AI-Driven Control and Processing System for Smart Homes with Solar Energy

Muhammad Hamza[1], Abdur Raheem[1], Syed Mohammad Ali Shah[2], Syed Ali Hasnain Naqvi[3], Zeeshan Ahmad Arfeen[1*], Muhammad Salman Saeed[4], Nusrat Husain[5], Muhammad Rashid[1]

[1] Department of Electrical Engineering, The Islamia University of Bahawalpur, Bahawalpur, 63100, Pakistan.

[2] Science and Technology Park Mehran University of Engineering & Technology, Jamshoro, Sindh. Pakistan.

[3] Faculty of Social Sciences, Sir Syed University of Engineering and Technology (SSUET), Karachi, Pakistan.

[4] Multan Electric Power Company (MEPCO), Multan, Pakistan.

[5] Department of Electronics & Power Engineering, National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan.

Correspondence: Zeeshan Ahmad Arfeen; zeeshan.arfeen@iub.edu.pk

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In recent years, the utilization of solar energy has grabbed attention in the industrial and domestic zones. The existing systems to use the services of solar cells are conventional. These systems require parameters (irradiance and temperature) for desirable results that are unknown to the end user. These parameters change with regions and human to human. Therefore, an Artificially Intelligent, Control and Processing System is designed to get more accurate results with the unique feature of empowering the end user, which uses the parameters assembled on different regions. The proposed system has an improved PV model based on (ANN) that resembles experimental results with a few readily available, reprogrammable input parameters from the PV module datasheet. The developed system uses regional irradiation data which exhibits minimal fluctuations. In the model presented here; to avoid overburdening problems, loads were divided into manageable chunks MK. In this case load chunks (needed) were moved from solar to utility more stably and economically. Briefly stated the suggested solution provides a complete package for integrating solar energy systems with the grid in an automated and resilient way.

Keywords: Consumer-Based Load Profiles, Load Curves, Solar Capacity, AI Energy Systems.

Artificial Neural Network	ANN
Artificial Intelligence	AI
Internet of Things	IoT
Smart Home Energy Management System	SHEMS
Peer-to-Peer	P2P
Measured in Kilowatts	MK

Introduction:

Traditional residential energy systems are frequently inefficient and rely largely on fossil fuels, resulting in environmental pollution and energy waste [1]. Smart grids, which use advanced information and communication technology, are critical for handling the complexities of incorporating renewable energy sources such as solar power into the electricity system [2]. There is an increasing demand for energy systems that can incorporate renewable energy sources, optimize energy use, and facilitate the development of smart networks. Smart homes use modern technologies like (AI), (IoT) devices, smart meters, and home automation systems to manage and control energy usage. Integrating smart energy systems in homes can result in significant energy savings, increased energy security, and lower greenhouse gas emissions [3].

The recent advancement in information technology has benefited people in all aspects of life. It has brought automation and control to one's hand through software and mobile applications [4]. Today switching of devices like generators and power-generating plants through mobile software is common. The same idea exists when considering a Smart Home [5]. The concept of a smart home includes independent generation. So, it must have automation and control in both generation and usage [6]. Electrical load management systems are common today. The evolution of renewable energies demands these systems to be modified [7]. The use of renewable energy sources like solar panels and wind turbines in smart homes can intelligently switch between grid power and renewable sources based on real-time energy needs and availability [8]. Automated lighting and remote appliance management not only improve comfort but also motivate homeowners to decide on more environment-friendly routines [9]. The concept of the smart home includes both load management and renewable energy systems [10].

Objectives

The objectives of this research are:

- To predict load based on consumer experience.
- Divide loads into multiple manageable chunks (MK) to move towards the utility to avoid overload problems.
- To develop one consumer-friendly application as a comprehensive solution for integrating solar energy systems with the grid in an automated and reliable way.

Novelty of Work:

The current research introduces a simpler and more flexible system compared to previous studies. This study is real-time based and has minimum losses with increased power generation. Current research also aims to provide a solution to overloading. The manuscript is organized as follows: - Section 2 presents the literature on "AI-Driven Control and Processing Systems for Smart Homes with Solar Energy". The methodology section details how the research was conducted, including the participants, materials, and data collection procedures. The results section presents the findings of the study, including data analysis and key observations. Finally, the conclusion summarizes the main points of the research and suggests directions for future investigation.

