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Techno-Economic Optimization of Electrified Airports as Collaborative Energy Hubs

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ABSTRACT

The electrification of regional aviation requires coordinated planning of airport energy systems that integrate renewable generation, energy storage, and hydrogen technologies in a cost-efficient and resilient manner. This paper presents a scalable techno-economic optimization framework that models multiple airports as collaborative energy hubs. An object-oriented mixed-integer linear programming (MILP) formulation is combined with a genetic algorithm (GA) to optimize infrastructure sizing and energy dispatch. The framework is applied to three Swedish regional airports—Västerås, Jönköping, and Visby. A set of scenarios, including parties operating under shared wind-energy contracts using power purchase agreements (PPAs) and dynamic pricing (DP), was studied. Detailed representations of battery energy storage, hydrogen production and storage, and market interactions are included. Results show that coordinated operation and airport collaboration under a smart energy management system can reduce total annual cost by up to 5% while enhancing operational flexibility and resilience to demand peaks and grid disturbances.

Keywords: Optimization, Genetic Algorithm, Energy Systems, Renewable and Sustainable Energy, Hydrogen

INTRODUCTION

Over the past decade, there has been an increasing effort to reduce greenhouse gas emissions. Under the Paris Agreement and net-zero goals, countries should reduce their carbon emissions by at least 55% relative to 1990 levels by 2030. Transport remains a major source of anthropogenic CO_2, and aviation presently accounts for about 2.5 % of total emissions; without effective mitigation, this share could increase to around 22 % by 2025 [1]. Although aviation's footprint is comparatively modest today, expanding demand, further stimulated by new air mobility services, could drive substantial emissions growth.

In response, researchers are developing low-carbon propulsion technologies for aviation. Hydrogen-fueled aircraft, which emit only water vapor, rely on advances in fuel cell technology and cryogenic storage systems, while electric propulsion for short-haul routes requires significant improvements in battery energy density and power-to-weight ratios [2].

Electrified aviation starts with short-haul flights, which show how regional airports can serve as energy hubs and provide an affordable transportation option. However, transitioning to electrified airports requires significant infrastructure investments, including airport energy systems, grid connections, power generation, and storage. This transition will be especially tough for medium-sized and smaller regional airports.

The resilience of the energy system is another challenge in electrification. The term resilience was first introduced by Holling et al. [3] to describe the capacity of ecosystems to absorb change. Molyneaux et al. [4] adopt the concept of resilience in energy systems and review different scenarios to measure the system's resilience. Resilience is the ability to adapt to change and uncertainty while maintaining a consistent performance during the transformation [5].

The integration of hydrogen into the energy system poses challenges, including balancing cost efficiency with infrastructure scalability. These challenges are compounded by the need for flexibility to adapt to dynamic market conditions and by the integration of renewable energy sources. In a study, Almansoori et al. [6-7] propose a mixed-integer linear programming (MILP) framework to optimize hydrogen supply chains by minimizing sizing and dispatching costs across different demand profiles.

Multiple objectives are often involved in optimizing hybrid energy systems. In a study, Zheng et al. [8] designed a multi-objective framework to assess the potential of photovoltaic (PV) systems and battery energy storage for grid integration and deployment in the charging infrastructure. Yan et al. [9] investigated the combined use of wind and solar energy with hydrogen systems for off-grid applications like airports. Despite the potential benefits of integrating PV panels and wind turbines, some studies [10] highlight conflicts with existing safety regulations.

Xiang et al. [11] employed MILP to model an integrated hydrogen-solar storage microgrid and evaluate scenarios involving combinations of hydrogen production, PV energy, and battery storage systems. Their study highlighted the need for further investigation into effective grid integration strategies.

The resilience of the hybrid energy system was evaluated by Zhao et al. [12], focusing on the airport with the hydrogen-integrated technologies. The study introduces a MILP framework to optimize hydrogen storage and operation under various levels of disruptions in grid capacity and hydrogen permeability. As a result, integrating hydrogen increases the system's resilience but also raises the total annual cost.

A more detailed MILP model for the airport energy network was investigated by Vouros et al. [13] for a regional airport, where the total annual cost was evaluated across different resilience levels.

This paper advances the techno-economic assessment of airport energy systems through a scalable, object-oriented framework combined with a hybrid MILP–genetic algorithm approach. Unlike conventional single-site studies, it captures inter-airport collaboration, renewable energy flexibility markets, and modular system expansion, enabling a more realistic and extensible analysis of coordinated multi-airport energy hubs.

Electricity Pricing Schemes and Flexibility-Oriented Operation

Modern airport microgrids require the capability to adjust electricity supply and demand in near real time. Europe's electricity-market reform recognizes the role of flexibility markets in ensuring fair compensation for flexible resources such as energy storage, demand response, and dispatchable generation, while providing clear price signals for investment [14].

Long-term power-purchase agreements (PPAs) represent a common mechanism for valuing renewable electricity. Under a PPA, a buyer commits to purchasing a predefined quantity of electricity from a generator at a fixed price for 10–15 years. This agreement hedges against market volatility and allows risk sharing between contracting parties [15]. The contract price is often benchmarked against average wholesale market prices or a long-term forecast, with margins reflecting financing costs and risk preferences. Airports such as JFK [16] and Bristol [17] have adopted long-term renewable energy contracts.

The alternative dynamic pricing (DP) approach links electricity prices to real-time or day-ahead market outcomes. Dynamic tariffs reflect market-clearing prices and convey short-term supply conditions to consumers, incentivizing them to shift loads or operate storage systems [18]. In practice, suppliers often add a margin above the wholesale price to cover project financing and risk, which directly affects the economic attractiveness of storage and demand-response technologies that exploit price variability under dynamic pricing schemes.

