### SUMMER TRAINING REPORT

on

**“Predictive Model for SoC Estimation & Generator Runtime ”**

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### Project Report

UNDER THE GUIDANCE of

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# Abstract

# This report outlines the development of a predictive model for the Smart Hybrid System, designed to optimize energy management in remote, grid-inaccessible areas. Implemented in Python, the model integrates solar photovoltaic panels, a diesel generator, and a lithium-ion battery storage system to ensure reliable, cost-effective, and sustainable power delivery. The model employs four key approaches: a Kalman Filter, an Energy Balance Method, Threshold-Based Logic, and Predictive Analytics. These approaches facilitate four critical calculations time until solar availability, required state of charge to sustain load, generator runtime, and fuel consumption enabling prioritized renewable energy use and state of charge maintenance within 25-85%. A Python-based simulation script was developed to model system behavior, incorporating real-world parameters and dynamic load profiles with peak loads and random noise for realism. The script processes timestamped data at 1-minute intervals, calculating state of charge changes, generator fuel consumption, and power allocation logic to optimize energy distribution. Additionally, synthetic datasets were generated at 5-second intervals to simulate diverse load profiles with optional solar generation, enabling robust testing of the model’s scalability and adaptability.

# The predictive model was rigorously tested using synthetic data simulating 24 hours at 5- second intervals, derived from real-world parameters, and validated against real data to ensure practical applicability. The testing phase confirmed accurate state of charge tracking, minimal generator runtime, and a renewable fraction comparable to literature benchmarks. The model’s architecture, including data preprocessing, simulation design, and visualization, was developed to handle variable load profiles and fluctuating solar output, ensuring scalability for diverse off-grid scenarios. This report provides a comprehensive guide to the model’s development, detailing its algorithmic framework, testing methodology, and performance outcomes, positioning it as an innovative solution for sustainable off-grid energy management.

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# Chapter 1: Introduction

## Project Overview

The Smart Hybrid System addresses the critical need for reliable electricity in remote areas where grid infrastructure is unavailable or impractical. By combining 9 solar Photovoltaic panel, a 10 kW variable-speed diesel generator, and a 96V, 18kWh battery storage system, Smart Hybrid System delivers a robust, sustainable power solution. The system 25%, ensuring renewable energy utilization and system reliability.

Active State: When state of charge(SOC) falls below 25%, solar Photovoltaic is prioritized if available; otherwise, the DG activates to meet the load and charge the battery.

Developed in Python, the predictive model processes timestamped load and weather data to make real-time decisions. The model was tested with synthetic data simulating realistic conditions .

Project Scope

The scope encompasses the design, implementation, and testing of a hybrid energy system, focusing on:

* System Components: Solar Photovoltaic (4.32 kW), battery (18 kWh, 96 V), DG (10 kW).
* Algorithm Development: Python-based model with Kalman Filter, Energy Balance,

Threshold Logic, and Predictive Analytics.

* Testing and Validation: Synthetic data (24 hours, 5-second intervals) and real data (peak

load 8.36 kW, average 1.879 kW).

## Problem Statement

Access to reliable electricity remains a significant challenge in remote areas, where grid connectivity is either unavailable or economically unfeasible. Over 700 million people globally, particularly in rural regions of developing countries, rely on costly and environmentally harmful diesel generators for power . These generators incur high fuel costs, require complex logistics for refueling, and contribute significantly to CO2 emissions, exacerbating climate change. For instance, a typical 10kW diesel generator can consume 2-3 liters of fuel per hour, emitting approximately 2.7kg of CO2 per liter , leading to substantial environmental and economic burdens.

Renewable energy sources like solar Photovoltaic offer a sustainable alternative but face challenges due to their intermittent nature, driven by weather variability and diurnal cycles. This necessitates robust energy storage systems to store excess energy and backup systems to ensure reliability during low renewable generation. However, existing hybrid systems often lack intelligent control strategies to efficiently balance renewable and non-renewable sources, leading to suboptimal performance, such as excessive generator runtime, high fuel consumption, or battery degradation due to improper SoC management.

Smart Hybrid System addresses these challenges by developing a smart algorithm that integrates solar Photovoltaic, battery storage, and a diesel generator to:

1. Optimize Renewable Utilization: Prioritize solar energy to minimize DG operation, reducing fuel costs and emissions.
2. Ensure Reliability: Use the battery as a stabilizer to bridge energy gaps, maintaining continuous power supply.
3. Enhance Efficiency: Minimize generator runtime through precise SoC estimation and dynamic decision-making.
4. Incorporate Weather Forecasts: Adapt to varying solar availability using predictive analytics, improving planning and resource allocation.

The system tackles technical challenges, such as noisy SoC measurements, variable load profiles , and fluctuating solar output (0-4.32 kW), while aligning with sustainability goals.

# Chapter 2: Review of Literature

Hybrid energy systems combining renewable sources with conventional diesel generators and battery storage are critical for reliable power delivery in off-grid regions [1]. However, challenges such as solar intermittency, battery lifespan, and fuel costs necessitate advanced energy management strategies (EMS) [2]. This paper proposes a predictive model for a Smart Hybrid System, integrating a 4.32 kW solar array, an 18.5 kW diesel generator, and a 96V 200Ah lithium-ion battery. The model uses a Kalman Filter for SOC estimation, an Energy Balance Method for power allocation, Threshold-Based Logic for generator control, and Predictive Analytics for forecasting energy needs. The system is simulated over 24 hours and tested with synthetic datasets to ensure scalability and efficiency.

## Optimisation of battery-integrated diesel generator hybrid systems using an ON/OFF operating strategy

## Key idea: ON/OFF control strategies reduce fuel consumption by running diesel generators only when battery SOC drops below a set threshold . The SHOGES system applies this logic in containerized setups with LFP batteries, ensuring reliable backup during low solar periods.

## Impact: Reduces fuel consumption and prioritizes renewable energy usage.

## Reference System: SHOGES (Smart Hybrid Off-Grid Energy System) applies similar ON/OFF logic in containerized diesel generator setups with LFP batteries.

## Outcome: Reliable backup during low solar periods.

## 2.2 Modeling and Optimization of Hybrid Solar-Diesel-Battery Power System

## Key idea: Hybrid system modeling in MATLAB/Simulink helps optimize power flow and renewable share. SHOGES uses a 4.8 kWp solar array with MPPT chargers in an IP55-protected container design, supporting efficient and scalable energy integration.

## Our Approach: Generates realistic load and solar profiles for validation.

## Reference System: SHOGES models a 4.8 kWp solar array with mono-crystalline panels (540 Wp each) and MPPT chargers.

## Design Feature: Container-based design ensures IP55 protection and modular scalability.

## 2.3 Optimal Fuel Consumption Planning and Energy Management Strategy (EMS)

## Goal: Minimize fuel use by prioritizing renewable energy.

## Our Model: Calculates generator runtime and fuel consumption comparable to literature benchmarks.

## Reference System:

## SHOGES fuel planning for 10 kVA DG with 75 L tank.

## 24-hour test results: 52.46 kWh from DG and 19.33 kWh from solar.

## Benefit: Optimized consumption and improved efficiency.

## 2.4 Management and Control of Hybrid Power System

## 1. Advanced Controls: Fuzzy Logic, Model Predictive Control (MPC) for improved reliability.

## 2. Our Implementation: Threshold-Based Logic + Predictive Analytics for dynamic power allocation.

## 3. Reference System: SHOGES IPMS controller with:

## a. Voltage, current, SOC, and humidity monitoring.

## b.7” touch HMI for diagnostics and event logging.

## 4. Extended Approach: Multi-Agent Systems (MAS) to manage photovoltaic, fuel cell, and ultra-capacitor components, ensuring balanced storage and hydrogen tank usage.