Literature Review:

Solar energy is an important component of sustainable energy solutions for smart homes and a naturally advantageous and renewable source of power generation. Raza, et al. [11] expand a comprehensive estimation of the current status of smart home energy management systems, outlining important problems and topics for future research. By harnessing sophisticated technology and tackling the stated difficulties, (SHEMS) can play a critical role in improving energy efficiency, lowering expenses, and encouraging sustainable living in smart homes. Lee and Choi [12] offer a unique reinforcement learning-based method for energy management in smart homes. The suggested solution utilizes the RL's capabilities to maximize the usage of energy storage, residential appliances, and rooftop solar PV systems, improving energy efficiency and lowering costs. Dhage, *et al.* [13] demonstrated how machine learning algorithms may help to control solar energy in smart homes. The proposed framework uses predictive analytics and recommendation algorithms to optimize solar energy use, save expenses, and promote sustainable living.

Stecuła, et al. [14] applied AI to energy management in cities, and it focuses on two primary areas: residential systems such as smart homes and larger urban systems such as electric vehicle charging stations and smart grids. It points out that AI optimizes energy usage, aids in the integration of renewable energy, and enhances the overall efficiency of energy usage in cities. Binyamin, *et al.* [15] focused on the improvement of energy systems in smart homes using AI. It involves (P2P) energy trading and improving the efficiency of systems such as solar panels, energy storage, and electric vehicles. The researchers developed an advanced deep learning model system that allows efficient trading of energy while saving costs. They realized that AI can make energy sharing in several situations better, increase its use of renewable energy, reduce costs, and generally improve efficiency in energy usage in homes. The author in [16] presented a framework for enhancing energy efficiency in smart homes by combining AI with the IOT. This framework focuses on real-time monitoring of energy consumption, prediction analytics, and adaptive control mechanisms that optimize energy use. It is shown that AI can predict energy demands based on historical data and external factors like weather, while IoT allows for real-time adjustments in appliance operations. This integration cuts down significantly in energy consumption, brings down the costs involved, and favors renewable usage.

The public (end-user) is the main entity in scheming renewable energies. Anyhow, existing studies have flaws in the user's ability to interpret the system by itself. Moreover, the previous PV models have a major flaw with the increase in temperature. PV/IV curve and stability issues like grid overloading were neglected. Previous research is more focused on load and PV forecasting which in reality depends on user behavior and solar irradiations respectively. The most reliable way of load forecasting is to enable the user to present his load behavior. For PV forecasts the solar irradiation data is important which changes 0.1 % in an 11-year cycle. So, the change was minor and it doesn't require any complex probabilistic technique. Simply, previous data can be used. In short, systems in studies [17-20] have the following confines:

- Require parameters that are less likely to be understood by the end-user
- Unstable PV Models, The PV/IV curve drops abruptly with an increase in temperature
- No real-time solution
- Chances of overloading grids in case of shadowing or weather issues
- The user is unaware of its electricity demand and generation
- Overall, a lack of system stability and understanding hinders users from availing benefits from solar energy as it is supposed to.

Techniques for predicting PV generation have significant flaws. For instance, as temperature changes, the generated power drops sharply and often does not align with the manufacturer's data [21], [22-25], [26]. This is because the equation used to calculate the PV cell's temperature is inaccurate. According to [27] the temperature changes can cause only up to 19 percent drop in output power and it also changes open circuit voltage 'V_{oc}'. Other factors that affect PV generation are series and parallel resistance of cells. Almost all manufacturers don't provide that these parameters must be calculated. Therefore, a PV generation prediction system is required that needs parameters available in the manufacturer's datasheet and can be easily understood by the user. Prediction of PV generation requires irradiation data. In many papers where PV forecast techniques are introduced, irradiation data is assumed through a probabilistic approach which is not suitable for prediction. According to NASA, the solar energy data changes only 0.1 percent in 11 years, which is a minor change. Secondly, the predicted data doesn't account for changes due to cloudsor shadowing. As mentioned by NASA, the best way is to use mean daily irradiation data. These systems mainly lack the modification of load management techniques e.g. peak clipping, valley filling, etc. with the introduction of renewable energies.

