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PROVIDING LEVELIZED COST AND WAITING TIME INPUTS FOR HDV HYDROGEN REFUELING STATION PLANNING: A CASE STUDY OF U.S. I-75 CORRIDOR[1]

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ABSTRACT
Widespread use of diesel fuels in freight transportation leads to greenhouse gas (GHG) emissions that play an important role in air pollution. The air pollution, as well as the energy crisis, drives the transition from diesel fuel to cleaner and more energy-efficient fuels such as hydrogen fuels. With such a transition, the strategic planning and optimization of supporting refueling infrastructure along the national highway for heavy-duty vehicles (HDVs) become a necessity. Cost and service level are two essential factors to be considered in hydrogen refueling station location and capacity optimization. The service level in this study is assessed by the delay (waiting time) at fueling stations as well as the fueling demand fulfilled. To this end, this study presents a methodology to provide waiting time (delay) and levelized hydrogen fuel cost inputs under different station configurations (number of dispensers and fill rates) for hydrogen refueling station planning. Determining the station configurations based on the trade-off between the two inputs is further discussed. Particularly, this study points out that the levelized cost and waiting time are affected by hourly demand patterns and estimates the two inputs under different peak hour fueling demand scenarios. The results suggest that, with the same daily demand, the cost, as well as the waiting time, increases obviously with the peak hour demand. In the case study, the cost grows at least 30% when the peak hour visit frequency of the daily total visits increases from 5% (evenly distributed pattern) to 10% (the most common pattern for existing diesel fueling stations along I-75). Accounting for this peak hour effect in hydrogen refueling station planning is recommended. Overall, the waiting time model and cost analysis provide key inputs for optimizing hydrogen refueling station location and configurations based on anticipated refueling demand patterns. The paper is the second in a series that aims to build a comprehensive modeling plan and optimize hydrogen refueling infrastructure along the Interstate 75 (I-75) corridor for HDVs.

Keywords: Hydrogen refueling station, heavy-duty vehicle, waiting time modeling, levelized hydrogen fuel cost, hourly demand fluctuations

INTRODUCTION
According to the U.S. Energy Information Administration (EIA), the transportation sector accounts for the largest share of U.S. petroleum consumption. In 2020, the transportation sector consumed about 66% of U.S. petroleum. Consequently, emission generated by this sector is one of the highest, accounting for 29% of all GHG emissions in 2019 as reported by the Environmental Protection Agency (EPA). Road freight transport represents a substantial part of total emissions in the transportation sector - freight trucks made up about 24% of total GHG emissions among all transportation modes (EPA). Transitioning to clean energy fuels for freight transportation, therefore, would drastically accelerate the decarbonization of the transportation sector and help to achieve the zero-emission goals. Among various alternative fuel options, fuel cell vehicles (FCVs) provide a promising solution to environmental pollution and the energy shortage due to the cleanness, high energy efficiency, and wide availability of hydrogens. With converting existing diesel-powered trucks to FCVs, the plan and design of safe and economically feasible supporting infrastructures, particularly refueling infrastructures along national highways becomes more urgent.

Many factors play roles in the optimization of refueling stations on national highways, cost is the most crucial one. Industrial stakeholders and planning agencies generally want to minimize costs while maintaining the desired service level, especially at the early deployment stage. Cost involves two aspects: total investment cost and levelized cost - cost per fueling mass. Previous studies show that the investment cost to build hydrogen refueling stations depends on station configurations, such as station size, fill rate, dispensing technology, and fuel type (gaseous or liquid). The levelized cost, on the other hand, also depends on the total dispensed amount during the station lifecycle in addition to station configurations. The station service level involves many aspects. In this study, we focus on evaluating fueling demand served at a station and vehicle waiting time. Commercial vehicle drivers care more about waiting time because of the higher value of time compared to passenger vehicles. In 2016, the value of time for commercial vehicles is about three times the value of time for passenger vehicles (Ellis, 2017). Waiting time becomes more of a concern at the early development stage of hydrogen refueling stations because of the limited amount of accessible refueling stations along national highways.

To this end, this study aims to provide inputs and analysis procedures to evaluate the cost, and waiting time with different station configurations to answer the following question: With anticipated fueling demands and associated hourly variation patterns, which station configuration is preferred? Specifically, in this study, two variables: the number of dispensers and fill rate are evaluated. This study models vehicle waiting time with different station configurations and adopts the heavy-duty refueling station analysis model (HDRSAM) (ANL, 2017) to obtain associated costs. To evaluate the effect of peak hour demand variation on cost and waiting time, GeoTab diesel fuel station data is adopted to derive the fuel demand hourly variation pattern (Geotab, 2022). This study focuses on hydrogen refueling station planning along I-75. The same methodology can be extended and applied to provide key inputs for optimizing hydrogen refueling station location and capacity in other regions or corridors.

