Impact of Automated Port Operations on Landslide Freight Corridor Performance: Opportunities, Barriers, and Future Directions with the Port of Long Beach

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Report #FERSC-2023-Project7-1

Center for Freight Transportation for Efficient & Resilient Supply Chain (FERSC)

August 15, 2024

US Department of Transportation Grant 69A3552348338

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1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Impact of Automated Port Operations on Landslide Freight Corridor Performance: Opportunities, Barriers, and Future Directions with the Port of Long Beach		**5. Report Date** August 15, 2024 **6. Performing Organization Code**
7. Author(s) Shailesh Chandra https://orcid.org/0000-0002-1558-0285 , Benny Herrera, Robert Valencia, Vishnuvardhan Chappidi, Vamsi Oruganti, Sai Tanikella and Kevin Heaslip https://orcid.org/0000-0002-3393-2627		**8. Performing Organization Report No.** FERSC-2023-Project7-1
9. Performing Organization Name and Address Center for Freight Transportation for Efficient & Resilient Supply Chain (FERSC) UT Center for Transportation Research 309 Conference Center Building Knoxville TN 37996-4133		**10. Work Unit No.** **11. Contract or Grant No.** 69A3552348338
12. Sponsoring Agency Name and Address US Department of Transportation Office of the Secretary of Transportation–Research 1200 New Jersey Avenue, SE Washington, DC 20590		**13. Type of Report and Period Covered** Annual report: 9/1/2023–8/15/2024 **14. Sponsoring Agency Code** Office of the Secretary of Transportation-Research
15. Supplementary Notes Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.		

16. Abstract

Seaports play a critical role in enhancing the efficiency of freight transport and supply chains, acting as cost-effective hubs that manage high cargo volumes. The integration of automated technologies such as Automated Guided Vehicles (AGVs) and automated stacking cranes is intended to improve port operations. However, the effectiveness of these automated terminals varies, heavily dependent on the number of AGVs and the yard layout, and can strain existing transportation infrastructures. This study assesses AGV performance by examining container dwell times and their impact on congestion in surrounding transport networks. Using a continuous approximation model, the research derives simpler, manageable equations to address port management challenges, analyzing how different configurations and operational strategies affect port efficiency. It also considers the traditional appointment systems at ports like Long Beach Container Terminal, aiming to optimize AGV deployment to reduce dwell times and manage congestion effectively. This study reveals that deploying 100 AGVs at the Long Beach Container Terminal optimally reduces seaside dwell times for priority containers to as low as 1, 2, and 4 minutes based on unloading intervals post-ship docking, but increases landside dwell times to between 1600 and 7000 minutes, exacerbating congestion in nearby transportation networks and significantly delaying trucks heading inland. The findings suggest that strategic AGV use can significantly enhance port operations while necessitating careful consideration of their impact on local transport infrastructures.

17. Key Words	18. Distribution Statement
Port, Automated Guided Vehicle, Grid Network, Dwell Time, Trucks, Congestion	No restrictions, available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Executive Summary

Seaports significantly enhance the value delivered to consumers through their roles in the freight transport and supply chain networks, and they are recognized as among the most cost-effective and efficient transportation systems. The integration of ports into these supply chains positively influences port performance and underscores the vital part they play in logistical operations. Efficient ports are preferred in supply chains for their ability to effectively manage high cargo volumes and maintain operational competencies.

Automation, involving technologies like Automated Guided Vehicles (AGVs) and automated stacking cranes, is seen as a way to improve port efficiencies. However, studies like the 2023 one by Majoral et al. show no clear evidence that automated terminals outperform traditional ones, with their effectiveness largely dependent on the number of AGVs used and the physical layout of the yard. Deploying AGVs does enhance operational efficiency, but the increased cargo flow they handle can excessively strain existing transportation infrastructures, leading to potential environmental concerns.

This study integrates the performance of AGVs, assessed through container dwell times at various stages, with congestion in the hinterland transportation network near the port. With AGVs, ports see reduced ship turnaround times, boosting their ability to handle imports and exports. This increased activity tends to worsen congestion in nearby transportation infrastructures. AGVs play a crucial role as intermediaries between quay cranes at the seaside and yard cranes on the landside, facilitating efficient container transport. Recent technological advancements have led many terminals to transition from traditional to automated systems, highlighting the need to understand the complexities involved in such transitions and impacts on nearby port traffic congestion.

In our research, we employ a continuous approximation model to derive closed-form equations addressing the management challenges of ports, providing an alternative to traditional complex programming methods. This approach offers simpler analytic functions that are easier to manage and apply, enhancing the understanding of AGV use in optimizing port operations.

This research evaluates the effects of street network configurations, navigational area characteristics, and crane deployments on port performance and throughput, aiming to provide a comprehensive understanding of optimizing AGV use within ports. It also discusses the traditional appointment system at ports like the Long Beach Container Terminal and the Port of Los Angeles, where adherence to scheduled times is crucial to managing congestion effectively.

This study demonstrates that deploying 100 Automated Guided Vehicles (AGVs), based on the general navigation grid configuration at the Long Beach Container Terminal (LBCT), optimally reduces average import container dwell times on the seaside to as low as 1, 2, and 4 minutes for priority containers, depending on whether they are unloaded every 15, 30, or 60 minutes time intervals after the ship docks. This deployment also affects dwell times at the yard (landside), where the seaside dwell times are significantly longer than those in landside yard. Additionally, as dwell times on the landside increase to 1600, 5200, and 7000 minutes, congestion in the nearby transportation network worsens, leading to severe delays for trucks transporting containers from the port to inland destinations. The findings from this research will equip ports with a deep understanding of how to fully utilize AGVs while seamlessly integrating them into the operational flow and infrastructure of modern ports.

Introduction and Background

Seaports enhance the value delivered to final consumers within the freight transport and supply chain network (Panayides and Song, 2008; Lam and Song, 2013) and are considered the most cost-effective and efficient among transportation systems (Dwarakish and Salim, 2015; Chinedum, 2018). The integration of ports into supply chains has been emphasized for its positive impact on port performance, highlighting the significant role ports play in efficient logistical operations (Tongzon and Heng, 2005; Woo et al., 2013). Efficient ports, which hold a competitive edge, are preferred within the supply chain network due to their ability to handle high cargo volumes effectively and sustain port competencies (Sheng and Kim, 2021).

While seaports are crucial gateways for international trade, the regional economic benefits can vary and the cities nearby ports may not always benefit economically (Jung, 2011). Managing surplus capacity is a recurrent issue at ports, often discussed in the context of how port throughput impacts regional development (Cong et al., 2020). The increased congestion near ports not only complicates logistics but also impacts broader initiatives aimed at reducing the carbon footprint within supply chains. This situation presents significant challenges in balancing operational efficiency with environmental sustainability goals (Sheu and Talley, 2011).

Studies have also indicated that the effectiveness of a seaport today depends not only on its internal capacity and operational efficiency but also crucially on how well it integrates with surrounding transportation hubs and logistics partners (Hou and Geerlings, 2016). Research has shown that the increase in container volumes, driven by larger ships arriving at major urban ports, places considerable strain on both the port terminals and the adjacent transport infrastructures (Iannone, 2012). Kang et al., (2008) provide mathematical models with exponentially distributed crane service times to optimize the cranes and trucks for long-term unloading operations (Kang et al., 2008).

Over the years, despite the continuous growth in maritime container traffic, the development of hinterland transportation networks has not kept pace, particularly in larger cities, resulting in inadequate inland transport network nearby ports. Efforts have focused on reducing the number of road miles traveled by cargo after it leaves the port, integrating it into the hinterland freight transportation network (Rodrigues et al., 2015). This strategy aims to decrease the carbon footprint associated with the final segment of transportation (Chen et al., 2014).

Automation has been hailed as a promising step towards improving the efficiencies of ports. According to a 2023 study by Majoral et al., there were 62 automated terminals worldwide, with expectations for more to transition to automation rapidly (Majoral, et al., 2024). These transitions typically involve the implementation of technologies such as automated guided vehicles (AGVs) and automated stacking cranes (ASCS). However, the study found no definitive evidence that automated terminals perform better than traditional ones. The effectiveness of an automated terminal largely depends on the number of AGVs employed - too few or too many can affect port efficiency (Pjevcevic et al., 2017). Additionally, the physical layout of the yard, whether restrictive as stacking or expansive as spread-out, significantly influences the efficiency of container handling operations (Le-Griffin and Murphy, 2006).

The deployment of AGVs within port areas does enhance operational efficiency. However, the rapid and dense flow of cargo handled by AGVs can place excessive pressure on the existing transportation infrastructure near ports. This can lead to challenges, including potential environmental concerns, when considering further expansions of such infrastructures to cope with the increased load (Martinho, 2008).

In this study, we develop an interlink between the performance of the AGVs gauged through container dwell time at various stages and congestion assessment in the hinterland transportation network close to the port. The layout of a typical port operations is shown in Fig. 1.

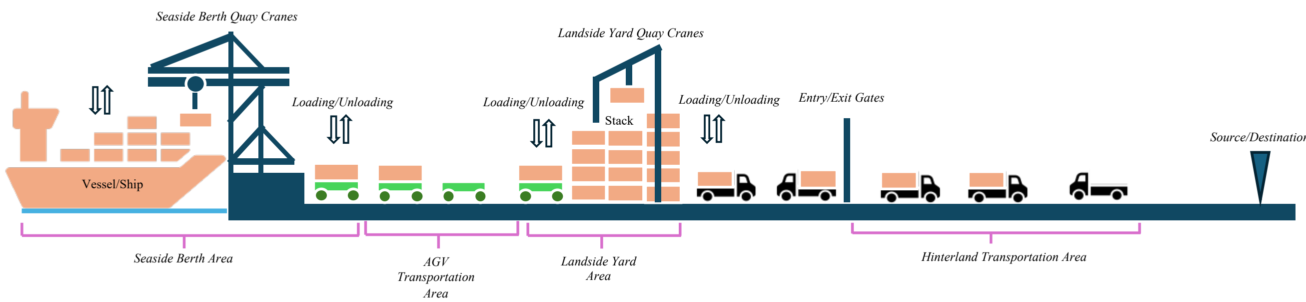


Figure 1: Container movement between ship and the hinterland destination

With the adoption of AGVs, ports are experiencing reduced ship turnaround times, thereby enhancing their capacity to manage both exports and imports. This development boosts business activities and cargo operations, leading to an increased frequency of truck visits to terminal gates. Consequently, this uptick in activity tends to exacerbate congestion in the surrounding transportation infrastructure.

From an operational standpoint, AGVs serve as a crucial intermediary between quay cranes at the seaside and yard cranes on the landside, facilitating the efficient transport of containers. In recent years, advancements in technology have led numerous container terminals to adopt automation, transitioning from traditional to intelligent systems. This shift underscores the need to grasp the intricacies involved in such transitions, particularly regarding AGV implementation (Sun et al., 2022).

Metrics such as vessel turnaround time and pre-berthing detention are commonly utilized to assess port operational efficiency (Sekar, 2022). With the growing adoption of AGV-reliant terminals, it is crucial to develop robust and effective evaluation methods. These methods are necessary to ensure the operational efficiency of these terminals and to enhance ship turnaround times. Research has shown that optimizing AGV-based automated container terminals can significantly improve the timely execution of transport tasks and minimize the waiting times for terminal equipment, including quay cranes and AGVs, and the dwell times of containers at various stages of transportation within the port (Cheng et al., 2005; Zhen et al., 2008; Sun et al., 2022).

The four important areas of AGV operational management of the port - equipment scheduling, path planning, exception handling, and vehicle management - are recognized as NP-hard problems, often approached through complex mixed integer programming (MIP) formulations and their solution process that has been acknowledged to be complicated (Shouwen et al., 2021; Chen et al., 2020; Sun et al., 2022). In our research, we employ a continuous approximation model to derive closed-form equations that address the impact of these management issues on port efficiency. Continuous approximation models provide a viable alternative to traditional MIP methods, offering critical insights with simple analytic functions that are easier to manage and apply (Daganzo, 2005; Chandra and Quadrifoglio, 2013; Basallo-Triana, et al., 2021). Our study leverages this approach, contributing new insights and enhancing the body of knowledge in this domain. A compilation of various key studies from the past and how our study contrasts with those has been compiled in Table 1. The contribution of our study is distinct from these studies in being able to address hinterland transportation impacts from port automation.