Materials and Methods:

As the electric load changes entirely depending upon the user's behavior, the end-user is the only entity that can govern the system most appropriately. This study assumes that the environment is defined by an (ANN) model. The proposed model is portrayed in Figure 1 which utilizes a load curve to understand user behavior, providing the best way to understand load changes. The system enables a user to enter its hourly electricity usage data and then based upon that it plots a load curve. The area under the curve gives the daily energy consumed. The proposed model also possesses a PV block. PV block takes solar irradiation and temperature from the user. Daily irradiation and temperature data can be obtained from NASA's renewable energies website. PV block calculates the PV generation of the day. A noteworthy about the PV block is its accuracy as compared to previous designs. Moreover, it is programmable for every available solar panel in the market as it uses parameters mentioned in the manufacturer's datasheet. The proposed model also deputes another block called the load block. It provides the maximum demand of the user and the number of PV modules needed to satisfy that maximum demand.

The full load block is designed to estimate the maximum demand of the user and the number of PV modules required to serve that maximum demand. The block takes electrical appliance data and PV module data as input from the user. The wattage of different electrical appliances is presented in the block database. The user enters the specific appliances it has. The block multiplies the numbers with already present wattage data respectively to calculate the energy consumption of each device. Finally, the block sums up and shows all the energy to be consumed. The final block is the optimization block, in this block usage, and generation are compared based on suggestions provided by the user for load management. The average irradiance of the region can be found in the global irradiance maps available. PV generation depends upon irradiance directly so, under regional average irradiance data, the average regional power of PV is calculated. The number of PV modules is calculated by dividing the required energy by the average regional power of the PV module. Two input dialogs of this 'PV' module are, 'DATA' and 'Total Load Calculation'.

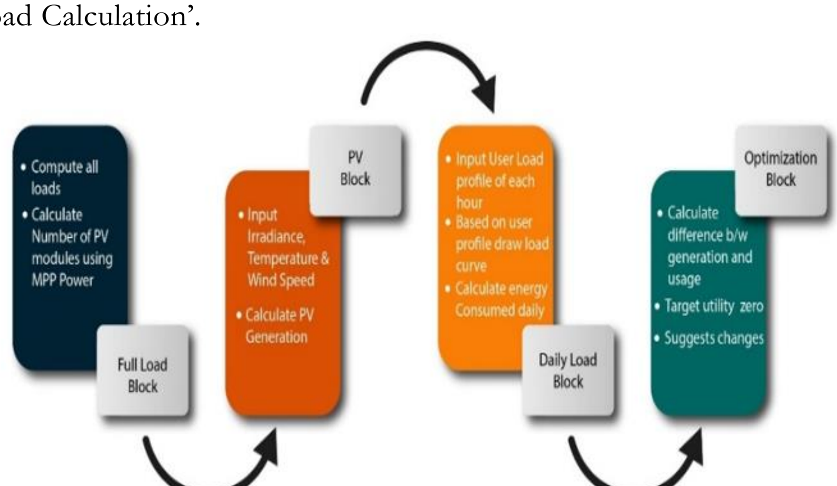

Figure 1. Block diagram of the proposed model.

PV Block:

The PV block is designed in Simulink. The accuracy of the PV block, compared to previous designs, is noteworthy. Moreover, it is programmable for every available solar panel in the market as it uses parameters that are mentioned in the manufacturer's datasheet. The number of 'PV modules required' is calculated in the full load block. The Parameters of PV modules taken as input from the user are directly transferred to the PV block. This takes irradiance, temperature, and wind speed as input from the user as input. The irradiance, temperature, and wind speed data can be taken from NASA renewable energy websites. The parameters taken as input are, open circuit voltage (V_{oc}), short circuit current (I_{sc}), number of cells (N_s), nominal operating temperature (N_{oct}) and maximum power (M_{pp}). Other parameters are calculated using the equations (12).

