A STUDY ON EMERGING TRANSPORTATION SERVICES BASED ON EFFICIENT NETWORK DESIGN AND OPERATION

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By

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

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a candidate for the degree of Doctor of Philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

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ABSTRACT

Rapid growth in modern technologies has provided new tools for flexible and convenient transportation to the public. These new avenues for commuting would enable promoting non-driving modes of conveyance while shifting the economics of movement via traditional methods such as cars, subways, buses, etc. These innovative services would be advantageous in reducing dependability on privately-owned vehicles, thereby reducing the impact on the environment while providing a faster mode of travel. They would also play a crucial role in decreasing bottleneck due to heavy traffic, which has a detrimental impact on people's health, lifestyle and productivity. Thus, logistic companies are aiming towards making use of emerging technologies, such as air taxis and hyperloop, for facilitating efficient transportation in the near future.

In this dissertation, a unique two-phase procedure integrating a multi-criteria warm start technique with an iterative k-means clustering algorithm is developed for optimal air taxi infrastructure location decisions. The proposed methodology was improved by utilizing a different clustering technique called clustering large applications (CLARA) which suggests developing 14 unique sites in New York City (NYC). However, establishing all the stations simultaneously might be challenging for any business, and therefore, a mathematical model is created to recommend these centers in multiple phases while maximizing the demand satisfaction in each scenario. Based on the available transportation literature, constraints such as rental cost, number of trips per day per 1000 customers, road facilities, and the employee salary are considered to be a part of the linear model.

Next, a multiple-criteria simulation optimization model is developed to determine the ideal station size, location and size of charging facilities, minimum threshold charge, number of vehicles required and, allocating customers to air taxis for a network of five skyports. The model proposes having 50 air taxis in the system for the base case. The commuter average time in system and wait time to be approximately 36 and 14 minutes respectively, with average vehicle utilization of nearly 76%.

While air taxis are expected to be utilized for intra-city commute, Hyperloop and High-Speed Rail (HSR) services would enable passengers for inter-city transport . A brief investigation is performed to examine the substitutability of HSR with Hyperloop services based on vehicle and passenger characteristics. A simulation model is developed to compare the performance of both these alternate transportation modes for a network of three major cities in Europe (Amsterdam, Paris, and Frankfurt). Our results indicate that with a significantly lower pod capacity, the Hyperloop system will still be able to serve more customers compared to the HSR services, while the vehicle utilization is observed to be higher in the latter alternative for a given period of time. We further compare the two transportation modes with respect to their estimated infrastructure and operational costs as well as CO_2 emission. Finally, a cost-benefit analysis is conducted to estimate the passenger ticket price for Hyperloop services.

Keywords: Emerging transportation services; Urban Air Mobility (UAM); Air taxi; Hyperloop; Multi-Criteria simulation optimization model.

Chapter 1: Introduction

Rapid urbanization and accelerated economic development have led to a considerable increase in automotive vehicles, which has resulted in a rise in traffic demand. However, traffic congestion in urban areas has been exacerbated in recent times due to a failure to meet the demand requirements (Sun et al., 2019). This has a significant impact on the national economy (Kan et al., 2019) as well as on an individual's health (Sanchez et al., 2020). A recent study by Texas A&M Transportation Institute (TTI) found that the total number of delays due to traffic congestion has increased from 1.8 billion hours in 1982 to 8.8 billion hours in 2017 in 494 urban cities in the United States. Simultaneously, the congestion cost (quantified value for total fuel wasted and time delay) rose to $179 billion from $15 billion during the same period (Urban Mobility Report, 2019). Similarly, the costs of death due to air pollution from excess traffic was estimated to be approximately $500 million in 2010 (Sanchez et al., 2020). Concern over high carbon emissions by buses and rails have led to advancements in technology to achieve carbon neutrality by developing autonomous vehicles that utilize other sources of energy such as electricity and hydrogen (Bakker and Konings, 2018).

It is widely expected that autonomous vehicles would not only reduce the cost of transportation but also improve the ease of traveling (Meyer et al., 2017). Rapid ground transit such as high-speed rails, Hyperloops, etc. and Urban Air Mobility (UAM) have received widespread attention due to their ability to alleviate traffic congestion and avail the advantages of autonomous vehicles (Kong et al., 2020; Straubinger et al., 2020; Voltes-

Dorta and Becker, 2018). These services would be a viable alternative to the existing modes of commuting.

Various logistics and transportation companies across the globe, such as Uber, Kitty Hawk, Airbus, German Lilium, and Boeing, have started to venture into emerging aviation technology called air taxis, which can provide a more efficient, faster, and cheaper way to commute across the city. Although it is expected that during the initial stages of operation, commuters would have to pay a premium price to avail the services (Holden and Goal, 2016; Shaheen et al., 2018), a market study by the National Aeronautics and Space Administration (NASA) concluded that increase in operational efficiencies and technological advancement would make the cost per passenger mile for air taxis comparable to ground transportation (Reiche et al., 2018). On the other hand, the Hyperloop system is primarily being developed by Virgin Hyperloop based on conceptualization by Elon Musk in 2013 (Musk, 2013). It is expected to connect several key urban cities, such as San Francisco – Los Angeles and St. Louis – Kansas City.

1.1 Overview of Air Taxi Services (ATS)

Air taxi, urban air mobility (UAM) service, operates using the concept of electric vertical takeoff and landing (eVTOL) while minimizing energy and power requirements (Johnson et al., 2018; Reiche et al., 2018). It can also be described as a system that facilitates an automated and on-demand carrying of shipments or passengers via air transportation around an urban environment (Winter et al., 2020). Air taxis can be used for a travel range of about 100 miles (Holden and Goel, 2016; Holmes, 2016), and hence, could cater to the transportation needs of customers in metropolitan cities and their neighborhoods. In recent years, the design, development, and testing of air taxis are pursued by several companies across the globe in countries such as China, India, New Zealand, Singapore, and the USA (Butterworth-Hayes, 2019; Hawkins, 2018; Warwick, 2018). For instance, Airbus has introduced the Airbus' A^3 Vahana program for testing the feasibility of self-piloting VTOL technologies (Airbus, 2019). Similarly, Uber established a business plan to launch its ATS, called Uber Elevate, by 2023 (Holden and Goel, 2016). Various parameters, such as cruise altitude, impact on the environment, speed of the vehicle, and completion time, are examined to evaluate the advantages in the design and use of air taxis (Bacchini and Cestino, 2019; Enconniere et al., 2017).

Due to rapid development in UAM, several studies have focused on examining various design concepts (Bacchini and Cestino, 2019; Ozdemir et al., 2014) and challenges in the implementation (Rajendran and Pagel, 2020; Vascik and Hansman, 2018). Numerous investigations have also been conducted to increase the competitiveness of air taxis by reducing operational costs, improving their safety, reducing noise, regulations, and policies (de Jong, 2007; Piwek and Wisniowski, 2016; Straubinger et al., 2020). All these factors combine to influence customers' decisions to avail of the new technology. There are many decisions to be considered from a management perspective that are associated with these operational issues, which can be divided into three management decision categories - strategic, tactical and operational (Figure 1.1).

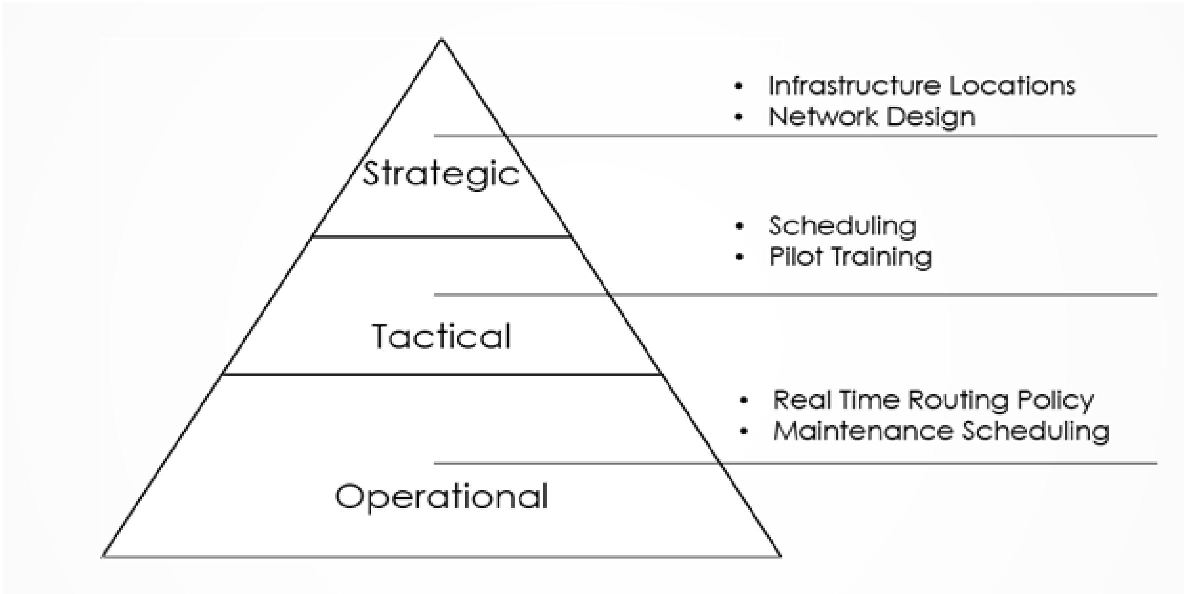


Figure 1.1: Management decision levels in air taxis

Long-term strategic decisions could include determining the number and size of air taxi stations, their locations, the feasibility of operations, and availability of space. ATS providers consider two types of infrastructure in the literature; vertiports - facilities used for functions such as docking, charging, maintenance, and repair of air taxis, and vertistops - sites for landing, customer dropoff and pickup, and takeoff (Rajendran and Shulman, 2020). A vertiport could also serve as a customer pickup/dropoff infrastructure, in addition to the intended service tasks discussed above. Whereas, the vertistop is solely utilized to serve customers. Tactical decisions have a medium-term impact, and an example would be the pricing strategy adopted by logistics companies to attract customers as well as pilot training. Finally, at an operational level (short-term decisions), the service providers would need to develop an efficient real-time routing policy for scheduling and dispatching multiple eVTOL vehicles.

1.2 System Overview

The sequence of events for a standard air taxi network is presented in Figure 1.2 (Holden and Goal, 2016; Hasan, 2019; Rajendran and Zack, 2019). A typical air taxi operation (as shown in Figure 1) includes the customer initiating the ride. Each passenger x_i can be defined as a tuple $(\lambda_i^o, \varphi_i^o, \lambda_i^d, \varphi_i^d, \theta_i)$ where $(\lambda_i^o, \varphi_i^o)$ pair represents the origin latitude and longitude, $(\lambda_i^d, \varphi_i^d)$ denotes the dropoff coordinates, and θ_i is the pickup time. The customer is assigned to the air taxi station s_a that is closest to $(\lambda_i^o, \varphi_i^o)$, $s_a \epsilon \mathcal{S}$, where $\mathcal{S}$ is the set of air taxi locations ($\mathcal{S} = \{s_1, s_2, s_3, \ldots\ldots s_K\}$) that will be determined using phase-1 of this research. The customer could travel from $(\lambda_i^o, \varphi_i^o)$ to s_a (i.e., first mile) either by car, walk, subway, bus or bike (i.e., they can leverage the concept of Mobility as a Service). Passenger x_i will then transported by air taxi to s_b ($s_b \epsilon \mathcal{S}$) in the middle mile, where s_b is the air taxi station closest to the destination $\left(\lambda_i^d, \varphi_i^d\right)$. For the last mile (i.e., from s_b to $\left(\lambda_i^d, \varphi_i^d\right)$), customer can either travel by car, walk, subway, bus or bike.

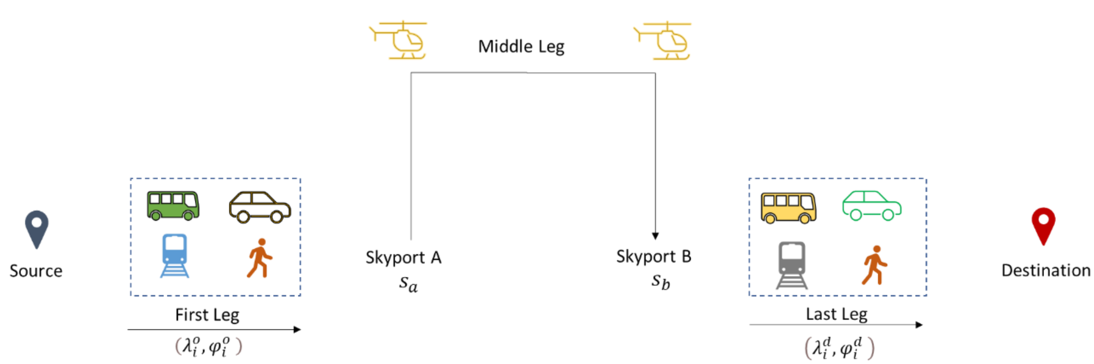


Figure 1.2: Typical layout of a ride using the air taxi

1.3 Hyperloop System

Hyperloop is based on Maglev system, which utilizes magnetic properties to propel a pod towards its destination in a vacuum at high speeds. This eliminates the use of wheels in pods and thereby removing any friction from the track (Abdelrahman et al., 2017). In terms of operation, Hyperloops are comparable to a subway system but have lesser stops within a city. A typical Hyperloop system would have passenger capsules going in either direction inside two tubes of diameter 2.23 m. A pod would travel at a maximum speed of 750 mph and accommodate 28 passengers (Dudnikov, 2017; Rajendran and Harper, 2020). In contrast, a subway car has a capacity of approximately 54 seated commuters (Rajendran and Harper, 2020). Irrespective of capacity constraints, Hyperloop would drastically reduce the travel time between two cities. For example, it is expected to cover the distance between LA and SF in about 35 minutes which is faster than standard air transportation services. It would also have a boarding/departing time of 60 seconds, thereby retaining the fast turnaround time of a subway train. Figure 1.3 displays a typical design of a Hyperloop pod as proposed by SpaceX in 2013 (Musk, 2013).

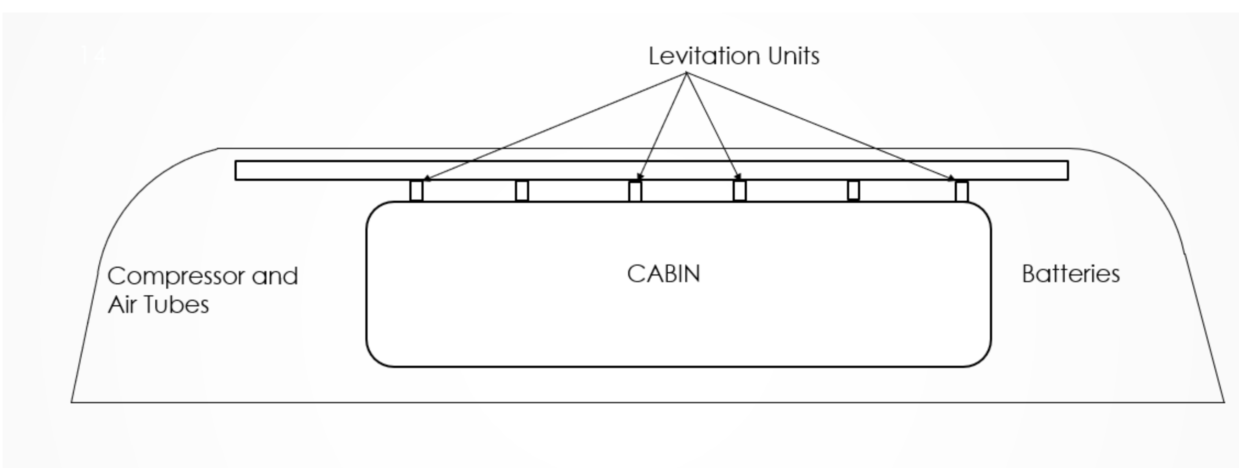


Figure 1.3: Design Concept of Hyperloop

1.4 High-Speed Rails

High speed rails, a type of mass transit, provide rapid energy efficient tranportation when compared to the traditional rail services (Zhou and Shen, 2011). Although these facilities were initially introduced in Japan, they are widely being used by major European countries, such as Germany, France and Spain. A typical HSR, has an average speed of approximately 150 mph on newer established tracks (Palacin et al., 2014). The seating capacity of a HSR vehicle is dependant on the design and ranges from over 400 passengers per train to approximately 1300 commuters per train (Givoni, 2006). Furthermore, it is observed that a HSR are nine times more energy efficient than airlines facilities and nearly four times more efficient than driving on road (EESI, 2018).

1.5 Motivations for this Research

- A recent study observed that passengers spend over 130 hours annually due to heavy traffic in major cities, such as Boston, Chicago, Washington DC, and New York City (Inrix, 2020. This causes an increase in accidents, in turn leading to stress, which negatively impacts the citizens.
- Gridlocks also have a significant impact on the economy due to a loss in productivity, as well on the environment because of an increase in pollution (Kan et al., 2019).
- Urban Air Mobility (UAM) can potentially become a future means of transportation and facilitate daily travelers to bypass congestions in metropolitan areas. Similarly,

Hyperloops can facilitate quicker inter-city movement thereby reducing the congestion on highways.

- Limited research is available on the optimal air taxi infrastructure locations across a city while having a high percentage of demand fulfillment.
- Considering that ATS are an emerging technology, it is critical to develop a decision-making system that proposes station locations in multiple phases. This would enable the logistic companies to conduct appropriate market studies based on selected sites during the initial stages of operations before further expansion.
- It is crucial to study the impact of factors such as passenger willingness to fly, percentage time savings, costs associated with the infrastructure developments, etc. on the viability of UAM.
- The efficiency of air taxi operations would be determined by optimizing customer wait times, cost of traveling and idle time of vehicles. Striking a balance between these parameters would enhance customer perception about UAM and potentially increase the demand.
- It is important to develop a framework that makes the following strategic (long term), tactical (medium term) and operational (short term) decisions: (i) determining size of operating facilities (strategic), (ii) deciding location and size of charging stations (strategic), (iii) determining the number of air taxis required to serve the demand at a certain customer service level (strategic) (iv) determining the threshold minimum charge (tactical), and (v) allocating customers to air taxis (operational).

- While air taxis are highly suitable for intra-city travel, Hyperloop services can be utilized for inter-city commute. Most previous researches has observed a positive impact of supplanting air transport with high-speed rails (HSR) (Castillo-Manzano et al., 2015; Takebayashi, 2014; Zhang et al., 2018). However, a similar study investigating substitutability of HSR with Hyperloop services is not available in literature.

1.6 Thesis Outline

The remaining theses is organized as follows. The review of literature on the overview on the air taxi system, design, infrastructure location decisions, and facility location decisions are presented in Chapter 2. The proposed multi-criteria warm start technique and the iterative k-means clustering algorithm are discussed in Chapter 3 along with a comparison of results with existing literature. Clustering large applications (CLARA) algorithm along with the linear model and the results obtained are described in Chapter 4. A multi-criteria simulation optimization model is developed in Chapter 5 while Chpater 6 explores substitutibility of HSR with Hyperloops. Conclusion and potential future work are discussed in Chapter 7.

Chapter 2: Literature Review

2.1 Air Taxi Overview

Several works have been conducted in recent years to examine the emerging air mobility design and network operations. Al-Haddad et al. (2020) studied the features influencing the consumer opinion for adopting UAM. By conducting a survey using exploratory factor analysis, the authors concluded that factors, such as the amount of time savings, service reliability, and cost, are highly influential amongst the people. National Aeronautics and Space Administration (NASA) explored the market potential for UAM for three different use cases: transfer of packages (last-mile delivery), autonomous public commuter system (air metro), and autonomous aviation service (air taxi). They found a majority of the users were comfortable with the use cases, but the logistics organizations could face potential operational and technical challenges in the form of travel distance, overall demand, and scheduling (Hasan, 2019). A different investigation by NASA focussed on two other use cases for UAM in air ambulance and air shuttle along with air taxi (Reiche, 2018). Both the studies concern that public acceptance of UAM is dependent on multiple complex issues such as safety, privacy, and environmental threats.

Factors such as safety, sustainability, and regulation policies, are also explored to gain an insight into the evolving technology (Cokorilo, 2020; Pisoni et al., 2019; Straubinger, 2019). Another research by Swadesir and Bill (2018) investigated the competitiveness of urban air transportation with automobiles, bikes, and other modes of public transportation in Melbourne, and they concluded that customers were mainly concerned about the safety aspects and noise generated by the aircraft.

Similar to other on-demand mobility (ODM) services, uncertainty in customer demand can lead to operational inefficiencies (Davis et al., 2018; Luo et al., 2020). One of the biggest challenges in forecasting demand using analytical tools has been due to inadequate historical data (Rajendran and Srinivas, 2020). At the same time, telecommuting or work from home culture has increasingly become extremely common and, therefore, adding further constraints in demand estimation (NASA Mobility UAM Market Study, 2018). Existing literature suggests two potential approaches for predicting eVTOL customer requests - (i) quantitative techniques, such as approximating the demand based on previous data from other similar services (eg. traditional or ridesharing taxi services) as proposed by Rajendran and Zack (2019) and (ii) qualitative methods, similar to surveys and market studies geared towards garnering experts and customers perception about the emerging ATS (Binder et al., 2018; Garrow et al., 2018). The present study utilizes the model developed by Rajendran and Zack (2019) for computing demand for UAM services from trip data of traditional taxis.

2.2 Air Taxi Design

Recent studies have focussed on developing concept vehicles and examine performance parameters for UAM to analyze the feasibility for its practical implementation (Al Haddad et al., 2020; Bacchini and Cestino, 2019; Johnson et al., 2018; Silva et al., 2018; Vascik and Hansman, 2018). The three major air taxi vehicle types are vectored thrust, lift+cruise and wingless (Bacchini and Cestino, 2019). Vector thrust allows the air vehicle to modify its path based on propulsion direction (Hua et al., 2015). It provides a highly efficient cruising ability and speed to the aircraft. Harrier series is the most popular example of an aircraft using vector thrust technology (Zhou et al., 2020). It is further classified into tiltrotor and tilt-wing (Johnson et al., 2018). The lift + cruise technology enables the manufacturers to add a dedicated lift engine alongside the cruise engine. This reduces excess drag and the amount of fuel used during the cruise. The thrust to weight ratio during the cruise is nearly 0.1 (Finger et al., 2019). It has multiple electric rotors and the failure of one propeller will have no impact on the performance of others (Moore, 2020). A wingless multicopter design, as the name implies, has no wings present on the vehicle (Ozdemir et al., 2014). They rely on multiple propellers for thrust propulsion and thus provide better control and less vibration (Lu et al., 2016).

Most air taxi vehicles have a minimum flying speed of 100km/hr and a passenger capacity of at least two passengers (Rajendran and Srinivas, 2020). Polaczyk et al., 2015 presented the characteristics of each type of eVTOL design. Their study indicated that each design has its own unique set of strengths and weaknesses in terms of speed, range, seating capacity, and impact on the environment. On the operational side, Mane and Crossley (2012) utilized integer programming to synchronously solve aircraft design for improved performance and allocation to operators' problems. In contrast, de Jong (2007) explored the operational costs associated with urban air mobility using dynamic programming. Piwek and Wisniowski (2016) defined parameters such as passenger capacity, fuel consumption and flight level to be critical for small air transport (SAT) aircraft.

Several other criteria affecting the opinion of customers, such as service reliability, percentage time savings, and cost of availing the facility, were identified by Al Haddad et al. (2020) through an online survey of residents in Munich. Similarly, Vascik and Hansman (2018) established three additional constraints in aircraft noise, a control system for air traffic, and ground infrastructure availability that potentially affects the market growth of UAM. According to Holden and Goel (2016), Uber elevate is projected to produce a noise level close to 60 dB. Therefore it is critical to design a quieter propulsion system for higher public acceptance (Johnson et al., 2018). Therefore, determining the optimal number of air taxis and their scheduling is crucial in achieving an ideal trade-off between operating cost, vehicle utilization, and service responsiveness.

