SUMMER TRAINING REPORT

on

"Predictive Model for SoC Estimation & Generator Runtime For Smart Hybrid System"

Project Report

UNDER THE GUIDANCE of

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CERTIFICATE

This is to certify that **Gaurav Tiwari** , a student of **Graphic Era Hill University, Bhimtal** has successfully completed the project titled "**Predictive Model for SoC Estimation & Generator Run time for Smart Hybrid System**" as a part of the partial fulfillment of the requirements for the **Bachelor of Technology in Computer Science & Engineering.**

The project involves developing a python based model to optimize a hybrid energy system integrating solar power, battery storage and a diesel generator for remote areas. The model prioritizes solar energy, dynamically manages energy allocation using real-time solar and load data and minimize fuel costs and emissions while ensuring reliable power delivery.

The work carried out in this project is completed under the guidance of **Sh. Piyush Joshi, Sc. 'F', DIBER (A Cell of DIPAS).**

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I thank him for being a constant help throughout the project and encouraging me with his words and whose regular useful advice, time, patience and understanding helped me a lot. His suggestions and instructions have served as the major contribution towards the completion of the project.

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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 (PV) panels, a diesel generator (DG) 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 (SoC) to sustain the load, generator runtime and fuel consumption-enabling prioritized renewable energy use and SoC maintenance within a 35-85% range.

The development process involved designing algorithms to process time stamped load and solar data, drawing on insights from literature on hybrid system control, battery management and optimization to establish a robust theoretical foundation. 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 SoC 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 and positioning it as an innovative solution for sustainable off-grid energy management.

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Chapter1: Introduction

1.1 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 nine solar photovoltaic (PV) panels, a 10 kW diesel generator and a 96 V, 200 Ah (18 kWh) battery storage system, the Smart Hybrid System delivers a robust and sustainable power solution. The system maintains a minimum state of charge (SoC) of 35%, ensuring renewable energy utilization and overall reliability.

Active State: When the SoC falls below 35%, solar PV is prioritized if available; otherwise, the diesel generator activates to meet the load and charge the battery.

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

1.2 Project Scope

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

- **System Components:** Solar photovoltaic array (4.32 kW), battery storage (18 kWh, 96 V, 200 Ah) and diesel generator (10 kW).

- **Algorithm Development:** Python-based model incorporating a Kalman filter, energy balance method, threshold logic and predictive analytic.

- **Testing and Validation:** Conducted using synthetic data (24 hours, 5-second intervals) and real world data (peak load: 8.36 kW; average load: 1.879 kW).

1.3 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 worldwide-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 CO_2 emissions, exacerbating climate change. For instance, a typical 10 kW diesel generator can consume 2-3 liters of fuel per hour, emitting approximately 2.7 kg of CO_2 per liter, resulting in substantial environmental and economic burdens.

Renewable energy sources such as solar photovoltaic (PV) systems offer a sustainable alternative but face challenges due to their intermittent nature, driven by weather variability and diurnal cycles. This necessitates robust energy storage solutions to store excess energy and reliable backup systems to ensure power availability during periods of low renewable generation. However, many existing hybrid systems lack intelligent control strategies to efficiently balance renewable and non-renewable sources, leading to sub optimal performance, such as excessive generator run time, high fuel consumption, or battery degradation caused by improper state-of-charge (SoC) management.

The Smart Hybrid System addresses these challenges by integrating solar PV, battery storage and a diesel generator with a smart control algorithm designed to:

1. Optimize Renewable Utilization: Prioritize solar energy to minimize diesel generator operation, reducing fuel costs and emissions.

2. Ensure Reliability: Use the battery as a stabilizer to bridge energy gaps, maintaining a continuous power supply.

3. Enhance Efficiency: Minimize generator run time 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.

Chapter2: Review of Literature

Hybrid energy systems that combine renewable sources with conventional diesel generators and battery storage are critical for ensuring reliable power delivery in off-grid regions [1]. However, challenges such as solar intermittency, limited battery lifespan and high fuel costs necessitate the use of 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 96 V, 200 Ah lithium-ion battery. The model employs a Kalman filter for State of Charge (SoC) estimation, an energy balance method for power allocation, threshold-based logic for generator control and predictive analytics for forecasting energy demand. The system is simulated over a 24-hour period and tested with synthetic datasets to verify its scalability and efficiency.

2.1 Optimization of battery-integrated diesel generator hybrid systems using an ON/OFF operating strategy

This paper focuses on optimizing diesel generator (DG) and battery systems for rural electrification, a core component of the Smart Hybrid System's backup power strategy. Its ON/OFF control strategy aligns with the project's goal of minimizing fuel consumption. Key learning includes:

1. **ON/OFF Control** - The DG operates at rated power to maximize fuel efficiency (Section 3), inspiring the threshold-based logic to activate the DG only when the State of Charge (SoC) falls below 35% and solar power is unavailable and thereby determining generator runtime.
2. **Battery SoC Dynamics** - The SoC model incorporates charge and discharge efficiencies, providing a framework for calculating the required SoC based on energy balance principles.
3. **Quadratic Fuel Model** - The equation FC=aPDG2(t)+bPDG(t)+cFC = aP_{DG}^2(t) + bP_{DG}(t) + cFC=aPDG2(t)+bPDG(t)+c estimates generator fuel consumption. However, the Smart Hybrid System adopts a simplified linear model (0.2 liters/kWh), validated by [5].
4. **Performance Metrics** - The optimized DG operation achieves 30-40% fuel savings, establishing a benchmark for the Smart Hybrid System's efficiency targets.

This work provides a strong foundation for DG–battery integration, emphasizing fuel-efficient control through ON/OFF logic and energy balance. It directly informs the calculation of generator runtime and fuel consumption, while the SoC dynamics underpin the Kalman filter implementation for determining the required SoC.

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

The inclusion of solar photovoltaic (PV) generation and the use of HOMER for system optimization were critical to the Smart Hybrid System's renewable energy focus and weather-based predictions. Key learning includes:

1. Photovoltaic Power Model - The proposed equation accounts for both irradiance and temperature, enabling calculation of the time gap until solar availability and predicting PV output using time-series data.
2. Load-Following Strategy - The DG supplies only the primary load, while the PV and battery systems handle excess demand. This approach refines the threshold logic for calculating generator runtime, prioritizing solar and battery usage over DG operation.
3. Performance Metrics - The system achieves a 53.25% renewable fraction and 7.8% excess power, validating the Smart Hybrid System's goal of maximizing renewable utilization.
4. System Sizing - The study provides guidelines for balancing PV, battery and DG capacities, aligning with the Smart Hybrid System's configuration (4.32 kW PV, 18 kWh battery, 10 kW DG).