While flexibility markets typically involve explicit participation of distributed energy resources through aggregators bidding into local or regional platforms operated by distribution system operators (DSOs), this study does not model such market structures explicitly. Instead, flexibility is represented implicitly through dynamic electricity pricing and coordinated dispatch of storage and conversion technologies at airport energy hubs. Long-term power purchase agreements (PPAs) are considered as bilateral contracts that provide price stability but do not constitute flexibility markets. On the other hand, dynamic pricing reflects changing system conditions over time and can encourage flexible operation of airport assets. This allows for system-level flexibility without the need for direct market involvement.

METHODS

This section describes the assumptions, algorithms, and model structure. First, the details of the algorithm are presented, followed by the model structure and problem assumptions.

Algorithm

The algorithm proposed in this work determines the optimal capacity and dispatch of the energy network for a multi-objective problem by combining MILP with the genetic algorithm (GA). The primary objective is to enable scalable modeling of energy networks for multiple airports. To achieve this, an object-oriented framework is implemented that leverages inheritance and encapsulation principles. Each component in the system inherits common base features, such as mass and energy balance constraints, while also retaining its own specific attributes. The overall problem formulation and optimization process are summarized as follows:

1. Airport object:

   An airport object is created and equipped with the required components, including energy storage units, production technologies, market interfaces, and transportation systems. The capacity of each component can be defined as either a decision variable or a fixed parameter. A single problem instance may include multiple airport objects.

2. System connections:

   System components are interconnected either by user-defined instructions or by automatic configuration. These connections are subsequently used to formulate the mass and energy balance equations.

3. Energy network formulation:

   The energy network model is formulated as an MILP framework. Unit capacities can be optimized either directly within the MILP solver or through an outer-loop GA that explores the design space.

4. Optimization and results:

   The optimizer determines the optimal values of the decision variables according to the defined objective functions. The resulting solution is stored as a problem object for post-processing and analysis. The same object can subsequently be used for dispatch optimization under fixed unit capacities.

The final MILP model is generated based on the added components and their corresponding connections. Therefore, the implemented framework can be used for various applications, such as smart charging stations.

Problem Definition

We study three potential airport infrastructures to support battery-electric and hydrogen-electric aircraft.

Västerås Airport (VST) is located in an industrial city near major cities such as Stockholm and Uppsala. The airport could use excess energy generated by local power plants and contribute to the network. In addition to handling short-haul training flights, this airport transports approximately 100, 000 passengers per year.

Visby Airport (VBY), located on the island of Gotland, experiences significant seasonal passenger inflow and supports occasional international traffic, particularly during the tourist season. While not a primary international hub, its island location and wind energy potential make it strategically relevant for decentralized electrification planning. According to Swedavia statistics, the airport handled around 300 flights per month in 2025. While recent studies focus on the current status and technical potential, several planning and expansion studies identify significant potential for increasing wind capacity on the island, both offshore and onshore. An offshore floating wind farm is planned for 2032 with a capacity of around 1.75 GW.

The third airport is Jönköping (JKG), which enables short-range flights to southern cities. Recent studies focus on the airport's future role by investigating various charging and battery-swapping scenarios.

Figure 1. Three airports in contract with a wind energy supplier collaborated to improve resilience under a smart energy management control system

In addition, all the candidates are based on the SE3 grid region and operate under the same grid company. Therefore, agreements between energy providers and airports that serve as hubs are easier to establish.
This paper examines different scenarios in which a smart energy management system dispatches energy for three airports with a PPA or DP contract with a wind energy supplier. The wind farm can provide up to 2 MW of capacity during peak production hours, as the energy must be shared among all three airports. This limit reflects near-term availability and grid access constraints, rather than the island’s full wind potential.

Table 1: Number of weekly flights for Västerås, Jönköping, and Visby airports

Airport	2025	2035*
Västerås (VST)	70	140 [13]
Jönköping (JKG)	18	58 [20]
Visby (VBY)	76	224 [21]

Flight Schedules

The flight schedule information was obtained from the OpenSkyNetwork [19] API. Figure 2 demonstrates estimated hourly flight schedules for VST, JKG, and VBY airports for a week. The number of flights and the fleet mix in 2035 are estimated based on the Swedavia Net Zero Roadmap and previous studies on Swedish airports, as shown in Table 1.

Hybrid Airport Energy Network Architecture

The airport's hybrid energy system can be divided into multiple sections. The storage and generation units, hydrogen conversion technologies, demand, and supply. Figure 3 shows the detailed structure of the hybrid airport energy network.

PV cells and wind turbines are the main electricity generation units. The weather data, including solar