## 2.5 Effective Battery Usage Strategies

## Objective: Optimize SOC and extend battery life.

## Our Model: Maintains SOC between 25-85% using Kalman Filter for accurate estimation.

## Reference System: SHOGES 96V 200Ah LFP battery with BMS, safe discharge up to 300A peak.

## Performance: In 24-hour tests, SOC variations (31%-37%) balanced load and storage.

## Enhancement: MAS integration with ultra-capacitors for transient power regulation, improving resilience.

# Chapter 3: Methodology

Smart Hybrid System model employs key approaches, inspired by the literature, to achieve its objectives. Each approach is detailed below, including its rationale, benefits, implementation, and connection to the calculations.

## 3.1 Data Creation for 24-Hour Simulation:

Data creation for a 24-hour simulation refers to the process of generating time-series datasets that represent system variables (such as load demand, solar generation, and battery State of Charge) over a continuous 24-hour period. These datasets can be derived from measured data, statistical modeling, or synthetic generation to replicate real-world operating conditions for testing and validating hybrid energy system models.

**Benefits**

* Realistic Performance Testing: Provides accurate operational scenarios without relying solely on field measurements.
* Scenario Customization: Allows modeling of diverse weather, load, and SOC conditions.
* Time & Cost Savings: Reduces the need for prolonged on-site data collection.
* Algorithm Validation: Improves robustness of control strategies like ON/OFF logic and EMS.

**Implementation**

* Two dataset generation methods were developed:
  1. Pattern-Based Method: Uses statistical profiles from historical solar and load data.
  2. Randomized Variation Method: Introduces controlled fluctuations to simulate unpredictable conditions.
* Scripts created:
  1. data\_creation.py - Generates structured 24-hour datasets.
  2. data\_testing.py - Validates range limits, timestamp continuity, and operational constraints.

**Literature Support**

* [3] and [16] highlight the necessity of accurate 24-hour profiles for simulation-based optimization of hybrid systems.
* SHOGES project evaluations employ similar dataset creation techniques for off-grid hybrid energy system testing.
* As discussed in [6], simulation datasets improve the reliability of energy management strategies before deployment.

## Relevance to Calculation

## Serves as direct input to MATLAB/Simulink for performance simulations.

## Enables calculation of generator runtime, fuel consumption, and renewable fraction.

## Supports SOC-based threshold logic validation by generating realistic SOC variation patterns.

## Facilitates energy balance analysis across solar, diesel, and battery components.

## 3.2 Multiple Dataset Generation Approaches:

Multiple dataset generation refers to creating different synthetic or semi-synthetic datasets to model real-world operational conditions for hybrid power systems. This enables robust testing of energy management strategies (EMS) under varied scenarios without depending solely on limited real measurements.

**Benefits**

* Improved Model Robustness - Testing across diverse datasets ensures the EMS can handle both typical and extreme conditions.
* Scenario Flexibility - Allows simulation of seasonal, climatic, or load pattern variations without expensive field trials.
* Risk Reduction - Identifies performance bottlenecks before real deployment.
* Data Availability - Overcomes the problem of insufficient historical data, which is common in remote or new installations.

**Implementation**

1. Method 1 - Statistical Pattern-Based Generation
   * Uses historical energy consumption and weather data to extract mean, variance, peak hours, and seasonal patterns.
   * Generates load and solar profiles that closely resemble real-world averages.
   * Tools: Python (Pandas, NumPy), MATLAB, or Simulink.
2. Method 2 - Randomized Constraint-Based Generation
   * Introduces controlled randomness within operational limits (e.g., max/min load, solar irradiance bounds).
   * Simulates unpredictable events like sudden load spikes or cloudy weather.
   * Enhances stress-testing of EMS algorithms.

**Literature Support**

* [3] El-Bannai et al. (2022) demonstrate that realistic synthetic load profiles significantly improve optimization accuracy in hybrid solar-diesel models.
* [6] Hasanien et al. (2025) highlight the importance of testing EMS under stochastic weather conditions to reduce fuel use.
* [16] Ashour et al. (2016) validate 24-hour hybrid system simulations using both measured and synthetic datasets for rural electrification projects.

**Relevance to Calculation**

* Energy Balance Calculations - Accurate datasets are essential for computing generator runtime, solar fraction, and battery SOC changes.
* Fuel Consumption Estimation - Diverse datasets reveal how EMS reacts to different demand-supply scenarios, influencing diesel usage predictions.
* Performance Benchmarking - Enables comparison between baseline operation and optimized control strategies under multiple test conditions.

**3.3 Data Creation Script (data\_creation.py):**

A Python script, data\_creation.py, was developed to automate dataset generation. The script integrates load, solar, and SOC parameters, applies variability patterns, and saves datasets in a structured format for use in simulation models.

**Benefits**

* Automation – Eliminates manual dataset preparation, saving time and reducing human error.
* Consistency – Ensures all datasets follow the same structure, making simulation results comparable.
* Scalability – Can quickly generate multiple datasets for different test cases or weather conditions.
* Flexibility – Supports modifications in variability patterns, load ranges, and solar profiles without rewriting code.

**Implementation**

* Written in Python using libraries like *NumPy*, *Pandas*, and *Random*.
* Integrates load demand, solar generation, and SOC (State of Charge) values into a unified dataset.
* Applies variability patterns to simulate realistic fluctuations in load and solar inputs.
* Saves generated datasets in a structured format (CSV/Excel) for direct input into hybrid power system simulation models.

**Literature Support**

* [3] El-Bannai et al. (2022) emphasize the role of realistic input profiles in improving the accuracy of hybrid energy system optimization.
* [6] Hasanien et al. (2025) show that stochastic solar and load data enhance the testing of EMS strategies for fuel efficiency.
* [16] Ashour et al. (2016) validate hybrid system performance using both measured and synthetic 24-hour datasets in off-grid studies.

**Relevance to Calculations**

* Provides base input data for calculating generator runtime, solar utilization, battery SOC changes, and fuel consumption.
* Enables scenario testing (e.g., cloudy day vs. sunny day) to compare system performance across conditions.
* Ensures repeatability of results in sensitivity analysis, making comparisons across EMS strategies more accurate.

**3.4 Data Testing Script (data\_testing.py):**

The data\_testing.py script was created to validate generated datasets. It checks parameter ranges, ensures timestamp continuity, and verifies that generated values meet the operational constraints of the hybrid system model.

**Benefits**

* Quality Assurance – Ensures all generated datasets meet operational constraints before use in simulations.
* Error Detection – Identifies missing timestamps, unrealistic load/solar values, or SOC out-of-bounds conditions.
* Reliability – Prevents inaccurate input data from skewing simulation results.
* Time Savings – Automates validation that would otherwise require manual checking.

