



QUANTIFICATION OF LANDSIDE CONGESTION IN PORTS: AN ANALYSIS BASED ON GPS DATA

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ABSTRACT

Hinterland transport is a critical segment in maritime cross-border logistics, which links the end-users of global supply chains to the maritime segment. Truck-based hinterland transport is known to cause congestion in and around ports. This study aimed to quantify the congestion caused by trucks at the Port of Colombo, which has not been a subject of a systematic study. To this end, the study makes use of GPS data. In addition to revealing heavy congestion within the port, the study also reveals significant variations in congestion during different times of the day with the duration of journeys peaking from 1200hrs to 1800hrs. Furthermore, the most congested segment of the truck journey is found to be the port exit gate. The findings provide a foundation for appraising infrastructure investments and other related improvement initiatives for easing congestion within and in the vicinity of the port. The study illustrates the potential for data to reveal insights that transcend its original purpose. From a theoretical point of view, the study proposes a novel way of conceptualising the truck turnaround time at ports which goes beyond the confines of the port and is more meaningful for users in the hinterland. The analysis presented in the study is limited to data obtained from a single haulage company.

Keywords: Cross-border logistics, port congestion, hinterland transport, GPS data, data mining, Port of Colombo

1. INTRODUCTION

Maritime cross-border logistics (CBL) networks play a prominent role in the growth and sustenance of value chains spanning the globe. While containerisation has brought significant efficiencies to these networks by lowering shipping costs [1], the swift and even flow of cargo through the border faces a multitude of challenges. The congestion created by trucks which serve shippers and consignees in the hinterland is one of the prominent problems.

As the interface between the ocean segment and land segment of the cargo flow, ports are critical infrastructure facilities in CBL. For a seaport to act as an effective node in the network, both the seaside and the land side need to operate at optimal performance [2]. On the land side of the port, hinterland transport is a critical link in CBL connecting the shippers and consignees to seaports. Trucks, trains, and barges on their own or as a combination are the transportation modes used in the hinterland. The choice of hinterland transport mode is determined by the layout of seaports and dry ports, availability of transportation networks, preference of forwarders, shippers and consignees [3] as well as the geography of the area. However, trucks remain the most commonly used transport mode due to their ability to use existing infrastructure [4].

While the vessel turnaround time is the key measure for the stakeholders on the seaside, The Truck Turnaround Time (TTT) can be seen as the analogous measure on the landside [5]. TTT is the total time spent by a truck inside the terminal area which includes arrival, inspection, documentation, unloading, and loading until the exit of the truck from the terminal. Due to the increase in the usage of trucks driven by large trade volumes, there is a need to develop a deeper understanding of the dynamics and impact of truck congestion on CBL performance.

Port of Colombo is a rapidly growing maritime hub in the South Asian region. Cargo originating from and destined for numerous ports all over the world are conveniently and efficiently transhipped through the Port of Colombo [6]. The strategic location makes the Port of Colombo a prominent port in the Indian Ocean and ranks at 25th place in the world in terms of the number of Twenty-foot Equivalent Units (TEU) handled [7].

Despite its advantages due to position and capacity, Sri Lanka has fared poorly in logistics performance as indicated by the Logistics Performance Index (LPI), published by the World Bank, ranking at the 73rd place in 2023 [8]. Even though substantial investments in logistics infrastructure and some policy changes were implemented over the last decade, the ranking suggests many areas demand improvements. The relative ease and efficiency with which goods can be moved

into and inside a country is one of the dimensions of LPI. Therefore, longer lead times and associated costs caused by road congestion could be major factors leading to the poor rank in LPI [9]. However, a quantification or an impact analysis of such congestion within or in the vicinity of the Port of Colombo is not available.

A number of haulage companies serving the port of Colombo have deployed GPS trackers to keep the customers informed of the pickup or drop-off time of cargo and to ensure that the drivers use optimal routes without taking unauthorized detours or stops. While the primary purpose of the GPS trackers is well served, the data generated by these trackers also allows for other analysis that promises deeper insights into truck movements. Knowledge discovery, through data mining, entails “non-trivial extraction of implicit, previously unknown and potentially useful information from data” [10, p. 2]. As such, this paper proposes to use data mining to extract novel insights about truck congestion within the port by re-purposing the data collected by GPS trackers. The study is designed to determine the most congested segments in the truck journey within and in the vicinity of the port and to determine the distribution of congestion during different times of the day.