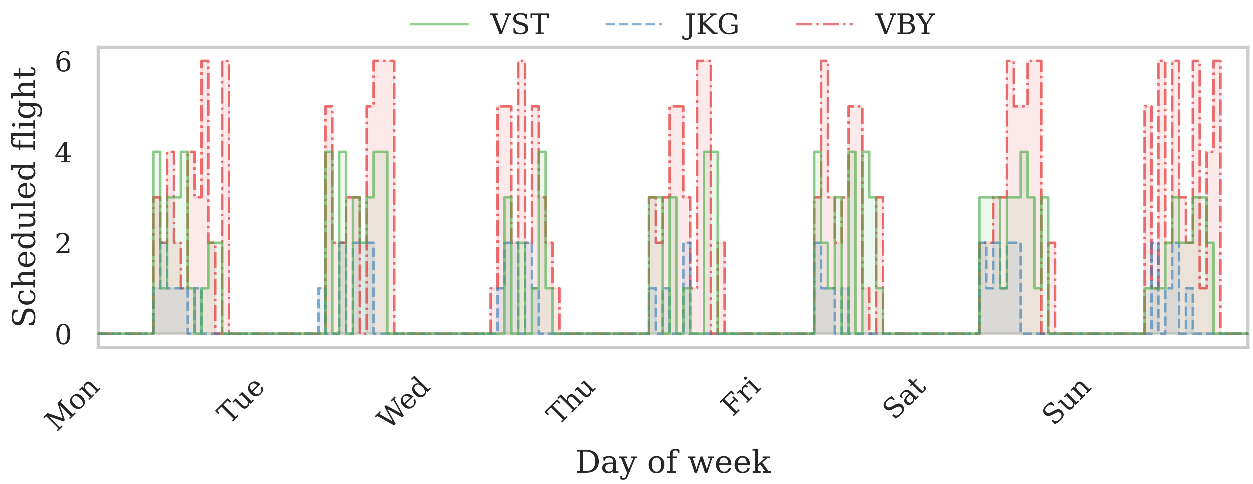

Figure 2. A representation of hourly flight schedules during a week

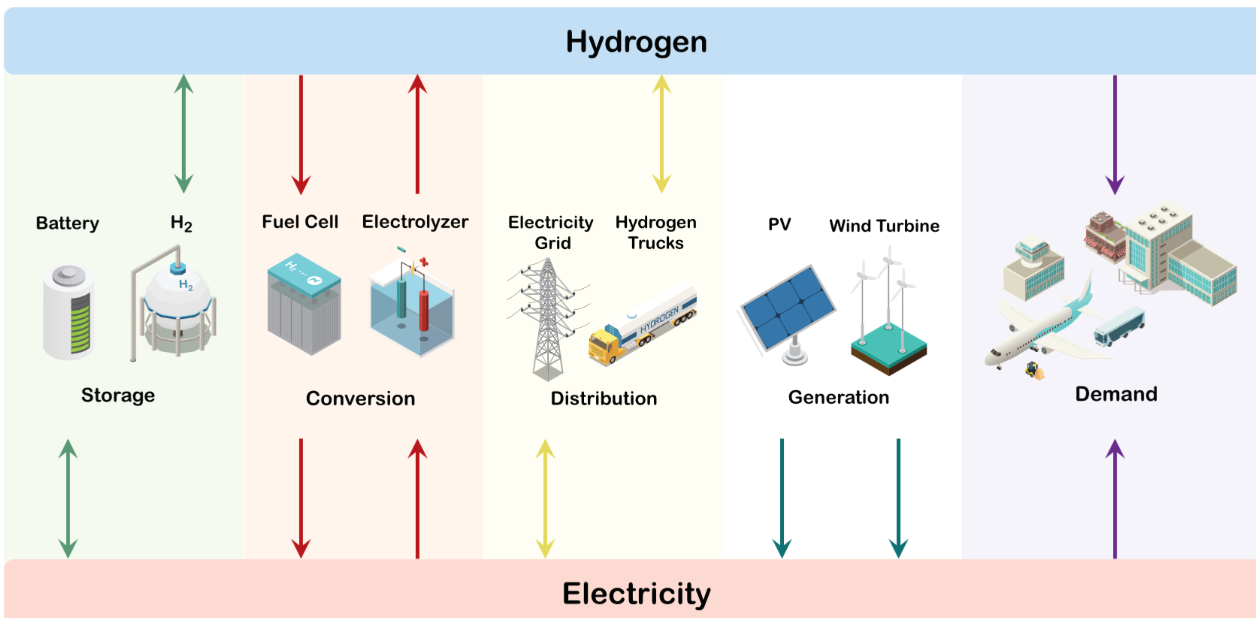

Figure 3. A schematic of mass and energy flow within an electrified airport energy network

irradiation and wind speed, are obtained from public databases such as SMHI [22] and PVLib [23]. Cut-in and cut-off wind speeds, as well as power curves, are considered during the data processing. Solar energy generation varies throughout the day based on the irradiation level and PV surface temperature. Equations (1-3) simplified, assuming panel and ambient temperatures are identical. Based on [24, 25], the equations for wind and solar energy are defined as:

$$P_k^{PV} = P_{STP}\frac{G_k}{G_{STP}}\left(1+\alpha_{pv}(T_{PV,k}-T_{STP})\right) \quad (1)$$

$$P_k^{WT} = P_k^{WT}(v_k) \quad (2)$$

The annual average accumulated global solar radiation is aligned with the Swedish records [26, 27].

BESS plays a critical role in peak shaving and providing short-term flexibility and buffering for the energy system. The battery model formulation, derived from [28], is outlined in Equation (3).

$$S_k^{bat} = S_{k-1}^{bat}(1-\beta^{bat}) + \left(\zeta_{ch}^{bat}\eta_{ch}^{bat}P_{ch,k}^{bat} - \zeta_{dch}^{bat}\frac{P_{dch,k}^{bat}}{\eta_{dch}^{bat}}\right)\Delta t \quad (3)$$

Where, the charging (η_{ch}^{bat}) and discharging efficiencies (η_{dch}^{bat}) in addition to a self-discharge term (β^{bat}) considered in the model to represent losses during the battery operation.

In order to isolate charging and discharging states, a pair of binary variables $\zeta_{ch,dch}$ is considered in (3), where:

$$\zeta_{ch} + \zeta_{dch} \leq 1 \tag{4}$$

Hydrogen tanks in both liquid (H_2^l) and vapor (H_2^v) phases are formulated in Equations (5-6). The term $\beta_{evap}^{H_2^l}$ shows the rate of evaporation for liquid hydrogen in the mass balance equations.

$$S_k^{H_2^l} = S_{k-1}^{H_2^l}\left(1 - \beta_{evap}^{H_2^l}\right) + \left(\zeta_{in}^{H_2^l} F_{in}^{H_2^l} - \zeta_{out}^{H_2^l} F_{out}^{H_2^l}\right)\Delta t \tag{5}$$

$$S_k^{H_2^v} = S_{k-1}^{H_2^v} + \beta_{evap}^{H_2^l} S_{k-1}^{H_2^l} + \left(\zeta_{in}^{H_2^v} F_{in}^{H_2^v} - \zeta_{out}^{H_2^v} F_{out}^{H_2^v}\right)\Delta t \tag{6}$$