2.3 Air Taxi Infrastructure Location Decisions

The literature on infrastructure location for air taxis is still in the evolutionary stage. Multiple tools, such as clustering algorithms (Lim and Hwang, 2019; Rajendran and Zack, 2019), mathematical models (Rath and Chow, 2019), and simulation (Balac et al., 2019), have been utilized to estimate demand and determine optimal vertiport and vertistop locations. Rajendran and Zack (2019) proposed integrating a multi-modal warm start approach with k-means clustering algorithm to determine 21 potential air taxi stations in New York City (NYC). Demand estimation for this service was made by employing publicly available taxi data and parameters provided by Holden and Goal (2016). They also examined the effect of various parameters, such as customer satisfaction and percentage time savings on prospective sites. Similarly, Lim and Hwang (2019) suggested a k-means algorithm for selecting skyport stations based on three heavily used routes in the Seoul metro area. However, cluster centroids generated from k-means approach are highly dependent on the initial value selected and it produces a different result with every run (Zahra et al., 2015). A research utilizing a mathematical model to identify optimal air taxi hubs was conducted by Rath and Chow (2019). Total travel cost was captured by the objective function to satisfy demand in NYC. They estimated that the model outperformed the clustering technique employed by Rajendran and Zack (2020) by approximately 7%.

Bonnefoy (2005) explored the use of simulation for estimating annual demand, fleet size, and network configuration for the air taxis. A similar investigation was conducted by Rothfeld et al. (2018), in which they used a transportation simulation tool to analyze the network and infrastructure placement by incorporating no-fly-zones, required flight path, and height restrictions in the model. Swadesir and Bill (2018) compared the travel time taken by commonly used transportation modes and air taxis in Melbourne and determined that UAM saved more than 24 minutes on average over driving. They inferred that each vertiport in the city should be placed at least 10 km (approx. 6 miles) apart due to the speed requirements of the vehicles.

Facility location problems that are studied in similar emerging technologies could be adopted for air taxi network design as well. For example, this strategic decision has been widely analyzed for establishing charging stations for electric cars (He et al., 2018; Liu and Wang, 2017; Lee and Madanat, 2017; Loeb et al., 2018; Riemann et al., 2015; Xylia et al., 2015; Yang et al., 2017) and last-mile delivery systems (Salama and Srinivas, 2020). Liu and Wang (2017) investigated the use of a heuristic algorithm to optimally locate recharging terminals by minimizing travel cost, time, and delay due to charging. Lee and Madanat (2017) proposed a convex parsimonious model for planning a charging station network with the objective of minimizing greenhouse gas emissions and constraints, such as budget and demand during peak hours. Similarly, Yang et al. (2017) utilized queuing theory to estimate customer wait time at each charging station and integer programming to reduce infrastructure investment.

2.4 Facility Location Problem

2.4.1 Clustering Algorithms

Aggregation of collected data points into numerous groups based on their properties is known as clustering (Yao et al., 2019). There are several modes of operation proposed in the literature such as partitioning algorithm, density-based algorithm, hierarchical algorithm, etc. (Mouton et al., 2020). Other than partitioning algorithms, most approaches automatically determine the ideal number of cluster centroids in the system. In the partitioning algorithm, the number of focal points is specified by the user. The current study focuses on using the k-means partitioning algorithm as the number of clusters can be easily varied to satisfy the restrictions in the sensitivity analysis.

Clustering algorithms are also applied for strategic facility locations in other emerging technologies such as charging stations for electric vehicles (Andrenacci et al., 2016; Helmus et al., 2020; Marino and Marufuzzaman, 2020; Riemann et al., 2015; Zhang et al., 2019) and delivery systems (Ferrandez et al., 2016; Salama and Srinivas, 2020). Andrenacci et al. (2016) utilized a fuzzy k-means cluster technique to generate optimal charging stations for electric vehicles in Rome. Similarly, Zhang et al. (2019) explored the amalgamation of barycentric methods with the k-means technique to reduce the impact of demand dispersion on site selection. On the other hand, Helmus et al. (2020) applied Gaussian mixture and partitioning around medoids (PAM) in a two-phase clustering approach. The first phase was used to identify 13 most common charging durations, while nine different user types were established in the second phase. Marino and Marufuzzaman (2020) investigated a two-step approach of integrating k-means algorithm with a stochastic model to determine potential charging station candidates and minimize total energy usage in Peru. They employed principal component analysis to reduce the dimensionality of the dataset and improve the algorithm's performance. They observed an 18.24% reduction in energy costs due to the integration strategy.

2.4.2 Mathematical Model

Stochastic programming techniques are widely used for facility location problems (Basu et al., 2015; Choudhary and Shankar, 2012; Gabor and van Ommeren, 2006; Kim and Kim, 2013; Rodriguez et al., 2020; Wichapa and Khokhajaikiat, 2017). Rodriguez et al. (2020) investigated the optimal vehicle assignment and fire station location problem by maximizing the coverage due to demand emergency for a city in Chile. Wichapa and Khokhajaikiat (2017) explored goal programming for optimizing facility, transportation, and operating cost for ideal waste disposal sites. They employed an analytical hierarchy process (AHP) to identify suitable weights for each criterion considered in the model. A similar study by Choudhary and Shankar (2012) evaluated the integration of multi-criteria decision making with fuzzy AHP for evaluating the potential locations for the thermal power plant stations.

Existing literature has also suggested utilizing stochastic optimization for locating charging stations for electric vehicles (Brandstatter et al., 2017; Kabli et al., 2020; Liu et al., 2012). Kabli et al. (2020) proposed a multi-phase model to maximize profits at each stage by increasing the number of existing charging centers over a particular time period. They estimated that an increase in the number of locations would also lead to a rise in the number of electric vehicles in the system during the latter stages. Brandstatter et al., 2017 investigated the impact of integrating on-demand ridesharing systems with electric vehicles by using a time dependent linear model along with a heuristic algorithm. They applied their approach in Vienna and concluded that heuristic techniques are suitable for large scale problems. Liu et al., 2012 focussed on developing a particle swarm optimization technique for minimizing total cost. The linear model in the present study utilizes some of the constraints mentioned in the literature (Brandstatter et al., 2017; Liu et al., 2012), such as traffic flow and available budget.

2.4.3 Simulation

Network operations for air taxis can also be studied using simulation. A recent research by Balac et al. (2019) evaluated the probable demand for eVTOL in Zurich using simulation. They observed a tradeoff between pricing structure, vehicle type, and time saved, i.e., increasing vehicle speed could attract more customers by reducing travel time while leading to a rise in the pricing structure. However, their model had an unconstrained number of available vehicles, which is practically infeasible. On the other hand, Rajendran and Shulman (2020) employed simulation to determine the feasible number of air taxis in NYC. They noted a linear rise in customer time in the system with an increase in vehicle utilization and customer density growth.

2.5 Scheduling and Routing using Simulation

A recent study by Rothfeld et al. (2018) utilized multi-agent transport simulation to develop a model that showcased the impact of infrastructure locations and various VTOL properties on the performances of the UAM services. Rajendran and Shulman (2020) proposed a discrete-event simulation model for the air taxi network scheduling in an urban city. They observed that 70 vehicles would be required to serve approximately 200,000 customers per week. However, the model does not capture several key parameters, such as individual station capacity, air taxi charging and discharging rates, etc. Luo et al. (2021) explored the influence of eVTOL's battery performance using simulation. They conclude that battery discharge rate depends on the specific motion (ascend, cruise or descend) of the vehicle. They also observe actual possible mileage for each eVTOL reduced by 20 km for every 100 m rise in the cruising altitude.

Several prior studies have explored the scheduling and routing problem in other emerging transport facilities using simulation techniques (Jian et al., 2016; Keskin et al., 2021; Ma et al., 2021; Seitaridis et al., 2020; Tookanlou et al., 2021). Keskin et al. (2021) integrated discrete event simulation with adaptive large neighborhood search (ALNS) for generating ideal routing of electric vehicles to minimize the commuter wait time at charging locations. A simulation optimization model was explored by Mota et al. (2017) for improving operations at an airport by minimizing turnaround time based on parameters, such as ground handling activities and taxi and runway networks. Integration of optimization and simulation was also investigated for determining the airport capacity, ground capacity and aircraft sequencing by Scala et al. (2019).

2.6 Hyperloop System

The Hyperloop system is expected to be a faster and economical alternative to conventional short-range aviation and high-speed rails. Moreover, a market study by NASA (Taylor et al., 2016) concluded that developing Hyperloop facilities would be cheaper than other high-speed railway networks. A recent research by Decker et al. (2017) focused on investigating multidisciplinary characteristics affecting the vehicle design, such as thermodynamic, aerodynamic, electromagnetic, and energy analysis. The authors concluded that expanding the passenger capacity of pods from the original volume of 28 commuters would not have a significant effect on the overall cost. This would enable logistics companies to vary the pod length based on actual market demand. Bordone (2018) developed a framework for exploring socio-economic issues faced by Hyperloop in European Union using a qualitative study.

Several recent studies have focussed on the operational side of the hyperloop network. For instance, Rajendran and Harper (2020) developed a simulation model to analyze the impact of parameters, such as the total number of pods, pod capacity and demand variability, between San Francisco (SF) and Los Angeles (LA). Voltes-Dorta and Becker (2018) investigated the effect of establishing this service on airports in SF and LA using an exploratory analysis. They concluded that the Hyperloop system would provide a feasible alternative to air travel. Similarly, Santangelo and Andrea (2018) determined that while the implementation of the Hyperloop system is feasible, the initial costs of developing the necessary infrastructure are relatively higher than other modes of transportation.

2.7 High-Speed Rails (HSR)

The emergence of high-speed rails has impacted the airline industry substantially on several aspects, such as environmental (D' Alfonso et al., 2015) and airfare and passenger demand (Chang and Lee, 2008; Suh et al., 2005). For instance, the introduction of HSR between the Frankfurt - Cologne route in 2002 led to an approximate 66% decline in the air passengers, eventually leading to the discontinuation of the air service (Clewlow et al., 2012). Similar trends were observed in other countries such as Japan (JR East, 2016), South Korea (Park and Ha, 2006), and China (Chen and Jiang, 2020; Zhang et al., 2017). Multiple researchers have focused on analyzing the complementarity and substitutability between the airline and high-speed rail industry (Castillo-Manzano et al., 2015; Sun et al., 2017; Wan et al., 2016). However, studies are yet to consider the impact of emerging transportation services, such as Hyperloops.

Gundelfinger-Casar and Coto-Millan (2017) explored the implications of competition between air travel and HSR in Spain. They analyzed the demand for the two mediums as a function of commuter income, traveling price, and cost of alternative modes. They concluded that the latter two variables have a substantive impact on whether the HSR would substitute or complement airline services. Similarly, other factors, such as service frequency, travel time, and distance, were considered to be significant parameters affecting the viability of HSR over air transport in the literature (Behrens and Pels, 2012; Zhang et al., 2018). Chen (2017) utilized regression analysis for investigating the intermodal competition by integrating the supply and demand perspectives. The authors observed that high-speed rails had the maximum substitutional effect over air service between cities within the range of 500-800 km. Likewise, Gleave (2003) determined that HSR was not competitive for journeys less than 150-200 km and greater than 800-1000 km.

Yang and Zhang (2012) investigated the implications of competitiveness between air and high-speed rail transport based on profit, price, and social welfare. They observed a greater influence on public welfare by the HSR management resulted in a decrease in profit for both the transport mediums as they were competing for the same demand. They also concluded that the overall profits due to price discrimination between leisure and business travelers using HSR services remained unaltered. Whereas fewer business passengers utilize air transport due to cost differences when compared to leisure commuters. Adler et al. (2010) conducted a cost-benefit analysis for four trans-European networks using game theory. They found that upgrading the infrastructure for the entire European network would maximize social welfare and shift the demand from airlines to HSR.

Gonzalez-Savignat (2004) developed a simulation model to study the impact of HSR on the market share of the airline facilities. They observed travel time to be a significant variable in determining the market penetration, concluding that a rise in customer cycle time utilizing HSR would reduce the overall generated business. Similar findings were reported by Danapour et al. (2018), in which they created a discrete binomial logit model as a customer decision-making tool. The researchers noted fare price and trip duration to be the most influential parameters.

Chapter 3: Iterative K-means Clustering Approach

This chapter focuses on integrating a multi-criteria warm start technique with an iterative k-means constraint clustering algorithm. Several studies have been conducted on the aggregation of geographical coordinates using cluster models (Lim and Hwang, 2019; Kim and Ham, 2019; Millward et al., 2019; Sodenkamp et al., 2019; Wang et al., 2020). However, these techniques are not feasible for our current research because of a few unique constraints that pertain to air taxi operations. For example, Holden and Geol (2016) and Rajendran and Shulman (2020) impose restrictions, such as a limit on first and the last mile on-road travel distance and threshold demand satisfaction rate. To incorporate these unique restrictions associated with eVTOL air taxi system, an iterative k-means cluster algorithm is adopted in this research as it allows the decision-makers to input a specific number of centroids. This method aims to minimize the distance between each data point and its associated center, hence satisfying the first constraint. Also, the number of facility locations can be modified based on the fulfillment of the second criteria.

3.1. Phase 1: Multi-Criteria Warm Start Technique

One of the limitations associated with the k-means clustering algorithm is that this approach randomly generates the initial solution, which significantly impacts the effectiveness of the final solution (Usman et al., 2013). To overcome this drawback, the current investigation proposes the use of a novel multi-criteria based warm start (MCWS) technique for preliminary seed generation.

Suppose if $x_1, x_2, \dots, x_n$ are the set of potential vertiport/vertistop locations, each site location l is defined by a tuple $T = (r_l, f_l, s_l, p_l, t_l)$, where r_l is the rental cost per month,

f_l is the road facility, s_l is the average salary per year, p_l is the population coverage and t_l is the total number of estimated trips made by air taxi per day per 1000 population in that region. Rental cost is defined as the median gross rent per month for each neighborhood in which the station is located. Population coverage represents the total population of the area, while trips per day per 1000 population for each district are determined using the customer pickup coordinates and the station location data. Road facility and employment costs are specified as the distance of the proposed air taxi station with a major road and average household income per year, respectively.

We use the weighted average multi-criteria approach to rank the set of potential site locations. If a criterion m in the tuple is supposed to be minimized (e.g., rental cost per month, average salary per year), then the optimal value of that criteria m (τ_m) is the minimum value observed across all the stations. The normalized value of criteria m for site location l ($N_{m,l}$) is calculated by dividing τ_m with the values of the measure ($V_{m,l}$), as shown by Equation (3.1). Similarly, if the criterion m has to maximized (e.g., road facility, population coverage, total number of estimated trips made per day per 1000 population), then the ideal value (τ_m) is the maximum value noted for all sites. In such a scenario, the normalized value ($N_{m,l}$) is computed by dividing $V_{m,l}$ with τ_m, as shown in Equation (3.2). Once the normalized values for each criterion are calculated, it is then necessary to obtain the weight (W_m), which indicates the order of importance of each objective, and is usually acquired from the decision-maker. The overall fitness value of each center and the total score for all locations are given by Equation (3.3) and (3.4), respectively.

$$N_{m,l} = \frac{\tau_m}{V_{m,l}} \tag{3.1}$$

$$N_{m,l} = \frac{V_{m,l}}{\tau_m} \tag{3.2}$$

$$F_l = \sum_{m=1}^{M} W_m \times N_{m,l} \tag{3.3}$$

$$TS = \sum_{l=1}^{n} F_l \tag{3.4}$$

3.2. Phase-2: k-means Clustering with MCWS technique

As mentioned earlier, the output of phase 1: multi-criteria warm start technique is provided as the input to Phase-2, as the seed solution. The goal of the algorithm involved in this phase is to minimize the average squared Euclidean distance between z data points and n cluster centers (Bock, 2008). Let x_l be the center of cluster l, as shown in Equation (3.5). According to Bock (2008), the variance is given by Equation (3.6). The objective is to minimize the sum of squares for all datapoints.

$$x_l = \frac{1}{|z|} \sum_{x \epsilon z} \vec{x} \tag{3.5}$$

$$Q = \sum_{\vec{x} \in z} |\vec{x} - x_l|^2 \rightarrow \quad min.\ Q \tag{3.6}$$

The general approach utilizing the MCWS technique coupled with the clustering algorithm to generate the ideal number of vertistops and vertiports, is presented below.

1 Initialize Parameters (a) On Road Travel limit (RL), (b) Demand Satisfaction rate (DS), (c) Tuple $T_m = (r_l, f_l, s_l, p_l, t_l)$ for each location l and (d) Weight of parameter m in T
2 Generate initial seeds, s_i = $[s_1, s_2, \ldots. s_5]$
3 For $l = 1$ to n
   Let τ_m be optimal value of parameter m in T
4 If m is to be minimized,
   $\mathrm{N}_{m,l} = \frac{\tau_m}{V_{m,l}}$
5 Else
   $\mathrm{N}_{m,l} = \frac{V_{m,l}}{\tau_m}$
6 # Fitness value of each location
   $\mathrm{F}_l = \sum_{m=1}^{M} W_m \times N_{m,l}$
7 # Select top five locations
   $s_i = top\_n\ (\mathrm{F}_l, 5)$
8 $x_i = s_i$
9 For l = 1 to n
10 #Re-computation of centroids
   Do $x_l = \frac{1}{|z|} \sum_{x \epsilon z} \vec{x}$
11 If Converge rate (CR) < CS for number of travelers within RL
12 $l = l + 1$
13 Repeat steps 9 to 12
14 Return $(x_1, x_2, \ldots., x_n)$

3.3. Validation

The metric, Davies Bouldin index (DBI), is chosen to evaluate the proposed two-phase approach. The reason behind specifically using this metric for testing the effectiveness of our model is as follows. DBI determines the performance of clustering by calculating the ratio of the total spread of points within clusters and the distance between each cluster center (Davies and Bouldin, 1979). However, most of the other metrics determine pairwise distances between the data points. However, since the present research deals with a high volume of data, DBI is leveraged as the evaluation of this parameter is computationally faster. The two major components of this measure are – (a) inter-cluster spread and (b) between cluster segregation.

3.3.1. Within cluster spread (ws_l)

Let X_v be a data point and x_u be the centroid for cluster l then the scatter within-cluster is given by Equation (3.7).

$$ws_l = \sqrt[p]{\frac{1}{|l|} \sum_{X_v \in l} (X_v - x_u)^p} \tag{3.7}$$

However, we need to obtain Haversine distance as the data being used have geospatial coordinates. Equation (3.8) provides the globular distance between two points u and v (Mwemezi and Huang, 2011).

$$d_{u,v} = r \times \theta_{u,v} \tag{3.8}$$

where r is the Earth's radius and $\theta_{u,v}$ represents the angle between two points u and v.

The coordinates of point u are represented by Υ_u (latitude) and λ_u (longitude). Similarly, coordinates of point v are indicated by Υ_v (latitude) and λ_v (longitude) respectively. The angle between these two points is given in Equation (3.9) (Mwenezi and Huang, 2011).

$$hav(\theta_{u,v}) = hav(\Upsilon_v - \Upsilon_u) + cos(\Upsilon_v) \times cos(\Upsilon_u) \times hav(\lambda_v - \lambda_u) \tag{3.9}$$

Thus, inter-cluster scatter (ws_l) can be rewritten, as shown in Equation (3.10).

$$ws_l = \frac{1}{|l|} \sum_{X_v \in l} d_{u,v} \tag{3.10}$$

3.3.2. Between cluster segregation

The distance between two cluster centers x_i and x_j for clusters i and j respectively is calculated as given by Equation (3.11).

$$D_{x_i,x_j} = r \times hav^{-1}\left(hav\left(\Upsilon_{x_j} - \Upsilon_{x_i}\right) + cos\left(\Upsilon_{x_i}\right) \times cos\left(\Upsilon_{x_j}\right) \times hav\left(\lambda_{x_j} - \lambda_{x_i}\right)\right) \tag{3.11}$$

Where $(\Upsilon_{x_i}, \lambda_{x_i})$ and $(\Upsilon_{x_j}, \lambda_{x_j})$ are geographical coordinates of centroids x_i and x_j respectively.

Thus, for any two clusters i and j, the ratio of within-cluster spread and between cluster segregation is calculated using Equation (3.12). The final DBI value is given by Constraint (3.13).

$$R_{x_i,x_j} = \frac{(ws_{x_i} + ws_{x_j})}{D_{x_i,x_j}} \tag{3.12}$$

$$DBI = \frac{1}{n}\sum_{l=1}^{n}\left(\max_{x_j \neq x_i} R_{x_i,x_j}\right) \tag{3.13}$$

3.4. Case Study - 1

3.4.1. Data Description

The dataset used in this study is the estimated air taxi demand data used by Rajendran and Zack (2019). They leveraged the publicly available taxi records from the New York City Taxi and Limousine Commission database. Each data point consists of significant parameters, such as pickup and dropoff coordinates, date, time, total distance traveled in miles, and the total number of passengers on each trip. After pre-processing the data, Rajendran and Zack (2019) estimated the potential demand for ATS is then determined based on the constraints mentioned in Section 3 along with the assumption that a customer is eligible for eVTOL service only if they save at least 40% ride time when compared with the on-road travel (Holden and Goel, 2016). However, the data estimated by Rajendran and Zack (2019) was under the assumption that there is one customer in each ride. Therefore, in the present study, we used the data available over a period of two years on the total number of passengers on each trip to estimate the actual customer population. Hence, the total number of estimated air taxi ride records considered in our study increased from 3.6 million to 6.4 million. Figure 3.1 (a) – (b) depicts the potential geo-mapping of customers on weekdays and weekends during the morning (9:00 AM – 12:00 PM) and night time period (10:00 PM – 12:00 AM). It can be noted that both during weekdays and weekends, there are more dropoffs compared to pickups during the morning time period. This is expected because many commuters travel to the city from suburban regions for work. We can also observe that the ride pickups near Queens during weekends are significantly lower when compared with weekdays.