The next section of the paper explores the extant literature related to hinterland transport, truck congestion and data mining techniques used in logistics. The methodology section that follows details the approach adopted in acquiring, and analysing the data. The results section tabulates the outcomes of the analysis followed by the discussion section where the implications are discussed. Finally, the conclusions and future research directions are presented.

2. LITERATURE REVIEW

This section begins with literature pertaining to hinterland transportation and problems posed by the congestion of trucks and the associated solutions. The literature revealing the critical role played by tracking and tracing in logistics and leveraging data generated from those technologies is explored next.

Transportation by barges is popular in some European ports such as Antwerp where rivers are readily accessible from the port [4]. In the USA, trains with double-stacked containers have proven successful [11]. While trains are often touted as the solution to road congestion, assembling space for long trains, manoeuvring within existing tracks, unloading infrastructure at stations, and competing for tracks with passenger trains have been noted as problems associated with rail transportation of containers [12]. While railways and barges

need dedicated infrastructure, trucks can use the existing road networks subject to load limitations. Therefore, despite road transport being significantly impacted by traffic conditions, fuel costs and environmental issues [13] truck-based transportation of containers remains the most popular mode of transport in the hinterland [4]. Excessive congestion of trucks inside the port, high truck TTT, and deficiencies at service points within the port are significant problems in CBL [14], [15].

The problems related to congestion and pollution generated by trucks due to a lack of coordination among stakeholders have been highlighted by Islam et. al. [16]. The study also alludes to the potential of truck appointment systems to reduce congestion and waiting times through the allocation of time slots to trucks by illustrating the reduction of TTT from 4 hours to 25 minutes at the case study port. The study points to the significant waste from trucks travelling to/from ports without carrying a container due to a lack of coordination among shippers and consignees, which accrues costs to all stakeholders. The study proposes a conceptual model where truck space is shared among users albeit without delving into the details of implementation. Despite the adoption of truck appointment systems in different ports as a solution to congestion, the success has not always been uniform [17].

The coordination problems in the hinterland transport chain attributable to a lack of incentives, opportunistic behaviour, and information asymmetry have been captured by Van der Host and de Langen [18]. The study notes the peak demand periods at container terminals are not only caused by the operating hours of end users and truck operators but also by vessels with increasingly large capacity, exchanging a significantly higher number of containers during port calls. The scholars suggest the introduction of incentives, the creation of interfirm alliances and collective action as solutions to the persistent problems. The authors affirm the compelling need for solutions given that hinterland transport costs tend to be higher than maritime transportation despite the latter being over significantly longer distances. Furthermore, the authors posit that inefficiencies in hinterland transportation could be a potential cause for this paradox, which increases port congestion, ship turnaround times, and congestion around the gates.

The study on landside transportation at Australian ports by Lubulwa et. al.[19] discuss congestion by trucks is not confined to the port but to the neighbouring metropolitan area as well. The study notes that providing preferential treatment to trucks carrying containers in both directions during port visits has helped to reduce the congestion at some Australian ports. The authors recommend implementing the practice of charging higher rates for visiting the port during

peak demand periods to shift the volumes to non-peak periods to reduce congestion which has been successful elsewhere. For example, in California, container terminals have been fined for truck queuing times in excess of 30 minutes while some other US ports charge a peak time fee [20]

With the advent of Industry 4.0 data-driven tools and approaches have made a significant impact on port operations [21]. The practice of extracting insights from operational data assists in reducing uncertainties and helps to identify and understand causes of inefficiencies, disruptions, and anomalies in intra and inter-organizational operations of ports [22]. Data mining [23], [24] and other statistical data analysis approaches [25], [26] have become more popular in the logistics sector since these techniques provide insightful results with a high level of accuracy.

GPS is widely used for tracking and tracing purposes and predicting traffic congestion on road networks [23], [27], [28]. GPS can also be used to provide insights into performance metrics such as travel time delays, and unauthorized stops [28], [29]. Tools like GIS (Geographical Information Systems), AI (Artificial Intelligence) and machine learning algorithms have been used to analyse GPS data. When the source data contains more attributes, more insightful information can be obtained regarding the transportation conditions in the considered geographical area [30].

Bartholdi et. al. presented a conceptual proposal to use GPS data from devices mounted on trucks to study their movements inside a container terminal [31]. The scholars have discussed the challenges pertaining to matching the GPS data to locations on maps and determining the service locations. The study also identified the advantages of the method such as being non-intrusive to operations and not utilising resources within the terminal. However, the study has not demonstrated the practicality of the proposal through actual data collection and analysis.