The paper is structured as follows: The Related Studies section reviews previous studies on refueling station waiting time modeling as well as refueling station costs. The Methodology section proposes a waiting time modeling and simulation method and discusses the cost model used. The Results and Discussion section presents the results for different scenarios. The final section concludes this study.

Literature Review

Waiting time modeling at fueling stations is used in many areas, including fuel station siting problems, dispenser allocation problems, electric vehicle routing problems, station service evaluation problems, etc. (Keskin et al., 2019; Lu & Hua, 2015; Qin & Zhang, 2011; Zenginis et al., 2016; Zheng et al., 2014). Table 1 summarizes related studies where vehicle fueling behavior is modeled to obtain the average waiting time at fueling stations.

In summary, most previous studies assume homogeneity of vehicle demand level and theoretically obtain average waiting time based on queuing theory. Keskin evaluated the impact of waiting time at an electric charging station on electric vehicle (EV) route selection (Keskin et al., 2019). To simplify the problem, the station is assumed to have only one charger. The recharge amount for each EV is uniformly distributed between 10% and 100% of the capacity. Zheng aims to allocate dispensers to minimize the total number of dispensers while ensuring satisfactory performance of vehicle queues (Zheng et al., 2014). Different from the previous studies, this one considers the traffic demand variation during a day and focuses on evaluating waiting time at the peak hour of a day. Again, this study assumes the remaining H_2 demand level following Beta distribution without considering different vehicle classes. Qin aims to find a charging scheduling scheme that can minimize the average waiting time of each vehicle for charging during its trip (Qin & Zhang, 2011). Instead of a theoretical method, this study adopts simulation to obtain the average waiting time. The effect of charging rate on queuing time and queue length is examined as well. All studies evaluated the average waiting time, but not the waiting time variation which measures the service level of a station from the drivers' perspective. Higher waiting time variation means an individual driver is more likely to experience prolonged service time and unexpected delay and is thus not preferred.

In our study, we consider the heterogeneity among truck types and adopt Monte Carlo simulation to estimate the average waiting time based on truck classes as defined by federal highway administration (FHWA, 2013) and associate stochastic hourly fueling demand. Simulation enables the study to evaluate not only the average waiting time but the waiting time variation. Additionally, this study also examined the impacts of fill rate on waiting time.

Table 1. Summary of previous literature on fueling station waiting time modeling

Study	Demand hourly variation	Vehicle type	Modeling method	Fixed charging rate	Number of chargers	Fueling behavior	Waiting time variation
(Lu & Hua, 2015)	No	EV	Queuing theory	Yes	Multi-chargers	first-in, first-out (FIFO)	No
(Qin & Zhang, 2011)	No	EV	Simulation	Variable charging rate	Multi-chargers	Greedy charging scheduling	No
(Zheng et al., 2014)	Peak hour	FCV	Queuing theory	Yes	Multi-dispenser	FIFO	No
(Keskin et al., 2019)	No	EV	Queuing theory	Yes	Single charger	FIFO	No
(Zenginis et al., 2016)	No	EV	Queuing theory	Yes	Multi-chargers	FIFO	No

A series of studies assessed how cost varies with different station configurations such as optimal delivering pressure, capacity utilization factor, station size, utilization rates, etc. (Lin et al., 2018; Reddi et al., 2017). One study examined the cost-effectiveness of both gaseous and liquid truck-supplied refueling stations based on various refueling station sizes and utilization rates (Mayer et al., 2019). Results show that total investment cost increased as the refueling station size increased while specific investment costs (cost per mass) decreased because of larger dispensing volumes. Similarly, another study found that The levelized cost of a gaseous refueling station for medium production volume with 1000 kg/day capacity is about 50% of the levelized cost for a station with 200 kg/day capacity (Reddi et al., 2017). The third study considers real traffic demand along major highways and examined the number of hydrogen refueling stations as well as storage capacity per station required to suit the long-haul heavy-duty truck fleet by evaluating the traffic distribution along major highways (Yaïci & Longo, 2022). In this study, in addition to refueling station size and demand level, different fill rates and traffic volume hourly variation are also examined.

The HDRSAM (DOE, 2017), a refueling station cost analysis tool developed by the Argonne National Laboratory, is publicly available. The tool enables users to define different scenarios and comprehensively evaluate the cost components associated with a hydrogen refueling station. This study adopts the HDRSAM tool and estimates the station investment cost and levelized cost associated with different configurations and anticipated fueling demand. Specifically, this study examines how the following four parameters affect the cost of refueling station optimization:

- **Daily fleet size served by a station:** larger fleet size, while increasing the station size requirement which results in larger station size, could still bring down the levelized cost because of large dispensing volumes.
- **Hourly refuel station visit frequency:** The hourly fueling demand variation affects refueling station design (Chen, 2010). To accommodate the refueling station demand hourly variation, a short-term capacity is proposed. Depending on the peak demand level compared to baseline demand, the number of compressors needed varies thus affecting the station investment cost.
- **Fill rate***:* Faster fills require higher capacity equipment and result in higher fueling costs.
- **Station size (number of dispensers):** larger station size requires larger land areas as well as higher dispenser costs, operation and maintenance costs, etc.

