An envisaged electric rail and electric road transport system for deep sea intermodal container freight in Qatar: An assessment of the freight volume potential capacity and impact on vehicular emissions

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INTRODUCTION

Qatar’s growth in international trade has surpassed expectations in the past few decades, achieving an impressive average annual GDP growth of 8.2% in the last 20 years [31].

However, this success has drawbacks. Emissions from their primary freight transport system, diesel trucks, are projected to rise due to increased freight transport, and the country is currently the leading emitter of carbon dioxide per capita [29]. One cause for this is that Qatar typically imports second-hand trucks from Western countries, which have higher emissions due to truck degradation over time. With the background of a global climate emergency, there is pressure for every country to reduce its carbon emission from transport. Moreover, studies have shown that high diesel emissions can lead to adverse health effects such as increased levels of asthma and cardiovascular diseases [30]. This presents the challenge of balancing economic growth while being environmentally sustainable.

Qatar handles an average of 1693 Twenty-foot Equivalent Units (TEU) daily through its ports – Port Hamad and Port Al Ruwais (Appendix 1). With expected economic growth, Qatar's trade volumes are expected to increase, leading to more TEUs entering its ports. Therefore, finding a solution to expand Qatar’s container-handling capacity in an environmentally responsible manner is critical.

Rail Growth Ltd. has proposed a solution to tackle both challenges by incorporating its Short Distance Rail Freight (SDRF) technology into Qatar's logistics system. These electric freight trains are designed with shorter lengths, which reduces loading time and allows for more frequent dispatches to various destinations. This report evaluates the effectiveness of SDRF in increasing freight capacity and reducing emissions.

Due to the lack of emissions data in Qatar, this report relies heavily on simulations. Our model establishes a railway network that connects the country via simulated dry ports (modest-sized inland rail terminals), which serve as hubs where warehouses are likely to cluster. As such, they are located close to existing and future warehouses. In this envisioned model, the trains will pass through these dry ports, and load/offload containers, which will then be transported to their respective warehouses by trucks.

This model is based on robust assumptions and calculations which have been verified by industry experts such as Dr. David Cohen, head of the Centre for Sustainable Road Freight at the University of Cambridge, and Lars Martensson, director of environment and innovation at Volvo. We also received valuable data from reputable sources like Helen Kneebone, Senior Commercial Attache of British Embassy of Qatar.

This report is divided into three sections. In the first section, we have simulated and estimated the diesel truck endpoint locations (warehouses), emissions and freight container capacities before implementing SDRF. The second section will consist of our proposed rail infrastructure – including the simulation of dry ports and mapping of the railway network. Lastly, we will recalculate emissions and improvements in container capacity on the proposed SDRF network.

METHODOLOGY

Section 1: Simulating Qatar’s current situation

1.1 Simulation of Average Warehouse Locations

Containers are moved between seaports and industrial warehouses using trucks. Therefore, knowing the warehouse locations is important as the distance between seaports and these warehouses impacts the calculations for container capacity and emissions. However, we do not have access to warehouse location data in Qatar.

To simulate Average Warehouse Locations (AWLs) and average demand in each region, we considered the most industrially dense areas, using simulated features such as population density, traffic, and environmental conditions.

Using multi-dimensional clustering analysis, we identified optimal locations and industrial demand. This approach is beneficial because, although we lack exact warehouse locations, determining AWLs based on clusters of warehouses allows us to calculate an average distance for trucks travelling to a central AWL. This approximation helps estimate both container capacity and emissions.

Data Preprocessing

Data Collection

We obtained population density data for different Zones on the official Qatar website [2]. In Qatar, zones are assigned numerically based on their geographical location and administrative divisions. They serve as subdivisions within municipalities. In total, Qatar is divided into 91 zones [2]. We used these zones to calculate the industry score.

Data Generation

Warehouse distribution is influenced by various factors including population, traffic, industrial activity, and environment. However, the only official data available is population density. To compensate, we simulated these features based on data from official websites.

In future versions of this project, preliminary data can be replaced by official data from Qatari authorities to improve the validity of the outcomes.

In Qatar, freight trucks can only travel on main roads. Due to these requirements, it is essential that warehouses are strategically located near these roads. Based on the transportation distribution (Figure 1), we set up a "Main Road" feature to score the traffic situation in each zone.

Table 1: Traffic score

Score	Description
0	No main road
1	One main road
2	More

Figure 1: Transportation Distribution [3]

Leveraging Qatar's unique geography, some areas are not suitable for industry. The eastern coastal areas, particularly around Doha, have high population densities exceeding 10,000 people/km^2, while the western and southern regions are sparsely populated. AWLs will represent industrial areas while balancing between minimising disruption in dense areas, addressing labour shortages in sparse regions and considering nature-protected areas. To address these complexities, we introduced the "Special Area" feature to evaluate zones, ensuring sites meet socio-environmental criteria.

Table 2: Special Area Score

Score	**Description**
0	• Large nature-protected area, OR • Population density > 10,000, OR • Population density = 0
1	Medium nature-protected area
2	Small nature-protected area
3	Normal zone

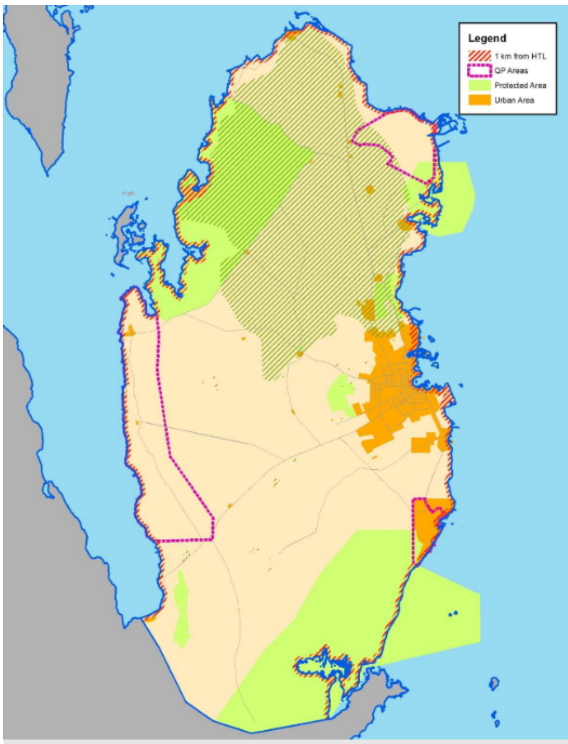

Figure 2: Nature-protected Area Distribution [4]

Due to limited data, we devised an industry score for each zone based on population distribution, traffic, and environmental factors. "Main Road" and "Special Area" are discretely scored, while population density, being continuous and skewed, poses a challenge. To address the influence of extreme values, we utilised quartiles alongside a population density heat map. Values that were exceptionally high or low were assigned a score of zero. High values typically signify urban areas less suitable for warehouses, while low values often indicate uninhabitable regions like deserts. Denser zones were assigned lower scores accordingly.

Table 3: Population Density score

Score	**Description**
0	• > 7359 (Q3) OR • < 73 (Q1)
1	5000 ~ 7359
2	2000 ~ 5000
3	1000 ~ 2000
4	73 ~ 1000

Industrial distribution significantly influences AWLs. We computed each zone's industry score through traffic, special areas, and population. We assigned weights: “Main Road” score 40%, Population Density score 30%, “Special Area” score 30%. However, a population density or special area score of 0 indicates unsuitability for industrial development, resulting in a 0-industry score.

We intended to also add features for geographical coordinates of each zone. However, the absence of a map outlining the zones prevented us from utilising specific location data. This limitation hinders our ability to cluster geographically adjacent zones, but we made the best use of the available resources.

Data Visualisation

We created a heat map across municipalities to see how these simulated features interacted. As shown in Figure 3, regions with small populations and no special area tend to have better traffic and higher industry scores. Umm Slal and Al Daayen (two municipalities of Qatar) perform best and can be focused on in subsequent analysis.

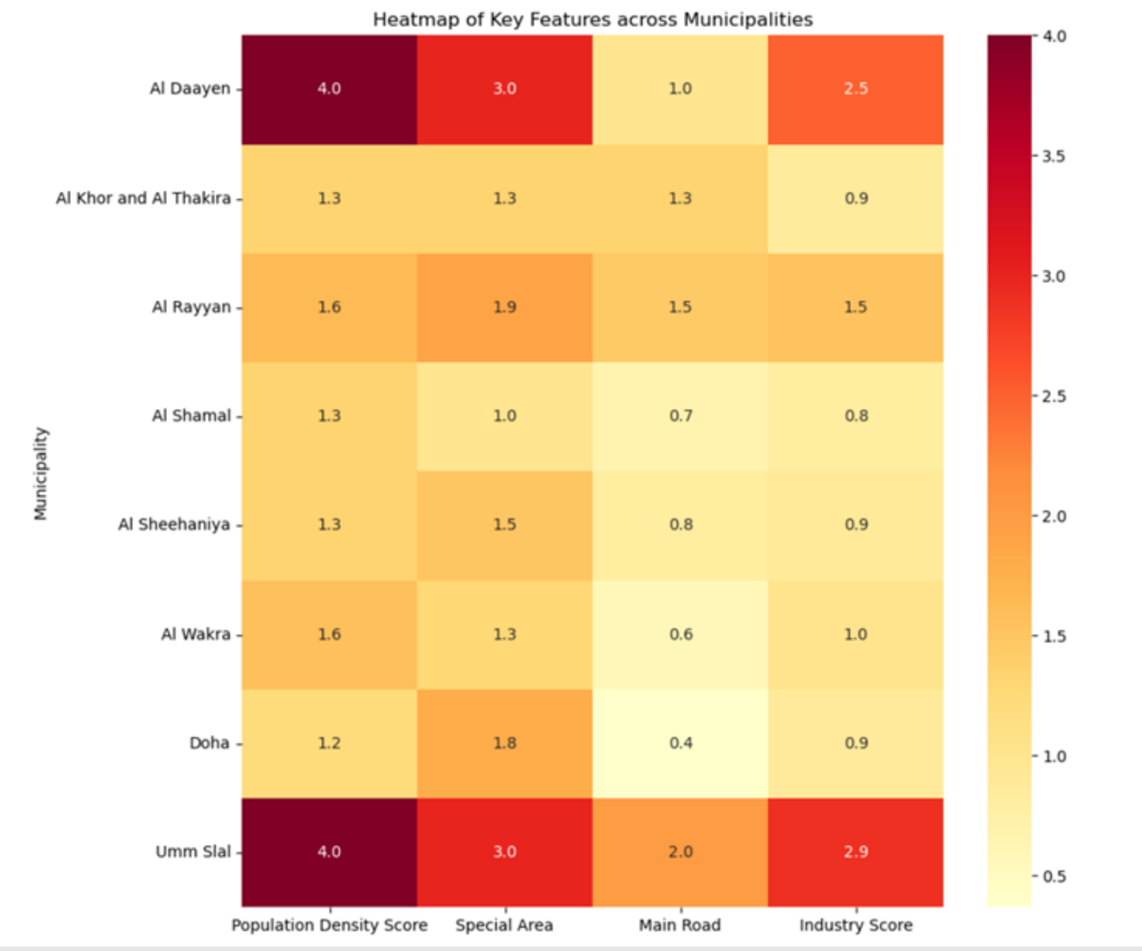

Figure 3: Heatmap across Municipalities

To simulate optimal AWLs, we analysed key features: "Population Density," "Special Area," "Main Road," and "Industry Score," plotting their squared distributions.

The population density shows an extremely skewed distribution, and most zones have extremely low population density. To maintain the original data distribution without impacting unsupervised classification, we used the "MinMaxScaler" from Python's sklearn library.

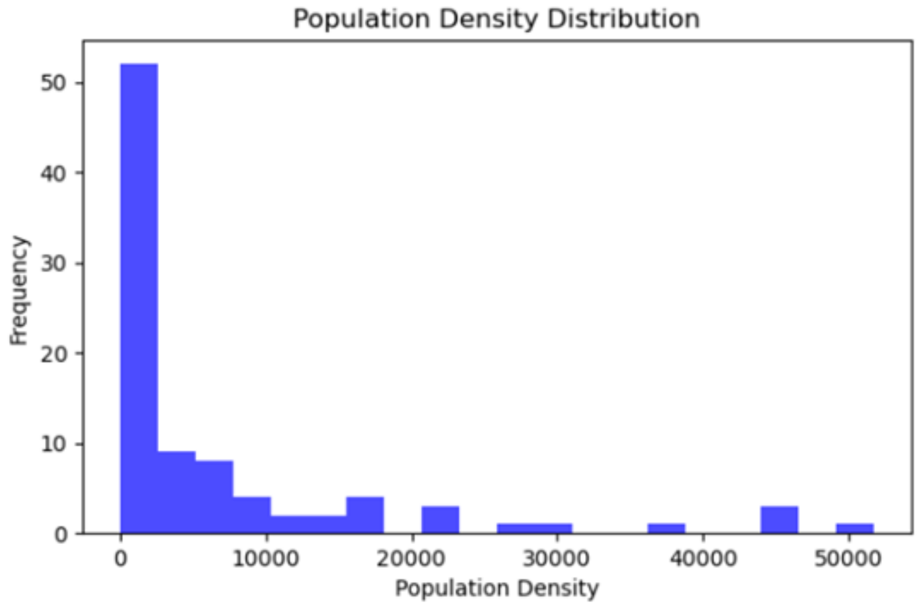

Figure 3: Population Density Distribution

Some zones may lack large main roads for trucks to travel through, making them unsuitable for establishing industry warehouses. However, Qatar's small size means that even if a zone doesn't contain main roads, the locations close to the edge of the zones might still be close to roads in neighbouring zones. This suggests that industrial warehouses could potentially be situated in these areas. Therefore, further analysis is required to account for these locations.

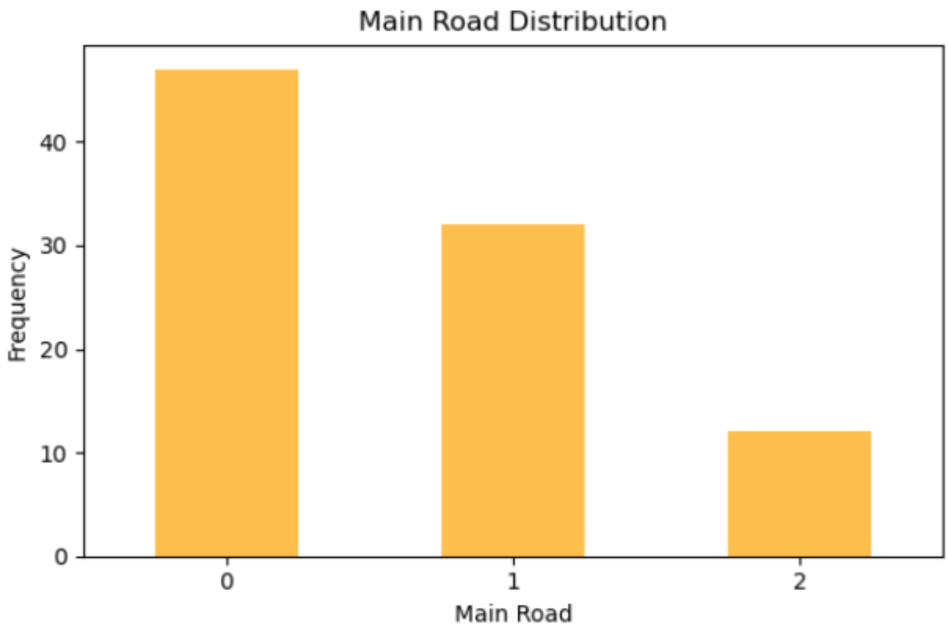

Figure 5: Main Road Distribution

Most of the zones are normal, with no nature-protected areas and normal population density.