Greaves & Figliozzi [32] have created an algorithm to extract truck travel information in urban Melbourne from passive GPS data using a rules-based algorithm. The authors were able to estimate the average truck stops per truck, the speed and the distance travelled each day leading to insights regarding the origin-destination patterns. Kinjarapu [33] has used an improved algorithm to identify the truck stops using passive GPS data which uses both the average speed from the previous point and the speed to the next point to detect a stop.

While there are studies that leverage other technologies such as RFID [34] and image processing [35] to analyse truck movements in CBL networks, such technologies require equipment to be installed within the facilities for capturing

the movement of trucks. Such installations can be expensive, and the data generated would be limited to the positioning of the reading stations. Comparatively, GPS data hold the advantage of only requiring the installation of equipment on trucks. Furthermore, the continuous data stream provided by GPS also enables analysis at high levels of granularity without additional investments.

This section has captured both the significance and the problems associated with truck-based hinterland logistics networks based on the relevant literature. Truck congestion is a significant issue that impacts CBL networks. Driven by the need for supply chain visibility, tracking and tracing of cargo in CBL has been gaining traction. The availability of such a stream of continuous data presents novel analysis opportunities. However, studies that make use of available GPS data to analyze the congestion in the vicinity of port premises are not prevalent. The authors were able to locate only one study [36] reporting on the TTT at the Port of Colombo; this revealed a significant research gap. As such, this research is aimed at investigating the existence of congestion at the port of Colombo and quantifying such congestion using GPS data. The study also aims to find any variations in congestion during different times of the day.

3. METHODOLOGY

This section explains the overall research design and methods used in gathering empirical data and the subsequent analysis. The overall methodology followed is outlined in Figure 1.

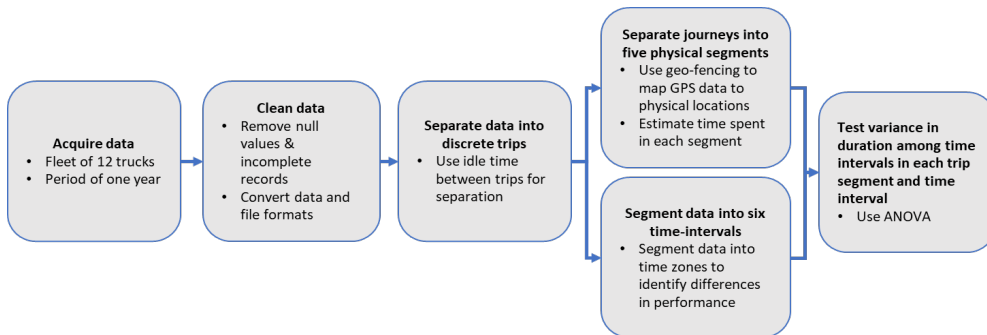


Figure 1: Overview of Methodology

Passive GPS data for a fleet of trucks hauling cargo to and from the Port of Colombo for a period of one year was obtained from a prominent freight forwarding company. To ensure privacy and confidentiality the data was truncated at a designated perimeter of the port to conceal sensitive information pertaining to the location of customers. The data comprised over one million records of time, coordinates, and point speed. A single record of data as received is shown in Table 1.

Table 1: Example of a record in the acquired data

| Time (Timestamp) | Coordinates (Float) | Speed (String) |
|---------------------|---------------------|----------------|
| 2022-05-27 20:43:16 | 6.951132, 79.874023 | 6 km/h |

As the first step, the GPS data were cleaned and pre-processed by converting to appropriate data structures and file formats to prepare them for analysis. Next, a suite of algorithms was developed using Python programming language to identify the discrete trips for each truck and their direction of travel. This involved computing the time between two consecutive GPS recordings where intervals of more than three hours were used for separation. Next, the attributes for each discrete trip (trip_ID, start_date_and_time, end_date_and_time, terminal, total_trip_duration etc.) were extracted from the data. Following that, trips were further segmented into physical blocks to identify the temporal performance within each of those segments. The data was also partitioned into groups based on the time of the day as well. Finally, a statistical analysis was carried out to check the variability of the trip duration with respect to the time of the day with the ANOVA (Analysis of Variance) test in R Studio.