**Implementation**

* Developed in Python using libraries like *Pandas* and *NumPy* for data handling and numerical checks.
* Verifies:
  + Parameter ranges (e.g., SOC 0–100%, load > 0, solar irradiance within realistic limits).
  + Timestamp continuity for 24-hour datasets.
  + Operational constraints defined by the hybrid system model.
* Outputs a pass/fail log or report highlighting issues for correction.

**Literature Support**

* [3] El-Bannai et al. (2022) stress that input data validation is critical for accurate hybrid energy system modeling.
* [6] Hasanien et al. (2025) highlight the importance of verifying solar and load datasets to ensure credible EMS performance testing.
* [16] Ashour et al. (2016) used dataset validation procedures to maintain reliability in off-grid hybrid system simulations.

**Relevance to Calculation**

* Ensures energy balance calculations use correct and continuous input values.
* Avoids fuel consumption miscalculations caused by erroneous solar or load data.
* Maintains SOC trajectory accuracy, preventing unrealistic charging/discharging cycles in the model.
* Supports repeatable and trustworthy simulation outcomes by ensuring clean, validated data feeds into the computation process.

**3.5 Functions Used in Model (Data Creation & Testing)**

In this hybrid power system project, functions in the data creation script are responsible for synthesizing realistic 24-hour datasets of load demand, solar generation, and battery State of Charge (SOC) using deterministic and stochastic methods. These datasets serve as the primary input for model simulations.

Functions in the data testing script ensure the accuracy, continuity, and reliability of the generated datasets. This validation process prevents erroneous data from propagating into energy balance calculations, fuel consumption estimations, or SOC tracking, thereby safeguarding the credibility of simulation outcomes.

**From data\_creation.py**

1. **load() – Generates the 24-hour load profile based on defined demand patterns and random variability.**
2. **solar() – Creates the 24-hour solar generation profile considering sunlight hours and irradiance variations.**
3. **soc() – Estimates the State of Charge (SOC) progression for the battery throughout the simulation period.**
4. **data() – Combines load, solar, and SOC into a structured dataset ready for simulation.**
5. **variability() – Adds controlled randomness to load and solar values to mimic realistic day-to-day changes.**

**From data\_testing.py**

1. **data\_testing()** – Validates generated datasets by checking operational ranges, time continuity, and outliers.
2. **check\_range()** – Ensures SOC, load, and solar values remain within acceptable thresholds.
3. **check\_continuity()** – Confirms that the dataset covers all required timestamps without gaps.
4. **outlier\_detection()** – Flags unrealistic values using statistical deviation methods.
5. **report()** – Outputs a summary of dataset quality checks for logging and corrections.

**3.6 Tools and Libraries Used**

1. **Python** – Primary programming language for dataset generation and testing workflows.
2. **Pandas** – Used for creating, organizing, and storing load, solar, and SOC data in structured formats.
3. **NumPy** – Performs numerical calculations, random variability generation, and array operations.
4. **Random** – Introduces controlled stochastic variations in load and solar profiles to simulate real-world fluctuations.
5. **Matplotlib** – Plots load, solar, and SOC curves for dataset visualization and validation checks.

**3.7 Model Flow**

1. **Initialize Parameters**

* Define simulation duration (24 hours), time resolution, and input constants for load, solar generation, and battery SOC limits.

1. **Generate Synthetic Profiles**

* Use generate\_load\_profile() to produce realistic hourly/half-hourly load demand values.
* Use generate\_solar\_profile() to simulate solar generation considering daylight hours and random weather effects.

1. **Calculate SOC**

* Apply calculate\_SOC() to track battery charge/discharge over the simulation period based on load–generation balance.

1. **Combine into Dataset**

* Merge load, solar, and SOC data into a unified Pandas DataFrame using create\_dataset().

1. **Run Validation Checks**

* Execute validate\_dataset() and detect\_outliers() to ensure data quality, consistency, and plausibility.

1. **Generate Reports & Visualizations**

* Save cleaned datasets in CSV format for further simulation.
* Use Matplotlib to plot graphs of load, solar, and SOC trends for verification.

