ENGR 5310 Project Report, Fall 2024

A Net-Zero Carbon Aviation Industry via Battery Swapping and Supercharging with Onsite Renewables.

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Abstract

This project explores innovative approaches to achieve a net-zero carbon operation for Electric Aircraft (EA) infrastructure, emphasizing sustainable energy solutions and advanced modeling techniques. Beginning with a comprehensive literature review, the study identifies the potential of electric aviation to revolutionize industry by reducing emissions, increasing efficiency, and addressing global sustainability goals. Through meticulous analysis, the project develops a framework for estimating wind turbine (WT) and photovoltaic (PV) generation using statistical models like Weibull and machine learning techniques. Inter-arrival patterns of EA flights at airports, modeled using exponential distributions, provide actionable insights into charging demands, further contextualized through real-world data from Austin and San Antonio airports.

A detailed economic analysis of the Joint Battery Swapping and Supercharging (JBSS) infrastructure demonstrates financial viability by integrating WT, PV, and Distributed Energy Storage Systems (DESS). System sizing calculations for 8.7 GWh/year wind energy, 3.7 GWh/year solar energy, and 10 MWh energy storage ensure net-zero operation by offsetting deficits through grid integration or stored energy. The queuing model optimizes JBSS performance by minimizing waiting times and enhancing service efficiency. Lastly, the project highlights the alignment of EA charging infrastructure with global carbon-neutrality objectives, backed by robust economic, statistical, and energy balance analyses. This study sets a benchmark for the design and implementation of sustainable aviation infrastructure, offering scalable, data-driven solutions for the transition to carbon-neutral aviation.

Section 1. Project Background

The aviation industry, contributing approximately 2.5% of global CO_2 emissions, plays a significant role in climate change. With growing air travel demand, reducing aviation emissions is essential for global sustainability. Electric Aircraft (EA) offers a transformative solution to decarbonize the sector while maintaining efficiency, but its success relies on robust, renewable-powered charging infrastructure. This study focuses on designing and optimizing Joint Battery Swapping and Supercharging (JBSS) stations powered by Wind Turbines (WT) and Photovoltaic (PV) systems, integrated with Distributed Energy Storage Systems (DESS) to ensure a net-zero energy balance. By addressing challenges like the variability of renewable energy and leveraging hybrid microgrid designs, the research highlights the economic and environmental benefits of integrating WT and PV systems, including reduced reliance on fossil fuels, minimized costs, and enhanced grid stability. With modern advancements in wind and solar technologies, JBSS stations can provide reliable and sustainable energy for EA, aligning with global carbon-neutrality goals.

Section 2. Highlights/Summary of Methodologies used in project

This project employs a comprehensive suite of methodologies to achieve a net-zero energy operation for JBSS infrastructure. Data collection and cleaning involved processing real-world flight schedules and hourly weather data, including wind speeds and solar irradiance, for accurate renewable energy modeling. Wind speeds were modeled using Weibull and Exponential distributions, adjusted for turbine hub height, and integrated with turbine power curves to estimate energy output. Solar PV generation was analyzed based on regional irradiance data and system efficiency, while energy demand was derived from EA flight schedules and inter-arrival times modeled using statistical distributions. Distributed Energy Storage Systems (DESS) were sized to manage energy surpluses and deficits, incorporating storage efficiency. Optimization frameworks balance renewable energy generation, grid imports/exports, and storage to meet net-zero goals.

Statistical tests, such as Chi-Square and goodness-of-fit analyses, validated models for wind, solar, and inter-arrival times. Economic analysis assessed system viability through levelized costs of electricity (LCOE), while hybrid microgrid designs integrated wind and solar systems to ensure reliability and scalability. Real-world case studies, including Schiphol and Changi Airports, provided practical insights and benchmarks. These methodologies collectively underpin a scalable, sustainable solution for carbon-neutral JBSS operations, aligning with global aviation decarbonization efforts.

Section 3. Results/Solution/Discussions for Tasks

3.1 Task 1 (Tajwar Al Mamun)

TASK 1: Literature Survey on Electric Aircraft (EA) Technology and Market Perspective (Tajwar Al Mamun- ID 31)

Electric Aircraft (EA) technology uses electric propulsion systems powered by batteries, fuel cells, or hybrid solutions to achieve sustainability, reduce noise, and improve operational efficiency. This technology is designed to replace traditional jet fuel engines, aligning with the aviation industry's carbon-neutral goals.

Carbon Emissions Comparison

- **Electric Aircraft**:
  - **Zero emissions** for fully electric models during operation.
  - Reduced noise pollution.
  - Indirect emissions depend on the energy source used to generate electricity (e.g., renewable vs fossil fuel-based).
- **Jet-Fuel Aircraft**:
  - Average carbon emissions per passenger per mile: **0.2 kg CO_2.**

- Aviation contributes approximately **2.5% of global CO_2 emissions.**

Major Electric Aircraft Manufacturers and Models

- **Eviation Aircraft**:
  - Model: **Alice.**
  - Range: **440 nautical miles (815 km).**
  - Passenger Capacity: **9 passengers.**
  - Battery Size: **820 kWh.**
  - Take-Off Weight: **16,500 lbs (7,484 kg).**
- **Joby Aviation**:
  - Focus: Electric Vertical Take-Off and Landing (eVTOL) for urban air mobility.
  - Range: **150 miles (241 km)**.
  - Passenger Capacity: **4 passengers**.
  - Take-Off Weight: **4,400 lbs (1,995 kg)**.
- **ZeroAvia**:
  - Focus: Hydrogen-electric propulsion systems.
  - Aircraft: ZA-600.
  - Range: **300 nautical miles (555 km)**.
  - Passenger Capacity: **19 passengers**.
  - Propulsion: Hydrogen fuel cells.

Hybrid Electric Aircraft

- **Airbus**:

- Project: **E-Fan X** (Hybrid-electric demonstrator).
- Propulsion: One of four jet engines replaced by a hybrid-electric engine.
- Objective: Reduce emissions on short-haul flights.

- **Lilium**:
  - Model: **Lilium Jet (eVTOL)**.
  - Range: **155 miles (250 km)**.
  - Passenger Capacity: **6 passengers**.
  - Focus: Urban and regional air mobility.