$$T_{cell} = T_{amb} + ((N_{oct} - 20)/800) * G \quad (1)$$

$$V_{ocn} = V_{oc}[1 - 0.0037(T_{cell} - 25)] \quad (2)$$

$$Pn = P[1 - 0.005(T_{cell} - 25)] \quad (3)$$

$$I_{gen} = I_g - I_o * \left[\exp\left(q * \frac{V + IR_s}{n} * K * N * T_{cell}\right)\right] \quad (4)$$

$$I_g = \boldsymbol{I_{sc}} + [K_i * (T_{cell} - 298)] * \frac{G}{1000} \quad (5)$$

$$Is = Ir * \left(\frac{T_{cell}}{N_{oct}}\right) * \exp\left[q * eg * \left(\frac{1}{N_{oct}}\right) - \frac{\frac{1}{T_{cell}}}{n} * K\right] \quad (6)$$

$$\boldsymbol{I_r} = \frac{\boldsymbol{I_{sc}}}{exp\left(q * \frac{V_{ocn}}{n} * N_s * \boldsymbol{K} * T_{cell}\right)} - 1 \quad (7)$$

$$\mathrm{I_{PRP}} = \frac{\mathrm{V + IR_s}}{\mathrm{R_p}} \quad (8)$$

$$\mathrm{P_{gen}} = \mathrm{I_{gen}} * \mathrm{V_{gen}} \quad (9)$$

$$R_s < 0.001 * V\frac{ocn}{\boldsymbol{I_{sc}}} \quad (10)$$

$$R_p > 100 * \frac{V_{ocn}}{\boldsymbol{I_{sc}}} \quad (11)$$

In the first iteration 'V_{gen}' equals the diode voltage then it grows up. The best way to represent it is as a ramp function in Simulink. In the next step, the power generated is calculated simply by multiplying current and voltage. The power generated is then multiplied by the number of modules to get energy in a day as a whole.

Daily Load Block:

The daily load block is designed to estimate the user load profile. The basic concept in understanding the user load profile is to understand the load curve. It graphically enables the reader to understand its behavior. It is a basic block in load management systems. It represents time on the X-axis in hours and power consumed in kilowatts on the Y-axis. The area under the curve represents the daily energy consumed in Kilowatt-hour (one unit). So, the daily load block takes usage hourly data from the user as input. It deploys this datato plot the daily load curve of the user. This data is then passed to the optimization block for applying load management techniques. Because the nature of the load changes during each season, another supportive feature is the season selector. Which enables users to choose the appropriate season. For each hour there is a separate input dialog.

Optimization Block:

The optimization block receives parameters from the PV block and daily load block. This block compares the difference between daily PV energy generation and daily energy consumed. It targets to make the difference zero. The block advises the user to utilize a non-critical load at noon timing. It also tries to keep the load within the limit of stored energy in off-PV hours. It uses load management techniques to achieve its target. The flow diagram of the whole process is shown below in Figure 2.