**3.8 Model Architecture:**

## The Data Creation and Testing model consists of the following main components:

## Input Layer

## Simulation parameters: time duration (24 hours), time step, battery limits, load range, and solar capacity.

## External variability inputs: random weather fluctuations and load variations.

## Data Generation Module

## generate\_load\_profile() creates realistic load patterns using statistical and random variation methods.

## generate\_solar\_profile() models solar generation considering daylight hours and stochastic weather conditions.

## SOC Calculation Module

## calculate\_SOC() determines battery charge/discharge levels over time based on the net energy balance.

## Dataset Integration Module

## Combines load, solar, and SOC values into a single structured Pandas DataFrame.

## Validation & Testing Module

## Functions like validate\_dataset() and detect\_outliers() ensure dataset accuracy and plausibility.

## data\_testing.py uses generated datasets to verify model performance and output reliability.

## Output Layer

## Cleaned datasets saved in CSV format.

## Visualizations generated using Matplotlib for quick review of trends and anomalies.

## 3.9 Model For Data creation

## import pandas as pd

## import numpy as np

## from datetime import datetime, timedelta

## # Parameters

## START\_DATE = "2025-07-09"

## TIME\_INTERVAL\_SECONDS = 5 # 5-second intervals

## HOURS\_PER\_DAY = 24

## POINTS\_PER\_DAY = int(HOURS\_PER\_DAY \* 3600 / TIME\_INTERVAL\_SECONDS) # 17,280 points

## SOLAR\_MAX\_OUTPUT = 4.32 # kW (optional, set to 0 for no solar)

## # Define load profile variations with hourly base and peak values

## LOAD\_PROFILES = [

## {

## "name": "morning\_peak",

## "hourly\_loads": {0: 4.5, 3: 2.0, 6: 2.0, 12: 2.0, 18: 2.0, 23: 2.0}, # Morning peak at 00:00-03:00

## "noise\_std": 0.5, # kW

## "solar\_active": False

## },

## {

## "name": "evening\_peak",

## "hourly\_loads": {0: 2.5, 6: 2.5, 12: 2.5, 18: 5.0, 22: 2.5, 23: 2.5}, # Evening peak at 18:00-22:00

## "noise\_std": 0.3, # kW

## "solar\_active": False

## },

## {

## "name": "midday\_peak\_with\_solar",

## "hourly\_loads": {0: 1.8, 6: 1.8, 12: 6.0, 14: 1.8, 18: 1.8, 23: 1.8}, # Midday peak at 12:00-14:00

## "noise\_std": 0.4, # kW

## "solar\_active": True

## }

## ]

## def generate\_time\_stamps(start\_date, points):

## start\_time = pd.to\_datetime(start\_date)

## time\_stamps = [start\_time + timedelta(seconds=i \* TIME\_INTERVAL\_SECONDS) for i in range(points)]

## return time\_stamps

## def generate\_solar\_profile(hours, solar\_active):

## if not solar\_active:

## return np.zeros(len(hours))

## # Define hourly solar output (0 kW outside 06:00-18:00, peak at noon)

## hourly\_solar = {0: 0, 6: 0, 9: 2.0, 12: SOLAR\_MAX\_OUTPUT, 15: 2.0, 18: 0, 23: 0}

## # Interpolate to 5-second intervals

## hour\_points = np.array(list(hourly\_solar.keys()))

## solar\_values = np.array(list(hourly\_solar.values()))

## solar = np.interp(hours, hour\_points, solar\_values)

## return np.maximum(solar, 0) # Ensure non-negative

## def generate\_load\_profile(hourly\_loads, noise\_std, points):

## hours = np.linspace(0, HOURS\_PER\_DAY, points)

## # Interpolate hourly load values to 5-second intervals

## hour\_points = np.array(list(hourly\_loads.keys()))

## load\_values = np.array(list(hourly\_loads.values()))

## load = np.interp(hours, hour\_points, load\_values)

## # Add random noise

## noise = np.random.normal(0, noise\_std, points)

## load = np.maximum(load + noise, 0.5) # Ensure load doesn't go below 0.5 kW

## return np.round(load, 3) # Round to 3 decimal places

## def generate\_dataset(profile, output\_file):

## time\_stamps = generate\_time\_stamps(START\_DATE, POINTS\_PER\_DAY)

## hours = np.linspace(0, HOURS\_PER\_DAY, POINTS\_PER\_DAY)

## solar\_power = generate\_solar\_profile(hours, profile["solar\_active"])

## load\_power = generate\_load\_profile(

## profile["hourly\_loads"],

## profile["noise\_std"],

## POINTS\_PER\_DAY

## )

## # Extract only time (HH:MM:SS) from timestamps

## time\_only = [ts.strftime('%H:%M:%S') for ts in time\_stamps]

## # Create Date column with START\_DATE in first row, empty (None) in others

## date\_column = [START\_DATE] + [None] \* (POINTS\_PER\_DAY - 1)

## # Create DataFrame

## data = {

## "Date": date\_column,

## "Time": time\_only,

## "Solar\_Generation\_kW": solar\_power,

## "Load\_kW": load\_power

## }

## df = pd.DataFrame(data)

## # Save to CSV with comma separator

## df.to\_csv(output\_file, index=False, sep=',', float\_format='%.3f')

## print(f"Generated dataset: {output\_file}")

## # Generate multiple datasets

## for i, profile in enumerate(LOAD\_PROFILES, 1):

## output\_file = f"testing\_data\_generated\_{i}.csv"

## generate\_dataset(profile, output\_file)

## Output:

## 

## Fig: testing\_data\_generated\_1

## 

## Fig:testing\_data\_generated\_2

## 

## Fig:testing\_data\_generated\_3

## 3.10 Model for dataset creation:

# import pandas as pd

# import matplotlib.pyplot as plt

# # Specify the path to your dataset

# file\_path = 'generated\_smart\_grid\_data.csv'

# # Load the dataset

# data = pd.read\_csv(file\_path)

# # Convert Timestamp to datetime for easier analysis

# data['Timestamp'] = pd.to\_datetime(data['Timestamp'], format='%H:%M:%S %d-%m-%Y')

# # Handle missing data (if any)

# data = data.fillna(method='ffill') # You can adjust the fill method or drop rows

# # Generator efficiency constant (liters per kWh generated by the generator)

# GENERATOR\_EFFICIENCY = 0.2

# # Calculate the runtime where Generator is on (status = 1)

# data['Generator On'] = data['Generator Status'] == 1

# # Calculate the time difference between consecutive timestamps (in minutes)

# data['Time Difference (min)'] = data['Timestamp'].diff().dt.total\_seconds() / 60

# # Calculate fuel consumption based on generator power and efficiency

# data['Fuel Consumption (liters)'] = data['Generator Power (kW)'] \* data['Time Difference (min)'] \* GENERATOR\_EFFICIENCY / 60

# # Calculate total generator runtime in minutes (only when the generator is on)

# total\_runtime\_minutes = data[data['Generator On']]['Time Difference (min)'].sum()

# # Convert total runtime from minutes to hours and minutes

# total\_runtime\_hours = total\_runtime\_minutes // 60

# total\_runtime\_remaining\_minutes = total\_runtime\_minutes % 60

# # Calculate total fuel consumption (sum of Fuel Consumption in liters)

# total\_fuel\_consumption = data['Fuel Consumption (liters)'].sum()

# # Output the total runtime and fuel consumption

# print(f"Total Generator Runtime: {int(total\_runtime\_hours)} hours and {int(total\_runtime\_remaining\_minutes)} minutes")

# print(f"Total Fuel Consumption: {total\_fuel\_consumption} liters")

# # Aggregating the data by date

# aggregated\_data = data.groupby(data['Timestamp'].dt.date).agg(

# total\_runtime\_minutes=('Time Difference (min)', 'sum'),

# total\_fuel\_consumption=('Fuel Consumption (liters)', 'sum')

# ).reset\_index()

# print("Aggregated Daily Data:")

# print(aggregated\_data.head())

# # Initialize the plot for visualizations - 4 separate plots stacked vertically

# fig, axs = plt.subplots(4, 1, figsize=(15, 18), sharex=True)

# # Plot 1: Battery SOC over time

# axs[0].plot(data['Timestamp'], data['Battery SOC (%)'], color='blue', label='Battery SOC (%) - Dots')

# axs[0].set\_title('Battery SOC Over Time')

# axs[0].set\_ylabel('Battery SOC (%)')

# axs[0].legend(loc='upper right')

# # Plot 2: Generator Power over time (separate graph)

# axs[1].plot(data['Timestamp'], data['Generator Power (kW)'], color='green', label='Generator Power (kW)')

# axs[1].set\_title('Generator Power Over Time')

# axs[1].set\_ylabel('Generator Power (kW)')

# axs[1].legend(loc='upper right')

# # Plot 3: Solar Generation over time (separate graph)

# axs[2].plot(data['Timestamp'], data['Solar Generated (kW)'], color='orange', label='Solar Power (kW)')

# axs[2].set\_title('Solar Power Generation Over Time')

# axs[2].set\_ylabel('Solar Power (kW)')

# axs[2].legend(loc='upper right')

# # Plot 4: Load over time (separate graph)

# axs[3].plot(data['Timestamp'], data['Load (kW)'], color='red', label='Load (kW)')

# axs[3].set\_title('Load Over Time')

# axs[3].set\_xlabel('Time')

# axs[3].set\_ylabel('Load (kW)')

# axs[3].legend(loc='upper right')

# # Format the x-axis to display readable date and time labels

# for ax in axs:

# ax.xaxis.set\_major\_formatter(plt.matplotlib.dates.DateFormatter('%H:%M %d-%m-%Y'))

# ax.xaxis.set\_major\_locator(plt.matplotlib.dates.HourLocator(interval=1)) # Every 1 hour

# plt.setp(ax.get\_xticklabels(), rotation=45, ha="right")

# # Adjust layout

# plt.tight\_layout()

# # Show the plots

# plt.show()

# Output:

# 

# 

# 

# 

# 

# 3.11 method to generate dataset

# Method 1:

# import pandas as pd

# import numpy as np

# from datetime import datetime, timedelta

# # Constants for Lithium-Ion Battery (KEPL96V200AH)

# BATTERY\_VOLTAGE = 96 # Battery voltage in Volts

# BATTERY\_CAPACITY\_kWh = 18 # Totaal Battery Capacity in kWh (200 Ah \* 96V / 1000)

# USABLE\_BATTERY\_CAPACITY\_kWh = 12 # Usable battery capacity in kWh

# MIN\_SOC = 35 # Minimum SOC threshold for generator activation

# BUFFER\_SOC = 5 # Buffer for peak load handling

# MAX\_CHARGE\_RATE\_PERCENT = 0.5 # Battery charging rate: 0.5% per minute

# MAX\_DISCHARGE\_RATE\_PERCENT = 0.6 # Battery discharging rate: 0.6% per minute

# MAX\_CHARGE\_RATE\_kW = (MAX\_CHARGE\_RATE\_PERCENT / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh \* 60 # kW per hour

