Evaluation of Solar Resource Availability and Smart Load Scheduling for Residential Buildings

William Olurotimi Falana[1][a], Ikechukwu Samuel Obidi[2][b] and Samuel Nii Tackie[1][c]
[1]*Dept. of Electrical and Electronic Engr, Near East University, Nicosia, Cyprus*
[2]*Dept. of Electronics and Computer Engr, University of Nigeria, Enugu, Nigeria*

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Abstract: Residential energy applications based on solar resources are rapidly becoming the norm due to the enormous advantages of solar energy. In this study we investigated and evaluated the amount of solar resources available around the year using Cyprus has a case study. This was done by understanding the seasonal trends and potential solar outputs that can be available to a hypothetical residential load which were classified into two. Fixed load of 2.5kw and flexible load of 1.5kw making the total load 4kw. To achieve this we used a dataset from NASA POWER that provides us with important information about our case study Cyprus such has All Sky Surface Shortwave Downward Irradiance and All sky isolation clearness index which was used for this analysis. An evaluation model is created using Python to simulate the availability and reliability of solar energy resources for a potential smart load scheduling strategy using the hypothetical residential load of 4kw. The results shows that during the summer period there is abundance of solar resources to cater for our hypothetical residential load of 4kw (fixed and flexible loads), with an average daily energy production of 6.83 kWh and a clearness score of 0.66, this suggest that during this period the sky conditions is perfect for solar collecting. During the winter period the result suggest that there was less solar resources availability to cater for our hypothetical residential load of 4kw, with an average daily energy production of 2.46 kWh and a clearness score of 0.49, suggest that during this period the solar resources can only cater for the fixed load, this is as a result of frequent cloud cover and limited sun. Spring and autumn indicated moderate levels with some variation.

1 INTRODUCTION

The energy demands around the world are steadily increasing, especially for clean, reliable and sustainable energy (Obaideen et al., 2023), indicating the need for intelligent and highly efficient energy management methods and strategies, particularly in residential buildings. Smart load scheduling involves methods and strategies used for managing and prioritizing electrical loads based on availability, cost, and user preferences (Yang et al., 2023). Residential buildings mostly have need for systems and gadgets which are mostly energy dependent and expensive to run. Sustainable energy sources like solar photovoltaic systems if properly explored, has the ability to reduce grid power consumption and save cost. An example of this optimization technique is smart load scheduling. This is critical for energy efficiency, lower energy costs, and grid sustainability.

The availability of Sustainable energy sources, such as solar energy, is fast becoming increasingly popular in Cyprus, particularly in residential applications (Kassem, Gokcekus, & Aljatlawe, 2023). With new innovations in smart grid technologies and efficient energy management systems, using solar energy in residential building is more feasible and effective. (Khan et al., 2022). Natural events like Seasonal and climatic changes have posed a major challenge on the solar energy supply, leading to solar energy's fluctuation which is a significant problem in maximizing its usage for load scheduling. Smart load scheduling is the process of

[a] https://orcid.org/0009-0002-4339-7418
[b] https://orcid.org/0009-0003-6357-7608
[c] https://orcid.org/0000-0002-5141-9974

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strategic management of energy resources. In the case of solar resources, it is the efficient management of energy consumption in accordance with periods of maximum solar energy availability (Dragomir & Dragomir, 2023). For effective load scheduling, it is critical to understand the patterns of solar irradiance and their implications on energy generation. Making use of dataset like that of NASA's power for the Prediction of Worldwide Energy Resources data (NASA, 2025), helps to provide a dependable method for analysing solar resource availability in Cyprus as a case study. In this study, our goal is to evaluate the seasonal changes in solar resources using NASA power dataset to estimate the monthly energy output by conducting an analysis using metrics like all-sky surface shortwave downward irradiance and all-sky isolation clearness index. This study is intended to support and provide useful and important insight to homeowners, planners, and policymakers in making informed decisions on the usage of solar resources and grid reliance throughout the year.

2 LITERATURE REVIEW

Smart load scheduling and solar resource availability are very important for efficient energy usage, especially in applications related to solar energy generation. With respect to this, there have been several related works on smart load scheduling strategies that have been considered in several instances and solar resource evaluations.