METHODOLOGY

This section proposes a simulation procedure to model the waiting time at hydrogen refueling stations and discusses the setup of the HDRSAM tool. This study focuses on providing cost and waiting time (delay) inputs for optimizing hydrogen refueling stations along I-75. Therefore, the data used in waiting time simulation and cost analysis are based on refueling station features and station visit patterns along I-75.

Waiting Time Modeling and Simulation

The queuing system at a hydrogen refueling station is based on the following assumptions:

a) A refueling station is a multi-server system because it generally has at least two nozzles.
b) A vehicle will be randomly assigned to a station with the shortest waiting line (the number of waiting vehicles) instead of the fastest line (FIFO) given that the fueling time information is unknown to the driver.
c) Vehicle arrival follows a uniform distribution in each hour.

Additionally, some features are considered in this study:

a) **Customer Heterogeneity (truck classes).** The fueling demand varies with truck classes. This study focuses on HDVs which fall into vehicle class 9 to class 13 as defined by FHWA (Fig. 1).
b) **Customer visit frequency hourly fluctuation**. Hourly customer visit frequency based on GEOTAB data is adopted in this study to investigate the impacts of hourly variation on average waiting time.
c) **Hydrogen fill rates.** Three different fill rates are assessed in this study: 1.8 kg/min, 3.6 kg/min, and 7.2 kg/min.

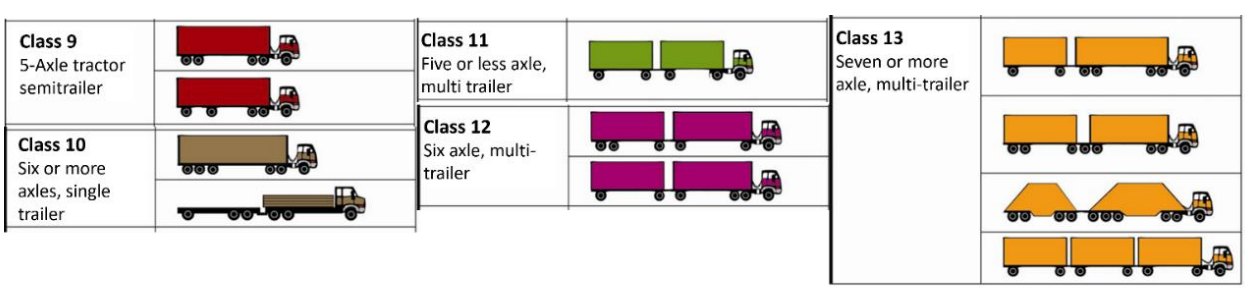

Fig. 1. Truck classes (FHWA, 2013).

Based on the above assumptions, a simulation procedure is devised to simulate vehicle queueing behavior at fueling stations, as described in the following steps.

Step 1. Randomly generate a truck seed list with class labels.
Fueling demand distribution varies with vehicle classes. In the simulation, for a given daily truck volume that visits a station, a truck seed list is randomly generated with class labels based on the share of each class as shown in Table 2 based on a model developed by Uddin (Uddin et al., 2022). The most common truck class on I-75 is class 9, followed by 11 and 10. Then, the truck seed list is distributed to each hour based on the hourly visit profile generated in Step 2.

Table 2. Percentage of truck classes on I-75.

Vehicle class	9	10	11	12	13
Total daily volume along I-75	18706	671	851	180	13
Share of HD truck on I-75	91.60%	3.29%	4.17%	0.88%	0.06%

Step 2. Obtain the number of trucks visiting the station each hour.
Hourly truck fueling frequency variation affects waiting time as well as cost and is thus being considered in this study. Representative hourly customer visit frequency pattern at fueling stations is obtained from Geotab (Geotab, 2022) fuel station data. The data represents the location of fuel stations and various metrics associated with these stations. Specifically, the dataset contains fuel types at each station and the hourly visit frequency. The stations that supply diesel were extracted to investigate the visit frequency patterns. In total, 164 major diesel stations along I-75 were selected.