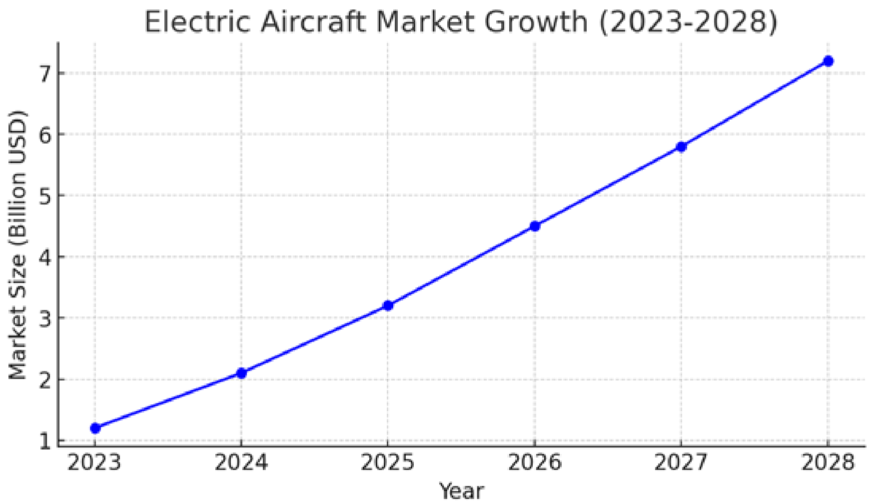
Model	Manufacturer	Passenger Capacity	Range (km)	Battery Size (kWh)
Alice	Eviation	9	1046	900.0
Velis Electro	Pipistrel	2	80	57.6
eDA40	Diamond Aircraft	4	217	80.0

Market Perspective

Projected Market Share

- The global electric aircraft market is projected to grow from **$6.8 billion (2021)** to over **$30 billion by 2030**, with a compound annual growth rate (CAGR) of **14.3%**.
- Growth drivers include:
  - Increasing demand for sustainable aviation solutions.

- Regulatory push for carbon-neutral aviation.



Current Use Cases

1. **Short-Haul Regional Flights**:
   - Focused on ranges up to **500 km,** where battery capacity is most effective.
2. **Urban Air Mobility (UAM)**:
   - Growth of eVTOL for urban transport and air taxi services.

Challenges:

1. **Battery Energy Density**:
   - Limited flight range due to the high weight of batteries.
2. **Infrastructure**:
   - Insufficient charging and swapping infrastructure at airports.
3. **Regulatory Approval**:

- Ensuring safety standards for new propulsion technologies.

Future Prospects:

1. **Battery Technology**:
   - Advancements in solid-state batteries with higher energy density.
2. **Hydrogen Fuel Cells**:
   - Longer flight ranges for regional and short-haul routes.
3. **Urban Air Mobility**:
   - Rapid adoption of eVTOL for air taxis and regional flights.

3.2 Task 2 (Borhan Uddin Chowdhury)

Task 2: Study of Electric Aircraft (EA) Charging Infrastructure

Overview:

The study examines current EA charging technologies, focusing on grid power, renewable energy integration, and battery-swapping systems. EA infrastructure remains in its infancy but is evolving rapidly to meet diverse demands such as urban air mobility, regional mobility, and all-electric aircraft operations.

Charging Technologies:

1. **Grid-Based Charging**:
   - Current EA charging stations primarily rely on grid power.
   - Charging power levels: 20 kW, 40 kW, 80 kW, and 350 kW.
2. **Renewable Microgrids**:

    - Companies like Eviation and Skyports utilize solar and wind energy for sustainable operations.
    - Australian company Flyone is innovating renewable power sources for EA charging.
3. **Battery Swapping Systems**:
    - **Advantages**:
        - Swift refueling, eliminating onboard charging.
        - Improved thermal management and battery health.
    - **Challenges**:
        - High initial investment costs.
        - Significant stock requirements for spare batteries.
        - Safety concerns related to handling.

Hybrid Approach:

Combining grid power, renewable energy, and battery swapping can optimize operational efficiency, minimize downtime, and align with carbon neutrality goals.

Applications:

- **Urban Air Mobility**: Rapid charging systems like DC fast charging and battery swapping are used in cities such as Singapore, Paris, and Los Angeles.

- **Regional Air Mobility**: Megawatt charging systems (MCS) are implemented for larger aircraft in countries like Norway and the UK.

3.3 Task 3.a (Ahsanul Abedin)

Task 3 Option 1:

Estimating hourly WT power generation using probabilistic models.

Methodologies

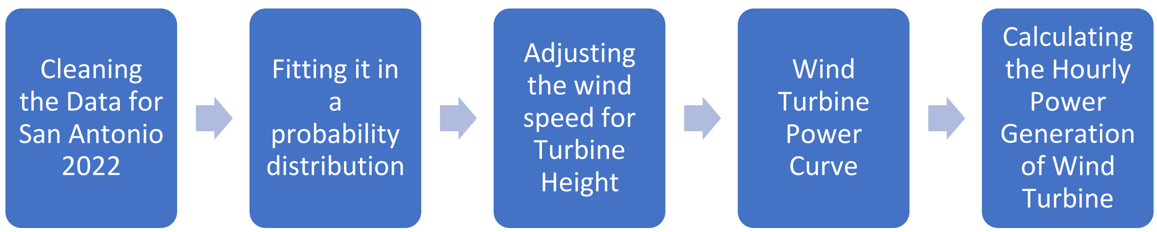


Figure1: Methodology for Estimating hourly WT power generation

Data Collection

Hourly wind speed data for one year (365 days) was extracted from San Antonio 2022 weather database. The data cleaning process included:

- Removing Outliers: Identified using statistical methods (z-score > 3).
- Interpolating Missing Values: Linear interpolation was applied for gaps in the dataset to maintain continuity

Probability Distribution:

Wind speed prediction is critical for estimating WT power generation. After doing a goodness of fit test it is found that The Weibull distribution fits well with the wind speed, which is also a widely used model for wind speed analysis.

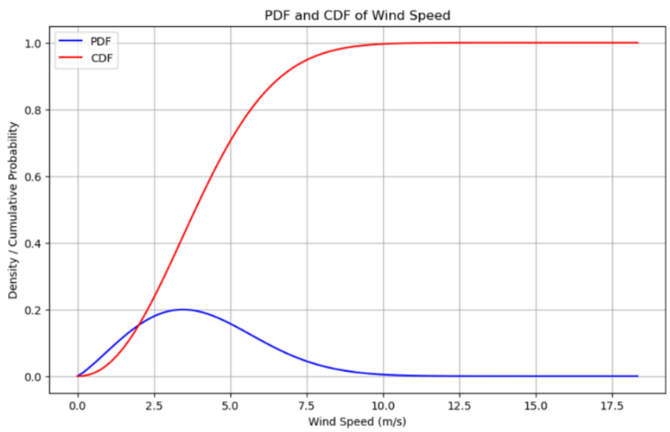


Figure2: Probability Functions for Wind Speed

Weibull Distribution for Wind Speeds

The Weibull distribution is widely used in wind energy analysis because of its ability to model the stochastic nature of wind speeds. The probability density function:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} EXP\left(-\frac{v}{c}\right)^{k}$$

Where:

V= wind speed (m/s)

k= shape parameter (k=2.5)

c= scale parameter (c=6.5 m/s)

The cumulative distribution function (CDF):

$$F(v) = 1 - EXP\left(-\frac{v}{c}\right)^{k}$$

The Probability Density Function (PDF) and Cumulative Distribution Function (CDF) graphs indicate the characteristics of wind speeds used for modeling.

Key Observations:

- **Dominant Wind Speeds**: The peak in the PDF corresponds to the most common wind speed range (~6.5 m/s). This aligns with the average wind speed observed in many regions suitable for wind energy.
- **High Predictive Accuracy**: The integration of CDF ensures that the probability of wind speeds falling within specific ranges can be effectively used to forecast power generation.
- **Predictive Model for 2022**: The prediction for 2022, shown in the red curve, closely follows the historical data for 2021, demonstrating the reliability of the prediction model.