3.1. Identifying corresponding GPS data in segments of interest

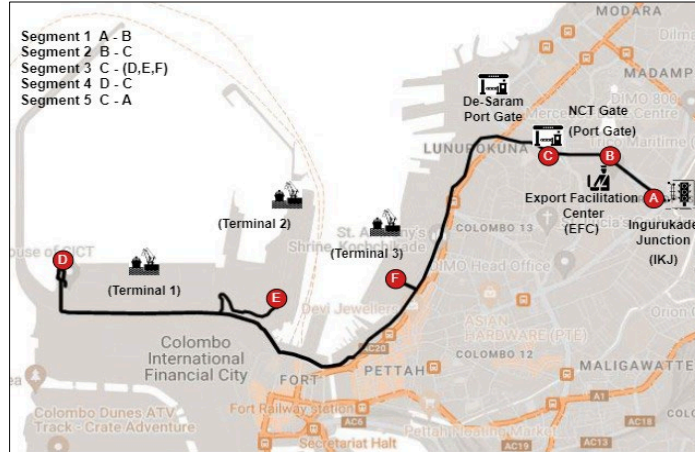


Figure 2: Layout of Facilities at the Port (base map from Google Maps)

The boundary considered for the study started at the beginning of the port access road (A in Figure 2) and extended up to the three operational container terminals in the port. Point B in the map represents the Export Facilitation Centre (EFC) where export containers are processed. The services provided at EFC include documentary and physical clearance by customs and quarantine agencies, verification of payments of port and terminal charges, verification of container weight and fumigation. Thereafter trucks proceed to the port gate (point C) where clearances are verified once again for

export containers and a check is performed if the container is within the cargo acceptance window of the corresponding vessel. The empty trucks entering the port to pick up import containers skip the EFC but the permit to pick an import container is checked at the port gate. Thereafter the containers go to one of the three terminals designated by D, E and F.

The truck route in Figure 1 was subdivided into physical segments so that the sources of bottlenecks, if any, along the path could be identified. Segments for export trips were identified as, segment 1 (A to B), Export Facilitation Center (at B), segment 2 (B to C), and segment 3 (C to D, E and F) whereas segments for import trips are segment 4 (D, E and F to C), segment 5 (C to A).

A geofencing approach was used to link the GPS coordinates to the road segment. Points of interest were first identified along the truck route using Google Maps and a geo-fence or a perimeter (50m-100m) was introduced considering the coordinates of GPS pings around the location. Thereafter the data files were scanned sequentially to observe whether the truck passed through the point of interest. Haversine formula (Formula 2) was used to calculate the distance between two GPS coordinates. The travel time between two points of interest was calculated using the 2 tuples that included the coordinates with the least distances between them.

$$Distance = \varphi \times R \text{ ----- Formula 1}$$

Where,

$$\varphi = 2 \times \arcsin \left(\sqrt{\sin^2 \left(\frac{\delta_1}{2} \right) + \cos(\text{radian}(\text{lat}_1)) \times \cos(\text{radian}(\text{lat}_2)) \times \sin^2 \left(\frac{\delta_2}{2} \right)} \right) \text{ ----- Formula 2}$$

R : average radius of earth

Coordinates of point 1: $(\text{lat}_1, \text{lon}_1)$

Coordinates of point 2: $(\text{lat}_2, \text{lon}_2)$

$\delta_2 = \text{radian}(\text{lon}_2) - \text{radian}(\text{lon}_1)$

$\delta_1 = \text{radian}(\text{lat}_2) - \text{radian}(\text{lat}_1)$

3.2. Classification of trips to time of the day

In order to determine if there is a significant difference in the travel time between segments during different periods of the day, the day was segmented into six time intervals based on the frequency distribution of trips. As depicted in Figure 3 the data indicated that number of the trips increased after midday. Therefore, the first half of

the day was divided into two intervals whereas the second half of the day was divided into four intervals (0000-0600hrs, 0600-1200hrs, 1200-1500hrs, 1500-1800hrs, 1800-2100hrs, and 2100-0000hrs). A time interval was assigned to a trip according to the start time of the trip. For example, if the trip started at 06.30 AM then the trip was classified into 0600hrs – 1200hrs time interval. The start times of all the trips were scanned and classified using a Python script.