Chreim et al introduce a price-based demand response system for residential smart homes that combines renewable energy, battery storage, and electric cars. It employs a hybrid algorithm for optimal load scheduling and a machine learning-based clustering technique to learn user preferences from real-world consumption data. The result was tested using actual smart house traces and put on a Raspberry Pi to assess performance and energy consumption. (Chreim et al., 2022).

Remani et al provide an average home load scheduling model that incorporates renewable energy sources such as PV into any tariff structure. It proposes a reinforcement learning (RL)-based strategy for managing load commitment under uncertainty while retaining customer satisfaction. (Remani et al., 2018).

Chen et al describe a demand response scheduling strategy for residential buildings that aims at four types of loads, including air conditioning and other deferrable/interruptible categories. It uses the Nondominated Sorting Genetic Algorithm II to balance power costs and user discomfort. The method is evaluated on an ASHRAE 140 standard building under both working and nonworking day conditions. The results indicate successful peak load shifting, lower power expenses, and sustained occupant comfort (Chen et al., 2022).

Albogamy et al proposed an (EMC) that uses a hybrid Enhanced Differential Evolution and Genetic Algorithm (EDGE) to automate home load scheduling. The EMC responds to demand response signals by managing three types of home loads: interruptible, non-interruptible, and hybrid. Simulation findings demonstrate that EDGE outperforms current algorithms such as BPSO, GA, WDO, and EDE across all performance measures (Albogamy et al., 2022).

Ikram et al Investigated Two meta-heuristic optimization strategies for scheduling flexible household loads in a smart home equipped with rooftop solar, battery storage, and grid connectivity. The goal is to cut power bills and peak-to-average ratios while keeping users comfortable. The simulation findings reveal a 4.5% decrease in daily power costs from 507.12 to 484.33 BDT, demonstrating the effectiveness of both optimization strategies without shutting off necessary loads (Ikram et al., 2024).

Abdelhameed et al present smart home load scheduling as a multi-objective restricted mixed-integer optimization problem (CP-MIP) for lowering power costs and increasing user comfort. The strategy is evaluated using time-of-use pricing and two power modes: grid-only and grid-tied PV. Four metaheuristic algorithms are compared, including CL-JAYA and SOH-PSO. The results demonstrate considerable bill savings (up to 56.1%), with CL-JAYA delivering the best user comfort (Abdelhameed et al., 2023).

Stroia et al present a networked sensor system for real-time monitoring and forecasting of domestic appliance power usage and ambient variables. It enables load modelling, database building, and testing of load-scheduling algorithms at various sizes, ranging from single residences to large cities. A hardware/software co-designed architecture combines building automation and energy management technologies. The use of piecewise linear (PWL) load profile representations is proven to enhance peak shaving compared to standard average-based techniques (Stroia et al., 2022).

Qayyum et al investigation looks into the integration of energy management systems in smart residential structures as key components of smart cities. It examines the relationship between smart grids, energy storage, infrastructure, and urban sustainability without using mathematical models. The study discusses how developing energy sources and efficient transportation affect smart urban systems, emphasizing the importance of cross-disciplinary, holistic methods. (Qayyum et al., 2023).

Tackie & Özerdem evaluated the performance of the 1.275 MW Kib-Tek solar power facility in Northern Cyprus. It evaluates plant efficiency, capacity factor (17.71%), and performance ratio (85.77%) using PVsyst simulations. The addition of a single-axis tracker decreased the payback period from nine to seven and increased production by 27.88%. At the simulated locations of Famagusta, Girne, and Lefkosa, grid-injected energy increased by 31.22% with tracking (Tackie & Özerdem, 2022).

Ozerdem et al. evaluated the performance of the 1.2 MW Serhatkoy PV power plant, the first grid-connected plant in North Cyprus. This study simulation was used to determine important parameters, including performance ratio (PR) and capacity factor (CF), using PVSyst software and NASA weather data. In order to facilitate future development, maintenance planning, and investment evaluation, the payback period is also approximated, taking currency exchange rates into account (Ozerdem et al., 2015).