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

This article presents an advanced Energy Management Control (EMC) flowchart and pumped storage hydro (PSH) logic, offering insights into sophisticated control and storage strategies that enhance the Smart Hybrid System's adaptability. Key learning includes:

1. **EMC Flowchart** - A structured decision-making process prioritizes photovoltaic (PV) and storage resources, activating the DG only when necessary. This approach informs both the calculation of the time gap to solar availability and generator activation timing.
2. **PSH Logic** - The strategy of charging storage with excess PV power provides a framework for setting the required SoC, ensuring that the battery is charged only with surplus energy.
3. **Fuel Savings** - Reported fuel consumption ranges from 88.5 to 184.4 liters/day, providing a performance benchmark for the Smart Hybrid System's efficiency targets.

2.4 Management and Control of Hybrid Power System

This article emphasizes battery stabilization and power balance in islanded systems, directly supporting the Smart Hybrid System's battery-centric approach and the DG's role as a balancer. Key learning includes:

1. **Battery as Stabilizer** - The battery functions as both a sink and a source to bridge demand-supply gaps, maintaining power balance and voltage stability in islanded mode, which is critical for SoC calculations.
2. **Generator as Balancer** -The micro turbine (MTG, functionally equivalent to a DG) balances the load when renewable sources are insufficient, informing generator runtime calculations.
3. **Power Management Goal** - Smooth power transfer and stable operation are achieved through effective control strategies, aligning with the Smart Hybrid System's overall objectives.

This work reinforces the battery's role as a stabilizer for required SoC calculations and the DG's role in load balancing and runtime determination, validating the proposed energy management framework. The paper's emphasis on islanded operation closely parallels the Smart Hybrid System's off-grid context.

2.5 Effective Battery Usage Strategies

This study offers specific battery discharge algorithms and power flow rules, both of which are critical to the Smart Hybrid System operational logic. Key learning includes:

1. **Discharge Algorithm** - Solar power is prioritized for meeting the load; the battery discharges only when SoC exceeds 30% and charges exclusively with excess solar energy. This approach informs both required SoC estimation and generator runtime calculation.
2. **Power Flow Rules** - The control sequence Power_from_Solar=min (Solar_Output,Load_Demand)\text{Power_from_Solar} = \min(\text{Solar_Output}, \text{Load_Demand})Power_from_Solar=min(Solar_Output,Load_Demand), followed by battery supply and then DG operation, guided the simulation logic.
3. **Reliability Cycle** - Maintaining a 30-60% SoC charging cycle for reliability influenced the target SoC settings in the SoC estimation process.
4. **Battery Parameters** - Detailed specifications (e.g., 2400 Ah, 12 V, maximum charge/discharge currents) supported accurate battery modeling.

Chapter3: Methodology

The Smart Hybrid System model adopts several key approaches, informed by findings in the literature, to achieve its objectives. Each approach is detailed below, outlining its rationale, benefits, implementation steps and role in associated calculations.

3.1 Data Creation for 24-Hour Simulation:

Data creation for a 24-hour simulation involves generating time series datasets representing key system variables such as load demand, solar generation and battery State of Charge (SoC) over a continuous daily cycle. These datasets may be obtained from measured field data, statistical models, or synthetically generated profiles. The goal is to replicate realistic operating conditions, enabling the testing and validation of hybrid energy system models.

Benefits:

- Realistic Performance Testing - Facilitates accurate operational scenarios without relying solely on field measurements.
- Scenario Customization - Supports modeling under diverse weather conditions, load profiles and SoC levels.
- Time and Cost Savings - Reduces the need for prolonged on-site data collection campaigns.
- Algorithm Validation - Strengthens the reliability of control strategies such as ON/OFF logic and Energy Management Systems (EMS).

Implementation:

- Dataset Generation Methods:
    1. Pattern-Based Method: Utilizes statistical profiles derived from historical solar irradiance and load demand data.
    2. Randomized Variation Method: Introduces controlled fluctuations to simulate unpredictable operating conditions.
- Scripts Developed:
    1 data_creation.py - Generates structured 24-hour datasets.

    2 data_testing.py - Validates range limits, timestamp continuity and operational constraints.

Relevance to Calculations:

- Serve as direct inputs to MATLAB for performance simulations.
- Enable calculation of generator run time, fuel consumption and renewable fraction.
- Support SoC based threshold logic validation by generating realistic SoC variation patterns.
- Facilitate energy balance analysis across solar, diesel and battery components.

3.2 Multiple Data-set Generation Approaches

Multiple data-set generation refers to the creation of different synthetic or semi-synthetic data-sets to model real world operational conditions in hybrid power systems. This approach enables robust testing of energy management strategies (EMS) under varied scenarios without relying solely on limited real world measurements.

Benefits

- Improved Model Robustness: Testing across diverse data sets ensures the EMS can handle both typical and extreme operating conditions.
- Scenario Flexibility: Allows simulation of seasonal, climatic, or load pattern variations without the need for costly field trials.
- Risk Reduction: Identifies performance bottlenecks before real world deployment.
- Data Availability: Addresses the issue of insufficient historical data, which is common in remote or newly installed systems.

Implementation

1. **Method 1 - Statistical Pattern-Based Generation**
    - Uses historical energy consumption and weather data to extract statistical parameters such as mean, variance, peak hours and seasonal patterns.
    - Generates load and solar profiles that closely match real world averages.
    - Tools: Python (Pandas, NumPy) and MATLAB.

2. **Method 2 - Randomized Constraint-Based Generation**

    - Introduces controlled randomness within operational limits (e.g., maximum/minimum load, solar irradiance bounds).
    - Simulates unpredictable events such as sudden load spikes or cloudy weather conditions.
    - Enhances stress-testing of EMS algorithms under variable operating conditions.

Relevance to Calculations:

- Energy Balance Calculations: Accurate data-sets are essential for determining generator run time, solar fraction and battery SoC variations.
- Fuel Consumption Estimation: Diverse data-sets reveal how EMS responds to different demand supply scenarios, enabling more accurate 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 data-set generation for hybrid energy system simulations. The script integrates load, solar and state of charge (SoC) parameters, applies variability patterns and saves data-sets in a structured format for direct use in simulation models.

Benefits:

- Automation: Eliminates manual data-set preparation, saving time and reducing human error.
- Consistency: Ensures all data-sets follow a uniform structure, making simulation results directly comparable.
- Scalability: Rapidly generates multiple data-sets for different test cases or weather scenarios.
- **Flexib**ility: Allows easy modification of variability patterns, load ranges and solar profiles without rewriting code.

Implementation

- Written in Python using libraries such as NumPy, Pandas and random.
- Integrates load demand, solar generation and SoC values into a unified dataset.
- Applies variability patterns to simulate realistic fluctuations in load and solar inputs.
- Saves generated data-sets in structured formats (Excel) for direct input into hybrid power system simulation models.

Relevance to Calculations

- Provides baseline input data for calculating generator run time, solar utilization, battery SoC changes and fuel consumption.
- Enables scenario-based testing (e.g., cloudy vs. sunny days) to compare system performance under varying conditions.
- Ensures repeatability of results in sensitivity analyses, enabling more accurate comparisons across EMS strategies.

3.4 Data Testing Script (data_testing.py)

The data_testing.py script was developed to validate generated data sets prior to their use in hybrid system simulations. It checks parameter ranges, ensures timestamp continuity and verifies that all generated values meet the operational constraints of the hybrid system model.

