LIFE CYCLE COST OPTIMIZATION FOR E-VTOL CHARGING AND SUPPORT INFRASTRUCTURE PLANNING IN ON-DEMAND URBAN AIR MOBILITY

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ABSTRACT

Seeking to minimize traffic congestion in cities, the aeronautical industry has recently intensified the exploration of Urban Air Mobility (UAM), focusing its efforts on developing electric Vertical Take-Off and Landing (e-VTOL) configurations and their supporting systems. The urban on-demand e-VTOL scenario requires a large dispersion of support infrastructure points and high operational dynamism. The current energy density of e-VTOL electric batteries makes their range limited, and electrical energy supply must be performed through charging or swapping stations during operation. There is a gap concerning modeling for urban e-VTOL to allow the operator, from the perspective of life cycle cost and fleet availability, to plan a cost-efficient allocation of its fleet support and energy supply infrastructure. This work addresses the development of a Life Cycle Cost (LCC) optimization model based on UAM e-VTOL support and energy supply infrastructure planning and allocation. The model was divided into two main steps: the energy supply infrastructure allocation; and the support, logistics, and spare parts supply network allocation. For the former, a Genetic Algorithm was applied to find optimal locations for energy supply infrastructure, minimizing LCC. We conduct the optimization of the spare parts for the latter in Systecon OPUS10. We implemented an e-VTOL as an air taxi operation in the city of São Paulo case study to verify the effectiveness of the model. As a result of the work, it was obtained the case study's LCC and the location and number of energy stations within the e-VTOL support infrastructure network for both battery-swapping and plug-in charging systems. The methodology and algorithms used proved efficient for planning the support and energy supply infrastructure for urban on-demand e-VTOL, given systems specifications and the operational profile. In addition, it was possible to compare both energy supply concepts in terms of LCC.

Keywords: e-VTOL, Urban Air Mobility, Supportability, Facility Location Problem, Charging Station Allocation Optimization.

1. INTRODUCTION

Worldwide, populations are growing every year, and consequently, more people need to move to urban areas, which have limited transport infrastructure. In São Paulo, according to recent estimates by Grandl *et al.* (2018), an inhabitant spends an average of 86 hours a year in traffic jams.

Urban Air Mobility (UAM) is presented as a solution for urban transport, given its faster trip characteristics and less need for operational infrastructures such as roads or rails. It comprises a low-altitude aerial operation with take-off and landing points built near or on top of buildings (Vieira *et al.*, 2019).

From the publication of Holden & Goel (2016) white paper, where Uber presented its vision for UAM in the coming years, electric vertical take-off and landing (e-VTOL) vehicles were indicated to perform urban air taxi on-demand service, with faster trips, less noise, and less environmental impact.

Their implementation as urban air taxis is subject to high dynamism and demand variations during the day or depending on geographic location and requires a large dispersion of infrastructure points. Hence, it presents high complexity in the planning, operation, and control.

The current maturity and energy density of electric vehicle batteries make their range limited. Therefore, the concentration or dispersion of energy supply and support bases directly affects their availability and operation. This restriction is one of the biggest challenges in providing adequate locations to support the operation of e-VTOL. In addition to design functionalities, considerations about the operation and disposal phases and their related costs must be performed.

The provision of operational and maintenance facilities should minimize acquisition costs and simultaneously fulfill customer demand. Current heuristics and models that plan support infrastructure do not consider the energy supply installations allocation optimization and the Life Cycle Cost (LCC) related to the acquisition, provisioning, and operation of these facilities.

Hence, the present work aims to perform the optimal allocation of e-VTOL energy supply and support infrastructure for Urban Air Mobility from the perspective of LCC and fleet availability. This process is divided into two main steps: the allocation of fast charging or battery swapping stations and the support network and spare parts optimization. The article also contributes to filling a research gap by addressing the supportability of UAM e-VTOL.

2. LITERATURE REVIEW

The current literature has some works with a similar focus as this research but in different applications, such as electric cars and buses. As it is a recent topic, studies on the planning of e-VTOL infrastructure are still scarce, and they do not aim to analyze the investments in infrastructure provisioning.