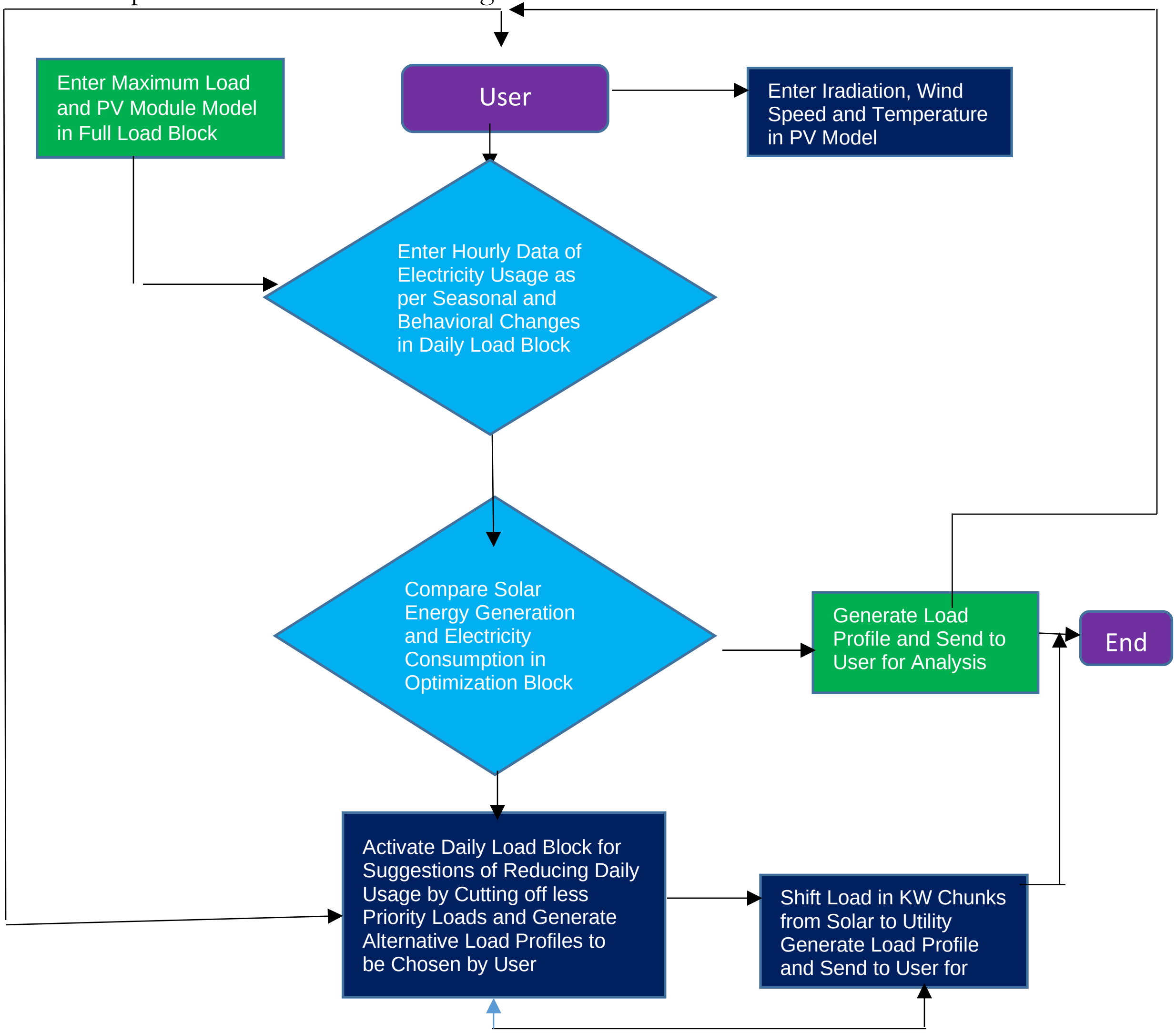

Figure 2. Flow chart of proposed work.

Results:

The purpose of this section is to assess how well the suggested model performs in terms of attaining grid independence and energy optimization. The model's potential to apply real-time solar energy regulation and prioritization to meet household energy demands sustainably is examined. To assess the performance of the model, a typical household load profile was utilized as the case study. The data set mentioned in Table 1 is used as a benchmark against which the ability of the model to redistribute and manage loads becomes evaluated.

Table 1. Electrical load arbitrary

No.	Electrical Appliances Name	Quantity
1	Air Conditioner	2
2	Washing Machine	1
3	Motor Pump	1
4	Microwave Oven	1
5	Vacuum Cleaner	1

6	Television	2
7	Iron	1
8	Light Bulb	12
9	Fan	6
10	Refrigerator	1
11	Geyser	1

Table 2 shows the energy demand variations by season and the PV module Canadian Solar Hiku CS3W-395 was used. The PV module data was used to compute results as shown in Table 3. R_s and R_p. As mentioned earlier, the values in the PV model were calculated using equations 10 and 11, respectively. The results were compared with the manufacturer's datasheet, it is shown that they are quite promising. They are well under the limits of 19 percent change as aforementioned in Section 3.

Table 2. Load Variation by Season

Season	Temperature	Key Energy Demands	Peak Load Period
Winter	Cold (4°C to 20°C)	Heating, lighting, water heating	Early morning (6 AM - 9 AM) & evening (6 PM - 9 PM)
Spring	Mild (15°C to 30°C)	Heating, lighting, water heating	Early morning (6 AM - 9 AM) & evening (6 PM - 9 PM)
Summer	Hot (30°C to 50°C)	Cooling (air conditioning, fans), lighting	Morning and evening for lighting (6 AM - 8 AM, 6 PM - 9 PM)
Autumn	Mild (15°C to 30°C)	Lighting, minimal cooling/heating	Evening for lighting (6 PM - 9 PM)

Table 3. PV Module Parameters

No.	PV Module Parameter Name	Parameter Value
1	Open Circuit Voltage	47 V
2	Short Circuit Current	10.86 A
3	Max Power	395 W
4	Nominal Operating Temperature	42 C
5	Number of Cells	72
6	Ki (Temperature Co-efficient Isc)	0.005 percent per °C

The V-I and P-V characteristics curve of the proposed design at standard temperature and irradiance are shown in Figure 3.