3 ANALYTICAL FRAMEWORK

3.1 Data Overview

The Goal of this evaluation is to study the availability and reliability of solar energy resources in Cyprus using NASA POWER satellite-derived data (NASA, 2025). And to evaluate the possibility of adopting intelligent load scheduling systems in residential buildings. Furthermore, to estimate solar energy output and analyse its temporal trends (daily, monthly, and seasonal). In regard to this, the dataset covers the period of 1st January 2019 to December 31st 2024, which contains the following:

- All Sky Surface Shortwave Downward Irradiance (kWh/m²/day): This contains the total amount of solar irradiance information that reached the earth irrespective of different sky conditions.
- All sky isolation clearness index: This contains the ratio of real solar irradiance to theoretical clear sky irradiance, which indicates cloudiness.

3.2 Seasonal Classification

To study seasonal patterns in solar irradiance and energy output, each record was labelled as winter, spring, summer, and fall for each month.

3.3 Solar Resources Analysis

To carry out this study, the daily solar irradiance data are analysed to calculate monthly averages for solar irradiance and clearness index. Classify days as Sunny, Partly Cloudy, or Cloudy using clearness index criteria (≥ 0.8 sunny, $0.5 \leq CI < 0.8$ partly cloudy, <0.5 cloudy).

3.4 Solar Energy Output Estimation

The goal is to estimate the solar energy output for a hypothetical household photovoltaic system. This is achieved by using the site-specific environmental data and panel characteristics such as the following parameters:

Panel area A = 6.4 m²

Panel efficiency μ=18%

Performance ratio PR = 0.8 (accounting for system losses)

The daily energy output was calculated as:

$$E\ daily = A \times \mu \times PR \times Irradiance......... (1)$$

These parameters were considered under standard conditions.

Panel Area

For a residential building in Cyprus

A normal solar panel = 1.63 m² (Mokhtara et al., 2019)

A residential building in this hypothetical simulation has an estimated number of 4 solar panels.

Panel area = 1.63 m² x 4 = 6.52 (rounded up to 6.5)

Panel efficiency

Considering the type of solar panel in this case, we considered a modern monocrystalline panel, whose efficiency of converting sunlight into electricity is around 18 – 22%. We selected the least case for this, which is 18% (Vodapally & Ali, 2022).

Performance ratio PR

We considered a PR value as a case of a standard and a well-maintained solar panel, which is 0.8 in this case.

Scenario 1:

To estimate the solar energy output for the 2nd day of January 2019.

Panel area A = 6.5 m²
Panel efficiency µ=18%
Performance ratio PR = 0.8

According to the dataset, the all-sky surface shortwave downward irradiance for the 2nd day of Jan 2019 is estimated to be 1.17 kWh/m²/day

$$E\ daily = A \times \mu \times PR \times Irradiance$$
$$E\ daily = 6.5\ m^2 \times 0.18 \times 0.8 \times 1.17 = 1.095\ kWh.$$

The total energy generated on the 2nd day of January 2019 is 1.095 kWh.

3.5 Smart Load Scheduling Model

To facilitate smart load scheduling, residential energy demand was estimated and divided into two categories: fixed loads and flexible loads. In a hypothetical situation, fixed loads were projected to consume around 1.5 kWh/day, while flexible loads consumed 2.5 kWh/day, for a total daily consumption of 4.0 kWh. The identified peak sun hours were projected to yield 40% of the total daily solar energy. The purpose of the scheduling model is to determine how much of a household's electricity use could be covered by solar energy during the four hours of the day when sunshine is at its strongest. Additionally, it examined how much electricity could be saved from the grid by relocating flexible appliances (such as water heaters or washing machines) to run during those sunny hours. Through the use of daily data on solar energy production and household power usage, the model assisted in assessing the monthly effectiveness of a potential smart load scheduling strategy to improve solar energy usage and lessen the load's reliance on the grid.
Grid Energy Savings (kWh): The amount of energy saved by using solar to replace grid usage.
Peak Grid consumption reduction (kW): An estimated decrease in peak electricity consumption based on a 4-hour peak period.

