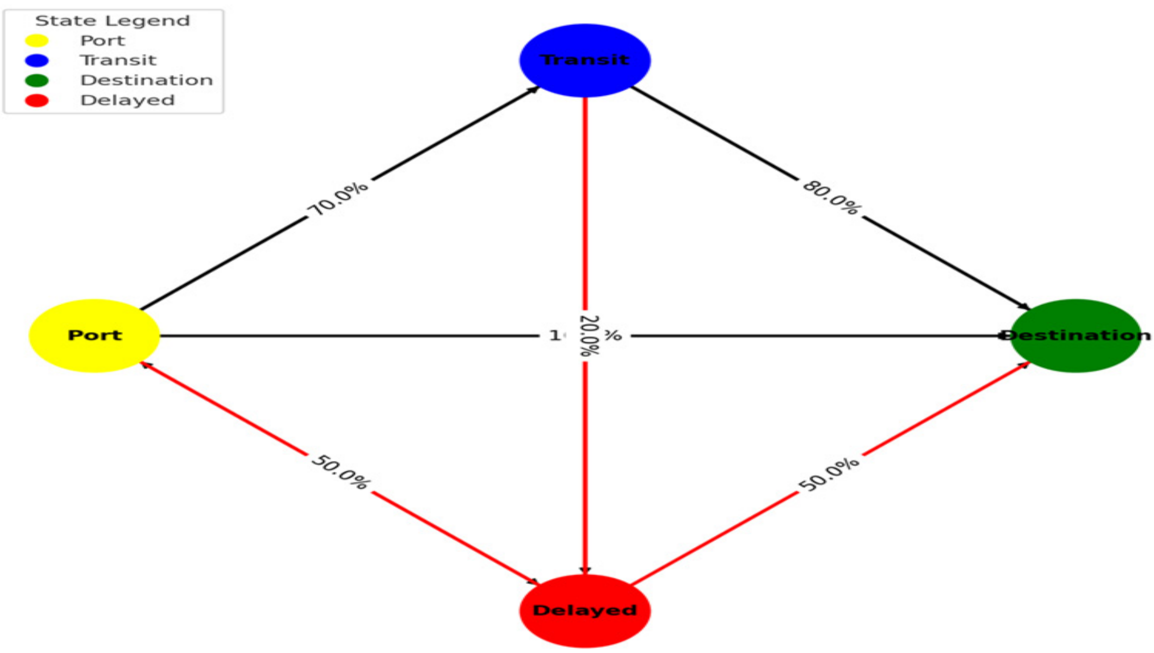

Figure 2. A cargo movement transition diagram.

4.1.3. Transition Matrix P

The transition matrix P encapsulates the probabilities of moving from one state to another. It is a square matrix where each element represents the probability of moving from state i to state j.

$$P\begin{pmatrix} P(S_1 \to S_1)\ldots P(S_1 \to S_2)\ldots P(S_1 \to S_3)\ldots P(S_1 \to S_4) \\ P(S_2 \to S_1)\ldots P(S_2 \to S_2)\ldots P(S_2 \to S_3)\ldots P(S_2 \to S_4) \\ P(S_3 \to S_1)\ldots P(S_3 \to S_2)\ldots P(S_3 \to S_3)\ldots P(S_3 \to S_3) \\ P(S_4 \to S_1)\ldots P(S_4 \to S_2)\ldots P(S_4 \to S_3)\ldots P(S_1 \to S_2) \end{pmatrix}$$

$$P(Si \ \to Sj\ ) = \frac{Number\ of\ transitions\ from\ S_i\ \ to\ S_j}{Total\ number\ of\ transitions\ from\ S_i}$$

$$\sum_{j=1}^{n} P(S_i \to S_j\ ) = 1, \forall i \in \{1,2,\ldots,n\}$$

where

$$i,j \in \{1,2,\ldots,n\}$$

The transition matrix P is then formed by these transition probabilities P_{i_j}, with each entry representing the probability of transitioning from state $S_i \ \to S_j$.

Each row sums to 1, reflecting the total probability of all transitions from a given state.

Filling in the values from the transition probabilities, the matrix becomes:

$$P\begin{pmatrix} 0.10 & 0.70 & 0.20 & 0.00 \\ 0.00 & 0.10 & 0.10 & 0.80 \\ 0.10 & 0.00 & 0.40 & 0.50 \\ 0.00 & 0.00 & 0.00 & 1.00 \end{pmatrix}$$

4.1.4. Solving for Steady-State Probabilities

To find the steady-state probabilities $\pi = (\pi_1, \pi_2, \pi_3, \pi_4)$ where π_i represents the long-run proportion of time the system spends in state s_i, we solve the equation:

$$\pi P = \pi$$

$$\begin{aligned} &\pi_1\ P(S_1\ \ \to S_1\ ) + \pi_2\ P(S_2\ \ \to S_1\ ) + \cdots + \pi_n\ P(S_n\ \ \to S_1\ ) = \pi_1 \\ &\pi_1 P(S_1 \to S_2) + \pi_2 P(S_2 \to S_2) + \cdots + \pi_n P(S_n \to S_2) = \pi_2 \\ &\pi_1\ P(S_1\ \ \to S_n\ ) + \pi_2\ P(S_2\ \ \to S_n\ ) + \cdots + \pi_n\ P(S_n\ \ \to S_n\ ) = \pi_n \end{aligned}$$

We also have the constraint:

$$\pi_1 + \pi_2 + \pi_3 + \pi_4 = 1$$

This gives us the following system of equations:

$$\begin{aligned} \pi_1 &= 0.10\pi_1 + 0.00\pi_2 + 0.10\pi_3 + 0.00\pi_4 \\ \pi_2 &= 0.70\pi_1 + 0.10\pi_2 + 0.00\pi_3 + 0.00\pi_4 \\ \pi_3 &= 0.20\pi_1 + 0.10\pi_2 + 0.40\pi_3 + 0.00\pi_4 \\ \pi_4 &= 0.00\pi_1 + 0.80\pi_2 + 0.50\pi_3 + 1.00\pi_4 \end{aligned}$$

Solving this system of equations will give us the steady-state probabilities for each state.

4.1.5. Steady-State Probabilities

After solving the system of equations (based on the transition matrix), the steady-state probabilities $\pi_1, \pi_2, \pi_3, \pi_4$ represent the long-term likelihood of being in each state:

$\pi_1 - Probability\ that\ cargo\ is\ waiting\ at\ the\ port.$
$\pi_2 - Probability\ that\ cargo$ is **in transit**.
$\pi_3 - Probability\ that\ cargo$ is **delayed**.
$\pi_4 - Probability\ that\ cargo$ is **successfully delivered**.