Dong *et al.* (2014) solved the electric vehicle charging location optimization problem to determine a set of locations where public chargers should be installed, as well as the type of chargers to be installed at each location. The solution algorithm chosen was the Genetic Algorithm (GA), and the problem aims to minimize the missed missions due to uncharged batteries, given a budget constraint for the construction of support infrastructures.

In their work, Zheng *et al.* (2014) developed a framework for the optimal design of battery charging or swapping stations for electric cars based on LCC. Their method made it possible to compare the two types of electric vehicle energy replenishment systems, but their contribution focuses on the energy distribution network.

The work of Kunith *et al.* (2017) involves modeling and optimizing the fast-charging point allocation problem for a Berlin bus network, considering three different types of buses for consumption.

Fadhil (2018) conducts a ground infrastructure allocation for urban e-VTOL based on an analysis using a geographic information system. The study, therefore, leans towards operational research, disregarding aspects of supportability or energy supply considerations.

Wu & Zhang (2019) optimize a dual model: e-VTOL charging scheduling and passenger scheduling integrated. Their optimization problem seeks to minimize the total waiting time for passengers as a function of various charging times and passenger queue constraints.

In their paper, Jordán *et al.* (2021) propose optimizing the electric car charging infrastructure configuration in the city of Valencia through an agent-oriented approach employing a GA. The objective of its optimization involves the minimization of cost and the fulfillment of a specific level of service.

From a heuristic that combined Quantum Annealing (QA) and GA, Chandra *et al.* (2021) solved the electric vehicle charger placement problem by minimizing travel distance from points of interest to the battery charging infrastructure. They focused only on the optimal geographic positioning of the chargers given a set of points of interest.

2.1. Energy Supply Allocation Optimization Problem

The charging station placement problem or battery swapping station allocation problem seeks to find the ideal location of energy supply stations in the transport network so that the operational parameters of the distribution network and the demand fulfillment are less affected. Its main objective is to minimize a specific function, which can comprise costs, distance, voltage deviation, and net benefit (DEB *et al.*, 2018). Exact optimization algorithms, linear integer programming or mixed-integer programming, and evolutionary algorithms can be adopted for the problem solution.

Since the objective functions of energy supply allocation optimization problems are multivariable and complex, works in this area commonly use evolutionary optimization algorithms to achieve robust solutions (DEB *et al.*, 2018). They follow the principle of survival of the fittest individual from randomly generated population sets.

According to Deb *et al.* (2018), computational and conceptual simplicity, a wide range of applications such as complex engineering problems, the possibility of hybridization with classical algorithms, and, finally, more agile convergence criteria are the main advantages of evolutionary algorithms, and the reason of them have wide application in energy supply allocation problem. Hybrid optimization algorithms that combine classical techniques with evolutionary algorithms can also be adopted to solve this problem (JORDÁN *et al.*, 2021; CHANDRA *et al.*, 2021).

Genetic Algorithm is one of the known techniques to solve complex optimization problems. They consist of elements such as population, generations of individuals, crossover, mutation, selection procedures, coding of an individual's genome, objective function, and stopping criteria (JORDÁN *et al.*, 2021). We describe a flowchart of the process performed by the GA in Figure 1.