Based on the percentage of peak hour visit frequency among total daily visits, the major diesel stations along I-75 are classified into four groups (Table 3):

- Group A: peak hour visit frequency ranges from 5% to 7.5%, suggesting that the visit frequency is almost evenly distributed throughout 24 hours of a day. As shown in Table 3, 0 stations are classified into this group. However, the group is still kept to provide a baseline for comparison.
- Group B: peak hour visit frequency ranges from 7.5% to 12.5%. This group has the largest sample size among all four groups - around 38% of 164 stations are classified into group B.
- Group C: peak hour visit frequency ranges from 12.5% to 17.5%.
- Group D: peak hour visit frequency ranges from 17.5% to 22.5%.
- Group E: peak hour visit frequency ranges from 22.5% to 27.5%.

Table 3. Station counts and shares of each group.

Station Group	**A**	**B**	**C**	**D**	**E**
Counts	0	60	43	39	22
% of total stations	0%	38%	27%	20%	14%

The location of major HDV fueling stations by station groups along I-75 is shown in Fig. 2. The star symbol denotes stations selected to represent the hourly distribution patterns in each station group (Fig. 3).

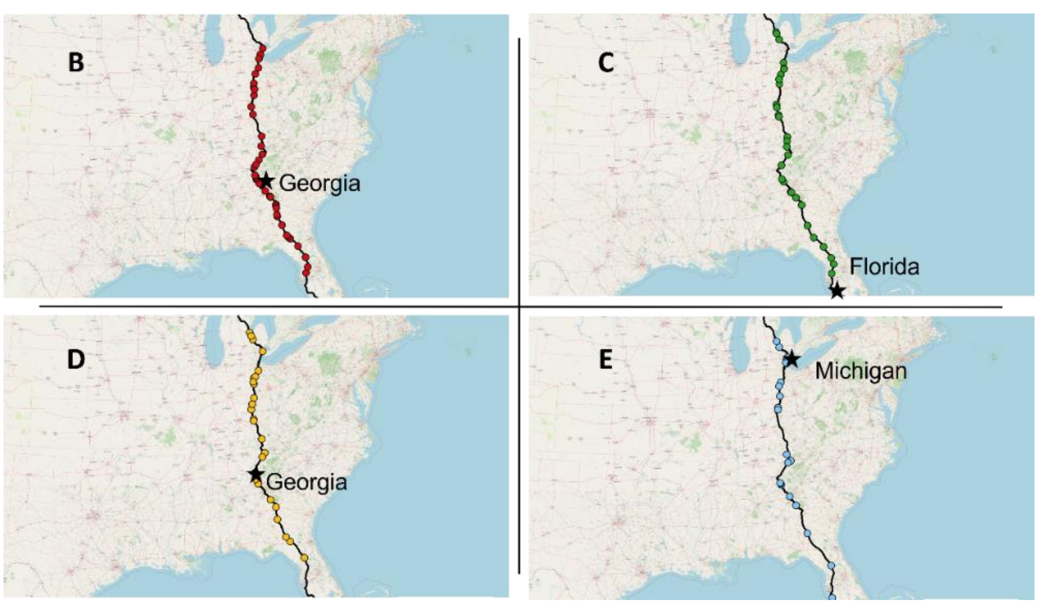

Fig. 2. Major HDV fueling station location along I-75 by station groups.

Fig. 3 shows the hourly refueling station visit frequency distribution patterns of the selected stations in each group in Fig. 2. For group A, an evenly distributed hourly profile is generated (Fig. 3 black line). The daily truck seed list in Step 1 is assigned to each hour based on the hourly profile for each group.

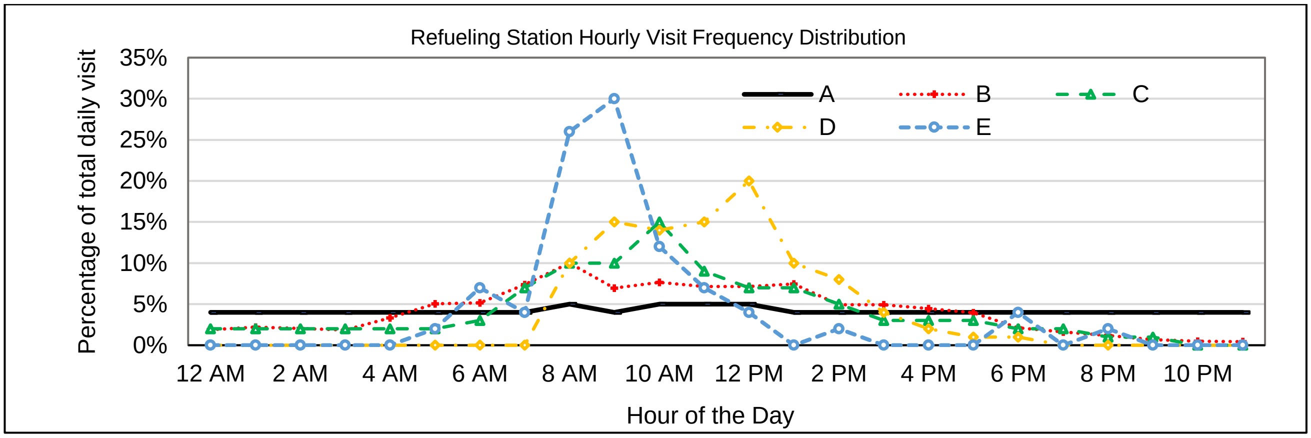

Fig. 3. Hourly refueling station daily visits frequency distribution of selected stations in each station group.

