CNN-LSTM Based Weather Forecasting and Its Application in A Residential Home Energy Management System

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Abstract: Meeting the escalating energy demand poses a contemporary challenge, and the utilization of renewable energy resources (RERs) has emerged as a compelling solution to this imperative issue. These resources can be strategically deployed within households, serving as decentralized generators at the consumer's end. In the current era, with households consuming nearly 40% of total energy, it is imperative to transition to smart appliances capable of adjusting according to provided signals. A demand response program stands out as a pivotal facet of smart grid technology, instrumental in optimizing the assimilation of RERs. Given the inherently intermittent nature of these sources, the resulting output exhibits considerable stochasticity. Hence, forecasting parameters for renewable power generation become indispensable for informed decision-making and the formulation of effective policies. This paper elucidates a research work that deploys a real time pricing-based demand response program, strategically orchestrating the scheduling of diverse general-purpose appliances within a smart household to minimize electricity expenditure. The work specifically leverages forecasted weather parameters for solar photovoltaic (PV) generation in the context of New Delhi, India. Forecasting is achieved through the synergistic application of a hybrid model, combining a convolutional neural network and a long short-term memory type recurrent neural network. The calculated payback period for the deployed PV panel has been determined to be 5.112 years. The comprehensive diminution in costs exhibited a noteworthy reduction of approximately 53.5% in comparison to the selected base case.

Keywords: Demand response program; renewable source integration; smart home; weather forecasting; energy management

1. Introduction

As delineated in the World Energy Outlook Report 2022, a conspicuous trend emerges, indicating a substantial and noteworthy surge in global energy demand[1]. Aligning energy demand with supply has evolved into a formidable challenge[2]. As a pivotal process, energy forecasting involves anticipating and predicting future energy demand and supply. It serves as a critical instrument for energy management, facilitating informed decision-making on energy policy[1], strategic planning for future energy requirements[3], and the efficient administration of energy resources. Nations can leverage forecasted information to inform decisions regarding investments in novel energy infrastructure, including the development of power plants and transmission lines. Notably, India occupies the fourth position globally in renewable energy production and maintains a parallel rank in global solar energy output, boasting an impressive capacity of 63.30 GW. India aims to achieve a remarkable milestone, targeting up to 50 percent of cumulative installed capacity from renewable energy sources by the year 2030[4]. India strategically employs energy forecasting to guide its ambitious initiatives aimed at augmenting renewable energy capacity and diminishing reliance on fossil fuels[5]. Nevertheless, inaccurate forecasting holds the potential for substantial financial losses and poses the risk of power network failures, as elucidated in[6].

1.1 Forecasting for a power network

In an electric power network, forecasting demand and power generation plays a pivotal role in ensuring economic efficiency and effective implementation of demand response (DR) functions. This forecasting process encompasses a variety of weather-dependent parameters associated with energy demand, contributing to the inherent intermittency observed in renewable power generation. Depending on the duration of the forecast, forecasting can be categorized into various temporal scales. These include very short-term forecasting, covering intervals from a few seconds or minutes up to a few hours; short-term forecasting, spanning from a few hours to weeks; medium-term forecasting; and long-term forecasting, extending over months[7]. Various types of forecasting methodologies can be employed for a power network, selected based on specific operational needs. Short-term forecasting (STF) emerges as a pivotal component, playing a crucial role in ensuring the efficient and reliable operation of an electric power network[8].

Cutting-edge literature in the field employs a diverse array of forecasting models to scrutinize the time series characteristics and physical behaviour of photovoltaic (PV) power generation. Physical models utilize satellite images as data sources, whereas statistical models rely on historical data pertaining to PV power generation, as outlined in[9]. Autoregressive Integrated Moving Average (ARIMA)[10], Kalman filter[11], and Generalized Additive Model[12], stand out as widely employed statistical models for STF. Conversely, artificial intelligence (AI)-based models, utilizing neural networks and other machine learning techniques, are adept at capturing the dynamic behaviour inherent in the time series of PV power[13]. A study[14] observed that statistical methods rely on past load or generation input data, often neglecting special events, distinctive features, and prevailing weather conditions. The study further highlighted that these statistical approaches tend to produce inaccurate predictions, primarily attributable to the nonlinear relationships present among lagged values within the input time series. Recent studies have witnessed the convergence of both statistical and artificial intelligence (AI) models, culminating in the proposal of hybrid models[15]. A comprehensive review presented in[16] underscores the efficacy of these hybrid models, revealing their superior performance compared to models reliant solely on metaheuristic, mathematical, or machine learning (ML) methodologies. In the context of short-term electrical load forecasting, a hybrid model was introduced by[10,17], combining the strengths of a wavelet neural network and ARIMA methods. The simulation results of this hybrid model surpassed those of support vector machines, Elman neural networks, and extreme learning machines.