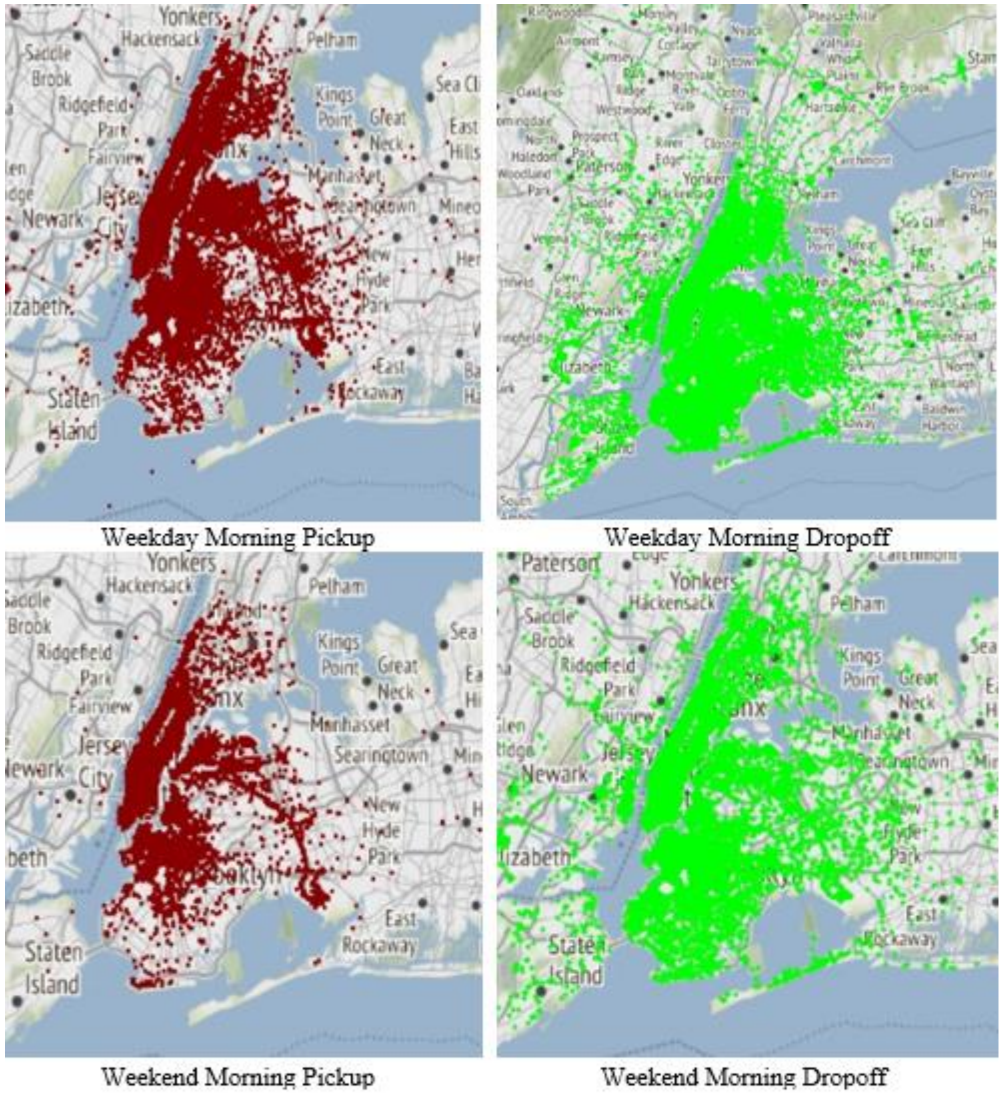


Figure 3.1 (a): Geospatial mapping of potential customers on weekdays and weekends during the morning time period

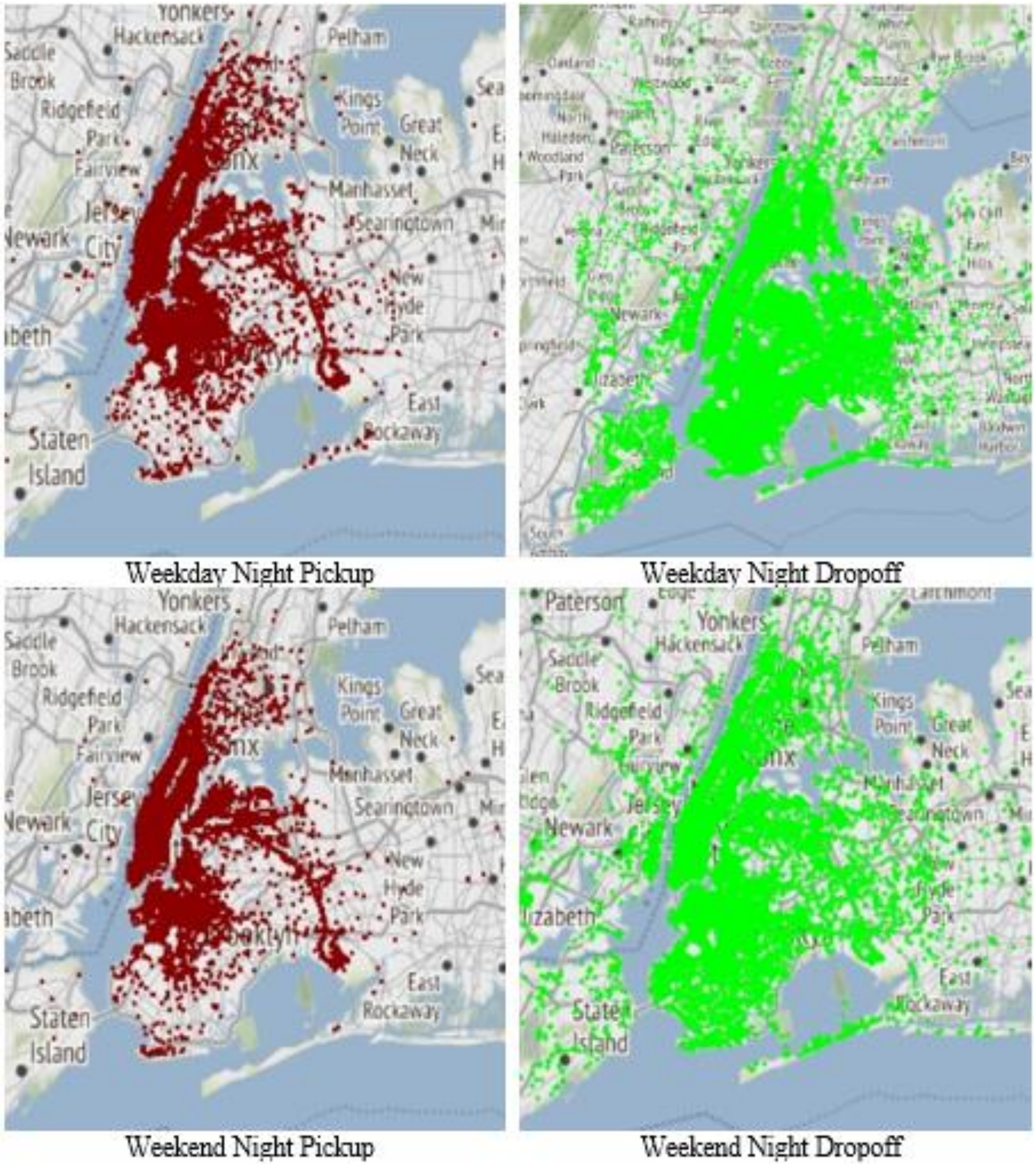


Figure 3.1 (b): Geospatial mapping of potential customers on weekdays and weekends during the night time period

3.4.2. Results and Discussion

Based on the clustering approach discussed in the previous section, we evaluate the locations for vertiports and vertistops for the baseline scenario. Sensitivity analysis is then conducted by altering the percentage values of the four key parameters (time savings, on-road travel limit, passenger willingness to fly, and demand satisfaction). The results obtained in the current investigation are compared with the findings discussed in Rajendran and Zack (2019).

3.4.2.1. Baseline Results

The multi-criteria warm start technique is first used to generate the list of potential seed solutions for the iterative clustering algorithm. There are 59 community districts distributed amongst the five major boroughs (Manhattan, Brooklyn, Queens, Bronx, and Staten Island) in NYC. As discussed earlier, the goal of the multi-criteria warm start technique is to identify the best trade-off solutions based on various criteria identified such as rental cost, population density of an area, number of trips per day per 1000 customers, average salary and road facility. Based on the procedure discussed in Section 4.1, and the recommended weights for each parameter provided in the literature (Hawas et al., 2016, Tzeng et al., 2002, Tzeng et al., 2005), the total score is computed, and the best five sites with the maximum weighted values are used as initial input seed in the k-means algorithm.

The ideal number of stations generated by our model for the base case setting is 18 when compared to 21 stations suggested by Rajendran and Zack (2019). Six (#3, #9, #12, #15, #16 and #17) of those sites are proposed to be built in Manhattan. Site #9 and #12 are approximately a mile apart. It is found that facility #12, which is near Times Square, serves over 12% potential commuters while station #9 near the South Central Park has approximately 10% customer demand. Other boroughs with a high volume of travelers are Queens and Brooklyn. A 2D view of the suggested potential locations is given in Figure 3.2.

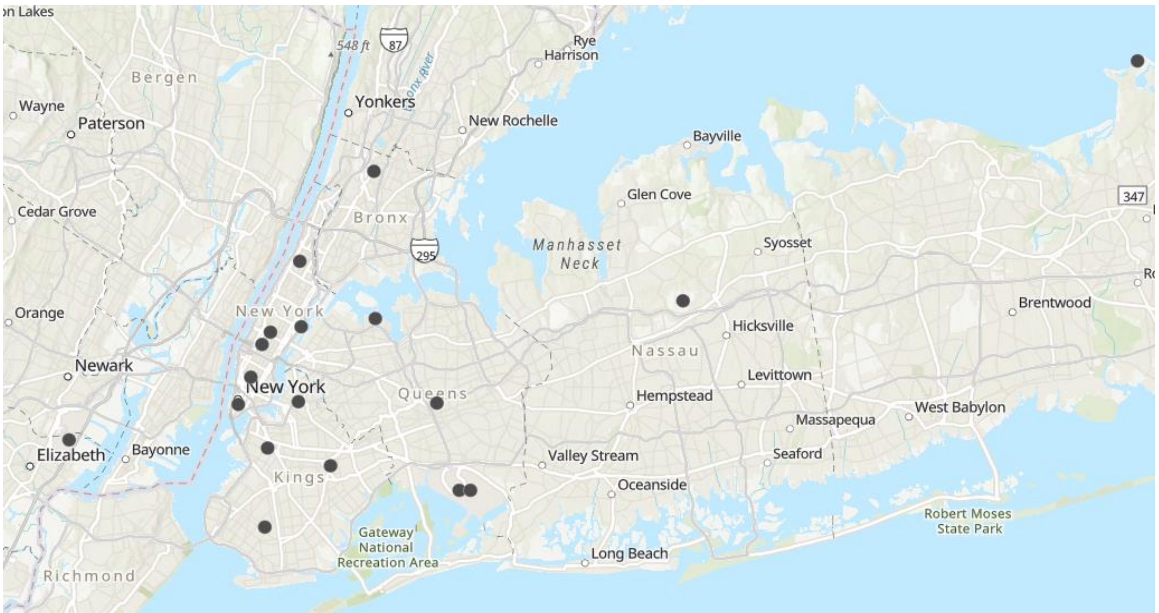


Figure 3.2: Recommended locations for infrastructure development by the clustering algorithm

We observe that two air taxi stations (#6 and #11) are located in the John F. Kennedy (JFK) International Airport and one each (#4 and #14 respectively) in Newark Liberty International Airport and LaGuardia Airport (LAG). JFK and LAG cater to over 50% of the customer demand in total. Thus, it is recommended to build one large vertiport at each of these locations. Other locations that experience a high volume of traffic are site #3 (near World Trade Center) and #17 (close to Empire State Building). It is seen that Columbia University is in close proximity to site #16. In addition, site #15 is located between

Roosevelt Island and the Upper Eastside in Manhattan and has only about 2% of the potential customers. Nevertheless, it would be challenging to build an infrastructure at site #15 since this facility has to be set up on the island to serve its customers. Despite the model recommending the construction of stations at site #2 and #13, from a practical standpoint, it is not recommended since these facilities contribute to less than 0.5% of the demand. Our algorithm does not suggest major locations such as Yankee Stadium and Washington Square Arch, which is counter-intuitive.

Table 3.1 shows the comparison of the locations reported by the current study and Rajendran and Zack (2019). It is to be noted that six of the 18 locations proposed in this study overlap with the prior literature. We can see that further six facilities are within one mile distance apart, whereas, our results propose new infrastructure recommendations for the remaining number of sites.

Table 3.1: Comparison of the locations reported by current study and Rajendran and Zack (2019)

Location	**Current Paper**	**Rajendran and Zack (2019)**
Briarwood, Queens (site #1)	✓	×
Long Island Sound (site #2)	✓	×
Vesey Street, Lower Manhattan (site #3)	✓	•
Newark Liberty International Airport (site #4)	✓	✓
61st Street, Brooklyn (site #5)	✓	•
JFK International Airport (repeated twice) (site #6 and #11)	✓	✓
Douglass Street, Brooklyn (site #7)	✓	✓
Woodland, Bronx (site #8)	✓	×
South Central Park (site #9)	✓	×
Grafton Street, Brooklyn (site #10)	✓	✓
40th Street, near Times Square (site #12)	✓	•
Jericho Union District (site #13)	✓	×

LaGuardia Airport (site #14)	✓	✓
Roosevelt Island (site #15)	✓	×
West Harlem (site #16)	✓	•
5th avenue, Midtown Manhattan (site #17)	✓	•
Lorimer Street, Brooklyn (site #18)	✓	•
East 53rd Street, Manhattan	×	✓
South Congress Avenue, Bronx	×	✓
43rd Street, Long Island City, Queens	×	✓
Old Orchard Street, West Harrison	×	✓
84th Avenue, Jamaica, Queens	×	✓
97th Street, Transverse, Manhattan	×	✓
Grand Blvd, Westbury	×	✓
West 36th Street and 7th Avenue, Manhattan	×	✓
Audubon Avenue, Manhattan	×	✓

Note: ✓ means the location is present in the study. × means location is not present in the study. • means the location reported by Rajendran and Zack (2019) and is within a 1-mile radius of the site in the current study

3.4.2.2. Sensitivity Analysis

In this section, we examine the influence of the four key input parameters appertaining to the performance of the model used in the current study. Table 3.1 presents a comparison of the results generated in all the cases with the findings discussed by Rajendran and Zack (2019) and using the traditional k-means algorithm.

3.4.2.2.1. Time savings (TS)

In accordance with the assumptions made in Section 3.2, ATS will only be availed by a customer if there is a time saving of at least 40% compared to ground transportation (Holden and Goel, 2016). The performance of the proposed approach is investigated by linearly varying the time savings (TS) percentage (Table 3.2). It is observed that the change in TS does not impact the number of facilities. Further, when compared to the number of sites obtained by Rajendran and Zack (2019), we find that the proposed model performs better for all the TS settings with a percentage deviation of 11%, 14%, 15% and 10% for TS-1 - TS-4, respectively.

In comparison with the locations proposed by the baseline case, it is seen that site #16 shifts 1.5 miles south from the original location in TS-3 and 1.5 miles north in TS-4. Similarly, site #12 moves in the north direction by a mile in the new settings closer towards South Central Park. The new location fulfills 18% of total demand when compared with the initial vertistop serving nearly 12% of potential customers. The location of the initial facility suggested for South Central Park (site #9) moved across in a similar direction by approximately 2.5 miles. The suggested number of stations for various scenarios are shown in Figure 3.3.

Table 3.2 Varying percentage time savings

Case	Time savings (TS) in %	Passenger willingness to fly rate (PR) in %	On-road travel limit (RL) in miles	Demand Satisfaction (DS) in %	# of stations
TS – 1	30	100	1	70	15
TS – 2 (Baseline)	40	100	1	70	18
TS – 3	50	100	1	70	17
TS – 4	60	100	1	70	18

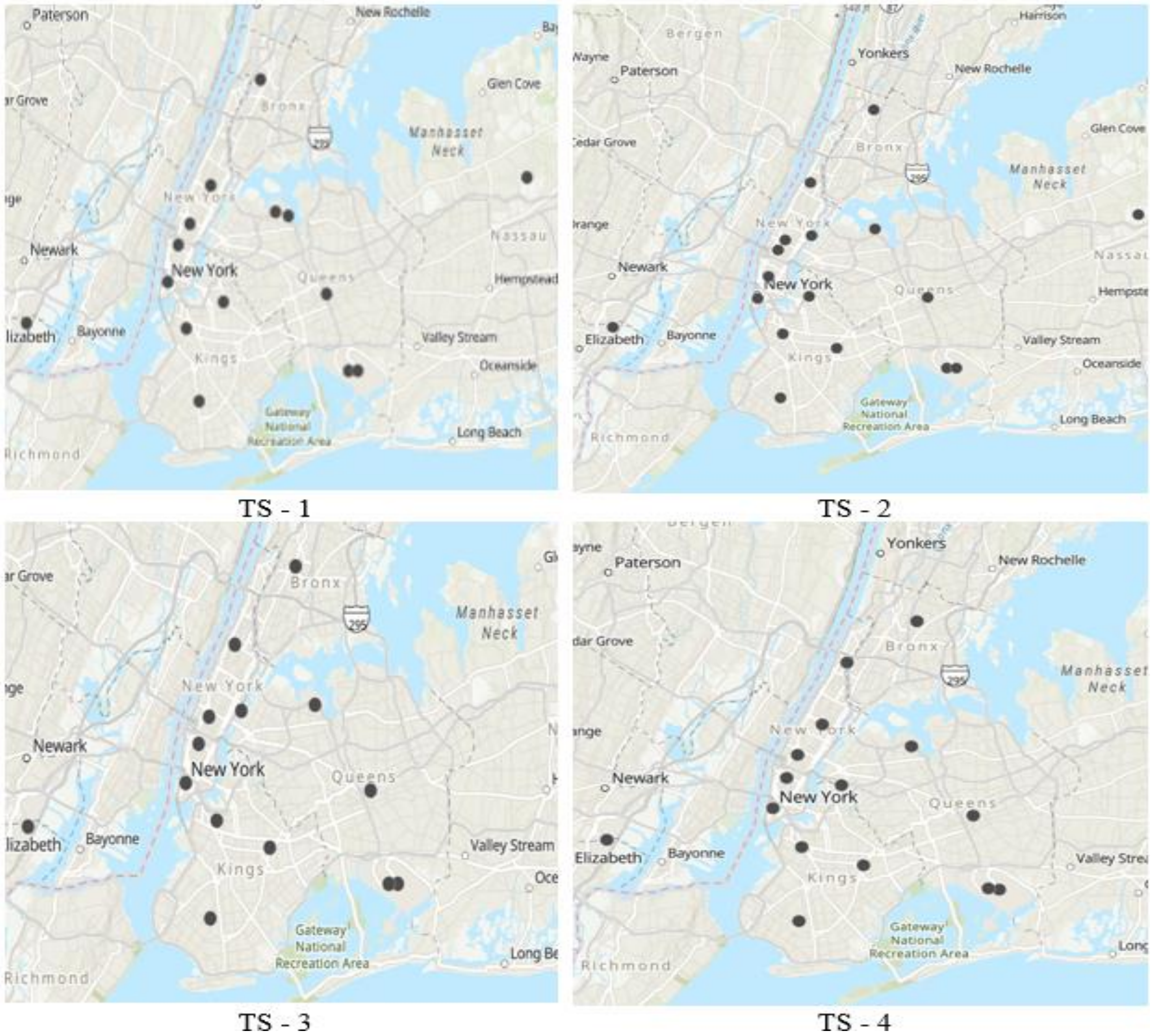


Figure 3.3: Infrastructure locations for various time-saving scenarios

3.4.2.2.2. Passenger willingness to fly rate (PR)

Aviation safety has been proclaimed as a crucial factor by commuters in the literature (Cokorilo, 2020; Swadesir and Bill, 2018). Therefore, a certain proportion of users might be hesitant in utilizing the ATS. In the baseline scenario, it is assumed that 100% of the eligible riders would be willing to fly in the air taxis. In this analysis, the passenger willingness to fly rate is decreased from 100% to 70% in steps of 10%. The corresponding number of eVTOL stations achieved using the algorithm is shown in Table 3.3. Across various cases, the number of facilities is found to be almost identical. However, when compared to the number of sites obtained by Rajendran and Zack (2019), we find that the developed approach performs better for all the PR settings with a percentage deviation of 14.28%, 15.00%, 10.53%, and 15.79% for PR-1 - PR-4, respectively.

Unexpectedly, it is observed that the number of commuters traveling from Brooklyn is reduced by nearly one-third for the PR-2 setting while remaining the same for the other two scenarios. It is also suggested to build vertiports near Washington Square Arch and Midtown Manhattan (one mile from Empire State Building), which are not suggested in the baseline model and provide service to over 7% and 10% customers in PR-2 and PR-4 respectively. Figure 3.4 depicts the station locations for different PR settings.

Table 3.3 Altering Passenger willingness to fly rate

Case	**Time savings (TS) in %**	**Passenger willingness to fly rate (PR) in %**	**On-road travel limit (RL) in miles**	**Demand Satisfaction (DS) in %**	**# of stations**
PR – 1 (Base)	40	100	1	70	18
PR – 2	40	90	1	70	17
PR – 3	40	80	1	70	17
PR – 4	40	70	1	70	16

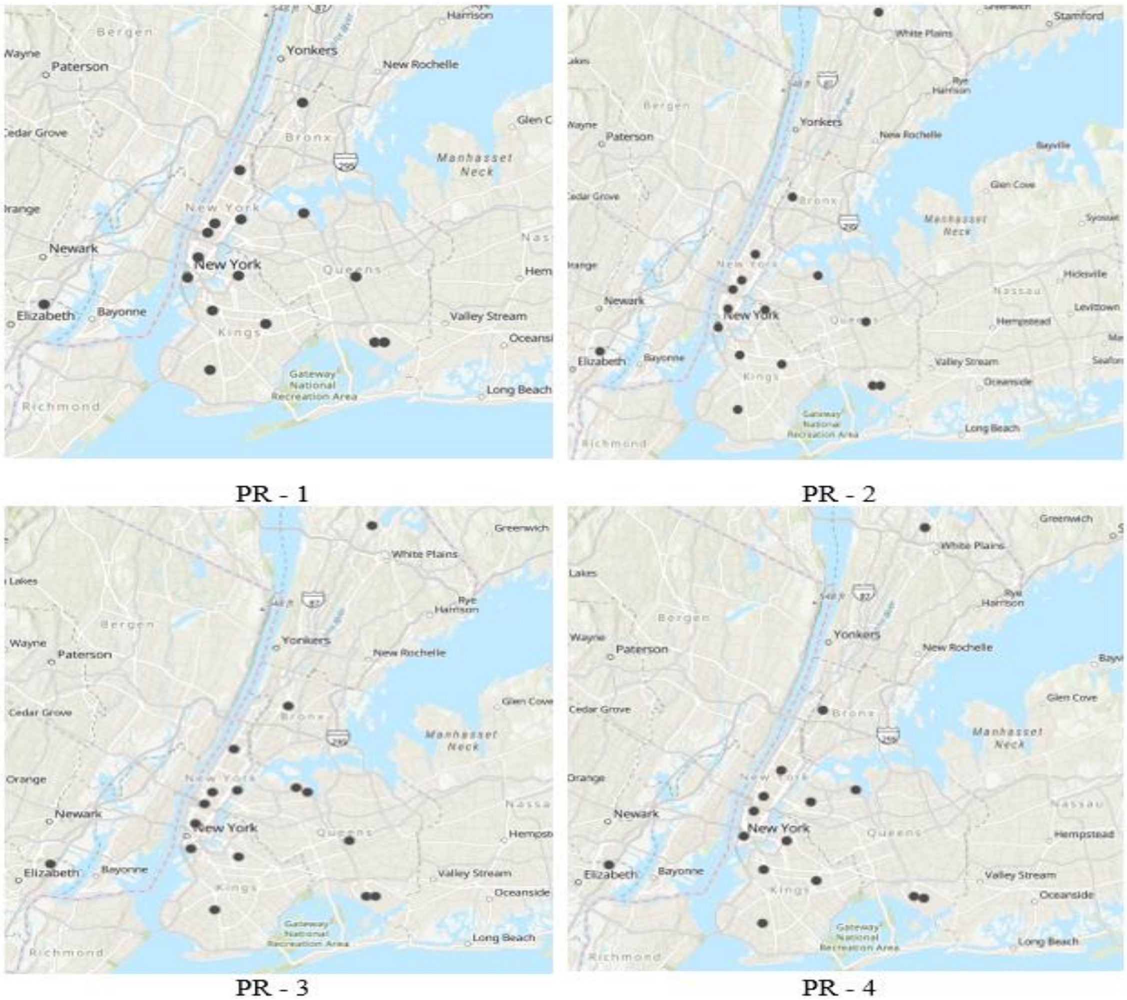


Figure 3.4: Infrastructure locations of various passenger willingness to fly rate scenario

3.4.2.2.3. On road travel limit (ML)

As mentioned above, in the baseline setting, on-road travel distance was limited to one mile for the first and the last legs. In this section, this parameter is altered linearly from 0.5 miles to 1.5 miles, as shown in Table 3.4. As expected, the number of sites increased by approximately 70% for the first scenario (ML-1), relative to the baseline setting, and reduced by 50% for the last case (ML-3). Furthermore, comparison with Rajendran and

Zack (2019) showcased a 7.94%, 14.28% and 10.00% deviation in the number of air taxi stations in the current study for settings ML-1 – ML-3.

It is noticed that the majority of the demand (approximately 60%) is fulfilled by only ten facilities (18% of total sites) in ML-1. Other newly suggested potential centers are Staten Islands, Jamaica, and Madison Square Garden. Furthermore, in ML-3, site #12 is relocated by a mile north where the number of users is doubled when compared with the baseline case. Thus, it is recommended to build a large vertiport to cater to this extra demand, as showcased in Figure 3.5.