The stored energy and hydrogen can be utilized in an electrolyzer and a fuel cell, respectively, to produce hydrogen and generate electricity during peak hours and provide flexibility for the system. The formulation for the fuel cell and electrolyzer is provided in (7-8).

$$F_k^{Elyz} = \frac{\eta^{Elyz}}{\alpha_{LVH}^{H_2}} P_k^{Elyz} \tag{7}$$

$$P_k^{FC} = \eta^{FC} \alpha_{LHV}^{H_2} F_k^{FC} \tag{8}$$

The airport can interact with the electricity and hydrogen market using the electricity grid connection and hydrogen transportation units, such as tube trucks and tank trucks. The hydrogen transportation units are limited and carry discrete amounts of hydrogen, with lower and upper limits. The electricity spot prices were retrieved from the Nord Pool platform. A synthetic DSO price is calculated taking into account the local energy tax and the DSO fee. While power purchases follow DSO prices, the selling value to the market is assumed to equal spot prices. In general form, each energy or mass stream in the system follows the balance equations. Mathematical formulation depends on the structure of hybrid energy networks. Equations (9-10) show the mass and energy balance.

$$P_k^i = \sum_j P_k^{ji} \tag{9}$$

$$F_k^i = \sum_j F_k^{ji} \tag{10}$$

Where ji represents the stream from item j to i. A non-negative constraint applied to the streams.

$$D_k^E \leq \sum_i P_k^i \quad \forall\, i \in \{bat, grid, FC, PV, WT\} \tag{11}$$

$$D_k^{H_2^l} \leq \sum_i F_k^i \quad \forall\, i \in \{liquef, H_2^l\} \tag{12}$$

$$D_k^{H_2^v} \leq \sum_i F_k^i \quad \forall\, i \in \{comp, H_2^v\} \tag{13}$$

The energy hub prioritizes airport demand while offering excess energy to the local grid to balance the load. The demand equations are shown in (11, 13).

The optimization includes design variables defined as:

$$N_{min}^i \leq N^i < N_{max}^i \;\; \forall\, i \in \left\{bat, FC, Elyz, H_2^l, H_2^v, comp, liquef\right\} \tag{14}$$

The objective of the design and optimization problem is to minimize total annual cost (TAC) while avoiding the power outage in (19).

$$\mathrm{CAPEX} = \sum_i \left(\frac{L_{sys}}{L_{cyc}^i}\right) N^i C_{cap}^i \;\; \forall\, i \in \left\{bat, FC, Elyz, H_2^l, H_2^v, comp, liquef\right\} \tag{15}$$

$$\mathrm{OPEX} = \sum_i \left(Q_{buy,k}^i C_{buy,k}^i - Q_{sell,k}^i C_{sell.k}^i\right) \;\; \forall\, Q \in \left\{P^{grid}, F^{tat}, F^{tut}\right\}, \forall\, i \in \{grid, tat, tut, wt\} \tag{16}$$

$$CRF = \frac{r(1+r)^{L_{sys}}}{(1+r)^{L_{sys}} - 1} \tag{17}$$

$$\mathrm{TAC} = \mathrm{CRF} \times \mathrm{CAPEX} + \left(\frac{\alpha}{\tau_{\mathrm{sim}}}\right) \times OPEX \tag{18}$$

$$\min \;\; TAC + \sum_i \sum_{k=1}^{\tau_{sim}} w^i \delta_k^i \quad \forall\, i \in \left\{D^E, D^{H_2^l}, D^{H_2^v}\right\} \tag{19}$$

System Parameters

This section covers both technical and economic parameters. Design variable constraints set upper and lower limits on decision variables. Table 2 presents the limits for the system's decision variables.

Table 2. Design variable constraints

Symbol	Description	Value
C_{max}^{bat}	Maximum battery capacity	200 MWh
$C_{max}^{H_2^v}$	Maximum vapor H_2 tank capacity	4000 kg
$C_{max}^{H_2^l}$	Maximum liquid H_2 tank capacity	6000 kg
C_{max}^{FC}	Maximum fuel cell capacity	7 MW
C_{max}^{Elyz}	Maximum electrolyzer capacity	10 MW
C_{max}^{comp}	Maximum compressor capacity	200 kg/h
C_{max}^{liquef}	Maximum liquefaction unit capacity	60 kg/h

To model airport energy system infrastructures incorporating hydrogen and energy storage technologies, it is essential to adopt up-to-date cost projections for both capital expenditures (CAPEX) and operation and maintenance (O&M) costs. Accordingly, this study synthesizes current and future cost estimates for key components, including green hydrogen production, battery energy storage systems, fuel cells, electrolyzers, hydrogen storage tanks in both compressed gaseous and liquid forms, and hydrogen delivery infrastructure. At present, green hydrogen production remains relatively costly due to its strong dependence on renewable electricity inputs. However, continued technological learning, economies of scale, and declining renewable energy costs are expected to substantially reduce production costs, with several projections indicating that green hydrogen could reach prices below 2 €/kg_{H_2} by 2035.

Table 3. Cost estimation per unit for key equipment in the hybrid energy system

Equipment	Unit	2025	2035	2050	Ref.
Electrolyzer (Alkaline/PEM)	€/kW	270 – 900 [600]	200 – 700 [450]	120 – 270 [200]	[29,30]
Fuel Cell (PEM, stationary)	€/kW	600 – 1200 [900]	250 – 600 [500]	80 – 300 [180]	[12,29]
H_2^v tanks (350-700 bar)	€/kg_{H_2}	500 – 900 [700]	400 – 600 [500]	250 – 450 [350]	[11,13]
H_2^l tanks	€/kg_{H_2}	1150 – 1450 [1350]	1200 – 1300 [1250]	900 – 1200 [1000]	[11,13]
Battery Storage (Li-ion)	€/kWh	260 – 350 [300]	180 – 270 [220]	95 – 275 [160]	[21,29]

Scenarios

This section describes the scenarios studied in this research. Table 4 lists the scenarios analyzed in the following section. The first scenario, which includes design and dispatch optimization, is considered the basis for comparison. Scenarios 2-5 ($S_{2\text{-}5}$) represent base-case sizing as we evaluate various combinations of contract type and involvement.