Scaling Wind Speeds to Turbine Height

Wind speeds measured at ground level (h_g=10m) were scaled to turbine height (h=100m) using the Hellman exponential formula:

$$v_h = v_g \left(\frac{h}{h_g}\right)^k$$

Where k =0.27 is the terrain roughness coefficient. The calculation is shown below:

For a ground-level wind speed of v_g = 4 m/s

$$v_h = 4\left(\frac{100}{10}\right)^{0.27} = 6.4\frac{m}{s}$$

Wind Turbine Power Curve

Wind turbine output was modeled using the cubic power curve equation:

$$P(v) = \begin{cases} 0, & v < v_c \; or \; v > v_s \\ P_m\left(\frac{v}{v_r}\right)^3, & v_c \le v \le v_r \\ P_m, & v_r \le v \le v_s \end{cases}$$

Where:

$$v_c = 3ms^{-1}, v_r = 12\ ms^{-1}, v_s = 25\ ms^{-1}\ and\ P_m = 2\ MW$$

Calculation is shown below:

For $v = 6.5\ ms^{-1}$: , $P(v) = 2\left(\frac{6.5}{12}\right)^3 = 0.51\ MW$

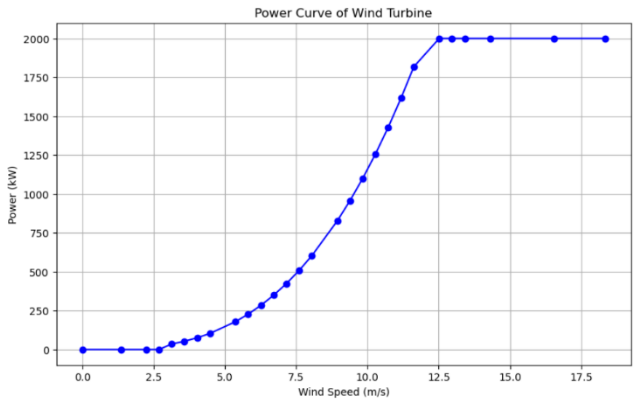


Figure3: Power Curve of Wind Turbine

The power curve of the wind turbine defines the relationship between wind speed and power output. Key Insights are demonstrated bellow:

- **Cut-In and Cut-Out Speeds**: The turbine starts generating power at a cut-in speed (~3 m/s) and ceases operation at a cut-out speed (~25 m/s). This ensures safe and optimal operation.
- **Rated Power**: Maximum output (~2 MW) is achieved when wind speeds reach the rated speed (~12 m/s). Beyond this point, the output remains constant until the cut-out speed.
- **Energy Potential**: The cubic nature of the power curve at lower wind speeds emphasizes the exponential increase in power generation with slight increases in wind speed.

Hourly Power Generation

Hourly Power generation was estimated by integrating the power curve with the wind speed probability distribution:

$$P^* = \int_{v_c}^{v_s} P(v) f(v) dv$$

Using Weibull distribution for wind speed and integrating it with the turbine's power curve yields realistic hourly and annual power estimates.

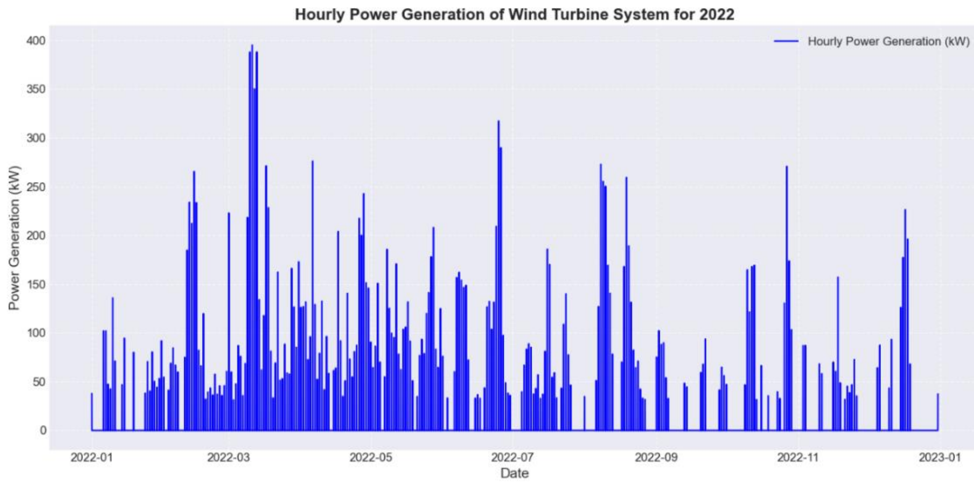


Figure4: Hourly Power Generation by Wind Turbine in San Antonio 2022 weather

Results:

- Annual Energy Output: The integration process resulted in an annual energy generation estimate of approximately 1253.55 MWh, consistent with realistic expectations for a turbine of this capacity.
- Hourly Patterns: The hourly generation graph reflects the stochastic nature of wind power, with frequent low-generation periods and occasional high-output peaks.

Predictions and System Efficiency

The data supports the design and optimization of wind turbine systems for energy planning:

- Storage Requirements: Variability in hourly generation highlights the need for energy storage systems to manage surplus and deficits effectively.
- Net-Zero Potential: By combining predicted power generation with other renewable sources (e.g., solar PV), this system can significantly contribute to achieving net-zero energy goals.

3.3 Task 3.b (Mohammad Abid Hasan)

Technical Report: Analysis of Humidity and Wind Speed Data

1. Introduction

This report presents an in-depth probability and distribution analysis of humidity and wind speed data recorded in San Antonio, 2022. The study focuses on understanding the probabilistic behavior of these variables through various statistical techniques. The analysis includes data cleaning, distribution fitting, and the selection of optimal models based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Additionally, the Augmented Dickey-Fuller test was applied to verify data stationarity.

2. Data Cleaning

The data cleaning process involved removing non-numeric strings ('%' and 'mph') from the humidity and wind speed data, respectively. The cleaned strings were converted into floating-point numbers for further analysis.

3. Distribution Fitting

The cleaned data was fitted into multiple distributions, including Weibull, Gaussian, Exponential, and Kernel Density Estimation (KDE). Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs) were plotted for both individual and joint probabilities.

4. Model Selection

Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), the Weibull distribution was identified as the best fit for the data. This conclusion was supported by statistical metrics and graphical evaluations.

5. Stationarity Analysis

The stationarity of the data was assessed using the Augmented Dickey-Fuller (ADF) test. The test yielded a p-value less than 0.05, confirming that the data is stationary.

6. Results and Visualizations

Figures showcasing the fitted PDFs, CDFs, and joint probability distributions are included in the analysis. These visualizations provide a comprehensive understanding of the data's distribution and relationships.