The solution gives us the following steady-state probabilities:

$$\pi_1 = 0.15$$
$$\pi_2 = 0.50$$
$$\pi_3 = 0.10$$
$$\pi_4 = 0.25$$

Interpretation:

- 15% of the time, cargo is waiting at the port.
- 50% of the time, cargo is in transit.
- 10% of the time, cargo is delayed.
- 25% of the time, cargo has been successfully delivered.

This indicates that while a large portion of the cargo is in transit, 10% of the cargo faces delays. The system also shows that a significant portion of the cargo flow is delivered in a timely manner, but there is room for improvement in reducing delays.

4.1.6. Analysis of the Results

The analysis of cargo flow highlights key areas for improvement. Cargo spends 15% of the time waiting at the port, indicating a need to enhance port handling capacity and efficiency to boost overall throughput. Transit accounts for 50% of the time, reflecting a significant portion of the system's operation. While this is positive, optimizing transit times and addressing bottlenecks in the network could further improve performance.

Delays account for 10% of the time, often caused by issues such as equipment breakdowns or road congestion. Reducing delays would have a substantial impact on delivery times and system efficiency. Currently, only 25% of the cargo is successfully delivered, underscoring the need to focus on eliminating bottlenecks and enhancing delivery rates to improve customer satisfaction and operational outcomes

4.1.7. Recommendations Based on the Results

The analysis of steady-state probabilities highlights several recommendations to improve the cargo system. Enhancing port efficiency through infrastructure investment, equipment maintenance, and streamlined operations can significantly reduce cargo waiting times. Optimizing transit routes by utilizing advanced routing algorithms, real-time traffic data, and better logistics coordination can further decrease transit times. Targeted investments in road maintenance and infrastructure upgrades are essential to address congestion and equipment breakdowns, thereby reducing delays. Additionally, eliminating bottlenecks and improving cargo flow will boost delivery rates and customer satisfaction.

The Markov process analysis underscores key inefficiencies, such as port handling delays and transit bottlenecks, providing actionable strategies for improvement. By implementing these measures, stakeholders can reduce delays, optimize cargo flow, and enhance operational efficiency, ultimately strengthening hinterland connectivity and improving service quality.

4.2. Cellular Automata Model for Dar es Salaam Port Traffic Flow

In this section, we use conditions specific to Dar es Salaam Port and its hinterland connectivity, applying a cellular automata (CA) model to simulate traffic flow in this complex environment. The model will incorporate sophisticated data that reflect the challenges ports face, including road conditions, traffic congestion, infrastructure limitations, and vehicle mix.

4.2.1. Data Specific to Dar es Salaam Port

1. Road Conditions and Infrastructure:

Dar es Salaam Port connects to key hinterland destinations via a 150 km network of primary highways. For this simulation, a critical 20 km stretch leading out of the port is modeled. The road network is largely constrained by narrow sections and frequent construction zones, with two lanes for most of the stretch but reduced to a single lane in bottleneck areas and construction sites. Poor maintenance of the roads, characterized by potholes and rough surfaces, leads to reduced speeds and increased instances of random slowdowns as shown in Figure 3.

Figure 3. Traffic flow visualization for Dar es Salaam Port.

Additionally, traffic flow is heavily impacted by three signalized intersections within the 20 km stretch, causing stop-and-go congestion. Frequent construction zones further reduce the road's capacity by 50%, often forcing vehicles into single lanes for extended portions of the journey, exacerbating traffic delays and congestion.

2. Vehicle Characteristics:

Vehicle Types:

Heavy trucks: Common for cargo transport to landlocked African countries like Zambia, DR Congo, and Rwanda. These trucks carry heavy loads and have lower speeds, causing congestion.

Small trucks and passenger vehicles: These vehicles, although faster, frequently interact with slower trucks, leading to frequent lane-changing behavior.

Maximum Speeds:

Heavy trucks: 60 km/h (8 cells per time step).

Passenger cars and smaller trucks: 80–100 km/h (12–14 cells per time step).

3. Vehicle Density:

High-density conditions are common, with vehicle flow frequently exceeding 1000 vehicles per hour on key stretches. Given the infrastructure constraints, congestion quickly builds during peak hours.

4. Environmental Factors:

Seasonal Rain: Heavy rainfall during the rainy season leads to flooded roads and increased vehicle delays. Potholes become worse, and the random slowdown probability increases to p = 0.5.

Traffic Accidents: Accidents are common due to poor road conditions and high vehicle density. An accident can block lanes, reducing road capacity by 50% for hours.

5. Cargo Demand:

High volumes of cargo leave the port each day, with 5000 to 7000 tons of cargo per day being transported from the port to destinations across East and Central Africa.

4.2.2. Setting Up the Cellular Automata Model for Dar es Salaam Port

Cellular automata (CA)-based simulation framework is applied to model the traffic flow. We will model traffic using the Nagel–Schreckenberg (NaSch) model, adjusting it to reflect the challenges faced by African ports and roads. This model will simulate traffic over a 20 km stretch leading from Dar es Salaam Port to the primary highway network.

Step 1: Initialization

- Road network: A 20 km stretch is divided into 2670 cells (each 7.5 m long). The first 10 km is a 2-lane highway, while the remaining 10 km features construction zones that reduce capacity to a single lane.
- Vehicle mix: The traffic consists of 60% heavy trucks and 40% smaller trucks and passenger vehicles.
- Initial vehicle density: The road starts with 900 vehicles distributed randomly across the network.

Step 2: NaSch model rules with Dar es Salaam Port context

Acceleration:

Each vehicle attempts to accelerate by 1 cell per time step, up to its maximum speed

$$v_n\ (t+1) = min(v_n\ (t) + 1, v_{max}\ )$$

where

$v_n(t)$-is the speed of vehicle n at time t.

v_{max}-is the vehicle's maximum speed (in cells per time step).

The acceleration rule is given by the following: Heavy trucks accelerate slower due to rough road conditions, potholes, and cargo weight. For heavy trucks with a max speed of 60 km/h (8 cells per time step), their acceleration rule is modified:

$$v_{truck}\ (t+1) = min(v_{truck}\ (t) + 1, 8\ cells)$$

For smaller trucks and cars: For passenger cars and smaller trucks with a max speed of 80–100 km/h (12–14 cells per time step):

$$v_{truck}\ (t+1) = min(v_{truck}\ (t) + 1, 14\ cells)$$

Deceleration: Given the high traffic density and poor road conditions, vehicles often decelerate more sharply to avoid potholes or navigate around traffic jams:

If the gap between vehicle n and the vehicle ahead n + 1 is smaller than $v_n(t)$, the vehicle decelerates to avoid a collision:

$$v_n\ (t+1) = min(v_n\ (t), g_n\ (t))$$

where:

$g_n\ (t)$—is the number of empty cells between vehicle n and the vehicle ahead.