The term "Collab" indicates the involvement of all three airports in contact with the wind energy supplier. While no collaboration considers only the VBY airport for accessing wind energy. S_{10} and S_{11} use the same design as S_7, and S_6 to evaluate the effect of switching to PPA while the system is optimized for the DP contract.

Table 4. Description of different scenarios

S_i	Sizing	Wind	Collab	Contract	Margin [%]
1	✓	-	-	-	-
2	-	✓	✓	PPA	0, ±5, ±10
3	-	✓	-	PPA	0, ±5, ±10
4	-	✓	✓	DP	0, 5, 10
5	-	✓	-	DP	0, 5, 10
6	✓	✓	-	DP	0, 5, 10
7	✓	✓	✓	DP	0, 5, 10
8	✓	✓	✓	PPA	0, ±5, ±10
9	✓	✓	-	PPA	0, ±5, ±10
10	-	✓	✓	PPA	0, ±5, ±10
11	-	✓	-	PPA	0, ±5, ±10

Computational Setup

The framework is implemented in Python 3.9 [29] using GEKKO Optimization Suite [30] for MILP formulation within an object-oriented structure, with AMPL [31] and CPLEX [32] as external solvers. Its modular design supports extension to larger airport networks and other multi-energy hub systems. The full GA optimization (40 generations, population 200) requires around 20 hours on an Intel i7-13700HX processor and 32 GB of RAM.

RESULTS AND DISCUSSION

The selection of the optimization time window can impact the final result. While a larger window yields a more general solution, it also increases computational cost. Therefore, the effect of window size is studied in Figure 4. A one-week window should reflect the system's demand and supply, given that flight schedules follow a weekly pattern at most airports.

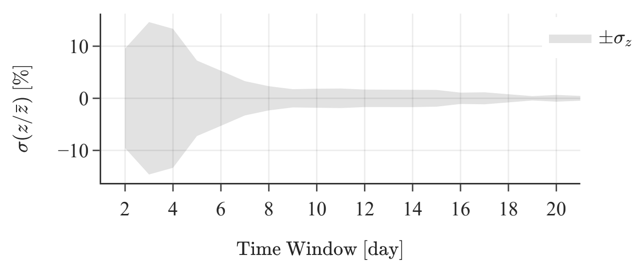

Figure 4. Variance of the difference between objective functions against different optimization window sizes for multiple starting dates in a year

Table 5 presents a selection of scenarios observed in this study, assuming a 5% margin for under-contract cases to ensure mutual benefits. The complete results report is available in the supplementary materials section. The MILP models for all scenarios were solved using CPLEX, with an optimality gap of 0.5%.

Table 5. CAPEX and OPEX values for selected scenarios

S_i	CAPEX [MEuro]	OPEX [MEuro]	$\Delta OPEX$ [%]	TAC [MEuro]	ΔTAC [%]
1	41.25	8.45	0.0	11.76	0
2	41.25	8.1	-4.1	11.42	-2.9
4	41.25	8.2	-2.9	11.51	-2.1
6	42.17	8	-5.4	11.38	-3.2
7	40.9	8	-5.3	11.29	-4
8	39.77	8.22	-2.7	11.41	-3
9	40.73	8.26	-2.3	11.53	-2
10	40.83	8.15	-3.5	11.43	-2.8

The base scenario has the highest capital and operating costs and suggests higher storage capacity to meet

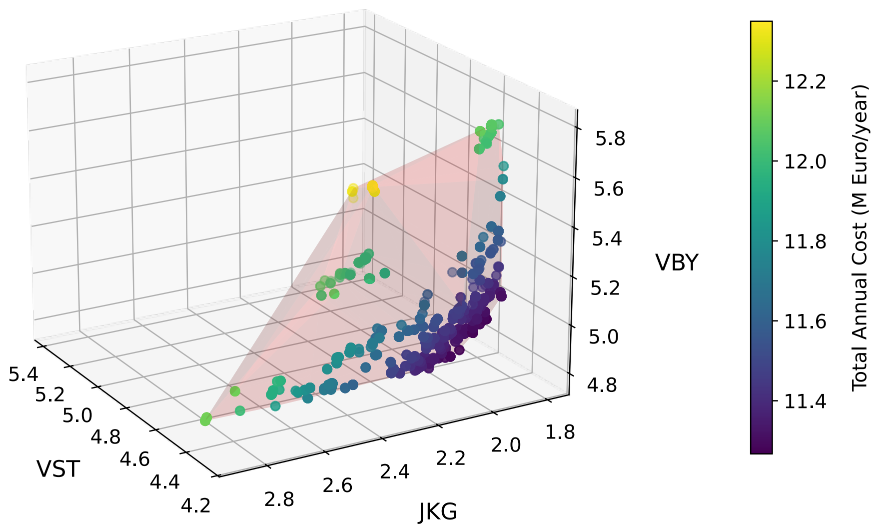

Figure 5. The optimal design and dispatch candidates from the last population of GA based on the total annual cost for VST, JKG, and VBY airports

demand during peak hours.

S_2 and S_3 show the effect of the contract with the wind farm, considering a fixed optimal design from the base scenario. In addition, S_2 represents the advantage of airport collaboration, reducing operational costs under normal conditions and providing room for resilience during unforeseen surges.

The scenarios with equipment sizing, while keeping up with demand, eliminate design redundancy and identify an optimal dispatch profile to reduce both OPEX and CAPEX. While the DP contract offers lower OPEX, a market study must still be conducted to reduce planning risk. On the other hand, PPA offers a fixed price for energy over a long period to mitigate spot price volatility. Considering the cost gap between S_7 and S_8, and the long-term energy price, one of these two scenarios may be the optimal choice. Despite a reduction of up to 5% in TAC, airports can meet demand and remain more flexible with the same base investment in the face of potential system disruptions.