Recurrent and Convolutional Neural Networks (CNN) have emerged as prominent machine learning methods employed for forecasting[18]. Recurrent Neural Networks (RNN) possess the capability of memory storage, rendering them particularly suitable for handling sequential data. In capturing long-term dependencies, the Long Short-Term Memory (LSTM), a subtype of RNN, proves more suitable, as highlighted in[19]. Given its inherent ability to retain temporal information, LSTM stands as a particularly apt choice for applications such as weather forecasting. In the study[20], LSTM was employed for short-term net energy and load forecasting, incorporating spatial information related to household appliances. The study concentrated on forecasting either individual household profiles or the aggregate load profile, with the LSTM model incorporating load profiles from all households. The results indicated that LSTM demonstrated greater adaptability to sudden changes at the individual household level. Conversely, the devised multi-input, single-output LSTM-based technique proved effective at the aggregate level. In a comparative study[21], various machine learning techniques such as multi-layer perceptron, CNN, LSTM, and bidirectional LSTM were juxtaposed with hybrid machine learning techniques. The findings underscored that hybrid machine learning techniques emerge as a superior option for time-series forecasting, showcasing enhanced accuracy.

1.2 Demand response in a power network

Different applications of smart grid, e.g., peak-load reduction techniques, work on DR programs and real-time monitoring of distribution networks, depending on the accuracy of forecasts[20]. The DR program stands out as a fundamental tool within the smart grid framework, designed to effectively manage the energy consumption of residential or commercial buildings[22]. The primary objective of a DR program is to curtail the load during periods of peak demand[23]. The integration of a DR program can enhance the efficiency of power networks by incorporating energy storage systems and renewable energy sources (RES), ultimately leading to a reduction in the overall electricity bill[24].

In response to a DR program, a consumer has the flexibility to curtail his load during peak pricing hours, strategically shift peak loads, or generate additional required power leveraging distributed generators available on-site. Consequently, the pattern of electricity consumption undergoes changes, and a consumer's engagement in the DR program can directly impact the electricity bill. The classification of a residential DR program is illustrated in Fig. 1[19]. An incentive-based DR program incentivizes a consumer with a discounted rate for curtailing or shifting their load during peak hours. On the other hand, price-based programs offer varying tariffs based on time and utilize signals to prompt consumers to adjust their loads during specified timeslots.

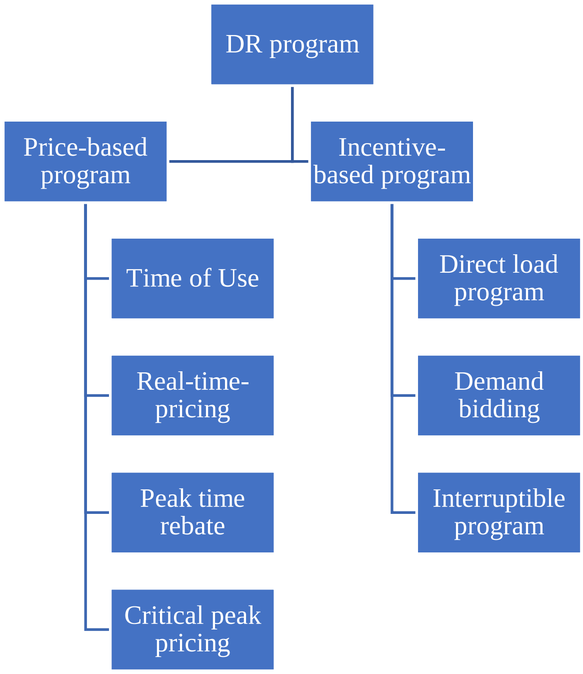

Fig. 1: Types of demand response programs.

Compared with a flat rate tariff (FRT) structure, dynamic pricing tariffs allow the effective implementation of any DR program. Real time pricing (RTP) and Time of Use (TOU) pricing are the globally implemented DR programs. The authors[25] compared FRT and TOU tariffs for different peak-limiting strategies to reduce the peak-to-average ratio (PAR). The study observed a reduction of about 41.4 percent in PAR value by implementing the DR program. A study[26] implemented a TOU pricing tariff for grid-connected houses in Australia. This work focused on reducing the peak demand on the grid, and it has been seen that the DR program was successful in reducing the peak demand up to 35 percent.

Various optimization algorithms can also be implemented with the DR programs to attain the desired scheduling operation of appliances in a smart home. The computational tools like genetic algorithm, game theory, and heuristic techniques like particle swarm optimization and grey wolf optimization are commonly used in a home energy management system. Although there are listed advantages of these heuristic techniques but a globally optimum solution can't be guaranteed[27].

The study[28] proposed a DR-based energy management program for smart household appliances using fuzzy logic and reinforced learning methods. Solar PV module was also included in the study as a renewable source, but forecasting of PV generation was not included. DR programs with weather forecasting can be a powerful tool to provide solutions for power network augmentation and this powerful combination is missing in most of the studies[20,22–24,28].