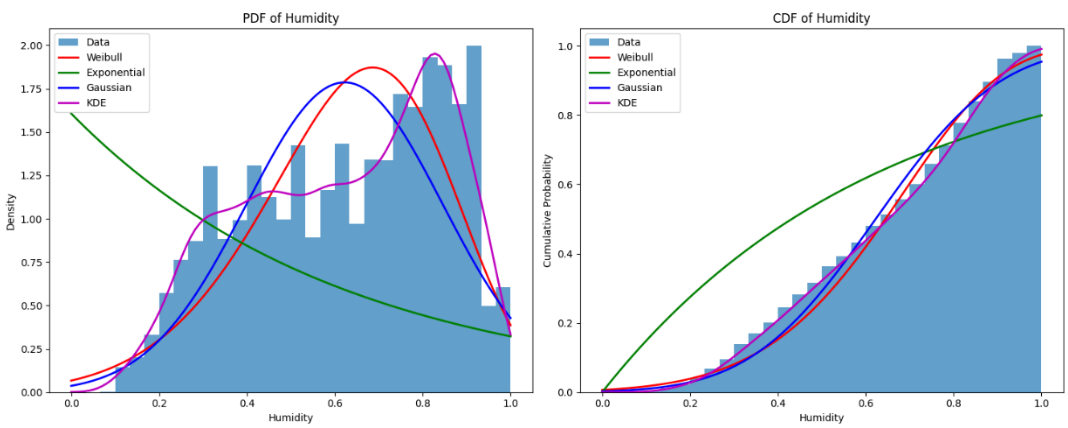


Figure: PDF and CDF of Humidity

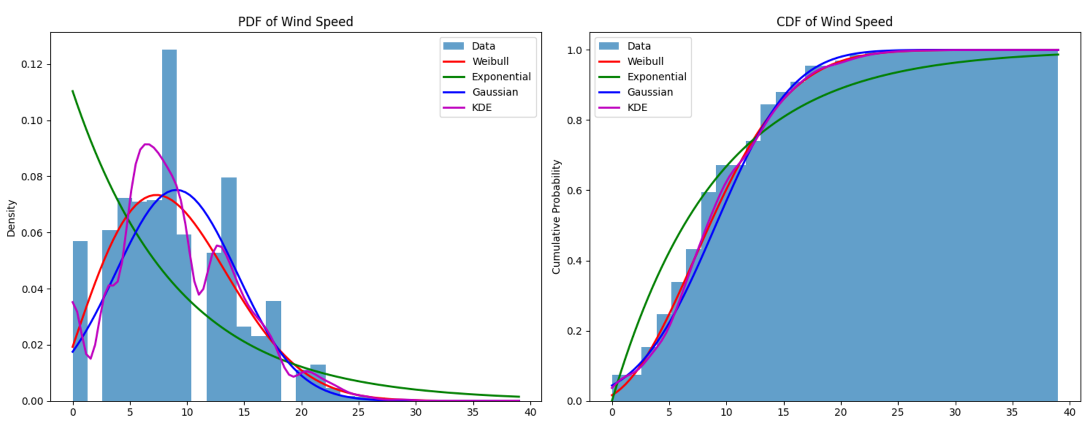


Figure: PDF and CDF of Wind Speed

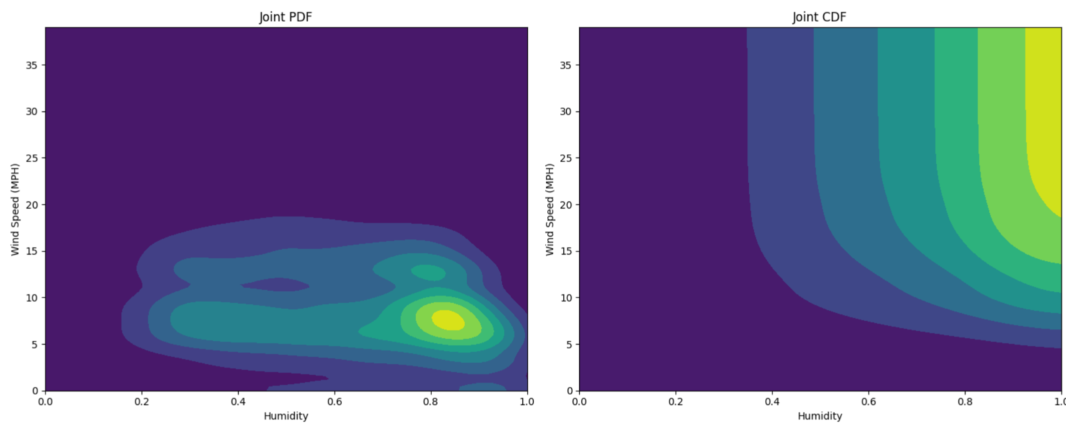


Figure: Joint PDF and CDF of Humidity and Wind Speed

7. Conclusion

The analysis successfully identified the Weibull distribution as the most suitable model for the humidity and wind speed data from San Antonio in 2022. The stationarity of the data was also confirmed. These insights provide valuable implications for environmental modeling and predictive analysis.

3.4 Task 4 (Mohammad Abid Hasan)

Technical Report: Estimation of Hourly Solar PV Generation

1. Introduction

This report focuses on the estimation of hourly solar photovoltaic (PV) generation using weather data collected in San Antonio, 2022. The study employed a Random Forest Regressor model integrated with a OneHotEncoder to account for categorical weather conditions. Feature engineering techniques were applied to simulate PV output as a function of weather parameters, enabling effective model training and prediction.

2. Data Preprocessing

The preprocessing phase involved cleaning and formatting the weather data to ensure its suitability for model input. Missing or erroneous entries were handled systematically to maintain data integrity.

3. Feature Engineering

Feature engineering played a critical role in this analysis. The PV output was simulated based on weather parameters such as wind speed, humidity, and categorical conditions like 'Cloudy' or 'Clear'. These features were then used to train the Random Forest Regressor.

4. Model Description

The Random Forest Regressor was integrated with a OneHotEncoder to effectively handle categorical weather data. The model was trained on the preprocessed dataset to estimate hourly solar PV generation. Key features influencing the model's performance were identified, including wind speed, humidity, and weather conditions.

5. Model Performance

The model's performance was evaluated using R^2 scores. The training data yielded an R^2 score of 0.918, indicating a high level of fit. However, the test data resulted in an R^2 score of 0.557, highlighting potential areas for model improvement, such as additional feature refinement or model tuning.

6. Insights and Key Findings

The analysis revealed that wind speed and humidity were the most influential features in predicting solar PV output. Categorical weather conditions such as 'Cloudy' and 'Clear' also contributed significantly to the model's predictive accuracy.