Step 3. Assign the arriving vehicle to a station and calculate the waiting time.
Step3.1. Generate arrival time and assign a vehicle to the dispenser with the shortest waiting line.
The vehicle arrival is assumed to follow uniform distribution in any given hour, while the hour-to-hour distribution is given by the frequency distribution discussed above. For a list of vehicles to be served in an hour, the arrival time is thus generated. Fig. 4 shows a fueling station with one vehicle waiting at dispenser #2. The next newly arrived vehicle will be randomly assigned to dispenser #1 or #3 when arrived because the two dispensers have the shortest waiting line. Note that either one is not necessarily the fastest line since the vehicle fueling time varies.

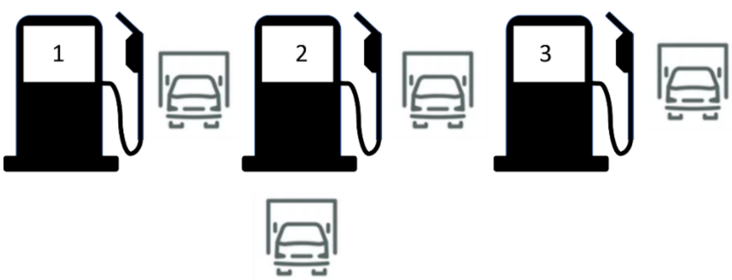

Fig. 4. fueling station waiting line illustration.

Step3.2. Generate fueling demand, calculate fueling time and update the waiting time at each station.
The hydrogen tank size for Class 9-11 is assumed to be 100 kg and 150 kg for Class 12-13. The heavy-duty (Classes 9-13) vehicle fuel (hydrogen) consumption from origin to destination along I-75 was modeled for a fuel cell electric powertrain using a charge sustaining algorithm. Using the Origin-Destination and freight volume information developed (Uddin et al., 2022), combined with the fuel consumption rates and refueling station locations, the total tank capacity requirements to complete the mission may be derived. The details behind this analysis will be developed in a future paper. The average truck fueling demand for different classes is summarized in Table 4.

Table 4. Average and standard deviation (STD) of fueling demand by truck classes along I-75.

Vehicle class	Size (kg)	Average fueling demand (kg)	demand STD
9	100	53.57	23.91
10	100	52.10	22.18
11	100	57.25	24.84
12	150	93.27	32.61
13	150	85.99	36.69

For each simulated vehicle, the fueling demand will be randomly generated based on the vehicle class and the associated fueling demand distribution given in Table 4. Then the fueling time for the vehicle as well as the waiting time for the station can be updated.

Repeating Step 1 to Step 3, the waiting time for each simulated vehicle can be obtained.

Hydrogen Refueling Levelized Cost

In this study, the HDRSAM tool is used to obtain the cost for various scenarios. Specifically, this study focused on gaseous hydrogen refueling stations with tube-trailer supply and 350 bar Cascade dispensing options. The cost evaluated is the levelized cost for hydrogen (measured by dollar per kg). Table 5 summarizes all four varying parameters. As explained in the Introduction section, all four parameters affect levelized hydrogen cost. The combined effects will be explained in the Results and Discussion section.

Table 5. Station parameters.

Parameter	Range
Daily fleet size served	100 vehicles & 200 vehicles
Hourly profile	5 hourly visit profiles (Fig. 3)
Fill rate	1.8kg/min, 3.6kg/min and 7.2kg/min
number of dispensers (hoses)	From 4 to 28 with an increment of 4

RESULTS AND DISCUSSION

This section evaluates the waiting time simulation and cost results with case studies. The waiting time and cost section discussed the trade-off between waiting time and cost considering hourly demand variation. The cost component and hourly profile section evaluates how the peak hour demand affects each cost component as well as the total cost. The demand and cost section analyzes how the total investment cost and levelized cost vary with demand.

Waiting Time and Cost

The waiting time and cost trade-off is assessed with a case study:

- The daily visit frequency is 200 hydrogen fuel cell trucks with Classes 9-13.
- The hydrogen fill rate ranges from 1.8kg/min to 7.2kg/min.
- The Number of dispensers ranges from 4 to 28 dispensers.
- The hourly visit frequency profile ranges from A to E.