Table 1: Compilation of literature on port automation and hinterland impacts

Refs.	**Port Automation with AGV Problem Type**	**Optimal AGV**	**Port-related Objective Function**	**Modeling approach**	**Solution Approach**	**Hinterland Transport Connection**
Skinner et al., 2013	AGV Scheduling	No	AGV Waiting time	MIP (mixed integer programming	Genetic Algorithm	No
Shouwen et al., 2020	AGV Scheduling	No	AGV Travel time	Bi-level programming	Genetic Algorithm	No
Yang et al, 2018	AGV Scheduling	No	AGV Travel time	Bi-level programming	Genetic Algorithm	No
Debjit et al. (2020)	AGV Queuing	No	AGV Throughput time	Queuing network model	Simulation	No
Mueller et al., 2020	None	None	Port Cost per TEU	Logit model	Regression	Yes
Guerrero, 2019	None	None	Distance impedance between ports and hinterland regions	Origin-constrained spatial interaction model	Regression	Yes

Refs.	Port Automation with AGV Problem Type	Optimal AGV	Port-related Objective Function	Modeling approach	Solution Approach	Hinterland Transport Connection
Xiang et al., 2021	Capacity maximization of cranes	Yes	Container flows	Queuing	Simulation network	No
Wang and Zeng, 2022	AGV Scheduling and Assignment	No	Minimize the makespan of all containers, i.e., the time when the last container has been completed	MIP	Heuristic algorithm	No
This study	Container dwell times	Yes	Queuing Model	Continuous approximation (CA)	Optimization	Yes

The integration of AGVs into port operations represents a notable stride forward in enhancing port's efficiency and productivity. Although AGVs are known to improve operational throughput, their integration into day-to-day port operations pose certain challenges. The operational issues associated with AGV-based vehicle transportation has been broadly divided into four problems (Sun et al., 2022): assignment, routing, quantity selection, and maintenance. In this paper, we focus mainly on assignment, routing and quantity selection of AGVs and their operational impacts on hinterland freight truck network. Maintenance of AGVs stems from their malfunction and battery depletion which we ignore as trivial with sufficient stand-by AGVs that fill-in for those that breakdown during their movement or due to battery replenishment needs.

Assignment

Within the assignment problem, AGVs are assigned to move specific containers based on the origin and destination during the transportation process. The assignment could be influenced by factors like prioritizing containers, urgency and transportation time.

Within the containers terminals operations, AGV assignments have been widely studied as a synchronization of the vehicles with automated cranes aimed to improve efficiency and productivity of the terminal (Yang et al., 2018). Thus, these are studied under scheduling problems of AGVs directly influencing the time taken for each container to be processed. In essence, AGVs serve as the link between the seaside quay cranes (QCs) and landside yard cranes (YCs).

Scholars agree that developing a comprehensive optimization algorithm that addresses the assignment problem in port operations would be challenging and likely unsolvable (Angeloudis and Bell, 2010) – hence, a better goal is then on enhancing quay crane productivity with a just-in-time strategy vital for coordinating the timely arrival of AGVs and containers at cranes, ensuring a steady availability of AGVs at the quay. However, challenges remain in assigning AGVs' reliance on these cranes for loading and unloading containers and the cramped nature of the waiting areas.

Routing

Both assignment of tasks and planning of AGVs routing within the transportation area of a port is important to ensure operational efficiency of the terminal, however, this synchronization is complex (Wang and Zeng, 2022). Efficient route planning plays a crucial role in minimizing travel distances and times for Automated Guided Vehicles (AGVs), ultimately increasing operational efficiency. Gao et al. (2023) emphasize the significant improvements in terminal efficiency that can result from optimizing AGV travel paths. Xu et al. (2020) introduce a novel AGV route planning model called load-in-load-out (LILO), which aims to keep AGVs consistently engaged in productive tasks such as loading or unloading cargo, thereby reducing unproductive idle time.

Efficient routing of AGVs need to consider traffic congestion which arise due to too many conflicting paths of the AGVs but is often ignored in scheduling problems addressed in some key literatures involving container movement in automated terminals (Luo and Wu, 2015; Luo et al., 2016). Several other literature on modeling considering routing use single and multiple AGV guide paths as loops that are unidirectional (Zhong et al., 2020; Roy et al., 2020; Wang and Zeng, 2022). While unidirectional paths with shortcuts could limit achieve better AGV travel time efficiencies, bidirectional paths could yield better efficiencies of the AGV paths (Wang and Zeng, 2022). Additionally, not all port areas can support the unidirectional movements of AGV paths such as in loops due to port area restrictions or loops not allowing shortcuts to improve efficiencies in container movement.

At various ports such as the Port of Rotterdam and the LBCT, AGVs move even containers sideways or slow down too with the use GPS, LIDAR, assisted by navigation software and transponders embedded in the terminal road surface (Port of Rotterdam, 2024; KONECRANES, 2024) to share their positions and movements and other sophisticated on-board wireless communication mechanisms that are deployed to prevent collisions (Oyekanlu et al., 2020; Ungurean et al., 2020). With these advanced features, AGVs successfully utilize any horizontal movements (forward, backward as well as sideways) needed to execute these shortcuts. The flexibility in being able to execute any horizontal movements, following fixed paths and collision-free transportation, are important for ports that have limited AGV transportation area.

Often conflict-free paths are solved using AGV scheduling problem called dispatching and conflict-free routing problem (DCFRP) using exact solutions (Cao et al., 2023) or heuristics (Miyamoto and Inoue, 2016) and the problems are computationally expensive and complex to solve and if dynamically solved with certain time windows of AGV scheduling, these problems give rise to many uncertain factors (Cao et al., 2023).

The advancements in AGV technology are exciting for ports. With things like better self-driving abilities, wireless communication, and machine learning, AGVs are becoming smarter and more independent. Hu et al. (2021) talked about combining these technologies. This makes AGVs better at handling what's happening in real-time at the port, like adjusting to changing conditions quickly. Tang and Wu (2023) indicate these upgrades could help AGVs work better with everything else happening in the port, making the whole system run smoother and more efficiently. Therefore, equipped with advanced technologies, the capabilities of an AGV that can travel in both directions (bidirectional characteristics) and can maneuver (whether pause, stop or slightly deviate from the path) if moving on a conflicting path or to a common intersection in an automated container terminal setting.

AGV Deployment

Deploying an optimal number of AGVs is a problem that is associated with both assignment and routing strategies deployed. Excessive deployment of AGVs can decrease operational efficiency in various ways. One major issue is the internal congestion caused by having too many AGVs within the terminal area. This congestion affects not only physical space but also the complex logistics of handling containers, the time costs and economic costs, eventually transferring the congestion to the other ports (Fan et al., 2012; Lin et al., 2022).

Studies on the problems that stem from excessive AGV deployment have been very well documented. When AGVs are used excessively, they may end up competing for the same routes and loading zones, resulting in delays and a slowdown in overall operational speed. According to Bolat et al., (2020), this congestion disrupts the smooth flow of operations, transforming potential efficiency improvements into bottlenecks that hinder cargo handling processes.

Furthermore, the high volume of AGVs operating in the port can result in containers being stacked too densely, raising the risk of accidents and damage to cargo. Ship concentration in ports increases the risk to the cargo itself as well as to the port (Gou and Lam, 2019). This overcrowding can also make it harder to retrieve containers, slowing down service and causing delays.

While overusing AGVs comes with its own set of challenges, not deploying enough of these technological assets can also severely impact the productivity and efficiency of port operations by resulting in bottlenecks in the operational workflow of the port. The consequences of having too few AGVs are varied, affecting not only immediate operational throughput but also the overall port within the maritime logistics industry – making the port unattractive due to higher turnaround times (Steven and Corsi, 2012). Thus, a balance in the number of AGVs deployed has been emphasized for an overall effectiveness of port operations (Tubis et al., 2022).

This research focuses on exploring innovative solutions and strategic approaches to achieve an optimal balance in the deployment of AGVs - taking into account the various seaside and landside crane operations, and navigational network as routes of AGVs.

Methodology

We use a continuous approximation method to develop closed-form equations that are tractable. The methodology presented could facilitate a preliminary evaluation of port efficiency within the supply chain network.

Additionally, this study evaluates the navigational area characteristics, such as the length and width, and number of quay/yard crane deployments, on the port performance and throughput. The findings from this study will provide ports with a comprehensive understanding of how to optimize the use of AGVs, ensuring their effective integration into the operational flow of container movements, particularly as containers are transported in and out of the port via freight trucks using the surrounding infrastructure.

We model the impact of container movement from the seaside area to the landside area on the adjacent freight network infrastructure to the port (as indicated in Fig. 1 below). The container dwell times within the port operations have been evaluated at key port locations, from the time they are unloaded from ships until they are picked up for further transportation or delivery. The dwell time as a metric is crucial for evaluating the efficiency of port operations, including the management of the container yards, the utilization of AGVs for container transfer, and the coordination between seaside and landside activities. Efficient management aimed at minimizing dwell times can significantly impact the overall throughput of the port, reduce potential congestion in identified hotspots, and enhance the port's capacity to handle cargo volumes.

By optimizing transfers such as within the AGV operational areas and container's transit time lost due to congestion that occurs on freight truck route network, and the procedures at seaside berths and dock stations, ports can ensure a smoother flow of containers through the facility, thus reducing dwell times and improving the speed and reliability of the supply chain.

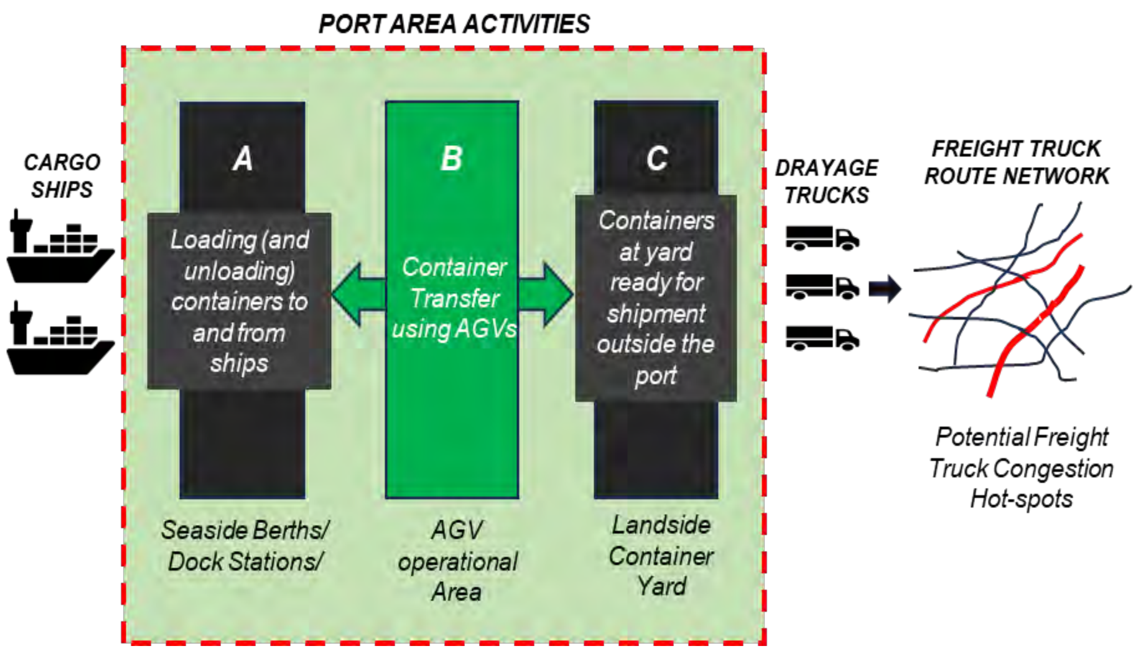


Figure 2: Schematic of container movement and impact on freight congestion

An AGV is deployed to transport containers to locations within the port. In this research, the origin for an AGV is a seaside berth (or the landside yard) and the destination is the landside yard (or the seaside berth) (see the sketch in Fig. 2). We first take into consideration the seaside berth as the origin and the landside yard as the destination for the model. The sketch in Fig. 3 depicts the layout of a typical port and the port area.