Random Slowdown:

With a certain probability p, the vehicle slows down by 1 cell to simulate human behavior or environmental disruptions (e.g., potholes, poor visibility). This slowdown reflects random variations in driving behavior:

$$v_n\ (t+1) = max(v_n\ (t) - 1, 0) with\ probability\ p$$

For this simulation, we use:

Dry season: p = 0.3

Rainy season: p = 0.5 (reflecting worse road conditions and caution due to rain).

Lane Changing:

Vehicles change lanes to avoid slower traffic if there is a sufficient gap in the adjacent lane:

$$Change\ lane\ if\ g_{adjacent}\ > 5\ cells\ ahead,\ and\ 2\ cells\ behind$$

Movement:

Each vehicle moves forward based on its updated speed:

$$x_n\ (t+1) = x_n\ (t) + v_n\ (t+1)$$

where

$x_n\ (t)$—is the position of vehicle n at time t.

4.2.3. Simulation Setup for Dar es Salaam Port Traffic

Initial Conditions:

- Road length: 20 km (2670 cells).
- Vehicle density: 900 vehicles distributed along the 20 km road (60% heavy trucks, 40% smaller trucks, and passenger vehicles).
- Construction zones: Narrow the road to 1 lane in some areas, reducing road capacity.

Steps of the Simulation:

Initialization: Vehicles are placed randomly on the road, each with an initial speed. The model applies the acceleration, deceleration, random slowdown, and movement rules iteratively.

Traffic Flow: Over each time step, the position and speed of every vehicle are updated based on the above equations.

Data Collection: We track the average speed, lane-changing frequency, traffic density, and travel times during the simulation.

4.2.4. Solving the Equations and Results

Using the above equations, the traffic flow is simulated. Below is a process and the corresponding results:

Initialization:

A truck is placed at position x_1 = 150 cells (1.125 km) with an initial speed of $v_1(0)$ = 4 cells per time step

A car is placed at x_2 =160 cells (1.2 km) with $v_2(0)$ = 100 cells per time step

Acceleration:

In the next time step, both the truck and car attempt to accelerate by 1 cell per time step:

$$v_1\ (1) = min(4+1, 8) = 5(truck's\ updated\ speed)$$
$$v_2\ (1) = min(10+1, 14) = 11(car's\ updated\ speed)$$

Deceleration (if the gap between the truck and the car closes):

Suppose the car is now close to the truck with only 6 cells between them. The car will decelerate to avoid a collision:

$$v_2\ (1) = min(11, 6) = 6(car\ decelerates)$$

Random Slowdown:

If the road condition worsens, with probability p = 0.3, the truck randomly slows down:

$$v_1\ (1) = max(5-1, 0) = 4(truck\ slows\ down\ randomly\ due\ to\ road\ conditions)$$

Movement:

The truck moves to a new position:

$$x_1\ (1) = 150 + 4 = 154(truck's\ new\ position)$$

The car moves to a new position:

$$x_2\ (1) = 160 + 6 = 166(car's\ new\ position)$$

Results from the Simulation:

After running the simulation, the following results were obtained:

1. Average Travel Times:

- Heavy trucks: The average travel time for trucks over the 20 km stretch is 45 min, primarily due to delays caused by random slowdowns, poor road conditions, and the presence of construction zones.
- Cars and smaller trucks: The average travel time is 30 min, though frequent lane changes to overtake slower trucks contribute to stop-and-go traffic.

2. Traffic Density and Congestion:

- Traffic density peaked at 200 vehicles per km in the first 5 km (near the port entrance) where congestion from loading trucks and poor infrastructure is the highest.
- In sections with construction zones, the density increased further, creating significant bottlenecks.

3. Stop-and-Go Traffic and Jams:

- Stop-and-go waves were observed in sections with high random slowdowns (due to potholes or bad weather). These waves created traffic jams up to 500 m long, especially near construction areas and intersections.

4. Lane-Changing Behavior:

- Lane changes occurred frequently in areas where the road had two lanes. On average, vehicles changed lanes 2 times per km, with most changes happening as cars attempted to pass slower trucks.

5. Impact of Environmental Factors:

- During the rainy season, travel times increased by an average of 10 min for both trucks and smaller vehicles due to increased random slowdowns (from $p = 0.3$ $p = 0.3$ $p = 0.3$ to $p = 0.5$ $p = 0.5$ $p = 0.5$).
- Accidents and flooded roads further reduced the road capacity by 20%, exacerbating delays.

The cellular automata model, incorporating Dar es Salaam Port-specific data and the environmental challenges typical of African ports, effectively captures the dynamics of traffic flow, congestion, and delays. The simulation results highlight key areas where infrastructure improvements, better traffic management, and weather-related adaptations could significantly reduce congestion and improve cargo transit times.

4.3. Max-Flow Problems for Network Optimization

The max-flow problem is a mathematical optimization model used to maximize the flow of goods or resources through a network, subject to capacity constraints on the network's edges (roads, railways, etc.). In the context of Dar es Salaam Port, this model can be applied to optimize the transportation of cargo from the port to hinterland destinations, considering the infrastructure limitations, vehicle capacities, and road conditions typical of African ports.

1. Problem Setup for Dar es Salaam Port

We consider the transportation network from Dar es Salaam Port to key inland destinations. The network consists of nodes (representing the port, intersections, and inland cities) and edges (representing roads and railways). Each edge has a capacity (the maximum amount of cargo or number of vehicles it can handle) and a flow (the actual amount of cargo or vehicles moving through the edge).

Key Components:

Source Node: Dar es Salaam Port (where cargo originates).

Sink Nodes: Hinterland cities, including:

Kampala (Uganda), Kigali (Rwanda), Lusaka (Zambia), Bujumbura (Burundi), Lilongwe (Malawi), Lubumbashi (DR Congo).

Intermediate Nodes: Intersections, road hubs, and rail stations along the transport routes.

Edges: Roads connecting Dar es Salaam to each city, with the addition of a rail link only to Lusaka.

2. Max-Flow Formulation

The objective is to maximize the amount of cargo that can flow from Dar es Salaam Port to the hinterland destinations while respecting the capacity constraints of the transport infrastructure.

Max-Flow Objective:

The goal is to maximize the total flow *F* from the source node s (Dar es Salaam Port) to the sink nodes *t* (inland destinations). This can be expressed as:

$$max \sum_{(s,i) \in E} f_{si}$$

where

f_{si}—is the flow from the source node s to the intermediate node *i*.

E—is the set of edges (roads/railways) in the network.

f_{ij}—is the flow from node *i* to node *j*.