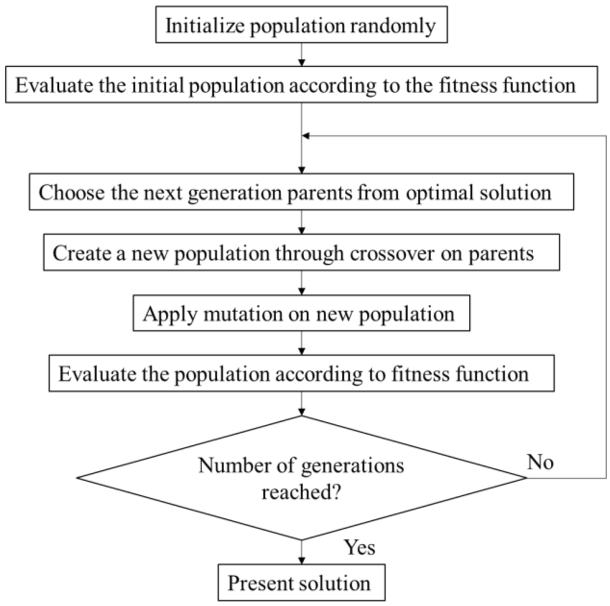

Figure 1 - Genetic Algorithm Flowchart

3. MATERIALS AND METHODS

3.1. Computational Tools Overview

OPUS10 is a spare parts optimization and logistic support analysis tool. The models simulated in OPUS10 aim to reduce inventories and invested capital, detail the support organization, and observe its impact on system performance (SYSTECON, 2019). We employed the software version 2019 64-bit in this work.

Pymoo is a complete Python framework for multi-objective optimization with customizable implementation (BLANK; DEB, 2020). In this work, we used Python V3.7.6 and Pymoo V0.6.0, free on official websites.

3.2. Energy Supply Allocation Optimization

This model has as its main objective to indicate at which points of the ground infrastructure network, or Points of Interest (PoI), it is necessary to install or build the equipment for charging or swapping electric batteries. The set presented must respect operational restrictions and meet the expected demand.

According to German *et al.* (2018), the cost of building a vertiport is expected to be significant. The number of available locations is limited, which encourages building as few vertiports as possible. For electric cars, the optimization problem of electric vehicle charger placement has become of great interest since the costs associated with providing electric chargers for these vehicles have increased with the uptake. However, as the number of charging stations for allocation increases, the problem becomes less manageable due to its characteristic of a hard non-deterministic polynomial time (NP) problem (CHANDRA *et al.*, 2021).

The problem definition of this work is based on the activity-based approach for electric car charging infrastructure planning presented by Dong *et al.* (2014), and is given by:

$$\min \sum_{n} (y_n * C_{station}),\ n = 1, \dots N \qquad (1)$$

$$y_n = \begin{cases} 0 \rightarrow If\ there\ is\ not\ energy\ supply \\ 1 \rightarrow If\ there\ is\ energy\ supply \end{cases} \qquad (2)$$

Subject to:

$$y_n \in \{0; 1\} \qquad (3)$$

$$\sum_{n \in N} y_n \geq 1, \forall n \in N \qquad (4)$$

$$SOC \geq 0.3 * Re \qquad (5)$$

$$SOC \leq 0.8 * Re \qquad (6)$$

The formulation above defines a single-objective optimization problem with N decision variables. The objective function in (1) aims to minimize the total cost of building the energy supply network. The constant $C_{station}$ refers to the construction and installation costs of the energy supply equipment and assumes different values for the plug-in charging system and the battery-swapping system. N is the number of PoI of the evaluated support network and delimits the set of decision variables (y_n) of the problem. As shown in (2), they assume a value of 0 if they do not have energy supply infrastructure and 1 if they do.

The problem has four constraints: constraint (3) defines the decision variables as a binary, and constraint (4) enforces there to be at least one point of energy supply in the support network. The constraints (5) and (6), respectively, correspond to the lower and upper limits of the State of Charge (SoC) measured in the distance.

The lower absolute limit refers to a safety limit for the aircraft to perform emergency flights to the nearest landing point. The upper limit aims to guarantee a longer battery lifespan. The 30% and 80% of range values were determined based on the electric bus discharge presented in Kunith *et al.* (2017) electric bus charging stations optimization.

Once the charging location problem objective function is generally a mixed-integer nonlinear and nonconvex programming problem, its solution through conventional mathematical programming methods is difficult (ZHENG *et al.*, 2014).

Thus, recent research works have sought to implement heuristics to solve this problem, presenting satisfactory performance. Evolutionary algorithms have advantages commonly implemented in this type of solution, among them, more specifically, the Genetic Algorithm. In the present work, we implement the package *pymoo algorithms soo nonconvex ga*, a basic genetic algorithm for single-objective problems offered by Pymoo in Python.