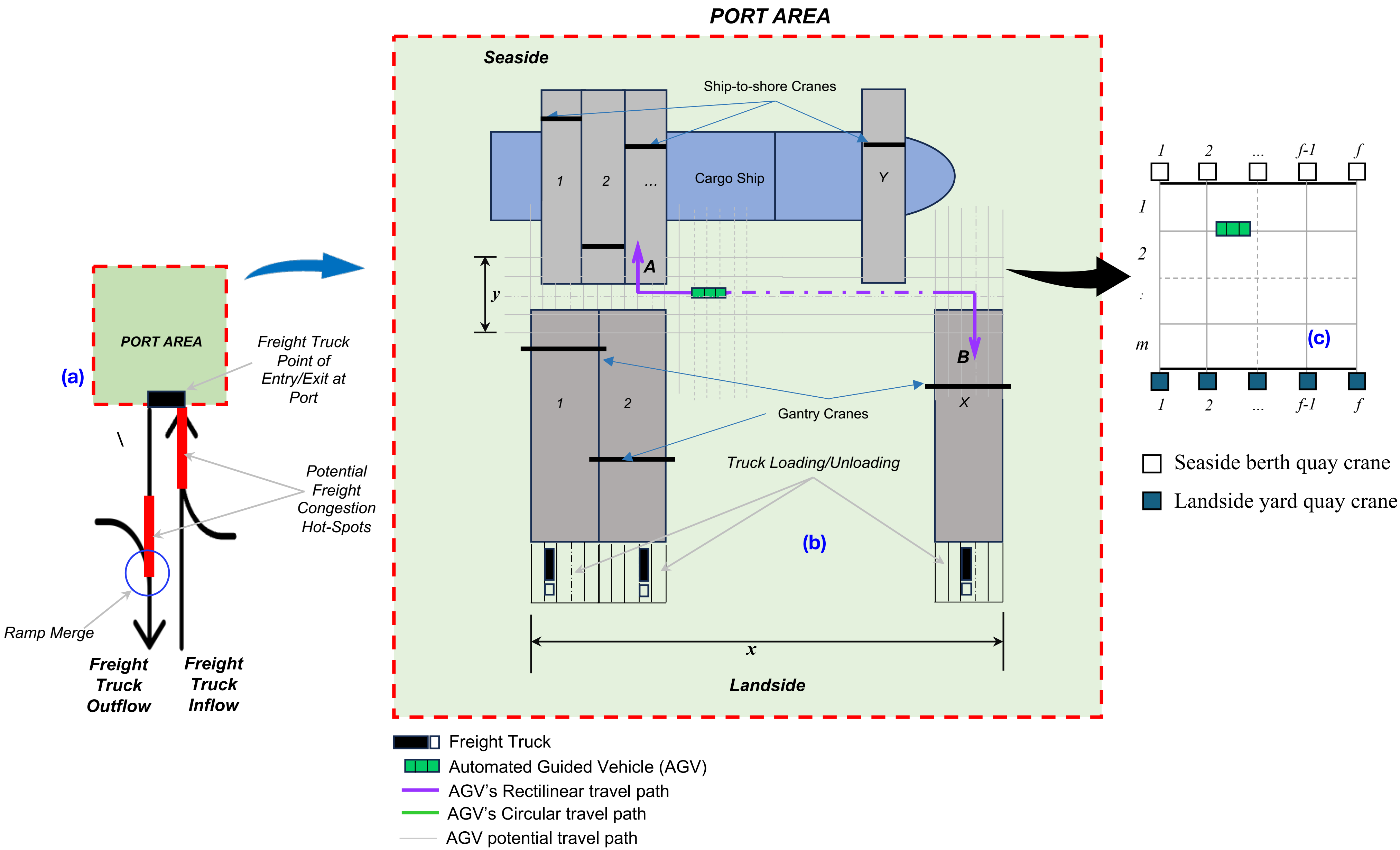


Figure 3: a) Freight truck inflow and outflow b) schematic representation of AGV movement, and c) simplified circular and grid network of AGVs paths.

In all instances of an AGV's movement modeled in this study, the assumption is that it makes every trip with a container from the seaside berth to the landside yard locations and with no container from the landside yard to the seaside berth. This supports the preferred utility policy of an AGV deployed to first unload the ship with most or all of its containers before beginning to transport containers from the landside yard to the seaside berth to load the ship.

A timely pick-up and drop-off of containers by AGVs (assisted by the quay cranes), whether at the seaside berth or the landside yard, would promote fewer waiting times for ships during loading and unloading. Similar savings in waiting times may result on the landside yards for trucks waiting to be loaded or unloaded if the container pick-up and drop-off of AGVs (assisted by the quay cranes there) is efficient. These savings in waiting times (on the seaside or landside) translate to reduced congestion and emissions for cargo ships and trucks that carry these containers back and forth to the terminal. Various studies have also pointed out that truckers often spend a considerable amount of time in a queue at the gates of the container terminals, impacting the nearby traffic flow on the transportation network (Chen et al., 2013). Thus, the knowledge of the operations and movements of the AGVs in alleviating congestion and reducing emissions around the port area would be a crucial step towards attaining the sustainability goals various port authorities across the nation aim for.

AGV operational policies

To ensure an efficient operational efficiency of the AGVs, it is assumed that they operate uniformly random between any two seaside berths and the landside yards till all *N* containers are unloaded from the ship. Ideally these movements must occur with shortest paths pre-determined for AGV movements within the port premised. This process will ensure energy savings for operating an AGV and a faster transportation of containers between origin and destination points that are the seaside berth and the landside yard, respectively. It is expected that, with this policy, AGVs will operate with a fixed average travel time between seaside berth and landside yard.

In a typical container transport operation, after container-laden AGVs leave landside yard they reach seaside berth, and similarly the AGVs transport the containers from the seaside berth to the landside yard. Subsequently, the quay cranes on the seaside berth and the landside yard alternate between loading/unloading these AGVs, placing them in the ships or stacks and loading other containers onto the AGVs to the other side ready for transportation.

The quay cranes (on the seaside berth or landside yard) balance servicing both import and export containers, with a special focus on time-sensitive goods and high-priority ones that necessitate rapid transit from and to the yard (MAERSK 2014). This involves expeditious movement of high-priority containers, whether transferring them onto AGVs for export or dispatching them out of the port by freight trucks, to ensure they're promptly loaded onto ships. The Port of Los Angeles, in an effort to streamline this process, is piloting a novel, collaborative strategy which employs an internal artificial intelligence system to systematically schedule trucking companies for container retrieval based on priority (Hunt, 2023). This policy is complemented by having port appointment system as the containers get ready for a sequential pick-up/drop-off by the truckers from/to the port.

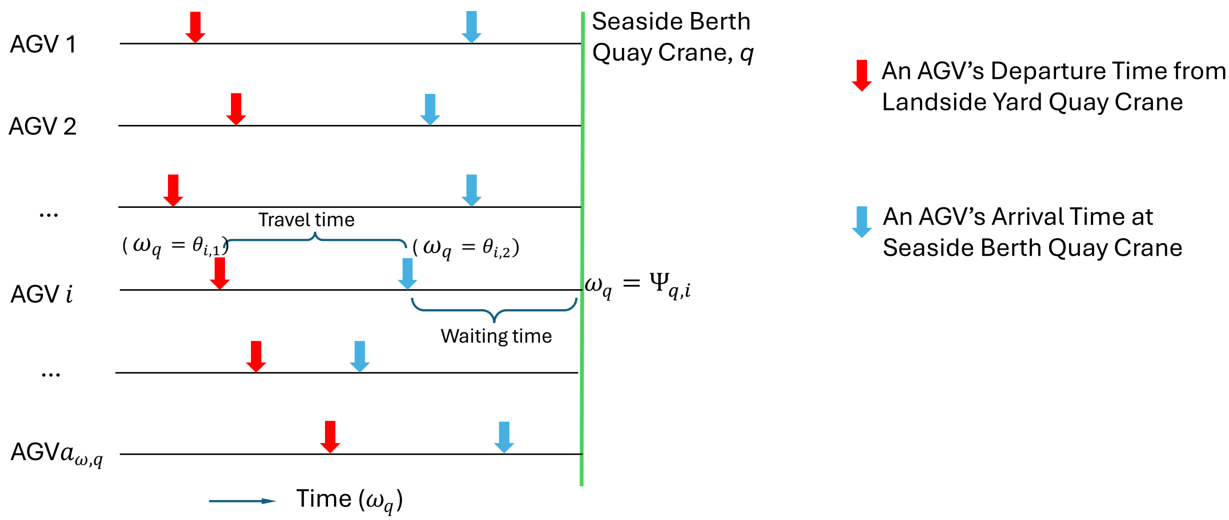
Automated containers terminals with AGVs also complement in expediting the movement of prioritized containers and improve port efficiency in this process. In this study, we consider container priority model in terms of loading or unloading, from/to the ship and yard, which might depend on the type of commodity they carry – such as perishable goods, hazardous materials, or just that some containers are scheduled for early onward transportation and need to be transported before the others. These priority containers are strategically placed above other containers for quick retrieval by the quay cranes. Thus, in this policy, the topmost containers (in the ship or yard stack) are prioritized to be picked up first expediting timely transportation of the containers. This would facilitate increased efficiency in unloading (loading) of the import (export) containers off the ship by the seaside berth quay cranes. Subsequently, the import and export containers are also stacked in the yard as per this policy. Therefore, the arrangement of all the containers in the ship/yard is known throughout the unloading/loading process carried out by all the quay cranes deployed at the port. During the unloading process, once all the priority containers are removed the regular containers are handled upon by the cranes.

Thus, in the next sections, our derivations on dwell times of the containers rests on the above important policy consideration of container loading/unloading by quay cranes.

AGV Dwell Times

A quay crane controlled by a human operator is involved in the most complex task undertaken at the port. The crane not only unloads containers off AGVs and places the containers back onto the AGVs, it also stacks the containers in order. The order may further vary depending on the priority of the containers to be picked up for loading/loading an AGV.

In the operational set-up of for $a_t = a_{\omega,q}$ AGVs shown in Fig. 4, their assignment to pick up a container at the seaside quay crane is an important decision. AGVs, such as AGV 1 and AGV 2, start their journey from the landside yard quay crane. Each AGV can depart at a certain time (notated as $\theta_{i,1}$) when its prior job is over and has an estimated arrival time at the seaside berth quay crane ($\theta_{i,2}$) to attend to the next job. This assignment involves choosing one of the $a_{\omega,q}$ AGVs that is available to do the job such that with a minimum waiting time the scheduling synchronizes with a set-time $\omega_q = \Psi_{q,i}$ at the respective seaside berth.



AGV *i* assigned to pick-up a container at seaside berth quay crane, *q*, at time $\omega = \Psi_{q,i}$
An AGV i's departure time from landside yard quay crane (say, $\omega = \theta_{i,1}$), $i \in \{1,2,\dots,a_{\omega,q}\}$
An AGV i's arrival time at seaside berth quay crane ($\omega = \theta_{i,2}$), $i \in \{1,2,\dots,a_{\omega,q}\}$
An AGV i's travel time from the landside yard quay crane to seaside berth quay crane = $(\theta_{i,2} - \theta_{i,1})$
An AGV i's waiting time at the seaside berth quay crane = $(\Psi_{q,i} - \theta_{i,2})$
Container Pick-up/drop-off Time at the seaside berth quay crane, *q*, is $\omega_q = \Psi_{q,i}$

Figure 4: Schematic of the arrival and departure time windows of the AGVs at quay cranes

Thus, the efficiency of this operation hinges on precise timing and coordination. The travel time for each AGV from the landside yard to the seaside berth is calculated by the difference between its departure and arrival times ($\theta_{i,2} - \theta_{i,1}$,). Upon arrival, AGVs might face a waiting period if they arrive before the scheduled pick-up time, calculated as $(\Psi_{q,i} - \theta_{i,2})$. This waiting time is critical as it influences the overall efficiency of the terminal operations, dictating how soon the AGV can return for another load. Each AGV's performance, therefore, is not just about speed but also about optimizing travel and waiting times to align perfectly with the crane's schedule, ensuring a seamless flow of container pick-ups and drop-offs. However, a perfect synchronization may not be feasible for every container transfer since the containers are picked-up or loaded by a human operator remotely. With this being considered, a container from a ship is moved by the seaside crane only when there is a an AGV parked and available to receive it. A container-laden AGV leaving the landside yard would move directly to the seaside berth crane and wait there to be unloaded.

Only the available AGV among $a_{\omega,q}$ AGVs will arrive at the seaside berth at *q* at $\omega_q = \Psi_{q,i}$ and rest would go to other seaside berth quay cranes or even arrive at the same quay crane *q* dictated by a demand consideration. With uniform random distributed departures and arrivals from the landside yard to seaside berth and demand consideration by each seaside berth quay crane, *q*, the mean waiting time for the AGVs, w_ω, at the seaside berth would be, $w_{\omega_q} = \sum_{i=1}^{a_{\omega,q}} \frac{(\Psi_{q,i} - \theta_{i,2})}{a_{\omega,q}}$ and the mean travel time, rt_ω, would be $rt_\omega = \sum_{i=1}^{a_{\omega,q}} \frac{(\theta_{i,2} - \theta_{i,1})}{a_{\omega,q}}$. With waiting time, three scenarios arise for the arrivals of AGVs at q: 1) the AGVs arrive one-by-one and in a manner that each AGV incurs a least or minimal waiting time at q, 2) all AGVs , $a_{\omega,q}$, arrive at the same time, and 3) AGVs continue to arrive randomly to the seaside berth quay, q. The first scenario presents the best-case situation with clear synchronization between AGV arrival and quay crane operations for container movement and while the second scenario, is the worst with largest waiting times overall for AGVs in waiting and opportunity for containers to be moved sooner with available AGVs in line. The third scenario is an approximate that is between scenarios one and two in terms of AGV utilization and efficiency in container movement. Thus, the two scenarios one (best case) and two (worst case) - provide respective lower and upper bounds on mean waiting times of the AGVs at quay crane q and also bounds on the container movement efficiency for the third scenario.

The expression for $w_{\omega_q} = \sum_{i=1}^{a_{\omega,q}} \frac{(\Psi_{q,i} - \theta_{i,2})}{a_{\omega,q}} = \tau_s$ where, τ_s is the average time taken by the quay crane in a round trip movement from the AGV's location to the ship to pick-up a container and return with the container to the AGV location for loading at the seaside berth. And $w_{\omega_q} = \tau_L$ for the AGV's dwell time at landside yard quay crane.