3.6 Average Percentage of Load Met by Solar

The average percentage of load met by solar metric indicates how much of a household's or building's energy demand could be catered for by solar energy, often during peak sunshine hours.

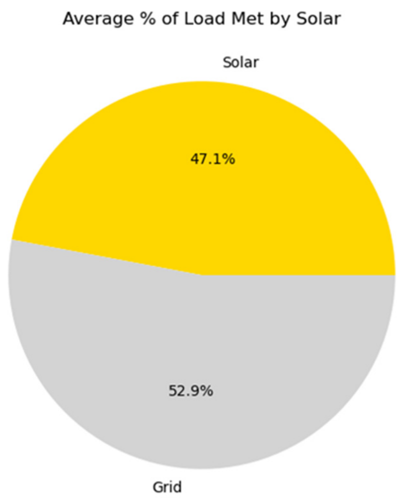

Figure 1: Average Percentage of Load Met by Solar.

From Fig. 1, the data reveal that solar energy accounts for roughly 47% of the home load during peak hours. Solar energy makes a significant contribution, but does not entirely meet energy demand with present system characteristics (PV size = 6.5 m², efficiency = 18%, PR = 0.8). A 47% solar contribution shows the possibilities for partial load scheduling or battery integration. To attain more independence from grid power, expanding PV capacity, enhancing system efficiency, or optimizing flexible load scheduling may be put into consideration.

Scenario 2:

From Scenario 1 on the 2nd of January 2019, the total energy generated is 1.095 kWh of electric energy.

We have a fixed load of 1.5kwh/day
And a flexible load of 2.5kwh/day
Total load = 4kwh/day

Total energy generated on the 2nd of January 2019 = 1.095 kWh

Grid Energy Savings (kWh) = Total energy generated on day 2 = 1.095 kWh
During the Peak solar hours, it was anticipated to generate 40% of the daily solar energy
40% of daily solar energy = 438wh.
Peak Grid Consumption Reduction (kW) = an estimated decrease in peak electricity consumption based on a 4-hour peak period.
= 438wh/4h = 109.5 watt.

Average percentage of load met by solar on 2nd of Jan 2019 = Total energy generated on 2nd of Jan 2019 / Total load energy x 100% = 27.3%.

Average percentage of load met by solar on 2nd of Jan 2019 at Peak solar hours = Solar Energy during 4-hour peak (kWh)/ load during the 4-hour peak period x 100%

Assume all 4 kWh is available during the 4-hour peak period

Load during 4 hours peak period = 4.000kwh/4h =1000watt

Average percentage of load met by solar = 109.5/1000 x 100 = 10.95%

4 EVALUATION OUTCOMES

4.1 Monthly Average Solar Irradiance

The monthly average solar irradiance graph (Irradiance vs. Month) is an important tool for accessing solar energy potential throughout the year.

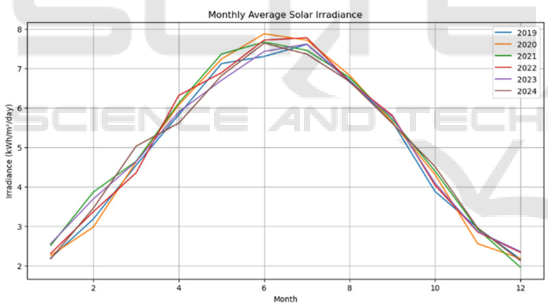

Figure 2: Monthly average solar irradiance.

- Seasonal Trends

From Fig. 2, it is observed that there is higher irradiance between March and October, corresponding to Cyprus's late spring in March, summer, and early fall. This is due to the fact that between these months, there are often clearer skies.

- Solar planning insights:

From Fig. 2, it is observed that months with the highest irradiation, which are between June to August, are the best for solar PV performance. This helps us to anticipate system performance, particularly for off-grid or hybrid solar systems.

- Yearly Comparison

From Fig. 2, it is observed that there is consistency and slight variation from 2019 to 2024 solar resource, which further suggests reliable energy yield planning.

4.2 Estimated Daily Solar Energy Output

The Estimated Daily Solar Energy Output graph is an important outcome of this study because it converts solar irradiance into real usable energy (in kWh) that a solar photovoltaic (PV) system would produce daily.