1.3 Contribution of the work

- The literature review indicates that a predominant portion of research is typically dedicated to individual aspects, specifically either load or generation forecasting or DR programs. The current research work uniquely integrates generation forecasting with an RTP-based demand response program, thereby enhancing the overall planning efficacy of the current energy management system.
- The present work forecasts the PV generation based on predicting the irradiation and temperature using a hybrid deep learning technique based on CNN and LSTM, which enhances the effective learning of feature extraction and temporal relations in the data.
- Payback period analysis has been done to see the economic impact of solar generation, and the performance of the system has been observed by analysing the sensitivity and uncertainty with the variation of input parameters.

Further, this study encompasses nearly all categories of household appliances, a comprehensive inclusion that is notably absent in numerous papers focused on residential energy management systems. This broad coverage contributes to a more holistic understanding of energy consumption patterns within households. To guarantee a globally optimal solution, the objective function is addressed through the Mixed Integer Linear Programming (MILP) method and solved using the CPLEX solver within the GAMS software. This meticulous approach ensures an exhaustive exploration of potential solutions for enhanced optimization.

The subsequent sections of this paper are organized as follows. Section 2 provides an in-depth exploration of the implemented home energy management system, delineating the chosen solar power plant and pricing scheme employed in this study. In Section 3, forecasting architectures have been discussed, which are used for the proposed forecasting model. Moving on to Section 4, the paper delves into the problem formulation and solution, encompassing details about the proposed forecasting model and energy management function. Section 5 comprises the case study and result analysis, exploring various scenarios presented in the paper. Additionally, this section incorporates the data on appliances & forecasting and the outcomes of the proposed forecasting model and home energy management system. Further, this section also includes the calculation of payback period, uncertainty analysis, and sensitivity analysis. The study culminates in Section 6, presenting key findings and concluding remarks.

2. Home energy management system

The scope of this study is centered around a residential consumer situated in the capital of India. The consumer possesses the capability to install smart appliances in its household and demonstrates a willingness to actively participate in a DR program proposed by the utility. A home energy management controller (HEMC) has been employed to schedule the household's smart appliances. A day horizon (T) of twenty-four hours has been considered for scheduling the appliances, which is hourly divided (one timeslot = 1 hour), i.e., T= {1,2,3……..24}. The energy consumption vector Q_l^t is denoted as

$$Q_l^t \triangleq [Q_l^1, Q_l^2 \ldots\ldots\ldots\ldots Q_l^{24}] \tag{1}$$

where Q_l^t shows the energy consumption of appliance $l \in L$ at time slot *t,* and set 'L' groups the employed appliances in the household. For complete operation of any appliance, the required energy is written as E_l such that

$$\sum_{t \in T} Q_l^t = E_l \quad \forall\ l \tag{2}$$

The calculation of time schedules for uninterruptible appliances and constraints for all non-thermostatic appliances has been done, as explained in the authors' previous work [27].

To reduce the peak demand by the household, the energy imported from the grid in any timeslot (E_t^{gr}) is limited by constraint as shown by (3) so that the house can be allowed a maximum energy up to L_{mx}.

$$E_t^{gr} \leq L_{mx} \qquad \forall\ t \tag{3}$$

2.1 Solar PV plant

The residential consumer under consideration is assumed to possess a small rooftop solar Photovoltaic (PV) plant as a distributed energy source situated in close proximity to the house. The photovoltaic power generation is facilitated by a 330W-24V polycrystalline solar panel manufactured by Vikram Solar, which comes with a performance warranty extending up to 25 years[29]. A collective arrangement of 8 panels, organized in a 2x4 configuration, forms the rooftop solar panel array with a combined rated power generation capacity of 2.64 kW for the building. The power generated by the Photovoltaic (PV) system at a given timeslot 't' can be represented as:

$$E_{t\,dc}^{PV} = N_{PV} * f_{PV} * PV_{rated} * \frac{G_t}{G_{STC}} * \{1 + \alpha_T * (\theta_t - \theta_{STC})\} \tag{4}$$

In (4), N_{PV} is the number of PV panels in the module, PV_{rated} is the rated power of a PV panel specified by the manufacturer, G_t is the forecasted irradiance in slot 't', G_{STC} is taken 1000 W/m2, θ_t is the forecasted temperature at the respective slot, α_T is temperature coefficient given in the datasheet (-0.38%/°C), of power specified by t θ_{STC} is taken 25^{0}C and f_{PV} is taken as the derating factor of PV.

4.1 Pricing structure

A price-based DR program has been implemented with the support of an RTP pricing structure managed by the Indian Energy Exchange, which is online and publicly available[30]. The RTP tariff in Indian rupee (INR)/kWh used in this study is shown in Fig. 2.