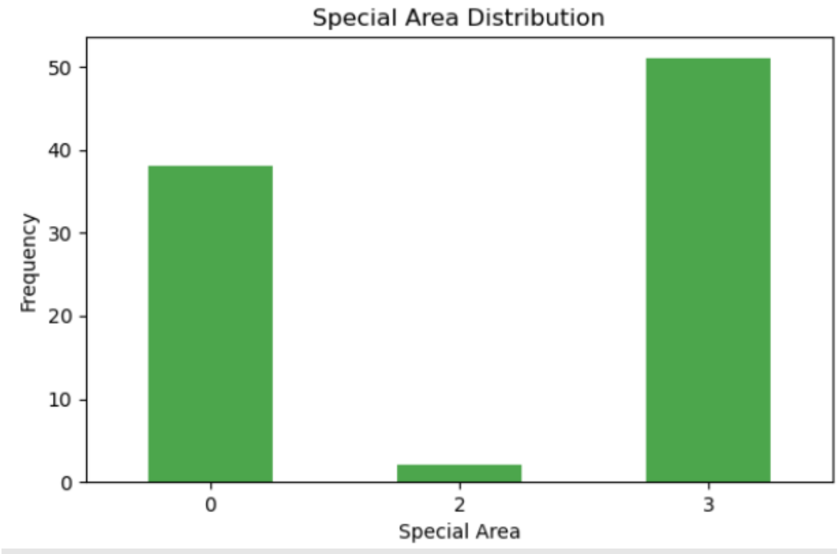

Figure 4: Special Area Distribution

Figure 7 shows that 45 zones have a 0 industry score due to either extremely high/low population density or large areas of the nature-protected area within the zone. We removed zones with 0 industry score before clustering to improve accuracy.

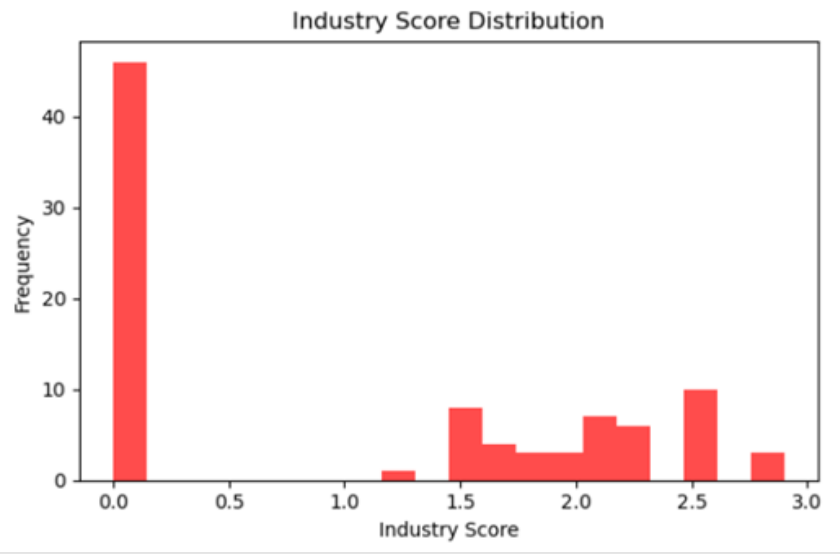

Figure 5: Industry Score Distribution

Clustering Analysis

In our project, we employed multiple rounds of K-means clustering to determine the most suitable AWLs. This technique demonstrated excellent performance in handling multidimensional data, effectively addressing various factors such as population, industry, and transportation. Additionally, each cluster exhibits similar characteristics, making it easy to interpret, and enabling us to select suitable locations based on clustering results.

We plotted an elbow plot to select the optimal number of clusters, followed by K-means clustering. Subsequently, based on the actual situation of various zones in Qatar, we identified clusters of zones suitable for AWLs through clustering. We repeated these steps until the third iteration, ultimately confirming appropriate AWLs.

First Clustering

As shown in Figure 8, the elbow plot shows that the decline trend slows down significantly after k=3. Therefore, we utilised 3 clusters.

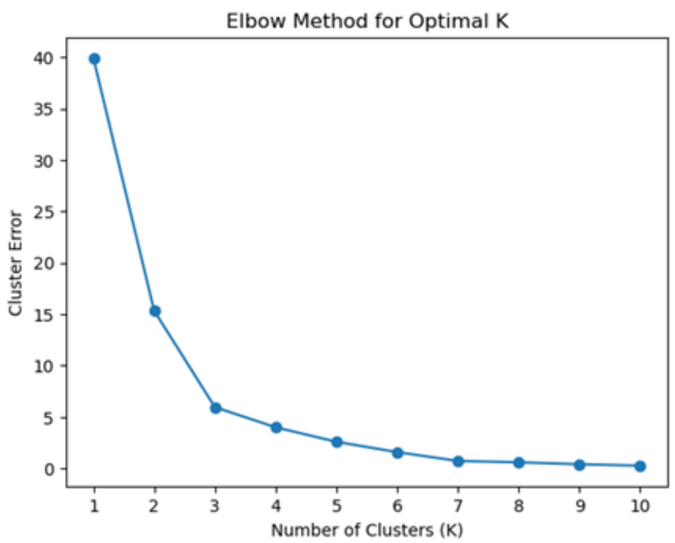

Figure 6: Elbow Plot of First Clustering

After clustering, we examined the features of the three clusters by plotting graphs and checking the map of Qatar. We discovered that Cluster 2 is located near the area with extremely high population density in Doha, and its small area makes it unsuitable for industrial activities.

However, Clusters 0 and 1 exhibit high industry scores, suitable population density, and convenient transportation. Consequently, we merged Clusters 0 and 1 and proceeded with the next round of clustering.

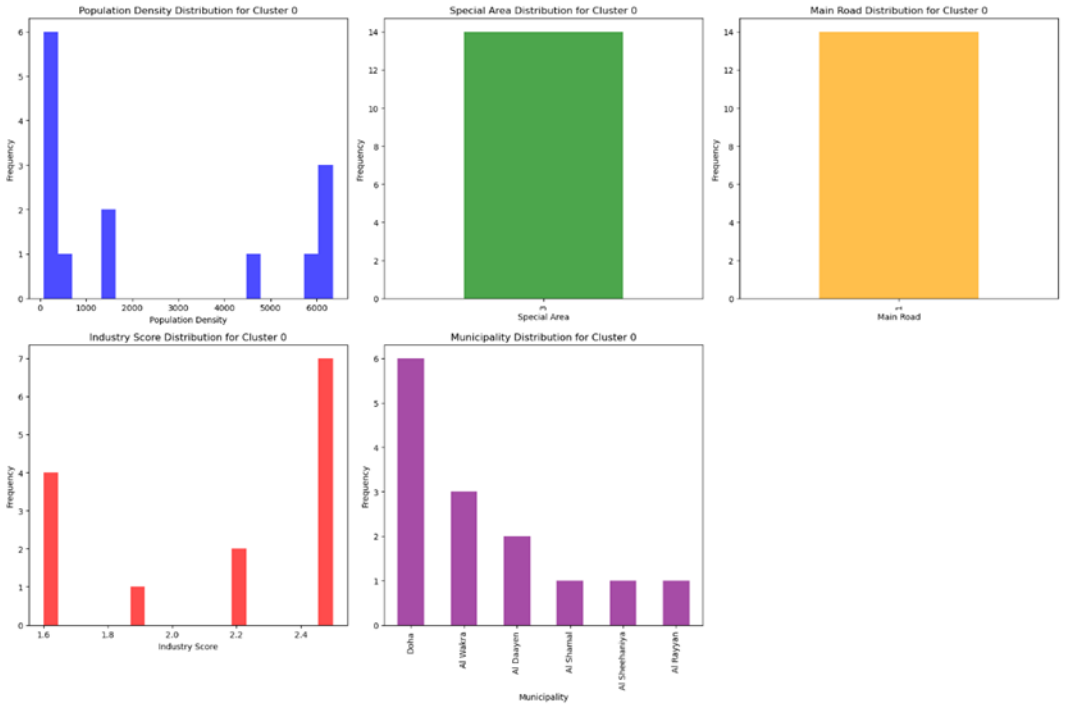

Figure 7: Result of Cluster 0

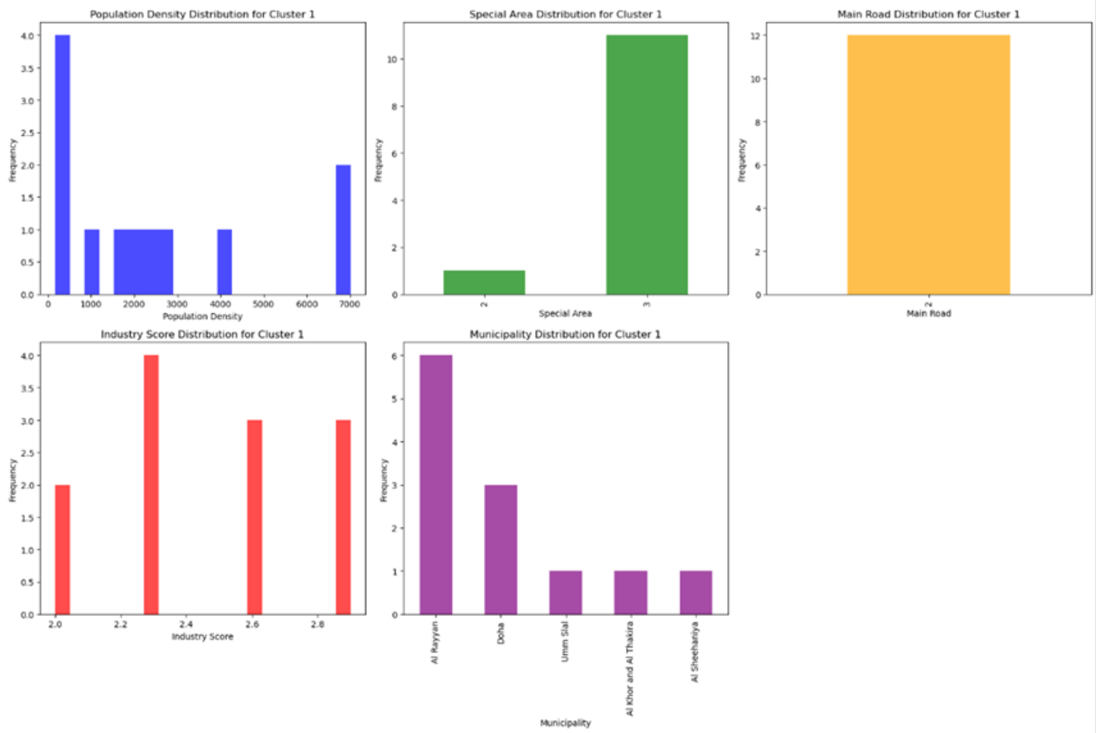

Figure 8: Result of Cluster 1

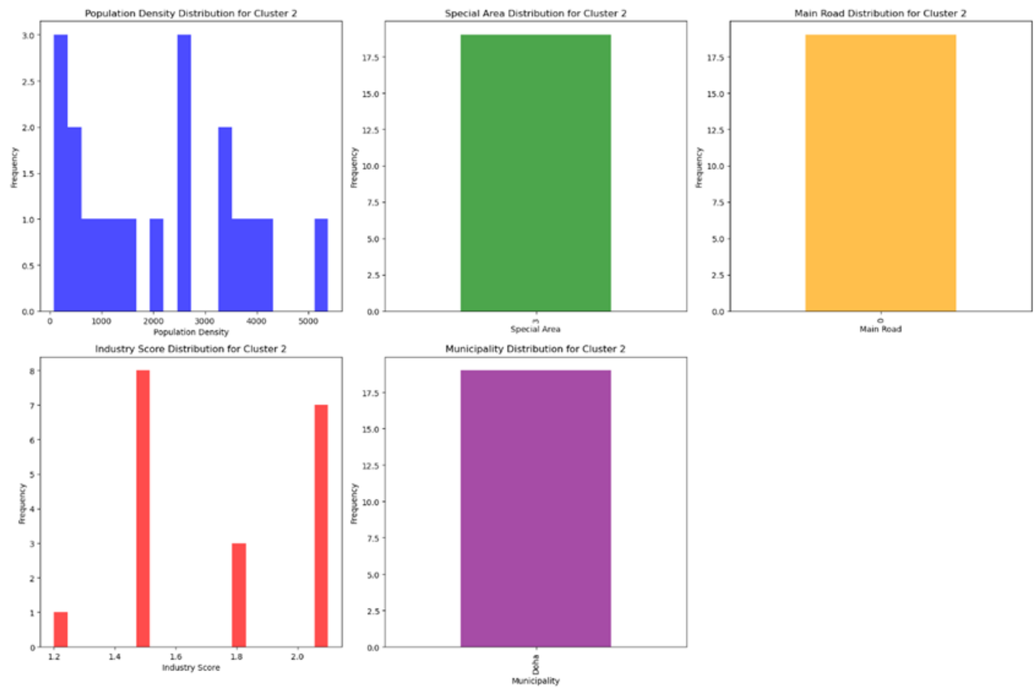

Figure 9: Result of Cluster 2

Second Clustering

After plotting the elbow plot, we opted for 3 clusters. The analysis revealed that Clusters 0 and 1 consisted of zones with appropriate population density, high industry scores, and convenient transportation. Conversely, Cluster 2 exhibited high population density and the lowest industry scores. Therefore, we excluded Cluster 2 and proceeded to merge Clusters 0 and 1 for further clustering with the total 14 zones.

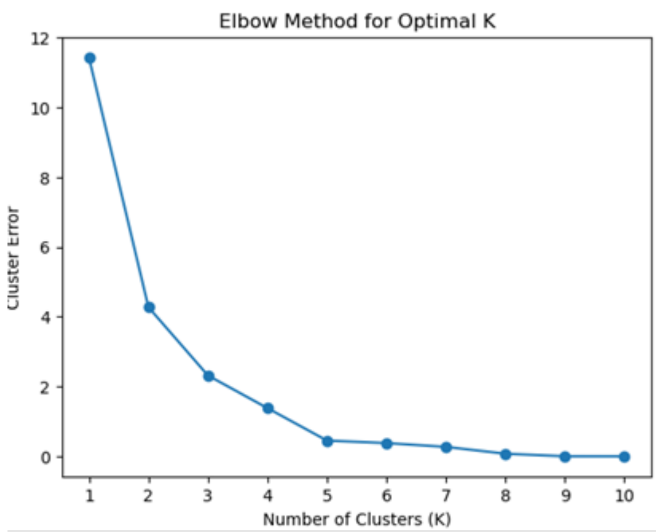

Figure 10: Elbow Plot of Second Clustering

Third Clustering

After plotting the elbow plot, we chose 2 clusters. However, the results were not satisfactory as both clusters contained areas suitable for industrial development. We therefore sorted the 14 zones based on their industry scores.

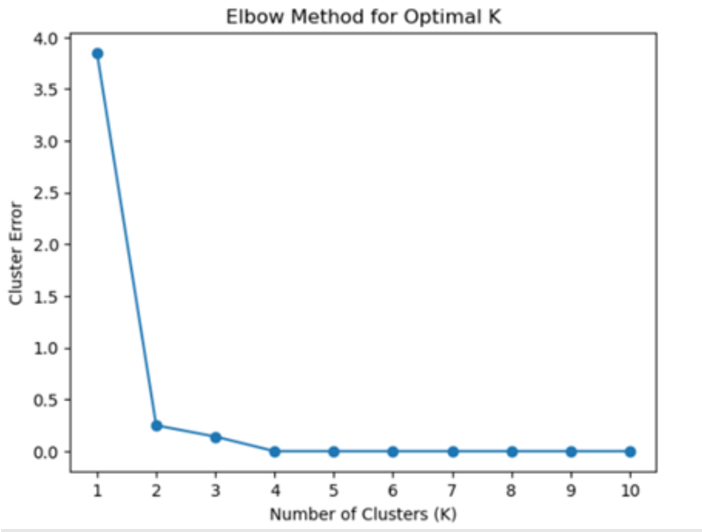

Figure 11*: Elbow Plow of Third Clustering*

	Zone No.	Industry Score	Municipality
45	50	2.9	Doha
65	71	2.9	Umm Slal
76	82	2.9	Al Sheehaniya
46	51	2.6	Al Rayyan
48	53	2.6	Al Rayyan
63	69	2.5	Al Daayen
64	70	2.5	Al Daayen
73	79	2.5	Al Shamal
74	80	2.5	Al Sheehaniya
75	81	2.5	Al Rayyan
82	91	2.5	Al Wakra
83	92	2.5	Al Wakra
24	29	2.2	Doha
81	90	2.2	Al Wakra

Figure 12*: Sorting Result*

After evaluating those 14 zones, we prioritised those with high industry scores and favourable traffic distribution. Selecting locations near main roads ensures comprehensive coverage across Qatar without concentration in specific areas. Given Doha's compact size and dense population, the industry demand is low. We selected the AWL location of the eastern region near Doha, rather than within the city itself. Additionally, due to the large nature reserves in the southeast region, industry in the south is concentrated around the Hamad Port. Hamad Port can be used directly as an AWL for the southeast region. Following this approach, our analysis led us to identify the following locations:

- 71: Covering northern region
- 82: Covering southwestern region and part of middle region
- 53: Covering eastern region
- 80: Covering north-western region and part of middle region
- Hamad Port: Covering south-eastern region

Given the persistent high population density in Zone 53, we concluded that the eastern AWL at the intersection of Zone 53 and Zone 80 would best serve our objectives.

