### SUMMER TRAINING REPORT

on

**“Predictive Model for SoC Estimation & Generator Runtime For Smart Hybrid System”**

### 

### Project Report

UNDER THE GUIDANCE of

### SH. PIYUSH JOSHI, SCIENTIST ‘F’ DIBER(A Cell of DIPAS), DRDO

SUBMITTED BY

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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).**

(Sh. Piyush Joshi)

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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 timestamped 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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# 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 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 timestamped 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 CO₂ 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 CO₂ 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.

# Chapter 2: Review of Literature

Hybrid energy systems that combine 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 limitations, and high 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 96 V, 200 Ah lithium-ion battery. The model employs 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 verify scalability and efficiency.

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

This paper focus on optimizing diesel generator and battery systems for rural electrification, a core component of Smart Hybrid System’s backup power strategy. Its ON/OFF control strategy aligns with the project’s goal of minimizing fuel use. This paper contains some key learnings:

1. ON/OFF Control: The DG operates at rated power to minimize fuel consumption (Section 3), inspiring the threshold-based logic to activate the DG only when SoC < 35% and solar is unavailable for Generator runtime.
2. Battery SoC Dynamics: The SoC model accounts for charge/discharge efficiencies , providing a framework for required Soc calculation to estimate required SoC based on energy balance.
3. Quadratic Fuel Model: The equation ( FC = a P2DG(t) + bPDG(t) + c ) offers a method for generator fuel consumption, though Smart Hybrid System uses a linear model (0.2 liters/kWh) for simplicity, validated by [5].
4. Performance Metrics: Achieves 30–40% fuel savings through optimized DG operation , setting a benchmark for Smart Hybrid System’s efficiency goals.

This provides foundation for DG-battery integration, emphasizing fuel-efficient control through ON/OFF logic and energy balance, directly informing calculation of generator runtime and fuel consumption. The SoC dynamics guided the Kalman Filter implementation for required SoC calculation.

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

## This paper contains inclusion of solar Photovoltaic and use of HOMER for system optimization

## was critical for Smart Hybrid System’s renewable energy focus and weather-based predictions.

## This paper contains some key learning:

## Photovoltaic Power Model: The equation accounts for irradiance and temperature, informing in calculating the time gap until solar availability to predict solar availability based on time-series data.

## Load-Following Strategy: The DG meets only primary load, with Photovoltaic and battery handling excess , refining the threshold logic for Calculating of generator runtime to prioritize solar and battery.

## Performance Metrics: Achieves a 53.25% renewable fraction and 7.8% excess power , validating Smart Hybrid System’s goal of high renewable utilization.

## System Sizing: Provides guidelines for balancing Photovoltaic, battery, and DG capacities, aligning with Smart Hybrid System’s parameters (4.32 kW Photovoltaic, 18 kWh battery, 10 kW DG).

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

## This article contains advanced Energy Management Control (EMC) flowchart and pumped

## Storage hydro (PSH) logic offered insights into sophisticated control and storage strategies,

## enhancing Smart Hybrid System’s adaptability. This paper contains some key learning:

## EMC Flowchart: A structured decision-making process prioritizes Photovoltaic and storage, activating DG only when necessary, guiding time gap and generator activation.

## PSH Logic: Charging storage with excess Photovoltaic power informed required SoC to charge the battery only with surplus energy.

## Fuel Savings: Reports 88.5–184.4 liters/day fuel consumption , providing a benchmark for Smart Hybrid System’s efficiency.

## 2.4 Management and Control of Hybrid Power System

## This article emphasis on battery stabilization and power balance in islanded systems

## Directly supports Smart Hybrid System’s battery-centric approach and DG role as

## a balancer. This paper contains some key learnings:

## Battery as Stabilizer: The battery acts as a sink/source to bridge demand/supply gaps, maintaining power balance and voltage stability in islanded mode, critical for Calculation.

## Generator as Balancer: The microturbine (MTG, equivalent to DG) balances load when renewables are insufficient, informing generator runtime.

## Power Management Goal: Smooth power transfer and stable operation via control strategies, aligning with Smart Hybrid System’s overall objective.

## It reinforces the battery’s role as a stabilizer required SoC Calculation and DG’s role in load

## balancing Generator runtime, validating the energy management framework. The paper’s focus

## on islanded operation mirrors Smart Hybrid System’s off-grid context.

## 2.5 Effective Battery Usage Strategies

It offered specific battery discharge algorithms and power flow rules, critical for Smart Hybrid System’s operational logic. This paper contains some key learning:

1. Discharge Algorithm: Solar prioritizes load, battery discharges only above 30% SoC, and charges with excess solar, informing required SoC estimation and generator runtime.
2. Power Flow Rules: ( Power\_from\_Solar = min(Solar\_Output, Load\_Demand) ), followed by battery and DG, guided the simulation logic.
3. Reliability Cycle: A 30–60% SoC charging cycle for reliability influenced target SoC settings in SoC estimation calculation.
4. Battery Parameters: Detailed specs (e.g., 2400 Ah, 12 V, max charge/discharge currents) supported battery modeling.

It provides precise algorithms for battery and power management, enhancing SoC calculation and runtime generator calculation.

# Chapter 3: Methodology

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

## 3.1 Data Creation for 24-Hour Simulation:

Data creation for a 24-hour simulation refers to generating time-series data-sets that represent system variables-such as load demand, solar generation, and battery state of charge (SoC) over a continuous 24-hour period. These data-sets may be obtained from measured data, statistical models, or synthetically generated profiles to replicate real-world operating conditions, enabling the testing and validation of hybrid energy system models.

**Benefits:**

* **Realistic Performance Testing:** Enables accurate operational scenarios without relying solely on field measurements.
* **Scenario Customization:** Supports modeling of diverse weather, load, and SoC conditions.
* **Time and Cost Savings:** Minimizes the need for prolonged on-site data collection.
* **Algorithm Validation:** Enhances the robustness of control strategies such as ON/OFF logic and energy management systems (EMS).

**Implementation:**

* Two dataset generation methods were developed:
  1. Pattern-Based Method: Utilizes statistical profiles derived from historical solar and load data.
  2. Randomized Variation Method: IIntroduces controlled fluctuations to simulate unpredictable operating conditions.
* Scripts created:
  + data\_creation.py - Generates structured 24-hour datasets.
  + 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.
* **Flexibility:** 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:

## 

## *Fig1: testing\_data\_generated\_1*

## 

## *Fig2:testing\_data\_generated\_2*

## 

## *Fig3: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:

# 

# 

# 

# 

# 

# *Fig4: 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:

# 

# *Fig: data frame record (terminal format)*

# Output:

# 

# *Fig : 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:

# 

# *Fig5: 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.

* **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.
* **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:

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

* **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.

* **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.

* **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.

1. **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.

1. **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.

1. **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.

1. **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.

# Chapter 6: 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 |