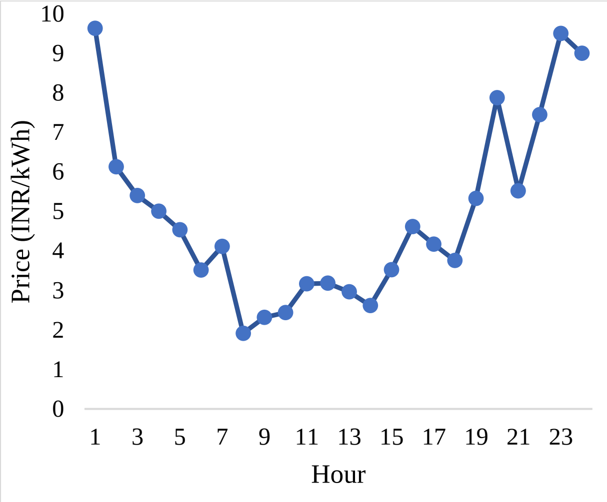

Fig. 2: Implemented RTP tariff.

3. Forecasting architectures

3.1 Convolutional neural network

CNN applies the basics of neural networks with few additional layers[31] and has been a popular tool for image processing for a quite long time. Beyond their conventional use in image analysis, CNNs exhibit a remarkable capability to learn both temporal and spatial patterns from input data, rendering them well-suited for extracting relationships within time series data. A schematic CNN architecture is shown in Fig. 3.

3.2 Long short-term memory

To overcome the shortcomings of the vanishing gradient problem in RNN, Hochreiter proposes LSTM[32]. The LSTM architecture comprises a cell designed as a memory unit and incorporates three gates: the input gate, the output gate, and the forget gate. These gates play crucial roles in managing the flow of information within the network. Specifically, the forget gate is responsible for selecting information from the previous cell state that should be discarded, contributing to the network's ability to selectively retain or forget certain information over time. The input gate decides the new information to be stored in the current cell state. The output gate forwards the information to the rest part of the network. Due to the inherent ability of LSTM to deal with highly fluctuating data, this has proved immensely useful in time series analysis and weather forecasting.

4. Proposed model and problem formulation

The research work is executed in two phases. Phase -1 discusses the PV generation forecasting using a hybrid deep learning technique, and the output of phase -1 is given to phase-2 to execute the demand response program for the smart home management system.

4.1 Proposed forecasting model

For the forecasting of PV-generated power, a hybrid model based on CNN and LTSM is developed and shown in Fig. 4. The forecast work is developed in four steps. Step-1 deals with data import and processing. The second step involves the model training using training data. The third step predicts the irradiance and temperature, and the final step involves the calculation of PV power using predicted values.

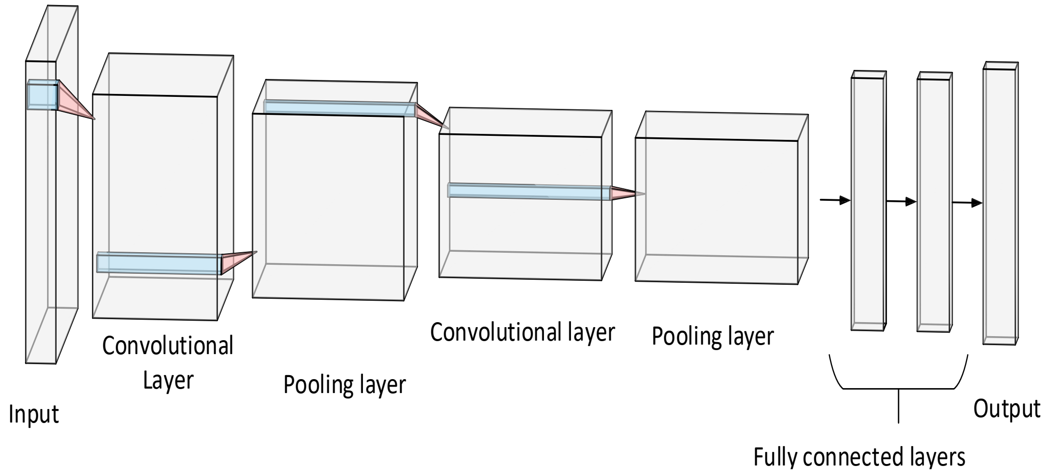

Fig. 3: Architecture of convolutional neural network.