Figure 13: AWLs Distribution

Calculating Industry Demand

Each AWL is responsible for a different region. We multiplied the industry score by the area within the responsible region to assign weights (representing industry demands). This approach helps prevent disproportionally low weight allocation in regions characterised by a small number of zones but large areas.

Industry demand refers to proportion of industrial goods needed within an AWL, which will serve as an important feature in calculating how many containers are allocated to these AWLs.

*Table 4:*1 *AWLs and Industry Demand Weight*

Point	Longitude	Latitude	Weight
point1	51.402961°E	25.549366°N	28%
point2	51.146825°E	25.417691°N	38%
point3	51.182531°E	25.130414°N	17%
point4	51.298972°E	25.359959°N	5%
Hamad Port	51.624497°E	25.029457°N	12%

1.2 Simulated Diesel Truck Network

TEU distribution to AWLs

Following the previous section, the AWLs that are simulated for the distribution of TEUs from Hamad and Al-Ruwais Port are used for this calculation. According to the Mwani Qatar Annual Report 2022, the nation handled 1,435,252 TEUs that year, of which 617,800 were imports and 432,280 were exports [5]. It's worth noting that the annual figure also accounted for Transhipment TEUs, which are not relevant to this project as they are not included in Qatar's emissions and are solely stored in the port before being transported to another destination.

The Doha port does not currently handle containers as it is only used for passenger service. It was therefore not considered in the computations. It might, however, also be viewed as a scalable choice if there are plans to increase the port's operations for foreign trade [6].

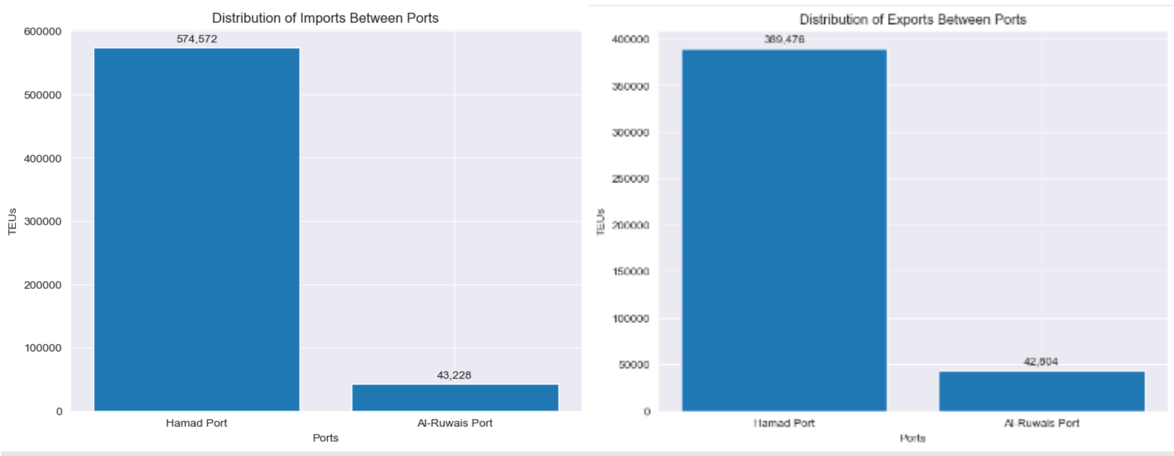

Figure 14: Distribution of TEUs for Imports and Exports

The TEU distribution among the ports of Hamad and Al-Ruwais is depicted in Figure 16 [5]. The amount of TEUs that must be supplied from each seaport and, conversely, the amount of TEUs that must be transported from each AWL back to the corresponding seaport were estimated using the weights assigned to each AWL. This arrangement of import and export for the corresponding AWLs is shown in Figures 17 and 18, respectively.

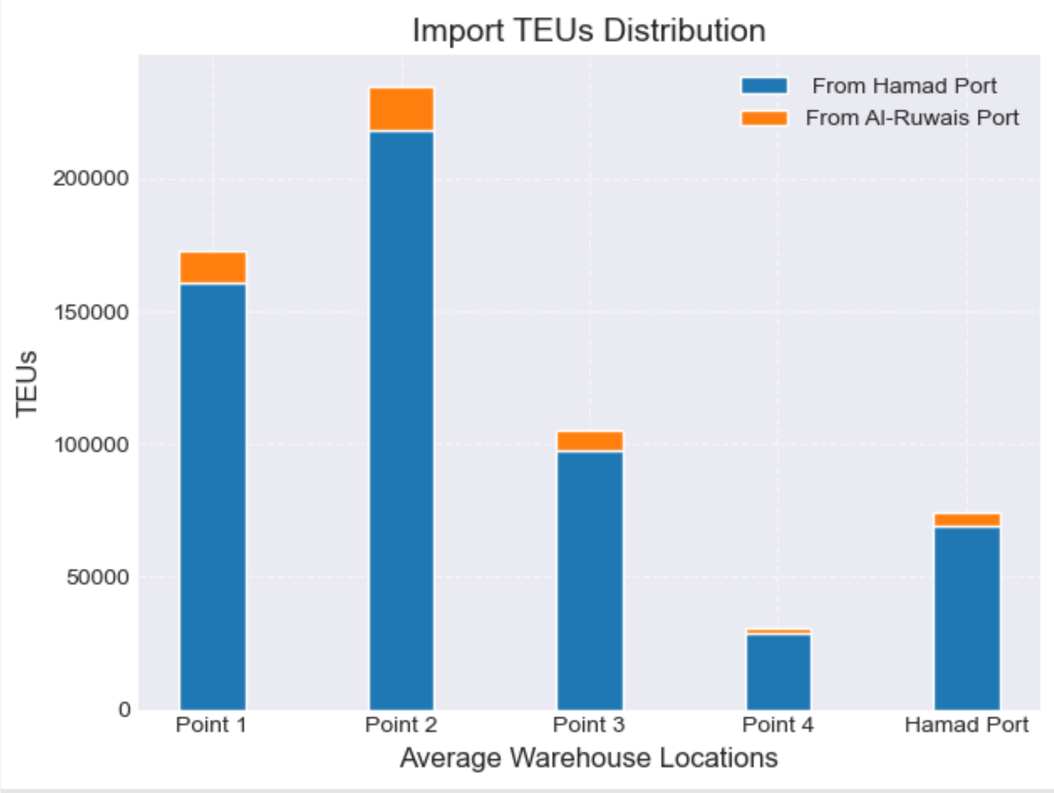

Figure 15: Import TEUs Distribution to AWLs

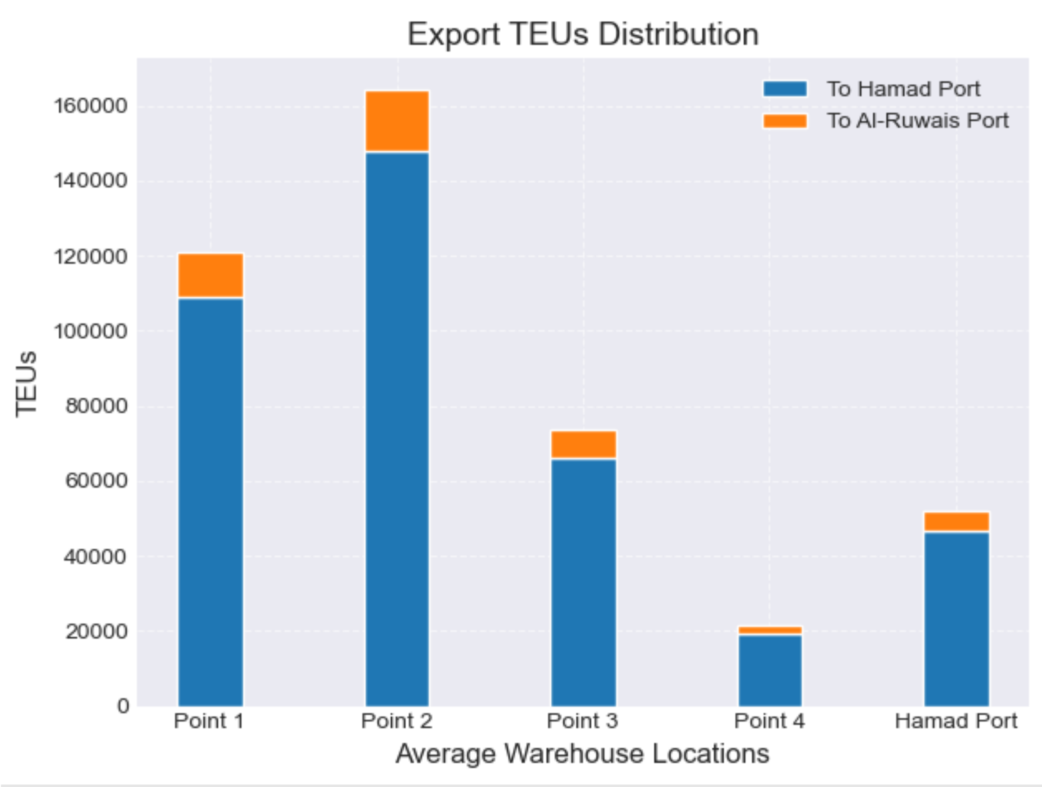

Figure 16: Export TEUs Distribution to AWLs

Each seaport's weight of the overall logistics is considered when determining the allocation of TEUs to be sent or received; for example, Hamad port and Al-Ruwais port account for roughly 93% and 7% of the volume of import TEUs, respectively. In the same way, 10% goes to Al-Ruwais port and 90% goes to Hamad for exports. As Hamad Port serves as an AWL for the nearby industries, the TEUs recorded for import and export distribution that originate at the port itself do not require relocation and do not contribute to additional transportation emissions. The Kingdom of Saudi Arabia (KSA) and Qatar's export and import through the GCC network are taken into separate consideration. The destination for import/export with KSA is the Hamad port. An examination of their total import/export figures for 2022 indicate that freight transportation between KSA and Qatar is expected to be very small with estimates for import and export being 3% and 2% respectively [28].

Simulated Diesel Truck Network

Figure 17: Simulated Diesel Truck Network

Utilising the import and export TEU distribution data from the previous section, a simulation of the truck route and number of trucks was created using data from official sources [5][7] and ArcGIS. This simulation operates on the premise that trucks typically return with containers from seaports to warehouses after delivering them. It specifically addresses two scenarios: import and export. This process ensures a thorough assessment of the truck route.

To produce quantitative data that allows for a direct comparison with a proposed rail network, all simulations are run over the course of one day. Assuming an average truck capacity of approximately 1.7 TEUs [28], the required number of trucks to meet the daily demand of each AWL is calculated using the methodology outlined below. An important performance metric derived from the simulation is the "Truck Trip Time" (TTT), which encompasses various elements crucial for efficient logistics operations.

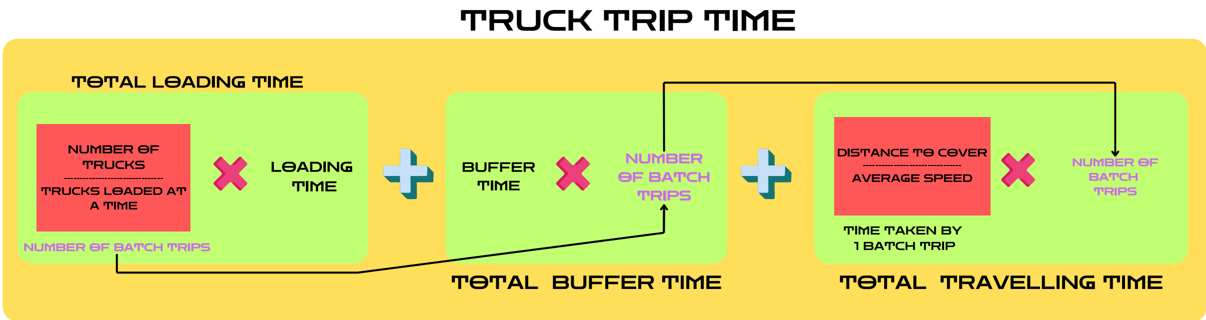

Figure 18: Formula to calculate Truck Trip Time

TTT includes the loading time, total buffer time relative to the number of batch trips being performed, and the overall journey time for all the batch trips necessary to meet the daily TEU figures of a particular AWL (Figure 20). The loading time is determined by the truck turnaround time, which refers to the duration from gate-in to gate-out for each individual seaport [5]. The number of trucks loaded during a single batch trip is determined by both the loading time and the proportion of each seaport's weight relative to the overall weight of trucks. The trucks' average speed is 46.5 km/h average speed of heavy-duty vehicles before, during, and after midday times [7]. Therefore, we assume the average speed of trucks to be 50 km/h to account for the increase in speed during peak hours.

To demonstrate this calculation, to move 441 TEUs from Hamad port to AWL 1, we will require roughly 259 (441/1.7) trucks. ArcGIS and Google Maps were used to compute the 105 km distance between these locations. The average speed is 50 km/h, the loading time for Hamad Port is 30 minutes, 50 trucks can be loaded in a single batch trip, and the buffer time is 10 minutes. Using the formula (Figure 20), the TTT between these locations is 14 hours 11 minutes.