Table 3.4 Varying on-road travel limit

Case	Time savings (TS) in %	Passenger willingness to fly rate (PR) in %	On-road travel limit (RL) in miles	Demand Satisfaction (DS) in %	# of stations
ML – 1	40	100	0.5	70	58
ML – 2 (Baseline)	40	100	1	70	18
ML – 3	40	100	1.5	70	9

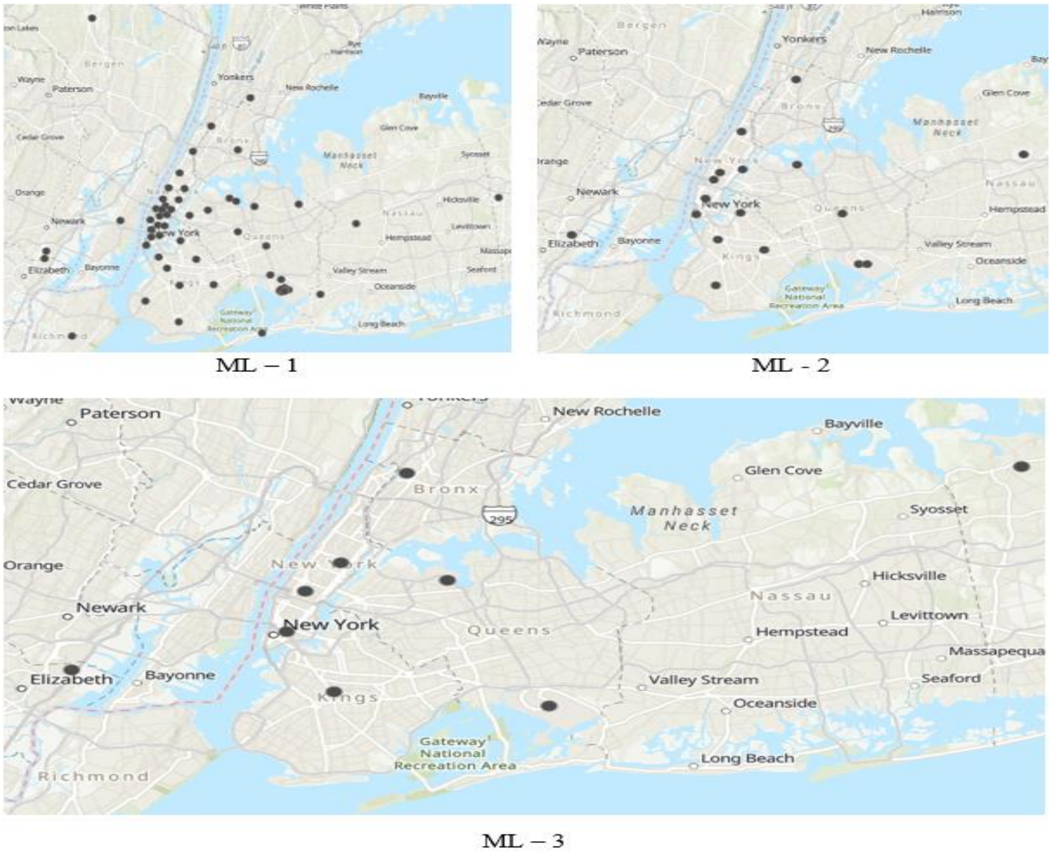


Figure 3.5: Infrastructure locations for different on-road travel limit scenario

3.4.2.2.4. Demand satisfaction (DS)

In the baseline case, we assumed that 70% of the total customers would be eligible to avail of the ATS. In this analysis, the demand satisfaction rate is varied from 60% to 90%, incrementing by 10% for different settings, as shown in Table 3.5. A linear increase in DS percentage generates an exponential growth in the number of locations. A similar trend was indicated by Rajendran and Zack (2019) as well. It is seen that the number of locations outside the five major boroughs also increases, and it is recommended that the logistics company conducts a market study to determine the feasibility of stations from these hubs.

Figure 3.6 depicts the recommended facility locations for all the scenarios investigated in this subsection.

The number of infrastructure sites rises by nearly 75% for DS–4 from the base case in the present investigation, which is comparable to the previously reported literature. Almost three-quarters of the total demand is fulfilled by 25% of sites in DS-3 and DS-4 settings. For DS-1, it is proposed to develop a vertistop in a facility close to site #12 (Times Square) as the number of customers is observed to double, which is similar to ML-3. The total number of eligible riders increased by 29% from DS-1 to DS-2. However, only 13% of the growth was observed when the commuter satisfaction level was increased from DS-2 to DS-3. A further increase to the next scenario noted only an 11% rise in the overall number of rides.

Table 3.5 Altering the percentage demand fulfillment

Case	Time savings (TS) in %	Passenger willingness to fly rate (PR) in %	On-road travel limit (RL) in miles	Demand Satisfaction (DS) in %	# of stations
DS – 1	40	100	1	60	12
DS – 2 (Baseline)	40	100	1	70	18
DS – 3	40	100	1	80	30
DS – 4	40	100	1	90	78

3.4.3. Comparison of Results of the Proposed Method with Prior Methods

3.4.3.1. Evaluation using the DBI and Number of Clusters

In order to evaluate the results and compare the performance of the proposed approach with the existing methods, we examine the DBI metric and the number of stations reported by Rajendran and Zack (2019) and those obtained under the traditional k-means algorithm.

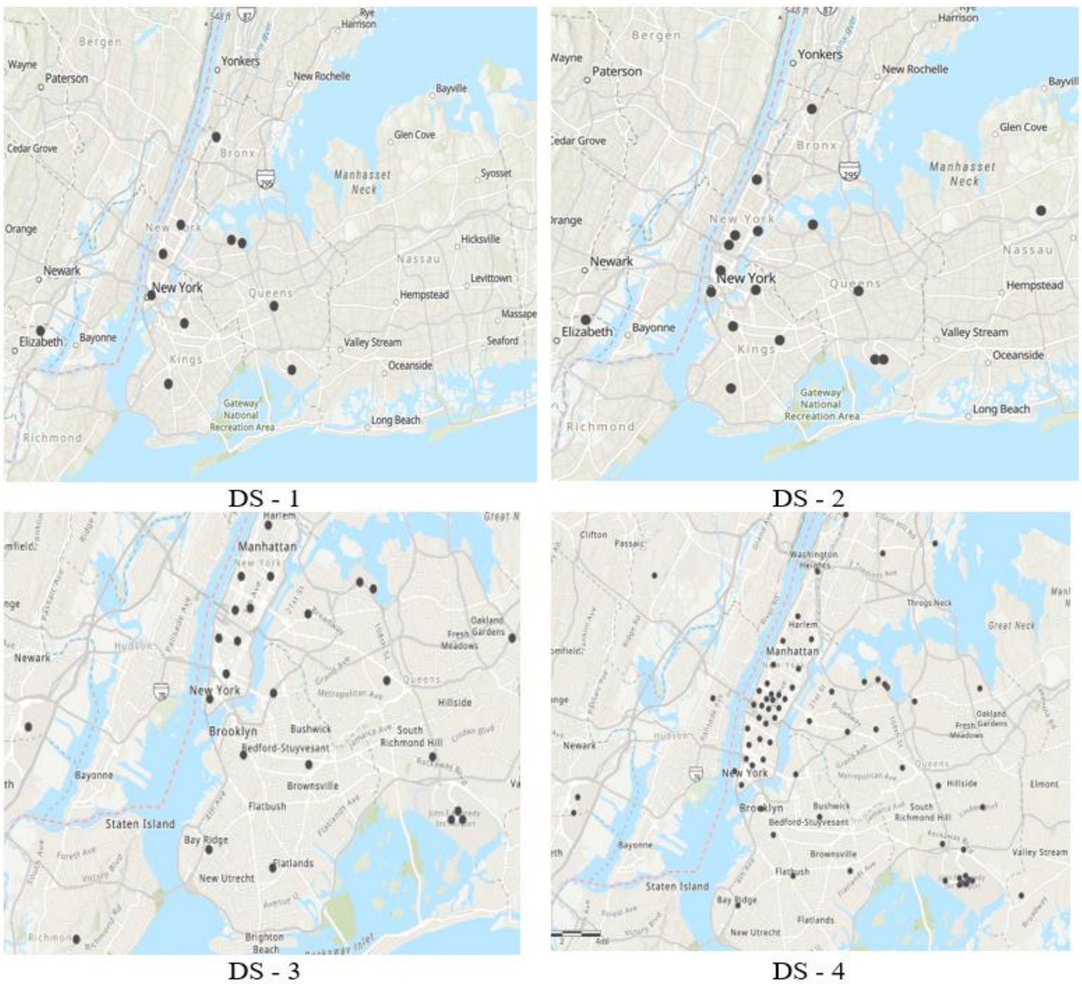


Figure 3.6: Infrastructure locations for demand satisfaction scenario

Based on Table 3.6, it can be noticed that both these measures are observed to be lower under the present study than both the traditional k-means algorithm as well as the approach proposed by Rajendran and Zack (2019). This clearly indicates that the proposed method outperforms the existing air taxi facility location approaches discussed in the literature.

Table 3.6 Comparison of the number of facilities and DBI metric obtained from the current study with the traditional k-means algorithm and method discussed by Rajendran and Zack (2019)

Scenario	Number of stations					Davies- Bouldin Index				
	Current study	Rajendran and Zack (2019)*		Traditional k-means*		Current study	Rajendran and Zack (2019)*		Traditional k-means*	
		#	% deviation	#	% deviation		#	% deviation	#	% deviation
TS-1	16	18	11.11	19	15.79	0.39	0.41	4.87	0.42	7.14
Base case	18	21	14.28	22	18.18	0.36	0.45	20.00	0.46	21.73
TS-3	17	20	15.00	20	15.00	0.40	0.45	11.11	0.39	2.56
TS-4	18	20	10.00	21	14.28	0.39	0.42	7.14	0.42	7.14
Base case	18	21	14.28	22	18.18	0.36	0.45	20.00	0.46	21.73
PR-2	17	20	15.00	19	10.52	0.38	0.45	15.55	0.47	19.14
PR-3	17	19	10.53	19	10.52	0.42	0.43	2.32	0.46	8.69
PR-4	16	19	15.79	18	11.11	0.39	0.44	11.36	0.40	2.50
ML-1	58	63	7.94	61	4.91	0.22	0.73	69.86	0.71	69.01
Base case	18	21	14.28	22	18.18	0.36	0.45	20.00	0.46	21.73
ML-3	9	10	10.00	14	35.71	0.57	0.39	46.15	0.40	42.5
DS-1	12	13	7.69	15	20.00	0.42	0.41	2.43	0.43	2.32
Base case	18	21	14.28	22	18.18	0.36	0.45	20.00	0.46	21.73
DS-3	30	33	9.09	30	0.00	0.40	0.61	34.42	0.59	32.20
DS-4	78	85	8.24	82	4.87	0.33	0.75	56.00	0.94	64.89

*As reported by Rajendran and Zack (2019)

3.4.3.2. Evaluation using the Multi-Criteria Decision-Making Approach

While Section 3.4.3.2 evaluates the effectiveness of the proposed approach theoretically, this section compares the model results from a practical standpoint. Based on the five criteria discussed in Section 3.1 (i.e., rental cost per month, road facility, average salary per year, population coverage, and the total number of estimated trips made by air taxi per day per 1000 population), this section analyzes the overall ranking of the location insights presented in our study and prior studies. Traditionally, the decision-maker is involved in providing the weights for each criterion. Since air taxi is still in the developmental stage, we used the weights suggested by Hawas et al. (2016), Tzeng et al. (2002) and Tzeng et al., (2005). The scaled weights for rental cost, population coverage, trips per day per 1000 population, road facility, and employment cost are 0.14, 0.39, 0.26, 0.06, and 0.15, respectively. These are used for calculation of the weighted average for each location and the overall fitness values.

Tables 3.7 and 3.8 provide the values for each criterion of all the proposed sites under the current research as well as by Rajendran and Zack (2019). The data are obtained from multiple publicly available government sources (Department of city planning, NYU Furman Center, and United States census bureau). These data are normalized based on Equations (3.1) and (3.2), and then the weighted score for each station location is computed using Equation (3.3). Based on Equation (3.4), the total score per site of 0.45 is obtained for our suggested air taxi stations, which is higher than the score calculated for the location results reported by Rajendran and Zack (2019), which is 0.42. This implies that the two-phase technique implemented in the present study provides a better solution than the existing literature.

Table 3.7: Values for different criteria for locations obtained in the current study

Site #	Rental cost ($/month)	Population coverage	Trips per day per 1000 population	Road facility (miles)	Employment cost ($/year)
1	1,800	165,000	0.0281	1	65,000
2	1,420	12,000	0	2.1	43,000
3	2,610	148,000	0.8102	0.009	147,641
4	1,140	128,000	0.1417	0.001	47,000
5	1,450	146,000	0.0223	0.2	46,229
6	1,590	139,000	0.1634	0.001	75,300
7	2,280	116,000	0.2886	0.7	137,000
8	1,410	150,000	0.0101	0.6	60,000
9	2,150	153,000	1.8109	0.2	104,000
10	900	111,500	0.0338	0.001	20,640
11	1,590	139,000	2.1713	0.001	75,300
12	2,150	153,000	2.3838	0.07	104,000
13	2,044	14,000	0.000106	3.2	161,771
14	1,530	170,000	1.4878	0.001	58,000
15	2,380	215,000	0.3156	1.4	134,000
16	1,280	136,000	0.0939	1.5	51,000
17	2,610	149,000	1.0350	0.4	147,600
18	2,980	152,000	0.1920	0.5	78,000

Table 3.8: Values of various criteria for locations obtained by Rajendran and Zack (2019)

Site #	Rental cost ($/month)	Population coverage	Trips per day per 1000 population	Road facility (miles)	Employment cost ($/year)
1	2,490	149,000	0.49	0.001	114,500
2	1,590	139,000	1.19	0.001	75,300
3	2,280	116,000	0.11	0.7	137,000
4	1,300	120,000	0.01	0.3	49,000
5	1,590	139,000	0.31	0.001	75,300
6	1,670	164,000	0.06	0.5	67,670
7	1,690	7,900	0.00	1.3	163,795
8	1,150	152,000	0.02	0.08	71,200
9	1,777	15,000	0.00	0.3	142,928
10	2,610	149,000	0.78	0.001	147,600
11	1,450	146,000	0.01	0.3	46,229
12	900	111,000	0.01	0.001	20,640
13	910	128,000	0.25	0.1	37,500
14	1,140	128,000	0.08	0.001	47,000
15	2,610	148,000	0.36	0.001	147,641
16	1,838	15,000	0.00	0.1	98,065
17	2,980	152,000	0.12	0.8	78,000
18	2,610	149,000	0.90	0.001	147,600
19	1,300	219,000	0.04	0.1	57,500
20	1,530	170,000	0.80	0.001	58,000

21	2,610	149,000	0.61	0.05	147,600

3.4.4. Implications and Recommendations

Even though the results obtained in the two studies that are compared in the paper are based on NYC, several generic practical implications can be made to extend this for other cities as well. First, urban areas having international airports are expected to have a high volume of customers using air transport and thus require huge vertistops to be built to satisfy the demand. Second, it is anticipated that popular tourist sites and downtown areas of a city would be the next highest in terms of proportions of commuters served and require a large number of air taxi vehicles at their respective stations. Third, varying percentages of time savings and passenger willingness to fly rate have no substantial effect on the total number of facilities. Lastly, linear change in on-road travel limit and customer demand satisfaction levels causes an increase in the number of customers assisted, and therefore, an exponential rise in the number of urban air locations in the city.

Based on the results and observations, the following managerial recommendations are proposed:

1. The model found a potential to build 16 air taxi stations in NYC with two infrastructures being in the neighborhood near Long Island Sound and Jericho Union District.
2. It is essential to launch a large vertiport at JFK, LAG, and New York Liberty International Airports since they cater to a combined 60% of the total demand.
3. It is observed that the average number of dropoffs are greater than the average number of pickups in Brooklyn, Queens, Bronx, and Staten Island. Therefore, it is

recommended to build smaller vertiports in these areas and the air taxi vehicles to be routed back to Manhattan for pickups.

4. Sites serving South Central Park and West 40^{th} Street (0.2 miles from Times Square) are approximately a mile apart. Therefore, a common air taxi station can be developed catering to the demand from both locations.
5. Midtown and Lower Manhattan experience a high volume of commuters due to popular tourist attractions such as the Empire State Building, Madame Tussauds, World Trade Center, etc. Thus, we propose a high fraction of the fleet to serve the two areas.
6. Only 3% of total customers (approximately 200,000) utilize the four stations in Brooklyn; therefore, smaller vertistops are suggested to be built in the region.
7. The two closest locations in the Brooklyn borough are 61^{st} Street and Grafton, and thus, a logistics company might choose to have only one infrastructure site considering a low demand.
8. The most common locations observed across all the cases are JFK International Airport, LaGuardia Airport, Newark Liberty International Airport, Times Square, Central Park, Empire State Building, and 61st Street, Brooklyn. Therefore, it is recommended to begin services in at least these places, if the logistics company has operational restrictions.

3.4.5. Conclusions

The present study attempts to propose air taxi vertiport and vertistop location decisions in metropolitan cities using a two-phase approach. This study addresses the limitation of the previous research (Rajendran and Zack, 2019) by considering the number of passengers in each ride as different data records in the model. Based on the estimated air taxi demand in New York City (NYC), the potential sites are identified within the city and its neighborhood by coupling the multi-criteria warm start technique with an iterative k-means clustering algorithm. Our study reports 18 site locations, which is less than the number reported in the existing literature. It is also observed that approximately three-fifths of the demand is based on the three major airports located in the city.

Parameters such as percentage of time savings and passenger willingness to fly rate have a negligible impact on the number of sites, whereas on-road travel limit and percentage of customer demand satisfaction have an exponential effect on the same. Therefore, it is essential for logistics companies to take the implications of these factors into account. Also, if the organization favors beginning with limited service, then they can consider establishing their operation from the seven common locations (JFK International Airport, Laguardia Airport, Newark International Airport, Times Square, Central Park, Empire State Building and 61st Street, Brooklyn). The performance of the developed method is theoretically evaluated by computing the Davies-Bouldin Index (DBI) and the number of clusters. Both these measures obtained in the current research are lower than those reported by Rajendran and Zack (2019) and the traditional k-means algorithm. To evaluate the solution from a practical standpoint, we utilize the multi-criteria decision-making technique to compute the total score of the sites suggested in the present study as well as in the previous investigation. It is noted that the total score per facility for this research is higher suggesting that the proposed model is better than the traditional k-means and Rajendran and Zack (2019), even with looking at more data points.

However, there are certain limitations in the present research. The current investigation does not consider tactical and operational level decisions for the effective functioning of the facility. Therefore, a study on policies involving scheduling, routing, number of vehicles at each location, etc. can be considered as a potential area of improvement. Moreover, it is assumed that a traveler is eligible to avail of the services if only they have at least 40%-time savings. However, a customer's mode choice could be more complicated. Future studies could involve examining other factors, such as cost and wait time, in order to determine overall demand. Also, a mathematical or simulation model could be developed to aid the logistic companies in deciding the set of sites to be developed in multiple phases to mitigate the impact of unknown variables such as community acceptance, safety record etc.

Chapter 4: Single Objective Model for Multi-Phase Location Decision

In this chapter, a facility selection model is developed using an iterative clustering algorithm with a mathematical model to identify potential vertiports and vertistops for air taxis in a metropolitan city. Previous literature on strategic location of air taxis (Holden and Goel, 2016; Rajendran and Zack, 2019) suggests certain unique constraints that are incorporated in the present study. First, a customer is eligible to utilize ATS only if the estimated time saved is more than 40% when compared with the estimated time through ground transportation. Second, the first and last leg of the trip should not exceed one mile respectively. Third, minimum demand fulfillment rate is satisfied i.e. at least 70% of the eligible passengers have to avail the eVTOL services. Therefore, a clustering algorithm which enables the decision-makers to adjust the specific number of cluster centers is used to suggest certain air taxi station locations. The value of the centroids is increased until all the constraints mentioned above are satisfied. However, any logistic company would intend to minimize the number of facility locations and thus, the objective of the algorithm is to minimize the number of stations while fulfilling the above conditions. The results from the first stage of the research are used as an input for the mathematical model which is used to determine the specific locations to be opened in each phase while maximizing the overall demand fulfillment.

4.1 Clustering algorithm

A traditional k-means algorithm minimizes the squared Euclidean distance between m objects and their respective cluster center, as shown in Equation 4.1 (Bock, 2008). Where,

x_c is the cluster center for point c. On the other hand, partitioning around medoids (PAM) focuses on minimizing the total dissimilarity between the data points and the nearest k representative object in the data, also known as medoid, making it more robust than the k-means technique. Equation 4.2 presents the objective function for PAM (Schubert and Rousseeuw, 2019). A typical PAM algorithm integrates two techniques called BUILD and SWAP for initial cluster selection and generates locally optimum solutions (since the global optimum problem is NP-hard) by improving the clusters, respectively (Schubert and Rousseeuw, 2019).

$$P = \sum_{\vec{x} \in m} |\vec{x} - x_c|^2 \quad \rightarrow \quad min.\ P \tag{4.1}$$

$$\min_{k=1\ldots K} \sum_{i=1}^{m} d(x_i, m_k) \tag{4.2}$$

For initial construction using the BUILD algorithm, a point that has the smallest distance to all other points in the data set is considered as the first medoid. Subsequently, further $k - 1$ points that reduce the value of Equation (4.2) are considered as medoids. Each data point is assigned to the nearest specific cluster. The SWAP algorithm then considers all possible exchanges between a non-medoid and medoid similar to a greedy steepest-descent method to improve the initial clustering. This is repeated until no further reduction of the objective function is possible. However, this technique increases the run time of the algorithm significantly, making it complicated to use for large data sets (Schubert and Rousseeuw, 2019). To reduce this complexity, Kaufman and Rousseeuw (1986) developed a technique known as clustering large applications (CLARA), which is a variant of partitioning around medoids (PAM).

CLARA chooses a sample set from the complete data record and then utilizes PAM to produce optimal medoids for that representative data. In order to mitigate sampling bias, the process of sampling and clustering is repeated numerous times until the next medoid sets are generated as final clustering (Kaufman and Rousseeuw, 1990). It has a faster execution time and requires less storage when compared with PAM (Schubert and Rousseeuw, 2019). A study by Wei et al. (2003) concluded that CLARA outperformed other algorithms in clustering quality along with computational time and is less susceptible to data randomness and cluster distinctness degree. Therefore, we use CLARA to determine the optimal station locations for our study. Table 4.1 presents the code used by CLARA for a data set D (Kaufman and Rousseeuw, 2008).

Table 4.1: Pseudo Code for CLARA Algorithm

```
Create number of samplings = s;
Repeat 's' times
    Draw sample data set from D;
    Apply PAM to generate a set of medoids M = {m_1, m_2...... m_k};
    Compute total score TS = Σ_{i=1}^{m} d(x_i, m_k);
    If
        TS < minimum total score;
        Return M;
    End If;
End Repeat;
Assign all data points to M;
```

S_i

4.2 Mathematical model

The locations suggested by the clustering algorithms are used as an input for the linear programming model, which is developed to determine the set of stations to be opened in different phases. The constraints are selected based on several parameters affecting the strategic location decisions as suggested in previous literature (Hawas et al., 2016, Tzeng et al., 2002, Tzeng et al., 2005). The set of notations used in the current study are given below -

Let i be set of phases	$\forall\ i\ = 1, 2, 3, \ldots\ldots I$
Let j be set of locations	$\forall\ j\ = 1, 2, 3, \ldots\ldots J$

Decision variables

δ_{ij}	1 if location j is opened in phase i otherwise 0

Input parameters

r_j	Rental cost at location j
p_j	Population density at location j
t_j	Number of trips per day per 1000 customers at location j
s_j	Average salary of population density at location j
f_j	Distance between an ATS station at location j and its nearest road (Road facility)
D_j	Demand at each location j
N_i	Maximum number of sites to be opened at each phase i
R_i	Maximum allowable budgeted rental cost for each phase i
S_i	Maximum allowable salary expenditure in phase i

T_i	Maximum allowable number of trips per day per 1000 population for phase i
F_i	Maximum allowable distance from the nearest road facility for phase i

Objective function –

Max. $\sum_i \sum_j \delta_{ij} \times D_j$ (4.3)

Constraints –

$$\sum_i \delta_{ij} = 1 \qquad \forall j \qquad (4.4)$$

$$\sum_j \delta_{ij} \leq N_i \qquad \forall i \qquad (4.5)$$

$$\sum_i r_j \times \delta_{ij} \leq R_i \qquad \forall i \qquad (4.6)$$

$$\sum_i t_j \times \delta_{ij} \geq T_i \qquad \forall i \qquad (4.7)$$

$$\sum_i s_j \times \delta_{ij} \leq S_i \qquad \forall i \qquad (4.8)$$

$$\sum_i f_j \times \delta_{ij} \geq F_i \qquad \forall i \qquad (4.9)$$

The objective is to maximize the demand fulfillment at each phase. The demand data at each location is generated based on the total number of riders eligible to avail of the air taxi facility. The constraints utilized in the model are given by Equations (4.4) – (4.9). Equation (4.4) ensures that a facility can be opened in only one phase. Equation (4.5) places a restriction on the number of establishments to be deployed in each phase. Previous research on multi-period facility locations concluded that more stations should be opened during the earlier periods to maximize the total flow (Chung and Kwon, 2015; Li et al., 2016). Therefore, in the present investigation, N_i is set as a decreasing value for each phase. Equation (4.6) describes that the total cost of renting the site should be less than the budgeted rental cost for that specific phase. Similarly, Equation (4.7) ensures that the average salary is less than the average base salary. On the other hand, Equations (4.8) and (4.9) represent that the total number of trips per day per 1000 population and accessibility of air taxi stations to a major road must be greater than their respective threshold values.