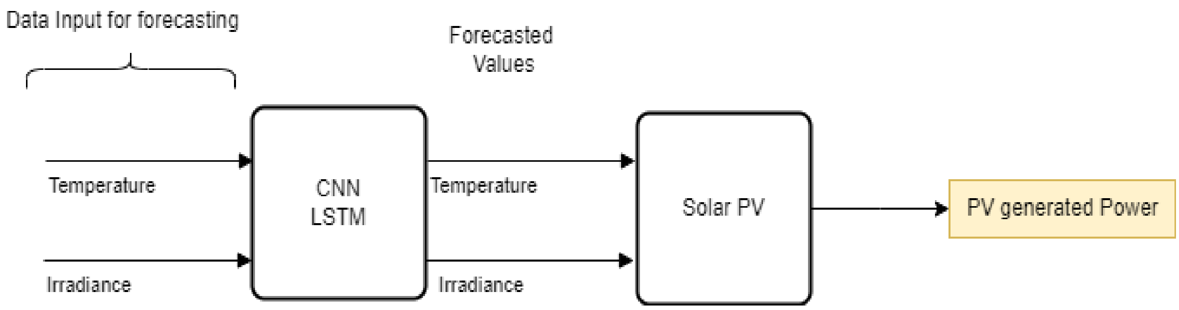

Fig. 4: Architecture for PV forecast.

Step-1 involves importing weather data, including the temperature, irradiance, clear sky irradiance, and wind speed. The imported raw data may consist of outliers and missing values. The algorithm checks for the missing values and excludes the empty cell. After removing the missing values, the data is normalized using Z-score normalization (5) to remove the effect of outliers. The processed data is divided into training and testing data on the ratio of 90:10. The normalized value 'G' has a value between (0,1) and can be expressed as

$$G = \{(G_t - \overline{G_t})|\sigma_g\} \tag{5}$$

Here G_t is the value needed to normalize, $\overline{G_t}$ is the mean of all values of set G_t and σ_g is the standard deviation of the set G_t.

Step-2 involves training the model using a CNN-LSTM network using training data. The network is designed using the sequence of layers as shown in Fig. 3. The initial layer of the network is the sequence input layer to feed the data to CNN layers. The present research used one-dimensional CNN, relu, and pooling layers to extract the temporal data characteristics. The output data from the CNN layer is given to the LSTM layer and fully connected layers to improve the data learning capability of the network. Finally, the trained result is taken from the regression layer.

Step-3 predicts the temperature and irradiance that are required to calculate the PV power of the location. The performance indices are calculated to know the performance of the proposed forecast algorithm. Step-4 finally calculates the PV power from the predicted values using (4).

4.2 Proposed energy management function

The other objective of the study is to reduce the overall electricity bill by employing a local power-generating resource with an RTP pricing tariff. The objective function of the problem can be written as

$$Cost = \sum_{t\in T}\left(\left(E_t^{appl} + E_t^{AC} + E_t^{EWH}\right) * P_t^{buy}\right) \quad (6)$$

$$E_t^{gr} = E_t^{appl} + E_t^{AC} + E_t^{EWH} \quad (7)$$

In equations (5) & (6), E_t^{appl}, E_t^{AC} and E_t^{EWH} are the energy consumed by non-thermal appliances, heating, ventilation, air conditioning system (HVAC), and electric water heater, respectively. The abbreviation P_t^{buy} shows the RTP at the tth timeslot and shown in Fig.2.

With the integration of solar PV with the grid, the effective energy drawn from the grid (E_t^{efct}) is reduced, and now the effective electricity cost may be written as

$$Cost = \sum_{t\in T}\left(E_t^{efct} * P_t^{buy}\right) \quad (8)$$

$$E_t^{efct} = E_t^{gr} - E_{t\,dc}^{PV} \quad (9)$$

The work's objective is to minimize the electricity cost purchased from the grid, as shown in (6) and (8). All the modelling equations and constraints, including those taken from[27] are either integer or binary in nature. These constraints make the problem linear and simple, which are designed in GAMS software and solved using an inbuilt solver CPLEX on a 64-bit, Intel Core I5-1035G1 CPU @1.00GHz laptop.

5. Case study and results analysis

For this study, a resident of New Delhi, India, is considered; however, the study may be carried out on any location using required input data from that particular location. The consumer is supposed to have a small solar unit on its rooftop and smart appliances in the household with a communication interface for sending and receiving control signals[33]. All the appliances are classified as Type 1: interruptible, Type 2: uninterruptible, and Type 3: must-run load. The appliances and their type may vary for different consumers. Considering the consumers' comfort level, they are supposed to give their preferred slots to the utility, including the rating and required time of operation of a particular appliance.

5.1 Data for appliances

The data on appliances used in the study is provided in Table 1.

Table 1. Appliances installed in the household.