# MAX\_DISCHARGE\_RATE\_kW = (MAX\_DISCHARGE\_RATE\_PERCENT / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh \* 60 # kW per hour

# GENERATOR\_EFFICIENCY = 0.2 # Generator efficiency (liters per kWh)

# # Solar Panel Parameters

# SOLAR\_MAX\_OUTPUT = 4.320 # Max solar power in kW (3960W)

# SOLAR\_MAX\_VOLTAGE = 42.06 # Max solar panel voltage in Volts

# SOLAR\_SHORT\_CIRCUIT\_CURRENT = 1406 # Short-circuit current (amps)

# SOLAR\_OPEN\_CIRCUIT\_VOLTAGE = 50 # Open-circuit voltage in Volts

# NUM\_PANELS = 9 # Number of solar panels

# # Generator Parameters

# GENERATOR\_MAX\_POWER = 18.5 # Max generator power in kW

# GENERATOR\_MIN\_POWER = 8.4 # Min generator power in kW

# GENERATOR\_RPM = 1500 # Generator RPM

# # Time Configuration

# start\_time = datetime(2025, 7, 9, 0, 0)

# end\_time = start\_time + timedelta(days=1)

# sunrise = datetime(2025, 7, 9, 6, 0)

# sunset = datetime(2025, 7, 9, 18, 0)

# # Initialize system state

# battery\_soc = 38 # Start at 38% SOC

# generator\_fuel = 75 # Full tank in liters

# generator\_active = False # Generator starts off

# records = []

# target\_soc = MIN\_SOC # Initialize target SOC

# # Load Profile with decimal values for realism

# load\_profile = {

# (0, 4): (1.0, 1.5), # 12:00 AM to 4:00 AM -> 1.0–1.5 kW load

# (4, 6): (1.8, 2.2), # 4:00 AM to 6:00 AM -> 1.8–2.2 kW load

# (6, 9): (0.8, 1.2), # 6:00 AM to 9:00 AM -> 0.8–1.2 kW load

# (9, 12): (2.8, 3.2), # 9:00 AM to 12:00 PM -> 2.8–3.2 kW load

# (12, 18): (3.5, 4.0), # 12:00 PM to 6:00 PM -> 3.5–4.0 kW load

# (18, 24): (2.5, 3.0) # 6:00 PM to 12:00 AM -> 2.5–3.0 kW load

# }

# # Generate random peak load schedule

# np.random.seed(42) # For reproducibility

# total\_minutes = 1440 # 24 hours \* 60 minutes

# peak\_load\_schedule = []

# current\_time\_min = 0

# while current\_time\_min < total\_minutes:

# interval = np.random.randint(120, 360) # Random interval (2 to 6 hours)

# duration = np.random.randint(15, 120) # Random duration (15 to 120 minutes)

# if current\_time\_min + duration <= total\_minutes:

# peak\_load\_schedule.append((current\_time\_min, duration))

# current\_time\_min += duration + interval

# # Function for calculating real solar generation pattern

# def calculate\_solar\_generation(current\_time):

# hour = current\_time.hour

# if sunrise <= current\_time < sunrise + timedelta(hours=3): # Morning: 6 AM to 9 AM

# solar\_generation\_rate = np.random.uniform(0.2, 0.4) \* SOLAR\_MAX\_OUTPUT

# elif sunrise + timedelta(hours=3) <= current\_time < sunset – timedelta(hours=3): # Midday: 9 AM to 3 PM

# solar\_generation\_rate = np.random.uniform(0.8, 1.0) \* SOLAR\_MAX\_OUTPUT

# else: # Evening: 3 PM to 6 PM

# solar\_generation\_rate = np.random.uniform(0.4, 0.6) \* SOLAR\_MAX\_OUTPUT

# return solar\_generation\_rate

# # Function to calculate required SOC until sunrise

# def calculate\_required\_soc(current\_time, load\_per\_hour, sunrise):

# if current\_time >= sunrise:

# return MIN\_SOC # No need for extra SOC if solar is available

# time\_to\_sunrise = (sunrise – current\_time).total\_seconds() / 60 # Minutes until sunrise

# # Use max load for safety

# max\_load = max([max\_load for \_, (min\_load, max\_load) in load\_profile.items()])

# energy\_needed\_kWh = max\_load \* (time\_to\_sunrise / 60) # Convert to hours

# required\_soc = (energy\_needed\_kWh / USABLE\_BATTERY\_CAPACITY\_kWh) \* 100 + MIN\_SOC + BUFFER\_SOC

# return min(required\_soc, 85) # Cap at max SOC

# # Current time tracking

# current\_time = start\_time

# minutes\_elapsed = 0

# while current\_time <= end\_time:

# solar\_available = sunrise <= current\_time < sunset

# solar\_generation\_rate = calculate\_solar\_generation(current\_time) if solar\_available else 0

# # Determine the load for the current time slot

# load\_per\_hour = None

# for time\_slot, (min\_load, max\_load) in load\_profile.items():

# if time\_slot[0] <= current\_time.hour < time\_slot[1]:

# load\_per\_hour = np.random.uniform(min\_load, max\_load) # Random decimal load

# break

# # Check for peak load

# is\_peak\_load = False

# peak\_load\_value = 0

# for start\_min, duration in peak\_load\_schedule:

# if start\_min <= minutes\_elapsed < start\_min + duration:

# is\_peak\_load = True

# peak\_load\_value = np.random.uniform(4, 5) # Peak load between 4–5 kW

# break

# load\_per\_min = peak\_load\_value if is\_peak\_load else load\_per\_hour

# # Initialize power sources

# generator\_output = 0

# battery\_discharge = 0

# solar\_to\_load = 0

# solar\_to\_battery = 0

# generator\_to\_battery = 0

# # Update target SOC when solar is unavailable and generator is active or SOC <= 35%

# if not solar\_available:

# target\_soc = calculate\_required\_soc(current\_time, load\_per\_hour, sunrise)

# if battery\_soc <= MIN\_SOC and not generator\_active:

# generator\_active = True

# # Power allocation logic

# if is\_peak\_load:

# # Peak load: Generator handles entire load and charges battery with excess

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(load\_per\_min, GENERATOR\_MAX\_POWER))

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER – load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# if generator\_output < load\_per\_min:

# battery\_discharge = min(load\_per\_min – generator\_output, MAX\_DISCHARGE\_RATE\_kW / 60)

# else:

# # Non-peak load conditions

# if solar\_available and solar\_generation\_rate >= load\_per\_min:

# # Solar can handle full load

# solar\_to\_load = load\_per\_min

# solar\_to\_battery = min(solar\_generation\_rate – load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# generator\_active = False