All the case studies so far assume TAC is the sum of TAC across all individual airports. However, when it comes to collaboration and resilience, airports have the right to invest independently to achieve their own goals. To address conflicts among objectives, a three-objective optimization problem was solved using a GA to minimize TAC for the studied airports, under the assumptions in S_7. Figure 5 shows the optimal GA population after 50 generations with a population size of 200.

Three samples from the corners of the optimal surface were selected to represent cases in which each airport takes a major part in the investment. Another sample was selected to demonstrate minimal investment across all airports, bringing the total to four. The selected candidates are shown in Figure 6. By moving away from the optimal area, we offset the economic decision by increasing the system's flexibility. However, the pool of optimal candidates provides a guideline for moving toward a more resilient design.

While the TAC is almost identical across these cases, the individual's share of the total investment ranges from 0% to 90%, compared with the minimum-investment case. The TAC for these candidates is shown in Figure 7. An airport network represents a selected candidate and the objective value associated with each airport. The amount of TAC for all three airports aligns with their weekly load.

Figure 8 shows the decision variables for all airports among the selected candidates. One option to increase the VST airport's resilience is to invest in a fuel cell to handle sudden grid interruptions or utilize hydrogen to generate electricity on demand. This results in an 18% increase in TAC, representing the worst optimal point for VST. The same information applies to the VBY airport in describing candidate three.

The second network has the highest investment share for JKG, suggesting that investing in Battery is optimal. Based on the observations, BESS capital cost dominates the problem's objective value. In other words, the cost of battery storage technologies has a high impact on the future of electrification. In this case, increasing battery storage capacity improves disturbance rejection and peak shaving at JKG airport. As a result, BESS is a short-term solution to meet demand and handle grid outages for a couple of hours.

Hydrogen storage, on the other hand, despite its

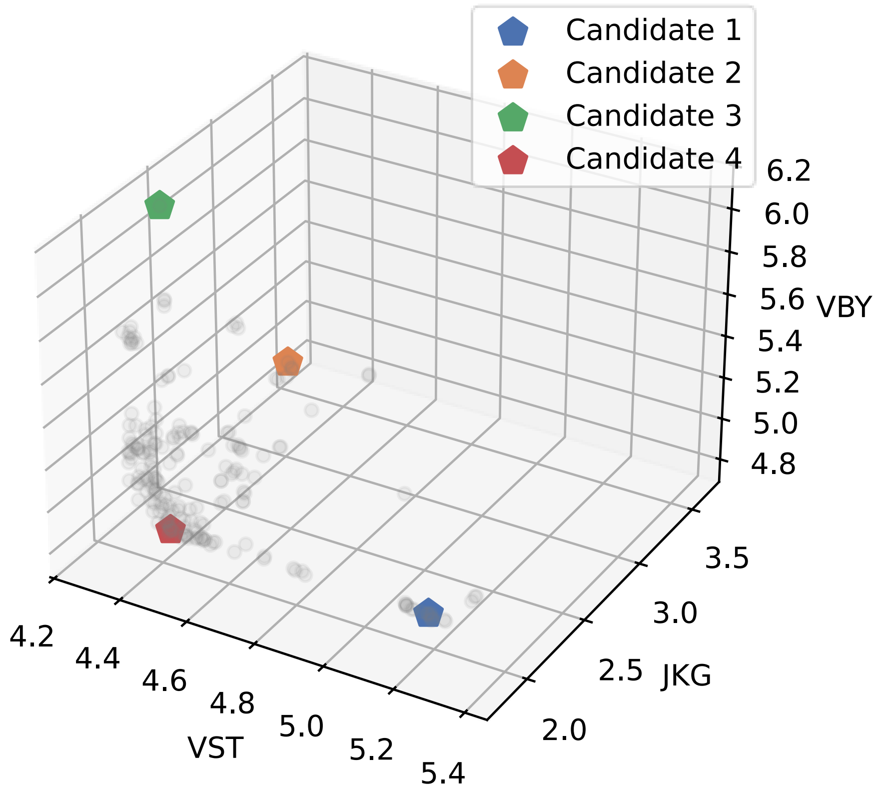

Figure 6. Total annual cost of VST, JKG, and VBY airports with respect to optimal candidates from the GA final population

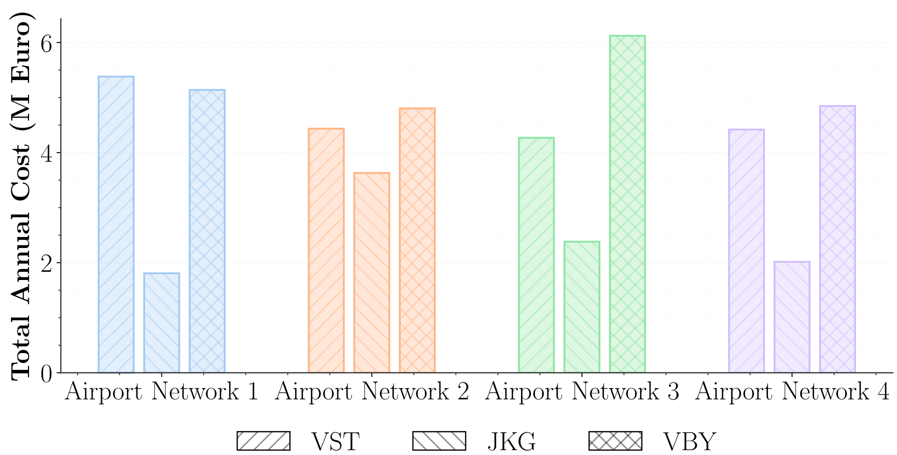

Figure 7. Total annual cost of VST, JKG, and VBY airports for the selected optimal candidates

lower efficiency at converting to electricity, is considered better at withstanding higher load spikes and sustaining longer grid outages. Therefore, investing in hydrogen technology is recommended for larger airports such as VST and VBY to increase the system's resilience.