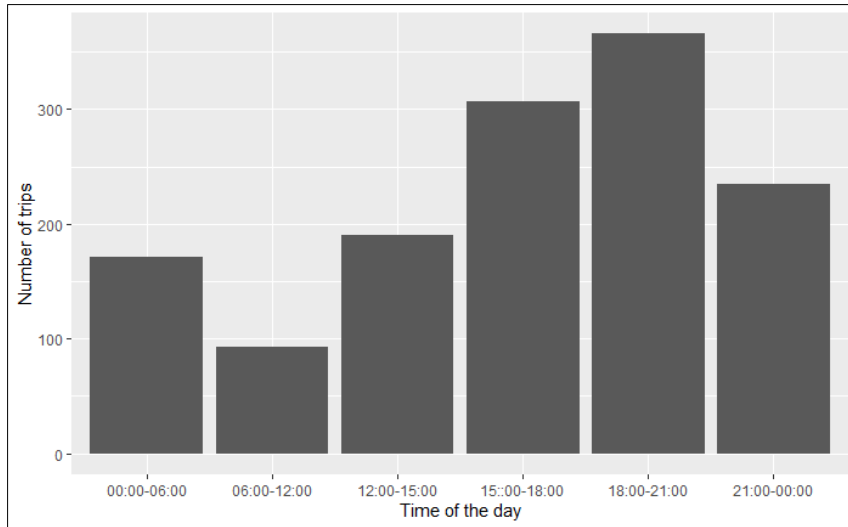


Figure 3: Frequency distribution of the number of trips in each time interval

3.3. ANOVA Test

The collected raw data contained only the timestamp, GPS coordinates and, point speed. From the processed data, the time spent by a truck within different road segments on the route was calculated. Since the focus of the study was to identify congestion in route segments, one-way ANOVA was selected to compare the mean travel time between segments. Time of the day was selected as the independent variable and time taken on a particular road segment was selected as the dependent variable. Even though the data was spread over one-year, seasonal variations within the period were not considered as sufficient data points were not available as the data emerged from a single haulage company.

The hypothesis for ANOVA is stated below.

H₀: Travel times have no significant difference in the same segment

H₁: Travel times have a significant difference in the same segment

ANOVA tests were conducted at a 0.05 significance level (α). The ANOVA test can be described as follows:

$$y_{ij} = \mu + \tau_i + \varepsilon_{ij} \text{-----Formula 3}$$

Where;

i : the time interval

j : a discrete trip within the time interval “ i ”

y_{ij} : Observed time for trip “ j ” in the time interval “ i ”

μ : Grand mean of time duration within the segment

τ_i : Deviation of the mean in each time interval from the grand mean

ε_{ij} : Residuals

4. DATA ANALYSIS AND RESULTS

4.1. Analysis of export trips

Frequency distributions in Figure 4 depicts the spread of durations within each segment of the inward path.