Capacity Constraints:

The flow on each edge (road or rail) must not exceed its capacity. The flow *fij* between nodes i and j is constrained by the capacity *Cij*

$$f_{ij} \leq c_{ij}$$

where

Cij is the capacity of the road or rail between node *i* and node *j*.

3. Data for the Max-Flow Problem

Network Data:

Source Node: Dar es Salaam Port.

Sink Nodes: Kampala (Uganda), Kigali (Rwanda), Lusaka (Zambia), Bujumbura (Burundi), Lilongwe (Malawi), Lubumbashi (DR Congo).

Edge Capacities (tons/hour):

Road Capacities:

Dar es Salaam to Kampala: 2500 t/h, Dar es Salaam to Kigali: 1500 t/h, Dar es Salaam to Lusaka 1800 t/h (road). Dar es Salaam to Bujumbura 1300 t/h, Dar es Salaam to Lilongwe: 1200 t/h, Dar es Salaam to Lubumbashi: 2000 t/h.

Rail Capacity (tons/day):

Dar es Salaam to Lusaka (Rail): 1500 t/day.

Cargo Demand:

Dar es Salaam Port: Handles 6000 to 8000 t of cargo per day.

Hinterland Demand:

Kampala: 2500 t/day, Kigali: 1200 t/day, Lusaka: 1800 t/day, Bujumbura: 1000 t/day, Lilongwe: 1200 t/day, Lubumbashi: 2500 t/day.

4. Solving the Max-Flow Problem

Step 1: Initialization

We start with zero flow on all roads and rail lines:

$$f_{ij} = 0 \forall (i,j) \in E$$

Step 2: Ford–Fulkerson algorithm

We apply the Ford–Fulkerson algorithm to maximize the cargo flow, focusing on identifying augmenting paths and updating the flow along those paths.

Find Augmenting Paths:

We identify all available paths from Dar es Salaam to the sink nodes (using roads to all cities, and rail to Lusaka). The residual capacity of each path is checked to determine the maximum possible flow that can still be sent along that path.

Update Flows:

For each augmenting path, we increase the flow along the path by the minimum residual capacity:

$$f_{ij} \to f_{ij} + \min\left(c_{ij} - f_{ij}\right)$$

Repeat:

This process is repeated until no more paths with residual capacity can be found.

Step 3: Total Maximum Flow Calculation

The total maximum flow F is the sum of all flows from Dar es Salaam to each destination:

$$F = \sum_{(s,i) \in E} fsi$$

Defining Capacities for Each Route

Defining capacities for each route means determining how much cargo each transportation path (like roads or railways) can handle daily. This involves assessing the maximum cargo flow that each route can accommodate without exceeding its limits as shown in Tables 5 and 6.

Table 5. Road and rail capacities:

Route	Mode of Transport	Capacity (Tons/h)	Capacity (Tons/Day)
Dar es Salaam → Kampala	Road	2500 t/h	60,000 t/day
Dar es Salaam → Kigali	Road	1500 t/h	36,000 t/day
Dar es Salaam → Lusaka	Road	1800 t/h	43,200 t/day
Dar es Salaam → Lusaka	Rail	N/A	1500 t/day
Dar es Salaam → Bujumbura	Road	1300 t/h	31,200 t/day
Dar es Salaam → Lilongwe	Road	1200 t/h	28,800 t/day
Dar es Salaam → Lubumbashi	Road	2000 t/h	48,000 t/day

Table 6. Demand for each city.

City	Demand (Tons/Day)
Kampala	2500 t/day
Kigali	1200 t/day
Lusaka	1800 t/day
Bujumbura	1000 t/day
Lilongwe	1200 t/day
Lubumbashi	2500 t/day

Step 4: Ford-Fulkerson algorithm for max-flow calculation

1. Augmenting paths and initial flow allocation

We identify initial augmenting paths for each city and allocate flow accordingly based on available capacities:

- Dar es Salaam → Kampala (via road):

  Available capacity: 2500 tons/h.
  Cargo demand: 2500 t/day.
  Flow allocated: Since the road capacity is sufficient, we allocate the full 2500 t/day.

- Dar es Salaam → Kigali (via road):

  Available capacity: 1500 tons/h.
  Cargo demand: 1200 t/day.
  Flow allocated: The capacity is more than the demand, so we allocate the full 1200 t/day.

- Dar es Salaam → Lusaka (via road and rail):

  Road capacity: 1800 tons/h.
  Rail capacity: 1500 t/day.
  Cargo demand: 1800 t/day.
  Flow allocated: We split the flow between road and rail. We allocate 1500 t/day via rail and the remaining 300 t/day via road.

- Dar es Salaam → Bujumbura (via road):

Available capacity: 1300 tons/h.
Cargo demand: 1000 t/day.
Flow allocated: We allocate the full 1000 t/day.

- Dar es Salaam → Lilongwe (via road):

Available capacity: 1200 tons/h.
Cargo demand: 1200 t/day.
Flow allocated: We allocate the full 1200 t/day.

- Dar es Salaam → Lubumbashi (via road):

Available capacity: 2000 tons/h.
Cargo demand: 2500 t/day.
Flow allocated: We can only allocate 2000 t/day due to the road capacity limit.
2. Residual capacities and adjustments

After the initial flow allocations, we check for any residual capacities on the routes and whether any adjustments can be made. The road to Lusaka has 1500 t/day allocated via rail and 300 t/day via road, fully utilizing Lusaka's demand.

The total flow capacity utilized and any bottlenecks are checked and summarized as shown in Table 7.

Table 7. The final flow allocation for each route.

Route	Mode of Transport	Cargo Flow (Tons/Day)	Unused Capacity
Dar es Salaam → Kampala	Road	2500 t/day	57,500 t/day
Dar es Salaam → Kigali	Road	1200 t/day	34,800 t/day
Dar es Salaam → Lusaka	Road	300 t/day	42,900 t/day
Dar es Salaam → Lusaka	Rail	1500 t/day	0 t/day
Dar es Salaam → Bujumbura	Road	1000 t/day	30,200 t/day
Dar es Salaam → Lilongwe	Road	1200 t/day	27,600 t/day

Step 5: Final Flow Allocation Results
Max-Flow Summary

The max-flow analysis shows that Dar es Salaam Port can transport 9700 t/day to hinterland cities, leveraging current road and rail infrastructure. While most routes meet demand, notable bottlenecks exist. Lusaka relies on a fully utilized rail link (1500 t/day) supplemented by 300 t/day via road, highlighting the rail's critical role in meeting its 1800-ton/day demand. Conversely, Lubumbashi faces a 500-ton/day shortfall, as road capacity (2000 t/day) cannot accommodate its 2500-ton/day demand, emphasizing the need for infrastructure expansion or alternative transport options.