To define the population size and number of generations of the algorithm, we tested the convergence of results and computational consumption, measured by the time taken to execute the application and the results. Then, we set the population size to 1000 and the number of generations to 500 with random and binary population sampling. Each gene of the individual in the simulation represents a PoI, that is, a site of the support infrastructure, and its content represents the binary decision variables of the problem. Figure 2 illustrates an example of an individual chromosome implemented in the algorithm.

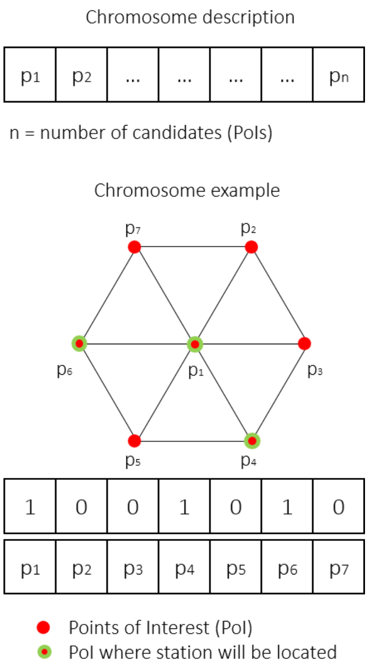

Figure 2 - Individual Chromosome

The module used to define the selection of parents for reproduction during the simulation was the Tournament Selection. In the crossover, we adopted the Binary Half Uniform Crossover method. Finally, for the mutation of some individuals in the population after the creation of descendants through the crossing, we resort to Bit Flip Mutation (PYMOO, 2022).

The problem execution counts as input the operational horizon, the fleet size and its location at the beginning of the operation day, the distances between the support sites, the list of daily routes executed by each e-VTOL, the turnaround time (TAT) in minutes, the available electric power in battery charging stations and the e-VTOL range and power consumption rate specifications. The simulation follows: for each e-VTOL in the fleet and each route performed, it calculates the possible energy replenishment (R), measured in the distance, at the route's destination site.

In the case of vehicles with the battery-swapping system, this is equivalent to the complete refueling of the vehicle, that is, the aircraft returns to its design range R_e from the State of Charge on departure from the previous site SoC_{pre}, as presented in equation (7).

$$R_{swapping} = y_n * (R_e - SoC_{pre}) \qquad (7)$$

Equation (8) concerns the possible energy replenishment of vehicles with the plug-in charging system, calculated by the increase in range (P/r) that occurs when the vehicle is parked on the site, that is, its TAT. If the TAT is more than enough to charge the battery, charging stops when it reaches its design range. For both systems, the possible energy replenishment will only occur if the decision variable corresponding to the destination site of the route is equal to 1.

$$R_{plug-in} = y_n * \frac{P * TAT}{r} \qquad (8)$$

Then, it calculates the State of Charge (SOC) of the e-VTOL in the next e-VTOL departure. It is equal to the sum of the State of Charge in the departure of the previous site (SoC_{pre}), and the energy charging in the site in question (if any), subtracted from the last flight leg traveled, which represents the battery charge loss measured in the distance, as described in equation (9). The simulation respects the constraints of the problem. It returns the objective function, that is, the cost of building the optimal energy supply network, given the demand and the set of sites with energy supply stations.

$$SOC = SoC_{pre} + R - distance \qquad (9)$$

3.3. Support Network Optimization

In this work, support network optimization takes place in two steps. The first one is the optimization of inventories and spare parts in the network, based on the OPUS10 software calculator.

The second consists of the support organization definition based on the exhaustive simulation of 47 possible scenarios for this support network. The scenarios consist of possible support organizations in the set of PoIs of the case study, considering stocks and depot levels internal or external to the network.

This simulation is followed by comparing their effectiveness and choosing the one that presented the lowest costs for the highest availability values.

OPUS10 performs an optimal allocation of spare parts in the support organization. It generates a cost *versus* effectiveness (CxE) curve, which in this research is translated into spare/repair parts cost and availability, respectively.