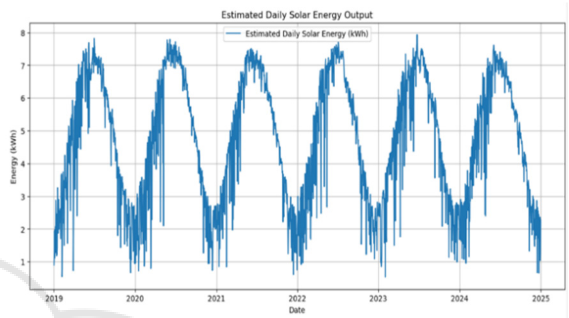

Figure 3: Estimated daily solar energy output.

- Daily Variability:

From Fig. 3, Peaks indicate clear, bright days with a high solar output, while the dips indicate cloudy or rainy days, or periods with reduced irradiance. From 2019 to 2024, we estimated daily solar energy output for 2025, taking the average of irradiance from 2019 to 2024 for each day.

- Seasonal Performance:

From Fig. 3, it is observed that during the summer season, between June to August, output is high and consistent. During winter seasons, output drops due to cloud cover.

- Energy Forecasting:

From this information, it is easier to forecast how much energy you can expect daily/monthly, which is important for battery size, load planning, and determining grid backup requirements.

- Supports Smart Load Scheduling:

From this information, it helps indicate when flexible appliances can be booked on peak solar generating days.

4.3 Monthly Grid Energy Savings and Demand Reduction

From the estimated daily solar energy consumption, we are able to calculate how much grid electricity can be saved each month by using solar power during peak hours, as well as how much this solar usage decreases the grid's maximum demand.

Table 1: Monthly Grid Energy Savings and Demand Reduction for Jan – May 2019.

Year	Month	Grid Energy_Savings (kWh)	Peak Grid Demand Reduction (kW)
2019	Jan	25.496	0.205
2019	Feb	33.418	0.298
2019	Mar	52.779	0.425
2019	Apr	64.126	0.534
2019	May	75.696	0.610

The monthly grid energy savings and demand reduction statistics show how solar PV integration reduces dependency on traditional grid electricity. For example, in January 2019, solar power reduced roughly 25.5 kWh of energy that would otherwise have come from the grid, resulting in a 0.21 kW reduction in peak demand. This shows the ability for solar energy to not only lower monthly energy bills but also reduce too much load on the power grid during peak demand hours, contributing to more reliable and sustainable energy systems.

4.4 Irradiance vs Load

The goal here is to determine if the solar irradiation on each day is adequate to fulfil a household's energy requirements, especially during peak seasons.

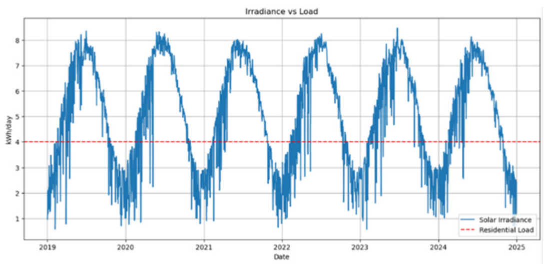

Figure 4: Irradiance vs load.

From Fig. 4, the irradiance versus load graph shows how solar resource availability varies over time in relation to residential energy consumption. The curve steadily grows, reaches a peak (summer), and finally decreases (winter). The red dashed line represents a fixed value, which is the daily energy requirement of the hypothetical household or system.
Above the red line shows the months in, solar irradiation meets or exceeds demand, allowing the building to be self-sufficient or even create extra energy. Below the red line shows months that solar irradiation is not enough, necessitating grid help to satisfy electricity demand.

- Energy Surplus Periods: the period when irradiance exceeds load suggests the possibility of grid export, battery charging, or load scheduling.
- Insufficient Periods: the period when irradiance falls below demand, during this period there is grid reliance, backup generators, or load prioritizing becomes more necessary.

4.5 Average Monthly Solar Irradiance

The average monthly solar irradiance is the amount of solar energy received per square meter per day in each month. This helps in sizing solar panels, predicting seasonal energy output, and designing smart load scheduling systems.