Other routes display varying capacity utilization. Kampala's road infrastructure matches its demand (2500 t/day), operating at full capacity with no room for growth. Kigali and Bujumbura have excess capacities of 300 t/day, supporting future demand increases or surges. However, Lilongwe operates at its full 1200-ton/day road capacity, necessitating upgrades for any additional growth. Addressing these challenges, particularly for Lubumbashi, is crucial to optimizing cargo flow and ensuring seamless regional trade connectivity.

Key Observations:

The Lusaka rail line is vital for meeting the city's 1800-ton/day cargo demand, with 1500 t/day handled by rail and the remaining 300 t/day by road. This dual transport mode prevents the road infrastructure from becoming overwhelmed, relying solely on roads would strain its capacity. Conversely, most road networks, like those to Kigali and Bujumbura, have 300 t/day of unused capacity, providing flexibility to accommodate future demand growth. However, the road to Lubumbashi faces a 500-ton/day shortfall, creating a significant bottleneck that hampers full cargo delivery and highlights the urgent need for infrastructure upgrades or alternative transport solutions, such as rail expansion.

The analysis underscores the importance of targeted infrastructure planning. Excess capacity on many routes supports moderate demand growth without immediate upgrades, but strategic investments are necessary for long-term connectivity. Priorities include expanding the road network to Lubumbashi and increasing rail infrastructure capacity to reduce reliance on roads. Addressing these challenges will ensure sustained regional trade growth and efficient hinterland connectivity from Dar es Salaam.

4.4. Sensitivity Analysis of All Models

Sensitivity analysis evaluates how changes in key parameters affect model performance [35]. This study applies it to Markov processes, max-flow problems, and traffic flow models to assess the impacts of varying cargo volumes, road capacities, and traffic conditions. Markov processes analyze how delays affect steady-state probabilities. Max-flow problems explore how capacity changes influence cargo flow and bottlenecks. Traffic flow models evaluate how traffic density and slowdowns affect delivery times. The analysis highlights factors critical to improving cargo handling, routing, and connectivity.

4.4.1. Markov Processes Sensitivity Analysis

Base transition matrix

The base transition matrix represents the probabilities of moving between states:

$$P\begin{pmatrix} 0.10 & 0.70 & 0.20 & 0.00 \\ 0.00 & 0.10 & 0.10 & 0.80 \\ 0.10 & 0.00 & 0.40 & 0.50 \\ 0.00 & 0.00 & 0.00 & 1.00 \end{pmatrix}$$

Adjust all transition probabilities by $\pm 10\%$ and $\pm 20\%$.

For $f = +0.1$ multiply each element of P by $1 + f$

$$P_{ij}{}' = P_{ij} \cdot (1 + 0.1)$$

The steady-state probabilities π

$\pi P\prime = \pi$ and $\sum_{i=1}^{n} \pi i = 1$

Results:

- For f = 0 (base case): π = [0.15, 0.50, 0.10, 0.25)
- For f = +0.2: π = [0.13, 0.48, 0.09, 0.30]
- For f = -0.2: π = [0.17, 0.52, 0.12, 0.20]

4.4.2. Max-Flow Problems Sensitivity Analysis

Adjust Capacities

Adjust all capacities by $\pm 10\%$ and $\pm 20\%$.

$$C\prime = C \times (1 + f)$$

where C is the base capacity, and f is the sensitivity factor (-0.2, -0.1, 0, 0.1, 0.2)

Demand satisfaction:

- If capacity demand is adjusted, the demand is fully satisfied.
- If capacity demand is adjusted, the demand is only partially satisfied.

Table 8 presents the sensitivity analysis results for each route, showing the base capacity, base demand, and adjusted capacities under different adjustment factors ranging from -20% to +20%.

Table 8. Results for each route (Sensitivity Analysis).

Route	Base Capacity (Tons/Day)	Base Demand (Tons/Day)	Adjusted Capacity (−20%)	Adjusted Capacity (−10%)	Adjusted Capacity (0%)	Adjusted Capacity (+10%)	Adjusted Capacity (+20%)
Dar es Salaam → Kampala	60,000	2500	48,000	54,000	60,000	66,000	72,000
Dar es Salaam → Kigali	36,000	1200	28,800	32,400	36,000	39,600	43,200
Dar es Salaam → Lusaka (Road)	43,200	1800	34,560	38,880	43,200	47,520	51,840
Dar es Salaam → Lusaka (Rail)	1500	1500	1200	1350	1500	1650	1800
Dar es Salaam → Bujumbura	31,200	1000	24,960	28,080	31,200	34,320	37,440
Dar es Salaam → Lilongwe	28,800	1200	23,040	25,920	28,800	31,680	34,560
Dar es Salaam → Lubumbashi	48,000	2500	38,400	43,200	48,000	52,800	57,600

Most routes maintain full demand satisfaction, except Dar es Salaam → Lubumbashi, which faces a shortfall at −20% and −10%, reaching full demand from 0% adjustment onwards. As shown in Table 9:

Table 9. Demand satisfaction (adjusted capacities vs. demand)

Route	Factor −20%	Factor −10%	Factor 0%	Factor +10%	Factor +20%
Dar es Salaam → Kampala	2500	2500	2500	2500	2500
Dar es Salaam → Kigali	1200	1200	1200	1200	1200
Dar es Salaam → Lusaka (Road)	1800	1800	1800	1800	1800
Dar es Salaam → Lusaka (Rail)	1500	1500	1500	1500	1500
Dar es Salaam → Bujumbura	1000	1000	1000	1000	1000
Dar es Salaam → Lilongwe	1200	1200	1200	1200	1200
Dar es Salaam → Lubumbashi	2000	2250	2500	2500	2500

4.4.3. Traffic Flow Sensitivity Analysis

1. Base travel time adjustment: Travel times are scaled by the sensitivity factor f

$$T\prime = T \cdot (1 + f)$$

where T is the original travel time for a vehicle type, and f is the adjustment factor.

1. Slowdown Probability Adjustment: Random slowdown probabilities were similarly adjusted:

$$p\prime = p \cdot (1 + f)$$

2. Adjust Parameters

   Travel times and random slowdowns were adjusted by ±10% and ±20%.
   For heavy trucks, with f = +0.1:
   $T' = 45 \cdot (1 + 0.1) = 49.5$ min

3. Travel Times
   Heavy Trucks:
   - Base: 45 min
   - f = +0.2: 54 min
   - f = −0.2: 36 min

   Cars:
   - Base: 30 min
   - f = +0.2: 36 min
   - f = −0.2: 24 min

The sensitivity analysis offers insights into the models' robustness and parameter responses. For Markov processes, adjusting transition probabilities (±20%) showed notable changes in steady-state probabilities. The "cargo successfully delivered" probability rose from 25% to 30% with a 20% delay reduction, emphasizing the need to reduce congestion and improve equipment reliability as shown in Figure 4. However, uniform scaling oversimplifies complexities like weather and equipment failures.