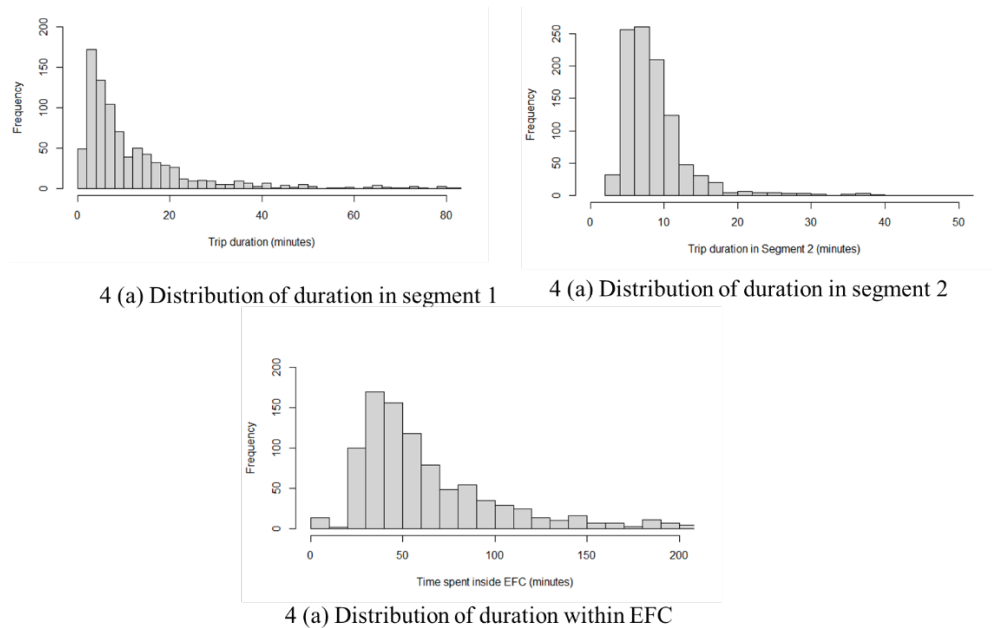


Figure 4: Distribution of duration in segments in the inward journey

Table 2: Time Spent on Different Segments in Export Trips

| Time of the day | Mean time spent in the segment (minutes) | | |
|----------------------------|--|------------|--------------|
| | In Segment 1 | Inside EFC | In Segment 2 |
| 0000hrs - 0600hrs | 20.0 | 67.0 | 8.7 |
| 0600hrs - 1200hrs | 30.5 | 79.9 | 9.6 |
| 1200hrs - 1500hrs | 41.6 | 75.0 | 10.6 |
| 1500hrs - 1800hrs | 30.5 | 92.1 | 8.9 |
| 1800hrs - 2100hrs | 15.2 | 80.6 | 9.1 |
| 2100hrs - 2400hrs | 14.6 | 61.1 | 12.2 |
| Statistically Significant? | Yes | No | No |

Table 2 shows the mean time spent on different segments during export trips. The time variation within segment 1 (a distance of 430m) is statistically significant with a p-value of 2.01×10^{-7} where the speed of the trucks varies from 0.6 km/h to 1.8 km/h a very low speed showing congestion. This variation is graphically shown in Figure 5, where the travel duration peaks from 1200 hrs to 1500 hrs.

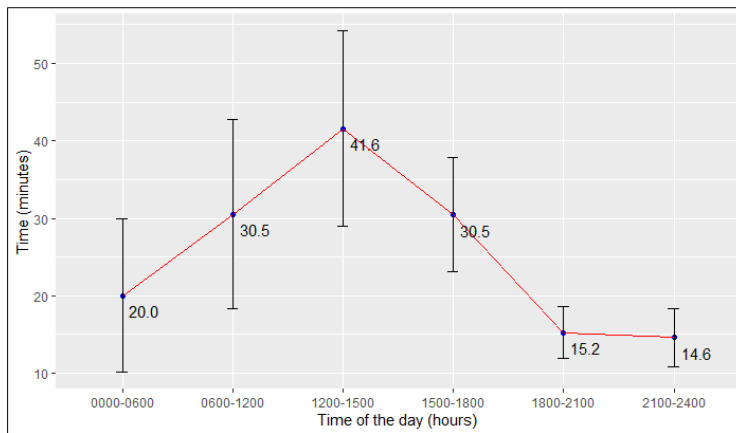


Figure 5: Distribution of Time in Segment 1 of Export Trips

The trucks spent about 1 hour across all time intervals inside the EFC without any statistically significant difference across time intervals. Similarly, the duration spent in segment 2 (a distance of 580m) is not statistically significant, but the speed is slow – this varied between 2.3 and 3.3 km/h.

4.2. Analysis of time spent inside the terminal

According to the ANOVA results, the time spent by trucks inside the three terminals had no significant difference with respect to the time of the day. However, the time spent inside a terminal considering each terminal is statistically significant. The

longest time was spent within terminal 3 which was 45 minutes and the shortest time was within terminal 2 amounting to 20 minutes.

4.3. Analysis of the outwards journeys

Frequency distributions in Figure 6 depict the spread of data points within each segment of the inward path.

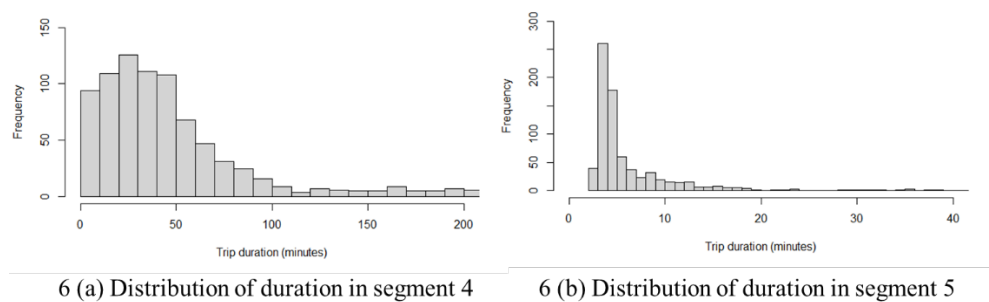


Figure 6: Distribution of data in segments in the outward journey

Table 3 shows the mean time spent in different segments of the outward journey by trucks. Given the accuracy of GPS coordinates inside the terminals, it was not possible to differentiate trucks leaving the port after dropping off containers and trucks carrying an import container, and the data comprises both categories of trucks. Furthermore, since only the trucks exiting terminal 1 had a sufficient number of trips to produce statistically significant results, only those trips were considered in the analysis for segment 4.