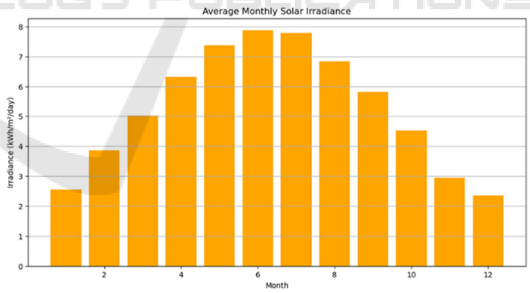

Figure 5: Average monthly solar irradiance.

The average monthly solar irradiance in Cyprus shows a unique seasonal trend, with peak values observed during the summer season (June–August) and a noticeable dip during the winter season (September - May). These seasonal changes and variations are very important for optimizing solar power system performance and load scheduling methods in residential buildings.

4.6 Seasonal Solar Energy Summary

Seasonal Solar Energy Summary shows how solar energy availability and sky conditions fluctuate throughout the year. This includes:
Mean Daily Energy Output (kWh): is defined has the average quantity of solar energy gathered each day during each season.
Maximum and Minimum Energy: The best and worst daily performance recorded throughout that season.
All-sky isolation clearness index is a measure of sky clarity (near 1 = clear skies, < 0.5 = hazy).

Table 2: Seasonal Solar Energy Summary.

Season Daily Energy Kwh	Mean	Max	Min	Clearness Index
Fall	3.98	6.14	0.94	0.59
Spring	5.50	7.76	0.73	0.59
Summer	6.83	7.92	4.37	0.66
Winter	2.46	4.82	0.53	0.48

- Daily energy (kWh)

From Table 2, summer has the highest mean daily solar energy (6.83 kWh), with the lowest difference between minimum and maximum values, showing a consistent excellent solar performance. Winter has the lowest average (2.46 kWh), with greater unpredictability and less dependable solar energy output. Spring and autumn are transitional seasons, with modest sun availability.

- Clearness Index (CI)

The CI is the ratio of real solar radiation to clear-sky radiation (0–1). Higher readings (~0.66 in summer) indicate a cleaner sky and improved sun conditions. Lower values (~0.49 in winter) imply cloudier circumstances and more atmospheric interference.

5 CONCLUSIONS

This study used NASA POWER dataset from 2019 to 2024 to assess solar resource availability and its implications for smart load scheduling in Cyprus residential buildings. There were several Key characteristics that are were considered which were daily solar irradiance, clearness index, predicted solar energy output, and the extent to which solar energy can balance grid demand during peak solar hours. The investigation indicates that the monthly average solar irradiation is high enough throughout the year to sustain dependable photovoltaic (PV) power. Daily solar energy output (based on a 6.5 m² panel at 18% efficiency and a 0.8 performance ratio) ranged from 2.5 to 6.1 kWh/day, with greater performers seen during the summer season. During peak sunshine hours, solar output met 49% of the home load (which included both fixed and flexible components). This implies a high potential for load-shifting solutions, particularly for flexible appliances or battery charging. The irradiance vs. load study revealed that solar generation outperformed basic home consumption levels for several months, particularly during the summer season. The monthly grid energy savings and peak demand reduction estimations indicate that solar integration can considerably decrease strain on the national grid infrastructure. In months with high irradiance, flexible loads might be totally powered by solar energy, saving money and improving grid dependability.
The seasonal solar energy summary showed strong trends:

- Summer is the best time to schedule big or important solar-dependent loads due to high irradiance and reasonably predictable weather patterns.
- Winter poses problems, with lower irradiance levels and more fluctuation, demanding a larger dependence on grid assistance or energy storage options.
- Spring and fall offer intermediate conditions in which partial battery storage or adaptive scheduling may be most effective in ensuring energy dependability.

The result of this study demonstrates the potential of solar-assisted smart load scheduling as a means of ensuring sustainable energy access, particularly in Cyprus. Energy planners are advised to use these seasonal insights when developing demand-side management programs, home solar incentives, or hybrid solar-grid systems to increase energy reliance.

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