4.3. Results

4.3.1 Case Study

4.3.1.1 Clustering Algorithm

Since the air taxi operations are currently in the trial and testing phase, the potential demand is assessed to be a fraction of the current demand of regular taxis. The dataset used in previous literature (Rajendran and Zack, 2019) has been employed in the present investigation. The subset of the data records for estimating air taxi demand is considered based on assumptions mentioned by Holden and Goel (2016) and Rajendran and Zack (2019), which are also discussed in Section 4. Certain records associated with each data point are pickup and dropoff coordinates, total distance covered, trip time, date of the trip, and number of passengers on each trip. Approximately 300 million taxi records are considered in a period of two years, out of which 20 million are removed during the data cleaning process. Data pre-processing stage consists of eliminating all missing, negative, zero, and erroneous values. In the present study, each customer is considered as an individual trip, unlike the values used by Rajendran and Zack (2019). Based on the given constraints, close to 6.5 million data points are utilized for the clustering algorithm in the present study, whereas the previous investigation considered about 4 million data points.

For the base case, our model generates a total of 14 sites across five boroughs in New York City (Manhattan, Queens, Brooklyn, Bronx, and Staten Island) when compared with Rajendran and Zack (2019), who proposed 21 locations. This indicates that CLARA provides better results when compared to k-means as it is non-sensitive to noise and reduces outliers. This was also observed in previous studies comparing the two algorithms (Arora et al., 2016; Gupta and Panda, 2019). Seven sites (#2, #3, #5, #9, #11, #12 and #13) are suggested to be built in Manhattan while four locations (#1, #4, #7 and #8) are proposed in Queens. Similarly, the number of stations identified in Brooklyn and New Jersey are two (#6 and #10) and one (#14), respectively. Table 4.2 presents the locations along with their site number.

It is observed that the locations associated with the two airport stations in Queens (#8 and #1), John F. Kennedy (JFK) and LaGuardia International Airport (LAG) cater to over 55% of the total customer demand. Surprisingly, demand from the Newark Liberty International Airport (#14) is found to be the least when compared to other sites. Rajendran and Zack (2019) also reported similar findings. Therefore, it is proposed to build a large vertiport at JFK and LAG for maximum demand fulfillment. Following that, Washington Square Park

(#11), W 31st Street near Empire State Building (#12), and Time Square (#13) in Manhattan cater to about 30% of the aggregate demand. However, the algorithm does not suggest major locations such as Yankee Stadium in Bronx and Columbia University in Upper Manhattan, which is counter-intuitive.

Table 4.2: Cluster Centers Suggested by the Algorithm

Center Number	**Locations**
1	LaGuardia International Airport
2	263 Nagle Avenue
3	881-899 Amsterdam Avenue
4	36th Street, Astoria, Queens
5	854 Park Avenue, near Central Park
6	Prospect Park West, Brooklyn
7	Ozone Park, Queens
8	John F. Kennedy International Airport
9	200 Water Street, Lower Manhattan
10	84th Street, Brooklyn
11	Washington Square Park
12	W 31Street near Empire State Building
13	Times Square
14	Newark Liberty International Airport

4.3.1.2 Mathematical Model

Based on the results obtained from the clustering algorithm, all 14 sites can be expected to be functioning within three phases for the base scenario. Existing literature on multi-period strategic location decisions suggests the deployment of more stations in the earlier phase to maximize demand fulfillment than later stages (Chung and Kwon, 2015; Li et al., 2016). Therefore, for the base setting, it is assumed that six stations would be opened in the first phase, followed by five and four in the second and third periods, respectively. The impact of changing these values on each center is discussed under the sensitivity analysis section. It is observed that all suggested sites are located in a different district. The data required for each neighborhood (average rental cost, trips per day per 1000 population, average salary, and road facilities) is obtained from various official sources (Department of City Planning, NYU Furman Center, and United States Census Bureau). The mathematical model is developed and solved using the simplex linear programming solver in Microsoft Excel.

Figure 4.1 shows the various infrastructure locations suggested in the three phases. It is observed that approximately half of the overall air taxi demand is fulfilled by the six stations in Phase #1. However, Ozone Park (#7) caters to less than one percent of the demand, and therefore, it is recommended that logistic companies develop one common vertiport to serve the customers at Ozone park and its nearest proposed station at JFK International Airport (#8). In Phase #1, the model indicates three centers to be built in Manhattan, two in Queens and one in New Jersey (#14). Phases two and three have a demand satisfaction rate of almost 40% and 10%, respectively. Similar to Phase #1, the model suggests three stations be developed in Manhattan in Phase #2 along with facilities for LaGuardia International airport (#1) and 84th Street, Brooklyn (#10).

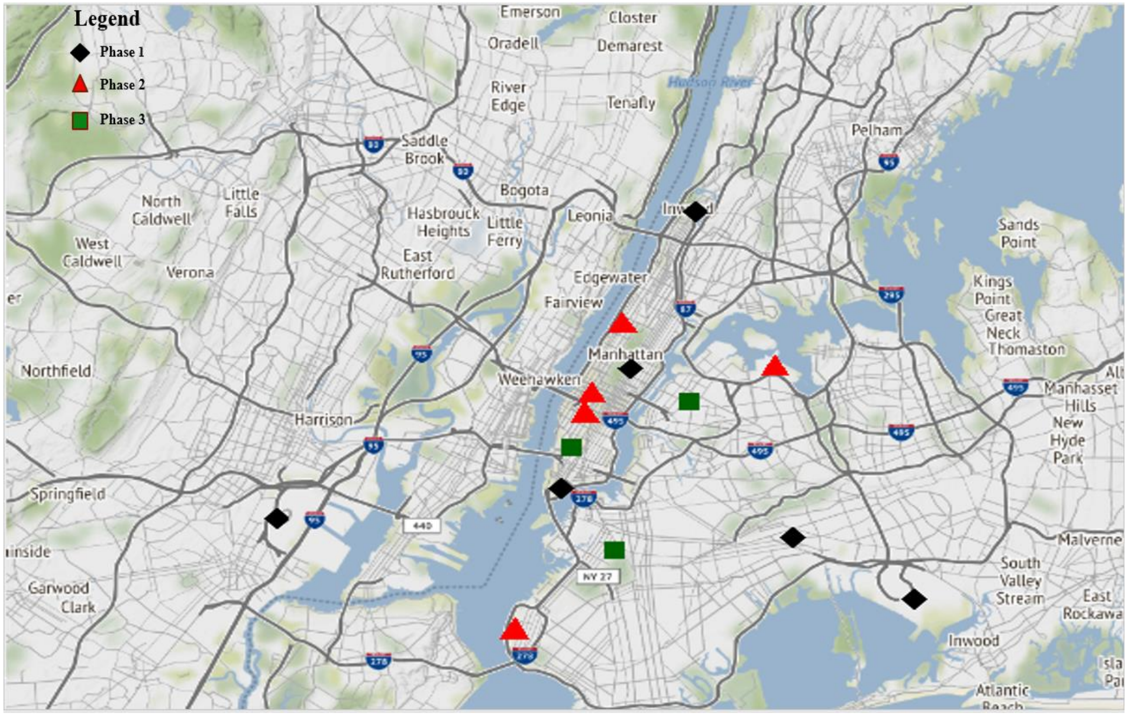


Figure 4.1: Infrastructure Locations to be Opened in Different Phases

4.3.2 Sensitivity Analysis

The mathematical model recommends various sites to be developed in certain phases. In this section, we examine the impact of various input parameters on the suggested phase for each center.

4.3.2.1 Number of stations in each phase

As mentioned in the previous section, the number of stations in the base case decreases based on the sequence (6, 5, 3) for the three phases, respectively. The aim of this section is to analyze the impact of variation in the tuple on certain locations and the overall demand realization. Multiple scenarios that are considered in the present study with regards to change in the number of centers are exponential decrease (9, 3, 2), linear decrease (7, 5, 2), exponential increase (2, 3, 9), linear increase (2, 5, 7) and balance (5, 5, 4). It is observed that the highest demand satisfaction rate in Phase #1 (approximately 60%) is achieved for an exponential increase in sites. Both LAG (#1) and JFK (#8) are recommended in the first phase in this scenario. Linear increase and linear decrease showcase the maximum percentage demand fulfillment for Phase #2 (around 70%) and Phase #3 (around 65%), respectively. In the balanced setting, the demand satisfaction follows an increasing trend, which is counter-intuitive.

In terms of locations, it is interesting to note that the model suggests LAG (#1) in Phase #2 in all scenarios except for an exponential increase in the number of stations. Newark Liberty International Airport (#14) is reported in Phase #1 for every instance besides the exponential and linear increase settings. Another station near Central Park (#5) is proposed in Phase #1 for all the cases in which the number of sites decreases while it is recommended for higher stages in other situations, as shown in Table 4.3. Similarly, 881 Amsterdam Avenue (#3) is indicated in Phase #1 for both linear and exponential decrease while it is desired in Phase #3 for other instances. Only Ozone Park (#7) and Washington Square Park (#11) are found to be in the same phase between exponential increase and exponential decrease. On the other hand, only six centers remain in the common phase between linear increase and linear decrease.

Table 4.3: Variation in Number of Stations in Each Phase

Center Number	Base Case (6, 5, 3)	Exponential Decrease (9, 3, 2)	Linear Decrease (7, 5, 2)	Exponential Increase (2, 3, 9)	Linear Increase (2, 5, 7)	Balance (5, 5, 4)
1	2	2	2	1	2	2
2	1	3	1	3	3	1
3	2	1	1	3	3	3
4	3	1	3	2	3	3
5	1	1	1	3	2	3
6	3	1	1	3	2	2
7	1	2	1	2	1	1
8	1	3	2	1	3	3
9	1	1	2	3	2	2
10	2	1	2	3	2	2
11	3	2	1	2	3	2
12	2	1	2	3	1	1
13	2	1	3	3	3	1
14	1	1	1	3	3	1

4.3.2.2 Rental Cost (RC)

In this section, the value of the budgeted rental cost (RC) is varied from the base setting (RC1) for all three phases. The rental cost is increased in steps of 5% while keeping the number of facilities for each stage constant for all settings. It is observed that a 5% rise in cost from RC1 to RC2 led to six locations being shifted from their initial phase. Both Central Park (#5) and JFK (#8) are recommended from Phase #1 to Phase #3 in RC2, which results to an increase in the demand fulfillment for Phase #3 to approximately 45%. On the other hand, only 36th Street, Astoria (#4), which has one of the lowest rental costs amongst all the other locations, switched from Phase #3 to Phase #1. Similarly, two stations, Prospect Park (#6) and Washington Square Park (#11), changed from Phase #3 to Phase #2. However, the demand satisfaction for Phase #2 in RC2 remains similar to the base case scenario. It is interesting to note that despite a linear increase in the cost, no further changes are obtained in the other scenarios. Table 4.4 presents the suggested phases for all the sites for various rental cost cases considered in the present study.

Table 4.4: Variation in Each Phase for Changes in Rental Cost

Center Number	RC1 (Base case)	RC2	RC3	RC4	RC5
1	2	2	2	2	2
2	1	1	1	1	1
3	2	1	1	1	1
4	3	1	1	1	1
5	1	3	3	3	3
6	3	2	2	2	2
7	1	1	1	1	1
8	1	3	3	3	3
9	1	1	1	1	1
10	2	3	3	3	3
11	3	2	2	2	2
12	2	2	2	2	2
13	2	2	2	2	2
14	1	1	1	1	1

4.3.2.3 Number of trips per day per 1000 customers (TR)

As described by Hawas et al. (2016) and Meyer (2001), the number of trips per day per 1000 customers (TR) depicts the transportation supply. In this section, TR is varied from TR1 to TR5 in steps of 10% for all three phases simultaneously with the values in TR3 considered in the base case. As expected, a rise in the initial number of available air taxi trips per day led to a higher overall demand satisfaction in Phase #1, supporting the findings in previous literature. It is observed that the locations having the highest trips per day per 1000 customers are selected in Phase #1 for TR5. Therefore, LAG (#1) and W 31st Street (#12) are recommended to be developed in Phase #1 for the TR5 scenario, while the model proposes both these locations to be built in Phase #2 for all other cases. These two sites contribute heavily to increasing the customer fulfillment rate for Phase #1 from the base case.

On the other hand, a decrease in the number of trips has a minimal impact on the demand satisfaction rate. While most stations are proposed in a different phase, the overall demand percentage is almost the same for TR1 and TR2 with the base settings (TR3). While Times Square (#13) is expected to be in Phase #1 for TR5 because of a high number of trips per day per 1000 customers, it is also proposed at the same stage for TR1. Interestingly, the model recommends the location in Phase #2 for all other settings. Another key observation is that only three locations, 263 Nagle Avenue (#2), 36th Street, Astoria (#4), and JFK (#8) remain in the same phase for all five scenarios. This indicates that TR is an important criterion for making air taxi infrastructure decisions. Table 4.5 shows the various vertiport and their corresponding phases for different TR settings.

Table 4.5: Variation in Each Phase for Changes in Number of Trips per Day per 1000 Customers

Center Number	TR1	TR2	TR3 (Base case)	TR4	TR5
1	2	2	2	2	1
2	1	1	1	1	1
3	2	1	2	1	3
4	3	3	3	3	3
5	3	3	1	2	2
6	3	1	3	1	3
7	1	3	1	2	2
8	1	1	1	1	1
9	2	2	1	3	2
10	1	1	2	1	2
11	1	1	3	1	1
12	2	2	2	2	1
13	1	2	2	2	1
14	2	2	1	3	2

4.3.2.4 Average Salary (AS)

Based on existing trends, it is expected that the average employee salary (AS) would increase for all neighborhoods in the coming years (Duffin, 2020). Therefore, in this section, AS is increased linearly from the base case (AS1) by 5% till AS5. Only five locations remain in the same phase for all the scenarios in this analysis, out of which four are in Phase #1 (263 Nagle Avenue (#2), Central Park (#5), Ozone Park (#7), and Newark Liberty International Airport (#14)). Another interesting result to note is that despite this consistency, the demand fulfillment in Phase #1 reduces drastically with a rise in employee wages. This is probably because the model prefers cheaper locations at the initial stages. The phases suggested for different locations are presented in Table 4.6.

It is worth noting that there is no change in any scenario after AS3, with Phase #2 having the highest customer satisfaction rate (approximately 70%) when compared with the other two stages. Another key pattern observed is that 881 Amsterdam Avenue (#3) and Times Square (#13) is recommended in Phase #2 for AS1 and in Phase #1 and Phase #3 for all other settings. While it is expected that the logistic companies would prefer minimizing the average employee salary, a separate case is considered in the present investigation for maximizing customer salaries. This factor is examined to identify the sites most easily affordable by the consumers. However, the model shows an infeasible solution and requires further research in this area.

Table 4.6: Variation in Each Phase for Changes in Average Salary

Center Number	**AS1 (Base case)**	**AS2**	**AS3**	**AS4**	**AS5**
1	2	2	2	2	2
2	1	1	1	1	1
3	2	1	1	1	1
4	3	2	3	3	3
5	1	1	1	1	1
6	3	2	1	1	1
7	1	1	1	1	1
8	1	3	2	2	2

9	1	2	2	2	2
10	2	3	2	2	2
11	3	2	3	3	3
12	2	1	2	2	2
13	2	3	3	3	3
14	1	1	1	1	1

4.3.2.5 Road Facility (RF)

Road facility (RF) is described as the features required for the utilization of alternative vehicles (Tzeng et al., 2005). In this section, it is varied with 10% intervals, and the impact of reducing (RF1 and RF2) and improving (RF4 and RF5) road facilities are investigated in comparison to the base case (RF3). As expected, creating easier access to the vertistops and vertiports led to an increase in the demand satisfaction rate in Phase #1. This is because better accessibility leads to certain important sites such as Washington Square Park (#11), W 31st Street (#12), and Times Square (#13) to be recommended in Phase #1 for RF4 and RF5. All three stations are proposed in later stages for all other scenarios.

Interestingly, the model suggested locations having the two highest demand in JFK (#8) and LAG (#1) in Phase #3 for RF2 and RF5, respectively. Potential reasoning for this could be that both JFK and LAG are situated in the outskirts of Queens, and any change in road infrastructure might have an impact on facilitating customer access. It is observed that only 263 Nagle Avenue (#2), 36th Street Astoria (#4), and Ozone Park (#7) remain in the same stage for all five cases. Table 4.7 showcases the different phases recommended for each station.

Table 4.7: Variation in Each Phase for Changes in Road Facility

Center Number	**RF1**	**RF2**	**RF3 (Base case)**	**RF4**	**RF5**
1	2	2	2	2	3
2	1	1	1	1	1
3	2	1	2	3	2
4	3	3	3	3	3
5	1	2	1	2	3
6	3	1	3	3	2
7	1	1	1	1	1
8	1	3	1	1	1
9	1	1	1	2	2
10	2	2	2	1	2
11	3	3	3	1	1
12	2	2	2	2	1
13	2	2	2	1	1
14	1	1	1	2	2

4.4 Managerial Implications

While the present study focuses on integrating the clustering algorithm and linear programming model for strategic infrastructure decisions in New York City, the methodology and several related implications can be replicated for other major cities, as well. Based on the results obtained, the following managerial recommendations are proposed:

1. Based on results from the clustering algorithm, there is a potential to build 14 stations in NYC with seven facilities proposed in the Manhattan borough.

2. Based on the taxi data, larger vertiports are suggested for JFK (#8) and LAG (#1) since they serve approximately 55% of the overall demand.
3. It is not essential to develop a center at Ozone Park (#7) in Phase #1 as it caters to less than one percent of customers. Interested users can leverage the nearest station at JFK.
4. Similarly, only a negligible proportion of consumers are expected to avail the air taxi facilities from Newark Liberty International Airport (#14). Therefore, it is recommended not to provide initial services until latent demand arises.
5. It is noticed that market demand in Brooklyn is fairly low despite having a few popular tourist destinations such as Prospect Park and Ozone Park. Therefore, small vertistops are suggested to be constructed for these sites.
6. It was observed that CLARA performed considerably better than the k-means clustering algorithm for a large volume of data.
7. The total number of air taxi facilities to be developed in each phase has a significant impact on the overall demand fulfillment for all stages.
8. The logistic companies can prefer to set up less number of infrastructure locations during the initial phase to observe customer response to the product before investing heavily in other locations. In such a situation, an exponential increase in the number of stations and balanced scenarios would give a fairly high demand satisfaction rate for Phase #1 while minimizing incurred cost.
9. Results indicate that varying percentages of budgeted rental cost and employee salary have minimal effect on the total number of stations.

10. A linear increase in the number of trips per day per 1000 customers favors the locations having higher demand during the initial phases.
11. While it was expected that improving road facilities would expand the demand satisfaction rate in Phase #1, it was interesting to note that no substantial changes were viewed for decreasing road facilities when compared with the base case.

4.5 Conclusions

The current research focuses on proposing optimal infrastructure locations for the air taxi facility in urban cities using a two-step procedure. While New York City was chosen as a case study in the present investigation, the procedure can be easily replicated for any other major city. The first step was to obtain the current taxi records from a prior study. After that, they were pre-processed, approximately 6.5 million data points were selected as the potential demand. clustering large applications (CLARA) was utilized to generate 14 ideal sites satisfying the customer eligibility constraints mentioned in the available literature. Next, a linear mathematical model was developed to recommend specific stations to be built in multiple stages. This would give logistic companies an opportunity to further analyze the market and improve the existing services. The constraints chosen in the model were based on key factors impacting the strategic location decisions in previous studies. Finally, a sensitivity analysis was conducted to study the influence of these constraints on the centers and their corresponding phases.

The present study reported lesser potential locations than the existing literature. The base case assumed six, five, and three sites to be built respectively in order to maximize the demand fulfillment. Approximately 50% of the overall demand was satisfied in Phase #1. Whereas Phase #2 and #3 had close to 41% and 9% demand completion rate. It was observed that out of the 14 stations, the two major airports in the city (JFK and LAG) catered to over half the potential demand. However, only JFK was proposed to be developed in Phase #1, while LAG was suggested in Phase #2 for the base setting. Parameters, such as the number of stations to be recommended in each phase, the number of trips per day per 1000 customers, and road facilities, had a substantial impact on the demand fulfillment for each stage. It is expected that the air taxis would improve citywide transportation, and the current research could provide a foundation for logistic companies that might be interested in venturing into the eVTOL market.

While the current investigation is based on providing strategic decisions on urban air mobility, several operational and tactical level insights have not been considered. Future work could involve researching optimal scheduling and effective routing of air taxi vehicles to reduce operational costs. Furthermore, the clustering algorithm does not take certain conditions, such as an allowance to fly over private property, accepted noise level, etc., into account. Therefore, a study on the policies involved can be conducted, which could further enhance the performance of the suggested algorithm. Additionally, only the commuter taxi data have been considered in this research. However, additional demand can arise from other sources of public transportation and on-demand taxi services such as Uber. Therefore, complementary market studies can be performed in the future to analyze the extra demand and its impact on the suggested infrastructure locations.

Chapter 5: Capacitated Vertiport and Charging Station Location-Allocation Problem for Air Taxi Operations with Battery and Fleet Dispatching Considerations

Although the operation of air taxis is similar to that of helicopters, several challenges might arise when they are being used for frequent everyday commutes. First, the sizing and placement of regular operating stations and charging stations is a long-term strategic decision that companies have to make before venturing into the market. Selecting these locations will be a function of several characteristics, such as demand density, space availability, and accessibility to other facilities (Holden et al., 2018). Second, determining the number of air taxis required to serve the customer demand is another strategic decision due to low production volume. Third, companies also need to focus on developing operational-level decisions for effective functioning, such as charging and maintenance scheduling (Cohen et al., 2021; Falck et al., 2018). Fourth, since UAM is in the nascent stages, it is important for the businesses to establish ideal pricing strategies to attract more customers in the future. Fifth, customer willingness to fly is highly dependent on the perceived safety levels especially due to its autonomous nature (Reiche et al., 2019; Ward et al., 2021).

The present chapter is the first to recommend a multiple criteria simulation optimization model that facilitates the logistic companies to make strategic, tactical and operational level decisions. The strategic level decisions consist of determining the optimal location and capacity of skyports, number of air taxis required for maximum demand fulfillment, and location and number of charging stations. On the other hand, the tactical and operational level decisions include investigating the minimum threshold charge by the vehicles before they are required to be charged again and real-time allocation and dispatching of air taxis, respectively. A two-phase approach is employed in the current study to examine the problem under investigation. Potential infrastructure locations are identified in phase-1 using a clustering algorithm known as clustering large applications (CLARA). The suggested air taxi centers are used as input in phase-2 for the simulation optimization model. The estimated demand for air taxis using the quantitative techniques applied in the previous chapters is utilized to test the effectiveness of the proposed model.

5.1 Methodology

As discussed earlier, this study proposed a two-phase approach in which the set of potential air taxi infrastructure locations is obtained using a clustering algorithm known as clustering large applications (CLARA) in phase-1. This is then given as an input to the simulation optimization model (phase-2). Figure 5.1 depicts the proposed methodology in the present chapter.