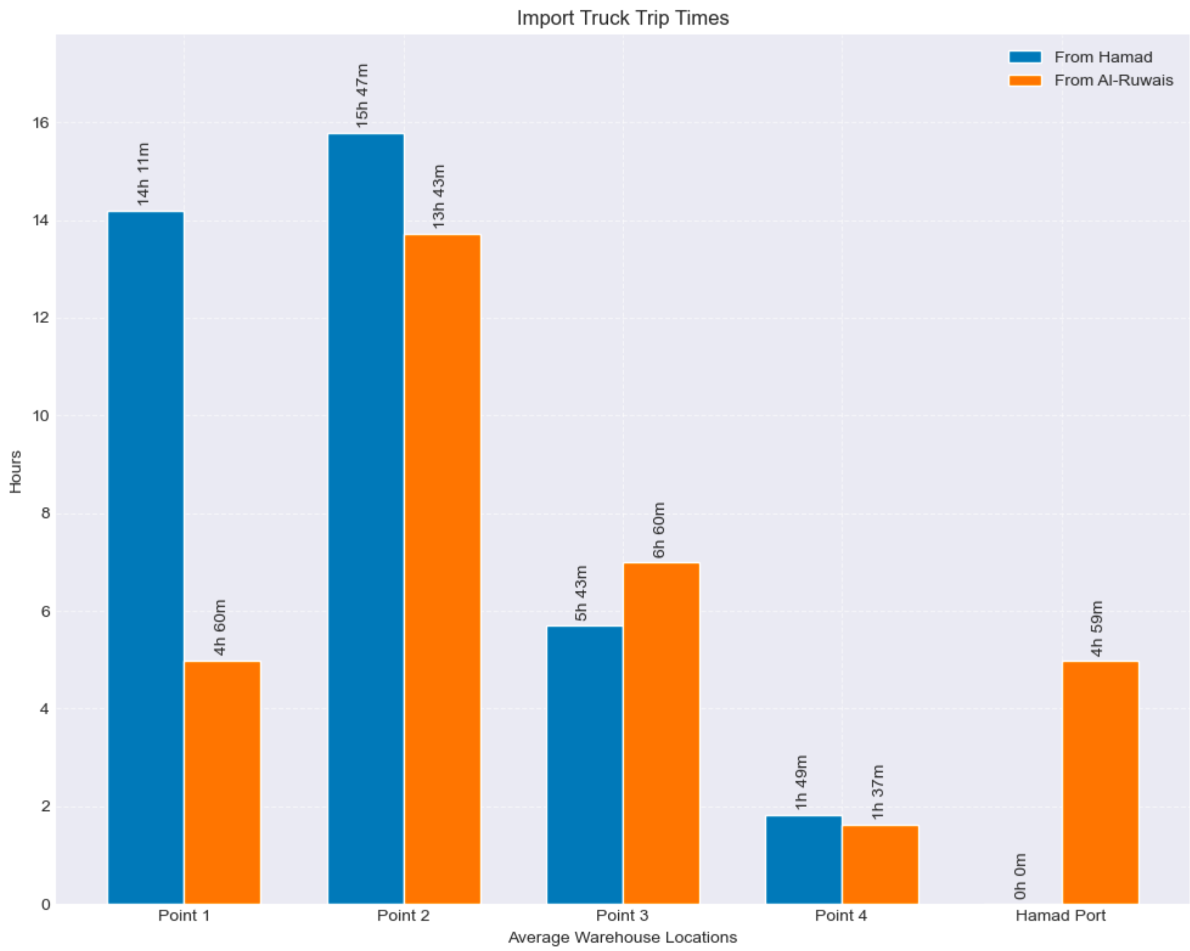

Figure 19: TTT for Import TEUs Distribution

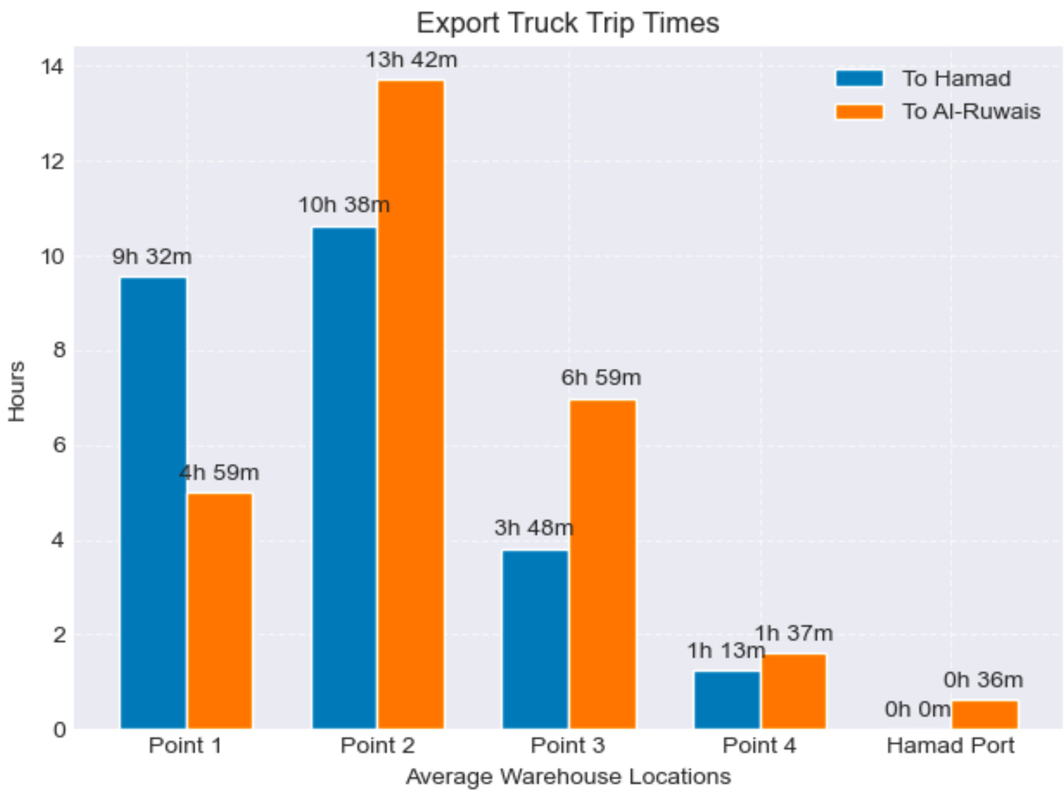

Figure 20: TTT for Export TEUs Distribution

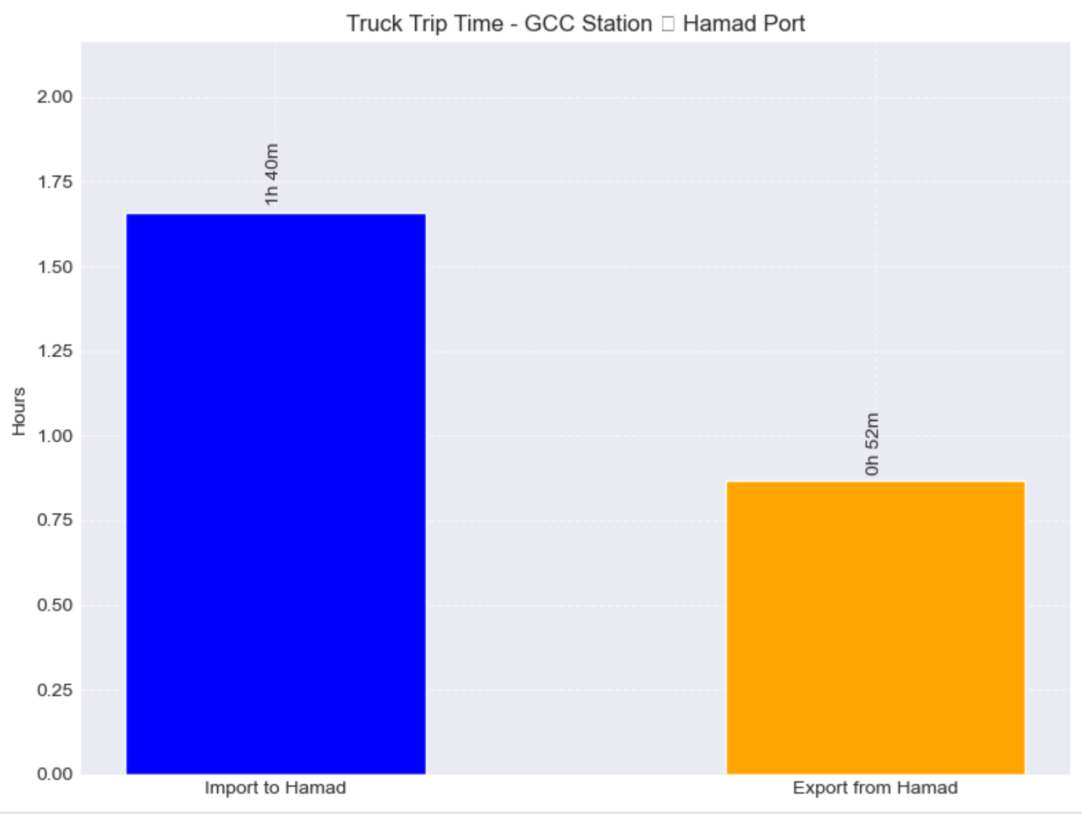

Figure 21: Import and Export TTT for KSA & Qatar trade

Using the above methodology, we computed TTT for all import and export journeys, including truck journeys between the KSA and Qatar. These are displayed in the figures above.

The entire loading process at Hamad Port, including buffer time, takes roughly 10 hours 46 minutes for imports and 7 hours 3 minutes for exports. It takes about 2 hours and 25 minutes for imports and 2 hours and 26 minutes for exports at the Al-Ruwais port.

To calculate truck emissions, we estimated the number of freight trucks in Qatar per day and have calculated a total of 914 trucks for import and 635 trucks for export. Assuming that imported trucks complete their route with a trip back to a seaport for export, we consider 914 trucks per day. There is a discrepancy between import and export number of trucks, however, for simplification purposes we will assume that some trucks may not be loaded during their journey back to the seaports and use 914 as the baseline truck journey value.

For gross error check purposes Peter Kelly confirmed this working looks in-line with what might be expected to be seen in other seaports around the world and industry observation.

Table 2: Import Average Distance

AVERAGE DISTANCE FOR 1 TRUCK (Including KSA trucks) (IMPORT)	
Total Distance Travelled Daily (km)	77251.77
Total Number of Trucks	914
Average Distance Travelled by 1 Truck (km)	84.51

Table 3: Export Average Distance

AVERAGE DISTANCE FOR 1 TRUCK (Including KSA trucks) (EXPORT)	
Total Distance Travelled (km)	54925.17
Total Number of Trucks	635
Average Distance Travelled by 1 Truck (km)	86.44

The average truck distance is then calculated by averaging the mean truck travel distances for import and export, which equates to 85.47km. The following section's emissions calculation will make use of the reported numbers in Tables 5 and 6.

1.3 Calculating truck emissions in Qatar

Basic overview of the calculation

A key justification for developing a rail freight system in Qatar is to reduce the country's overall emissions. This involves comparing current emissions with those projected for the rail system to determine if it significantly reduces environmental impact. In this section, we have estimated the daily total truck emissions for carbon monoxide (CO), nitrogen oxide (NOx), hydrocarbons (HC) and carbon dioxide (CO_2) in Qatar.

We first calculated the emissions generated by each truck per kilometre to estimate the overall emissions. To calculate the total emissions for all trucks in Qatar per kilometre, we multiplied this amount by the total number of trucks. To get the total truck emissions in Qatar, we further multiplied this value by the average distance driven by each vehicle. In the part before this one, the average distance and total number of trucks were computed.

Due to the lack of truck emission data, especially in Qatar, we mostly relied on simulation and assumptions for these computations. Nonetheless, we have obtained confirmation from experts in this domain, field such as Dr. David Cebon, the head of the Centre for Sustainable Road Freight, and Martensson Lars, the Director of Environment and Innovation at Volvo.

Calculating the emissions produced for each truck

Calculating CO, NOx, and HC

We calculate the emissions for each truck using their Emission Factor (EF). EFs are metrics used to estimate how much pollutants are released into the atmosphere. We utilised an official document from Volvo that describes the emissions for their trucks [1]. It outlines several key metrics including the expected fuel consumption of a truck, the typical EFs for new trucks measured in grams/litre and a methodology for converting EF from grams/litre to grams/ton-kilometre to reflect distance covered. The EFs vary based on different regulatory standards (Euro3, Euro4, Euro5, and Euro6), which set the maximum permissible emissions.

Additionally, we converted these values into grams/ton-km to account for total emissions based on distance and payload of a truck. For this estimation, we found the emission factor of a truck in grams per litre and converted it into grams per ton-km using the method shown in the datasheet shown below:

$$\textbf{EF (g/ton-km) = fuel consumption * EF (g/litre) / payload}$$

As we assumed that our trucks are semi-trailers, we assumed that the trucks have an average **payload** of 26 tons and a **fuel consumption** of 0.32 litres/km.

Table 7: 4 Volvo Fuel Consumption Chart [1]

Typical fuel consumption in litres per 100 km				
	Payload in tons	Total weight in tons	litres / 100 km empty*	litre / 100 km full load*
Truck, distribution traffic	8.5	14	20-25	25-30
Truck, regional traffic	14	24	25-30	30-40
Tractor and semi-trailer, long-haul traffic	26	40	21-26	29-35
Truck with trailer, long-haul traffic	40	60	27-32	43-53

As truck degradation has a substantial impact on a truck's EF, we also had to take this into account when calculating the emissions these trucks produced. A paper found that a truck's distance travelled was linearly correlated with the amount of pollution produced per kilometre [24].

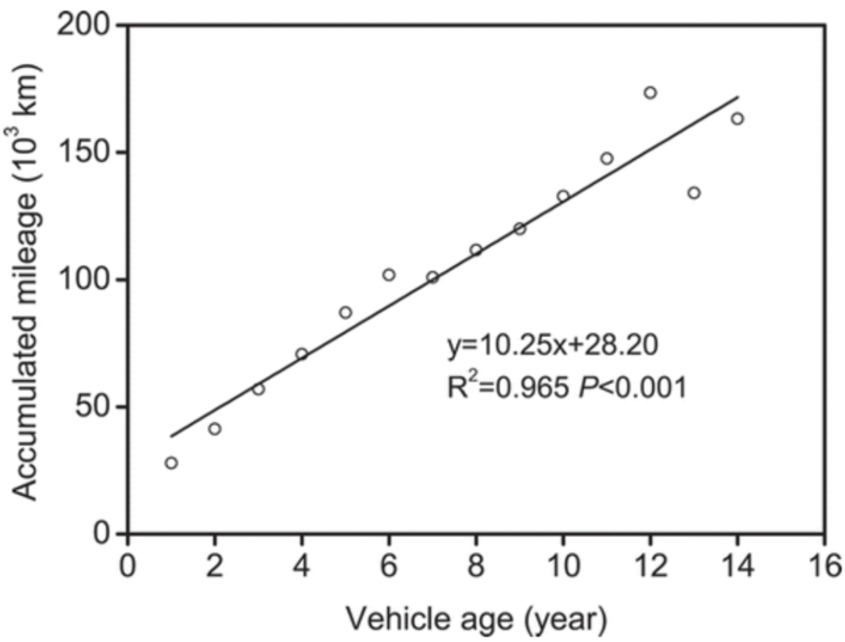

Figure 22: Age against Mileage Correlation Graph [24]

The study also established a linear correlation between the age of a truck and its mileage. By employing the function described in this paper, we can estimate truck emissions by first determining its age and using it to predict the mileage. Subsequently, this estimated mileage is input into another linear function that converts mileage into emissions, allowing for an estimation of the truck's EFs based on age.

One limitation that we have found was that the truck emissions for a truck at age 0 in the report were slightly different from the ones presented by Volvo's document. These might be due to a various number of reasons such as driving conditions and certification standards.

As the Volvo truck emission data was a reputable source based on standardised methods and test conditions, but we wanted a way to measure its degradation, we decided to use the linear regression function to compute an average annual percentage increase for truck's EFs and apply that percentage to Volvo trucks. We did this by finding the EFs of a 20-year-old truck and calculating the percentage increase per year using the formula below for each emission standard:

Annual EF percentage increase = [(X age EF – new truck EF) / new truck EF] / X age

This way, we have considered truck degradation and combined it with the reputable Volvo data. While this limitation might hinder the accuracy of our estimations, we believe that this is the most accurate way to calculate the emissions. By mapping the annual percentage increase in truck degradation onto Volvo's document, we can estimate a truck's emissions based on its age. The graphs below show these emissions, accounting for truck age. The EFs for Carbon Monoxide (CO) and Hydrocarbons (HC) are significantly higher for Euro3 standards [25], largely due to the significant advancements in regulations and technology in subsequent standards.