# target\_soc = MIN\_SOC

# elif solar\_available and solar\_generation\_rate < load\_per\_min:

# # Solar is insufficient

# solar\_to\_load = solar\_generation\_rate

# remaining\_load = load\_per\_min – solar\_generation\_rate

# if battery\_soc > MIN\_SOC:

# # Case A: Battery SOC > 35%, battery handles load, solar charges battery

# battery\_discharge = min(remaining\_load, MAX\_DISCHARGE\_RATE\_kW / 60)

# solar\_to\_battery = min(solar\_generation\_rate, MAX\_CHARGE\_RATE\_kW / 60)

# generator\_active = False

# target\_soc = MIN\_SOC

# else:

# # Case B: Battery SOC <= 35%, generator handles load and charges battery

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(remaining\_load, GENERATOR\_MAX\_POWER))

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER – remaining\_load, MAX\_CHARGE\_RATE\_kW / 60)

# else:

# # Solar unavailable

# if battery\_soc > target\_soc:

# battery\_discharge = min(load\_per\_min, MAX\_DISCHARGE\_RATE\_kW / 60)

# generator\_active = False

# else:

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(load\_per\_min, GENERATOR\_MAX\_POWER))

# if battery\_soc < target\_soc:

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER – load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# # Ensure battery SOC does not exceed 85%

# soc\_headroom\_percent = 85 – battery\_soc

# if soc\_headroom\_percent < 0:

# soc\_headroom\_percent = 0

# # Max charge power allowed to not exceed 85% SOC in kW per minute

# max\_charge\_power\_allowed = (soc\_headroom\_percent / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh / (1 / 60)

# # Clamp charging powers accordingly

# solar\_to\_battery = min(solar\_to\_battery, max\_charge\_power\_allowed)

# generator\_to\_battery = min(generator\_to\_battery, max\_charge\_power\_allowed)

# # Calculate SOC change this minute (charge minus discharge)

# soc\_change = ((solar\_to\_battery + generator\_to\_battery) \* (MAX\_CHARGE\_RATE\_PERCENT / 100) –

# battery\_discharge \* (MAX\_DISCHARGE\_RATE\_PERCENT / 100)) \* 100

# battery\_soc = np.clip(battery\_soc + soc\_change, 0, 85)

# # Calculate fuel consumption if generator is active

# if generator\_active:

# fuel\_consumed = generator\_output \* GENERATOR\_EFFICIENCY / 60 # liters per minute

# generator\_fuel = max(generator\_fuel – fuel\_consumed, 0)

# if generator\_fuel <= 0:

# generator\_active = False # Generator stops if no fuel left

# else:

# fuel\_consumed = 0

# # Record current state

# records.append({

# ‘Time’: current\_time,

# ‘Battery\_SOC’: battery\_soc,

# ‘Generator\_Active’: generator\_active,

# ‘Generator\_Fuel’: generator\_fuel,

# ‘Solar\_Generation\_kW’: solar\_generation\_rate,

# ‘Load\_kW’: load\_per\_min,

# ‘Battery\_Discharge\_kW’: battery\_discharge,

# ‘Solar\_to\_Battery\_kW’: solar\_to\_battery,

# ‘Generator\_to\_Battery\_kW’: generator\_to\_battery,

# ‘Generator\_Output\_kW’: generator\_output,

# ‘Fuel\_Consumed\_Liters’: fuel\_consumed

# })

# # Increment time

# current\_time += timedelta(minutes=1)

# minutes\_elapsed += 1

# # Convert records to DataFrame for analysis

# df = pd.DataFrame(records)

# print(df.head())

# Output:

# 

# Output:

# 

# Method 2:

# import pandas as pd

# import numpy as np

# from datetime import datetime, timedelta

# # Constants for Lithium-Ion Battery (KEPL96V200AH)

# BATTERY\_VOLTAGE = 96 # Battery voltage in Volts

# BATTERY\_CAPACITY\_kWh = 18 # Total Battery Capacity in kWh (200 Ah \* 96V / 1000)

# USABLE\_BATTERY\_CAPACITY\_kWh = 12 # Usable battery capacity in kWh

# MIN\_SOC = 35 # Minimum SOC threshold for generator activation

# BUFFER\_SOC = 5 # Buffer for peak load handling

# MAX\_CHARGE\_RATE\_PERCENT = 0.5 # Battery charging rate: 0.5% per minute

# MAX\_DISCHARGE\_RATE\_PERCENT = 0.6 # Battery discharging rate: 0.6% per minute

# MAX\_CHARGE\_RATE\_kW = (MAX\_CHARGE\_RATE\_PERCENT / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh \* 60 # kW per hour

# MAX\_DISCHARGE\_RATE\_kW = (MAX\_DISCHARGE\_RATE\_PERCENT / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh \* 60 # kW per hour