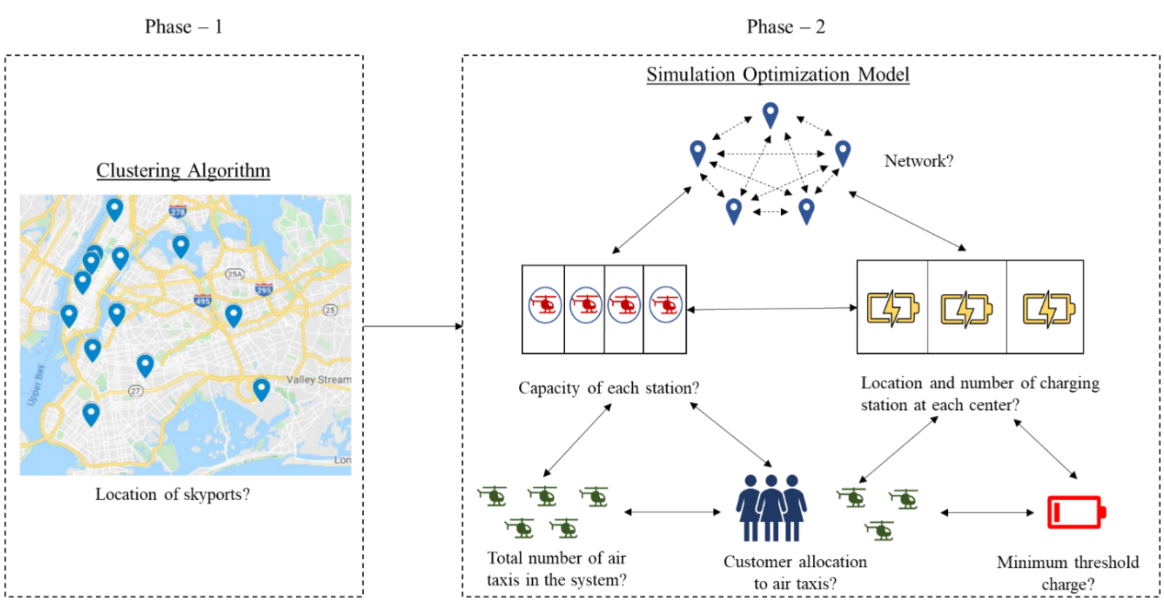


Figure 5.1: Proposed Methodology utilized in the current chapter

5.1.1 Phase 1: Clustering Algorithm

In Phase-1, we determine the set of air taxi stations $\mathcal{S} = \{s_1, s_2, s_3, \ldots\ldots s_K\}$ considering the estimated air taxi demand data from a prior study. The location of these facilities is determined such that at least one station is within a mile radius of $(\lambda_i^o, \varphi_i^o)$ and $(\lambda_i^d, \varphi_i^d)$ for no less than ε% of the demand instances, based on the conditions specified by prior studies (Holden and Goel, 2016; Rajendran and Shulman, 2020). The present study utilizes a variant of partitioning around medoids (PAM) known as clustering large applications (CLARA) instead of the traditional k-means approach due to the latter generating different solutions in each iteration and being sensitive to outliers (Zahra et al., 2015). PAM is a more robust approach that minimizes the total dissimilarity between the medoid (or centroids) and each data point in the cluster (Schubert and Rousseeuw, 2019). A typical PAM technique comprises two algorithms known as BUILD and SWAP. The BUILD algorithm is employed to construct initial groups by selecting k centers and assigning other data points to the nearest respective clusters. The SWAP algorithm evaluates all possible pairwise substitutions between a medoid and a non-medoid. This process is similar to the greedy steepest descent method and is continued until no further improvement in the objective function can be achieved (Schubert and Rousseeuw, 2019; Struyf et al., 1997). However, this approach is computationally expensive, and therefore, in order to decrease its complexity, its variation known as CLARA was developed by Kaufman and Rousseeuw (1990). CLARA selects a sample set and employs BUILD and SWAP algorithms as discussed previously to generate ideal centers for the representative data. This process is repeated several times to minimize sampling bias until final solutions are proposed (Kaufman and Rousseeuw, 1990). Numerous factors, such as improved clustering quality, less computational time and required storage, make CLARA a superior algorithm for large data sets when compared with other techniques (Wei et al., 2003).

5.1.2 Phase 2: Multiple Criteria Simulation-Optimization

As discussed earlier, in phase-2, we propose a multiple criteria simulation-optimization model that will enable the logistic companies to determine the sizing and placement of operating facilities as well as the charging stations, number of air taxis required to serve the customer demand, vehicle charging metrics, and air taxi dispatching and allocation. Phase-2 determines the total number of vehicles ν_p in the network, optimal station capacity τ_k, and number of charging ports ξ_k required at all k centers with the objectives of minimizing average commuter time in system and wait time, and maximizing vehicle utilization. It is assumed that customers arrive at the air taxi station s with an arrival rate following a Poisson distribution having a mean of λ_s. Set of air taxi vehicles $\mathcal{V} = \{\nu_1, \nu_2, \nu_3, \ldots\ldots \nu_P\}$, each having a passenger capacity c and travel speed η, is dispatched to transport customers from s_a to s_b in the air taxi network using the algorithm proposed in this phase.

Recall that $s_a \epsilon \mathcal{S}$, $s_b \epsilon \mathcal{S}$, where $\mathcal{S}$ is the set of air taxi locations ($\mathcal{S} = \{s_1, s_2, s_3, \ldots\ldots s_K\}$), and was obtained from phase-1 of this research. As indicated earlier, air taxis operate using the eVTOL concept. Let t^d be the landing time of the air taxis. Subsequent to the descend of vehicle ν_p, existing customers depart ν_p with an unloading time of t^u and new customers who are assigned ν_p enter into the air taxi for a loading duration of t^l. Following that, air taxi departs with a takeoff time of t^k. After dropping off a traveler at station s_b, the simulation optimization model decides whether the vehicle can (i) remain idle at s_b, (ii) remain idle at any other station s_f, where $f \epsilon S \not\ni b$, (iii) obtain full charge for a duration of $t_e(100 - \gamma)$, where t_e is the time required to charge one unit, and γ is the current remaining charge percentage, (iv) pickup customers at s_b, (v) pickup customers at any s_f, $f \epsilon S \not\ni b$. At the beginning of the day, all vehicles are assumed to be fully charged. The charge deteriorates at the rate of α per minute, and if the remaining charge reduces below the pre-specified threshold level β, then the air taxi must definitely get fully charged. Figure 5.2 presents the flowchart of the model in the current study.

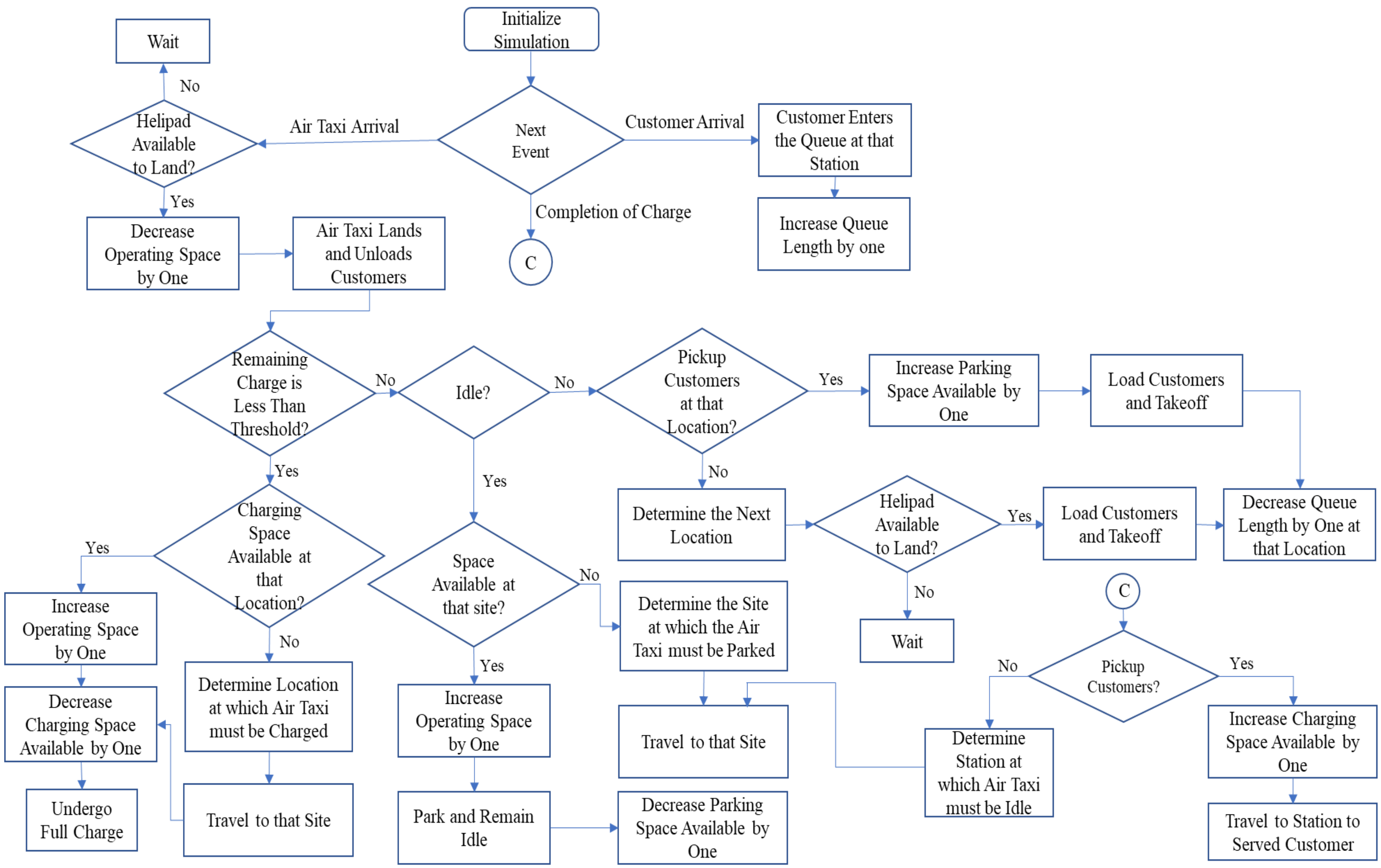


Figure 5.2: Flowchart of the Simulation Optimization Model

5.2 Results

This section presents the results obtained in the base case and for various sensitivity analysis settings. The clustering algorithm was coded in R, and the simulation optimization model was developed in SIMIO®.

5.2.1 Data Description and Input Parameters

In order to establish a UAM system in metropolitan cities, the present study utilizes the quantitative approach explored in previous literature for demand estimation (Holden and Goel, 2016; Rajendran and Zack, 2019) in NYC. The data utilized consists of roughly 6.5 million potential air taxi demand records. A market study by NASA observed that only about 60% of the travelers were willing to utilize the UAM services (Goyal, 2018). Therefore, the demand setting for the base case is also set at the same level.

Liu et al. (2021) suggested using fast chargers to reduce the overall time required for charging and consequently increase vehicle utilization. Previous literature observed that such chargers can completely charge the batteries in 15 minutes (Li et al., 2020; Sieg et al., 2019). Moreover, most common air taxi types have a flying range of 100 km and an average speed of approximately 200km/h (Rajendran and Srinivas, 2020). Therefore, in the present research, the air taxi charging and discharging rates are set at 15 minutes and 30 minutes, respectively. Based on the recommendation by Holden and Goel (2016), the threshold charge before the vehicles require full charging is set at 20%. According to the key eVTOL design classifications, the maximum passenger capacity for the base case is set at two (Polaczyk et al., 2019).

For the simulation optimization model (phase-2), the number of helipads and charging ports at each location is varied in the range [1, 5] in steps of 1, while the number of air taxis are altered from 30 to 100 in steps of 10 for the optimization add-in. The model is run for 100 replications and 168 hours (or one week) for all settings. The current study investigates key performance metrics such as vehicle utilization, customer time in system and wait times. It is assumed that the three criteria have equal priority in the base case. All the parameters discussed in this section are varied and the impact on the performance measures is reported in Section 5.2.3.

5.2.2 Base Case

Since UAM operations are currently in the testing stage, the logistic companies would prefer deploying fewer stations to minimize the initial infrastructure and operational costs while maximizing demand fulfillment (Straubinger et al., 2021). Therefore, we varied the number of centers from one to ten, and observed that when there are five operating stations, more than 45% of the overall demand is fulfilled. The percentage increase in the demand fulfillment decreases beyond five facilities. For example, previous research by Rajendran and Zack (2019) observed 21 skyports to be required across the five boroughs in New York for achieving a 70% demand satisfaction rate. The five locations recommended in this study are John F. Kennedy (JFK) airport, LaGuardia airport (LAG), Times Square, Prospect Park and 55 Kenmare Street.

Based on the results obtained, the simulation optimization model recommends one port to be developed at each hub. It also proposes two charging ports at JFK and LAG each while suggesting one station at the other centers. The three key performance metrics (vehicle utilization, customer time in system and wait time) are reported in Table 5.1. Furthermore, the model proposes using only 50 air taxis initially to achieve a tradeoff between utilization and traveler time in system.

Table 5.1: Base Case Results

Performance Measure	Value
Number of operating stations	5
Number of charging stations	8
Number of Vehicles	50
Vehicle Utilization (%)	76.43
Time in System (minutes)	36.47
Wait Time (minutes)	14.30

5.2.3 Sensitivity Analysis

In this section, all the input parameters are varied to investigate their impact on the performance metrics (air taxi utilization, average customer time in system and waiting time (WT)). Various sensitivity analysis settings are summarized in Table 5.2.

Table 5.2: Sensitivity Analysis Settings

Setting	Demand Variation (DV)	Charging Time (CT)	Priority Settings (PS) (Utilization, WT)	Vehicle Capacity (VC)	Battery Threshold (BT)

Demand Variation					
DS#1 (Base Case)	60%	15 min.	(0.50, 0.50)	2	20%
DS#2	70%	15 min.	(0.50, 0.50)	2	20%
DS#3	80%	15 min.	(0.50, 0.50)	2	20%
DS#4	90%	15 min.	(0.50, 0.50)	2	20%
DS#5	100%	15 min.	(0.50, 0.50)	2	20%
Charging Time					
CT #1 (Base Case)	60%	15 min.	(0.50, 0.50)	2	20%
CT#2	60%	20 min.	(0.50, 0.50)	2	20%
CT#3	60%	25 min.	(0.50, 0.50)	2	20%
CT#4	60%	30 min.	(0.50, 0.50)	2	20%
Priority Settings					
PS#1 (Base Case)	60%	15 min.	(0.50, 0.50)	2	20%
PS#2	60%	15 min.	(0.90, 0.10)	2	20%
PS#3	60%	15 min.	(0.10, 0.90)	2	20%
Vehicle Capacity					
VC#1	60%	15 min.	(0.50, 0.50)	1	20%
VC#2 (Base Case)	60%	15 min.	(0.50, 0.50)	2	20%
VC#3	60%	15 min.	(0.50, 0.50)	4	20%
Battery Threshold					
BT#1 (Base Case)	60%	15 min.	(0.50, 0.50)	2	20%

BT#2	60%	15 min.	(0.50, 0.50)	2	25%
BT#3	60%	15 min.	(0.50, 0.50)	2	30%
BT#4	60%	15 min.	(0.50, 0.50)	2	35%
BT#5	60%	15 min.	(0.50, 0.50)	2	40%

5.2.3.1 Demand Variation (DV)

As discussed earlier, for the base case, we assume that only 60% of the total eligible customers will avail of the air taxi service. In this section, the demand is varied linearly to explore the impact of its growth on the proposed network. The optimal number of station capacity and charging port capacity required at each skyport is determined using the simulation optimization model. It is observed that the minimum skyport capacity and charging ports remain constant despite altering the demand.

As expected, the average commuter travel time and wait time increased linearly by approximately 8% and 42%, respectively. This may be due to the fact that customers have to wait for other ridesharing passengers to arrive before the air taxi could take off. Similarly, the vehicle utilization decreased by 10% from DV#1 (Base Case) to DV#4. This is also perhaps because the latter scenario requires the vehicle to carry more passengers and therefore is idle for a longer period of time. Table 5.3 presents the impact of demand variation on various performance metrics. A paired sample t-test at 95% significance level showcases that all three-performance metrics are significantly different for all DS scenarios.

Table 5.3: Impact of Variation in Various Parameters on Performance Metrics

Setting	Vehicle Utilization (%)	Time in System (minutes)	Wait Time (minutes)
Demand Variation			
DS#1 (Base)	76.43	36.47	14.30
DS#2	75.08*	39.32*	20.91*
DS#3	72.84*	49.98*	33.33*
DS#4	69.52*	59.82*	43.61*
DS#5	67.46*	70.60*	57.38*
Charging Time			
CT #1 (Base)	76.43	36.47	14.30
CT#2	71.03*	43.62*	23.61*
CT#3	67.52*	50.10*	31.58*
CT#4	62.53*	64.04*	48.81*
Priority Settings			
PS#1 (Base)	76.43	36.47	14.30
PS#2	74.35*	34.98*	13.06*
PS#3	75.73*	35.89*	13.86*
Vehicle Capacity			
VC#1	67.85*	104.07*	88.58*
VC#2 (Base)	76.43	36.47	14.30
VC#3	76.39	29.43*	2.68*
Battery Threshold			
BT#1 (Base)	76.43	36.47	14.30
BT#2	75.28*	34.45*	12.46*
BT#3	73.88*	34.43*	12.94*

BT#4	44.47*	60.56*	26.16*
BT#5	42.42*	60.63*	26.37*

Note: * denotes significance at 95% significance level

5.2.3.2 Charging Time (CT)

A study by Roni et al. (2019) observed that charging batteries comprises approximately 70% of the total downtime in electric vehicles. Therefore, it is recommended to take advantage of fast chargers that will reduce the eVTOL idle time and improve its utilization (Liu et al., 2021). However, such chargers are also known to be energy-intensive and higher battery degradation (Bennaceur et al., 2021). The charging rate in the base case is based on using fast chargers that increase that state of charge by 80% in 15 minutes (Li et al., 2020; Sieg et al., 2019). In this section, the impact of increasing the rate of charge in steps of 5 minutes (Table 5.2) on station capacity and number of charging ports, along with the three performance metrics, is examined.

It is noticed that the overall station capacity and charging ports are not sensitive towards variation in vehicle charging rate. Similar conclusions regarding vertiport size were made by Rimjha and Trani (2021). Furthermore, the overall air taxi utilization decreases linearly with a linear increase in charging time. An approximate 20% decrease is detected from the base case (CT#1) to the highest charging rate considered in this study (CT#4). On the other hand, the average customer time in system and wait time are exacerbated by nearly 75% and 250%, respectively from CT#1 to CT#4. The maximum rise in TIS is seen between CT#3 and CT#4 of approximately 27%. Interestingly, the greatest increase in WT is between CT#1 and CT#2. Table 5.3 shows the effect of varying the air taxi charging time on the performance measures. It is also noted that all three performance measures are significantly different at $\alpha = 0.05$.

5.2.3.3 Priority Settings (PS)

In a multi-criteria problem, various conflicting criteria are assigned a specific priority to solve the optimization model (Bandeira et al., 2018; Sherif et al., 2021). In the present study factors, such as vehicle utilization and the average time a commuter spends in the system, are contradictory. However, in the base case (PS#1), all the performance measures are assigned a similar weight. In this section, PS#2 gives a higher priority to air taxi utilization, while a higher rank is allocated to customer TIS and WT in PS#3. Interestingly, the station capacity at JFK and LAG increases by one each for PS#2 compared with PS#1. Simultaneously, the number of charging ports at both locations decreases by one. The skyport capacity for PS#3 remains the same as recommended in PS#1. In contrast, the overall number of charging stations decreases by one for PS#3. It is proposed to establish four charging ports at JFK and one each at Times Square and LAG. Even though altering the assigned priority had minimal effect on the results, a paired sample t-test at 95% significance level showcases significant difference for utilization, TIS and WT metrics as seen from Table 5.3.

5.2.3.4 Vehicle Capacity (VC)

As mentioned in the previous section, each air taxi can carry at most two passengers in one trip for the base case. However, various eVTOLs that are in development currently have a different capacities (Polaczyk et al., 2019). In this section, the vehicle capacity (VC) is varied based on different settings, as shown in Table 5.2. As expected, the average commuter time in system and wait time decrease exponentially by approximately 250%

and 3200%, respectively, with an increase in VC from one to four. It is observed that air taxi utilization decreases by 12% from VC#3 to VC#1. This is probably caused because the vehicles require frequent charging as they are completing more trips and are thus in an idle state. However, there is no discernable variation in the utilization parameter between VC#2 and VC#3 because of equal charging rates. This is also supported by the paired sample t-test at 95% significance level. Table 5.3 presents the impact of variation in passenger capacity on the performance measures.

The simulation optimization model proposes the station capacity of JFK to increase by one for VC#1 when compared to the base case (VC#2) with all other capacities remaining the same. Similarly, it recommends an additional capacity to be developed at both LAG and JFK for VC#3, with every other station having a constant capacity to the base case. The model suggests establishing only one charging port at JFK, LAG and Times Square for VC#1 and none at the other locations. On the other hand, a separate charging station is required at all centers for VC#3.

5.2.3.5 Battery Threshold (BT)

Although no official regulations related to minimum energy reserve for air taxis exist (Melo et al., 2020), previous literature suggests having a reserve of at least 20% of the original battery capacity (Holden and Goal, 2016; Melo et al., 2020). The current study also utilizes the same battery threshold value for the base case (BT#1). This section evaluates the effect of incrementing it linearly in steps of 5%. The paired sample t-test displays a significant difference for the utilization, TIS and WT at 95% significance level. Approximately 5% decrease in performance measures from BT#1 to BT#3 is observed. On the other hand, nearly 70% decrease in the eVTOL utilization is observed for BT#4 and BT#5. Simultaneously, the commuter average TIS and WT rose by 66% and 83%, respectively. Therefore, we can conclude that the minimum BT can potentially be increased up to 30% without any substantial negative impact on the results. However, this would also increase the charging frequency, which would consequently lead to a faster battery degradation and electricity requirements for charging the vehicles. The minimum station capacities and charging ports remain constant for all BT settings.

5.3 Environmental Impact

The battery technology for powering eVTOL's is still under the developmental phase. According to a research by Melo et al. (2020), several factors such as number of passengers in the air taxi, vehicle flying range, altitude etc. impact the life cycle of the battery. They also conducted the life cycle analysis to investigate the environmental impact of eight different types of batteries supporting UAM. The specific energy varies substantially leading to dissimilar environmental impacts for different batteries. They observed that for a payload of 175 kg (385 lbs.) and flying range of 100 km, 811-NMC battery had an approximate total greenhouse gas (GHG) emission of 200 g CO_2/km (313 g CO_2/mile). On the other hand, According to Environmental Protection Act (EPA), the average greenhouse gas (GHG) emission standard for passengers' cars was set at 178 g CO_2/mile for 2021 (Center for Climate and Energy Solutions, 2020). The total GHG emission ρ for vehicle type ω can be approximated by Equation (5.1). Each air taxi covers nearly 600 miles/week (31,200 miles/year) as recorded by the SIMIO simulation software. Therefore, 50 eVTOL's travel a total distance of 1,560,000 miles/year. Similarly, the distance traveled by the regular taxis is obtained from the "trip distance" records available in the taxi data set.

Since, for the base case the overall demand satisfaction rate for the five centers considered in the present study is approximately 45% and we assume that only 60% of the eligible passengers are willing to avail the UAM services, the total distance covered by regular taxis is approximated as 141,742 miles/week or 7.37 million miles/year. It is observed that the UAM system would reduce the average GHG by approximately 65% annually. However, a major limitation of this analysis is that it does not consider the impact of several factors such as battery degradation and charging capacity on GHG emissions.

$$\rho_{\omega} = \text{Distance traveled by the vehicle} \times \text{Emission per unit distance} \tag{5.1}$$

$$\rho_{air\ taxi} = 1{,}560{,}000 \text{ miles/year} \times 313 \text{ g } CO_2\text{/mile}$$

$$\rho_{air\ taxi} = 488{,}280 \text{ kg } CO_2$$

$$\rho_{regular\ taxi} = 7{,}370{,}000 \text{ miles/year} \times 178 \text{ g } CO_2\text{/mile}$$

$$\rho_{regular\ taxi} = 1{,}311{,}969 \text{ kg } CO_2$$

5.4 Managerial Implications

The following managerial insights are recommended based on the results obtained in the present investigation:

i. It is observed that a linear increase in demand leads to a linear rise in air taxi utilization and average TIS and WT. Therefore, in case latent demand arises, logistic companies can decide to have more vehicles in the system to offset the decline in performance metrics.

ii. Results showcase vehicle utilization decreases substantially with a rise in charging time. This also impacts the customer waiting time and time in system. Thus, to mitigate the increased air taxi idle time, the decision-makers can develop additional charging ports. However, a cost-benefit analysis would need to be performed to realize the effectiveness of establishing more infrastructure.

iii. While varying the assigned weight has no impact on utilization, TIS and WT as discussed in the previous sub-section. It does, however, change the overall station capacity and number of charging facilities. Thus, further cost viability study might be required to evaluate the pros and cons of the three settings.

iv. No significant deviation in the performance metrics was found in scenarios that increased the station capacity at each location. Consequently, adding more station capacities at different skyports might not be advantageous.

v. The base case recommended 50 air taxis in the system with a capacity of carrying a maximum of two customers at once. As discussed in the previous section, increasing the vehicle capacity to four led to a considerable decrease in commuter average TIS and WT. Therefore, the decision-makers can elect to have vehicles with higher passenger capacity. They can also prefer having multiple eVTOLs with different capacities. However, further analysis might be required to determine the optimal number for the various vehicle types.

vi. The battery threshold limit can be increased up to 30% without any notable variation in the results. Future research can investigate the tradeoff between increasing the minimum energy reserve and its environmental impact.