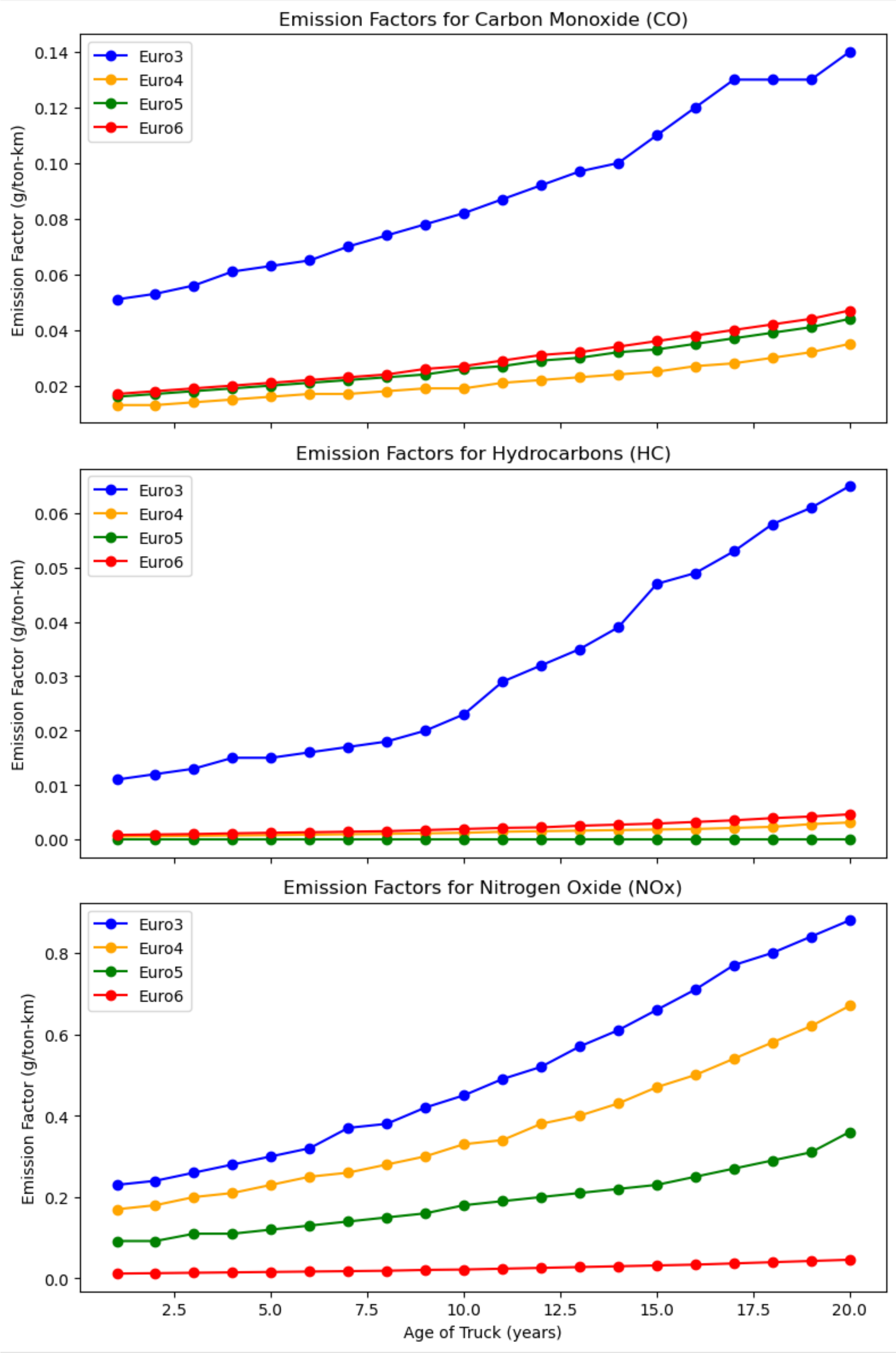

Figure 23: Simulation Truck EFs and Degradation under Various Regulations

Calculating CO_2 EF

CO_2 emissions are calculated differently from other emissions due to their specific EFs. Since CO_2 results from combustion, burning a litre of diesel fuel produces 2600g of CO_2 [1]. We have not considered truck degradation in our calculations because we could not find studies linking truck degradation with increased CO_2 levels. Therefore, we have assumed CO_2 emissions to remain constant regardless of the truck's age. This gives us an EF of 23.5 g/ton-km across all trucks.

Simulation of age and emission standard of trucks

As mentioned previously, the emission regulatory standards set the maximum permissible emissions for trucks. To determine the proportion of trucks that comply with various regulatory standards, we developed a Python script to assist with our simulation. In our estimation, we assumed that a truck's compliance with a specific regulatory standard depends on its age, meaning the year it was manufactured relative to the date when each regulatory standard was introduced.

For this simulation, we utilised data sourced from the official Ministry of Interior database [26] which shows the production date of trucks which determines the trucks age. Between the years 2001 and 2015, there was only data for the years 2001, 2004, 2009, 2010 and 2015. Therefore, we interpolated the data to simulate the estimated number of trucks that were produced in between those years for each year. The graph below visualises the age of trucks based on their production year.

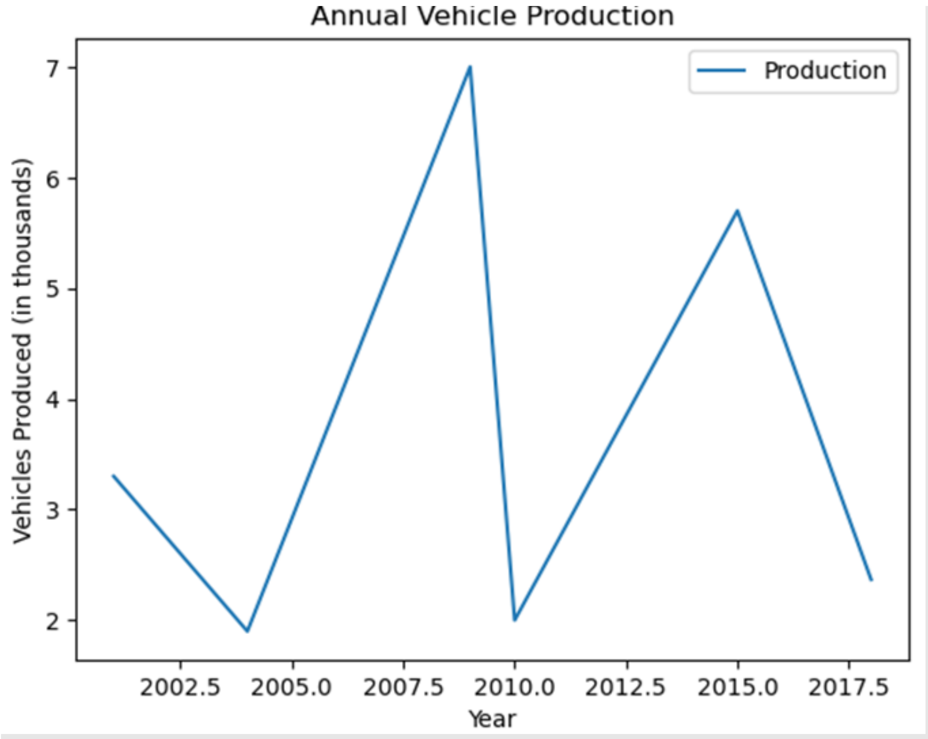

Figure 24: Simulated Annual Truck Production

We then mapped these production years to the years the regulatory standards were passed, and the table below shows the estimated percentage of trucks in Qatar that follow each regulatory standard.

Table 8:5 Estimated Truck Compliance Rates by Regulatory Standard

Standard	**Percentage of trucks (%)**
Euro3	15.13
Euro4	36.08
Euro5	18.10
Euro6	30.69

Calculating total emissions

To calculate total emissions in Qatar, we used the average total number of trucks and distance travelled calculated in section 1.2. As the travelling distance for the trucks are slightly different for trucks transporting imports from seaport to warehouses and exports from warehouses to seaports, we have calculated the total emissions for container imports and exports using different values. The simulated percentages of different types of trucks determine the number of each truck type by multiplying their respective percentages by the total number of trucks. Each truck type's emissions per gram/ton-kilometre are calculated based on its age and regulatory standards. The total emissions in grams/ton-kilometre are then derived by multiplying this emission rate by the number of each truck type. To calculate the total emissions in grams, this value is multiplied by the payload (26 tons) and the distance travelled. This methodology enables us to estimate the emissions for each truck type and the overall fleet, providing an understanding of emissions across different regulatory standards and truck ages. Based on this methodology, the total truck emissions in a single day are shown at the table below.

Table 9:6 Estimated Daily Total Truck Emissions

Total truck emissions	**Total CO**	**Total HC**	**Total NOx**	**Total CO_2**
g	135480.97	37389	1311567	128375104
kg	135.48	37.39	1311.57	128375.10

Section 2: Creating Dry Ports and simulating the railway system

Rail Network

To create the dry ports, we initially used Google Earth to verify the listed AWLs created in Section 1.1 and assess their suitability. We used the AWLs as these were the areas with warehouse clusters. If a location was deemed unsuitable (e.g., already occupied), the dry port was relocated within a 5-kilometer radius to a more suitable site capable of handling the loading and unloading operations of the rail network. These dry ports were then connected to seaports via rail lines. ArcGIS software was used to plot the potential locations of the dry ports on the Qatar map. The main objective for mapping out the rail route was to connect the dry ports with highest weightage to a seaport. We took special care to avoid crossing any natural reserves when designing the train route from Hamad Port to Saudi Arabia. It is noteworthy that the GCC Connection, as illustrated on the map, is a connecting point to KSA and is not a dry port. The final rail network was designed with Rail Growth Ltd.'s influence and all these factors were considered as shown in Figure 27 below.

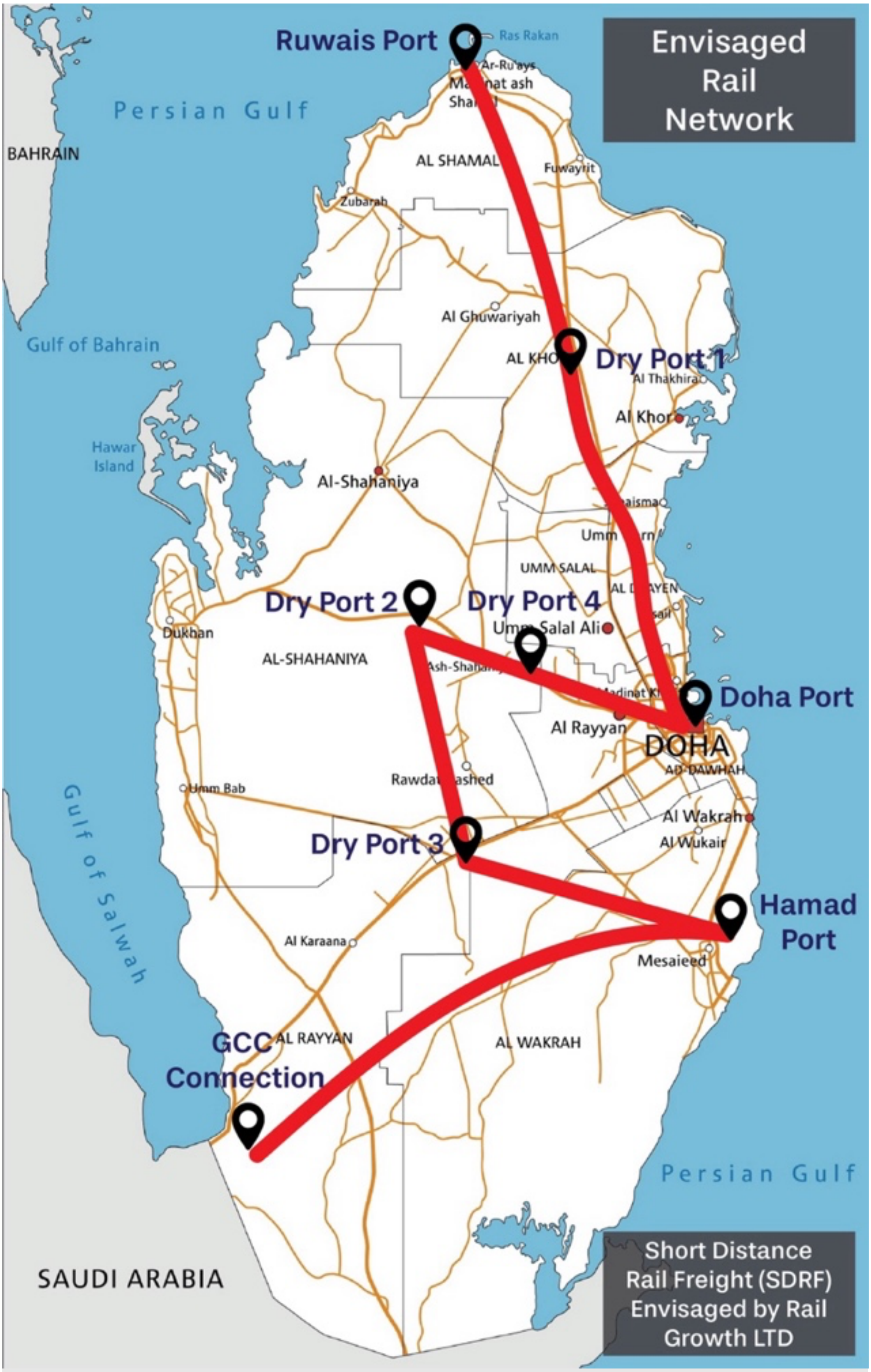

Figure 25: Proposed Rail Network in Qatar

SDRF Model

Rail Growth Ltd. proposed this strategy, which seeks to reduce loading time and increase the frequency of trains dispatched to destinations. This model of rail freight is revolutionary as it is based on a shuttle system of movement, where the number of wagons on each train is quite small. This allows for much quicker loading times onto the train. The effect is a higher frequency of train services being able to compete with road haulage. It is a contrast to the rail models in Australia, USA, Canada (long, slow, heavy trains taking several days to load) and it allows the unique characteristics of Qatar (very small land area) to be served in a highly efficient way. The whole methodology has been demonstrated to work between 2008-2013 on Tilbury-Felixstowe rail services (4R97 and 4R98) and Tilbury-Bristol rail services. Therefore, we consider that there is a very high confidence level that this rail operational methodology would work in the context of Qatar.

Rail Simulation

The quantity of TEUs that must be transported each day between seaports and dry ports was calculated using the data provided in Section 1.2. Following that, different combinations of TEUs per wagon, the number of wagons, and the starting and final ports were used to simulate the total number of trains required per day. It was found that, a wagon can hold 2 or 3 TEUs, and these numbers were used for the number of TEUs per wagon in the simulations [8]. The number of wagons were taken within the range of 5 to 25, which corresponds with the emphasis on SDRF.

The ideal values for every parameter were determined using the simulated data. The graphs depicted in Figures 28 and 29 are obtained by combining the total trains with the TEUs per wagon, starting port, and final port. This shows that employing 3 TEUs per wagon instead of 2 TEUs per wagon requires a significantly smaller number of trains.

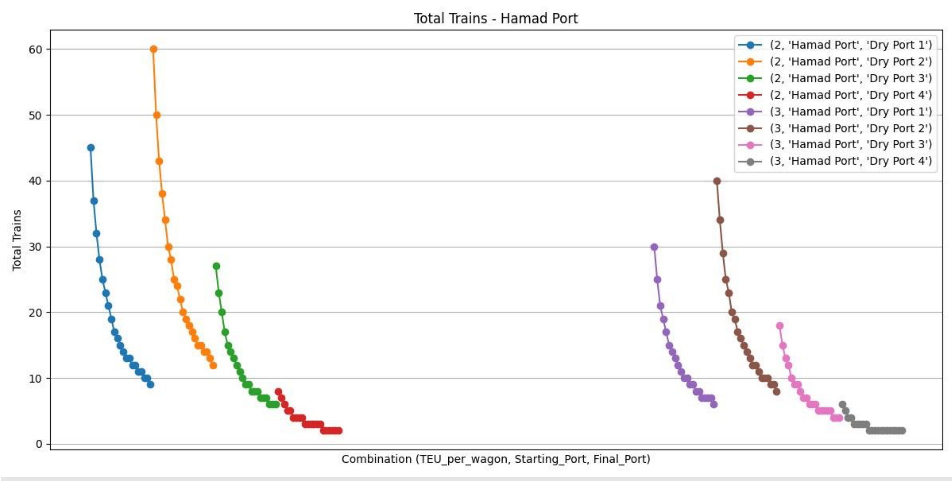

Figure 26: Total trains going from Hamad Port

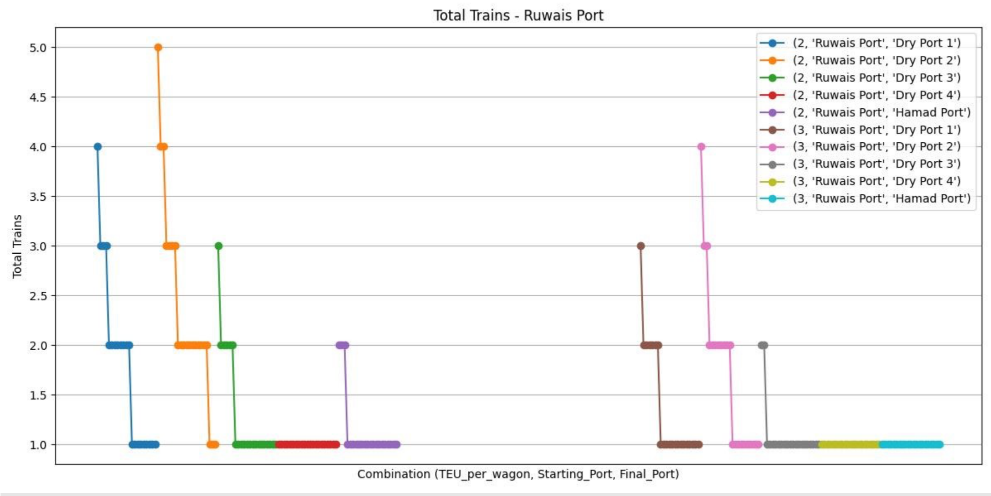

Figure 27*: Total trains going from Al-Ruwais Port*

After determining that 3 TEUs per wagon was the ideal number, we calculated the number of wagons per train. The total number of trains leaving from Hamad port and going to all dry ports was taken into consideration when calculating the different numbers of wagons per train. When a graph was plotted as in Figure 30, it is evident that the number of trains needed does not change significantly beyond 20 wagons per train. Although choosing 25 wagons per train results in the fewest number of trains required from Hamad Port, it is not consistent with the SDRF principle. Consequently, 20 wagons per train was estimated to be the ideal number.