S. NO	Appliance	Quantity	Type	Preferred slots (hours)	Slots required for operation	Consumption per slot (kW)	Energy consumed per day(kWh)
1	TV	1	1	18 hr - 24 hr	3	0.05	0.15
2	WATER PUMP	1	1	3hr-9hr	2	0.25	0.5
3	VACUUM CLEANER	1	1	8hr-13hr	1	0.8	0.8
4	WASHING MACHINE	1	2	6hr-9hr	1.5	0.7	1.05
5	WATER PURIFIER	1	3	All	24	0.025	0.6
6	DISHWASHER	1	2	18hr-23hr	1.5	1.2	1.8
7	REFRIGERATOR	1	3	All	24	0.1	2.4
8	PC	1	1	8hr-20 hr	8	0.03	0.24
9	LIGHT	6	1	12hr-24 hr	9	0.24	2.16
10	FAN (BED ROOM)	3	2	20hr-10hr	10	0.15	1.5
11	FAN (LIVING ROOM)	2	1	18hr-24hr	2	0.1	0.2

In addition to the above appliances, an HVAC and electric water heater are also employed in the home for the user's thermal comfort. The specifications, working hours, and modelling of the thermostatic appliances have been done as in[27].

5.2 Data for forecasting

The hourly solar irradiance and temperature data (Dates (month/day/year): 01/01/2022 through 30/06/2023) is collected from NASA's website[34] for the geographical coordinates of New Delhi, India (Latitude 28.634, Longitude 77.188). This data is used to train the network and predict next-day irradiance and temperature, which are used in the modelling and designing of the PV plant.

5.3 Outcomes of the proposed forecasting model

The proposed CNN-LSTM based forecasting method is used to forecast the irradiance and temperature data for 01/07/2023 and compared with the actual data of the day as shown in Fig. 5.

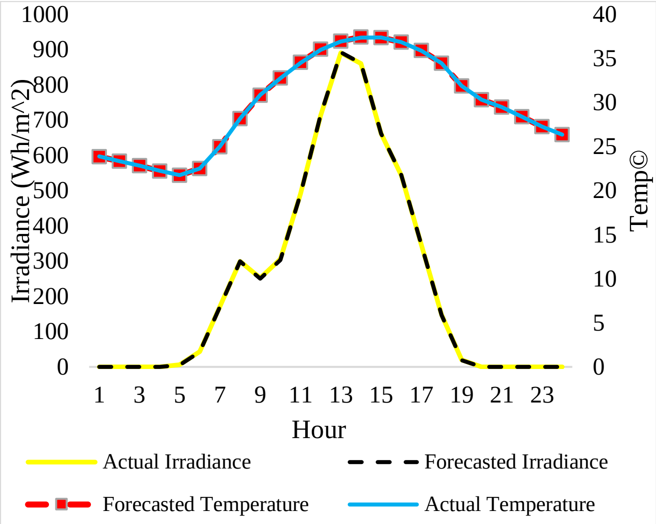

Fig. 5: Actual and forecasted parameters.

After comparison, the error magnitudes of the irradiance and temperature achieved by the proposed forecasting method are shown in Fig. 6. The observed temperature error is near to zero, and the irradiance error is less than 0.12 percent, which indicates the high accuracy of the proposed forecast method.

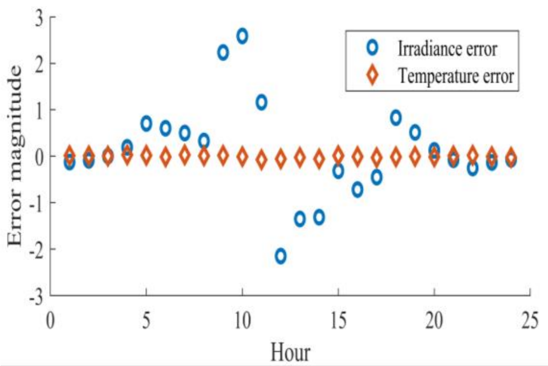

Fig. 6: Forecasting errors.

Further, the forecasted irradiation and temperature data are used to calculate PV output power using (4) and is shown in Fig. 7.

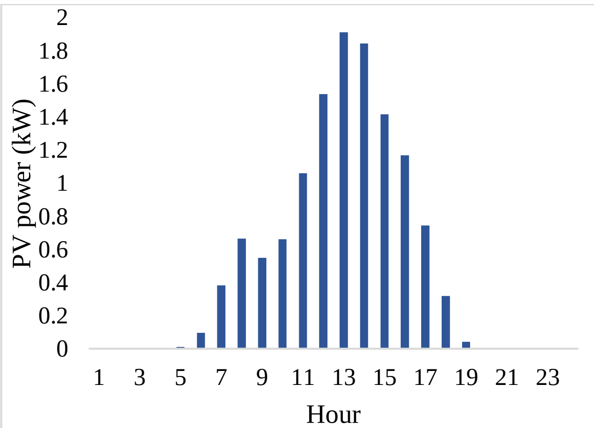

Fig. 7: PV-generated power.

5.4 Analysis of home energy management system with forecasted solar power

Further, to observe the effect of slot selection for appliances and the inclusion of forecasted solar power, different cases have been considered

I. Self-scheduling of household appliances.
II. Scheduling of smart household appliances by HEMC.
III. Scheduling of smart household appliances by HEMC, including forecasted solar power.