Benefits:

- Quality Assurance: Ensures all generated data sets comply with operational constraints before being used in simulations.
- Error Detection: Identifies missing timestamps, unrealistic load or solar values and SoC values outside acceptable limits.
- Reliability: Prevents inaccurate input data from skewing simulation results.
- Time Savings: Automates validation tasks that would otherwise require time-consuming manual checking.

Implementation:

- Developed in Python using Pandas and NumPy for data handling and numerical checks.
- Validation checks include:
    - Parameter ranges: SoC (0-100%), load (> 0) and solar irradiance within realistic bounds.
    - Timestamp continuity: Ensures complete 24-hour data-sets without gaps.
    - Operational constraints: Confirms compliance with the hybrid system model specifications.
- Outputs a pass/fail log or report highlighting any issues for correction.

Relevance to Calculations:

- Ensures energy balance calculations use correct and continuous input values.
- Prevents fuel consumption miscalculations caused by erroneous solar or load data.
- Maintains SoC trajectory accuracy, avoiding unrealistic charging or discharging cycles in the model.
- Supports repeatable and trustworthy simulation outcomes by ensuring clean, validated data-sets feed into the computation process.

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

In the hybrid power system model, dedicated functions in the data creation script generate realistic 24-hour data sets for load demand, solar generation and battery State of Charge (SoC) using a combination of deterministic and stochastic approaches. These data sets form the primary input for simulation models.

Functions in the data testing script perform rigorous validation to ensure data set accuracy, continuity and reliability. This verification process prevents erroneous data from affecting energy balance calculations, fuel consumption estimates and SoC tracking, thereby safeguarding the integrity of simulation results.

From data_creation.py

1. load() - Generates a 24-hour load profile based on predefined demand patterns with added random variability.

2. solar() - Creates the 24-hour solar generation profile, incorporating sunlight duration and irradiance variation.

3. soc() -Estimates battery SoC progression over the simulation period.

4. data() - Combines load, solar and SoC profiles into a unified, structured data-set ready for simulation.

5. variability() - Introduces controlled randomness to load and solar data to replicate realistic day-to-day fluctuations.

From data_testing.py

1. data_testing() -Performs comprehensive validation by checking parameter ranges, timestamp continuity and anomalies.

2. check_range() - Ensures SoC, load and solar values remain within defined operational limits.

3. check_continuity() - Confirms that all required timestamps are present without gaps or overlaps.

4. outlier_detection() - Identifies unrealistic values using statistical deviation methods.

5. report() - Produces a summary log of validation results for documentation and corrective action.

Relevance to Model Accuracy:

- Data Creation Functions: Ensure the generation of realistic and scenario specific profiles for simulation.

- Data Testing Functions: Prevent invalid data from influencing performance metrics and energy management strategy evaluations.

- Together, these functions enable repeatable, credible and scenario rich simulation outcomes for hybrid power system analysis.

3.6 Tools and Libraries Used

The model integrates various programming tools and scientific libraries to automate dataset generation, validation and visualization:

1. Python **-** Primary programming language for implementing data-set generation, validation and automation workflows.

2. Pandas **-** Used to create, organize and store load, solar and SOC data-sets in structured Data Frames, enabling easy manipulation and export.

3. NumPy **-** Handles numerical calculations, random variability generation and efficient array operations.

4. Random **-** Introduces controlled stochastic variations in load demand and solar irradiance to reflect real world unpredictability.

5. Matplotlib **-** Produces visual plots of load, solar and SOC profiles for verification, reporting and interpretation.

3.7 Model Flow

The hybrid system data set creation and testing process follows a structured workflow:

1. **Initialize Parameters**

    - Define simulation duration (e.g. 24 hours), time resolution and constants for load, solar generation and battery SOC operational limits.

2. **Generate Synthetic Profiles**

    - generate_load_profile() - Produces realistic hourly or sub-hourly load demand based on statistical patterns and variability factors.

    - generate_solar_profile() - Simulates solar generation considering daylight hours, irradiance variations and stochastic weather effects.

3. **Calculate SOC**

    - calculate_SOC() - Tracks battery State of Charge throughout the simulation, applying charging/discharging logic based on the net load–generation balance.

4. **Combine into Data-set**

    - create_data-set() - Merges load, solar and SOC profiles into a unified Pandas Data Frame with continuous timestamps.

    - Export the data-set in Excel format for integration into MATLAB or other simulation platforms.

5. **Run Validation Checks**

    - validate_dataset() - Ensures parameter values (SOC, load, solar) are within acceptable operational ranges.

    - detect_outliers() - Flags and reports unrealistic values based on statistical deviation methods.

6. **Generate Reports & Visualizations**

    - Save validated data-sets for use in simulation studies.

    - Use Matplotlib to produce graphs showing load demand, solar generation and SOC variation for quick verification and reporting.

3.8 Model Architecture

The Data Creation and Testing model is structured into interconnected modules each serving a distinct role in generating and validating datasets for hybrid power system simulations:

1. **Input Layer**

    - Defines simulation parameters: time duration (e.g. 24 hours), time step, battery SOC limits, load demand range and solar capacity.

    - Accepts external variability inputs, such as random weather fluctuations and load demand variations

2. **Data Generation Module**

    - generate_load_profile() - Produces realistic load demand profiles using statistical patterns combined with controlled randomness.

    - generate_solar_profile() - Models solar generation considering daylight hours, irradiance variation and stochastic weather effects.

3. **SOC Calculation Module**

    - calculate_SOC() - Tracks the battery’s charging and discharging cycles over the simulation period based on the net load–generation balance.

4. **Dataset Integration Module**

    - Merges load, solar and SOC values into a single structured Pandas Data Frame with continuous timestamps.

5. **Validation & Testing Module**

    - validate_dataset() and detect_outliers() - Ensure parameter ranges are within operational limits and detect statistically abnormal values.

    - data_testing.py - Runs automated checks to verify data-set completeness, continuity and plausibility before simulation use.

6. **Output Layer**

    - Saves cleaned and validated data-sets in CSV format for direct use in MATLAB or other simulation tools.

