

A Markov Chain-Based Methodology for Prioritizing Statewide Funding for Airport and Vertiport Infrastructure in the Electrified Aviation Economy

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Abstract

This proposal outlines a rigorous, data-driven methodology leveraging Markov Chains and extensions such as Markov Decision Processes (MDPs) to assist U.S. states in prioritizing funding for airport infrastructure improvements and new vertiport developments. The focus is on identifying underserved or economically disadvantaged airports that require enhanced financial support to integrate into the emerging electrified aviation economy, particularly for electric vertical takeoff and landing (eVTOL) aircraft and regional electrified fixed-wing operations. By modeling aviation networks as stochastic processes, the approach predicts long-term utilization probabilities, quantifies network imbalances, and optimizes new infrastructure placements to promote equity, economic viability, and sustainability. Key innovations include incorporating electric-specific constraints (e.g., battery range, charging infrastructure) into transition probabilities and using sensitivity analysis for scenario planning. The methodology is feasible for statewide networks with dozens of nodes, drawing on historical flight data, geospatial analytics, and optimization algorithms. Potential impacts include reduced funding inefficiencies, improved access for disadvantaged communities, and accelerated adoption of low-emission aviation.

Introduction and Problem Context

The transition to an electrified aviation economy, driven by advancements in eVTOL and battery-electric aircraft, presents states with opportunities to revitalize regional air mobility while addressing environmental and equity challenges [1, 2, 3, 4, 5, 6, 7]. However, existing airports—particularly in rural or economically disadvantaged areas—often lack the infrastructure (e.g., charging stations, upgraded runways) to support these technologies, leading to underutilization and exclusion from economic benefits like job creation and tourism [8, 9]. Similarly, strategic placement of new vertiports is critical for urban air mobility (UAM) networks, yet current approaches often overlook probabilistic demand flows and socioeconomic factors [10].

Markov Chains offer a foundational probabilistic framework for modeling such systems, where airports/vertiports represent discrete states, and aircraft movements are transitions governed by probabilities estimated from data [11, 12, 13, 14, 15]. This enables prediction of stationary distributions (long-term utilization probabilities) to identify underserved nodes requiring funding priority. For optimization, MDPs extend this by incorporating decisions (e.g., adding vertiports) and rewards (e.g., equity metrics) [16, 12, 17, 18, 19, 20, 21, 22, 23, 24, 25]. This proposal refines prior conceptual drafts by integrating empirical literature, specifying computational methods, and emphasizing equity in funding allocation for the electrified economy.

Literature Review and Feasibility Assessment

Markov Chains have been successfully applied to aviation networks for modeling aircraft movements, queuing, and resource allocation, making them feasible for statewide electrified systems [26, 16, 14, 15, 27, 10]. Their memoryless property suits systems where future utilization depends primarily on current network states, scalable to fixed networks of 50–100 airports using linear algebra solvers (e.g., solving $\pi P = \pi$ for stationary distribution π , where P is the transition matrix) [12, 13, 28].

For airport utilization in electrified networks, Markov Chains can forecast equilibrium probabilities by embedding constraints like battery range limiting transitions to distant states [29, 30, 1, 31]. Analogous applications include second-order chains for air traffic sequencing and Monte Carlo simulations for airport queuing, extendable to electric fleets by factoring energy consumption [32, 33, 34, 27]. Feasibility is enhanced for pre-existing networks, as states provide baseline data; limitations (e.g., assuming ergodicity) can be addressed via absorbing states for disruptions or higher-order chains for path dependencies [26, 12, 13].

For vertiport placement, MDPs build on Markov Chains by adding actions (e.g., site selection) and rewards (e.g., maximizing coverage for disadvantaged areas), proven in UAM for routing, collision avoidance, and fleet management [17, 18, 19, 20, 21, 22, 23, 24, 25, 35, 10]. Examples include dynamic routing in stochastic UAM networks and risk-aware contingency planning for eVTOL [18, 25]. This is practical for states, as candidate sites can be evaluated iteratively, with computational efficiency via policy iteration or reinforcement learning algorithms like Q-learning [19, 22].

A simple illustrative example: Consider a state with airports A (urban, high-demand), B (rural, underserved), and C (mid-tier). Transition matrix P based on historical flights and electric range constraints yields stationary distribution $[0.50, 0.20, 0.30]$, highlighting B's

underutilization for funding priority. Adding vertiport D (optimized via MDP) shifts to [0.40, 0.25, 0.25, 0.10], balancing the network [11, 12, 17].