Case I: This case is selected as the base case for the study in which the user manually controls household appliance switching within preferred slots, as given in Table 1. It has been observed that peak demand in the base case is found to be 5.195 kW with an average of 1.641 kW and PAR is calculated to be 3.166. With the applied RTP tariff shown in Fig. 2, the overall electricity bill is calculated as 223.87 INR. The resulted scheduling of appliances and hourly power drawn from the grid for this case is shown in Fig. 8.

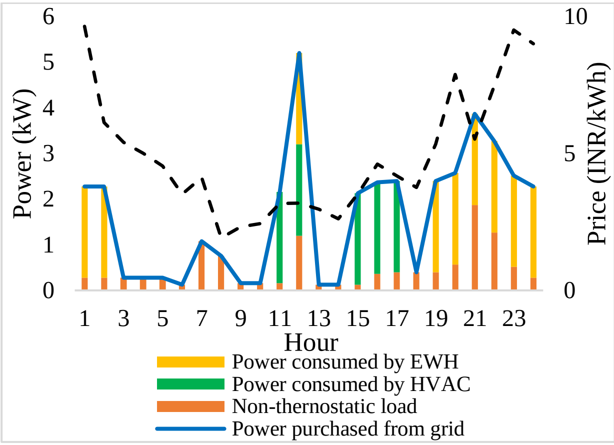

Fig. 8: Self-scheduling of the household appliances.

Case II: In this case, the switching of smart appliances of household appliances has been done by HEMC, implementing all the constraints discussed in sections 2 & 3. The main focus of the HEMC was on reducing the peak demand and overall electricity cost using a peak-limiting strategy. The resulted scheduling for case II is shown in Fig. 9, and the peak demand is observed to be equal to 4.395 kW, which is reduced by 15.39 percent compared with the base case. The flatness of the power curve is also improved due to which the PAR is also reduced by 15.4 percent compared to case I.

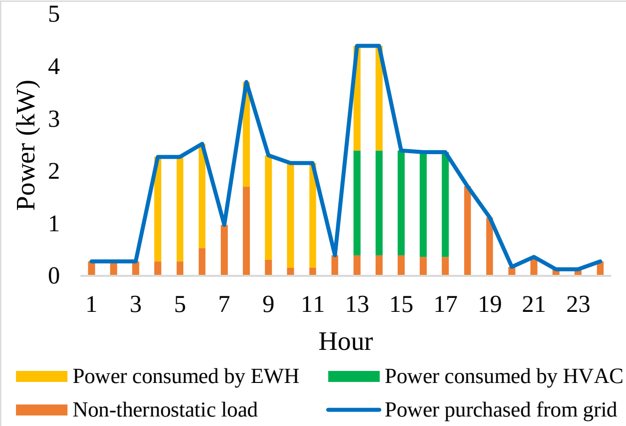

Fig. 9: Scheduling of household appliances by HEMC.

It is clearly visible in Fig. 9 that loads during high-priced slots (1st, 2nd and 19th – 24th) have been shifted towards low-priced slots. The overall electricity bill in case II has been calculated as 140.24 INR as per RTP tariff, which is reduced by nearly 37.35 percent compared to the base case. This reduction in peak demand and PAR shows the effectiveness of the employed HEMC.

Case III: In the 3rd case, a solar rooftop PV source is also used along with the grid, keeping all previous appliances' constraints same as in case II. It is also considered that all PV-generated power is consumed in the home itself without selling it to the grid.

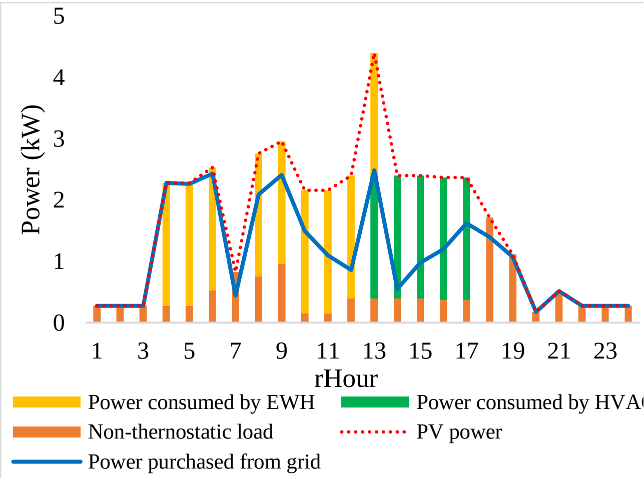

Fig. 10: Scheduling of the appliances including PV.

The resulted hourly scheduling and power contribution for case III is shown in Fig. 10, which shows the stacked PV generation and power purchased from the grid.