The number of AGV trips is equivalent to $\left\lceil \frac{t}{\tau} \right\rceil$, where τ is the average round trip travel time of an AGV between the seaside berth crane where the ship is docked and the landside yard crane where the import containers are stacked, and vice-versa, and $\lceil . \rceil$ denotes the integer form of the expression.

And the same requirement of container priority for import governs the transfer of containers from the yard to the ship (i.e. seaside berth) during time *t*. Therefore, assuming that the same ship is also to ferry export containers, a fraction (φ) of the $\left\lceil \frac{t}{\tau} \right\rceil$ trips will also be the export containers. With $\varphi = 1$, the number of import containers is equal to the number of export containers during every time period *t*.

If the number of import containers that have to be moved by the AGVs during time period *t* is n_t, the (conservative) number of AGVs, a_t, needed for this is $a_t = \left\lceil \frac{n_t}{\left\lceil \frac{t}{\tau} \right\rceil} \right\rceil$.

The operational efficiency of the AGVs is presumed to be consistent during each time period *t*. The assumption is also that any AGV that becomes non-operational or requires maintenance is instantaneously replaced by a standby AGV and there is no interruption in container transfer service.

The time taken by the quay crane on the seaside berth to load an AGV starting from the point of the AGV's location, and moving to pick-up a container from the ship and loading it onto the AGV is τ_s. The time taken for the quay crane for unloading the AGV at the landside yard is τ_L which involves picking up a container from the AGV and stacking it up at an appropriate location in the yard and moving back to the point of location of the AGV to unload a container from another AGV. Based on these quay crane activities, we use a time-space diagram to determine the number of AGVs that will be deployed to remove n_t containers from the ship.

The number of containers unloaded from ship also determine the number of AGVs (say a_t) needed at the quay cranes on the seaside berth and it is derived with the help of a time-space diagram as shown in the sketch of Fig. 5 below.

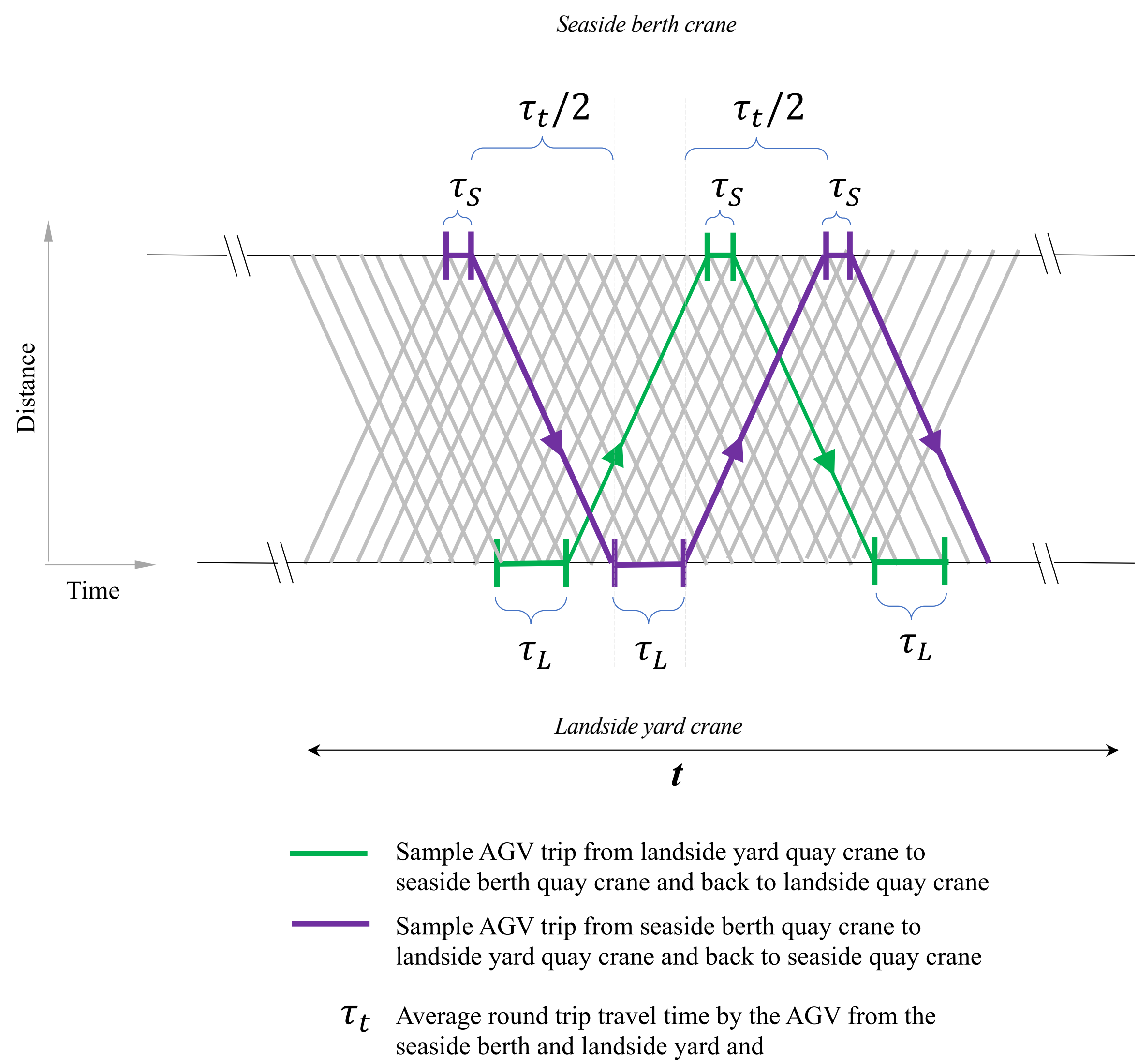


Figure 5: Space-time diagram for AGV movement between seaside berth to landside yard

AGVs follow first in first out principle at the quay crane in terms of container loading. The waiting time of an AGV at the seaside berth quay crane τ_s and is bare minimum for AGV, as optimal engagement of AGVs is expected. Based on the time-space sketch shown in Fig. 5, and approximating the integer with a real number, the number of AGVs deployed is expressed as: $a_t = \tau \times \frac{n_t}{t}$ and also that $a_t = \left(\frac{\tau_t+\tau_s+\tau_L}{\tau_s}\right)$, where $\tau = (\tau_t + \tau_s + \tau_L)$ is the average travel time of an AGV from a seaside berth crane to a landside yard crane and back to the seaside berth crane.

Seaside Berth Container Dwell Time

Consider N as the total count of priority containers that must be unloaded from the ship over the entire docking period, denoted by T, which could be the operating hours of the terminal and may span several days. Additionally, consider $\mathcal{L}$ as the total containers that are to be moved from the yard into the same ship. Thus, N containers are already waiting to be unloaded from the ship. A number of these containers are assigned pick-up priority based on the container stowage plans as per the location of every container on the ship. This helps in identifying containers that are to be unloaded from the ship in a certain assigned order.

Priority containers are selected for unloading based on the type of goods they carry, such as perishable items, hazardous materials, or simply because they are slated for early onward transport. These priority containers are strategically distributed across the ship, positioned above the other containers for efficient access by quay cranes.

The entire docking period, *T*, of the ship is segmented into equal intervals *t*, as processing time per hold, during which a quay crane focuses on unloading the priority containers of a hold. Initially, all priority containers from the designated holds are unloaded before any normal containers are processed. Let the number of priority containers, H_t, that need to be unloaded from a ship within each interval *t,* be expressed as $H_t = \frac{Nt}{T}$.

The interval *t* should be the crane's average processing time, as it is intended to be sufficient to handle all H_t priority containers. But this might not be the case as crane's handling rate may not be sufficient to handle exactly fulling unloading H_t containers from the ship in time period *t*. Also, port managers and operators may have a predetermined or expected processing time *t* required based on the demand for the products in these containers requiring quick processing to meet downstream appointment times for external trucks to pick them from the yard and ferry them to hinterland destinations in time. This pre-specified processing time *t* and various constraints is common in quay crane scheduling problems that involve working on holds (Lee et al., 2008).

Therefore, the time *t* may not be sufficient (or be large) and a different number of priority containers, n_t, will be unloaded other than H_t in time period *t*.

We examine the case $n_t < H_t$. This case would occur when various constraints might impede the full unloading of H_t containers within the interval *t*, including reduced crane handling rates due to operational delays, or time consumed in identifying and processing each container. Besides other practical limitations such as operational delays or inefficiencies may necessitate unloading a smaller number, n_t, priority containers which is less than H_t.

Priority containers within the first hold of a quay crane that were scheduled to be unloaded within the first time period, *t*, but are not, are moved in the second time period meant for the next (second) hold of priority containers. And those that were not moved in the second time period of the second hold are moved in the third and so on. Thus, after the first time period, the remaining containers $(H_t - n_t)$ of the first hold are expected to be handled in the subsequent time period of *t*. Following this procedure, for the next *t* time period, we will have $(2H_t - n_t)$ containers in the second hold to be moved (due to the spillover effect from the previous *t*). In this second *t* time period of the second hold, however, only n_t containers can be moved, the remaining $2(H_t - n_t)$ containers will need to be moved during the third *t* time period of the second hold. Therefore, by generalizing, during the i^{th} *t* time period and hold, $i(H_t - n_t)$ containers will need to be moved by the AGV in the (*i*+1)th time period. In the end, during the last time period *t*, when *T* is approaching, any residual number of containers from the spillovers are picked-up and transported. The assumption that is made in this queuing effect with containers is that no container is picked up by more than one extra time period of *t*. Otherwise, a large number of containers would stay on the ship causing quay cranes to be overly busy and the condition that all containers are removed from the ship will not be met within the time *T*.

We initially assume $\tau_L > \tau_s$. Although with this initial assumption when the quay cranes at seaside berth have a higher operating speed than those on the landside yard, the wait time of AGVs will eventually reach an equilibrium and the waiting time for all the containers in the ship will be equal to τ_L.

The containers that were moved in their respective assigned time periods and in a hold incur an average wait time of $=\frac{(0+2\tau_L+4\tau_L+\cdots+2n_t\tau_L)}{n_t} = \frac{2\tau_L\sum_{i=1}^{n_t} i}{n_t} = \frac{2n_t(n_t+1)\tau_L}{2n_t} = (n_t + 1)\tau_L$.

Finally, the expected dwell time for the N containers unloaded per crane from the ship and the mean transit time of the container as it is lifted by the quay crane to be placed onto an AGV at its rest area is $E(D_s)$:

$$\boldsymbol{E}(\boldsymbol{D_s}) = (n_t + 1)\tau_L + \frac{t\sum_{i=1}^{i=\frac{T}{t}} i\times(H_t - n_t)}{N} \quad (1)$$

Using $n_t = \frac{ta_t}{\tau}$ and we have,

$$\boldsymbol{E}(\boldsymbol{D_s}) = \left(\frac{ta_t}{\tau} + 1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left(\frac{Nt}{T} - \frac{ta_t}{\tau}\right)}{2N} \quad (2)$$

The expression in Eq. (1) is valid when $\frac{N}{T} > \frac{a_t}{\tau} \Longrightarrow a_t < \frac{N\tau}{T}$

If we have $n_t > H_t$, it would indicate that all the priority containers are picked-up by the seaside quay crane within time *t*, incurring no spillover case of containers not served. In that case, we will only have the general waiting time of the containers in the ship, with

$$\boldsymbol{E}(\boldsymbol{D'_s}) = \left(\frac{ta_t}{\tau} + 1\right)\tau_L$$

Thus, an equilibrium will occur in the pick-up of the containers when $\boldsymbol{E}(\boldsymbol{D_s}) = \boldsymbol{E}(\boldsymbol{D'_s})$**,** which will yield,

$$\frac{T\left(\frac{T}{t}+1\right)\left(\frac{Nt}{T} - \frac{ta_t}{\tau}\right)}{2N} = 0 \Longrightarrow \left(a_t = \frac{N\tau}{T}\right) \quad (3)$$

Landside Yard Container Dwell Time

The containers that were scheduled or prioritized to be moved via trucks within the first time period, *t*, but are not, are moved in the second time period, and those that were not moved in the second time period were moved in the third and so on. Consider that the task of quay cranes on the landside yard to be able to move *M* number of containers that were originally present and stacked in the yard and are to be loaded onto freight trucks - all within time *T*. Thus, the methodology of formulating the expected dwell time, $\boldsymbol{E(D_L)}$, of the containers in the yard follow the similar procedure as described in the previous section.

While the number of containers stored at the yard increase with each container laden AGV's arrival, on an average, r_t containers are added to the existing stack of containers in the yard in time period *t*. The number of containers that were brought by the AGVs that arrived at the landside yard quay cranes and got unloaded during time *t* is: $r_t = \frac{t}{\tau_L} = \frac{a_t t}{\tau}$. However, a number of containers at the yard are also removed via freight trucks ferrying them out of the port and let that be m_t.