Refined Problem Statements and Objectives

To enhance clarity and alignment with Markov mechanics, the problems are refined as follows:

1. Airport Utilization and Funding Prioritization: Develop a discrete-time homogeneous Markov Chain to estimate stationary utilization probabilities for existing airports in electrified regional air mobility networks. States are airports; transitions incorporate electric constraints (e.g., $P_{ij} \propto \text{demand} / \text{distance}$, capped by battery range).
 - a. Objective: Rank airports by deviation from equitable utilization (e.g., minimize Gini coefficient of π), prioritizing funding for underserved/economically disadvantaged sites based on socioeconomic indices [11, 26, 1, 31, 8, 9, 36].
2. Optimal Vertiport Location for UAM Integration: Employ an MDP to select new vertiport sites, extending the base chain by adding candidate states.
 - a. Actions: Add/remove sites; rewards: Weighted sum of utilization balance, economic impact, and equity (e.g., access for low-income areas).
 - b. Objective: Maximize expected long-term reward via value iteration, ensuring vertiports enable electrified economy participation [17, 18, 19, 20, 21, 22, 23, 24, 25, 35, 10].

These support state funding decisions by quantifying ROI (e.g., utilization uplift per dollar invested) [33, 34, 1, 2, 5, 7].

Proposed Methodology

The methodology integrates data collection, model construction, simulation, and optimization:

1. Data Acquisition and Transition Estimation:
 - a. Collect historical flight data (e.g., FAA TFMSC), demand proxies (population, GDP), and electric parameters (battery range $\sim 100\text{--}300$ km) [1, 4, 6, 36].
 - b. Use regression or maximum likelihood to estimate $P_{ij} = \Pr(\text{flight from } i \text{ to } j \mid \text{current at } i)$, weighted by factors below [11, 32, 28, 33, 34].
 - c. For equity, overlay Census data on economic disadvantage (e.g., poverty rates) [8, 9].
2. Markov Chain Modeling for Utilization:
 - a. Compute stationary distribution π via eigenvalue decomposition or iterative power method [12, 13, 28].

- b. Identify underserved airports: Those with $\pi_i < \text{threshold}$ or high disparity (e.g., relative to population share) [26, 31, 9].
 - c. Simulate scenarios (e.g., infrastructure upgrades increasing $P_{\{ij\}}$) using Monte Carlo for transient behaviors [14, 15, 27].
- 3. MDP for Vertiport Optimization:
 - a. State space: Existing airports + candidate vertiports (identified via GIS, e.g., rooftops near demand centers) [21, 35, 1, 10].
 - b. Solve MDP using policy iteration: $V(s) = \max_a [R(s,a) + \gamma \sum P(s'|s,a) V(s')]$, where γ is discount factor [12, 17, 18, 19, 22].
 - c. Output: Ranked sites by reward impact, prioritized for funding [20, 23, 24, 25].
- 4. Validation and Sensitivity Analysis:
 - a. Validate against real data (e.g., backtest on existing networks) [36].
 - b. Sensitivity: Vary parameters (e.g., range increases from tech advances) to assess robustness [30, 4, 31].

Implementation in Python (e.g., NumPy for matrices, PuLP for optimization) ensures accessibility for state agencies.

Key Factors Influencing Utilization Probabilities

Transition probabilities and rewards are informed by multifaceted drivers, quantified via multi-criteria analysis (e.g., AHP for weighting):

- Demand and Socioeconomic Factors: Population density, business hubs, tourism, and equity metrics (e.g., prioritize areas with high poverty for funding). For electrified aircraft, short-haul demand in congested regions boosts transitions [1, 8, 9, 36].
- Infrastructure Constraints: Charging availability, runway compatibility, and power grid capacity; electric aircraft require rapid charging, reducing $P_{\{ij\}}$ for unprepared sites [29, 30, 37, 38, 5, 6, 7, 31].
- Geospatial and Accessibility: Proximity to hubs, land use (e.g., rooftops for vertiports), elevation ($450 \pm 150\text{m}$ ideal). Network distance biases toward nearby transitions [21, 35, 1, 10].
- Regulatory and Environmental: Zoning, noise limits (favoring quiet eVTOL), safety buffers; environmental impact assessments zero non-compliant probabilities [21, 1, 39].
- Economic and Performance: Costs (land, operations), range limitations ($\sim 100\text{--}200\text{km}$ for eVTOL), competition from ground transport. Funding prioritization favors high-ROI sites [33, 34, 2, 3, 4, 5].
- Uncertainties: Weather, tech maturity; model via scenario transitions or stochastic MDPs [25, 30].