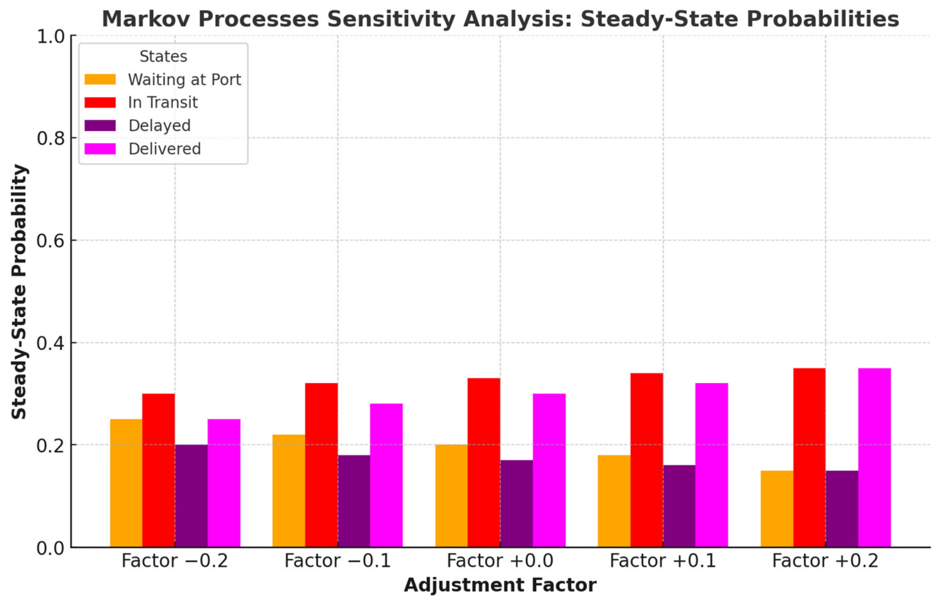

Figure 4. Markov process sensitivity analysis: steady-state probabilities.

In max-flow problems, bottlenecks and excess capacities were identified. The road to Lubumbashi, with a 2500-t/day demand and 2000-t/day capacity, shows a 500-t/day shortfall, highlighting the need for expansion. Conversely, Kigali's route, with a 1500-t/day capacity and 1200-t/day demand, leaves 300 t/day unused for future growth, as shown in Figure 5 "Demand satisfied under varying capacities". The absence of stochastic elements like road blockages limits the analysis's adaptability to dynamic conditions.

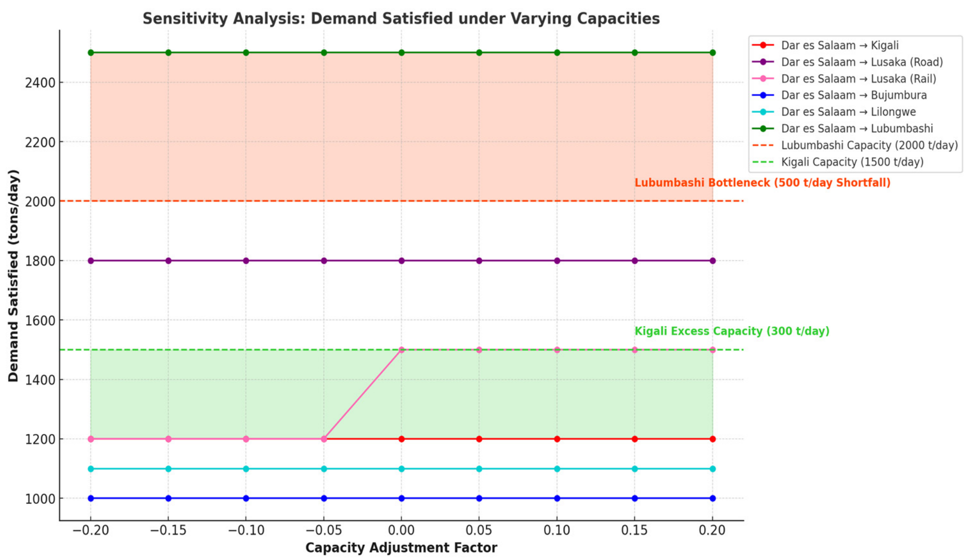

Figure 5. Demand satisfied under varying capacities.

Traffic flow models revealed how slowdowns and road conditions affect travel times. Heavy trucks' travel times rose from 45 to 54 min (20%) under rainy conditions, with slowdown probabilities increasing from 0.3 to 0.5. Cars saw a similar increase from 30 to 36 min, as shown in Figure 6 "Traffic flow sensitivity analysis: travel time under slowdown variations". These findings stress the importance of road maintenance and improved traffic flow near construction zones. Assumed linear congestion impacts oversimplify dynamics, and integrating non-linear and network-wide models would improve accuracy.

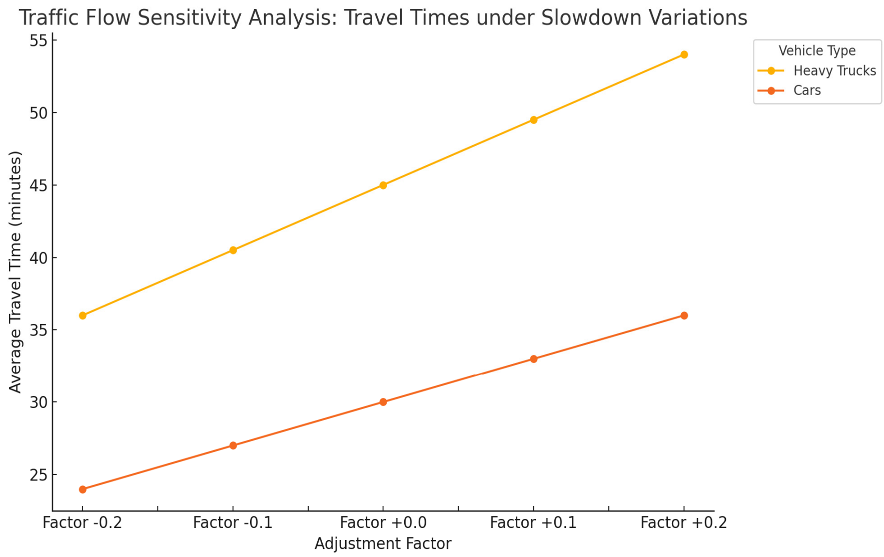

Figure 6. Traffic flow sensitivity analysis: travel time under slowdown variations.