5.5 Conclusion

With the increase in the number of privately owned vehicles and rapid economic development, traffic congestion has become an inevitable issue in metropolitan cities. In order to ameliorate this situation, several logistic companies are investigating the plausibility of employing electric vertical takeoff and landing vehicles known as air taxis. The present research proposes a two-phase technique that develops a framework for introducing air taxi operations. The first phase recommends the optimal infrastructure locations using an iterative clustering algorithm called clustering large applications (CLARA).

The second phase proposes a multiple criteria simulation optimization model that enables logistic companies to make the following strategic (long-term), tactical (medium-term) and operational (short-term) decisions: (i) location and size of operating facilities (strategic), (ii) location and size of charging stations (strategic), (iii) number of air taxis required to serve the demand at a certain customer service level (strategic) (iv) threshold minimum charge required for efficient air taxi operations (tactical), and (v) allocating and dispatching air taxis for customer pickup and vehicle charging in real-time (operational). The model makes these decisions considering the objectives of maximizing vehicle utilization and minimizing customer time in system and waiting time.

The clustering algorithm proposes five locations (JFK, Times Square, LAG, Prospect Park and 55 Kenmare Street) be developed in NYC that serve approximately 45% of the expected UAM demand. The simulation optimization model suggests the minimum capacity for each hub to be one. Similarly, it recommends establishing one charging port at Times Square, Prospect Park and 55 Kenmare Street and two ports at JFK and LAG. Moreover, the ideal number of aircraft in the system is found to be 50. The average customer time in system and wait time for this particular setting is observed to be nearly 36 minutes and 14 minutes, respectively, while the average air taxi utilization is 76%.

Sensitivity analysis is conducted by varying the overall demand, charging rate, weight assigned to the multi-criteria model, vehicle capacity, and battery threshold. The average commuter TIS and WT rise, whereas the overall utilization decreases with a rise in demand and rate of charge. On the other hand, all three performance measures are unaffected by a change in the priority levels. An increase in vehicle capacity showcases a considerable reduction in the TIS and WT parameters. For the base case, the minimum amount of charge remaining before the air taxis require charging is set at 20%. However, it is observed that it can be increased up to 30% without any substantial impact on the performance metrics.

Chapter 6: Can Hyperloops Substitute High-Speed Rails in the Future?

In this chapter, the substitutability of High-Speed Rails (HSR) with Hyperloop services is investigated. A discrete event simulation model is developed to compare the performance of both these alternate transportation modes for a network connecting the busiest airports and rail stations in Europe. For this purpose, we choose Paris (France), Amsterdam (Netherlands), and Frankfurt (Germany) (Eurostat, 2019). The juxtaposition between the Hyperloop and HSR is performed by considering several parameters, such as the number of pods (or rail cars), pod utilization (rail utilization), passenger cycle time, and overall lead time. Further comparison is performed with respect to their estimated infrastructure and operational costs as well as CO_2 emission. Moreover, a cost-benefit analysis is conducted to estimate the passenger ticket price for Hyperloop services.

6.1 Model Description

Consider three cities (Φ_1, Φ_2, and Φ_3) in the system with the customer *c*, commuting from one city to another by utilizing a travel mode represented by m, where $m \in \{h, r, f, c\}$.

1. h – Hyperloop
2. r – High-Speed Rail
3. f – Airlines
4. c – Conventional Rail

It is assumed that the passenger arrival rate for each hour p by mode m, follows a Poisson distribution with a mean of $\lambda_{m,p}$. Further, the ticket price for Hyperloop is estimated to be greater than HSR and conventional rails but less than air transport i.e., $t_f > t_h > t_r > t_c$. Let the total time to complete a trip via mode m be depicted by θ_m^T.

A customer c, would prefer traveling by h if the following condition is met:

$$\mu_c \leq \rho_i$$

Where μ_c is a uniformly distributed random variable $U \sim (0, 1)$ and ρ_h is the probability of the passenger switching from mode $i \epsilon \{r, f, c\}$ to option h.

A customer would prefer substituting traveling via HSR and conventional rails with Hyperloops if they are willing to tradeoff the time saved $(\theta_h^T - \theta_i^T)$, with the difference in the ticket prices $(t_h - t_i)$, where $i \epsilon \{r, c\}$. It is to be noted that certain air transport passengers might have multiple connecting flights and thus might not prefer switching to Hyperloop, and hence $\rho_f < 1$.

Based on this information, the expected hourly demand for the Hyperloop service $(\lambda_{h,p})$ is given below.

$$\lambda_{h,\mathrm{p}} = \sum_{i \epsilon \{r,f,c\}} \rho_i \times \lambda_{i,p}$$

Now, since the sum of independent random Poisson variables is a random Poisson variable, it is expected that the passenger arrival rate per hour for the Hyperloop services would be Poisson distributed with mean $\lambda_{h,\mathrm{p}}$.

6.2 Model Development

We develop simulation models to demonstrate the appropriateness of substitutability of HSR with Hyperloop services. The first step involves the customer arrival in the system. Subsequent to the their arrival at the station, they enter a queue and wait for the vehicle to pick them up. It is assumed that travelers do not balk (enter the facility and leave instantly) or renege (wait in the queue for a certain time period after entering the facility and then leaving without traveling) in both Hyperloop and HSR services.

To test the proposed models, we utilize the available flight and rail travel data between three major European cities - Paris, Amsterdam, and Frankfurt. The reason for particularly considering these three cities are as follows. According to Eurostat (2019), the Charles de Gaulle airport in Paris had over 76 million travelers in 2019. It was the maximum amongst all the airports in the European Union, followed by Schiphol airport in Amsterdam (72 million) and Main airport in Frankfurt (70 million). Similarly, Gare du Nord station in Paris is widely considered to be the busiest railway station in Europe (Dugdale, 2019), with approximately 214 million passengers availing of its facilities.

The performance of the Hyperloop and HSR are investigated based on comparing various parameters such as vehicle utilization, average commuter cycle time, and lead times. We define lead time as the difference between the traveler's actual and desired departure times (i.e., traveler lead time = actual departure time of customer at Station 1 – time that passenger desires to depart from Station 1). The cycle time is defined as the sum of the lead time and the customer travel time.

6.3 Data Description

Since Hyperloops are still in the design and testing phase, demand is estimated based on the procedure described in Section 3.1. In other words, the future market for the Hyperloop network is assessed based on the total number of commuters utilizing the existing flight and rail services between the three cities under consideration.

To anticipate the number of passengers traveling by air between Paris, Amsterdam, and Frankfurt, all flights serviced by major carriers were recorded. Flight details were obtained using the Google flights website (2019). The flight data from 2020 was not considered in this study due to the effects of the COVID-19 pandemic, which decreased the customer demand (Budd et al., 2020). Subsequently, the total seating capacity information was recorded to estimate the maximum number of commuters flying from one city to another. Since the air travel demand is seasonal, this process is repeated every hour of every day of the week to develop an accurate representation of the passenger demand. This establishes the upper limit on the number of travelers utilizing the air services. However, not every flight would be expected to function at 100% capacity. Therefore, the estimated upper limit was then multiplied by a parameter defined in the literature as the commuter variability (CVV <1) to generate an hourly rate table (Rajendran and Harper, 2020).

The process for determining the passenger demand by rail is similar to that of air travel. The number of trains commuting between the three cities was recorded based on their train schedules obtained from the EU Rail website (https://www.eurail.com/en/plan-your-trip/eurail-timetable). The maximum seating capacity based on the train type was then documented. It was observed that the trains operate at a far less frequently when compared to flights but have a much higher capacity. The travel times were noted, and the process identical to estimating customers transitioning from air travel mentioned above is repeated. Finally, the hourly rate table for each day of the week was created by multiplying it with the commuter variability parameter to obtain an estimated travel demand from each city. Table 6.1 depicts the average weekly passenger volume leveraging the air and rail facilities between the three cities. It was observed that a more significant percentage of commuters preferred traveling via the rail system when compared to the airlines. Furthermore, a larger deviation was noted for rail services, potentially due to less demand during the weekends. Figure 6.1 presents the average weekly demand experienced in various routes.

Table 6.1: Descriptive Statistics of the Air and Rail Traffic per Week

City Pairs	Rail		Air	
	Mean	Standard Deviation	Mean	Standard Deviation
Frankfurt to Paris	1758	159	2164	205
Frankfurt to Amsterdam	2801	512	1700	103
Amsterdam to Paris	3370	563	1833	130
Amsterdam to Frankfurt	2540	537	1691	25
Paris to Frankfurt	1824	131	2117	277
Paris to Amsterdam	3195	734	1832	132

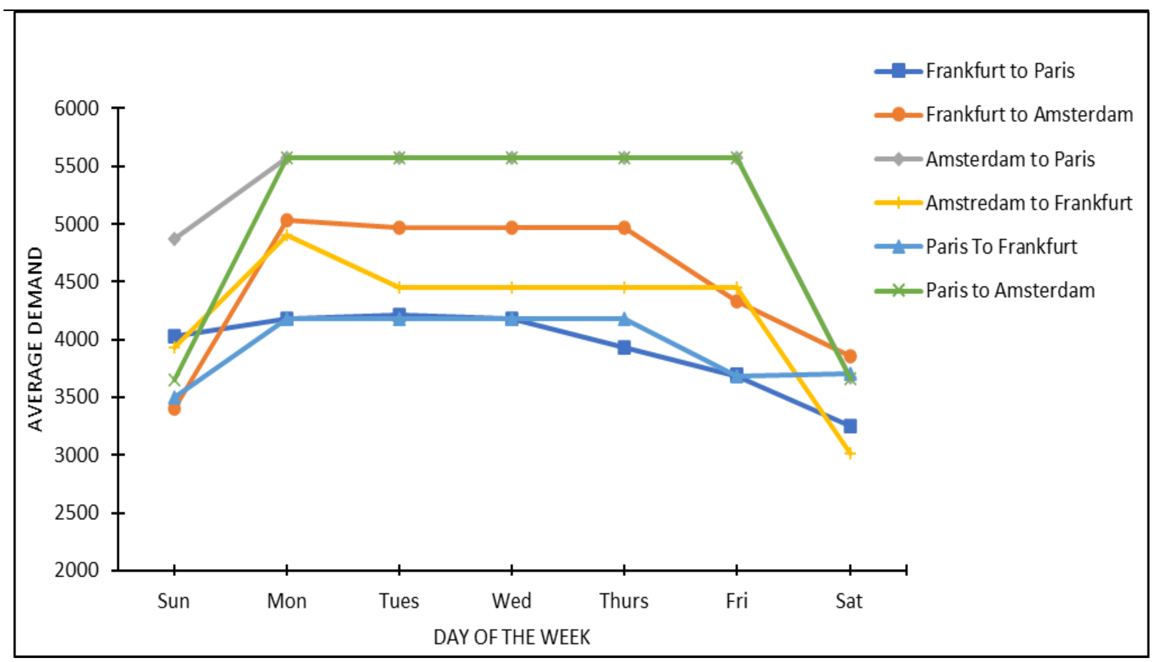


Figure 6.1: Average Demand Variation for Different Routes

6.4 Results

6.4.1 Baseline Case

For the baseline setting, we set the seating capacity of Hyperloop to be 28 passengers in a single ride, whereas a single HSR vehicle can carry a maximum of 480 commuters, based on prior research. The commuter volume variability (CV) was assumed to be 0.8 from a previous literature (Rajendran and Harper, 2020). Based on the grid search method, the number of Hyperloop pods in the system is set at 30. For the purpose of comparison, a similar number of rail cars was considered for the HSR services (even though the capacity of an HSR vehicle is substantially higher than that of an Hyperloop). The simulation models were executed for one week with 100 replications.

The results for the baseline case comparing the performance of the Hyperloop and HSR services are showcased in Table 6.2. A Hyperloop pod travels at a higher speed and completes its journey substantially faster than any HSR. Therefore, a Hyperloop capsule is expected to remain idle for a longer time duration. This is supported by the findings in Table 2 as well, where it is observed that the vehicle utilization for HSR is greater than that of Hyperloop for all the routes. We can also note that the vehicle utilization for the journey between Amsterdam and Paris is approximately 10% higher when compared to other routes. This is because of the highest estimated passenger flow between these two cities, compared to the other pairs. Similarly, the commuters traveling between Amsterdam and Paris face over 50% and 70% greater cycle time and lead times, respectively, due to the highest passenger volume.

It is observed that the average HSR commuter's lead time is approximately 33% of the total cycle time. Moreover, the maximum capacity utilization is shown in the Frankfurt to Amsterdam route. This could be due to having the highest traveling time between any city that is considered in the present study, which would entail a greater vehicle utilization. However, the average customer lead time for this route is 40% less when compared to the maximum lead time in the system (which is noted for the Amsterdam to Frankfurt route). This could be primarily due to a more balanced commuter arrival distribution rate in the system. Furthermore, passengers going to Frankfurt face the highest cycle and lead times since the travel time from Paris and Amsterdam to Frankfurt is greatest compared to the other way around. Similarly, trains going to Amsterdam are on average 10% more utilized as they have a higher demand. In contrast, vehicles operating between Paris and Frankfurt are nearly 17% less used due to a low traveler demand, as described in Table 1. A paired sample t-test at 95% significance level showcases that all three performance metrics are significantly different.

Table 6.2: Comparison between Various Performance Metrics of Hyperloop and High-Speed Rails

Travel Route	**Vehicle Utilization (%)**		**Cycle Time (minutes)**		**Lead Time (minutes)**	
	Hyp.	**HSR**	**Hyp.**	**HSR**	**Hyp.**	**HSR**
Frankfurt – Paris	63.86	74.15*	74.26	362.41*	39.36	112.20*
Frankfurt – Amsterdam	62.17	94.35*	55.32	339.28*	28.37	89.45*
Amsterdam – Paris	72.33	89.12*	115.03	308.06*	125.10	110.62*
Amsterdam – Frankfurt	59.76	90.47	54.08	399.84*	27.13	152.54*

Paris – Frankfurt	58.89	86.14*	89.03	405.01*	54.03	151.77*
Paris - Amsterdam	67.76	93.57*	165.14	320.80*	135.60	121.68*

Note: * denotes significance at 95% significance level

Based on the results, it can be concluded that the Hyperloop system significantly outperforms HSR with respect to the performance metrics analyzed in the present study. Therefore, for a similar travel distance, HSRs could be substituted with Hyperloop services considering these measures. Nevertheless, there are other metrics, such as cost and sustainability, that have to be taken into consideration to evaluate the substituitability of HSR with Hyperloops. Therefore, we further compare the two transportation modes with respect to their estimated infrastructure and operational costs, as well as CO_2 emission, in Section 6.

6.4.2 Sensitivity Analysis

In this section, various parameters, such as the number of vehicles in the system, commuter volume variability, and pod capacity are varied and their impact on the performance metrics is examined.

Table 6.3: Sensitivity Analysis Settings

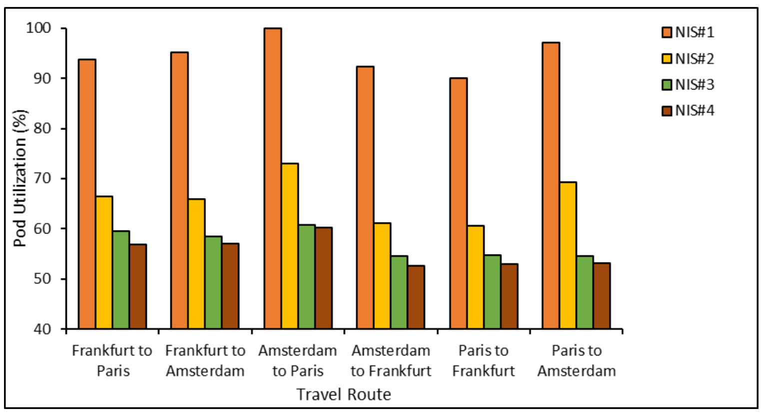
Setting	Number of Pods in System (NIS)	Capsule Capacity (CC)	Commuter Variability Parameter (CVV)
Number of Pods in the System			
NIS – 1	20	28	0.8
NIS – 2 (Base)	30	28	0.8
NIS – 3	40	28	0.8
NIS – 4	50	28	0.8
Capsule Capacity			

CC – 1 (Base)	30	28	0.8
CC – 2	30	32	0.8
CC – 3	30	36	0.8
	Commuter Variability Parameter		
CVV – 1	30	28	0.7
CVV – 2 (Base)	30	28	0.8
CVV – 3	30	28	0.9

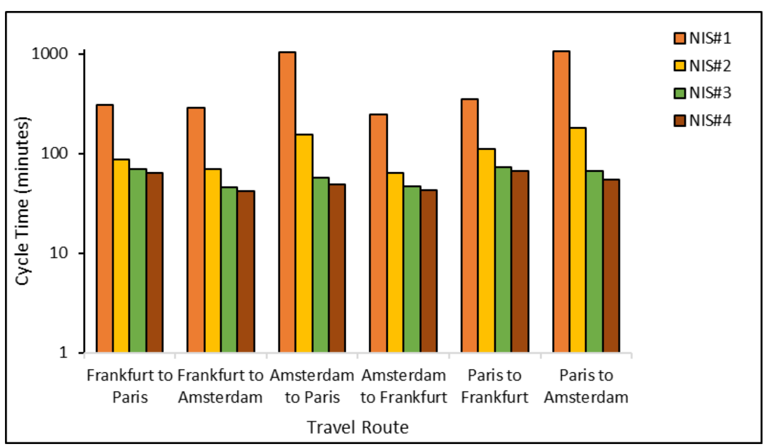
6.4.2.1 Number of Hyperloop Pods in the System

As discussed earlier, the baseline setting has 30 Hyperloop pods in the system. In this section, the total number of capsules in the system (NIS) is varied linearly in steps of 10 from NIS#1 - NIS#4 (Table 6.3). Figure 6.2 (a) – (c) presents the results obtained for various settings. As expected, the overall vehicle utilization (Figure 6.2 (a)) decreased on average by approximately 40%, with a linear increase in the number of pods. While NIS#1 showcases a superior capacity utilization, the customer cycle time and lead time are observed to be extremely high between all three cities. Therefore, a rise in NIS led to a reduction in average commuter CT and LT by approximately 90%. Passengers traveling between Amsterdam and Paris encounter the greatest CT (Figure 6.2 (b)) and LT (Figure 6.2 (c)) for NIS#1 and NIS#2. For NIS#1, the overall cycle time and lead time for remaining routes are comparable with the results obtained by HSR services other than for those between Amsterdam and Paris.

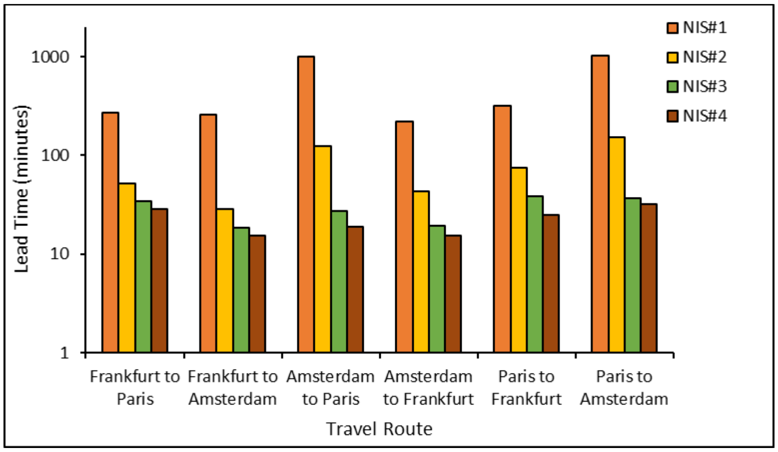
On the other hand, commuting between Frankfurt and Paris displays over 25% higher CT and LT values for NIS#3 and NIS#4, which is counter-intuitive considering the fact that it has the lowest demand. An average decline of 15% in vehicle utilization can be noticed between NIS#2 and NIS#4. A two-sample t-test indicates a significant difference for all scenarios. Similarly, the average commuter cycle time and lead time were reduced by approximately 50% and 70%, respectively, between the two settings. Therefore, in order to regulate excess demand, management can decide to increase the number of pods, which will have a substantial impact on reducing the total travel time, thereby also improving the customer satisfaction rate.



(a)



(b)



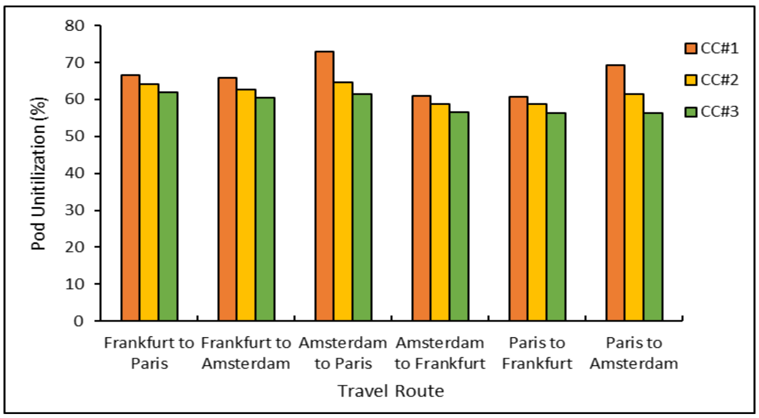
(c)

Figure 6.2: Impact of Variation of Number of Vehicles in the System on (a) Utilization, (b) Cycle Time, and (c) Lead Time

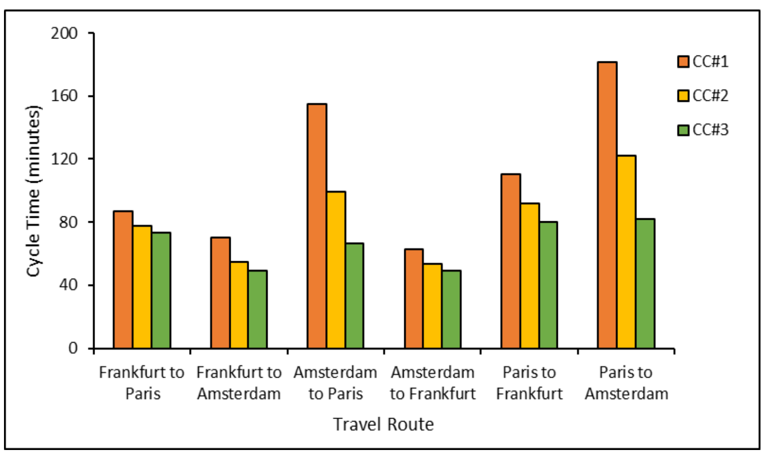
6.4.2.2 Hyperloop Capsule Capacity (CC)

In this section, the impact of increasing the capsule capacity (CC) on vehicle utilization (Figure 6.3 (a)), customer cycle time (Figure 6.3 (b)), lead time (Figure 6.3 (c)) is investigated. In the baseline case (CC#1), we assumed the pod capacity to be 28. Whereas each vehicle has a carrying capacity of 32 and 36 customers respectively for the subsequent cases, as shown in Table 6.3. As expected, the average vehicle utilization decreased by approximately 10% for all cities, with an increase in CC. A similar trend is identified for the customer cycle time and lead times with a decline of nearly 40% and 30%, respectively, from CC#1 to CC#3. The results obtained in the present study follow a comparable pattern as described by Rajendran and Harper (2020) for the Hyperloop operations between LA and SF.

The trip between Amsterdam and Paris showcases a maximum decline between CT and LT (~40%) due to an increase in CC from the baseline case (CC#1). A two-sample t-test establishes that the decline demonstrated by all parameters for CC#2 and CC#3 is significant at a 95% significance level. Similar to the baseline case (CC#1), Amsterdam to Paris has the highest capacity utilization, whereas Paris to Amsterdam has the maximum CT and LT for CC#2 and CC#3. Based on the results from two-sample t-tests, it can be concluded that the rate of change in the hyperloop capsule capacity has a significant impact on the performance metrics.