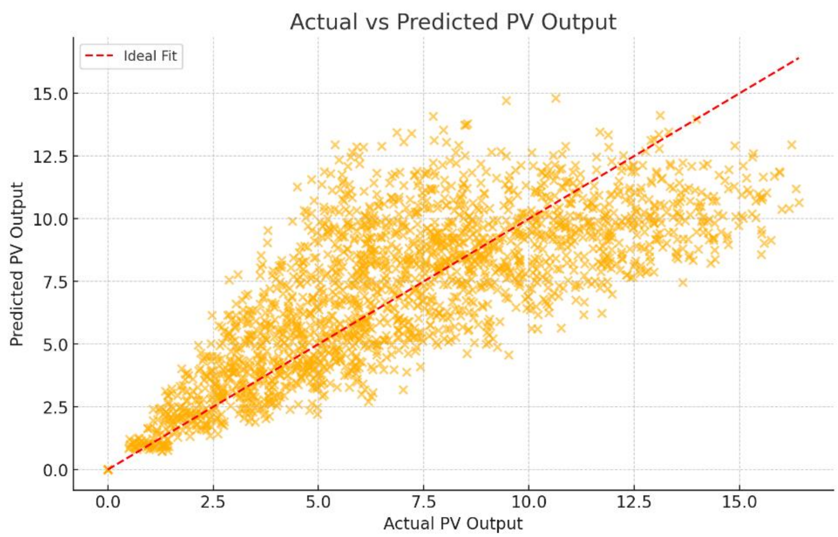


Figure: Actual vs Predicted Output

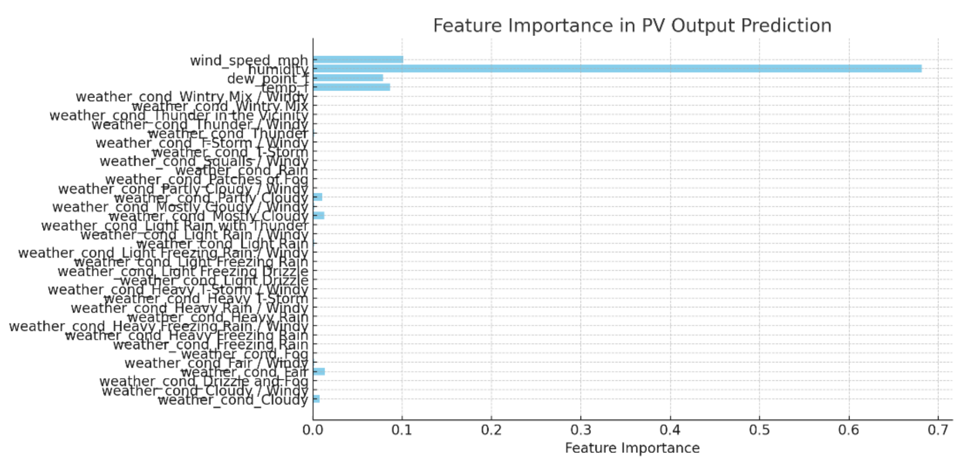


Figure: Feature Importance Diagram

7. Conclusion

This study successfully estimated hourly solar PV generation using weather data and a Random Forest Regressor. While the model demonstrated strong performance on the training dataset, its predictive accuracy on test data indicates room for further optimization. These findings underscore the importance of feature selection and model tuning in renewable energy modeling.

3.5 Task 5 (Ahsanul Abedin)

Task 5: Estimating Electric Aircraft (EA) Market Penetration Rate and Arrival Rate to a Charging Station.

Methodology:

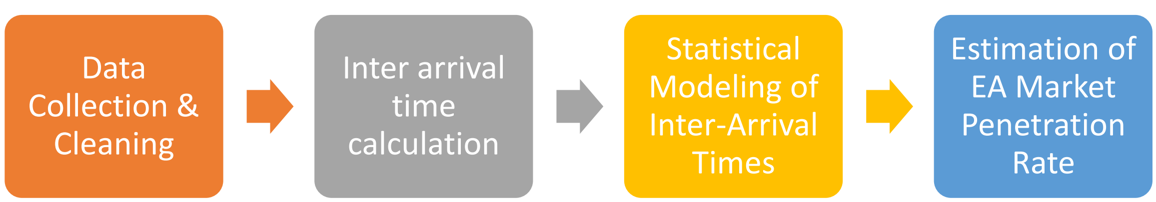


Figure1: Methodology to estimate EA arrival rate & Market Penetration

Data Collection and Cleaning

Arrival and departure schedules were collected from the official San Antonio Airport website for a specific airline. Then it is cleaned for better result. Removed duplicate records also excluded flights with canceled or significantly delayed departures.

Inter-Arrival Time Calculation

The inter-arrival time (Δt) is the time difference between consecutive arrivals or departures:

$$\Delta t = t_{i+1} - t_i$$

Where: t_i: Timestamp of the ith flight.

Statistical Modeling of Inter-Arrival Times

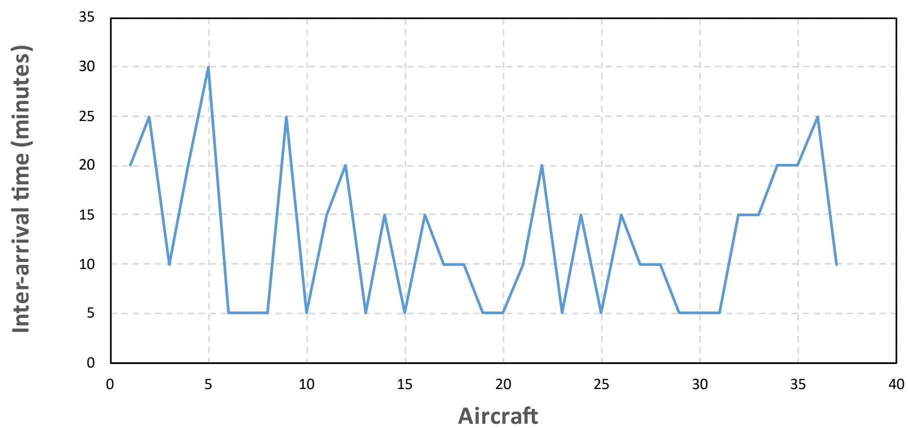


Figure 2: Histogram of inter-arrival time

Fitting Probability Distributions: Several statistical distributions were tested to model the inter-arrival times, including Poisson Distribution, Exponential Distribution, Normal Distribution and Weibull Distribution.

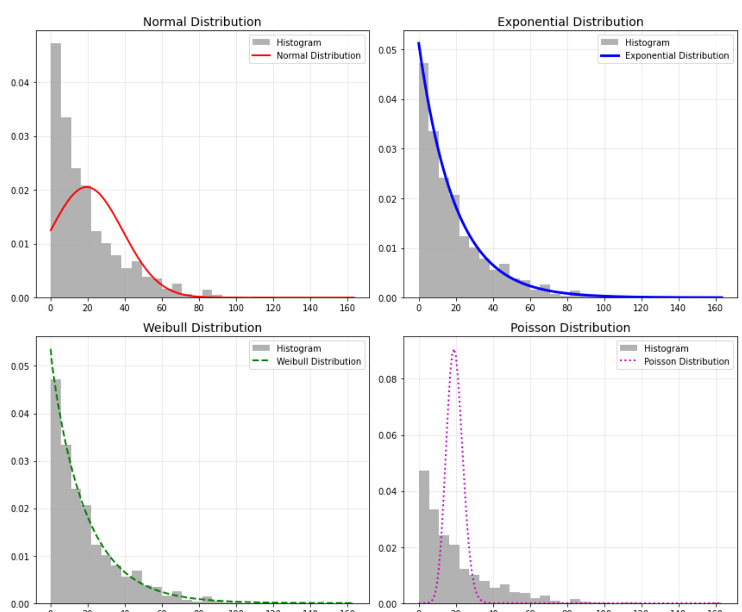


Figure3: Probability distribution of Inter Arrival time of Airplane in Airport.