The fourth airport network suggests greater investment in hydrogen storage, a liquefaction unit, and an electrolyzer. The result is promising, as this candidate has the lowest TAC across all airports. In conclusion, airports can take advantage of hydrogen production units rather than relying on the market. A detailed market study that accounts for safety and operating costs is required to reach a final conclusion.

From a system perspective, coordinated airport operation provides implicit benefits to the electricity grid by smoothing demand peaks and absorbing excess renewable generation. Optimized dispatch of battery and hydrogen storage enables load shifting away from high-

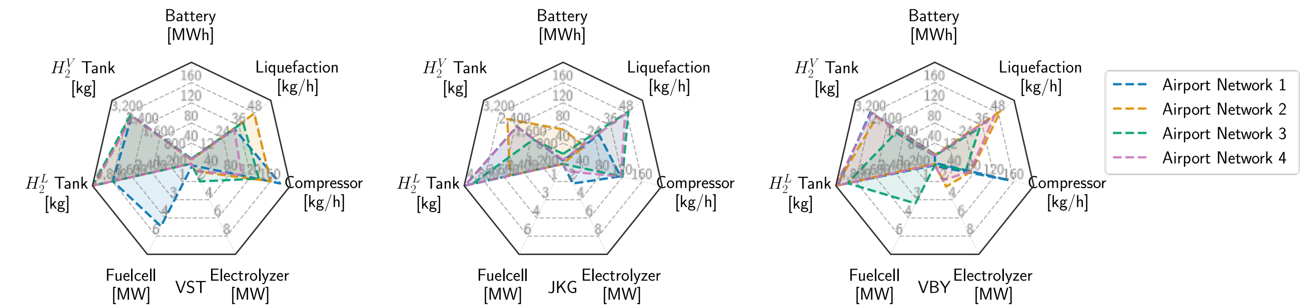

Figure 8. A comparison of decision variable values for the selected optimal population

priced periods and reduces reliance on grid imports during peak hours. In addition, the ability to export surplus electricity during periods of high renewable generation helps balance the local grid and mitigate congestion. Although these services are not monetized through an explicit flexibility market in this study, the results demonstrate that airport collaboration can provide flexibility-relevant services that are valuable for distribution system operation.

Beyond airport applications, the proposed framework is transferable to other multi-energy systems with distributed assets and flexible market interactions, such as smart charging networks, industrial energy hubs, and islanded microgrids. Its object-oriented structure enables scalable representation of interconnected nodes and shared resources, making it suitable for analyzing coordinated operation in energy communities and regional energy clusters. This highlights the framework's potential as a scalable decision-support tool for designing and operating complex, multi-vector energy systems under evolving market and regulatory conditions.

CONCLUSION

This work formulates a mixed-integer linear programming (MILP) model, embedded in an object-oriented framework and combined with a genetic algorithm, to optimize the sizing and operation of electrified airport energy hubs. Applied to a network of three regional airports, the approach demonstrated that coordinated operations and shared renewable contracts can reduce total annual costs by up to 5% while increasing flexibility during demand surges. Battery energy storage emerged as the primary contributor to capital cost and is effective for short-term resilience, whereas on-site hydrogen production and storage provide longer-duration security and can further lower costs for larger facilities. The study also illustrates that contract selection (dynamic pricing versus fixed price) influences the balance between operating costs and market exposure and that coordinated dispatch yields ancillary benefits for the local grid by smoothing peaks and absorbing excess renewable generation. These results suggest that future airport energy systems should prioritize coordinated operation, hybrid storage integration, and market-aware design to achieve cost-effective and resilient electrification.

DIGITAL SUPPLEMENTARY MATERIAL

Digital supplementary material for this study, including a spreadsheet of all scenarios, is available here.

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REFERENCES

1. Dolšak N, Prakash A. Different approaches to reducing aviation emissions: reviewing the structure-agency debate in climate policy. Clim Action 1: (2022). https://doi.org/10.1007/s44168-022-00001-w
2. Xue D, Chen XM, Yu S. Sustainable aviation for a greener future. Commun Earth Environ 6: (2025). https://doi.org/10.1038/s43247-025-02222-3
3. Holling CS. Resilience and stability of ecological systems. Annu. Rev. Ecol. Syst. 4:1-23 (1973). https://doi.org/10.1146/annurev.es.04.110173.000245
4. Molyneaux L, Brown C, Wagner L, Foster J. Measuring resilience in energy systems: insights from a range of disciplines. Renewable and Sustainable Energy Reviews 59:1068-1079 (2016). https://doi.org/10.1016/j.rser.2016.01.063
5. Folke C. Resilience (republished). E&S 21: (2016).