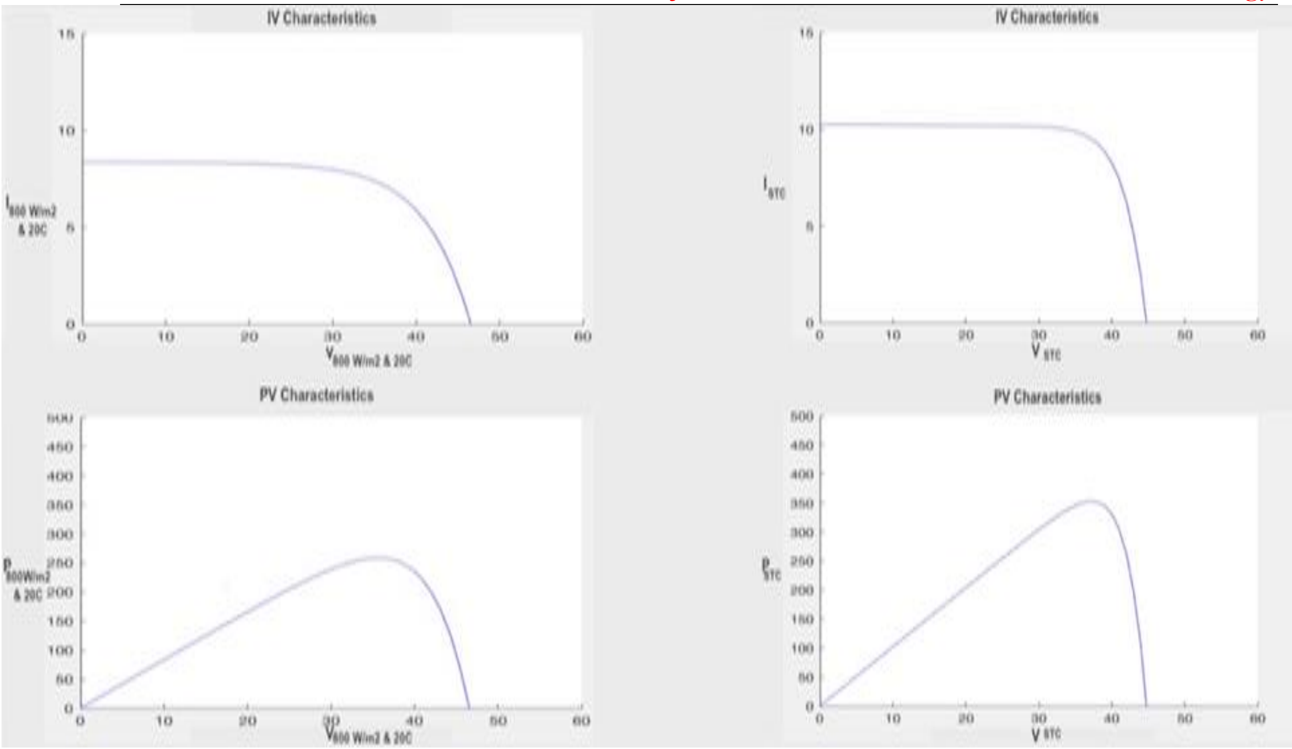

Figure 3. V-I and P-V Characteristics at 800W/m^2 and 20°C.

Cases for Consideration and Result Verification:

Table 4 depicts that the full load block calculated a maximum demand of 14.922 kW. To fulfill this maximum demand, the PV modules required were also calculated in the same block which is 74. For verification, the following cases areconsidered based on the probability of occurrence.

Full Load and Nominal Conditions:

Under full Load and nominal conditions after processing MATLAB provided results as shown in Table 3. Nominal conditions for our region (South Asia) were irradiance of 258 W/m^2 and 30°C throughout the day. Conditions closely matching these values were achieved, resulting in no recommendations from the optimization block. **Table 4.** Generation and Load Gap FL and NC

Generation (kW)	Load (kW)	Difference - kW
14.19830	14.922	-0.7

The number of modules calculated by full load block is 74. Also, the daily load curve for random cases is displayed in Figure 4.