The resulting waiting time variation and levelized cost for different station configurations are demonstrated in Fig. 5. As shown in the figure, all three parameters, fill rate, the number of dispensers, and hourly profile affect the levelized cost. In general, the levelized cost per kg increases with the increase in fill rate, number of dispensers, and peak hour demand. The impact of the peak hour effect on levelized cost is obvious. Comparing group A to group B, the levelized cost increases at least 30% regardless of the station configurations. The increase is more obvious with higher fill rates. The waiting time, on the other hand, drops with the increase of dispenser numbers, fill rate, and peak hour demand.

There are cases where the station configuration cannot meet the demand during peak periods. The average waiting time and cost are left black for most of those cases (e.g., a station with 4 dispensers and a fill rate at 1.8 kg/min cannot meet the peak demand for profile B as shown in Fig. 5 based on simulation results). There are cases where the unmet demand is relatively low. The number of trucks that cannot be served with such configurations is then labeled in each profile from A to E. For example, as labeled in Fig. 5 profile A, on average, 5 trucks among 200 trucks cannot be served with the station equipped with 4 dispensers and fill rate at 1.8 kg/min, based on simulation results.

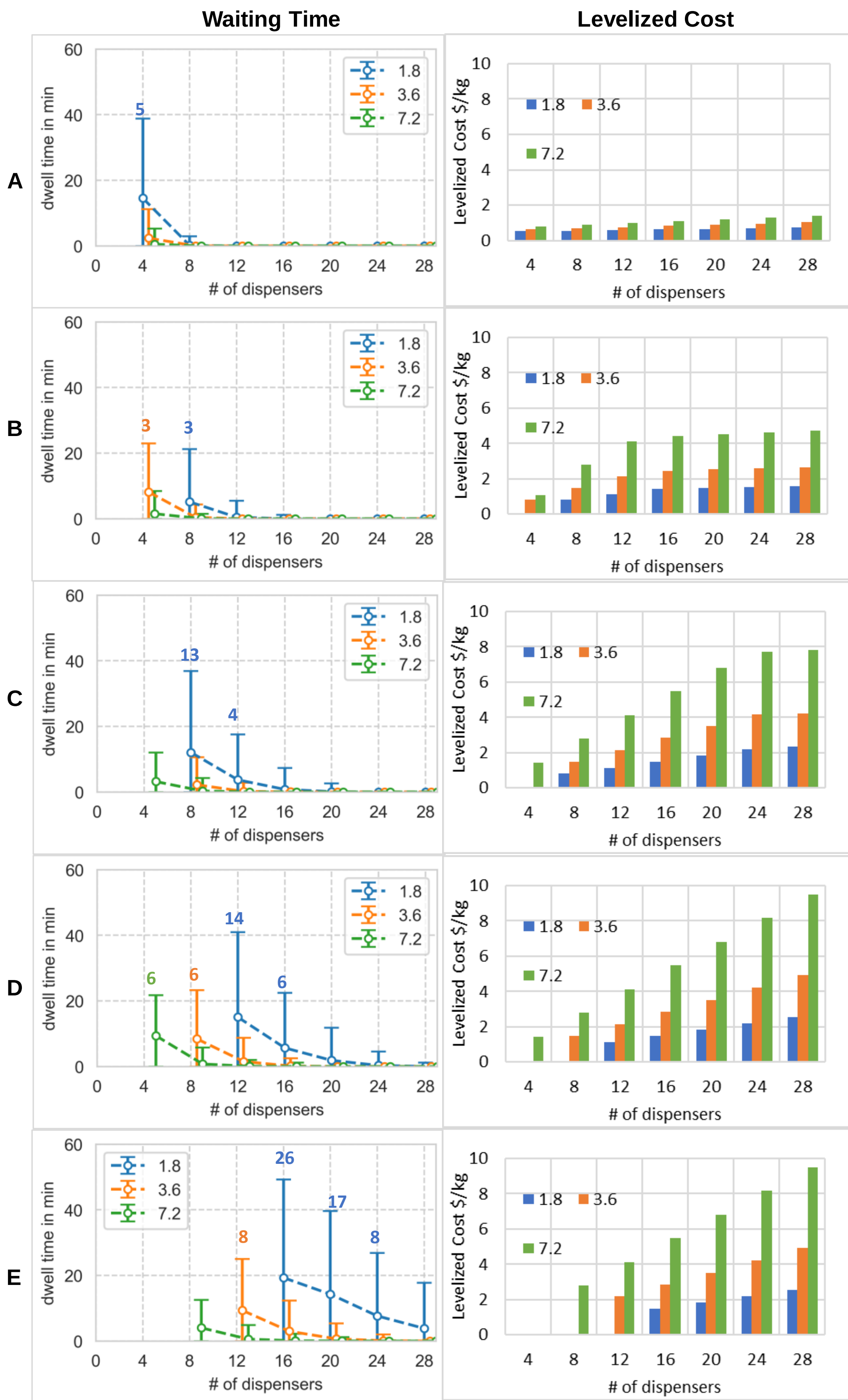

Fig. 5. Waiting time and levelized cost by number of dispensers and refueling rates.