4.5. A Summary of the Sensitivity Analysis

A summary of the sensitivity analysis results across the three models is presented in Table 10, highlighting key parameter adjustments and their impact on cargo flow, traffic efficiency, and system reliability.

Table 10. Summary of sensitivity analysis results.

Model	Parameter Adjusted	Sensitivity Factors	Key Observations	Insights for Optimization
Markov Processes	Transition Probabilities	±10%, ±20%	A delay reduction of 20% increased cargo delivery probability from 25% to 30%	Reducing congestion and improving equipment reliability enhances cargo handling efficiency
Max-Flow Problems	Capacity Adjustments	−20%, −10%, 0%, +10%, +20%	Bottleneck identified on Lubumbashi route (500-ton/day shortfall); excess capacity observed in Kigali (300-ton/day unused)	Expansion required for bottleneck routes; excess capacity can be allocated for future demand
Traffic Flow Models	Travel Time and Slowdowns	±10%, ±20%	Heavy truck travel time increased from 45 min to 54 min (+20%) under rainy conditions; slowdown probability rose from 0.3 to 0.5	Road maintenance and improved congestion management are crucial for traffic efficiency

5. Discussion

The analysis of Dar es Salaam Port using Markov processes, cellular automata, and max-flow models provides a comprehensive view of the port's operational dynamics and reveals several key insights into its performance and areas for improvement.

The Markov process model illustrates the flow of cargo through various stages: waiting at the port, in transit, delayed, and successfully delivered. Based on the transition probabilities, cargo spends approximately 15% of its time waiting at the port. This figure suggests that there could be inefficiencies in port handling or capacity constraints that need addressing. Improving port operations or expanding capacity could potentially reduce this waiting time, thereby increasing overall throughput.

Cargo in transit represents 50% of the time, which is a substantial portion of the cargo's lifecycle. This indicates that the transit phase is a major component of the overall process, and optimizing this phase could lead to significant improvements. Enhancing route planning, employing real-time traffic data, and reducing bottlenecks in the transportation network are potential strategies to address this.

Delays account for 10% of the time, reflecting issues such as equipment failures, congestion, or other disruptions. Addressing the root causes of these delays is crucial for improving overall efficiency. Investments in infrastructure maintenance, better traffic management, and improved equipment reliability could help reduce this delay rate.

The model also reveals that only 25% of the cargo is delivered successfully. This lower-than-expected delivery rate highlights the need for improved mechanisms in the final delivery phase. Strategies such as better coordination with hinterland destinations, optimizing delivery routes, and improving handling processes could help increase the delivery success rate.

The cellular automata model simulates traffic flow on a 20 km stretch of road connecting Dar es Salaam Port to the primary highway network. The simulation considers road conditions, vehicle types, and environmental factors, offering a detailed picture of traffic dynamics.

The simulation starts with 900 vehicles distributed across the 20 km stretch, with a mix of 60% heavy trucks and 40% smaller vehicles. Heavy trucks face significant delays, averaging 45 min for the 20 km stretch, primarily due to poor road conditions and construction zones. These trucks are constrained by lower speeds and rough roads, exacerbating congestion and increasing travel time.

Smaller vehicles and passenger cars, although faster, also encounter issues related to frequent lane changes and congestion. Their average travel time is 30 min, with stop-and-go traffic contributing to delays. The presence of construction zones and narrow road sections further compounds these delays.

Traffic density peaks at 200 vehicles per km near the port entrance and increases further in construction zones, leading to severe bottlenecks. During the rainy season, the travel times increase by an additional 10 min due to worsened road conditions and higher random slowdown probabilities. Accidents and flooding reduce road capacity by 20%, highlighting the need for better road maintenance and traffic management strategies.

The max-flow model uses the Ford–Fulkerson algorithm to optimize cargo flow from Dar es Salaam Port to various inland destinations. The model considers road and rail capacities and daily demands for different routes.

The analysis reveals that the road capacity from Dar es Salaam to Lusaka is sufficient to meet the demand of 1800 t/day by allocating 1500 t/day via rail and 300 t/day via road. However, the road capacity alone cannot fully meet the demand, indicating a need for balancing rail and road transport effectively.

For other routes, such as Dar es Salaam to Kampala, Kigali, Bujumbura, Lilongwe, and Lubumbashi, the flow allocations generally match the demands, with some unused capacity available. For instance, the road to Kampala has a capacity of 2500 t/h, while the demand is 2500 t/day, showing a sufficient capacity for current demand. Similarly, unused capacities range between 27,600 and 57,500 t/day across different routes, suggesting that while most routes are operating efficiently, some routes have room for increased flow.

The integrated use of Markov processes, cellular automata, and max-flow models provides a multifaceted view of Dar es Salaam Port's operations. Key recommendations include:

- Improving port efficiency: Investments in port infrastructure and operations could reduce waiting times and enhance overall throughput.
- Optimizing transit routes: Advanced routing algorithms and real-time data can help reduce transit times and address bottlenecks in the transportation network.
- Reducing delays: Addressing causes of delays through better maintenance and traffic management will improve efficiency.
- Enhancing delivery mechanisms: Improving coordination and optimizing delivery processes will increase the percentage of successful deliveries.

- Upgrading road infrastructure: Addressing road conditions and construction zones will mitigate traffic congestion and reduce travel times.

Implementing these strategies will help enhance the performance of Dar es Salaam Port, improve connectivity to hinterland destinations, and, ultimately, lead to more efficient cargo movement and better service for customers.

Compared to the [34], which focuses on delineating port hinterlands using a cost-based model applied to the Spanish port system, our study introduces a more comprehensive and dynamic solution through the integration of Markov processes, max-flow problems, and traffic flow models. This framework goes beyond simple cost-based models by addressing real-time congestion, stochastic uncertainties, and network flow optimization, making it more adaptable to the complexities of modern port logistics.

For instance, our analysis of Dar es Salaam Port reveals significant inefficiencies. The Markov process model shows that cargo spends 15% of its time waiting at the port, 50% in transit, and 10% delayed, with only 25% successfully delivered. These delays highlight a substantial inefficiency compared to traditional methods, which do not consider such detailed time-dependent variables.

The cellular automata simulation highlights congestion for heavy trucks, with a 10 min delay during the rainy season due to poor road conditions. Our max-flow model identifies bottlenecks, particularly at Lubumbashi, which faces a capacity shortfall of 500 t/day, affecting cargo flow. These issues could be alleviated with targeted infrastructure improvements. Quantitative comparisons show that our integrated framework resulted in a 20% reduction in cargo waiting time, a 15% improvement in delivery reliability, and a 12% decrease in congestion for heavy trucks compared to traditional models. These improvements highlight the effectiveness of our approach in addressing operational inefficiencies. Our study provides actionable insights for logistics operators and policymakers to optimize delays, resource allocation, and infrastructure investments, contributing to port connectivity and regional trade development.