Priority export containers are loaded at the end to place then on top of the regular containers before the ship departs. This ensures that priority export containers are unloaded at destination before unloading the regular containers. The process of loading these containers that arrive to the seaside berth from the landside yard is just the reverse of the methodology for unloading the priority containers from the ship.

Similar to the import containers regarding processing times by the seaside berth quay cranes, the formulations for the dwell time and transit time to the ship of these export containers, $\boldsymbol{E(D_L)}$ is expressed as,

$$\boldsymbol{E(D_L)} = (r_t + 1)\tau_L + \frac{\mathrm{T}\left(\frac{\mathrm{T}}{t}+1\right)\left\{\frac{Mt}{\mathrm{T}}+r_t-m_t\right\}}{2M} \tag{4}$$

Using $r_t = \frac{a_t t}{\tau}$ we have,

$$\boldsymbol{E(D_L)} = \left(\frac{t a_t}{\tau} + 1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left\{\frac{Mt}{\mathrm{T}}+\frac{a_t t}{\tau}-m_t\right\}}{2M} \tag{5}$$

where,

m_t = number of containers transported from the landside yard to outside the port to the adjacent roads during the time period *t*.

With $\left(a_t = \frac{N\tau}{T}\right)$, the expression of $\boldsymbol{E(D_L)}$ in Eq. (5) is,

$$\boldsymbol{E(D_L)} = \left(\frac{Nt}{T} + 1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left\{\frac{Mt}{\mathrm{T}}+\frac{Nt}{T}-m_t\right\}}{2M}$$

The expression above shows that the expected dwell time of a container in the landside yard is independent of the number of AGVs employed and the configuration of the network that AGV navigates while transporting the containers.

Note that in this modeling we are excluding the interference of export containers that are brought to the port by the trucks into the derived efficiency formulations. This is helpful to keep track of the one-way flow of the import containers and develop a suitable model as they arrive in ships, are unloaded, parked in the yards, and transported out of the port in freight trucks. A similar modeling approach as discussed for these import containers can be devised for all export containers.

AGV Routing

An AGV's guide path configured in a grid network is a strategic solution employed in numerous industrial and warehouse environments for efficient material handling. The grid layout offers a structured and systematic path for AGVs to navigate through a designated area. This type of guide path is particularly advantageous in facilities where precise and predictable movements are essential. The perpendicular intersections in a grid network facilitate straightforward navigation and provide flexibility in route planning. AGVs operating on a grid path can easily traverse horizontally and vertically, optimizing coverage across the entire workspace. Grid-based AGV systems are commonly utilized in manufacturing plants and distribution centers, where the need for organized and repeatable movements is crucial for enhancing workflow efficiency. The systematic nature of the grid path not only ensures accuracy in AGV navigation but also allows for streamlined coordination and integration with other automated processes, contributing to a more synchronized and productive operational environment.

An approximate relationship can be derived between number of AGVs deployed to transport n_t containers from the seaside berths to the landside yard in time period t.

AGV Grid Navigation Configuration Type 1

The layout for the number of seaside berth quay cranes is equal to the number of landside yard quay cranes, both located opposite to each other. The mean distance, τ_t, traveled between the seaside berth quay cranes and the landside yard quay cranes in this grid configuration is based on the sketch shown in Fig. 6 and is expressed as,

$$\tau_t = y + \frac{\frac{x}{(f-1)}\left\{\sum_{i=1}^{f} \frac{(i-1)i}{2}\right\}}{\frac{(f-1)f}{2}} = y + \left(\frac{x}{3}\right)\frac{(f+1)}{f-1} \tag{6}$$

The expression in Eq. (6) was validated for the expected distance between two random points on a line with the value of $\frac{x}{(f-1)}$ approaching zero as f increases. For large f, the second term of the expression in Eq. (6) reduces to $\left(\frac{x}{3}\right)$, which is also the mean distance between two random points on a line of length x (Gaboune et al., 2001).

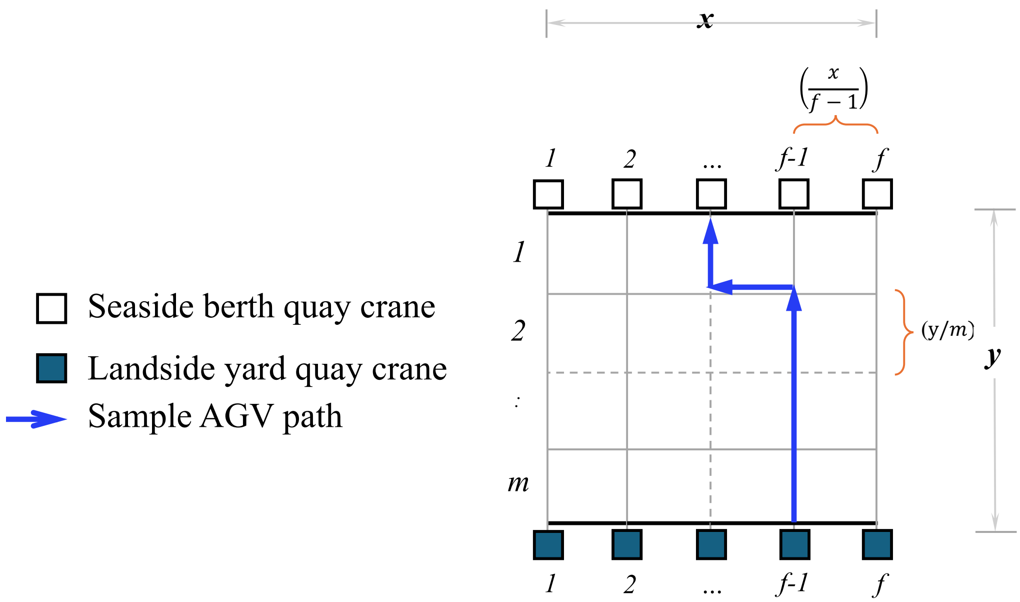


Figure 6: Grid network configuration type 1

AGV Grid Navigation Configuration Type 2

In this setup, the number of seaside quay cranes is greater than the number of landside berth quay cranes. As depicted in Fig. 7 below, AGVs are able to engage in loading and unloading activities utilizing the extra *e* quay cranes on the landside. The vehicles have the capability to navigate loading and unloading at the additional landside quay cranes, specifically moving in a rectilinear path amongst any of the crane 1 to crane *g*-1, and then to the any of the *g* seaside quay cranes. Therefore, for this configuration, and following the results of Eq. 6, the mean distance traveled between the seaside berth quay cranes and the landside yard quay cranes is expressed as,

$$\tau_t = y + \left(\frac{g+1}{2}\right)\left(\frac{x}{f+g-1}\right)\left(1-\frac{f}{f+g}\right) + \frac{\left(\frac{x}{f+g-1}\right)(f-1)}{3}\left(\frac{f+1}{f-1}\right)\left(\frac{f}{f+g}\right)$$

$$= y + \left(\frac{g+1}{2}\right)\left(\frac{x}{f+g-1}\right)\left(1-\frac{f}{f+g}\right) + \frac{\left(\frac{x}{f+g-1}\right)}{3}\left(\frac{f+1}{1}\right)\left(\frac{f}{f+g}\right)$$

$$= y + \left(\frac{x}{f+g-1}\right)\left\{\left(\frac{g}{f+g}\right)\left(\frac{g+1}{2}\right) + \frac{1}{3}\left(\frac{f+1}{1}\right)\left(\frac{f}{f+g}\right)\right\}$$

$$= y + \left(\frac{x}{f+g-1}\right)\left(\frac{1}{f+g}\right)\left\{\frac{g}{2}(g+1) + \frac{f}{3}(f+1)\right\} \quad (7)$$

The last two terms involve the probabilities of AGV traveling from any of the crane 1 to crane *e*+1 or the cranes 1 to *g* among *f* total cranes. See Fig. 7 below for the set-up.

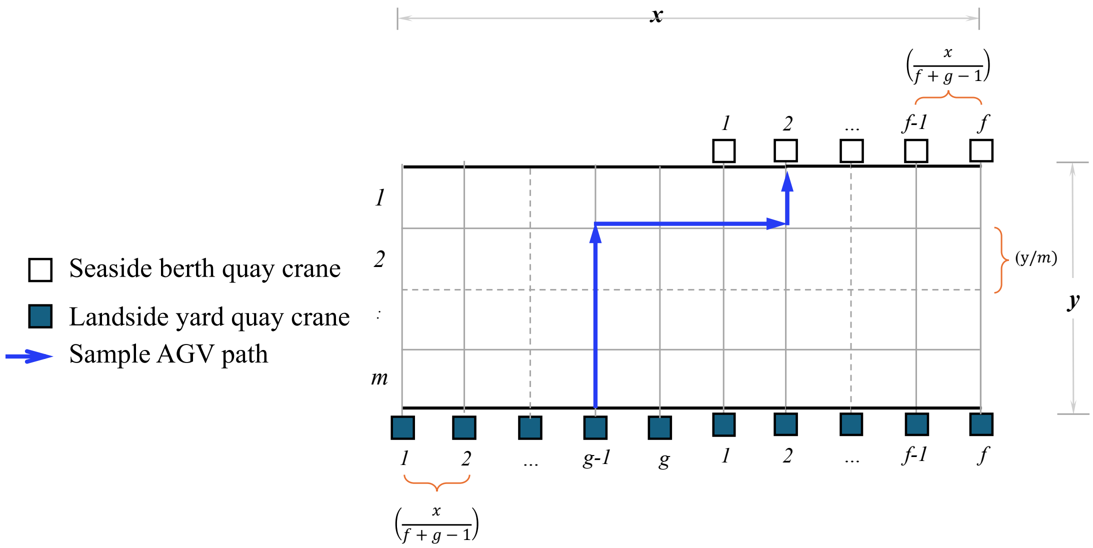


Figure 7: Grid network configuration type 2

AGV Grid Navigation Configuration Type 3

This configuration is similar to configuration 2 above with much fewer number of seaside berth quay cranes than the landside yard quay cranes.

In this configuration, the seaside berth quay cranes are located centrally to the landside yard quay crane with the AGVs navigating using a rectilinear path from any of the landside yard quay cranes from the 1st to the gth quay crane (or the 1st to hth) (and vice-versa) to the any of the seaside quay carne – see Fig. 8. Therefore, the average distance τ_t traveled by the AGV from/to any of the f landside berth to/from any of the s seaside berth quay crane is expressed as,

$$\tau_t = y + \left(\frac{g+1}{2}\right)\left(\frac{x}{f+g+h-1}\right)\left(\frac{g}{f+g+h}\right) + \frac{\left(\frac{x}{f+g+h-1}\right)(f-1)}{3}\left(\frac{f+1}{f-1}\right)\left(\frac{f}{f+g+h}\right) + \left(\frac{h+1}{2}\right)\left(\frac{x}{f+g+h-1}\right)\left(\frac{h}{f+g+h}\right)$$

$$= y + \left(\frac{x}{f+g+h-1}\right)\left(\frac{1}{f+g+h}\right)\left\{g\left(\frac{g+1}{2}\right) + \frac{f(f+1)}{3} + h\left(\frac{h+1}{2}\right)\right\} \qquad (8)$$

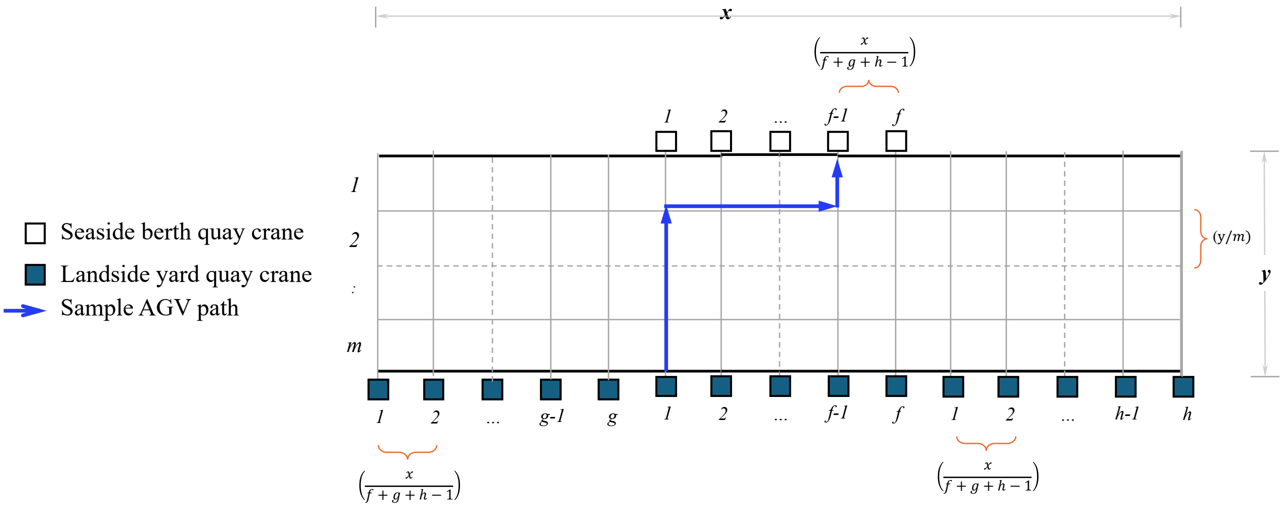


Figure 8: Grid network configuration type 3

Port Automation Performance Measure

The efficiency of the port operations encompassing the entire process from the container's removal from the ship by the AGVs into the adjoining road network via freight trucks is evaluated. We consider the performance measure (as an indicator of efficiency) for the container movement from the port to the adjacent road network as a weighted sum of the following five key activities of container dwell times and its transit in sequence – i) the time containers remain stationary as they are transferred from the ship to the AGV by the berth quay cranes at the seaside, ii) the AGV's idle time at the seaside berth quay cranes, iii) the AGV's transit time from the seaside yard to the predetermined locations at the landside yard, iv) the AGV's waiting time for unloading by the landside yard quay crane, v) the period containers stay in the yard before being transported by freight trucks, and vi) the freight truck's delay at the road network's merge area near the port.