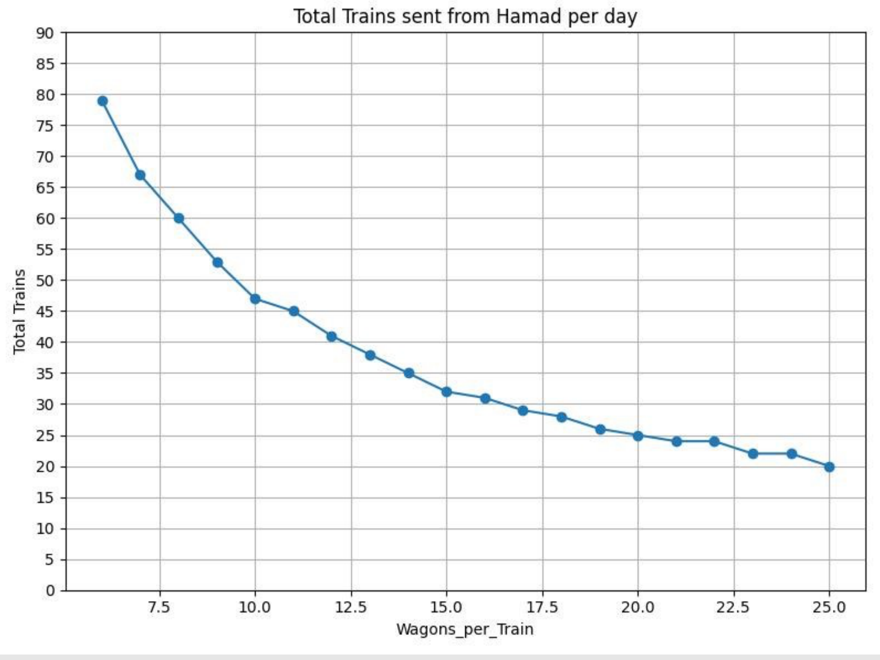

Figure 28: Daily Total Train Departures from Hamad Port

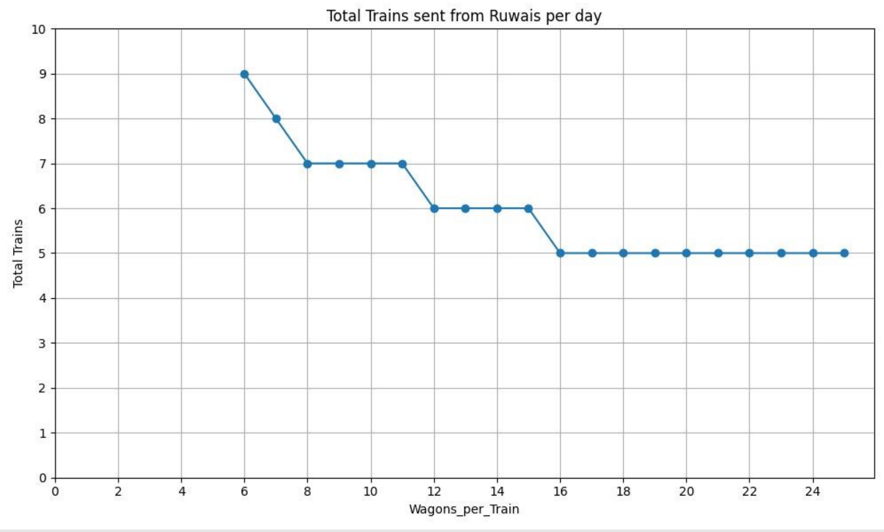

Figure 29: Daily Total Train Departures from Al-Ruwais Port

Figure 31 illustrates that, in the case of Al-Ruwais Port, the total trains remain unchanged even after 16 wagons. This is due to its lower import and export volumes, which means fewer trains would be needed to transport containers to each of the dry ports. 16 wagons are therefore determined to be the ideal number in this instance.

The primary goal of the following railway simulation is to determine each port's operational time. Reachstackers are being used in this instance to load and unload containers. A single reachstacker can operate effectively up to 100 metres of the train [9]. A 3 TEU wagon length is approximately 19.8 metres [8]. Considering this, a train of 20 wagons is roughly 396 metres long, while a train of 16 wagons is 317 metres long. Therefore, loading and unloading a 20-wagon train and a 16-wagon train can be accomplished with 4 and 3 reachstackers respectively. The loading and unloading time using 1 reachstacker is shown in Figure 32 [9].

Container size	20' containers	40' containers
Unloading train (per container)	1 min 30 sec	1 min 45 sec
Loading train (per container)	1 min 45 sec	2 min 0 sec

Figure 32: Loading and Unloading time for 20' and 40' containers [9]

A 20-feet container can hold 1 TEU whereas 40-feet can hold 2 TEUs. For our calculations we assumed that each port has an equal number of 20-feet and 40-feet containers [9]. This results in a loading time of 18.75 minutes and an unloading time of 16.25 minutes for a 20-wagon train. For a 16-wagon train loading and unloading time are 20 minutes and 17.3 minutes, respectively. For calculations of loading and unloading time, refer Appendix 6.

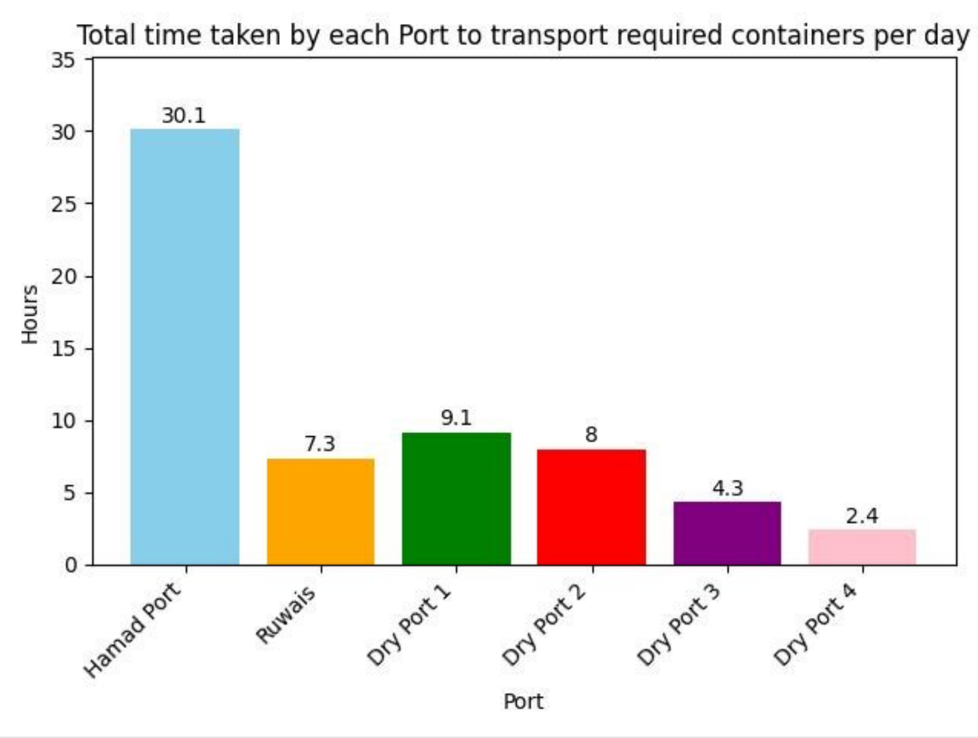

Figure 33: Daily Total TEU Transport Time by Port

As seen in Figure 33, the total amount of time needed to transport the necessary number of TEUs from each port each day is calculated by adding the loading and travel times for each train. The figure shows that it takes Hamad Port 30 hours 6 minutes per day to transport the required amount of TEUs. To reduce this time, the strategy entails loading several trains simultaneously. As per Peter Kelly's suggestion, a 2-minute interval between the departure of two trains was considered. Considering all these factors, the formula for calculating the total time to transport the required TEUs from each port, where n number of trains are being loaded at the same time is shown in Figure 34.

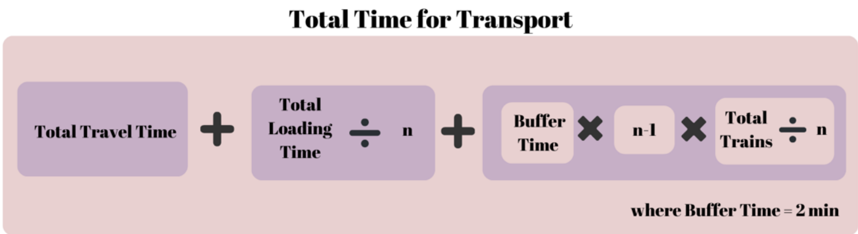

Figure 34: Formula - Daily Total TEU Transport Time Requirement

We assume that dry ports can load 2 trains and seaports can load 4 trains at the same time. Figure 35 shows that the total time for transport at the ports of Hamad and Al-Ruwais was 25 hours and 6.2 hours, respectively.

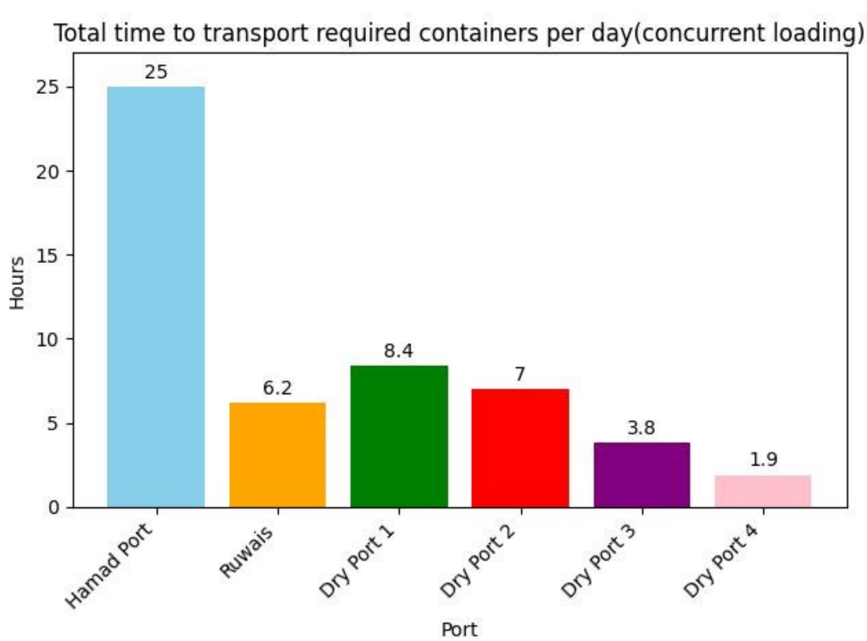

*Figure 33*0*: Daily Total TEU transport time per port (multiple concurrent train loadings)*

The goal of unloading is to maximise efficiency by figuring out how many reachstackers is the right amount. This means that for 20 and 16 wagon trains, there will be 4 and 3 reachstackers respectively. The ability to unload multiple trains at once also impacts unloading time. We assumed that four trains can be unloaded simultaneously at Hamad and Al-Ruwais ports, whereas two trains can be unloaded simultaneously at dry ports. Figure 36 shows the corresponding time taken by each port for unloading.

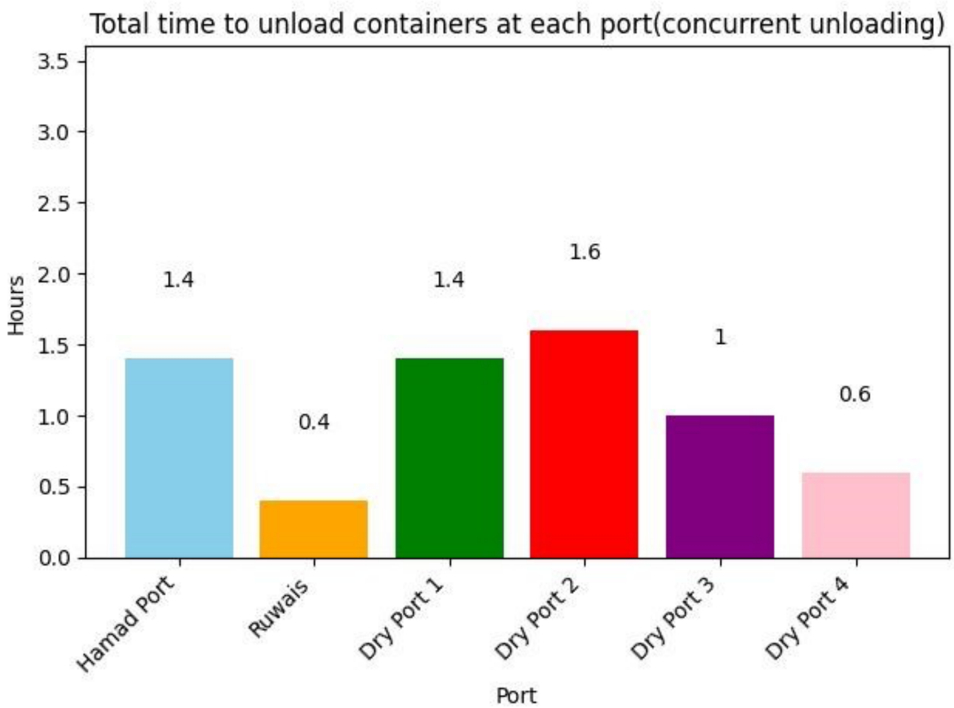

Figure 331: Total time taken by each port to unload containers

Hamad Port is responsible for managing the goods to and from KSA. One train can meet the daily requirements of Qatar-KSA trade according to Section 1.2. Under current circumstances, Hamad Port can meet these requirements.

As mentioned earlier, electric trains are used to move the containers from the seaports to the dry ports. Electric trucks are then used to transport containers from these dry ports to nearby warehouses. Because necessary baseline data was not available, this part of the procedure was not simulated.

Section 3: Calculation of emissions and improvements in container capacity after SDRF creation

Rail emissions

For the rail emissions estimation, instead of focusing solely on operation emissions, we decided to also consider the emissions created by the construction and maintenance of rail infrastructure. This is because, depending on the study, emissions related to rail infrastructure can represent most of rail's carbon emissions, which is not the case for road infrastructure and trucks ([16]; [19]; [10]). This is in part due to how low rail operation emissions can be. [10] even found maintenance to be more polluting than construction. Furthermore, in this instance, train infrastructure would need to be built, while road infrastructure is already in place.

Regarding operation emissions, we also opted to incorporate Well-to-Wheel (WTW) emissions, which considers the fuel's life cycle emissions. Electric rail produces no exhaust or tank-to-wheel (TTW) emissions. However, the generation of energy does create greenhouse gases (GHG), particularly in countries with a more carbon intensive power generation mix, such as Qatar, and this is factored into WTW. Electric rail can even be as polluting as diesel trains [18].

Rail infrastructure emissions

The emissions from rail infrastructure construction and maintenance are mostly determined by the materials used, particularly steel and concrete. Estimating these emissions is a notoriously challenging task, so different methodologies yield vastly different results ([16]; [19]). The differences in bridges, tunnels, and viaducts account for some of [19] more dramatically dissimilar figures. We chose to use [11] methodology because it takes a more granular, yet generalisable approach, and allows us to input the number of bridges or tunnels.

[11] suggested different estimates depending on location. When provided, we chose their Morocco estimations due to geographical similarities with Qatar. We also assumed the track would be ballasted, not ballastless, as it is more common. Then, we multiply their estimates by the number of kilometres that our rail network would span, as well as the number of stations and bridges.

Table 10: Construction and maintenance emissions for rail

Stage	**Emissions per km or unit (tonnes CO_2/year per km or unit)**	**Distance (km)**	**Unit (station or bridge)**	**Total emissions per year (tonnes CO_2/year)**
Design	0.45	286.5	N/A	128.925
Earthwork	5	286.5	N/A	1432.5
Ballasted Track	22.8	286.5	N/A	6532.2
Small bridges (over roads)	68	N/A	8	544
Tunnels (trenched)	243	50.46	N/A	12261.78
Railway equipment	3.5	286.5	N/A	1002.75
Secondary station	33	N/A	5	165
Main station	82	N/A	0	0
			Total emissions per year:	22067.155

Rail operation emissions

For operating emissions, we needed to calculate both the carbon intensity of the Qatar electricity grid, and the power consumption of the trains in our network.