For each of those scenarios, we run an optimization of inventories and spare parts via OPUS and generate the CxE curve. We then compare these curves in terms of spare/repair parts cost and availability and define which one is the most appropriate organization for the case study. After defining the optimal support structure, we calculate de system LCC.

3.4. Life Cycle Cost Calculation

To calculate the LCC of the problem proposed in this research, we are based partly on the Cost Breakdown Structure presented by Blanchard & Blyler (2016), which covers development, investment and maintenance, and operation costs, in addition to those related to system retirement. In our calculation, we consider the construction of maintenance facilities cost (CICM), initial spare/repair parts cost (CILS), test and support equipment acquisition cost (CILX), maintenance spare/repair costs (COMX), and system phase-out and disposal cost (COP).

The total LCC of the system is given by the sum of all the cost portions, as described in equation (10).

$$LCC = CICM + CILS + COMX + CILX + COP \quad (10)$$

CICM and CILX values come from energy supply allocation, while CILS and COMX come from support network optimization and inventory dimensioning. The COP refers to battery disposal and is calculated by the number of batteries defined for the two types of aircraft based on their average utilization rate.

3.5. Case Study

The implementation of a case study of the e-VTOL operation as an air taxi in the city of São Paulo that aims to verify the model's effectiveness is presented in this subsection.

In the initial phase of data collection for the case studies, the literature defines Points of Interest (PoIs), candidate locations to host the energy supply infrastructure. From the PoIs, the GA will define which subset is the most appropriate for the allocation of refueling stations, considering the definition of the objective function and the problem's constraints.

Kohlman & Patterson (2018) used a simplified generic UAM network model, composed of seven distributed vertiports in which six of them form a hexagonal pattern and the seventh is located in the center of the hexagon.

Figure 3 illustrates the model used, based on Kohlman & Patterson (2018). To calculate the distances between the PoIs, we measured the straight line between the points of the model, when projected on the map of São Paulo. They are described in Table 1.

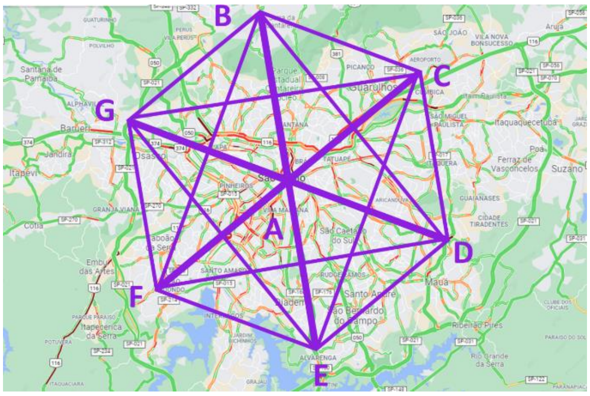

Figure 3 - E-VTOL graph for ground infrastructure distribution analysis in São Paulo, Brazil.

We used a list of routes to be performed by each e-VTOL daily generated from a simulation developed in previous author's work. It considers two types of demands in the ground infrastructure network: a higher one, present in PoIs A, B and C, and a more relaxed one, present in PoIs D, E, F and G. The demand is composed of one or more Poisson Distributions that represent the arrival of passengers every half hour in the 12 hours of the operational horizon.

Table 1 - Distances of UAM ground infrastructure distribution pairs.

VERTIPORT PAIR	DISTANCE (Km)
AB, AC, AD, AE, AF, AG	20
BC, CD, DE, EF, FG, GB	20
BE, CF, DG	40
BD, BF, CG, CE, DF, EG	34.6

In 2018, Porsche Consulting developed a market study on the implementation of e-VTOL as air taxis in major cities around the world and projected the number of vehicles that would come into operation, as well as the number of passengers and market value involved (Grandl *et al.*, 2018).

For the city of São Paulo, in the initialization phase, it was estimated that a network of five vertiports would serve 120 e-VTOL.