(a)



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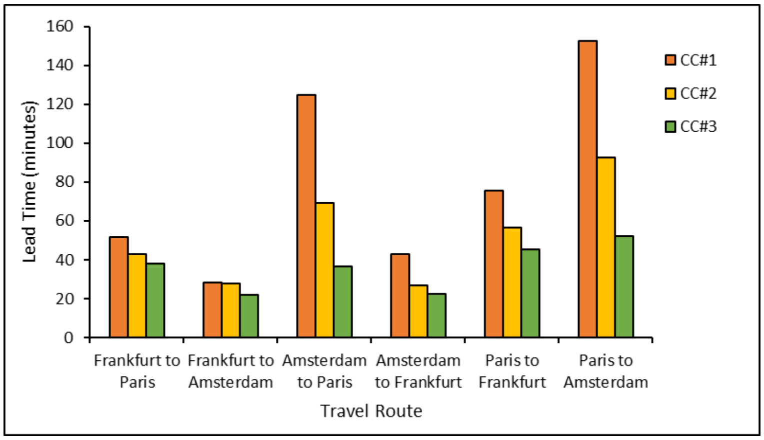


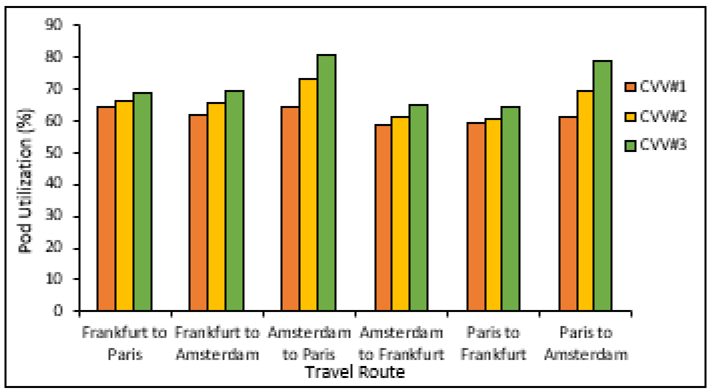
(c)

Figure 6.3: Impact of Variation of Capsule Capacity on (a) Utilization, (b) Cycle Time, and (c) Lead Time

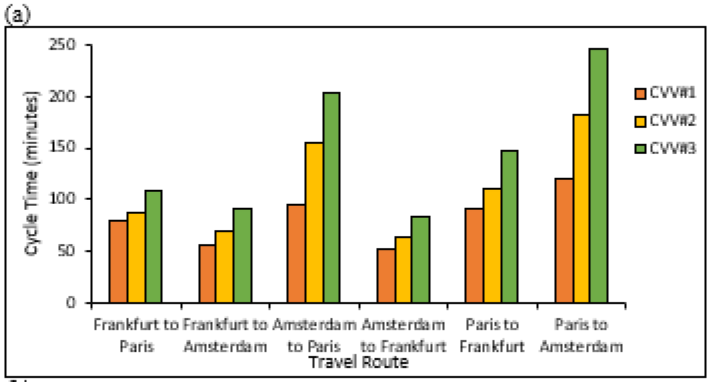
6.4.2.3 Commuter Variability Parameter (CVV)

It is expected that not all eligible passengers would be willing to avail of the Hyperloop services. Therefore, the commuter volume variability (CVV) is modified to capture the effect of altering overall demand on the performance parameters. While the baseline case (CVV#2) is set at 80% similar to Rajendran and Harper (2020), the other scenarios are modified in steps of 10% with CVV#1 and CVV#3 evaluating the demand at 70% and 90% respectively (Table 6.3). Figure 6.4 (a) displays the impact of changing CVV on pod utilization. Similarly, Figures 6.4 (b) and (c) depicts the effect of varying the parameter on CT and LT, respectively.

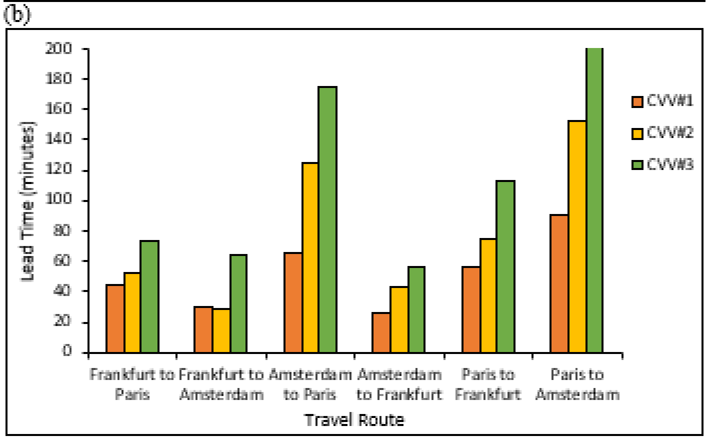
It is observed that a decrease in CVV led to a reduction in cycle time for customers traveling the Amsterdam - Paris route by over 50 minutes. Whereas an approximately 46% increase in CT is observed for the same journey in CVV#3. A similar trend is noticed for the lead time as well. Even though transitioning from CVV#1 to CVV#3 increments vehicle utilization by 10% on average, the CT and LT rise close to 77% and 123%, respectively, showcasing that CVV is an important factor that affects the system efficiency and client satisfaction. Similar to our previous analysis, a two-sample t-test indicates that the results presented in Figure 6.4 (a) – (c) are significantly different from each other at a 95% significance level.



(a)



(b)



(c)

Figure 6.4: Impact of Variation of Commuter Variability Parameter on (a) Utilization, (b) Cycle Time, and (c) Lead Time

6.5 Discussion

The results obtained in the previous section showcase the efficiency of the Hyperloop services over HSR based on time savings and vehicle utilization. However, the feasibility of substituting HSR with Hyperloops is also contingent on several other critical parameters, such as infrastructure and operational costs, sustainability, and ticket prices. These factors are discussed in detail in this section.

6.5.1 Infrastructure Costs

Similar to other emerging transportation services, several cost components such as infrastructure and operational costs are involved in the Hyperloop system. These costs would have a significant influence on the overall travel fare, which could in turn lead to a decline in the commuter's willingness to utilize this emerging service. The infrastructure costs include the expenses associated with developing new stations, constructing tunnels between each city, land acquisition, and environmental planning (Taylor et al., 2016). Musk (2013) estimated the initial capital costs for the Hyperloop technology to be approximately $17 million per mile for the LA-SF route. On the other hand, the infrastructure development costs for the high-speed rail network for the same route are evaluated at $65 million per mile (Taylor, 2016). Nevertheless, the existing literature indicated that the actual infrastructure costs for both the services would be more analogous to each other due to the Hyperloop system requiring expenditure for constructing tube and vacuum pumps (Hansen, 2020; van Goeverden et al., 2018).

6.5.2 Operational Costs

The operational costs comprise the employee costs, maintenance and system control, etc. The California High-Speed Rail Authority (CHSRA) estimated the maintenance cost for the LA-SF corridor to be approximately $200,000 per mile and incurring $83.22 per revenue service hour (CHSRA, 2012). While the literature on similar parameters for the Hyperloop facility is not available, a previous study by van Goeverden et al. (2018) suggested pod capacity to be a potential limitation for the Hyperloop system affecting its financial performance. Furthermore, Musk (2013) suggested an electronic ticketing system to reduce staffing costs. However, further research integrating various parameters, such as utility and IT costs, customer service, security, etc., would be required before juxtaposing it with the HSR network.

6.5.3 Sustainability

It is expected that the Hyperloop services would be energy efficient by more than two times when compared to HSR due to low track friction, less air resistance, and utilization of solar panels (Taylor, 2016). A recent study by Janic (2020) observed comparable CO_2 emissions (approximately 40 gCO2/s-km) between HSR and Hyperloop. They also concluded that the CO_2 emission level was substantially lower than a standard aircraft (100 gCO2/s-km). The energy consumption and CO_2 emissions by both services decrease proportionally with increasing travel distance and seating capacity (Janic, 2020). Similar research by Decker et al. (2017) observed that the energy consumption costs due to increasing the seating capacity remained fairly constant. Therefore, the decision-makers can consider expanding the capaciousness of Hyperloop pods for maximizing demand fulfillment.

6.5.4 Cost-Benefit Analysis

It is expected that the travel cost incurred by the Hyperloop passengers would be relatively higher during the initial stages of operation. In this section, we perform a cost-benefit analysis (CBA) for an ex-ante evaluation between the two transportation modes to suggest the optimal pricing structure to attract passengers to utilize the Hyperloop facility over HSR.

The total cost tc_m incurred by the customer traveling from mode m for any pair of cities is given by Equation (1).

$$tc_m = t_m + (V \times \theta_m^T) \tag{6.1}$$

Where, C_i is the average ticket cost in transportation alternative m between two cities in dollars, V is the value of time for passengers in dollars/hour and θ_m^T is the total travel time between the two cities using alternative m in hours. Previous literature suggests that the time value is a function of the wage rate (Hultkrantz, 2013; Wardman et al., 2016; Zhao et al., 2015).

The total cost for HSR and Hyperloop passengers are given by Equations (2) and (3), respectively.

$$tc_h = t_h + (V \times \theta_h^T) \tag{6.2}$$

$$tc_r = t_r + (V \times \theta_r^T) \tag{6.3}$$

Equation (4) needs to be satisfied in order for Hyperloop services to be comparable with HSR in terms of costs experienced by the customers.

$$tc_h \leq tc_r \tag{6.4}$$

Substituting Equations (2) and (3) in Equation (4) we can analyze the ideal ticket price for availing the Hyperloop facilities, as shown by Equation (5).

$$t_h \leq t_r + (V \times (\theta_r^T - \theta_h^T)) \tag{6.5}$$

The total travel time for each pair of cities (i.e., difference between cycle time and lead time) is calculated from the results shown in Table 6.2. The ticket cost of high-speed rails is estimated based on the seven-day average prices available on the EU rail website. The time value is obtained from the meta-analysis conducted by Wardman et al. (2016).

The price difference between the two transportation modes is shown in Table 6.4. It is observed that the travel fare for Hyperloop services exceeds the current ticket cost for HSR services by approximately 320%. Furthermore, the price suggested in the present study for Hyperloop services is comparable to the existing airline operations while also being considerably higher than the originally proposed price structure of USD 20 (Musk, 2013). Therefore, in order for the emerging technology to become comparable in terms of commercial and marketability values, a significant reduction in the ticket costs would be necessary for the future.

Table 6.4: Ticket Price Difference between the Hyperloop and HSR Services

City Pairs	C HSR ($)	Vt ($/hr.)	C HL ($)
Frankfurt to Paris	18.86	35.49	146.12
Frankfurt to Amsterdam	49.00	35.49	173.21
Amsterdam to Paris	21.55	40.55	138.33

Amsterdam to Frankfurt	56.50	40.55	198.42
Paris to Amsterdam	38.96	32.04	131.34
Paris to Frankfurt	16.00	32.04	130.81

The following managerial insights are proposed based on the results obtained in the present study:

i. A linear increase in the number of pods in the system leads to an exponential decline in vehicle utilization, passenger cycle time, and lead time. Therefore, it is recommended to determine the optimal number of pods in the system for maximum customer satisfaction.

ii. All parameters showcase a linear decrease with a linear increase in the seating capacity of the pod. Based on a previous study by Decker et al. (2017), capsule capacity can be increased without a significant impact on the overall structural cost. Therefore, it is suggested to perform a cost-benefit analysis of expanding the number of seats in the pod. Consequently, if the logistic companies decide to decrease the number of vehicles in the system, then the supply shortfall could be offset by increasing the capsule capacity.

iii. It is observed that a linear increase in demand results in all the three performance metrics rising linearly. Thus, when the latent demand arises, it is proposed to immediately increase the number of capsules in the system. This would mitigate the customer density growth for the facility by reducing the cycle time and average commuter lead time.

iv. The average lead time for passengers availing of the high-speed rail facilities is significantly higher than the Hyperloop services. Consequently, introducing additional trains would aid in reducing the long lead times.

v. In order to increase the customer willingness to utilize the Hyperloop services, it is recommended to reduce the ticket price by approximately 80% in the future based on the results obtained from the cost-benefit analysis.

6.6 Conclusion

Traffic congestion has led to a significant loss of productivity and increased the cost of travel. Several researchers and practitioners are examining emerging transportation methods that are economically viable and significantly reduce transit time, such as Hyperloops, air taxis, and high-speed rails (HSR). Previous literature has concluded that HSR have a considerable impact on traditional airline services over short and medium distances with respect to cost and ride time. To the best of our knowledge, this study is the first to focus on exploring the substitutability of high-speed rails with Hyperloop systems, which are expected to commence services in forthcoming years for equivalent distances. Simulation models are developed in the present work to compare the overall customer time in system, lead time, and vehicle utilization between Hyperloops and HSR between three major European cities. Furthermore, juxtapose the two tranportation means based on several catergories such as sustainability, infrastrucutre and operational costs. We estimate the average ticket prices for commuters utilizing the Hyperloop services through a cost-benefit analysis.

The base case results showed that passengers would experience approximately 75% and 34% decrease in cycle time and lead time while commuting through the Hyperloop system compared to HSR services. However, pod utilization is nearly 25% lower than the HSR services due to its higher speed. It is observed that Hyperloop customers transporting between Paris and Amsterdam would encounter the greatest CT and LT. On the other hand, HSR users traveling to Frankfurt experience the highest performance metrics when compared to other routes. Sensitivity analysis is performed to investigate the impact of various alternate Hyperloop scenarios, such as a change in the number of pods in the system, capsule capacity, and commuter variability parameter. The outcomes indicate a significant influence of the three parameters on all the performance measures.

The proposed simulation model can serve as a decision support tool for any logistic companies interested in advancing into the Hyperloop business. Typically, a commuter is expected to compare the feasibility of availing a service based on various factors such as price, distance, perceived safety, and familiarity. Therefore, a major limitation of this study is that it does not consider the impact of customer willingness to utilize the Hyperloop services based on these factors. Future work could investigate the influence of these parameters on demand variation. Similarly, the effect of multiple socio-economic criteria affecting usability is not included in the current research. Therefore, multiple criteria models can be developed in the future to generate tradeoff alternatives. While the present study proposes reducing the ticket price significantly to make the Hyperloop facility more comparable with HSR, future work can conduct a more detailed investigation by considering the impact of infrastructure, overhead, and maintenance costs. Another major drawback of the current research is that it does not consider the impact of introducing Hyperloops on the existing air and rail services. Thus, future work can explore the differences between cooperation and competition between these services on the market.

Chapter 7: Conclusion and Future Work

Traffic congestion in Metropolitan cities has increased rapidly due to increase in urban employment, privately owned vehicles and inadequate public transport and road infrastructure. Consequently, cities experience an increase in vehicle operating cost, air pollution and revenue loss across various sectors. For example, over $2 billion are wasted in New York due to fuel consumption coupled with nearly $6 billion loss to industries annually. However, problems related to gridlocks are not just limited to intra-city travel. Increase in congestion on major highways is also a detriment towards economic growth. Recent studies observed a loss in operational costs of over $74 billion to the trucking industries. Another major impediment of expressway vehicle saturation is the disruption to the nation's supply chain by generating supplemental costs due to late deliveries while simultaneously requiring industries to maintain large inventories to compensate for the unpredictable nature of product arrival.

While it is apparent that improving the existing road facilities would be a good solution to address this issue, Winston and Langer (2006) observed that allocating funds to highways for constructing additional lanes would have minimal impact on the bottlenecks. Therefore, in recent years, with advancements in technology, several emerging transportation services, such as High-speed rails (HSR), Hyperloops, and Air Taxis, are evolving to improve the existing traffic condition. These facilities are expected to provide a faster and efficient mode of commute.

In the present dissertation, optimal air taxi infrastructure locations were identified using the multi-criteria based warm start technique integrated with the k-means algorithm. New York City (NYC) was considered in the research for the case study. The model proposed 18 stations to be developed in NYC initially. However, a different algorithm known as clustering large applications recommended 14 stations to be established instead. It is expected that the management would prefer developing specific centers in multiple phases to reduce the infrastructure costs of the emerging transportation systems. Therefore, various socio-economic factors are then considered in a mathematical model to achieve that objective. The framework is further extended by determining ideal station size, location and size of charging stations for the vehicles, assessing threshold minimum charge, total number of air taxis required to serve a certain customer service level, and commuter allocation through a simulation optimization model. Finally, we examine the substitutability of HSR with Hyperloop services according to the passenger and vehicle characteristics. The performance of these modes is juxtaposed for a network of three urban European cities through a simulation model. Further comparison is done based on the estimated infrastructure and operational costs, and CO_2 emissions. A cost-benefit analysis is performed to estimate the average passenger ticket price for the Hyperloop service.

7.1 Theoretical Contributions

In previous studies on urban air mobility, researchers have focused on strategic (Holden and Goel, 2016, Johnson et al., 2018; Rajendran and Zack, 2019), tactical (Hasan, 2019; Sun et al., 2018) and operational (Baik et al., 2008) level decisions. However, for effective functioning, integration of the three decision levels from management's viewpoint are required to be considered. The framework developed in this dissertation would enable the logistic companies to establish and operate emerging transportation systems such as air taxis and hyperloops across major cities in the world and reduce issues related with traffic congestion.

This research provides a multifaceted contribution to the existing literature. K-means clustering algorithms are widely utilized in existing research for solving the facility location problem (Andrenacci et al., 2016; Marino and Marufuzzaman, 2020; Rajendran and Zack, 2019). However, this procedure randomly assigns the initial solutions which in turn affects the final clustering (Usman et al., 2013). In order to address this major limitation, the present study is one of the first to propose a multi-criterion based warm start (MCWS) technique for initial seed selection as presented in Chapter 3. The integration of MCWS with k-means algorithm improved the final generated solution by approximately 20% and simultaneously reduced the number of cluster centers to be developed when compared with Rajendran and Zack (2019) and the traditional k-means algorithm.

Previous research suggests that a variant of partitioning around medoids (PAM) known as clustering large applications (CLARA) has a significant advantage over k-means by reducing the impact of outliers and being non-sensitive to noise (Arora et al., 2016). This observation is supported by the findings in Chapter 4. The analysis presented clearly indicates that the total number of infrastructures to be developed while maintaining similar demand satisfaction rates was decreased in the case study when compared with the k-means algorithm integrated with MCWS technique. In addition, a multi-criteria based mathematical model is also developed as a recommender system to propose establishing of stations in various phases.

There has been very limited work on facility size and vehicle dispatching problem for the air taxi services conducted in the past. In Chapter 5, a two-phase approach is developed to determine to ideal station infrastructure location using the clustering algorithm (phase one) from the previous chapter in phase one. A simulation optimization model is developed in phase two to determine the ideal station capacity at each location. The model also considers vehicle charging to ascertain the number of charging ports required at each center (strategic) along with the threshold battery requirement (tactical) and commuter allocation to the air taxis (operational). Another contribution is based on exploring the impact of varying the assigned priority to the conflicting criteria's along with demand variation and charging rate.

While logistic companies are concentrating on air taxis for intra-city travel, Hyperloops are an emerging transportation system geared towards reducing the inter-city travel time. The existing literature has focused on the impact of High-Speed Rails (HSR) on the current airline industry. On the other hand, Chapter 6 is one of the first to examine the substitutability of HSR with Hyperloop services. The two transportation modes are compared with respect to their estimated infrastructure and operational costs along with CO_2 emission. Furthermore, we analyze a multi-city network operation, whereas most previous literature is based on evaluating the system between two cities.

7.2 Methodological Contributions

Existing research on demand estimation assumed each taxi data to have just one customer (Rajendran and Zack, 2019). However, in reality, each ride could have multiple commuters traveling at once. This assumption is removed in Chapter 3 by replicating each data point with the total number of passengers. Furthermore, logistic companies would prefer minimizing the total infrastructure to be established while maximizing the demand satisfaction. Therefore, the proposed linear mathematical model in Chapter 4 can be used as a decision-support system for suggesting the specific stations to be developed in different phases. Since, UAM is an emerging mode of transportation, they can also opt to set up lesser number of stations during early stages before substantially investing in the technology as described in Chapter 4.

After dropping the passengers, existing air taxi dispatching problem have focused on real-time decisions such as (i) picking up new customers from the same station or travel to a different location, and (ii) staying idle (Rajendran, 2021). The simulation optimization model presented in Chapter 5 further contributes to the literature by integrating these decisions with charging the vehicle if the charge is below the threshold level. The model also determines the ideal location for charging or staying idle based on space availability. Furthermore, the results presented in this chapter can assist the management in deciding the optimal station and charging ports size at each center based on several conflicting criteria’s like maximizing aircraft utilization and minimizing customer average TIS and WT.

The Hyperloop network in Chapter 6 analyzes the impact of various parameters such as number of pods in the system, customer seating capacity and commuter variability on utilization levels, commuter cycle time and lead time. The competitiveness between the Hyperloop system and HSR is also examined through a cost-benefit analysis that estimates the optimal passenger ticket price.

7.3 Contributions to Practice

With the increase in the number of privately owned vehicles and rapid economic development, traffic congestion has become an inevitable issue in metropolitan cities. Therefore, in recent years, with advancements in technology, several emerging transportation facilities, such as High-speed rails (HSR), Hyperloops, and Air Taxis, are evolving to improve the existing traffic condition. Logistic companies would be interested in developing a framework that enables faster and efficient mode of commute. The mathematical model developed in Chapter 4 consists of several socio-economic parameters that impact infrastructure development such as rental costs, average salary, and population density. The model can be easily implemented using an Excel spreadsheet and can act as a recommender system to the management.

In Chapter 5, a multi criteria simulation optimization model is developed that integrates the strategic (long term), tactical (medium term) and operational (short term) decisions for the urban air mobility services. Under this model, after dropping off a customer at a station, the vehicles need to make the following decisions, (i) to go to charging station if the remaining charge is less than threshold level, (ii) transfer to the parking station if idle, and (iii) pick up new passengers. In addition, it also establishes whether the above decisions take place at the drop off skyport or a different center based on space availability. The model solves the air taxi dispatching problem while also determining the number of vehicles required for maximum demand satisfaction.

Furthermore, a comparison between HSR and Hyperloop facilities are performed in Chapter 6. While the Hyperloop outperforms HSR in terms of customer average cycle time and lead time, it is suggested to decrease the average ticket prices by approximately 80% in order to make it more attractive to the potential consumers.

7.4 Future Work

The following are the potential future research directions for UAM and Hyperloop systems:

Vehicle Routing Policies: The simulation optimization model picks up customers based on the First in First Out (FIFO) technique. Future work could investigate the effect of various other dispatching policies that might reduce travel costs in the cyber physical system while striking a balance between vehicle utilization and idle time. It can be extended further by incorporating efficient optimization models that incorporates arrival and departure scheduling and sequencing for achieving the highest operational efficiency.

Utilizing Mobility as a Service (MaaS) for Improving the UAM Services: The present study only considers data from the existing taxi services in the city. However, future research using the concept of MaaS can explore incorporating existing multimodal transportation facilities such as bikes, cars, buses and subways for the first and last mile travel with the air taxi services. This would also increase commuter travel options and provide affordable travel by developing various scheduling algorithms (eg. car - air taxi - bus or subway - air taxi - bike).

Integrating emerging transportation modes with Supply Chain: Recent research on utilizing unmanned drone systems for last mile delivery has garnered popularity. Future studies can explore developing an integrated system for drone dispatching from air taxis. This would be extremely beneficial for reducing congestion on roads and improving supply chain reliability by enabling timely delivery. Moreover, it can also be used if the traditional transportation network is damaged under extreme situations such as a disaster. Similarly, faster freight movement between multiple cities can be achieved through the Hyperloop systems instead of relying on the trucking industry.

Optimal Pricing Strategy: Typically, a commuter is expected to compare the feasibility of availing a service based on various factors such as price, distance, perceived safety, and familiarity. Therefore, optimal market penetration strategies are required to be implemented by the logistic companies to increase customer demand for the emerging transportation systems.

Impact on sustainability: Both air taxis and Hyperloop services are expected to be more energy efficient when compared with the existing modes of transport. However, researchers could investigate the life cycle analysis (LCA) based on the total greenhouse emissions and energy consumption for infrastructure development.

Vehicle Capacity Variation: The model developed in Chapters 5 and 6 have vehicles with fixed capacity for the base case i.e., each air taxi can carry a maximum of two passengers whereas each Hyperloop pod has a capacity of up to 28 commuters. Future analysis can be performed by having an amalgamation of vehicle capacities to determine the optimal fleet for both services, respectively.

Impact of Customer Willingness to Fly Rate: Existing market studies observes that the customer demand is highly dependent on the willingness to fly rate. It is observed that several parameters such as safety, travel costs, automation, weather etc. impact the overall demand (Goyal et al., 2018; Hasan, 2019; Reiche et al., 2018). Major cities such as NYC, LA, Houston and SF are considered in the market by Goyal et al. (2018). However, the respondent demographics are not entirely representative of the region thus creating a sampling bias which is a major limitation of the research. Therefore, future studies can be to conduct surveys that reduces the sampling bias in the data as well as in other urban cities such as Chicago, St. Louis, Philadelphia, Seattle etc. Additional surveys can also be performed to investigate the impact of these factors across different regions in the country – e.g., do respondents favor automation in Mid-West when compared with the North-Eastern population.

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