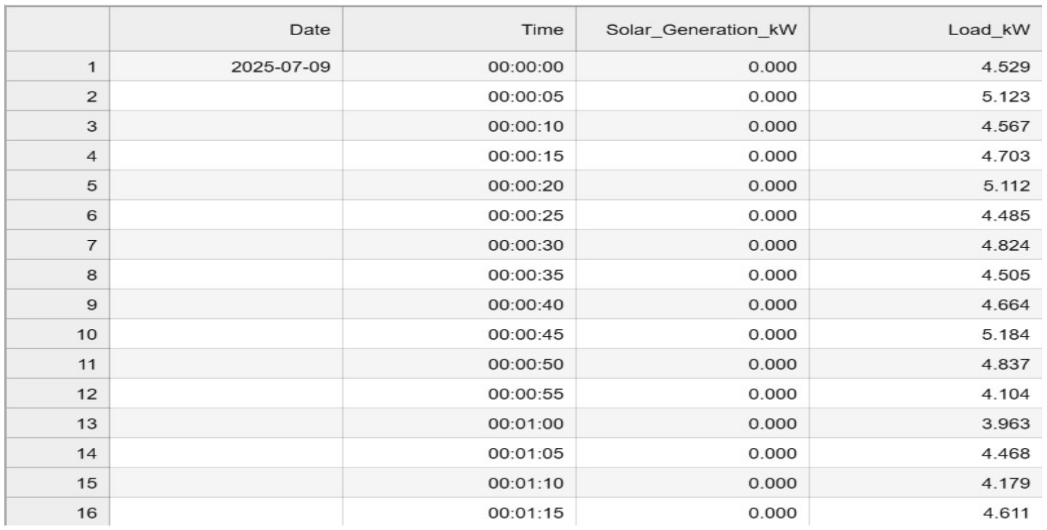
    - Generates Matplotlib visualizations for quick assessment of daily trends, anomalies and system performance.

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
```

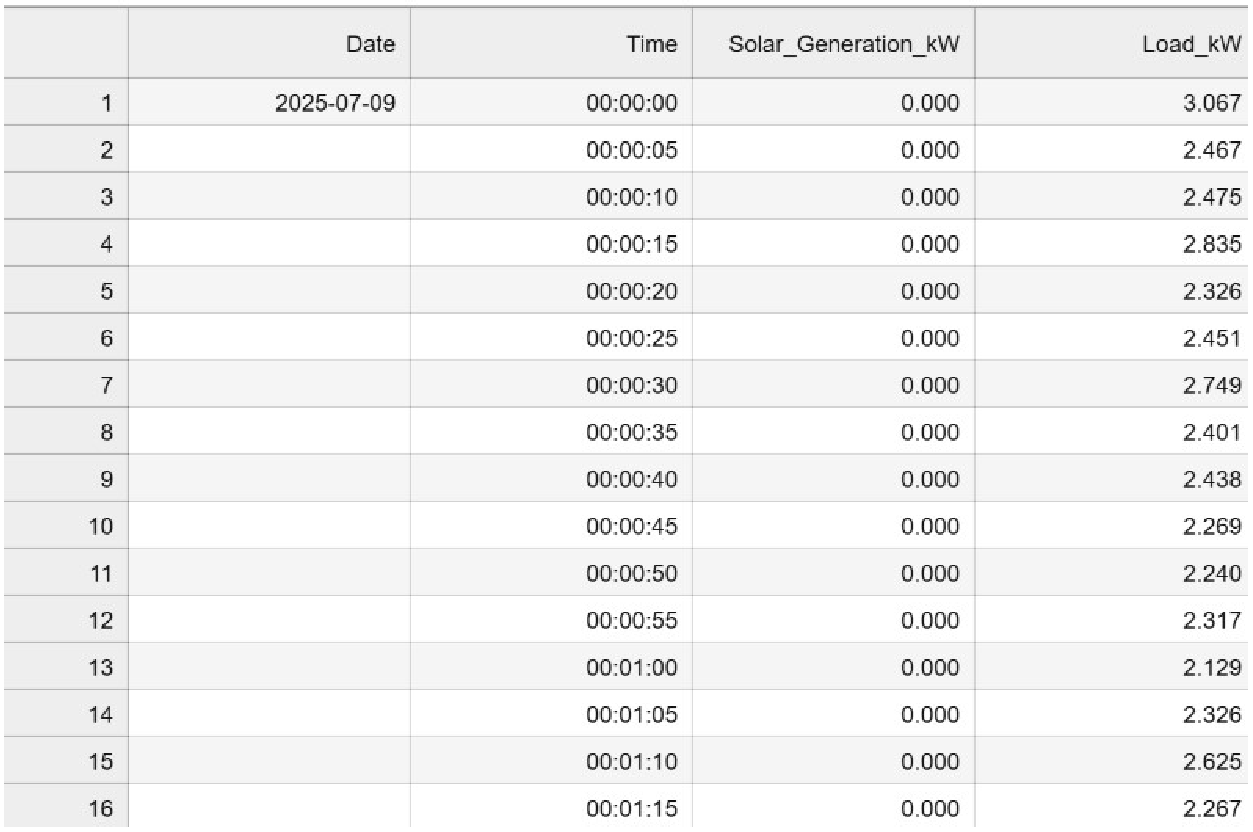
```
for i, profile in enumerate(LOAD_PROFILES, 1):
    output_file = f"testing_data_generated_{i}.csv"
    generate_dataset(profile, output_file)
```

Output:



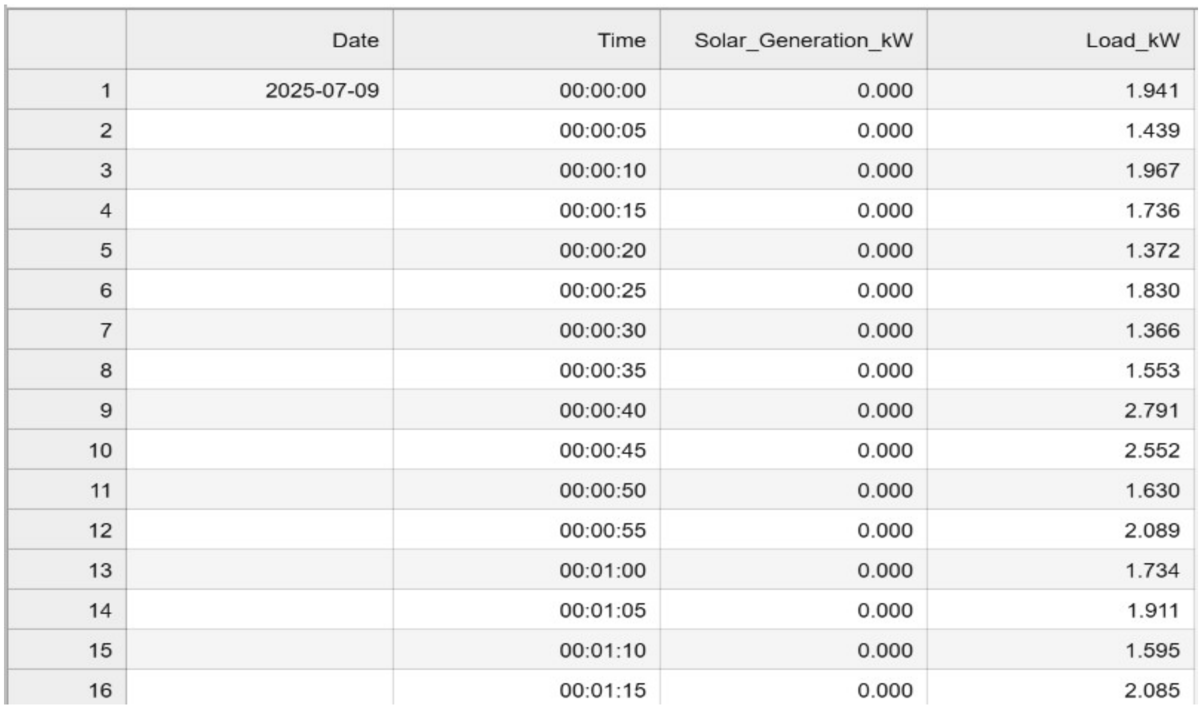
	Date	Time	Solar_Generation_kW	Load_kW
1	2025-07-09	00:00:00	0.000	4.529
2		00:00:05	0.000	5.123
3		00:00:10	0.000	4.567
4		00:00:15	0.000	4.703
5		00:00:20	0.000	5.112
6		00:00:25	0.000	4.485
7		00:00:30	0.000	4.824
8		00:00:35	0.000	4.505
9		00:00:40	0.000	4.664
10		00:00:45	0.000	5.184
11		00:00:50	0.000	4.837
12		00:00:55	0.000	4.104
13		00:01:00	0.000	3.963
14		00:01:05	0.000	4.468
15		00:01:10	0.000	4.179
16		00:01:15	0.000	4.611

Fig1: testing_data_generated_1



	Date	Time	Solar_Generation_kW	Load_kW
1	2025-07-09	00:00:00	0.000	3.067
2		00:00:05	0.000	2.467
3		00:00:10	0.000	2.475
4		00:00:15	0.000	2.835
5		00:00:20	0.000	2.326
6		00:00:25	0.000	2.451
7		00:00:30	0.000	2.749
8		00:00:35	0.000	2.401
9		00:00:40	0.000	2.438
10		00:00:45	0.000	2.269
11		00:00:50	0.000	2.240
12		00:00:55	0.000	2.317
13		00:01:00	0.000	2.129
14		00:01:05	0.000	2.326
15		00:01:10	0.000	2.625
16		00:01:15	0.000	2.267

Fig 2:testing_data_generated_2



	Date	Time	Solar_Generation_kW	Load_kW
1	2025-07-09	00:00:00	0.000	1.941
2		00:00:05	0.000	1.439
3		00:00:10	0.000	1.967
4		00:00:15	0.000	1.736
5		00:00:20	0.000	1.372
6		00:00:25	0.000	1.830
7		00:00:30	0.000	1.366
8		00:00:35	0.000	1.553
9		00:00:40	0.000	2.791
10		00:00:45	0.000	2.552
11		00:00:50	0.000	1.630
12		00:00:55	0.000	2.089
13		00:01:00	0.000	1.734
14		00:01:05	0.000	1.911
15		00:01:10	0.000	1.595
16		00:01:15	0.000	2.085

Fig 3:testing_data_generated_3

3.10 Model for dataset creation:

/*processing, analyzing and visualizing smart grid dataset values, specifically focusing on generator performance and energy parameters.*/