For the electricity grid, we first got the electricity sources distribution from [22], and we calculated what percentage each source represented. Then, we got the carbon intensity of electricity depending on its source from [23]. After this, we multiplied the medium estimate of carbon intensity by the percentage and added it. This allowed us to establish that, on average, 1kWh produces 676.52 g CO_2 equivalent (CO_2e).

Table 11: Carbon intensity of electricity in Qatar

	terawatt-hours (TWh)	**%**	**g CO_2e/kWh (low estimate)**	**g CO_2e/kWh (high estimate)**	**g CO_2e/kWh (medium estimate)**
Oil consumption	154.88	29.6%	510	1170	840
Coal consumption	0.11	0.0%	740	1689	1214.5
Gas consumption	366.96	70.1%	290	930	610
Solar consumption	1.07	0.2%	41	41	41
Other renewables	0.43	0.1%	7.5	7.5	7.5
Total (TWh)	523.45				
Total (g CO_2e/kWh)			354.45	998.60	676.52

We also decided to use [14]'s estimate of 490g CO_2e/kWh, as it comes from an official source.

Then, we needed to get an estimate of how much kWh per ton-km the train would require. We mainly relied on [12]'s estimate of an energy consumption of 0.049 kWh/ton-km for a short train carrying average goods. Additionally, we were also interested in simulations, as we found many papers proposing algorithmic models ([21]; [20]; [13]), with [17] even making their tool, *NeTrainSim*, publicly available. We used it to simulate our proposed rail network and ran a simulation with the same electric train they use on their paper, plus 20 cargo cars with containers (Appendix 7). This simulation found a total energy consumption of 0.078 kWh/ton-km. However, it did not reach the speed required (its average speed was 15.8 m/s, quite far from the desired 33.3 m/s), and the author of the paper suggested the locomotive did not have enough power. By using two locomotives, the train reached an average speed of 22.3 m/s and had a total energy consumption of 0.147 kWh/ton-km. Using only one locomotive with a power of 10,000 kW did reach the desired speeds, but consumed 0.221 kWh/ton-km. We used our model with all these possible values.

Then, we multiplied this number by the total ton-kilometre transported by our network in a day. This resulted in four estimates (using [14]'s carbon intensity), c.f. Table 12. We considered Scenario 1 to be the most reliable estimate as it is based on official figures.

Table 12: Total daily emissions by scenario

	Total daily emissions (kg CO_2 e)
Scenario 1 (Schmied and Knörr's estimate)	179,329.24
Scenario 2 (slow speed simulation estimate)	285,371.64
Scenario 3 (medium speed simulation estimate)	537,987.71
Scenario 4 (high speed simulation estimate)	808,811.46

EVALUATION

Logistics

The daily container requirements were transported by trucks in roughly 39 hours and 10 minutes from Hamad Port to AWLs and in 32 hours 19 minutes from Al-Ruwais Port to AWLs. Electric trains, on the other hand, showed a notable decrease in the amount of time needed to get from seaports to dry ports. The given figure shows that Al-Ruwais Port needed roughly 6 hours 12 minutes hours for container transport, while Hamad Port only needed 25 hours (Figure 37).

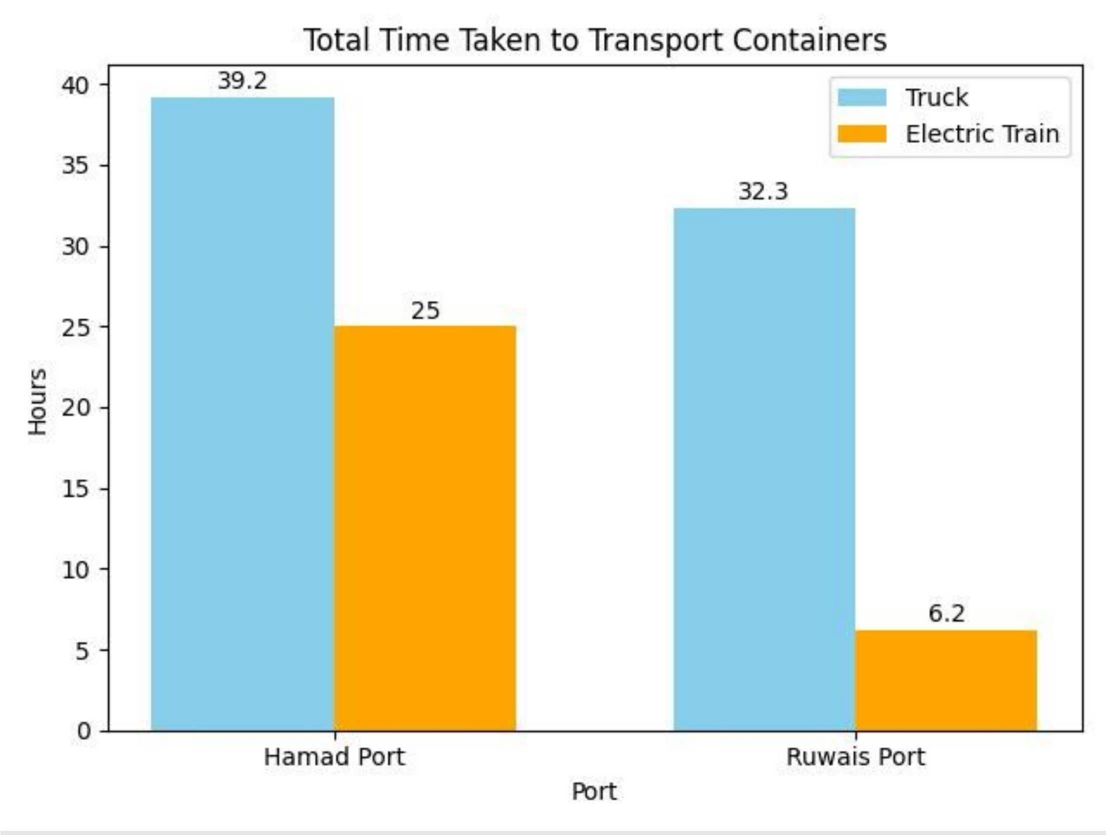

Figure 37: Total Container Transport Times from Hamad and Al-Ruwais Ports

A port's operating time includes buffer time in between train departures as well as loading and unloading operations. At Hamad Port, the total operating time is 4.4 hours, consisting of 3 hours for loading and buffering and 1.4 hours for unloading. Al-Ruwais Port operates for 1 hour as well. The operational times for diesel truck and electric rail transport at each port are shown in Figure 38. The graph shows that Hamad Port can handle 6 times as much freight with electric trains as port operates 24x7.

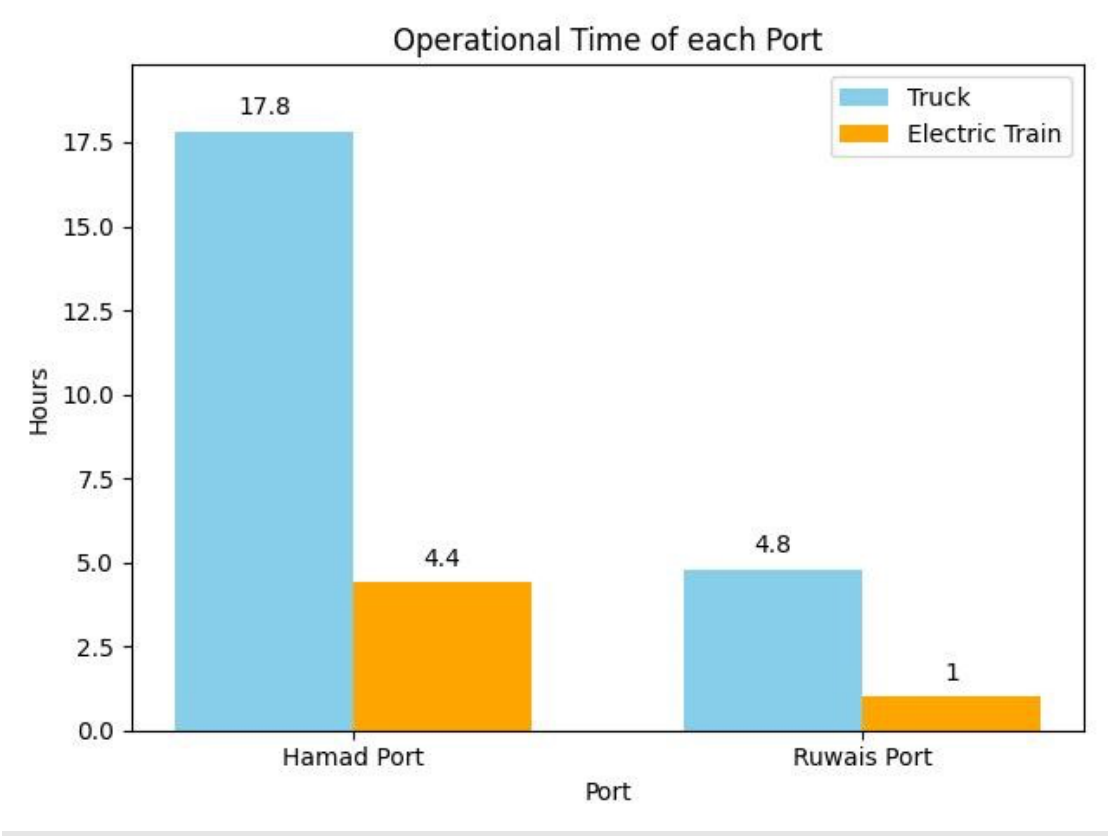

Figure 38: Operational Time for Hamad and Al-Ruwais Ports

We also found that rail is 76.1% more efficient than diesel trucks. According to the findings, there are numerous advantages to electric rail, such as better volume movement efficiency, fewer potential failure sites, and fewer instances of traffic congestion. Moreover, automation can be employed to maximize operational effectiveness. A single train can transport a significant amount of TEUs with this approach far more effectively than several tucks.

Emissions

To ensure that we were comparing equal figures, we quickly calculated the WTT and infrastructure emissions for trucks. For the first task, we used [27]'s WTT Conversion Factors and our estimates of fuel consumption for the network. For the infrastructure emissions, we used [11]'s estimates. We also converted the HC, NOx, and CO emissions to CO2 equivalent following [15]'s conversion table.

Our results for daily emissions of trucks and rails broken down by source in Figure 39.

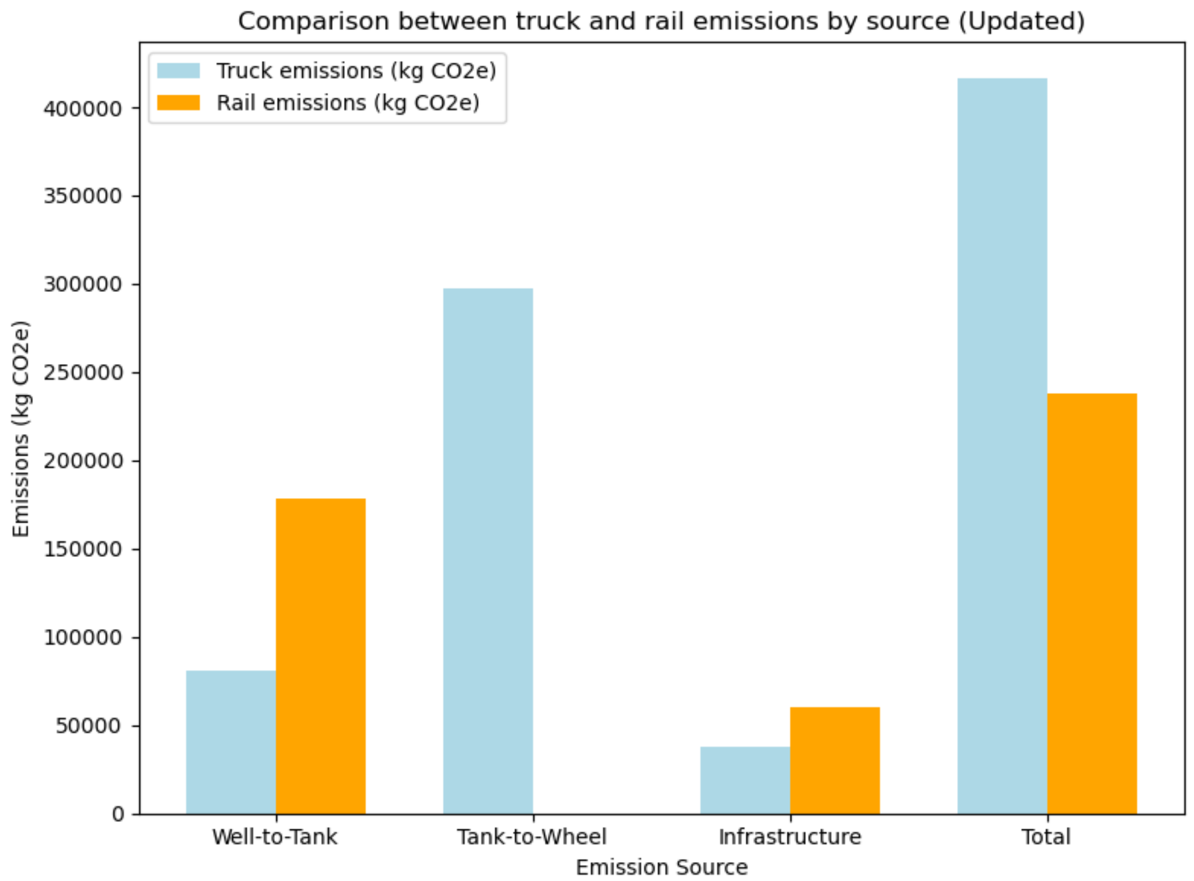

Figure 39: Truck vs. Rail Emissions Comparison by Source

Our study finds that a rail network would constitute a 57.2% cut in emissions, or, said otherwise, a 117t reduction in the number of greenhouse gases being emitted each day. This confirms that a rail network following the SDRF technology would greatly reduce transport emissions.

LIMITATIONS

As our work relies heavily on assumptions and simulations, there are many limitations to our study. One of this project's limitation is the lack of data we have on the current network, which is what led us to a simulation; the project would benefit from precise information on warehouses and freight volume and flows.

Furthermore, there are many intricacies regarding both logistics and emissions which we could not model given our resources, such as the influence of traffic, driver training, truck platooning, or the variance in cargo weight depending on load state and demand, etc.

Additionally, the estimation of carbon emissions is very complex. Regarding the infrastructure, there is significant variance between the estimates produced by different methodologies, and it's challenging to identify the most accurate one. Also, while the simulation tools were quite useful, a truly precise number for operation emissions would require information that is beyond our project scope, such as the rail line's curvature and the exact locomotives used.

Furthermore, while we could not confirm if the *NeTrainSim* estimates were accurate, if they were to be true the fast trains could emit more carbon than the current truck network.

Finally, we also could not find information regarding the rolling stock for freight carbon footprint, only for passenger transportation, so we could not compare emissions on this area.

GROUP DYNAMICS

To ensure that the project runs smoothly, certain standards were followed by all team members. We had weekly team meetings to track everyone's progress and keep each other updated about what had been done. During these meetings, we also informed each other about our challenges encountered and figured out ways to solve them.

Additionally, we set up biweekly meetings with our industry partner, Peter Kelly, where we reported our progress with him and got constructive feedback. Utilising platforms like LinkedIn, we also connected with numerous experts to verify our calculations. This ensured that our simulation and assumptions were accurate and logical.

Even though there were occasional instances of dispute and conflicting information exchange during our team meetings, we approached these challenges by communicating openly and respectfully, and we were always able to resolve our conflicts and reach a consensus. This collaborative effort not only strengthened the credibility of our project but also demonstrated our ability to work effectively as a team.

A primary bottleneck we encountered was the lack of data, which made finding relevant information challenging. This made the process less rewarding because the simulations we conducted didn't always feel accurate. However, our team adapted by leveraging creative problem-solving skills. We sought alternative sources and novel approaches to gather the necessary data, ultimately enabling us to move forward despite the challenges.