Full Load and Random Conditions:

Under full load and random conditions after processing, MATLAB provided results as shown in Table 5. The model suggested that, on a cloudy day, the irradiance might drop to 170 W/m^2 and 28°C in a whole day. This is a full load case but definitely with a decrease in temperature, the load will also fall. In this case, the optimization block will make recommendations to minimize the difference. The Optimization block might make a certain recommendation to the user. If the non-critical loads operate in off-peak PV timings, then these are suggested to operate in peak PV timings. Load in the steps/chunks is shifted to utility. If the user wants optimization, the block will help the user link up the load to generation after switching off the extra load optimally.

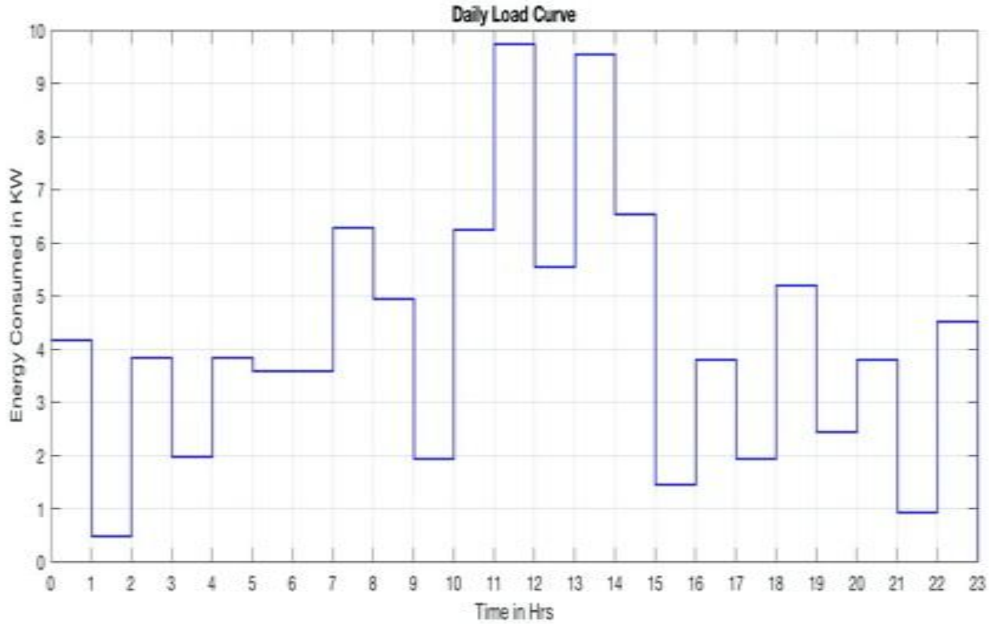

Figure 4. Load Curve Plotted by MATLAB.

Table 5. Generation and Load Gap FL and RC.

Generation – kW	Load - kW	Difference - kW
9.37	14.922	-5.62

Random Load and Nominal Operating Conditions:

The load was randomly computed in MATLAB for this case, and the results are shown in Table 6. It was observed that the result can be different depending on the user's input to the daily load block. Nominal conditions according to our region were irradiance 258 W/m^{2}and 30°C in a whole day. In this case, there were no recommendations by the optimization block as generation is more than usage.

Table 6. Generation and Load Gap RL and NC.

Generation – kW	Load – kW	Difference – kW
14.1980	**9.120**	**+ 6.07**

Random Load and Random Conditions:

Under random load and random conditions after processing, MATLAB gave results as shown in Table 7. Random conditions were supposed to irradiance 230 W/m^2 and 40°C temperatures in a whole day. The load was computed in MATLAB which is random and depends on the user. In this case, there were no recommendations by the optimization block.

Table 7. Generation and Load Gap RL and RC

Generation in kW	Load in kW	Difference in kW
11.3540	9.70	+1.670

Discussion:

The proposed model offers users the possibility to analyze and change the electrical load of a house in real time. The system aims to avoid the use of utility and depend on solar energy as a whole. It targets peak load demand at noon only where energy generation is maximum without affecting the ease of the user.