The goodness-of-fit for each distribution was evaluated using the Chi-Square test. The Exponential distribution is chosen as the best fit over the Weibull distribution because it not only has the highest p-value (0.2491 vs. 0.0973) but also a lower Chi-Square statistic (7.85 vs. 10.72), indicating a better alignment with the observed data.

Table1: The goodness-of-fit test.

DISTRIBUTION	CHI-SQUARE STATISTIC	P-VALUE
NORMAL	15.47498423	0.016867286
EXPONENTIAL	7.852142786	0.249137119
POISSON	230.7575929	5.28E-47
WEIBULL	10.72376485	0.097298298

The exponential distribution with most inter- arrival times clustered between 15-45 minutes.

The exponential distribution ($f(t) = \lambda e^{-\lambda t}$) provided the best fit with λ = 0.25 / minutes indicating a mean inter-arrival time of 1/ λ=*40* minutes. Also, the p value and chi-square value confirmed a good fit.

Estimation of EA Market Penetration Rate

The market penetration rate (PPP) for EA was calculated as:

$$P = \frac{Number\ of\ EA\ Flights}{Total\ Flight} \times 100$$

EA adoption rate was assumed to follow a gradual growth trend (e.g., 5% of flights in 2024). The adoption rate was projected based on annual growth rates derived from industry reports.

Observed Flights: A total of 500 flights were analyzed during the week.

EA Flights: 25 flights were identified as EA operations.

$$P = \frac{25}{500} \times 100 = 5\%$$

Projected Growth:

Based on industry trends, the EA adoption rate is expected to grow at 15% annually, reaching approximately 25% by 2030.

Real-World Implications

The EA market's rapid growth necessitates significant investments in airport infrastructure. For instance, Washington state airports are applying for federal grants to install electric aircraft chargers. The Federal Aviation Admn (FAA) has also allocated $20.4 million for zero-emission airport vehicles and charging systems, signaling a nationwide push towards sustainable aviation infrastructure. Despite this progress, concerns reading whether charging infrastructure can keep pace with the accelerating development of EA and air taxi technologies.

3.6 Task 6 (Tajwar Al Mamun)

TASK 6: JBSS modelling based on EA arrival data (Tajwar Al Mamun- ID 31)

Introduction

This analysis evaluates the performance of a **Joint Battery Swapping and Charging Station (JBSS)** for Electric Aircraft (EA) using queuing theory. The JBSS consists of two main systems: **Battery Swapping System** and **Mega charging System**, modeled to optimize service efficiency, reduce waiting times, and manage energy demand.

Flow Chart Summary

- **Arrival Process**:

  - EAs arrive at the station at an average rate (λ) of **5.83 EAs per hour** during an operational period of **5.145 hours** (approximately **30 EAs per day).**
- **Service Flow**:
  - Upon arrival, the EA first attempts to use the **Battery Swapping System.**
  - If swapping servers are busy or no spare batteries are available, the EA proceeds to the **Mega charging System.**
  - In the **Mega charging System**, EAs wait if all chargers are busy until a charger becomes available.

Battery Swapping System

- **Key Parameters**:
  - **Number of Swapping Servers (s)**: 3.
  - **Spare Batteries**: 15, with 33% reusable, adding 5 batteries during operations.
  - **Swapping Service Time (t_{swap})**: **15 minutes (0.25 hours)** per EA.
- **Service Model**:
  - **M/M/1 Queuing Model** used for the swapping system.
  - No waiting is allowed; EAs proceed to megacharging if swapping resources are unavailable.

Mega charging system:

- **Key Parameters**:
  - **Number of Megachargers (m):** 3 chargers.
  - **Service Rate (μ)**: 2 EAs/hour per charger.

- **Charger Power**: 250 kW per charger, 100% efficiency.
- **Queue Handling**: Waiting is allowed if chargers are busy.

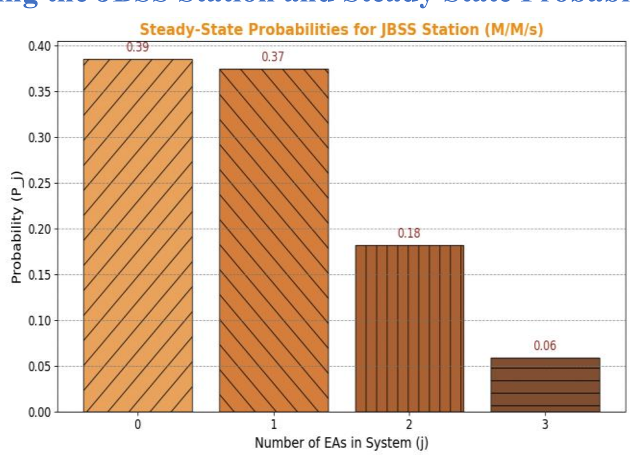
- **Service Model**:
  - **M/M/3 Queuing Model** applied to handle megacharger operations.

Operational Parameters

- **Total Arrival Rate (λ_{total})**: 5.83 EAs/hour over a **5.145-hour operational period.**
- **Service Efficiency**:
  - **Swapping Efficiency**: Battery swapping is faster, with no queuing.
  - **Megacharging Efficiency**: Queue waiting times depend on the number of chargers.
- **Energy Demand**:
  - **Average Charger Power**: 250 kW per charger.
  - **Annual Energy Use**: Scales with charger utilization and system efficiency

.

Question 1: Modelling the JBSS Station and Steady State Probabilities



The graph illustrates the **steady-state probabilities** (P_j) for the JBSS station modeled as an **M/M/s** queueing system with the following assumptions:

Model Description

1. **Queue Type**:
   - The system is modeled as **M/M/s**, meaning:
     - M: Poisson arrival process (λ).
     - M: Exponentially distributed service times (μ).
     - s: Multiple servers (e.g., megachargers).
2. **Key Parameters**:
   - Arrival rate (λ) = **5.83 EAs/hour**.
   - Service rate (μ) = **2 EAs/hour per charger**.
   - Number of servers (s) = **3 chargers**.
3. **Steady-State Probabilities (P_j)**:
   - P_j represents the probability of j EAs being in the system, including both those being serviced and those waiting in the queue.

Analysis of the Graph

The graph shows the steady-state probabilities for j=0 to j=3, calculated using: ρ^j

$$P_0 = \left(\sum_{j=0}^{s} \frac{\rho^j}{j!} + \frac{\rho^s}{s!} \cdot \frac{1}{1-\frac{\rho}{s}}\right)^{-1}$$

$$P_j = P_0 \cdot \frac{\rho^j}{j!} \quad \text{For } j \leq s$$

1. **State j=0**:
   - Probability = **0.39 (39%).**
   - The system is idle (no EAs in the station) almost 40% of the time.
2. **State j=1**:
   - Probability = **0.37 (37%).**
   - The system has **1 EA**, typically being serviced. This is the second most likely state.
3. **State j=2**:
   - Probability = **0.18 (18%).**
   - Both servers are busy with **2 EAs**.
4. **State j=3**:
   - Probability = **0.06 (6%).**
   - All servers are busy, and **3 EAs** are in the system, indicating occasional queuing or maximum system capacity.