Overall, we are happy with the effort everyone has put into this project and deem it to be a success. We all believe that these 3 months have taught us a lot about teamwork, setting deadlines, communicating with external partners, and communicating with leading experts in the field.

CONCLUSION

This project introduced the new concept of SDRF technology, aimed at optimising Qatar's logistical system while reducing environmental impact. Simulation work had to be done to make up for the shortfall in available data, particularly the absence of emissions data from older trucks.

Despite the challenges posed by the lack of data, the results indicate that the implementation of the rail network will significantly enhance freight efficiency and substantially reduce carbon emissions to the best of our knowledge.

The project successfully simulated the locations of dry ports and designed an efficient railway network that both increased throughput by 76.1%, and reduced carbon emissions of the entire logistics system by 57.2%. The railway system is generally unaffected by traffic congestion; hence it is expected that transportation efficiency will further improve.

However, due to the complexity of estimating carbon emissions, we had to rely on simulations to predict rail-network performance, which may affect the accuracy of decision-making. If the project is implemented in the future, it should replace research data with more detailed real-time data provided by official sources, and continuously optimise the model as technology evolves to ensure that the intermodal logistics system design aligns with national development strategies and environmental protection objectives.

In summary, despite some challenges and limitations, the combined transport mode of rail and electric trucks provides Qatar with a viable solution to effectively reduce carbon emissions and enhance logistical efficiency.

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APPENDICES

Appendix 0

Here is the link of the drive folder that contains all our supporting material including codebase, data used, excel sheets, etc.

Appendix 1

Simulation of AWLs is here

Appendix 2

Distribution of TEUs

Overview of Distribution Process Analysis

This outlines the method for calculating the distribution of TEU to various Average Warehouse Locations (AWLs) and evaluates the transport logistics, including the volume to be distributed to each AWL for Import and Export separately.

- **Data on Container Weights**
  - We have the recorded weights for the AWLs which are essential for calculating the volume and distribution of TEU.
    - **Weight for point 1: 28 %**
    - **Weight for point 2: 38 %**
    - **Weight for point 3: 17 %**
    - **Weight for point 4: 5 %**
    - **Weight for Hamad Port: 12 %**
- **Calculation of Container Volumes**
  - **Objective:** Determine the required number of TEU for delivery at each FDP based on their weights.

- **Distribution Proportions between Hamad and Al-Ruwais Ports**

· **IMPORT**
  - **Total TEU:** The combined count from both ports is 617,800, where Hamad Port accounts for 574,572 TEU, and Al-Ruwais Port for 43,228 TEU.
  - **Proportion Calculation:**
    - **Hamad Port:** 574,572 / 617,800 ≈ 93% of total volume.
    - **Al-Ruwais Port:** 43,228 / 617,800 ≈ 7% of total volume.

· **EXPORT**
  - **Total TEU:** The combined count from both ports is 432,280, where Hamad Port accounts for 389,476 TEU, and Al-Ruwais Port for 42,804 TEU.
  - **Proportion Calculation:**
    - **Hamad Port:** 389,476/432,280 ≈ 90% of total volume.
    - **Al-Ruwais Port:** 42,804 / 432,280 ≈ 10% of total volume.

Annual Container Movement

- **Container Allocation for KSA-Qatar Trade**

This section is calculating the % of TEUs that are involved in Qatar-KSA trade and the % are being validated by Peter Kelly. These containers will be going from/to Hamad Port from/to KSA.

· **IMPORT** (i.e., coming from KSA)
  - 3% of 617,800 import TEUs ≈ 18,535 (approx.)

· **EXPORT** (i.e., going to KSA)
  - 2% of 432,280 export TEUs ≈ 8,645 (approx.)

- **Detailed Container Allocation to AWLs**

· **Total Import TEUs: 617,800**

· TEUs for Each Point Based on Total Imports (617,800 TEUs):
  - **Point 1:** 172,984 TEUs

- **Point 2:** 234,764 TEUs
- **Point 3:** 105,026 TEUs
- **Point 4:** 30,890 TEUs
- **Hamad Port:** 74,136 TEUs

· Distribution of Imports from Each Port to each point based on their weights:
  - Distribution for Imports:
    - § From **Hamad Port (93%) and Al-Ruwais Port (7%)**
    - § Total **Import TEU:** 617,800 TEUs
  - **Point 1:**
    - § From Hamad Port: 160,875 TEUs
    - § From Al-Ruwais Port: 12,109 TEUs
  - **Point 2:**
    - § From Hamad Port: 218,331 TEUs
    - § From Al-Ruwais Port: 16,433 TEUs
  - **Point 3:**
    - § From Hamad Port: 97,674 TEUs
    - § From Al-Ruwais Port: 7,352 TEUs
  - **Point 4:**
    - § From Hamad Port: 28,728 TEUs
    - § From Al-Ruwais Port: 2,162 TEUs
  - **Hamad Port:**
    - § From Hamad Port: 68,946 TEUs
    - § From Al-Ruwais Port: 5,190 TEUs

- **Calculation for Exports TEUs**

· **Total Export TEUs: 432,280**

· TEUs for Each Point Based on Total Exports (432,280 TEUs):
  - **Point 1:** 121,038 TEUs
  - **Point 2:** 164,266 TEUs
  - **Point 3:** 73,488 TEUs
  - **Point 4:** 21,614 TEUs
  - **Hamad Port:** 51,874 TEUs

· Distribution of Exports to Each Point to each port based on their weights:

- **Point 1:**
    - § To Hamad Port: 108,935 TEUs
    - § To Al-Ruwais Port: 12,104 TEUs
- **Point 2:**
    - § To Hamad Port: 147,840 TEUs
    - § To Al-Ruwais Port: 16,427 TEUs
- **Point 3:**
    - § To Hamad Port: 66,139 TEUs
    - § To Al-Ruwais Port: 7,349 TEUs
- **Point 4:**
    - § To Hamad Port: 19,453 TEUs
    - § To Al-Ruwais Port: 2,161 TEUs
- **Hamad Port:**
    - § To Hamad Port: 46,686 TEUs
    - § To Al-Ruwais Port: 5,187 TEUs

Appendix 3

Here is the google excel sheet for the Diesel Truck Simulation and their emissions calculation. There are multiple sheets in this file. The ones named "Import" and "Export" and for Diesel Truck Network Simulation. The remaining ones are for calculation of truck emissions based on the numbers we get from the former 2 sheets.

Appendix 4

Tables for truck degradation effects on Emission Factors

FOR EURO3 TRUCKS	Carbon Monoxide (CO)	Hydrocarbons (HC)	Nitrogen Oxide (NOx)
Emissions factor for a 1-year-old truck	0.037	0.011	0.16
Emissions factor for a 2-year-old truck	0.039	0.012	0.17
Emissions factor for a 3-year-old truck	0.041	0.013	0.19

Emissions factor for a 4-year-old truck	0.043	0.015	0.2
Emissions factor for a 5-year-old truck	0.046	0.016	0.22
Emissions factor for a 6-year-old truck	0.048	0.018	0.23
Emissions factor for a 7-year-old truck	0.051	0.02	0.25
Emissions factor for an 8-year-old truck	0.054	0.022	0.27
Emissions factor for a 9-year-old truck	0.057	0.024	0.29
Emissions factor for a 10-year-old truck	0.06	0.026	0.32
Emissions factor for a 11-year-old truck	0.063	0.029	0.34
Emissions factor for a 12-year-old truck	0.067	0.032	0.37
Emissions factor for a 13-year-old truck	0.07	0.035	0.4
Emissions factor for a 14-year-old truck	0.074	0.038	0.43
Emissions factor for a 15-year-old truck	0.078	0.042	0.46
Emissions factor for a 16-year-old truck	0.083	0.046	0.5
Emissions factor for a 17-year-old truck	0.087	0.051	0.53
Emissions factor for an 18-year-old truck	0.092	0.056	0.58
Emissions factor for a 19-year-old truck	0.097	0.062	0.62
Emissions factor for a 20-year-old truck	0.1	0.068	0.67

FOR EURO4 TRUCKS	Carbon Monoxide (CO)	Hydrocarbons (HC)	Nitrogen Oxide (NOx)
Emissions factor for a 1-year-old truck	0.0095	0.00044	0.13
Emissions factor for a 2-year-old truck	0.01	0.00048	0.14
Emissions factor for a 3-year-old truck	0.011	0.00053	0.15
Emissions factor for a 4-year-old truck	0.011	0.00059	0.16
Emissions factor for a 5-year-old truck	0.012	0.00065	0.17
Emissions factor for a 6-year-old truck	0.012	0.00071	0.19
Emissions factor for a 7-year-old truck	0.013	0.00078	0.2
Emissions factor for an 8-year-old truck	0.014	0.00086	0.22
Emissions factor for a 9-year-old truck	0.015	0.00095	0.24
Emissions factor for a 10-year-old truck	0.015	0.001	0.25
Emissions factor for a 11-year-old truck	0.016	0.0011	0.27
Emissions factor for a 12-year-old truck	0.017	0.0013	0.29
Emissions factor for a 13-year-old truck	0.018	0.0014	0.32
Emissions factor for a 14-year-old truck	0.019	0.0015	0.34
Emissions factor for a 15-year-old truck	0.02	0.0017	0.37
Emissions factor for a 16-year-old truck	0.021	0.0019	0.4
Emissions factor for a 17-year-old truck	0.022	0.002	0.43
Emissions factor for an 18-year-old truck	0.024	0.0022	0.46
Emissions factor for a 19-year-old truck	0.025	0.0025	0.5
Emissions factor for a 20-year-old truck	0.026	0.0027	0.53

FOR EURO5 TRUCKS	Carbon Monoxide (CO)	Hydrocarbons (HC)	Nitrogen Oxide (NOx)
Emissions factor for a 1-year-old truck	0.012	0	0.068
Emissions factor for a 2-year-old truck	0.012	0	0.073
Emissions factor for a 3-year-old truck	0.013	0	0.079
Emissions factor for a 4-year-old truck	0.014	0	0.085
Emissions factor for a 5-year-old truck	0.014	0	0.092
Emissions factor for a 6-year-old truck	0.015	0	0.099
Emissions factor for a 7-year-old truck	0.016	0	0.11
Emissions factor for an 8-year-old truck	0.017	0	0.11
Emissions factor for a 9-year-old truck	0.018	0	0.12
Emissions factor for a 10-year-old truck	0.019	0	0.13
Emissions factor for a 11-year-old truck	0.02	0	0.14
Emissions factor for a 12-year-old truck	0.021	0	0.15
Emissions factor for a 13-year-old truck	0.022	0	0.17
Emissions factor for a 14-year-old truck	0.023	0	0.18
Emissions factor for a 15-year-old truck	0.025	0	0.19
Emissions factor for a 16-year-old truck	0.026	0	0.21
Emissions factor for a 17-year-old truck	0.027	0	0.22
Emissions factor for an 18-year-old truck	0.029	0	0.24
Emissions factor for a 19-year-old truck	0.031	0	0.26
Emissions factor for a 20-year-old truck	0.032	0	0.28

FOR EURO6 TRUCKS	Carbon Monoxide (CO)	Hydrocarbons (HC)	Nitrogen Oxide (NOx)
Emissions factor for a 1-year-old truck	0.0013	0.0011	0.0087
Emissions factor for a 2-year-old truck	0.0013	0.0012	0.0094
Emissions factor for a 3-year-old truck	0.0014	0.0013	0.01
Emissions factor for a 4-year-old truck	0.0015	0.0015	0.011
Emissions factor for a 5-year-old truck	0.0016	0.0016	0.012
Emissions factor for a 6-year-old truck	0.0017	0.0018	0.013
Emissions factor for a 7-year-old truck	0.0017	0.002	0.014
Emissions factor for an 8-year-old truck	0.0018	0.0022	0.015
Emissions factor for a 9-year-old truck	0.0019	0.0024	0.016
Emissions factor for a 10-year-old truck	0.0021	0.0026	0.017
Emissions factor for a 11-year-old truck	0.0022	0.0029	0.018
Emissions factor for a 12-year-old truck	0.0023	0.0032	0.02
Emissions factor for a 13-year-old truck	0.0024	0.0035	0.021
Emissions factor for a 14-year-old truck	0.0025	0.0038	0.023
Emissions factor for a 15-year-old truck	0.0027	0.0042	0.025
Emissions factor for a 16-year-old truck	0.0028	0.0046	0.027
Emissions factor for a 17-year-old truck	0.003	0.0051	0.029
Emissions factor for an 18-year-old truck	0.0032	0.0056	0.031
Emissions factor for a 19-year-old truck	0.0033	0.0062	0.033
Emissions factor for a 20-year-old truck	0.0035	0.0068	0.036

Total emission calculation for imports

truck types	Euro3	Euro4	Euro5	Euro6
percentages of truck type in Qatar	13.17	31.41	15.76	39.65
number of each truck type	102	243	122	307
average age of truck	20	17	12	5
Carbon Monoxide per truck journey(g/ton-km)	0.14	0.03	0.03	0.0021
Hydrocarbons per truck journey (g/ton-km)	0.061	0.0023	0	0.0012
Nitrogen Oxide per truck journey (g/ton-km)	0.88	0.54	0.2	0.016
Carbon Dioxide per truck journey(g/ton-km)	32	32	32	32
total CO (g/ton-km)	14.28	7.29	3.66	0.6447
total HC(g/ton-km)	6.222	0.5589	0	0.3684
total NOx (g/ton-km)	89.76	131.22	24.4	4.912
total CO2 (g/ton-km)	3264	7776	3904	9824
total CO (g)	31373.16	16016.13	8041.02	1416.41
total HC (g)	13670	1228	0	809
total NOx (g)	197203	288290	53607	10792

@Total emission calculation for exports

truck types	Euro3	Euro4	Euro5	Euro6
percentages of truck type in Qatar	13.17	31.41	15.76	39.65
number of each truck type	102	243	122	307
average age of truck	20	17	12	5
Carbon Monoxide per truck journey(g/ton-km)	0.14	0.03	0.03	0.0021
Hydrocarbons per truck journey (g/ton-km)	0.061	0.0023	0	0.0012
Nitrogen Oxide per truck journey (g/ton-km)	0.88	0.54	0.2	0.016
Carbon Dioxide per truck journey(g/ton-km)	32	32	32	32
total CO (g/ton-km)	14.28	7.29	3.66	0.6447
total HC(g/ton-km)	6.222	0.5589	0	0.3684
total NOx (g/ton-km)	89.76	131.22	24.4	4.912
total CO2 (g/ton-km)	3264	7776	3904	9824
total CO (g)	32079	16376	8222	1448
total HC (g)	13977	1256	0	828
total NOx (g)	201637	294773	54812	11034

- Graph for show truck vs rail emissions are here
- Graphs for truck degradation are here
- Code to find truck compliancy standards is here

Appendix 5

Here is the python notebook used to simulate the proposed rail system in Qatar

Appendix 6

Calculations for 20 wagon trains using 1 reachstacker are as below:

Total TEUs in 20 wagon train = 20*3 = 60 TEUs
Number of 20’ containers = 20
Number of 40’ containers = 20

Loading time for 20’ containers = 20*1.75 min = 35 mins
Loading time for 40’ containers = 20*2 min = 40 mins
Unloading time for 20’ containers = 20*1.5 min = 30 mins
Unloading time for 40’ containers = 20*1.75 min = 35 mins

Total Loading Time = 35+40 = 75 mins
Total Unloading Time = 30+35 = 65 mins
Total Time = 75+65 = 140 mins, or 2 hours and 20 mins using 1 reachstacker

Using the above data, loading time, and unloading time for 20 wagon trains using 4 reachstackers are as below:

Total Loading Time = 75/4 =18.75 mins
Total Unloading Time = 65/4 = 16.25 mins
Total Time = 18.75+16.25 = 35 mins using 4 reachstackers

Following the similar calculations, loading, and unloading time for 16 wagon trains are as below:

Using 1 reachstacker:
Total Loading Time = 60 mins
Total Unloading Time = 52 mins

Total Time = 112 mins, or 1 hours and 52 mins

Using 3 reachstackers:

Total Loading Time = 60/3 = 20 mins

Total Unloading Time = 52/3 = 17.3 mins

Total Time = 37.3 mins

Appendix 7

The excel file for construction and maintenance emissions is here

The excel file for our calculations for the Qatar grid carbon intensity is here

The excel file for our operation emissions calculations is here

The files for the *NeTrainSim* tool are here

Appendix 8

List of Tables and Figures