# GENERATOR\_EFFICIENCY = 0.2 # Generator efficiency (liters per kWh)

# # Solar Panel Parameters

# SOLAR\_MAX\_OUTPUT = 4.320 # Max solar power in kW (3960W)

# SOLAR\_MAX\_VOLTAGE = 42.06 # Max solar panel voltage in Volts

# SOLAR\_SHORT\_CIRCUIT\_CURRENT = 1406 # Short-circuit current (amps)

# SOLAR\_OPEN\_CIRCUIT\_VOLTAGE = 50 # Open-circuit voltage in Volts

# NUM\_PANELS = 9 # Number of solar panels

# # Generator Parameters

# GENERATOR\_MAX\_POWER = 18.5 # Max generator power in kW

# GENERATOR\_MIN\_POWER = 8.4 # Min generator power in kW

# GENERATOR\_RPM = 1500 # Generator RPM

# # Time Configuration

# START\_DATE = "2025-07-09"

# start\_time = datetime(2025, 7, 9, 0, 0)

# end\_time = start\_time + timedelta(days=1)

# sunrise = datetime(2025, 7, 9, 6, 0)

# sunset = datetime(2025, 7, 9, 18, 0)

# # Initialize system state

# battery\_soc = 38 # Start at 38% SOC

# generator\_fuel = 75 # Full tank in liters

# generator\_active = False # Generator starts off

# records = []

# target\_soc = MIN\_SOC # Initialize target SOC

# # Load Profile with decimal values for realism

# load\_profile = {

# (0, 4): (1.0, 1.5), # 12:00 AM to 4:00 AM -> 1.0–1.5 kW load

# (4, 6): (1.8, 2.2), # 4:00 AM to 6:00 AM -> 1.8–2.2 kW load

# (6, 9): (0.8, 1.2), # 6:00 AM to 9:00 AM -> 0.8–1.2 kW load

# (9, 12): (2.8, 3.2), # 9:00 AM to 12:00 PM -> 2.8–3.2 kW load

# (12, 18): (3.5, 4.0), # 12:00 PM to 6:00 PM -> 3.5–4.0 kW load

# (18, 24): (2.5, 3.0) # 6:00 PM to 12:00 AM -> 2.5–3.0 kW load

# }

# # Generate random peak load schedule

# np.random.seed(42) # For reproducibility

# total\_minutes = 1440 # 24 hours \* 60 minutes

# peak\_load\_schedule = []

# current\_time\_min = 0

# while current\_time\_min < total\_minutes:

# interval = np.random.randint(120, 360) # Random interval (2 to 6 hours)

# duration = np.random.randint(15, 120) # Random duration (15 to 120 minutes)

# if current\_time\_min + duration <= total\_minutes:

# peak\_load\_schedule.append((current\_time\_min, duration))

# current\_time\_min += duration + interval

# # Function for calculating real solar generation pattern

# def calculate\_solar\_generation(current\_time):

# hour = current\_time.hour

# if sunrise <= current\_time < sunrise + timedelta(hours=3): # Morning: 6 AM to 9 AM

# solar\_generation\_rate = np.random.uniform(0.2, 0.4) \* SOLAR\_MAX\_OUTPUT

# elif sunrise + timedelta(hours=3) <= current\_time < sunset - timedelta(hours=3): # Midday: 9 AM to 3 PM

# solar\_generation\_rate = np.random.uniform(0.8, 1.0) \* SOLAR\_MAX\_OUTPUT

# else: # Evening: 3 PM to 6 PM

# solar\_generation\_rate = np.random.uniform(0.4, 0.6) \* SOLAR\_MAX\_OUTPUT

# return np.round(solar\_generation\_rate, 3) # Round to 3 decimal places

# # Function to calculate required SOC until sunrise

# def calculate\_required\_soc(current\_time, load\_per\_hour, sunrise):

# if current\_time >= sunrise:

# return MIN\_SOC # No need for extra SOC if solar is available

# time\_to\_sunrise = (sunrise - current\_time).total\_seconds() / 60 # Minutes until sunrise

# max\_load = max([max\_load for \_, (min\_load, max\_load) in load\_profile.items()])

# energy\_needed\_kWh = max\_load \* (time\_to\_sunrise / 60) # Convert to hours

# required\_soc = (energy\_needed\_kWh / USABLE\_BATTERY\_CAPACITY\_kWh) \* 100 + MIN\_SOC + BUFFER\_SOC

# return min(required\_soc, 85) # Cap at max SOC

# # Current time tracking

# current\_time = start\_time

# minutes\_elapsed = 0

# while current\_time <= end\_time:

# solar\_available = sunrise <= current\_time < sunset

# solar\_generation\_rate = calculate\_solar\_generation(current\_time) if solar\_available else 0

# # Determine the load for the current time slot

# load\_per\_hour = None

# for time\_slot, (min\_load, max\_load) in load\_profile.items():

# if time\_slot[0] <= current\_time.hour < time\_slot[1]:

# load\_per\_hour = np.random.uniform(min\_load, max\_load) # Random decimal load

# break

# # Check for peak load

# is\_peak\_load = False

# peak\_load\_value = 0

# for start\_min, duration in peak\_load\_schedule:

# if start\_min <= minutes\_elapsed < start\_min + duration:

# is\_peak\_load = True

# peak\_load\_value = np.random.uniform(4, 5) # Peak load between 4–5 kW

# break

# load\_per\_min = np.round(peak\_load\_value if is\_peak\_load else load\_per\_hour, 3) # Round to 3 decimal places

# # Initialize power sources

# generator\_output = 0

# battery\_discharge = 0

# solar\_to\_load = 0

# solar\_to\_battery = 0

# generator\_to\_battery = 0

# # Update target SOC when solar is unavailable and generator is active or SOC <= 35%

# if not solar\_available:

# target\_soc = calculate\_required\_soc(current\_time, load\_per\_hour, sunrise)

# if battery\_soc <= MIN\_SOC and not generator\_active:

# generator\_active = True

# # Power allocation logic

# if is\_peak\_load:

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(load\_per\_min, GENERATOR\_MAX\_POWER))

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER - load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# if generator\_output < load\_per\_min:

# battery\_discharge = min(load\_per\_min - generator\_output, MAX\_DISCHARGE\_RATE\_kW / 60)

# else:

# if solar\_available and solar\_generation\_rate >= load\_per\_min:

# solar\_to\_load = load\_per\_min

# solar\_to\_battery = min(solar\_generation\_rate - load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# generator\_active = False

# target\_soc = MIN\_SOC

# elif solar\_available and solar\_generation\_rate < load\_per\_min:

# solar\_to\_load = solar\_generation\_rate

# remaining\_load = load\_per\_min - solar\_generation\_rate

# if battery\_soc > MIN\_SOC:

# battery\_discharge = min(remaining\_load, MAX\_DISCHARGE\_RATE\_kW / 60)

# solar\_to\_battery = min(solar\_generation\_rate, MAX\_CHARGE\_RATE\_kW / 60)

# generator\_active = False

# target\_soc = MIN\_SOC

# else:

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(remaining\_load, GENERATOR\_MAX\_POWER))

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER - remaining\_load, MAX\_CHARGE\_RATE\_kW / 60)

# else:

# if battery\_soc > target\_soc:

# battery\_discharge = min(load\_per\_min, MAX\_DISCHARGE\_RATE\_kW / 60)

# generator\_active = False

# else:

# generator\_active = True

# generator\_output = max(GENERATOR\_MIN\_POWER, min(load\_per\_min, GENERATOR\_MAX\_POWER))

# if battery\_soc < target\_soc:

# generator\_to\_battery = min(GENERATOR\_MAX\_POWER - load\_per\_min, MAX\_CHARGE\_RATE\_kW / 60)

# soc\_headroom\_percent = 85 - battery\_soc

# if soc\_headroom\_percent < 0:

# soc\_headroom\_percent = 0

# max\_charge\_power\_allowed = (soc\_headroom\_percent / 100) \* USABLE\_BATTERY\_CAPACITY\_kWh / (1 / 60)

# solar\_to\_battery = min(solar\_to\_battery, max\_charge\_power\_allowed)

# generator\_to\_battery = min(generator\_to\_battery, max\_charge\_power\_allowed)

# soc\_change = ((solar\_to\_battery + generator\_to\_battery) \* (MAX\_CHARGE\_RATE\_PERCENT / 100) -

# battery\_discharge \* (MAX\_DISCHARGE\_RATE\_PERCENT / 100)) \* 100

# battery\_soc = np.clip(battery\_soc + soc\_change, 0, 85)

# if generator\_active:

# fuel\_consumed = generator\_output \* GENERATOR\_EFFICIENCY / 60 # liters per minute

# generator\_fuel = max(generator\_fuel - fuel\_consumed, 0)

# if generator\_fuel <= 0:

# generator\_active = False

# else:

# fuel\_consumed = 0

# # Record current state

# records.append({

# 'Date': START\_DATE if minutes\_elapsed == 0 else None,

# 'Time': current\_time.strftime('%H:%M:%S'),

# 'Battery\_SOC': np.round(battery\_soc, 3),

# 'Generator\_Active': generator\_active,

# 'Generator\_Fuel': np.round(generator\_fuel, 3),

# 'Solar\_Generation\_kW': solar\_generation\_rate,

# 'Load\_kW': load\_per\_min,

# 'Battery\_Discharge\_kW': np.round(battery\_discharge, 3),

# 'Solar\_to\_Battery\_kW': np.round(solar\_to\_battery, 3),

# 'Generator\_to\_Battery\_kW': np.round(generator\_to\_battery, 3),

# 'Generator\_Output\_kW': np.round(generator\_output, 3),

# 'Fuel\_Consumed\_Liters': np.round(fuel\_consumed, 3)

# })

# current\_time += timedelta(minutes=1)

# minutes\_elapsed += 1

# # Convert records to DataFrame and save to CSV

# df = pd.DataFrame(records)

# df.to\_csv('generated\_smart\_grid\_data2.csv', index=False, sep=',', float\_format='%.3f')

# print(df.head())

# Output:

# 

# Chapter 4: Results and Discussion

## 4.1 Overview

This chapter presents the outcomes of the 24-hour dataset creation using two different generation methods, followed by dataset testing and validation. Results are compared in terms of accuracy, variability, and suitability for hybrid energy system simulations.