Question 2: Expected Waiting Time for Each EA in the Swapping System Queue

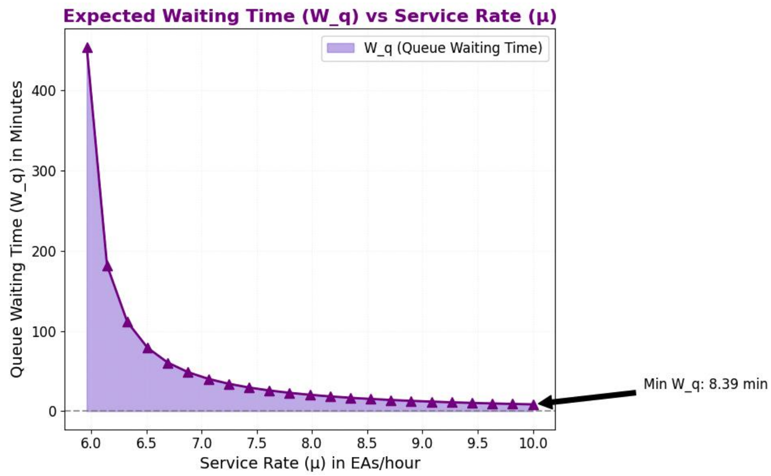
Key Formula:

$$W_q = \frac{\rho}{\mu(1-\rho)}$$

Where: $\rho = \frac{\lambda}{\mu}$ is the utilization factor

$$\lambda = 5.83 EAs/hour \text{ is the arrival rate}$$

μ is the service rate in EAs/hour



Question 3: Average Waiting Time in the Megacharger Section

Traffic intensity (ρ):

$$\rho_{mega} = \frac{\lambda_{mega}}{m * \mu_{mega}}$$

$$= 0.5\ EAs/hour$$

$$P_{wait} = \frac{\frac{(m\,\rho_{mega})^m}{m!(1-\rho_{mega})}}{\sum_{n=0}^{m-1}\frac{(m\,\rho_{mega})^m}{n!} + \frac{(m*\rho_{mega})^m}{m!(1-\rho_{mega})}}$$

=0.06

Average Waiting Time in Megacharger Section

- Average Number in Queue (Lq): $L_q = P_{wait} \frac{\rho_{mega}}{1-\rho_{mega}}$

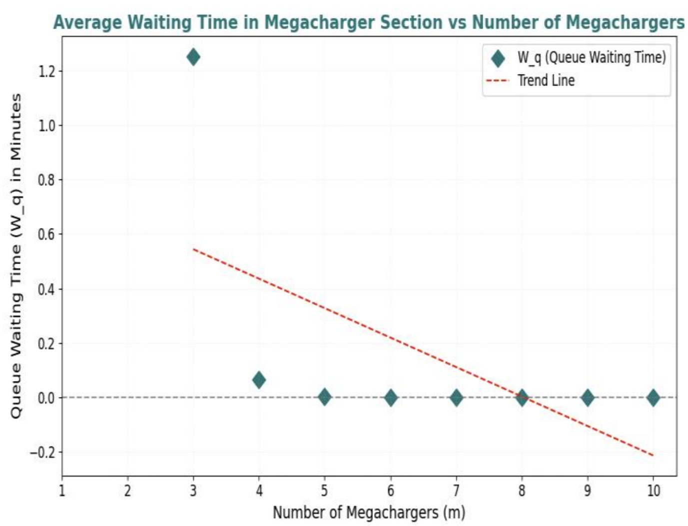
$$= 0.07\ EAs$$

- Average Waiting Time (Wq): $W_q = \frac{L_q}{\lambda_{mega}}$

$$= 0.03\ hour$$

$$= 1.82\ min$$

Answer: The average waiting time in the Megacharger section is approximately 1.82 minutes.

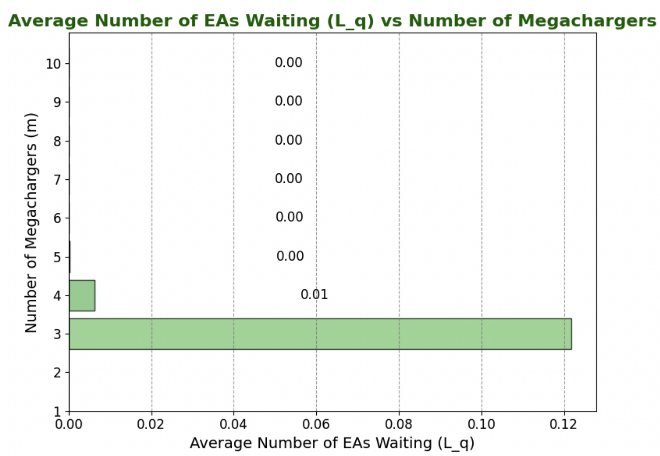


Question 4: Average Number of EA Waiting in the Mega charger Section

$$L_q = P_{wait} \frac{\rho_{mega}}{1-\rho_{mega}}$$

$$= 0.07 \ EAs$$

Answer: On average, approximately **0.07 EAs** are waiting in the Mega charger section.



Question 5: Average Number of EA in the swapping station

We can calculate the average number of EAs in the swapping station (Lswap) using the steady state probabilities:

$$L_{swap} = \sum_{J=0}^{S} J * \pi_J$$

$$= 0.91 \ EAs$$

Question 6: Steady State Service Time from EA Entry to Exit in the JBSS station.

$$P_{swap} = \frac{EAs\ swapped\ successfully}{Total\ EAs}$$

$$= \frac{20(\,1 - \mathrm{P}_{Block})}{30}$$

$$= 0.63$$

$$P_{mega} = 1 - P_{swap}$$

$$= 0.37$$

- Calculating Expected Service Times:

$$W_{swap} = t_{swap} = 0.25\ hours$$

$$W_{mega} = W_q + t_{mega}$$

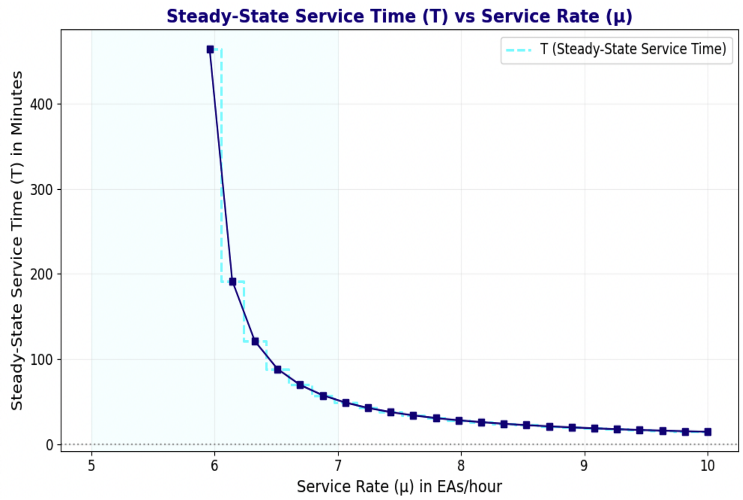
$$= 0.03 + 1$$

$$= 1.03\ hours$$

- Overall Expected Service Time:

$$W_{Total} \quad = W_{swap} * P_{swap} + W_{mega} = 0.54\ hours$$

$$= 32.45\ min$$



Question 7: Average Electric Power Demand and Annual Energy Use

Total Energy Consumption and Power Demand

Battery Swapping System

- EAs Swapped per Day:

$$EAs_{swapped} = 20\ x\ (1 - \ P_{block})$$

$$= 18.82\ EAs/day$$

- Energy required:

$$E_{swap} = \ EAs_{swapped} * Battery\ capacity$$

$$= 18.82 * 900\ kWh = 16939.8\ kWh\ /day$$

- Power demand:

$$P_{swap} = \frac{Energy\ required}{Time\ taken\ to\ charge\ all\ battery}$$

$$= \frac{17000}{5.145}$$

$$= 3304.17\ kW$$

Mega charging System

- EAs charged per Day:

$$EAs_{mega} = 11.18\ EAs/day$$

- Energy required:

$$E_{mega} = EAs_{mega} * Battery\ capacity$$

$$= 11.178 * 900\ kWh$$

$$= 10060.2\ kWh\ /day$$

- Power demand:

$$P_{mega} = No. of\ cahrger * Charger\ power$$

$$= 4 * 1000$$

$$= 4000\ kW$$

Total Energy Consumption and Power Demand

- Daily energy consumption:

$$E_{total_{daily}} = E_{swap_{input}} + E_{mega_{input}}$$

$$= 16939.8 + 10060.2$$

$$= 27000\ kWh/day$$

- Annual energy consumption:

$$E_{total_{annual}} = E_{total_{daily}} * 365$$

$$= 98{,}55{,}000\ kWh\ per\ year$$

$$= 9.85\ GWh\ per\ year$$

- Power demand

$$P_{total} = P_{swap} + P_{mega}$$

$$= 3304 + 4000$$

$$= 6304\ kW$$

Observations:

- Swapping batteries offer faster service compared to megacharging.
- Higher service rates (μ) or increasing the number of servers (m) drastically improve performance metrics.
- The utilization factor decreases as the number of chargers increases, offsets the increase in power demand due to more chargers.
- Optimization Trade-offs between the number of servers, spare batteries, and energy consumption must be maintained for the JBSS system's performance

3.7 Task 7 (Ahsanul Abedin)

Task 7: Achieving Net-Zero Energy Operation for JBSS Infrastructure

This task focuses on achieving a net-zero energy operation for the Joint Battery Swapping and Supercharging (JBSS) infrastructure at airports. By integrating renewable energy sources like Wind Turbines (WT) and Photovoltaic (PV) systems, alongside a Distributed Energy Storage System (DESS), the energy demand of 9.85 GWh/year is met sustainably. Excess energy is either stored or exported to the grid, while deficits are covered by storage or grid imports, ensuring a net-zero energy balance.

Table1: Energy Demand Analysis

Daily Energy Consumption	Annual Energy Consumption	Power Demand:
27,000kWh/day.	9.85GWh/year.	6,304kW.

Renewable Energy Generation

To achieve the net-zero target, WT and PV systems were modeled to generate sufficient energy to meet the annual demand of 9.85 GWh, Wind Turbine System required 5 turbines, each with a capacity of 2 MW, generating 8.7 GWh/year modeled using Weibull-distributed wind speeds and WT power curves. The Photovoltaic System requirement would be a 5 MW PV system, generating 3.7 GWh/year modeled based on solar irradiance data with a system efficiency of 20%. This exceeds the demand by 12.4−9.85=2.55 GWh/year, ensuring surplus energy can be exported or stored in Distributed Energy Storage System (DESS). The storage requirements would be DESS capacity of10 MWh with an Efficiency of 90%.

Table2: Energy generation and sizing of WT, PV and DESS

	WTs	PVs	Surplus
Energy Generation	8.7GWh/year	3.7GWh/year	2.55 GWh/year. Energy Storage (DESS) of 10 MWh
Sizing	5 turbines, each with a capacity of 2 MW	5 MW PV system with 10,000m^2 area per PV	

3.8 Task 8 (Borhan Uddin Chowdhury)

Task 8: Economic Analysis of Net-Zero EA Battery Swap and Mega Charging Infrastructure

Problem Statement:

The financial viability of EA infrastructure is evaluated by analyzing one-time investment and recurring operational costs.

Investment Costs:

1. **Components and Costs**:
    - **Wind Turbines**: $3.75 million (5 units at $1.5 million/unit).
    - **Solar Photovoltaic Systems**: $23.4 million (15,600 kW at $1,500/kW).
    - **Battery Systems**:
        - Operational Batteries: $22.26 million (63,600 kW at $350/kW).
        - Spare Batteries: $10 million (50 MWh at $0.2 million/MWh).
    - **Mega Chargers**: $3.5 million (5 units at $0.7 million/unit).

- **Facility Setup**: $10 million.

2. **Total One-Time Cost**:
    - $73 million.

Operational Costs:

1. **Annual Operating Costs**:
    - Labor: $0.3 million.
    - Maintenance:
        - Wind Turbines: $0.0075 million.
        - Solar PV Systems: $0.0468 million.
        - Battery Storage Systems: $0.5 million.
        - Mega Chargers: $0.015 million.
2. **Total Annual Cost**:
    - $3.1 million.

Conclusion:

The economic analysis confirms the financial feasibility of EA infrastructure. By leveraging renewable energy, advanced technologies, and optimized management strategies, the system achieves a balance between initial investment and sustainable operation, aligning with global carbon-neutrality goals.

Section 4. Conclusion and Future Works

Conclusion

This project demonstrates the feasibility of achieving net-zero energy operations for Electric Aircraft (EA) infrastructure through the integration of Wind Turbines (WT), Photovoltaic (PV) systems, and Distributed Energy Storage Systems (DESS) in Joint Battery Swapping and Supercharging (JBSS) stations. A hybrid microgrid design with 5 wind turbines (2 MW each), a 5 MW PV system, and a 10 MWh DESS effectively meets the annual energy demand of 9.85 GWh while balancing energy surpluses and deficits. Statistical analyses validated the modeling of EA inter-arrival times, and the system design minimizes dependency on fossil fuels, reduces emissions, and enhances cost-efficiency, aligning with global carbon-neutrality goals.

Future Works

Future efforts should focus on dynamic energy management using real-time forecasting and machine learning, scalability for larger EA fleets, and integrating emerging technologies like hydrogen fuel cells. Economic analyses, environmental impact assessments, and policy frameworks should be expanded to support broader adoption of renewable aviation infrastructure. These advancements will further enhance the reliability, scalability, and sustainability of net-zero energy systems.

Section 5: Reference

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