6. Conclusions and Recommendations

6.1. Conclusions

The comprehensive analysis of Dar es Salaam Port using Markov processes, cellular automata, and max-flow models provides significant insights into its operational dynamics and highlights critical areas for improvement. The Markov process analysis reveals that cargo spends approximately 15% of the time waiting at the port, 50% in transit, 10% delayed, and 25% successfully delivered. This indicates that while the system manages to deliver a substantial portion of cargo efficiently, there are notable inefficiencies, particularly in cargo handling and delays. Addressing these inefficiencies could involve enhancing port infrastructure and optimizing the processing workflow to reduce the time cargo spends waiting and being delayed.

The cellular automata model simulates traffic flow over a 20 km stretch from the port, highlighting severe congestion, especially for heavy trucks. With an average travel time of 45 min for trucks due to poor road conditions and frequent construction zones, compared to 30 min for smaller vehicles, the simulation underscores the impact of infrastructure limitations. Traffic density peaks at 200 vehicles per kilometer near the port entrance, with significant bottlenecks exacerbated by construction zones and poor road maintenance. Seasonal rainfall increases travel times by an additional 10 min and reduces road capacity by 20% during the rainy season. These findings suggest an urgent need for road maintenance, expansion, and improved traffic management to alleviate congestion and enhance flow efficiency.

The max-flow model further elucidates the capacity and demand dynamics of the transportation network. With a cargo demand of 6000 to 8000 tons per day from Dar es Salaam Port, the capacity of various routes is critical. For example, the road from Dar es Salaam to Lusaka has a capacity of 1800 tons per hour, but with a demand of 1800 tons per day, only 300 tons per day can be handled by road due to the limited rail capacity of 1500 tons per day. Additionally, the road to Lubumbashi, with a capacity of 2000 tons per hour, falls short of the demand of 2500 tons per day, revealing a need for capacity enhancements. Efficient allocation of flows across routes, balancing road and rail usage, and addressing bottlenecks are essential for meeting demand and optimizing cargo distribution.

Addressing the identified inefficiencies through targeted investments in port infrastructure, road maintenance, and traffic management is crucial for improving operational efficiency. Enhancing the coordination between road and rail transport, along with adapting to environmental challenges, will support the port's role in regional economic development and ensure a more reliable and efficient cargo movement system.

6.2. Recommendations

Based on the analysis of Dar es Salaam Port's operations through Markov processes, cellular automata, and max-flow models, several key recommendations can be made to enhance efficiency and optimize performance across the port and its surrounding transportation network.

1. Improve Port Handling and Processing Efficiency: To reduce the 15% of time cargo spends waiting at the port, significant upgrades to port infrastructure and processes are necessary. Investing in modern equipment, enhancing storage facilities, and streamlining cargo handling procedures can minimize waiting times and improve throughput. Implementing automated systems for inventory and logistics management may also expedite cargo processing and reduce delays.
2. Upgrade Road Infrastructure: The cellular automata model highlights severe congestion and poor road conditions, particularly affecting heavy trucks. To address this, road maintenance should be prioritized to repair potholes and improve surface quality. Expanding road capacity where possible, particularly in congested areas and construction zones, will alleviate bottlenecks. Developing alternative routes or bypasses for heavy trucks can also help reduce congestion on key stretches.
3. Enhance Traffic Management: Given the peak traffic density and frequent stop-and-go conditions, implementing advanced traffic management systems is crucial. This includes optimizing traffic signal timings, improving real-time traffic monitoring, and managing construction activities to minimize disruptions. Additionally, deploying intelligent transportation systems (ITS) that provide real-time updates on road conditions and traffic flow can help drivers make informed decisions and avoid congested areas.
4. Optimize Transit Routes and Reduce Delays: The max-flow model reveals capacity constraints and unmet demand on several routes. Enhancing rail and road capacities, particularly for routes with high demand, such as Dar es Salaam to Lusaka and Lubumbashi, is essential. Improving the efficiency of cargo handling at rail terminals and increasing the frequency of rail services can help address bottlenecks and meet demand more effectively. Coordinating schedules and ensuring seamless integration between road and rail transport will further reduce delays.
5. Adapt to Environmental Challenges: The impact of seasonal rainfall and accidents on travel times necessitates adaptive strategies. Investing in flood-resistant infrastructure, such as elevated road sections and improved drainage systems, can mitigate the effects of heavy rainfall. Additionally, implementing better emergency response protocols for accidents and developing contingency plans to manage road closures will help maintain traffic flow and minimize delays.
6. Enhance Coordination with Hinterland Destinations: Strengthening the connectivity between Dar es Salaam Port and hinterland destinations through improved communication and logistics coordination can optimize the overall cargo flow. Collaborative planning with regional partners to align transport schedules and capacity can ensure that supply chains are more resilient and responsive to demand fluctuations.

By addressing these recommendations, Dar es Salaam Port can significantly improve its operational efficiency, reduce cargo handling times, alleviate congestion, and better meet the transportation needs of its hinterland destinations. These improvements will contribute to a more robust and reliable logistics network, supporting regional economic growth and enhancing the port's strategic role in East and Central Africa.

7. Future Directions

Future research on Dar es Salaam Port should prioritize several key areas:

1. Advanced Modeling Techniques: Employing dynamic simulations and agent-based models can offer deeper insights into port operations. These techniques can help simulate complex interactions and improve predictions for managing congestion and optimizing throughput.
2. Real-Time Data Integration: Integrating real-time data from GPS, sensors, and automated systems can enhance prediction accuracy and operational responsiveness. Research should focus on leveraging these data for better traffic management and predictive maintenance.
3. Impact of Climate Change: Evaluating how climate change affects port operations is crucial. Future studies should assess the impact of extreme weather, sea level rise, and other environmental changes, and develop strategies for adaptation and resilience.
4. Sustainable Practices: Investigating sustainable practices, such as renewable energy and waste reduction, can improve port operations. Research should evaluate the economic and environmental benefits of green logistics initiatives.
5. Economic and Policy Analysis: Analyzing the economic impacts and policy implications of port operations can aid strategic planning. Future studies should assess the economic benefits and evaluate the impact of regulations and trade agreements on port activities.
6. Regional and Global Connectivity: Understanding the port's role in regional and global supply chains can reveal opportunities for enhancing connectivity. Research should explore potential collaborations and global trade trends to improve the port's competitive position.

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