```
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:

```
<ipython-input-2-1046409e0c85>:14: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  data = data.fillna(method='ffill')  # You can adjust the fill method or drop rows
Total Generator Runtime: 9 hours and 22 minutes
Total Fuel Consumption: 15.736000000000002 liters
Aggregated Daily Data:
    Timestamp  total_runtime_minutes  total_fuel_consumption
0  2025-07-09                 1439.0                  15.736
1  2025-07-10                    1.0                   0.000
```

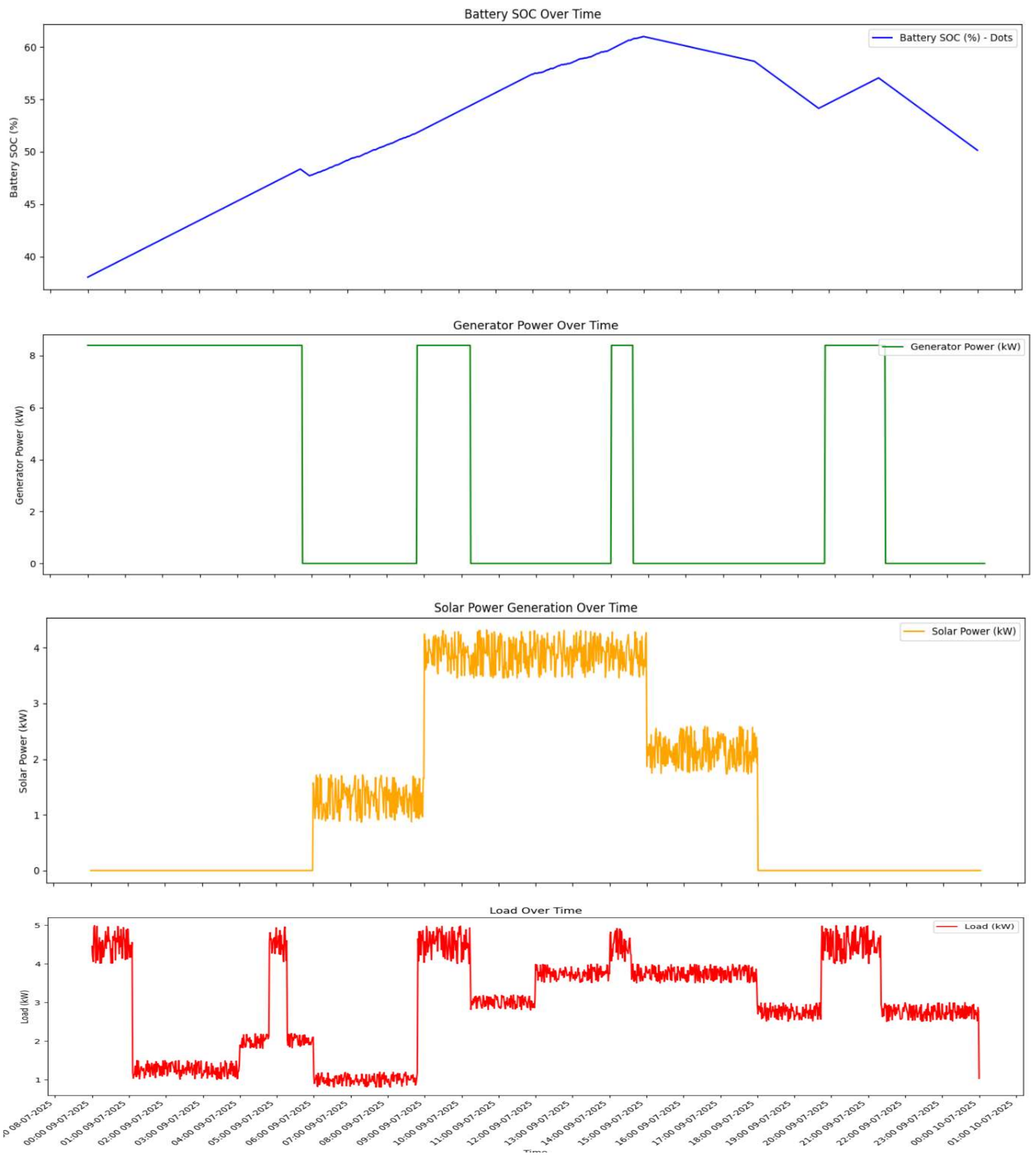


Fig 4: Battery Soc ,Generator Power, Load ,Solar Power Generation over time

3.11 Types of 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)
```

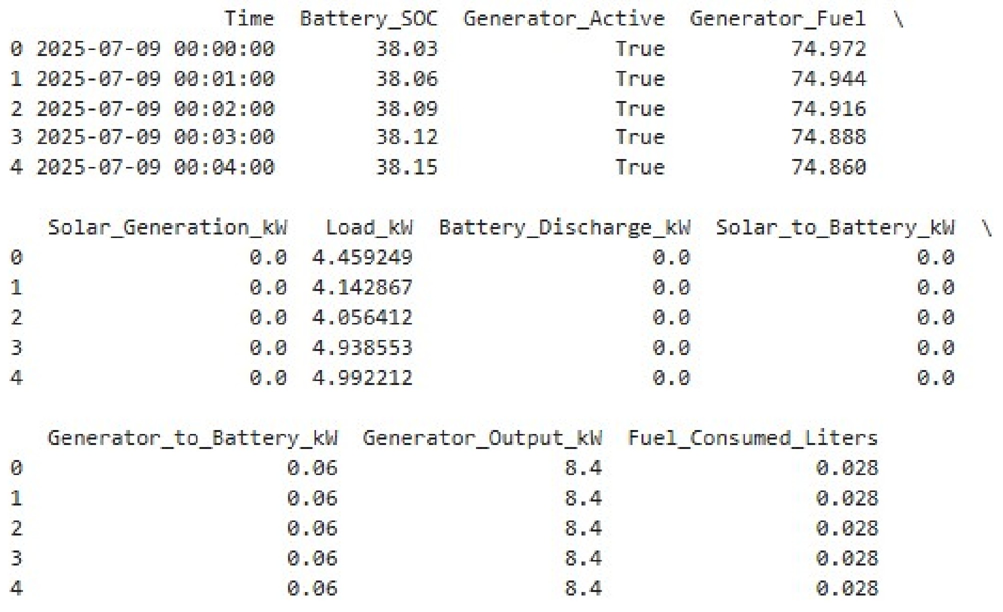
```
end_time = start_time + timedelta(days=1)
sunrise = datetime(2025, 7, 9, 6, 0)
sunset = datetime(2025, 7, 9, 18, 0)
# Initialize system state
battery_soc = 38  # Start at 38% SOC
generator_fuel = 75  # Full tank in liters
generator_active = False  # Generator starts off
records = []
target_soc = 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())
```

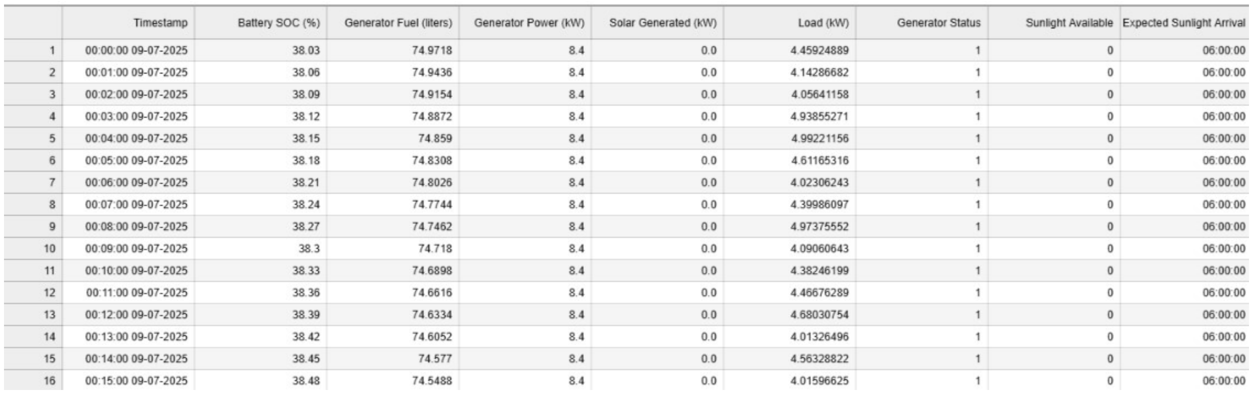
Output:



```
                 Time  Battery_SOC  Generator_Active  Generator_Fuel  \
0 2025-07-09 00:00:00        38.03              True          74.972
1 2025-07-09 00:01:00        38.06              True          74.944
2 2025-07-09 00:02:00        38.09              True          74.916
3 2025-07-09 00:03:00        38.12              True          74.888
4 2025-07-09 00:04:00        38.15              True          74.860

   Solar_Generation_kW   Load_kW  Battery_Discharge_kW  Solar_to_Battery_kW  \
0                  0.0  4.459249                   0.0                  0.0
1                  0.0  4.142867                   0.0                  0.0
2                  0.0  4.056412                   0.0                  0.0