Since the ground infrastructure network of the case study has seven vertiport candidates, we performed a linear interpolation with the data presented and obtained a demanded fleet of 132 aircraft. These 132 vehicles were distributed across the sites, 19 being allocated to PoIs A, B, C, D, E, and F, and 18 to PoI G.

Figure 4 presents the specifications of the e-VTOL used in the case study. As the focus is the comparison and impacts analysis of the difference in energy restoration systems, we only consider differences in the electric batteries used.

Battery Swapping e-VTOL			
Item / LRU	**Unit Price [$]**	**Failure Rate [1/MOPH]**	**Quantity**
AVNX module	30000	0,0035	1
Electric generator	15000	11,1	2
Electric battery	60000	45,66	2*(2+Op)
LDG shimmy damper	1200	6,49	2
Fire supression system	6000	0,0618	1
CMC	3000	15,3	1
Engine	80000	5,53	8
External light	1000	10	4
Recirculation fan w/ check valve	2000	5,19	2
Plug-in Charging e-VTOL			
Item / LRU	**Unit Price [$]**	**Failure Rate [1/MOPH]**	**Quantity**
AVNX module	30000	0,0035	1
Electric generator	15000	11,1	2
Electric battery	17500	45,66	8
LDG shimmy damper	1200	6,49	2
Fire supression system	6000	0,0618	1
CMC	3000	15,3	1
Engine	80000	5,53	8
External light	1000	10	4
Recirculation fan w/ check valve	2000	5,19	2

Figure 4 - e-VTOL systems specifications

The plug-in charging system has eight internal batteries, each with a list price of $17,500, having a failure rate of $5.66 * 10^{-6}$, which is equivalent to a Mean Time Between Failure of approximately 21,000 FH. As for the battery-swapping system, we consider that there are two battery packs with the same performance and reliability as the other system but with a list price of $60,000 each.

In the case of the battery-swapping system, for the calculation and optimization of inventories, there is the particularity that there must be storage of batteries for operation, not just for replacement. Thus, we multiply the number of base packs by a multiplicative factor for the purchase of these packs that are charged on the ground and await the landing of the aircraft to be installed in the vehicle after the removal of the one that is partially unloaded. This multiplicative factor considers Mean Time Between Swapping (MTBS), resulting from the average use of vehicles in operation.

The range considered for the aircraft was 180 km, and the turnaround time for boarding and departure of passengers was 10 minutes. The electrical power (P) available for fast charging was 100 kW. The consumption rate of the e-VTOL (r), used for converting the SoC of the batteries in the remaining range, was 0.3 kWh/km.

Table 2 presents the estimation of the LCC portions for both types of systems. The construction of maintenance facilities involves costs related to provisioning energy for electrical charging and sheltering equipment when necessary. The costs of plug-in systems, therefore, are considered more expensive, as this type of fast charging involves high power levels, which are more expensive to provide.

Table 2 - Energy Replenishment Infrastructure Involved Costs.

	Plug-In	Battery Swapping
CICM	1.000.000,00	800.000,00
CILX	20.000,00	500.000,00
COP	5.000/battery	10.000/battery

Finally, for the implementation of the case study, we adopted some assumptions. They were responsible for the simplification of the testing of the model, but they can be relaxed in other works after identifying which impacts the proposed methodology, if any. The assumptions are listed below.

- All e-VTOL fleet start their operation fully charged;
- At every stop at a site with electrification, there is energy restoration activity for both types of systems;
- The demand is fixed for every day and every season of the year in the present case study.

4. RESULTS

As a final product of the optimization model implementation, we indicate the optimal infrastructure to support and supply energy for UAM e-VTOL plug-in charging and battery-swapping energy replenishment systems. In addition, we compared these two e-VTOL configurations regarding the LCC of each of them.

From the number of landings in each PoI available in the input performed routes list, we can calculate the average utilization of the ground infrastructure. The calculation follows equation (11), which represents the total number of landings in the complete simulation ($landings_n$) divided by the number of simulated operating days (d_{op}) and by the operational horizon, that is, the number of hours of operation of the systems daily (h_{op}). N equals the number of PoIs.