Comparing different hourly profiles, a station configuration (fill rate and dispenser numbers) can be determined based on the trade-off between waiting time and levelized cost. Take profile D as an example, if all demand shall be served, then a 1.8kg/min fill rate with 20 dispensers is the best option given that it has the lowest unit cost ($1.8/kg) with an acceptable average waiting time of less than 1 min/vehicle. In all other scenarios where truck fueling demand can be met, the unit cost is higher than this option. However, if the restrictions on meeting all demand can be lifted, then the three scenarios below provide competitive prices:

- 7.2kg/min fill rate with 4 dispensers ($1.5/kg). On average 6 trucks among 200 trucks cannot be served at this station per day as labeled in the figure.
- 3.6kg/min fill rate with 8 dispensers ($1.5/kg). Same as above.
- 1.8kg/min fill rate with 16 dispensers ($1.5/kg). Same as above.

All three scenarios have the same unit price and demand serving capability. Comparing the waiting time, the waiting time variance is about the same for all three scenarios while the average waiting time decreases from 10 min to 5 min with the decrease of fill rate from 7.2 kg/min to 1.8kg/min. On the other hand, the average fueling time increases from about 8 minutes to 31 minutes. Combining both the fueling time and waiting time, 7.2 kg/min with 4 dispensers is the best option.

Cost Component and Hourly Profile

One interesting observation from Fig. 5 is that, with the increase of truck numbers in peak hour demand, the levelized cost grows noticeably. The cost growth is more evident for scenarios with a higher fill rate. Further breakdown of the cost by each component for profiles A & B with the 7.2kg/min fill rate is shown in Fig. 6.

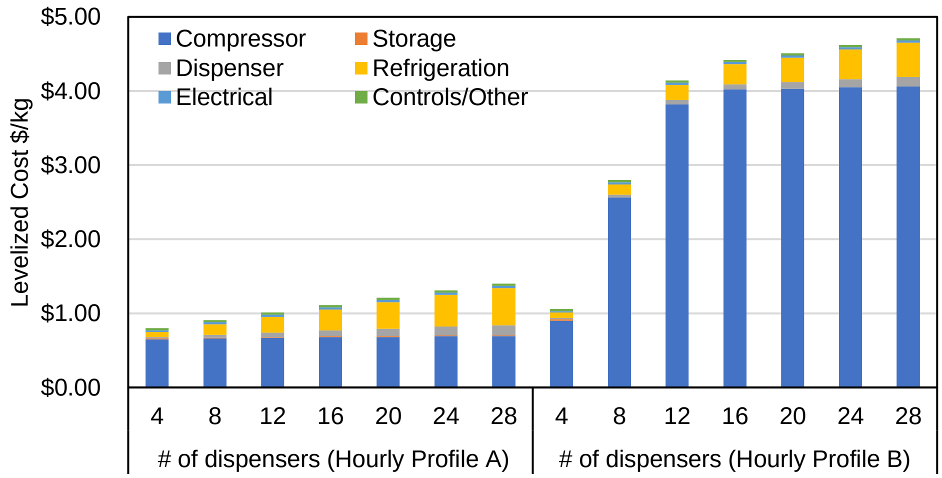

Fig. 6. Cost breakdown by refueling station components with 7.2kg/min fill rate.

With the increase in dispenser numbers, the cost of compressors, refrigeration, and dispensers increased, leading to the total increase in cost. Comparing hourly profile A to profile B, the compressor is the determinant component that leads to cost growth. With the same number of dispensers, the number of compressors needed increases obviously to meet the increased peak hour demand. This is a unique feature for hydrogen but not the conventional fuels. The impacts of peak hour demand on levelized costs shall be taken into consideration in hydrogen fueling station location and capacity optimization.

Demand and Cost

In this section, the relationship between cost and demand is discussed. Fig. 7 shows the levelized cost as well as the total investment cost for two different demand scenarios. Scenario 1 has a total demand of 100 hydrogen fuel cell trucks and Scenario 2 has a total demand of 200 hydrogen fuel cell trucks. As expected, total investment costs rise with the demand because of higher energy consumption costs, and operation & maintenance costs, etc. On the other hand, the levelized cost shows a reverse pattern. The levelized cost is reduced with higher demand (200 trucks) because more fuel was distributed in the higher demand scenario. Note that the levelized cost does not necessarily drop with the increase in demand. Depending on the total investment cost and dispensed amount, the levelized cost may decrease, increase or remain the same with the change in demand.