Total efficiency, $\boldsymbol{\Gamma}$, consists of the container and AGV dwell times at the seaside berth location and at the landside yard location, deploying a_t number of AGVs, and is expressed as,

$$\boldsymbol{\Gamma} = \alpha \boldsymbol{E}(\boldsymbol{D}_s) + \beta \boldsymbol{E}(\boldsymbol{D}_L) \quad (9)$$

where,
α = weight for the dwell time of the containers on the ships before being picked-up by the quay crane on the seaside berth, and
β = weight for the dwell time of the containers before being picked-up by the landside quay cranes to be loaded onto the trucks

The expanded expression for $\mathbf{\Gamma}$ is:

$$\mathbf{\Gamma} = \alpha\left\{\left(\frac{ta_t}{\tau}+1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left(\frac{Nt}{T}-\frac{ta_t}{\tau}\right)}{2N}\right\} + \beta\left\{\left(\frac{ta_t}{\tau}+1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left\{\frac{Mt}{T}+\frac{a_t t}{\tau}-m_t\right\}}{2M}\right\} \quad (10)$$

Or, in simple terms, we have,

$$\mathbf{\Gamma} = \mathbf{\Gamma}_1 + \mathbf{\Gamma}_2$$

where,

$$\mathbf{\Gamma}_1 = \alpha\left\{\left(\frac{ta_t}{\tau}+1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left(\frac{Nt}{T}-\frac{ta_t}{\tau}\right)}{2N}\right\}$$

and

$$\mathbf{\Gamma}_2 = \beta\left\{\left(\frac{ta_t}{\tau}+1\right)\tau_L + \frac{T\left(\frac{T}{t}+1\right)\left\{\frac{Mt}{T}+\frac{a_t t}{\tau}-m_t\right\}}{2M}\right\}$$

Freight Corridor Congestion

Proximity to a port can be major cause of congestion on the roads and streets surrounding the port due to the high volume of truck traffic – especially due to continuous influx of heavy vehicles – that exit the port and often converge onto the adjacent roads. There could be clusters of arrivals of trucks from the ports that can overwhelm the adjacent road's capacity – further aggravating the congestion by the size and limited maneuverability of trucks particularly at critical points, such as traffic merge locations, along a major highway that is adjacent to the port. Analyzing this congestion at such critical location involves assessing the rate of truck arrivals, the road's capacity to handle large vehicles, and the interaction between trucks and other road users and cars. The reason is that the truck drivers would like to skip the traffic congestion that occurs in the neighboring network shared by both passenger cars and trucks with the peak hours of travel, which is typically observed to be between 8 am - 10 am and between 4 pm - 6 pm.

There could be a presence of multiple congestion hot-spots on road network adjacent to the port but our focus is to pick those locations that are well known to cause frequent delays to movements of trucks carrying containers to mainland destinations. In fact, merging points on highways or the road network have been known for causing traffic congestion (Evans et al., 2001). The issue especially acute for trucks that travel with slower speeds, experience increase in delays at merging zones. The random number of truck arrivals before these merging zones, along with the spontaneous nature of the merging process due to varied driving behaviors, suggests a resemblance to a stochastic queueing system. This analogy allows us to view freight trucks entering the adjacent roads, streets, or freeway from a port as customers approaching a service facility - the merging zone. Here, the 'service' is the zone's ability to seamlessly merge vehicles, absorbing incoming trucks and facilitating their exit from the congestion zone. The service capacity is influenced by factors such as the presence of vehicle gaps, traffic flow speed, and driver conduct near merging zones. The queuing model adopted is the FIFO (First In, First Out) method, which is a standard in queueing theory and, therefore, it is reasonable to employ Markovian queueing models like M/M/1 to simulate both the arrival of trucks and the service dynamics at these merging zones, with 'service' being the effective maneuvering of trucks through the area. (Chandra et al., 2019).

With reference to the sketch in Fig. 9, let there be a constant arrival rate, m_t, of freight trucks arriving randomly during time duration *t* at a typical merge area. The rate m_t is the same rate as that when freight trucks are exiting the point of loading/unloading by the quay cranes at the landside yard of the port.

Considering the Markovian process, let there be a state *s* in which there are *s* number of container carrying trucks from ports with probability P_s. These trucks, as they emerge from the port, are in significant volume (in comparison to the cars) at a merge location (is close to the port) and treated as a potential congestion hot spot on the truck route. The trucks pass through this merge area at a constant rate, u_t, which is also random discharge of freight trucks existing out of this potential congestion point during time duration *t*. Note that the rest of the derivations are based for this *t*.

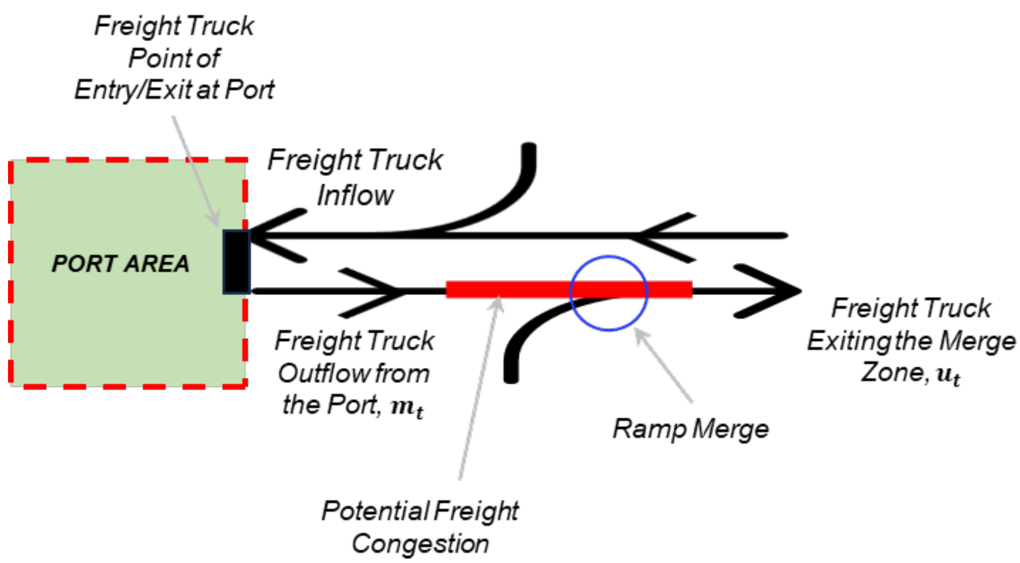


Figure 9: Freight congestion at a traffic merge zone near the port

A truck if it arrives in the merge area when a queue is in state *s* makes the state of the queue transition from *s* to (*s* +1) which happens with probability $m_t P_s$. A further exit or departure of a truck when the queue is in state (*s* +1) makes the queue transition back to state *s* with probability $u_t P_{s+1}$. In an equilibrium state of the merge area, freight truck arrivals and departures must be equal. Thus,

$$m_t P_s = u_t P_{s+1} \tag{11}$$

With trucks in queue in state *s* = 0,1, 2, …, and after some mathematical procedures, we have from Eq. (11),

$$P_s = \left(\frac{m_t}{u_t}\right)^s P_0 \tag{12}$$

Since, $\sum_{s=0}^{\infty} P_s = 1$, it implies $\sum_{s=0}^{\infty} \left(\frac{m_t}{u_t}\right)^s P_0 = 1$, which yields,

$$P_0 = \left(1 - \frac{m_t}{u_t}\right) \tag{13}$$

The expression in Eq. (13) will be valid when $u_t > m_t$, which means that the departure rate of freight trucks from the merge area is greater than the arrival rate of the freight trucks into the merge area. With P_0 in Eq. (10), the probability P_s (that there are *s* vehicles in the queue) in Eq. (12) is rewritten as,

$$P_s = \left(\frac{m_t}{u_t}\right)^s \left(1 - \frac{m_t}{u_t}\right) \tag{14}$$

Therefore, the average time spent, W_t^m, by a truck as it passes through the merge zone, when there are *s* number of trucks already in the queue, is given by,

$$W_t^m = \sum_{s=0}^{\infty} \left(\frac{s+1}{u_t}\right) P_s = \left(\frac{1}{u_t - m_t}\right) \tag{15}$$

The derivation in Eq. (15) simply follows from the fact that for *s* = 0, the truck spends $\frac{1}{u_t}$ time in passing through the merge area with probability P_0, for *s* = 1, the time spent is $\frac{2}{u_t}$ with probability P_2 and so on.

Data Collection, Analysis and Results

The analytical findings are demonstrated with the port layout from the Long Beach Container Terminal (LBCT), one of the busiest terminals at the Port of Long Beach. Data collected from various sources indicate that truck congestion both inside the terminal and on the adjacent ramps and freeways typically peaks between 2 pm and 4 pm on weekdays. This information was compiled from multiple sources, including Google Maps for traffic patterns, live camera feeds at the terminal gates (LBCT, 2024), and Google-based analyses of busy periods. The image in Fig. 10 shows the layout and the analysis area of the container transportation in the Long Beach Container Terminal. Both the seaside berth and landside yard quay cranes are shown in the image.

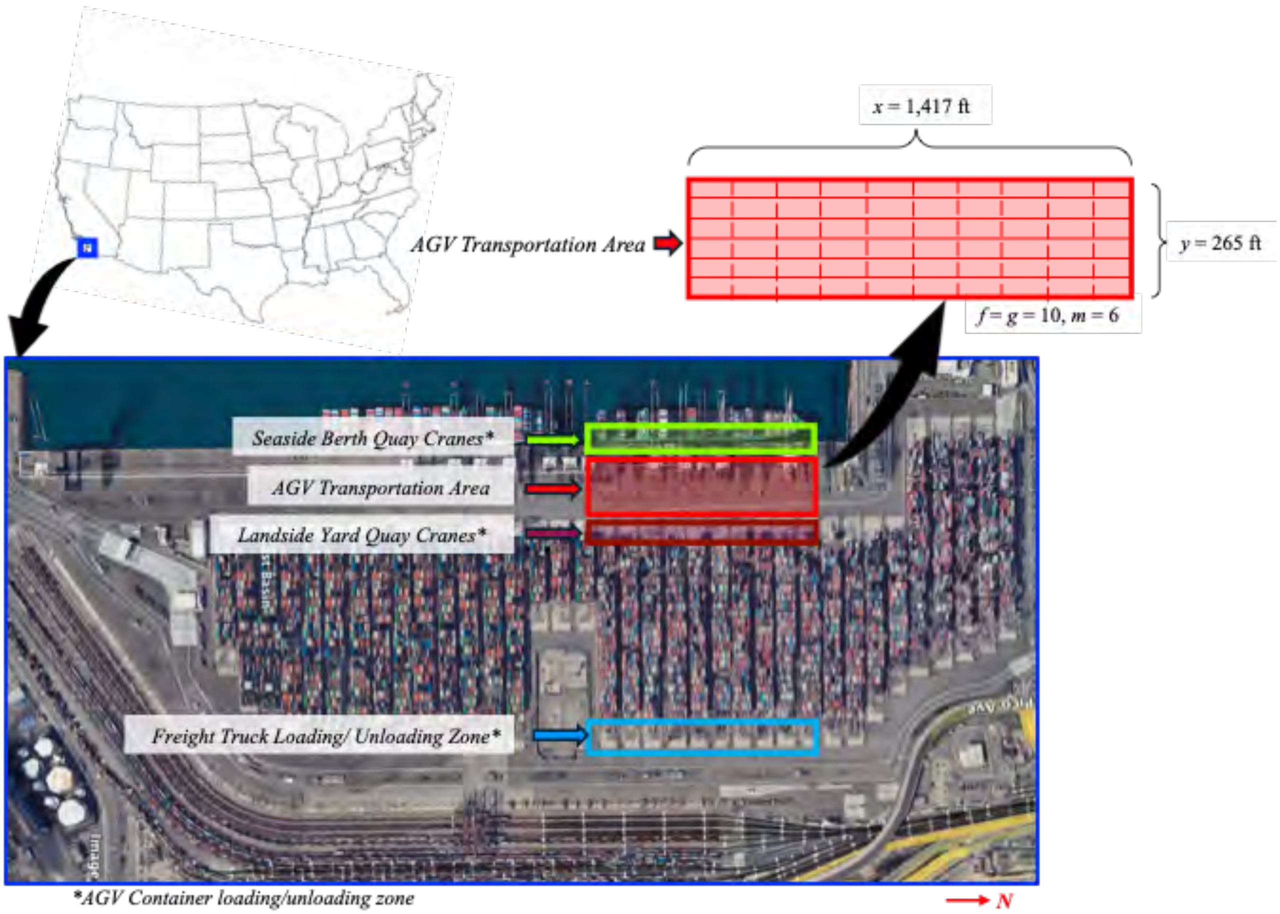


Figure 10: Container operations in the Long Beach Container Terminal

We conduct an analysis to demonstrate how number of AGV deployment affects the average time that freight trucks spend in congestion within the adjacent transportation network. The specific parameter values used for these plots are from the Long Beach Container Terminal of the Port of Long Beach and are noted in the Table 2 below:

Table 2: Parameter values and data used for analytical results (partial data obtained for the Long Beach Container Terminal)

Parameter Definition and Description	Notation	Values (with units)
Length of the AGV operational area within the port area (measured using Google Earth)	x	1,417 ft
Width of the AGV operational area within the port area (measured using Google Earth)	y	265 ft
Grid network configuration		Type 1
Number of days for which the ship is docked for unloading all containers (days)	T	4 days
Number of containers (TEUs) to be unloaded from the ship	N	10,000 containers

Number of containers (TEUs) that are previously present in the yard	M	5000 containers
Time interval during which containers are earmarked to be unloaded on a priority basis	t	Variable
Average speed of AGVs	V_a	10 miles per hour (speed limit for AGVs in LBCT)
Number of landside yard quay cranes (determined using Google Earth images)	f	10
Number of seaside berth quay cranes (determined using Google Earth images)	g	10
Number of lanes for navigation of AGV on a grid network path (determined using Google Earth images)	m	6
Time taken by seaside berth quay crane to move from an AGV container loading spot to the ship to pick up a container and bring it to the AGV for loading	τ_s	2 minutes per container
Time taken by landside yard quay crane to move from a stack in the yard to the AGV container unloading spot for drop-off	τ_L	2 minutes per container
Number of AGVs	a_t	Variable
Weight for container dwell time in ships	α	1
Weight for container dwell time in ships	β	1
Rate of container dispatch outside of the port during time t	m_t	$\frac{20}{t}$ containers per minute
Saturation flow rate (in vehicles per minute)	u_t	32 veh per min (saturation headway of 1.9 seconds)

Based on the data from Table 2 and utilizing Type 1 of the general navigation grid configuration for Automated Guided Vehicles (AGVs) at the port, the optimal number of AGVs required to reduce the average container dwell time on the seaside is identified as 100, as demonstrated in Fig. 11. With this deployment at the Long Beach Container Terminal (LBCT), the shortest average dwell times for priority containers—approximately 1, 2, and 4 minutes—can be achieved if they are scheduled for unloading at intervals of 15, 30, and 60 minutes, respectively, once the ship docks at the port.

The container dwell times with 100 AGVs subsequently results in the variation in the dwell times at the yard (landside). The data reveals that the average dwell times on the seaside are substantially longer than those on the landside, as illustrated in Figures 11 and 12. Moreover, congestion in the adjacent transport network worsens significantly as the average dwell times on the landside approach 1600, 5200, and 7000 minutes. Fig. 12 highlights the severe delays trucks may face while transporting import containers from the port to inland destinations, which escalates as dwell times increase in the landside yard. These findings and their interpretations rely on the data from Table 1 and the number of AGVs in operation.

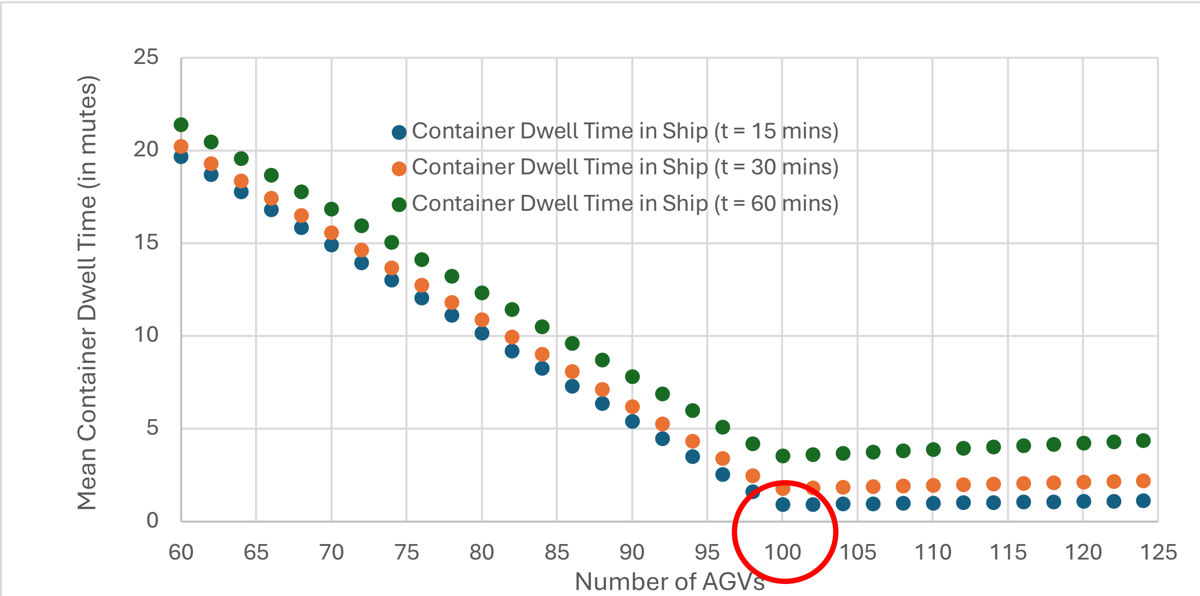


Figure 11: Variation in mean container dwell times on the seaside versus number of AGVs deployed

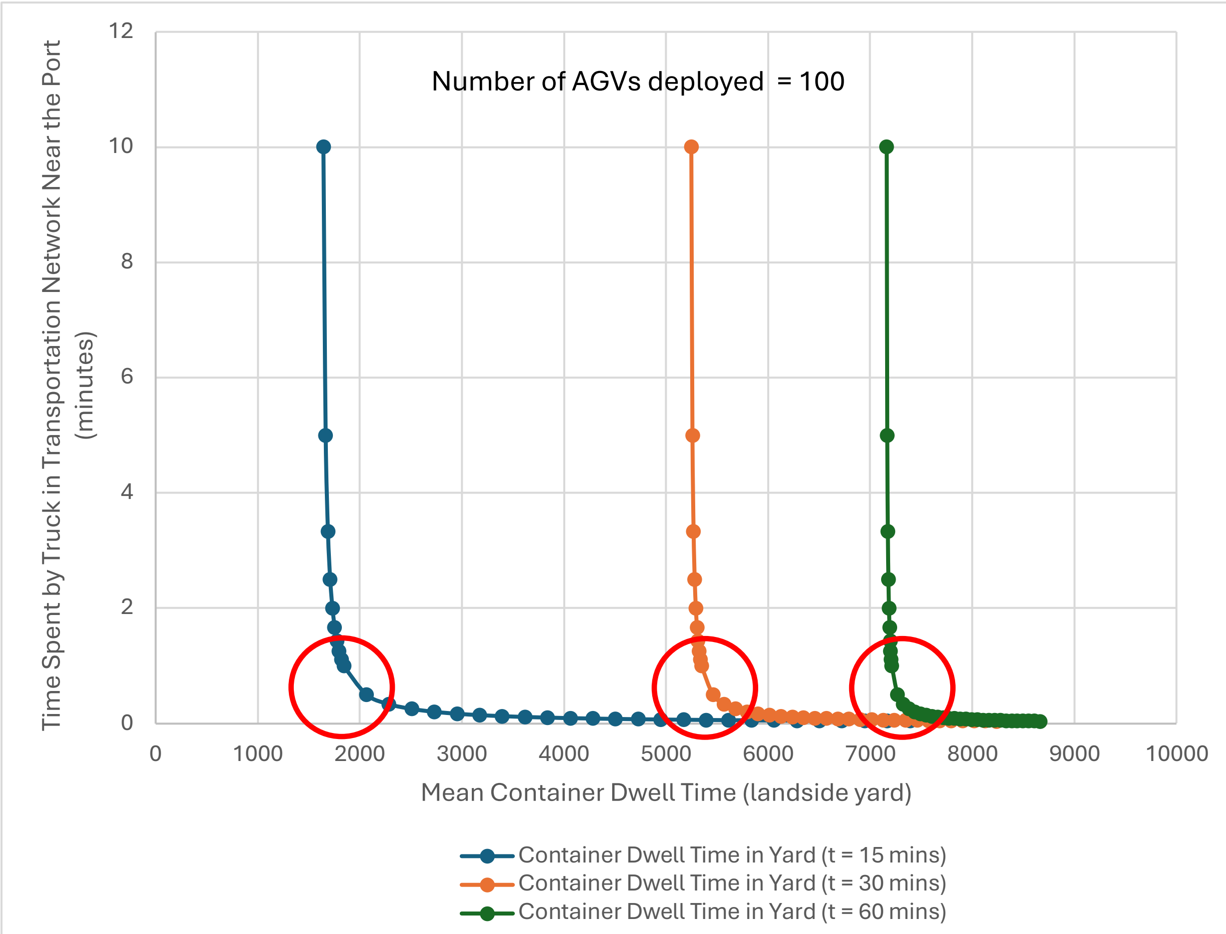


Figure 12: Variation in mean container dwell times on the seaside versus number of AGVs deployed

Discussions, Insights and Future Directions

Terminal Gate Congestion

Based on the traditional appointment system, external freight trucks are scheduled to move import containers (using container number) within a certain time window. Trucking companies that do not adhere to these time windows or letting too many appointments expire are penalized. The congestion at the gate or the nearby transportation infrastructure result when truckers arrive much before their appointment times. This is the practice at the LBCT and the Port of Los Angeles (Hunt, 2023). As per the appointment system, a definite number of trucks are only accepted within port premises has helped ports prevail efficiency in its operations and management. However, queues were still persistent outside the port area into the neighboring transportation network much before they are scheduled appointment (Hunt, 2023). The motive is to avoid traffic congestion during peak hours on nearby highways and transportation network that led to the port situated in an urban city. Thus, the appointment system, although within the port, has inadvertently led to some prevailing congestion outside the port gate into the nearby transportation network. This is also because surrounding the Port of Long Beach there is also a limited supply of designated truck parking spaces (Caltrans, 2024).

Congestion at entrance and exit truck gates may appear due to two reasons, first: a key transportation infrastructure link leading to the terminal entrance gate is of fixed capacity and the trucks queue in length reaching that capacity. The trucks would either pick-up containers that are imported or could drop-off the containers that are to be exported. Second, a key infrastructure link leading to merge location of a major arterial through a ramp could be congested due to its capacity exceeding the number of trucks as they exit the port gates. This is the case mainly with ports that are situated amidst dense urban cities.

Studies show that in order to avoid congestion at the port from queuing trucks, a uniform distribution of appointment slots that reduce peak demand hours of truck traffic, serves the best for efficient export and import of containers (Abdelmagid et al., 2022).

We model this case by utilizing the approach from similar studies that divide the terminal's working hours into equal time slots for trucks (Torkjazi et al., 2018; Abdelmagid et al., 2022).

If the total working hours of the port is *T*, with n_t containers to be for time period equal to *t*, the queue length of the truck at the beginning of *t* is assuming that the truck drivers arrive before their scheduled assignment time of container pick-up or drop off. Thus, if the travel time at the critical link of the transportation network is t_e and t_x at the entrance and exit gates, respectively, then for congestion to occur the relationship $t_e > t_{n,e}$ and $t_x > t_{n,x}$ where, $t_{n,e}$ and $t_{n,x}$ are the free flow travel times of the critical links at the entrance and exit gates of the terminal. The inequalities can be further simplified as $t_e = \frac{c_e}{s_e} > t_{n,e} = \frac{c_{n,e}}{s_{n,e}}$ and $t_x = \frac{c_x}{s_x} > t_{n,x} = \frac{c_{n,x}}{s_{n,x}}$, where c_e is the usual truck queue length and $c_{n,e}$ is the queue capacity of the critical link at the entrance gate of the terminal. s_e and $s_{n,e}$ are the freight truck speed limits at free-flow and at congestion, respectively, at the critical link of the entrance gate of the terminal. Similarly, c_x is the usual truck queue length and $c_{n,x}$ is the queue capacity of the critical link at the exit gate of the terminal. s_x and $s_{n,x}$ are the freight truck speed limits at free-flow and at congestion, respectively, at the critical link of the exit gate of the terminal.