These factors are integrated into P via weighted formulas (e.g., $P_{\{ij\}} = \text{softmax}(\beta \cdot \text{factors})$), calibrated empirically [32, 28, 37].

Expected Outcomes, Limitations, and Future Work

This methodology provides states with a tool for equitable funding allocation, potentially increasing underserved airport utilization by 20–30% through targeted investments [1, 6, 31, 9]. Limitations include data quality and the memoryless assumption, mitigable via hybrid models (e.g., with LSTM for sequences) [13, 38]. Future work could incorporate real-time data via online MDPs or expand to multi-state networks [18, 19, 22].

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Justification: A Markov Chain-Based Methodology for Prioritizing Statewide Funding for Airport and Vertiport Infrastructure in the Electrified Aviation Economy

The proposal is unique in its specific integration of Markov Chains for predicting long-term airport utilization probabilities to identify and prioritize funding for underserved or economically disadvantaged airports, combined with Markov Decision Processes (MDPs) for optimizing new vertiport placements—all tailored to statewide infrastructure in the emerging electrified aviation economy (e.g., eVTOL and battery-electric aircraft networks). While related elements exist in prior work, no focused research or methodology directly matches this comprehensive, equity-focused framework for funding prioritization.

Key Findings from Existing Work

To assess uniqueness, I reviewed academic literature, reports, and discussions via targeted searches on scholarly databases and platforms. Below is a synthesis of relevant prior efforts, highlighting overlaps and gaps:

- Markov Chains in Aviation Contexts: Markov Chains have been applied to airport operations, such as modeling queueing at vertiports for capacity analysis (e.g., using Continuous Time Markov Chains to evaluate steady-state behaviors like waiting times in UAM networks) or stochastic aircraft movements in traditional airports. However, these focus on operational efficiency (e.g., taxiing or departure sequencing) rather than long-term utilization probabilities for funding prioritization in electrified systems. **No instances tie stationary distributions directly to identifying underserved airports or economic equity in electrified aviation.**
- MDPs in UAM and Vertiport Operations: MDPs are commonly used in urban air mobility (UAM) for dynamic problems like fleet scheduling, routing, collision avoidance, and arrival sequencing at vertiports. For example, MDPs model real-time decisions in multi-vertiport networks, often extended with reinforcement learning (e.g., Proximal Policy Optimization) to handle stochastic demand and charging constraints. These are operational (e.g., scheduling eVTOLs to minimize delays) rather than infrastructural placement or funding oriented. **Extensions to add states for hypothetical vertiports are absent.**

- Vertiport Placement Optimization: Research on vertiport locations emphasizes equitable access, demand coverage, and integration with ground transport, using methods like genetic algorithms, clustering (e.g., agglomerative hierarchical), p-median models, or GIS-based approaches. Some address socioeconomic factors (e.g., accessibility for low-income areas) in electrified UAM, but without stochastic models like MDPs for site selection. **Funding prioritization is implied in cost-benefit analyses but not explicitly modeled via Markov processes for statewide equity.**
- Airport Utilization and Funding in Electrified Aviation: Studies on electrified aircraft infrastructure (e.g., FAA reports on vertiport electrical needs) discuss utilization forecasting and equity, but use deterministic simulations or regression, not Markov Chains. **MDPs appear in traditional airport ops (e.g., taxi clearance to reduce emissions) but not extended to electrified fleets or funding for disadvantaged sites.**
- Gaps Confirming Uniqueness: No work combines Markov Chain stationary distributions for utilization-based funding ranking with MDP state extensions for vertiport additions, specifically targeting underserved airports in an electrified context. Related efforts (e.g., MDPs in UAM fleet ops) are narrower and operational, lacking the proposal's equity-driven, statewide funding lens. **Public discussions (e.g., on X) yield no mention of such integrated methodologies.**

If emerging preprints or niche reports surface in future searches, they could overlap partially, but based on current evidence, this proposal innovates by bridging stochastic modeling with policy-oriented funding for sustainable aviation equity.