The results are shown in Table 3. When there is an energy replenishment infrastructure in PoI, for battery-swapping system vehicles, this average utilization denotes the total number of times we had batteries swapped in PoI. Hence, when we sum the total average utilization and divide by the fleet n_{fleet}, we obtain the battery-swapping rate for energy replenishment for each e-VTOL, which in this work we call 1/MTBS, as described in equation (12). MTBS is the Mean Time Between Swapping.

$$MeanUtilization_n = \frac{landings_n}{d_{op} * h_{op}}, n \epsilon N \qquad (11)$$

$$\frac{1}{MTBS} = \frac{\sum_n MeanUtilization_n}{n\_fleet}, n \epsilon N \qquad (12)$$

Table 3 - Average use of the energy replenishment infrastructure in case the PoI has a charging or swapping station.

PoI	Mean Hourly Utilization (h)
A	32,76
B	28,69
C	26,32
D	22,69
E	21,64
F	21,67
G	21,1

Thus, the battery-swapping rate for energy replenishment for each e-VTOL (1/MTBS) equals 1.32. With this value, we can estimate that, for each e-VTOL in the fleet, one operational replacement batteries will be needed, that is, those that must be charged on the ground and ready to be installed in the vehicle during the TAT. This value is the multiplier cited in the system specification presented earlier in this report.

Once six TATs can fit within an hour of operation, we can divide the average hourly utilization of the PoIs to determine how many chargers or swappers will be in each of them. 6 GSEs are required on PoI A, 5 on PoIs B and C, and 4 on PoIs D, E, F and G.

After the 30 days of operation routing performed, for each of them the Genetic Algorithm solves the problem of allocation of energy supply stations and informs in which PoIs there is a need to have a plug-in charger or a battery swapping station. The graphs presented in Figure 5 express the number of times that the PoIs were pointed out by the GA as a host of energy supply infrastructure, for both systems.

We consider those PoIs that recorded the need for refueling infrastructure in at least 80% of the simulations to be the chosen PoIs of our e-VTOL UAM ground infrastructure. This ensures that possible variabilities in the solution algorithm or random behavior in routing does not affect, in isolation, the provision of support and electrification infrastructure.

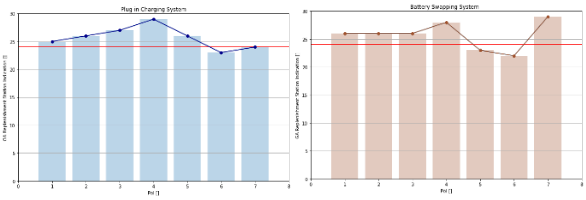

Figure 5 - Need for hosting charging stations or battery swapping by Point of Interest.

The objective function found in this scenario provides the LCC portions of CICM and CILX.

The Cost *versus* Effectiveness (CxE) curves obtained for each of the support organization scenarios simulated in OPUS10 for the plug-in replenishment system were compared. The best curves for both systems are shown in Figure 6 and Figure 7. In the figures, the numbers associated with the curves correspond to the 47 scenarios commented on previously.

As an evaluation criterion, we consider that the chosen support network should ensure availability of at least 95%. Scenario 35 presented the best CxE set in both energy replenishment systems, with the availability of 95,02% and 95,44%, and 132,900 and 271,400 spare or repair parts cost for plug-in charging and battery swapping, respectively. Those will be the CILS and COMX portion of the LCC.

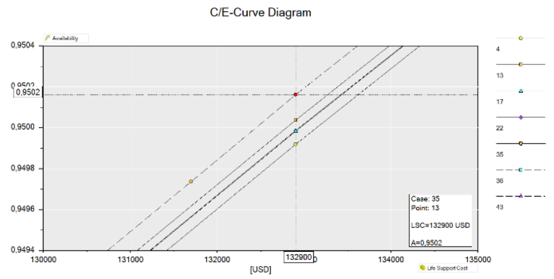

Figure 6 - Best support organization scenarios in terms of CxE for e-VTOL with the plug-in charging system.