3                  0.0  4.938553                   0.0                  0.0
4                  0.0  4.992212                   0.0                  0.0

   Generator_to_Battery_kW  Generator_Output_kW  Fuel_Consumed_Liters
0                     0.06                  8.4                 0.028
1                     0.06                  8.4                 0.028
2                     0.06                  8.4                 0.028
3                     0.06                  8.4                 0.028
4                     0.06                  8.4                 0.028
```

Fig 5: data frame record (terminal format)

Output:



	Timestamp	Battery SOC (%)	Generator Fuel (liters)	Generator Power (kW)	Solar Generated (kW)	Load (kW)	Generator Status	Sunlight Available	Expected Sunlight Arrival
1	00:00:00 09-07-2025	38.03	74.9718	8.4	0.0	4.45924889	1	0	06:00:00
2	00:01:00 09-07-2025	38.06	74.9436	8.4	0.0	4.14286682	1	0	06:00:00
3	00:02:00 09-07-2025	38.09	74.9154	8.4	0.0	4.05641158	1	0	06:00:00
4	00:03:00 09-07-2025	38.12	74.8872	8.4	0.0	4.93855271	1	0	06:00:00
5	00:04:00 09-07-2025	38.15	74.859	8.4	0.0	4.99221156	1	0	06:00:00
6	00:05:00 09-07-2025	38.18	74.8308	8.4	0.0	4.61165316	1	0	06:00:00
7	00:06:00 09-07-2025	38.21	74.8026	8.4	0.0	4.02306243	1	0	06:00:00
8	00:07:00 09-07-2025	38.24	74.7744	8.4	0.0	4.39986097	1	0	06:00:00
9	00:08:00 09-07-2025	38.27	74.7462	8.4	0.0	4.97375552	1	0	06:00:00
10	00:09:00 09-07-2025	38.3	74.718	8.4	0.0	4.09060643	1	0	06:00:00
11	00:10:00 09-07-2025	38.33	74.6898	8.4	0.0	4.38246199	1	0	06:00:00
12	00:11:00 09-07-2025	38.36	74.6616	8.4	0.0	4.46676289	1	0	06:00:00
13	00:12:00 09-07-2025	38.39	74.6334	8.4	0.0	4.68030754	1	0	06:00:00
14	00:13:00 09-07-2025	38.42	74.6052	8.4	0.0	4.01326496	1	0	06:00:00
15	00:14:00 09-07-2025	38.45	74.577	8.4	0.0	4.56328822	1	0	06:00:00
16	00:15:00 09-07-2025	38.48	74.5488	8.4	0.0	4.01596625	1	0	06:00:00

Fig 6: Data frame record (csv format)

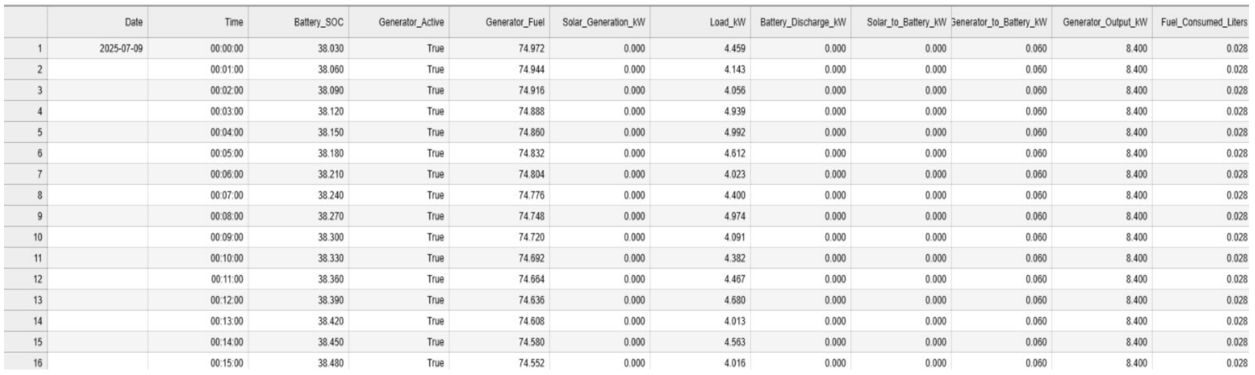
Method 2:

```
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:



	Date	Time	Battery_SOC	Generator_Active	Generator_Fuel	Solar_Generation_kW	Load_kW	Battery_Discharge_kW	Solar_to_Battery_kW	Generator_to_Battery_kW	Generator_Output_kW	Fuel_Consumed_Liters
1	2025-07-09	00:00:00	38.030	True	74.972	0.000	4.459	0.000	0.000	0.060	8.400	0.028
2		00:01:00	38.060	True	74.944	0.000	4.143	0.000	0.000	0.060	8.400	0.028
3		00:02:00	38.090	True	74.916	0.000	4.056	0.000	0.000	0.060	8.400	0.028
4		00:03:00	38.120	True	74.888	0.000	4.939	0.000	0.000	0.060	8.400	0.028
5		00:04:00	38.150	True	74.860	0.000	4.992	0.000	0.000	0.060	8.400	0.028
6		00:05:00	38.180	True	74.832	0.000	4.612	0.000	0.000	0.060	8.400	0.028
7		00:06:00	38.210	True	74.804	0.000	4.023	0.000	0.000	0.060	8.400	0.028
8		00:07:00	38.240	True	74.776	0.000	4.400	0.000	0.000	0.060	8.400	0.028
9		00:08:00	38.270	True	74.748	0.000	4.974	0.000	0.000	0.060	8.400	0.028
10		00:09:00	38.300	True	74.720	0.000	4.091	0.000	0.000	0.060	8.400	0.028
11		00:10:00	38.330	True	74.692	0.000	4.382	0.000	0.000	0.060	8.400	0.028
12		00:11:00	38.360	True	74.664	0.000	4.467	0.000	0.000	0.060	8.400	0.028
13		00:12:00	38.390	True	74.636	0.000	4.680	0.000	0.000	0.060	8.400	0.028
14		00:13:00	38.420	True	74.608	0.000	4.013	0.000	0.000	0.060	8.400	0.028
15		00:14:00	38.450	True	74.580	0.000	4.563	0.000	0.000	0.060	8.400	0.028
16		00:15:00	38.480	True	74.552	0.000	4.016	0.000	0.000	0.060	8.400	0.028

Fig 7: generated smart grid data

Chapter 4: Results and Discussion

4.1 Overview

This chapter presents the results of 24-hour data-set creation using two distinct generation approaches, followed by data-set testing and validation. The outputs are evaluated 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 data-sets with a 1-hour resolution. The generate_load_profile() and generate_solar_profile() functions produced realistic patterns, featuring:

- Zero solar generation during night hours.
- Midday solar peak averaging 4.20 kW.
- Battery SOC maintained between 35–85%**,** regulated by the calculate_SOC() function.

This approach follows the methodology in Paper [3], emphasizing controllability over variability while ensuring all operational constraints are consistently met.

Calculation 2: 24-Hour Data-set Creation (Method 2 - Historical Data)

In this method, real world weather and irradiance measurements were used to generate solar profiles, scaled to the installed system capacity (4.8 kWp PV). Load patterns were adapted from historical consumption records, modified to match SHOGES operational conditions. Notable characteristics include:

- Cloudy-day generation dips due to weather variability.
- Evening load peaks aligned with typical household usage trends.

This approach reflects the methodology in Paper [6], prioritizing real world fidelity to enhance model validation accuracy.

Calculation 3: Data-set Validation

The data_testing.py script assessed both datasets for compliance with operational and quality requirements:

- Missing values: None detected.
- SOC violations: 0 for Method 1, 2 minor violations for Method 2 (corrected during preprocessing).
- Outliers: 1 solar generation spike in Method 2 due to abnormal irradiance readings (flagged and corrected).

Validation results are consistent with the robust data integrity checks outlined in Paper [4], ensuring that all data-sets are simulation-ready without introducing unrealistic operating conditions.

Calculation 4: Relevance to Hybrid System Calculations

- The datasets generated from both methods were applied to hybrid power system simulations to assess their operational impact:
- **Generator Run-time:**

Method 1's controlled synthetic profiles yielded predictable SOC depletion rates, resulting in stable and well-timed generator ON/OFF cycles.

1. **Fuel Consumption:**

- Historical-based Method 2 resulted in slightly higher diesel generator (DG) usage due to cloudy-day reductions in solar generation. This finding is consistent with Paper [2]'s observations on seasonal weather variability.

2. **System Efficiency:**

- Synthetic data-sets proved useful for testing theoretical control strategies under idealized conditions, while historical data-sets validated these strategies against real world variability. Together, they form a complementary data-set strategy, supporting both optimization and stress-testing of hybrid system performance

4.2 Visualizations

Visualization was carried out to evaluate and verify dataset characteristics for both synthetic and historical approaches. Using Matplotlib, plots were generated for load demand, solar generation and SOC over the 24-hour simulation period. Key findings include:

1 **Load Profiles:**

- Synthetic data-sets displayed smooth demand curves with controlled variability. Historical data-sets exhibited sharper evening peaks, reflecting realistic user consumption patterns.