The discussion section focuses on the thermal behavior of solar cells in various environmental settings and the efficiency of the suggested plan in controlling cell temperature. On the ground, the actual cell temperature is usually 25 to 35°C warmer than the surrounding air. The suggested plan effectively keeps the cell temperature within reasonable bounds, guaranteeing peak performance. On the other hand, earlier methods recorded smaller temperature fluctuations, which might have underestimated the effect of temperature on power generation.

$$Tc = \left(1.14 * (T - Ts)\right) + \left(0.0175 * (G - 300)\right) - (k_r * w) + 30 \quad [28] \quad (12)$$

(Previous)

$$Tc = T + \left(\left(\frac{N_{COT} - 20}{800}\right) * G\right) \quad (13)$$

(Proposed)

Table 8. Overall Comparison of Generation and Load Gap RL and RC

Parameters	Previous Model	Proposed Model	Normal Range
Amb Temp	30 °C	30 °C	-
Temp of Cell	46.06 °C	57.5 °C	25-35 C
Output Power	365 W	371 W	-
Change in V_{OC}	2.7385	0.8695	1-2%
Change from Rated Power	6.345	5.8	19%

Figure 5 and Table 8 provide a comparison to the prior model, the output power of the suggested model is marginally higher. In contrast to the prior model, which showed a V_{oc} Change that was larger than the usual range, the suggested model indicates a change in V_{oc} That is significantly lower and within the normal range.

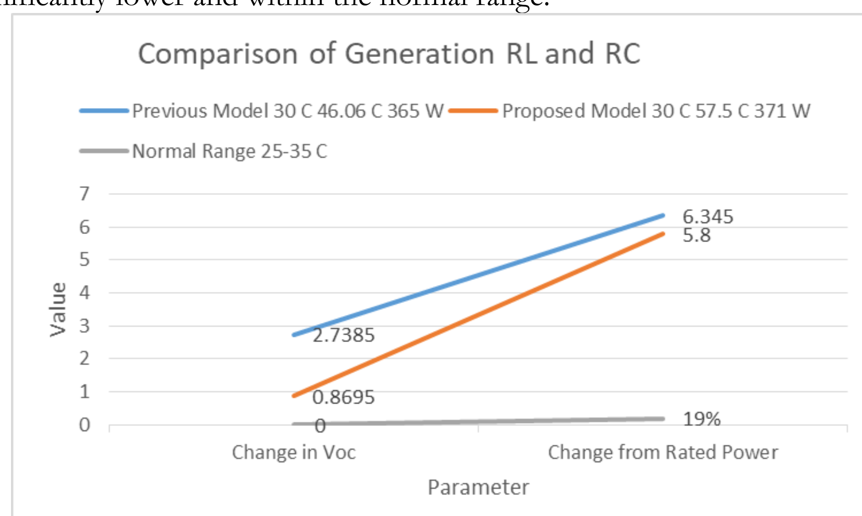

Figure 5. Comparison of Generation RL and RC.

Conclusion and Future Work:

The proposed design offers all the essential functionalities for integrating solar energy systems. The developed system enables the user to understand how many PV panels are required to fulfill its maximum demand. The proposed system is infallible as its PV model has a unique and stable design (with an increase in temperature PV/IV curve shows a calculated drop of 19 percent approximately) as given in Table 8. The proposed model replaced complex techniques for PV and load forecasting with simple and more proficient techniques for the same purpose. After implementing this system there is no need for any probabilistic approach for both load and PV generation forecasting. As mentioned above load forecasting is managed by empowering the user itself and PV forecasting is ruled out as according to world-renowned Institution NASA the change in the Sun's energy pattern is around 0.1 percent in 11 years. With this system, the user will be able to control and analyze its load profiles and generations. The proposed system also divides the load into chunks (MK) to relieve the grid in case of low PV generation. In short, the proposed system enables any person without technical knowledge to manage their home with solar cells optimally. At the domestic level, this system has a significant effect. This system can be easily expanded to hospitals, schools, industries, and Universities to manage their loads with renewable energies optimally and become self-capable along with an option of a 24-hour available power source (Utility).

Author contributions

Study conception and design: Hamza M., Raheem A.; **data collection**: Salman Saeed M, Hamza M; **analysis and interpretation of results**: Rashid M., Hamza M., Arfeen Z.A; **draft manuscript preparation:** Hasnain Naqvi, Rashid M., Hamza M. Visualization Ali Shah, Nusrat H. All authors reviewed the results and approved the final version of the manuscript.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data generated or analyzed during this study are included in this article.

Acknowledgments

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