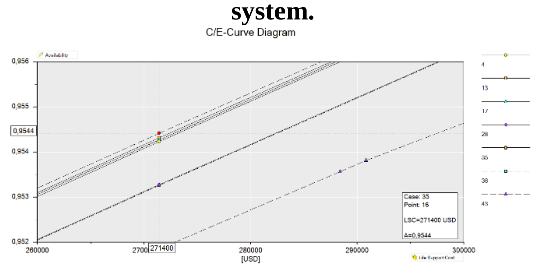

Figure 7 - Best support organization scenarios in terms of CxE for e-VTOL with the battery-swapping system.

Therefore, the optimal support network chosen for the case study is the one with a central depot located in PoI A and the other PoIs only as operational sites. This result is as expected since, in the graph used, site A is closer and equidistant from all other sites. However, it is important to keep in mind geographic, spatial, or cost constraints for implementing large infrastructures such as vertihubs. The extensive search of support organizations allows us if it is impossible to build the vertihub at the selected location, to choose the second best point, and so on.

Summarizing, regarding the energy supply infrastructure, for plug-in charging systems, the model pointed out the need to build stations in the following PoIs: 6 chargers in vertiport A, 5 in vertiports B and C, and 4 in vertiports D, E, and G. For e-VTOL with the battery-swapping system, we must build 6 stations in vertiport A, 5 in vertiports B and C and 4 in vertiports D and G.

4.1. Systems Comparison

To compare the two different e-VTOL energy replenishment systems, we calculated the life cycle cost for both with the information already collected in the previous steps. Table 4 presents the breakdown of those costs and the total LCC of both systems. Spare parts costs from OPUS10 inventory and support network optimization refer to the initial provisioning of spare parts (CILS) and the depreciation of the LRUs (COMX) in the 20 years of the simulated life cycle.

We observed that the LCC of e-VTOL with a battery-swapping energy replenishment system was higher. This is mainly due to the cost of building the robotic GSE used in the activity and the cost of recycling or discarding the batteries. The provision of battery inventories for the operation also had a relevant impact on the total cost.

Table 4 - LCC breakdown and total LCC for both e-VTOL energy replenishment systems.

	Plug-In		Battery Swapping	
CICM	$	28.000.000,00	$	19.200.000,00
CILS	$	132.900,00	$	271.400,00
COMX	$	6645,00 / year	$	13.570,0/year
CILX	$	560.000,00	$	12.000.000,00
COP	$	5.280.000,00	$	7.920.000,00
LCC	**$**	**34.105.800,00**	**$**	**39.662.800,00**

As the projects under development progress, more accurate data regarding costs, architecture, and reliability will be released and will be able to clarify and strengthen the calculation performed. In addition, demand surveys in São Paulo can directly influence the results obtained in allocating energy supply points for e-VTOL and in the comparison performed.

5. CONCLUSION

The proposed methodology allowed us to perform the optimal allocation of support and energy supply infrastructure support for UAM e-VTOL, considering Life Cycle Cost and meeting demand. In this work, we formulate the infrastructure allocation problem to determine the cost-effective allocation strategy for UAM e-VTOL support and energy supply infrastructure and validate its effectiveness in a case study in São Paulo.

The optimization model for the allocation of the infrastructure network obtained significant results for the planning of the UAM and a comparison between the different types of vehicles regarding the energy replenishment systems. The simulation of the proposed case study also generates inputs for e-VTOL developers and aeronautical authorities, as it demonstrates the feasibility or non-feasibility of the proposed Concept of Operations.

Furthermore, studies about the physical spaces available in the city for the construction of sites and the energy distribution network for the installation of charging stations are crucial for the foundation and validation of the results found by the proposed model. Information from these studies can be considered as restrictions in the optimization, aiming at improvements in the method.

Finally, we raise the importance of studies on the accuracy of the evolutionary algorithm used in the model. In future works, we must try to compare the same problem implemented with exact optimization algorithms or from a hybrid approach. Thus, the effect of random aspects involved in the Genetic Algorithm can be analyzed, and its implementation validated or evolved.

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