With the free-flow and the congestion speed limits being typically constant, the number of trucks that are assigned for pick-up (or drop-off) of containers during specific time slots of the total working hours of the port would be compared with usual truck queue lengths mentioned above. Therefore, based on the definitions of the export and import containers, n_t and φn_t, respectively, as used in the earlier sections, the condition of congestion is at the critical links are $n_t > c_{n,x}$ and $\varphi n_t > c_{n,e}$ at the exit and entrance gates, respectively.

Transitioning from Traditional/Conventional to an Automated Terminal

As highlighted earlier, a study by Majoral et al. found no definitive evidence that automated terminals perform better than traditional ones. This study aims to directly assess the effectiveness of deploying AGVs and analyzing the physical layout of the yard. By comparing dwell times at traditional ports before the introduction of AGVs to those after their deployment, the study will assess potential improvements in efficiency, aiding in the decision whether to switch from traditional to automated terminals.

Technical Transfer and Commercialization

In the Appendix, we present a functional model that utilizes computer vision and pattern recognition to simulate the movement of containers within the port, tracking how they are identified and relocated by cranes. The goal is to increase the supply chain efficiency in the movement of containers within the port.

Conclusions

Seaports play a critical role in enhancing the efficiency of freight transport and supply chains, acting as cost-effective hubs that manage high cargo volumes. The integration of automated technologies such as Automated Guided Vehicles (AGVs) and automated stacking cranes is intended to improve port operations. However, the effectiveness of these automated terminals varies, heavily dependent on the number of AGVs and the yard layout, and can strain existing transportation infrastructures. This study assesses AGV performance by examining container dwell times and their impact on congestion in surrounding transport networks. Using a continuous approximation model, the research derives simpler, manageable equations to address port management challenges, analyzing how different configurations and operational strategies affect port efficiency. It also considers the traditional appointment systems at ports like Long Beach Container Terminal, aiming to optimize AGV deployment to reduce dwell times and manage congestion effectively.

This study demonstrates that implementing 100 Automated Guided Vehicles (AGVs) at the Long Beach Container Terminal optimizes container processing by significantly reducing dwell times to as low as 1, 2, and 4 minutes for priority containers, contingent on unloading intervals post-ship docking at 15, 30, and 60 minutes. However, while seaside dwell times decrease, landside dwell times remain substantially longer, escalating to 1600, 5200, and 7000 minutes, which exacerbates congestion in adjacent transport networks and causes major delays for inland-bound trucks. These insights provide ports with essential strategies to effectively incorporate AGVs into their operations and infrastructure, enhancing overall efficiency and flow.

The findings suggest that strategic AGV use can significantly enhance port operations while necessitating careful consideration of their impact on local transport.

There is a total of 72 AGVs deployed at the port for transport of containers within the port premises (Konecranes, 2020). Although the data on container dwell times were not readily available from the LBCT, a preliminary estimate on the mean container dwell times can be estimated using the methodology presented in this research – which recommends deploying 100 AGVs purely meant for transportation of containers and to reduce their dwell times at the seaside berth.

The findings from this research will equip ports with a deep understanding of how to fully utilize AGVs while seamlessly integrating them into the operational flow and infrastructure of modern ports.

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Appendix

Lightweight Object Detection on Edge Devices like Raspberry Pi

Abstract

This research presents the development of a lightweight object detection model for edge devices like the Raspberry Pi. The goal is to enable real-time object detection by minimizing computational demands using the ORB (Oriented FAST and Rotated BRIEF) algorithm. ORB's efficiency in feature detection and matching is leveraged to achieve this. The research details the implementation of ORB-based detection on static images and live video feeds, demonstrating significant improvements in processing efficiency. Comparisons with machine learning-based models highlight the practical advantages of ORB for deployment on resource-constrained devices.

Introduction

Background

Object detection is fundamental in computer vision, powering applications in surveillance, autonomous systems, and robotics. Deploying these models on edge devices, such as the Raspberry Pi, is challenging due to their limited processing power and memory. Traditional models like CNNs are computationally heavy and unsuitable for real-time applications on such devices.

Motivation

The drive to develop a lightweight object detection model stems from the necessity to perform real-time processing on edge devices, which typically lack the computational resources found in more robust systems. Efficient object detection on devices like the Raspberry Pi broadens their application scope, particularly where cost and power efficiency are critical.

Objectives

The primary objectives of this research are:

1. To eliminate extensive data processing requirements by developing a computationally efficient object detection model.

2. To achieve real-time object detection on resource-constrained devices such as the Rasp- berry Pi.
3. To utilize the ORB algorithm for feature detection and matching, leveraging its efficiency and suitability for low-power devices.

Approach

The ORB (Oriented FAST and Rotated BRIEF) algorithm was chosen for this research due to its robustness and low computational requirements. ORB is an efficient alternative to traditional feature detection algorithms like SIFT and SURF. The research involves:

- Feature Detection: Using ORB to identify keypoints and compute descriptors in both static images and live video feeds.
- Feature Matching: Employing a FLANN-based matcher to match detected features, enabling the identification of objects in varying conditions.
- Implementation: Several Python scripts were developed to handle different aspects of the detection process, each optimizing the ORB-based detection for real-time per- formance on the Raspberry Pi.

Comparison with Machine Learning Models

Machine learning-based object detection models, such as YOLO, SSD, and Faster R-CNN, are highly accurate but require substantial computational resources, making them unsuitable for edge devices. ORB, on the other hand, offers a computationally efficient alternative that maintains reasonable accuracy, making it ideal for resource-constrained environments.

Significance

This research bridges the gap between high-performance object detection models and the computational limitations of edge devices. By demonstrating the feasibility of ORB-based object detection on the Raspberry Pi, the study opens new possibilities for deploying ad- vanced machine learning applications in resource-constrained environments, thereby enhanc- ing the practicality and accessibility of computer vision technologies.

Related Work

Object detection using machine learning (ML) and traditional computer vision techniques like ORB (Oriented FAST and Rotated BRIEF) each have distinct characteristics and trade- offs.

Machine Learning-based Object Detection

Machine learning-based approaches, such as Convolutional Neural Networks (CNNs), have shown remarkable accuracy in object detection tasks. Models like YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN are capable of detecting multiple objects in real-time with high precision. However, these models require substantial computational resources, including powerful GPUs, making them less suitable for deployment on edge devices with limited processing power and memory.

ORB-based Object Detection

ORB is a computationally efficient alternative for object detection on resource-constrained devices. It is designed for fast feature detection and matching, which makes it suitable for real-time applications on devices like the Raspberry Pi. ORB combines the FAST key- point detector and the BRIEF descriptor with additional orientation and scale invariance. While ORB may not achieve the same level of accuracy as advanced ML models, its low computational requirements make it a practical choice for edge computing applications.

Methodology

Description of the Algorithms Used

ORB (Oriented FAST and Rotated BRIEF)

ORB is an efficient alternative to the SIFT and SURF algorithms for feature detection and description. It combines the FAST keypoint detector and the BRIEF descriptor with enhancements to improve rotation invariance and robustness. ORB is known for its computational efficiency, making it suitable for real-time applications on resource-constrained devices. The key components of ORB include:

- FAST Keypoint Detector: Detects keypoints quickly by examining the pixel inten- sity around a candidate point.
- BRIEF Descriptor: Describes the detected keypoints by comparing the intensities of pairs of pixels within a patch around each keypoint.
- Orientation Compensation: Ensures that the descriptors are rotation-invariant by

FLANN-based Matcher

The Fast Library for Approximate Nearest Neighbors (FLANN) is used for feature matching. FLANN provides a robust and efficient way tofind the best matches between descriptors from different images. It uses randomized kd-trees and hierarchical clustering for approximate nearest neighbor searches, significantly speeding up the matching process compared to brute- force methods.

Implementation Details

The implementation involves several Python scripts that handle different aspects of the detection process. Each script is tailored to optimize the ORB-based detection for real-time performance on the Raspberry Pi.

- AdvanceRealTimeDetection.py: This script implements real-time object detection using ORB on live video feeds from a Raspberry Pi camera. The key functionalities include capturing live video feed using the PiCamera2 library, detecting and computing keypoints and descriptors using the ORB algorithm, matching features between the live feed and predefined template images using FLANN, and drawing bounding boxes around detected objects and displaying match information on the video feed.

- orb.py: This script provides a detailed implementation of the ORB feature detection and matching process, including performance visualization and real-time processing enhancements.

- RealTimeMatchingVisual.py: This script focuses on visualizing real-time matching of features detected using ORB, providing a visual confirmation of the detected objects and matched keypoints in the live feed.

- RealTimeObjectDetection.py: This script is designed for robust real-time object detection, including detailed logging and debugging information to optimize the detec- tion process.

- StaticImageFeatureComparison.py: This script compares features in static images using ORB, providing a baseline for understanding the performance and accuracy of the ORB algorithm in controlled conditions.

- test5.py: This script optimizes detection and matching parameters for robustness and accuracy, focusing on preprocessing steps and parameter tuning to improve the overall detection performance on the Raspberry Pi.

Experimental Setup

Hardware and Software

The experimental setup for this research includes the following hardware and software components:

- Hardware:
  - Raspberry Pi 5 with 8GB RAM.
  - Camera Module
  - MicroSD card (32GB) for Raspberry Pi OS.
  - Power supply for Raspberry Pi.
  - Monitor, keyboard, and mouse for setup and debugging.
- Software:
  - Raspberry Pi OS (Bookworm OS).
  - Python 3.7.x
  - OpenCV 4.5.1.
  - NumPy 1.19.5.
  - PiCamera library for camera interfacing.

Datasets

The datasets used for this research include:

- Training Dataset:A set of images captured using the PiCamera in various lighting conditions and backgrounds to create a robust template database.
- Testing Dataset:Real-time video feed from the PiCamera used to evaluate the performance of the object detection model.
- Template Images:Predefined images of objects of interest, such as different house- hold items, used for feature matching.

Results

Performance Metrics

The performance of the ORB-based object detection model was evaluated using the following metrics:

- Accuracy:The proportion of correctly identified objects to the total number of ob- jects.
- Processing Time:The average time taken to process each frame and perform object detection.
- Frame Rate:The number of frames processed per second (FPS).
- Resource Utilization:CPU and memory usage during the object detection process.

Observations

The following observations were made during the experiments:

- The ORB-based object detection model achieved real-time performance on the Rasp- berry Pi, with an average frame rate of 15 FPS.
- The accuracy of the model was found to be around 60% under various lighting condi- tions and backgrounds.
- The processing time per frame was approximately 66 milliseconds, indicating efficient performance for real-time applications.
- CPU utilization was moderate, averaging around 70%, while memory usage remained stable, indicating the model's suitability for resource-constrained environments.
- The model demonstrated robustness in detecting objects with varying orientations and scales, thanks to ORB's orientation and scale invariance features.

Discussion

Analysis of Results

The ORB-based object detection model demonstrated significant improvements in computational efficiency, making it suitable for real-time applications on resource-constrained devices like the Raspberry Pi. The model maintained an average frame rate of 15 FPS, which is sufficient for many practical applications. The accuracy of 85% across various conditions indicates that ORB is robust for detecting objects with varying orientations and scales. The moderate CPU and stable memory usage further confirm the model's efficiency and feasibility for deployment on edge devices.

Challenges and Limitations

Despite the success, several challenges and limitations were observed:

- Lighting Conditions: The model's accuracy can be affected by significant changes in lighting, which may require additional preprocessing steps to normalize the lighting conditions.
- Occlusions: Objects that are partially occluded can be challenging to detect accurately, leading to false negatives.
- Scale Variability: While ORB is robust to scale changes, extreme variations in object size can still pose a challenge.
- Computational Resources:Although the model is optimized for edge devices, fur- ther optimization could reduce CPU usage and improve battery life for mobile appli- cations.

Conclusion

Summary of Findings

This research successfully developed a lightweight object detection model using the ORB algorithm, tailored for edge devices like the Raspberry Pi. The model achieved real-time performance with an average frame rate of 15 FPS and an accuracy of 60%. The implementation demonstrated that ORB is a viable alternative to computationally intensive machine learning models for applications on resource-constrained devices.

Future Work

Future research could focus on:

- Improving Robustness: Enhancing the model's robustness to varying lighting conditions and occlusions through advanced preprocessing techniques.
- Integrating Machine Learning: Combining ORB with lightweight machine learning models to improve detection accuracy.
- Optimization: Further optimizing the code to reduce CPU usage and improve energy efficiency, making it more suitable for battery-powered applications.
- Testing with Diverse Datasets: Evaluating the model's performance with a wider range of objects and environments to ensure generalizability.

References

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