https://doi.org/10.5751/es-09088-210444
6. Almansoori A, Shah N. Design and operation of a future hydrogen supply chain. Chemical Engineering Research and Design 84:423-438 (2006). https://doi.org/10.1205/cherd.05193
7. Almansoori A, Shah N. Design and operation of a future hydrogen supply chain: multi-period model. International Journal of Hydrogen Energy 34:7883-7897 (2009). https://doi.org/10.1016/j.ijhydene.2009.07.109
8. Zheng P, Fang Z, Li H, Pan Y, Luo D, Zhang Z. Multi-objective optimization of hybrid energy management system for expressway chargers. Journal of Energy Storage 54:105233 (2022). https://doi.org/10.1016/j.est.2022.105233
9. Yan C, Zou Y, Wu Z, Maleki A. Effect of various design configurations and operating conditions for optimization of a wind/solar/hydrogen/fuel cell hybrid microgrid system by a bio-inspired algorithm. International Journal of Hydrogen Energy 60:378-391 (2024). https://doi.org/10.1016/j.ijhydene.2024.02.004
10. Morini M, Saletti C, Gambarotta A. A REVIEW OF SMART ENERGY PRACTICES AT AIRPORTS: CHALLENGES AND OPPORTUNITIES FOR SUSTAINABLE AVIATION. 37th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems (ECOS 2024) :144-155 (2024). https://doi.org/10.52202/077185-0013
11. Xiang Y, Cai H, Liu J, Zhang X. Techno-economic design of energy systems for airport electrification: a hydrogen-solar-storage integrated microgrid solution. Applied Energy 283:116374 (2021). https://doi.org/10.1016/j.apenergy.2020.116374
12. Zhao H, Xiang Y, Shen Y, Guo Y, Xue P, Sun W, Cai H, Gu C, Liu J. Resilience assessment of hydrogen-integrated energy system for airport electrification. IEEE Trans. on Ind. Applicat. 58:2812-2824 (2022). https://doi.org/10.1109/tia.2021.3127481
13. Vouros S, Margaritari K, Kyprianidis K. CO-OPTIMIZATION OF RESILIENT AIRPORT ENERGY HUBS FOR FLIGHT ELECTRIFICATION AND HYDROGEN PROPULSION. 37th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems (ECOS 2024) :120-131 (2024). https://doi.org/10.52202/077185-0011
14. Granado PC, Rajasekharan J, Pandiyan SV, Tomasgard A, Kara G, Farahmand H, Jaehnert S. Flexibility characterization, aggregation, and market design trends with a high share of renewables: a review. Curr Sustainable Renewable Energy Rep 10:12-21 (2023). https://doi.org/10.1007/s40518-022-00205-y
15. Kandpal B, Backe S, Crespo del Granado P. Power purchase agreements for plus energy neighbourhoods: financial risk mitigation through predictive modelling and bargaining theory. Applied Energy 358:122589 (2024). https://doi.org/10.1016/j.apenergy.2023.122589
16. Port Authority of New York and New Jersey, “Port Authority and TotalEnergies Launch New Solar Carport and Storage System at JFK Airport.” Apr. 2024. [Online]. Available: https://pv-magazine-usa.com/2024/04/24/a-second-solar-project-takes-off-at-jfk-airport/
17. Bristol Airport, “Bristol Airport enters milestone solar energy agreement with Luminous Energy.” Mar. 2024. [Online]. Available: https://www.bristolairport.co.uk/corporate/news-and-media/news-and-media-centre/2024/3/bristol-airport-enters-milestone-solar-energy-agreement-with-luminous-energy/
18. D. Holmberg, F. Omar, and T. Roth, “Impact of dynamic prices on distribution grid power quality, ” National Institute of Standards and Technology (U.S.), Gaithersburg, MD, NIST TN 2261, (2023). https://doi.org/10.6028/NIST.TN.2261
19. Schafer M, Strohmeier M, Lenders V, Martinovic I, Wilhelm M. Bringing up opensky: a large-scale ADS-B sensor network for research. IPSN-14 Proceedings of the 13th International Symposium on Information Processing in Sensor Networks :83-94 (2014). https://doi.org/10.1109/ipsn.2014.6846743
20. A. Holmberg, “Comparative Cost Analysis of PlugIn Charging and Battery Swapping Systems for Electric Aircraft: A Case Study of Jönköping Airport.” 2024. [Online]. Available: https://urn.kb.se/resolve?urn=urn%3Anbn%3Ase%3Akth%3Adiva-353827
21. Ollas P, Sigarchian SG, Alfredsson H, Leijon J, Döhler JS, Aalhuizen C, Thiringer T, Thomas K. Evaluating the role of solar photovoltaic and battery storage in supporting electric aviation and vehicle infrastructure at visby airport. Applied Energy 352:121946 (2023). https://doi.org/10.1016/j.apenergy.2023.121946
22. Swedish Meteorological and Hydrological Institute (SMHI), “Observed Meteorological Data from Swedish Weather Stations.” 2026. [Online]. Available: https://opendata.smhi.se/apidocs/metobs
23. Anderson KS, Hansen CW, Holmgren WF, Jensen AR, Mikofski MA, Driesse A. Pvlib python: 2023 project update. JOSS 8:5994 (2023). https://doi.org/10.21105/joss.05994
24. Waite M, Modi V. Modeling wind power curtailment with increased capacity in a regional electricity grid

supplying a dense urban demand. Applied Energy 183:299-317 (2016). https://doi.org/10.1016/j.apenergy.2016.08.078
25. Skoplaki E, Palyvos JA. On the temperature dependence of photovoltaic module electrical performance: a review of efficiency/power correlations. Solar Energy 83:614-624 (2009). https://doi.org/10.1016/j.solener.2008.10.008
26. J. Lindahl, "National Survey Report of PV Power Applications in Sweden".
27. Good C, Shepero M, Munkhammar J, Boström T. Scenario-based modelling of the potential for solar energy charging of electric vehicles in two scandinavian cities. Energy 168:111-125 (2019). https://doi.org/10.1016/j.energy.2018.11.050
28. Zou B, Peng J, Yin R, Li H, Li S, Yan J, Yang H. Capacity configuration of distributed photovoltaic and battery system for office buildings considering uncertainties. Applied Energy 319:119243 (2022). https://doi.org/10.1016/j.apenergy.2022.119243
29. Python Software Foundation, *Python 3.9*. Wilmington, DE, USA: Python Software Foundation, (2020). [Online]. Available: https://www.python.org
30. Beal LDR, Hill DC, Martin RA, Hedengren JD. GEKKO optimization suite. Processes 6:106 (2018). https://doi.org/10.3390/pr6080106
31. Fourer R, Gay DM, Kernighan BW. A modeling language for mathematical programming. Management Science 36:519-554 (1990). https://doi.org/10.1287/mnsc.36.5.519
32. IBM Corporation, *IBM ILOG CPLEX Interactive Optimizer 22.1.1.0*. Armonk, NY, USA: IBM Corporation, (2022). [Online]. Available: https://www.ibm.com/products/ilog-cplex-optimization-studio