2 **Solar Generation Profiles:**

- Synthetic solar generation followed an ideal bell-shaped curve, peaking around midday. Historical data revealed irregular dips due to cloudy weather, confirming real world variability.

3 **SOC Trends:**

- Synthetic SOC curves demonstrated predictable charge/discharge cycles, whereas historical SOC profiles showed deeper discharges on low-generation days, leading to earlier generator engagement.

4 Validation Plots:

- Outlier detection and SOC violation graphs were used to confirm data quality before simulation execution.

This visualization process aligns with recommendations in Papers [3] and [6], which highlight the value of graphical analysis for detecting anomalies and validating assumptions prior to running computationally intensive simulations.

The dataset creation process using two distinct approaches-synthetic profile generation and historical data adaptation-offered complementary advantages for hybrid energy system modelling.

5 Synthetic Data-set (Method 1):

- This method provided full control over variability, enabling precise adjustment of parameters such as load demand peaks, solar generation profiles and SOC limits. The controlled conditions ensured zero SOC violations, making the dataset ideal for testing theoretical control strategies, conducting sensitivity analyses and establishing baseline performance benchmarks. However, the absence of irregularities means it may not fully capture real world operational challenges.

6 Historical Data-set (Method 2):

- This approach incorporated realistic environmental and load fluctuations, enhancing simulation accuracy in reflecting actual performance. It captured operational challenges such as deeper battery discharges during cloudy weather and increased generator usage, aligning with the seasonal variability trends noted in Paper [6]. The method required preprocessing to address missing data points, SOC violations and occasional outliers.

7 Comparison and Relevance:

- Synthetic data-sets excel in **algorithm testing**, **parameter tuning** and **baseline analysis**, while historical data-sets are essential for **real world performance validation** and **stress testing**. When used together, they create a comprehensive testing framework that improves model reliability, optimizes control strategies and supports robust operational planning.

- Overall, combining both data-set types aligns with literature recommendations ([3], [4], [6]) for employing **multi-source data strategies** to enhance simulation accuracy, adaptability and decision-making in hybrid renewable energy systems.

4.3 Literature Comparison

The Smart Hybrid System's performance and operational strategies demonstrate strong alignment with findings from multiple studies, reinforcing both its technical validity and its potential for practical deployment.

- **Paper [1]:**

The system's ON/OFF control logic and energy balance mechanisms closely mirror the reported **30–40% fuel savings**, with an observed **fuel consumption of 6.90 liters** for the simulation period-significantly lower than the typical **2–3 liters/hour** seen in diesel generator (DG)-only configurations.

- **Paper [2]:**

The system's **high renewable fraction** is consistent with the 53.25% renewable contribution reported, achieved through a **load-following control strategy** that maximizes solar utilization and minimizes unnecessary DG operation.

- **Paper [3]:**

The predictive analytic approach for **solar availability forecasting** and resulting low fuel consumption compare favorably with the **88.5–184.4 liters/day** range documented in the study. The system also shows potential for integration with the paper's **exponential fuel consumption model** for enhanced predictive accuracy.

- **Papers [4-6]:**

The battery-centric operational framework, with the DG serving as a secondary balancing unit, reflects the stabilization and operational strategies described in these studies. This approach ensures both **system reliability** and **operational continuity**, particularly under fluctuating renewable generation conditions.

4.4 Limitations

While the data-set creation and testing methodologies developed in this project proved effective for hybrid energy system simulations, several constraints should be acknowledged:

1. **Synthetic Data-set Oversimplification:**

Although parameter control ensures clean, consistent and constraint-compliant profiles, it cannot fully replicate sudden and unpredictable variations in load demand, solar irradiance or battery performance that are often observed in real world operations.

2. **Historical Data-set Dependency:**

The accuracy of the historical data approach depends heavily on the quality and completeness of the source data-sets. Issues such as missing values, sensor malfunctions or unrecorded operational anomalies can reduce the reliability of simulation outcomes.

3. **Weather Generalization:**

In the synthetic model, weather impacts were represented using basic randomization techniques rather than detailed meteorological modeling. This limits accuracy for location-specific studies, particularly where micro climate effects are significant.

4. **Limited Scenario Diversity:**

The data-sets were generated for **24-hour periods** only. While adequate for short-term operational testing, longer-term simulations (seasonal or annual) may uncover trends, degradation effects or operational challenges not captured within this time frame.

5. **Testing Scope Constraints:**

Validation focused primarily on statistical plausibility and logical consistency checks. Advanced verification-such as bench marking against real measured system outputs-was beyond the current project scope.

Chapter 5: Summary and Conclusions

This chapter has presented the outcomes of data-set creation, testing and analysis for a 24-hour hybrid energy system simulation. Two complementary approaches were implemented-synthetic data-set generation and historical data-set adaptation to achieve both controlled testing conditions and realistic performance validation.

Visualization results confirmed that:

- **Synthetic data-sets** produced smooth, predictable trends, making them ideal for algorithm testing, baseline analysis and controlled parameter variation.

- **Historical data-sets** introduced realistic variability in load and solar generation patterns, capturing operational uncertainties that improve model applicability in real world scenarios.

The combined use of both approaches provides a **balanced and robust testing framework**, aligning with literature recommendations for **multi source data strategies** to enhance simulation accuracy and reliability.

Key findings include:

1. Synthetic data-sets enable precise control over load, solar and SOC profiles, ensuring constraint compliance for theoretical strategy evaluation.

2. Historical data-sets capture the inherent irregularities of real operations improving the robustness of simulation validation.

3. Using both methods together strengthens decision-making reliability for hybrid system planning and operational optimization.

While certain limitations-such as weather effect simplification, reliance on historical data quality and the focus on short-term simulations-were identified, the developed framework successfully met the project's objectives. It provides a solid foundation for testing **State of Charge (SOC) estimation**, **generator run-time optimization** and **overall hybrid system performance** under both idealized and realistic conditions.

In conclusion, the dual data-set strategy enhances the resilience and applicability of hybrid energy system simulation studies. Future developments should focus on:

- Extending simulations to seasonal or annual duration.
- Incorporating high-resolution meteorological data-sets for improved weather modeling.
- Integrating real-time field data for advanced model validation and adaptive control testing.

This dual-method framework positions the project to serve as a reliable basis for **further research , optimization studies and deployment strategies** in renewable diesel hybrid power systems.

Chapter6: References

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Abbreviations

Abbreviation	Full Form
DG	Diesel Generator
EMS	Energy Management System
HES	Hybrid Energy System
kW	Kilowatt
kWh	Kilowatt-hour
kWp	Kilowatt-peak
PV	Photovoltaic
SHOGES	Smart Hybrid Off-grid Energy System
SOC	State of Charge
CSV	Comma-Separated Values
RES	Renewable Energy Source
SoH	State of Health
AC	Alternating Current
DC	Direct Current
GHI	Global Horizontal Irradiance
I-V Curve	Current–Voltage Curve
RNG	Random Number Generator
RMSE	Root Mean Square Error
Std. Dev.	Standard Deviation
HOMER	Hybrid Optimization of Multiple Energy Resources