Table 3: Time Spent on Different Segments on the Outward Journey

| Time of the day | Mean time spent in the segment (minutes) | |
|----------------------------|--|--------------|
| | In Segment 4 | In Segment 5 |
| 0000hrs - 0600hrs | 48.56 | 18.20 |
| 0600hrs - 1200hrs | 59.35 | 22.61 |
| 1200hrs - 1500hrs | 65.82 | 26.63 |
| 1500hrs - 1800hrs | 85.15 | 25.35 |
| 1800hrs - 2100hrs | 58.11 | 21.51 |
| 2100hrs - 2400hrs | 55.12 | 19.91 |
| Statistically Significant? | Yes | No |

The mean time spent by trucks to travel from terminal 1 to the port gate in the outward journey is statistically significant with a p-value of 0.0031 which peaks in the time interval from 1500hrs to 1800hrs. The distribution pertaining to these trucks is tabulated in Figure 7. The average speed varies from 4.1km/h to 7.2km/h in the road segment 4 and 3.1 km/h to 4.6 km/h in the road segment 5.

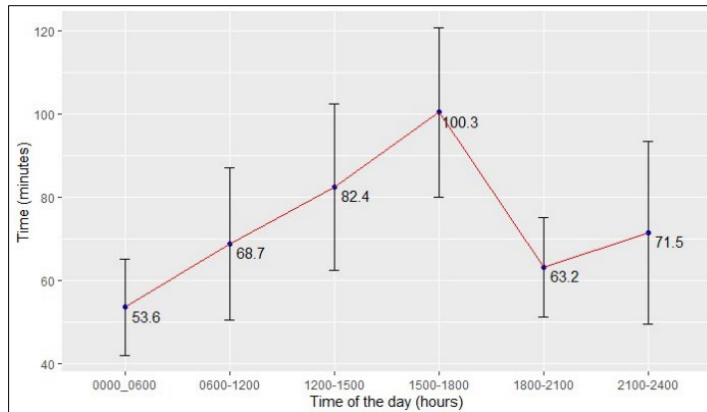


Figure 7: Time for Travelling from Terminal 1 to Port Gate

The statistical analysis reveals that there are significant variations in travel times of trucks depending on the time of day along the port entry road (segment 1) and in exiting the port (segment 4). Most trucks enter the port between 1200hrs to 1800hrs. The paper-based clearances for import cargo, which are usually performed during the morning office hours can be seen as the driver for the rush of trucks entering the port in the afternoon. Similarly, container stuffing operations in the morning can be seen as the reason causing export trucks to arrive at the port in the afternoon. Encouraging the execution of documentary clearances and container stuffing operations on the previous day or during non-office hours can be envisaged as a solution to this problem. However, such practices would require the cooperation of a multitude of other stakeholders who may not see the benefits of changing their work patterns.

The speed of trucks shows severe congestion in some segments of the truck journey considered in the study. For example, export trucks take around 42 minutes to travel 430 meters between 1200 hrs and 1500 hrs to enter the EFC, the first point of processing. A plausible cause is that export cargo destined for all three terminals must pass through a single EFC gate. While the processing time within the EFC is consistent at around 76 minutes from entry to exit, it represents a significant duration. There is the potential for some of the document processing activities taking place within EFC such as the payment verifications to be moved online to further reduce the processing time.

5. DISCUSSION

This section contains a discussion of the results of the study in comparison with the literature.

The results of the study show severe congestion within the port of Colombo. During peak hours, when the port facilities become extremely busy, the trucks spend significant time queueing. Haulage companies face minimal utilization of trucks, high fuel consumption, and additional payments to truck crews due to these problems. Furthermore, traffic congestion and environmental pollution are concerns for residents and other road users. Satisfying the food and sanitation requirements of truck crews who remain inside trucks for long periods of time poses another challenge. Driver fatigue from waiting could also be a concern for road safety. The cascading effects include the lost productivity for businesses that require high-performing cross-border logistics systems.

The results of this study provide a compelling case for investing in systems to organize the movement of trucks in a more systematic manner. The study by Rathnayake et. al. [36] also found excessive TTT at the port of Colombo using a survey and recommended establishing an inland port to alleviate the congestion. However, an investment in an inland port can be substantial and would also require associated investments in railways for effective connections [37]. Solutions with lower investments from other locations include charging peak usage fees, implementing smart gates at the port and adopting truck appointment systems [18], [19]. Considering the limitations of available funds, it is advisable to explore lower-cost solutions before investing in dry ports. A more focused study is required to determine which of these solutions would be most suitable at the Port of Colombo. While acceptable solutions are rolled out, haulage companies could attempt to make use of the non-peak hours to visit the port.

