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

Richard Walsh, MSc., A.A.E, a3i global aeronautics advisors, LLC

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., $P_{ij} \propto$ demand / 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 ~100–300 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 π_i < 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±150m 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 (~100–200km 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., $P_{ij} = \mathrm{softmax}(\beta \cdot \mathrm{factors})$), 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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