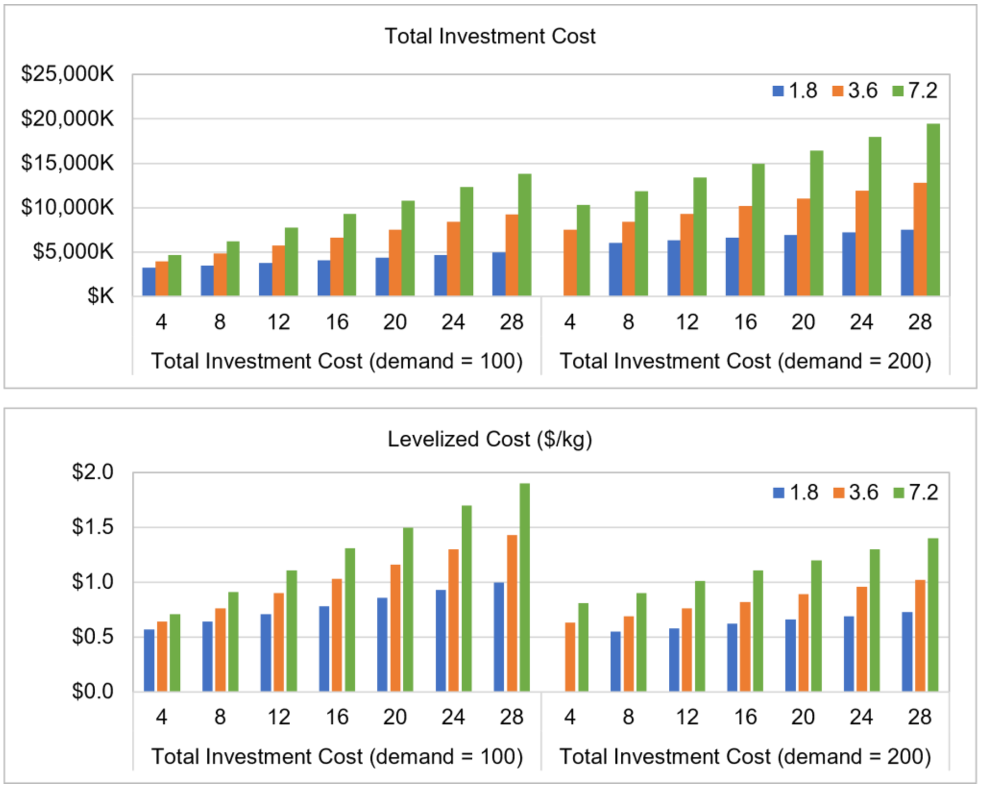

Fig. 7. Total investment cost and levelized cost by demand.

CONCLUSIONS

The introduction of a decarbonized energy economy will, in part, necessitate the development of a decarbonized commercial freight truck transportation system and supporting ecosystem. Characterizing and optimizing a national refueling infrastructure to support this decarbonized freight system is critical, where identifying both "spatial" and "temporal" requirements will be necessary to successfully launch and advance a sustainable solution. This process will need to factor in the specific characteristics of the fuel type and correlate that to the anticipated demand (due to freight volume and adoption scale up in time) to determine the optimized refueling sites on public access roadways. This paper is the second in a series that will build out a comprehensive model to optimize a consolidated national hydrogen refueling infrastructure eco-system targeted at commercial vehicles. In this study, combining waiting time and cost analysis based on various station configurations and demand fluctuations enables industrial companies and government agencies to compare different scenarios and select the best configurations for the desired level of service. Additionally, this study investigates how the variation in peak hour demand affects the levelized hydrogen fuel cost. In the case study scenario, with fixed daily visit frequency, the levelized cost increases obviously (a minimum of 30% increase under different configuration scenarios) when the peak hour pattern changes from pattern A to pattern B. The increased amount is particularly high for the 7.2 kg/min fill rate because more compressors are needed to meet both the high fill rate and the peak demand. This indicates that, for stations expecting obvious peak hour patterns in daily visit frequency, a high fill rate, while reducing the total waiting time, could significantly increase the cost and is thus not the preferred option. The quantitative relationship between the levelized cost and waiting time considering the value of time will be a focus of our future research. Furthermore, the relationships between demand, investment cost, and levelized cost are explored in a case study. The results suggest that a balance between investment cost and levelized cost under different demand levels shall be identified to determine the best station configurations. Overall, this research provides cost and delay inputs for HDV hydrogen refueling station siting and capacity optimization analysis. The work can be extended and applied to provide inputs for hydrogen refueling station optimization in other areas.

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