The study also reveals limitations of the frequently adopted measure of TTT [36], [38]. It may be a sufficient measure for terminal performance, especially in situations where the terminal gate and the port gate are the same. However, at the Port of Colombo, terminal gates and port gates are distinct with a considerable distance between them. As such, a meaningful TTT, from the point of view of haulage companies, should consider the time trucks spend waiting to enter the port until it gets back on the public road system.

Only one gate is available for entry and exit at the port for trucks from all three terminals, albeit with multiple lanes, creating a bottleneck. As such, in addition to the time spent within the terminal, trucks spend significant time entering and exiting the port which is non-value-added time. Therefore, possible improvements to the layout of the port need to be considered. Making use of more port gates for trucks closer to the terminal gates could be such a solution.

Studies on emerging tracking and tracing technologies in logistics are sometimes confined to conceptual ideas on how to leverage technology [31]. However, the

current study goes beyond the conceptual phase to a technology demonstration phase. It has been observed by scholars [31], that using technologies such as GPS, RFID or images captured by cameras provides the ability to collect and analyse operational data without using additional operational resources or interfering in operations. Such non-intrusive methods, as demonstrated in the current study, are highly effective in detecting issues in operations and conceptualising solutions.

It is possible to gain valuable insights from data mining that goes beyond the original purpose of generating the data. While owners of the data tend to safeguard the generated data, often with well-justified reasons, such data has the potential to reveal valuable insights especially when combined with similar data from other stakeholders. However, since these insights may assist competitors and other stakeholders the motivation to share even truncated data remains low. Therefore, accessing such data remains a significant challenge for analysts and academics in the field. Insights generated from available data sources are an important source of insights, especially in settings where investments to deploy more sophisticated systems are lagging.

This study was based on data obtained from a single haulage company which imposed limitations on the segments and intervals analysed. The truck usage patterns of a single organization could have also biased the analysis. Future studies could seek to obtain data from multiple entities to strengthen the analysis. Furthermore, the study is based solely on GPS data. If the data could be augmented with data pertaining to cargo types more revealing insights could be generated. For example, augmenting GPS data with contextual factors such as whether the journey is an import or export journey, and whether the container is full or empty can reveal more significant insights. Without such augmenting data, it was difficult to identify cases where trucks were dropping off and picking up containers in a single journey as the resolution of GPS data was not sufficient to differentiate between drop-off zones and pickup zones within a terminal. Future research can also be extended to study the congestion beyond the port, especially the cargo inspection centres which are located beyond the port perimeter.

6. CONCLUSIONS

This study focused on quantifying the land side congestion within a leading container port in South Asia using GPS data generated by devices mounted on trucks. While the port is a strategic hub port that has shown world-class performance on seaside operations, the land-side congestion was revealed to be severe. The study shows that the congestion within the port is excessive, especially during afternoon peak times as shown by very low travel speeds. The study also shows the congestion goes beyond

the perimeter of the port to the port access road as well. Congestion and the low speeds of haulage trucks could be significant contributors to Sri Lanka's poor performance in LPI.

The study revealed important insights that can guide improvements in landside operations at the port of Colombo. Significant gains in performance can be obtained by regulating the arrival pattern of trucks within the port. The current arrival pattern results in the under-utilization of trucks and overutilization of port infrastructure during peak hours. As such, rather than investing in expensive physical infrastructure, shifting the times of usage could be an effective first step. Implementing truck appointment systems and imposing peak usage charges are practices that have been implemented with success elsewhere. Until such systems are implemented the truck operators also have the option of switching to off-peak hours of operation albeit not without challenges.

The study also revealed limitations of truck turnaround time, usually measured at the terminal gate, which only captures the time a truck spends inside the port. At the Port of Colombo a truck spends significant time within the port but outside the terminal, as there are distinct gates at the perimeters of terminals and at the perimeter of the port. Currently, trucks exiting from all three terminals must exit the port through a single gate creating a bottleneck. As such, there are opportunities to improve the flow of traffic through additional port gates.

This study demonstrates how insights can be gained from analysing data that has been generated for a different purpose. While such data by themselves hold little value, when analysed with a proper context and purpose they can generate new knowledge. While a single stream of data can still reveal significant findings, much richer findings are obtained when data is combined from multiple sources. However, accessing comprehensive data from stakeholders engaged in CBL operations remains a significant challenge for analysts and academics in the field.

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