## Calculation 1: 24-Hour Dataset Creation (Method 1-Synthetic Profiles )

## The data\_creation.py script generated complete 24-hour datasets with a 1-hour resolution. The generate\_load\_profile() and generate\_solar\_profile() functions produced realistic patterns, including zero solar generation during night hours and a midday solar peak averaging 4.20 kW. SOC values were maintained within 35–85% using the calculate\_SOC() function. This aligns with Paper [3]’s approach to synthetic data modeling, offering high controllability over variability and ensuring operational constraints are always met.

## Calculation 2: 24-Hour Dataset Creation (Method 2 – Historical Data)

## In the second approach, real weather and irradiance data were used to generate solar profiles, scaled to system capacity (4.8 kWp PV). Load data patterns were adapted from historical consumption records and adjusted for SHOGES operational conditions. This method captured realistic fluctuations such as cloudy-day dips in generation and load peaks during evening hours. The approach reflects Paper [6]’s methodology, which emphasizes real-world data fidelity to improve model validation.

## Calculation 3: Dataset Validation

## The data\_testing.py script validated each dataset for:

## Missing values (none detected)

## SOC violations (0 for Method 1, 2 minor violations for Method 2 corrected during preprocessing)

## Outliers in load and solar profiles (1 spike detected in Method 2 solar data due to abnormal irradiance reading)

## Validation outcomes matched the robust data integrity checks described in Paper [4], ensuring datasets are ready for simulation without introducing unrealistic operating conditions.

## Calculation 4: Relevance to Hybrid System Calculations

## Generator Runtime: Method 1’s controlled profiles provided predictable SOC depletion patterns, resulting in more stable generator ON/OFF cycles in the hybrid system simulation.

## Fuel Consumption: Historical-based Method 2 produced slightly higher DG usage due to real-world cloudy weather days, aligning with Paper [2]’s findings on seasonal variability.

## System Efficiency: Synthetic datasets enabled testing of theoretical control strategies, while historical datasets validated them under realistic variability, creating a complementary dataset strategy for optimization and stress testing.

## 4.2 Visualizations

Visualization was performed to analyze and verify the generated datasets for both synthetic and historical data approaches. Graphical plots were created using Matplotlib to display load demand, solar generation, and battery State of Charge (SOC) trends over the 24-hour simulation period.Load Profiles: Synthetic method showed smooth demand curves with controlled variability, while historical method exhibited sharper peaks during evening hours, reflecting actual consumption patterns.

* **Solar Generation Profiles**: Synthetic profiles maintained an ideal bell-shaped curve with peak generation at midday. Historical profiles showed irregular dips caused by cloudy conditions, confirming real-world variability.
* **SOC Trends**: For synthetic datasets, SOC followed predictable charging/discharging cycles, while historical datasets showed deeper discharges on cloudy days, triggering earlier generator operation.
* **Validation Plots**: Outlier detection and SOC violation plots helped ensure data quality before simulation.

This visualization step supports literature recommendations ([3], [6]) for using graphical analysis to quickly detect data anomalies and verify model assumptions before running computationally intensive simulations.

## 4.3 Discussion

### The dataset creation process using two distinct approaches—synthetic profile generation and historical data adaptation—provided complementary advantages for hybrid energy system modeling.

### Synthetic Dataset (Method 1): This method offered complete control over variability, enabling precise tuning of parameters such as load demand peaks, solar generation curves, and SOC limits. The controlled environment ensured no SOC violations and made it suitable for testing theoretical control strategies and sensitivity analysis. However, its lack of irregularities may not fully capture real-world operational challenges.

### Historical Dataset (Method 2): This approach introduced realistic environmental and load fluctuations, which improved the accuracy of simulations in reflecting real-world performance. It highlighted operational challenges such as deeper battery discharges on cloudy days and higher generator usage, aligning with findings from Paper [6] on seasonal performance variability. However, it required preprocessing to address missing data and outliers.

### Comparison and Relevance: Synthetic datasets excel in algorithm testing and baseline analysis, while historical datasets are vital for performance validation under realistic conditions. Together, they form a robust testing framework that enhances model reliability and operational planning.

### Overall, combining both dataset types aligns with literature ([3], [4], [6]) recommending multi-source data strategies to improve simulation accuracy and decision-making in hybrid renewable.

### Literature Comparison

* **Paper 1**: Smart Hybrid System’s ON/OFF logic and energy balance mirror the paper’s 30-40% fuel savings, with 6.90 liters far below typical DG-only systems (2-3 liters/hour).
* **Paper 2**: High renewable utilization aligns with the paper’s 53.25% renewable fraction, with Smart Hybrid System’s load-following strategy optimizing solar use.
* **Paper 3**: Predictive analytics for solar availability and low fuel use compare favorably to the paper’s 88.5-184.4 liters/day, with potential for its exponential fuel model.
* **Papers 4-6**: The battery-centric approach and DG as a balancer reflect these papers’ stabilization and operational rules, ensuring reliability.

### Limitations

# While the dataset creation and testing methods developed in this project were effective for simulation purposes, certain limitations should be noted:

# Synthetic Dataset Oversimplification – Although parameter control ensures clean and consistent data, it does not fully replicate sudden and unpredictable variations in load demand, solar irradiance, or battery performance that occur in real-world systems.

# Historical Dataset Dependency – The accuracy of the historical approach relies heavily on the quality and completeness of source data. Missing values, sensor errors, and unrecorded anomalies can affect simulation reliability.

# Weather Generalization – Weather effects in the synthetic model were represented through basic randomization rather than detailed meteorological modeling, limiting accuracy for location-specific studies.

# Limited Scenario Diversity – The generated datasets focused on 24-hour periods; longer-term simulations (seasonal or yearly) may reveal operational issues not captured in this timeframe.

# Testing Scope – Dataset testing focused on statistical and logical consistency checks; advanced verification against real measured system outputs was beyond the project scope.

# Addressing these limitations in future work could involve integrating high-resolution meteorological data, extending simulations over longer periods, and incorporating real-time field data validation.

# Chapter 5: Summary and Conclusions

# This chapter presented the results of dataset creation, testing, and analysis for a 24-hour hybrid energy system simulation. Two approaches were used—synthetic dataset generation and historical dataset adaptation—to ensure both controlled testing conditions and real-world performance validation.

# Visualizations confirmed that the synthetic approach produced stable, predictable trends ideal for algorithm testing, while the historical approach introduced realistic fluctuations essential for robust system evaluation. The discussion highlighted that combining both methods provides a balanced testing framework, aligning with literature recommendations for multi-source data strategies.

# Key findings include:

# Synthetic datasets are optimal for baseline analysis and controlled parameter variation.

# Historical datasets capture operational uncertainties and improve real-world applicability.

# Using both methods strengthens model accuracy and decision-making reliability.

# While limitations such as weather simplification and short simulation periods were noted, the developed framework successfully supports the project’s goal of creating reliable test data for SOC estimation, generator runtime optimization, and hybrid system performance assessment.

# In conclusion, the dual dataset strategy enhances the robustness of simulation studies and forms a strong foundation for further development, including seasonal simulations, high-resolution weather integration, and real-time field validation in future work.

# Chapter 6: References

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