It has been observed that the maximum power drawn from the grid is reduced to 2.48 kW, which is nearly 43.5 percent and 52.19 percent reduced with respect to case II and base case, respectively. The PAR ratio in this case is found to be 2.2, which was 2.7 in the case II. With the inclusion of the PV energy source, the overall cost is reduced to 104.08 INR, and the cost savings per day is 39.724 INR with respect to case II.

By comparing cases I&II, it is observed that the implemented peak limiting strategy reduces the peak demand from the grid and hence PAR is also improved. After incorporating PV in case III, the peak demand and average demand from the grid get reduced but PAR is also further reduced, which shows the efficiency of the HEMC. The comparative analysis of the main outcomes from all three cases is depicted in Fig. 11.

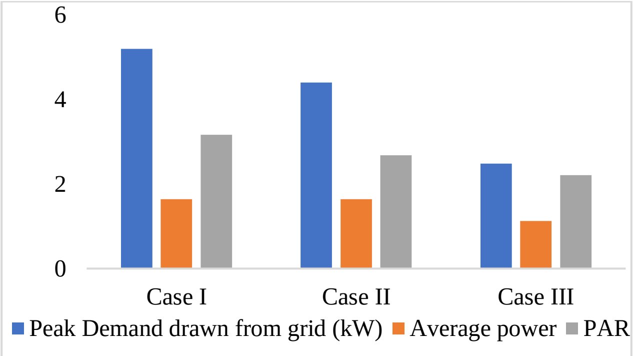

Fig. 11: Comparison of peak & average demand and PAR.

5.5 Payback period

Calculating the payback period is a key aspect for a consumer when installing an RES or an auxiliary storage[35]. In this work, savings by installing the PV are calculated as 39.724 INR per day and 14,499.26 INR yearly. According to the manufacturer[29], the total panel cost is calculated as 52,800 INR (6600*8). A study[36] has provided practical data for the calculation of life cycle costing for PV generation valid for the Indian scenario. It has been stated that costing of the plant varied in different states due to different implementation policies. The PV panel cost was only 42.65 percent of the project's total investment in New Delhi, India. Based on the work[36], different costs, including in the PV plant employed in the present work, are shown in Fig. 12. The total cost is calculated to be 1,23,552 INR, and with the 40 percent subsidy provided by the government[37], resultant investment remains 74,131.2 INR. With the applied RTP, it is calculated that the plant will start to make a profit after 5.112 years.

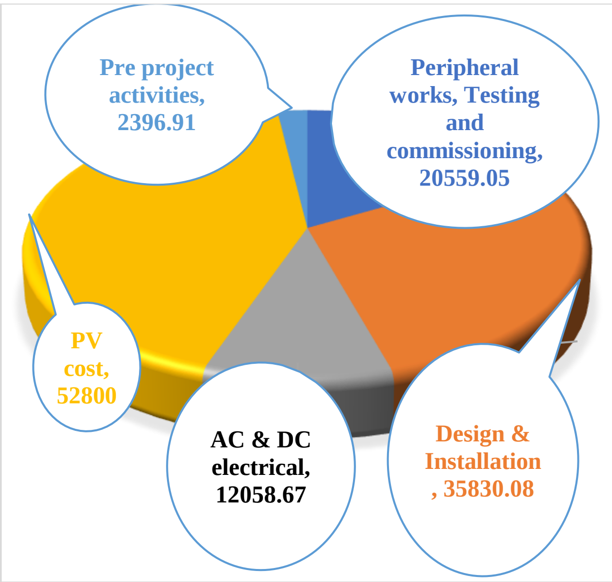

Fig. 12: Costing structuture for PV plant in INR.

5.6 Sensitivity analysis

Sensitivity analysis is a measurement of the performance of a system by observing the change in output of the system with respect to variation in the input parameters. In the present work, sensitivity analysis is done for the RTP tariff applied by observing the payback period of the project. For this analysis, the RTP tariff is changed by ±20%, and changes in yearly savings have been observed accordingly. It is calculated that with a 20% increase in the RTP tariff, the payback period is reduced to 4.26 years, a significant reduction of 16.67%, while the payback period has been increased to 6.39 years with nearly 25% increment for a 20% decrease in RTP tariff.

5.7 Uncertainty analysis

The generation from solar PV power plants depends on variable parameters like irradiance and temperature. Uncertainty analysis has been done in the present work to improve the decision-making and risk management. Uncertainty in irradiation is part of measurement and instrumentation, which can be systematically improved if analysed correctly. The uncertainty has been calculated as 3.226 for the applied irradiance data. From the temperature and PV-generated power data, uncertainties have been calculated as 1.139 and 0.149, respectively. According to[38)], the total uncertainty will be equal to the square root of the sum of squares of individual uncertainties and calculated as 3.425.

6. Conclusion

The research work introduced a novel approach by proposing a DR program based on PV generation forecasts to tackle the challenges of residential energy management. A hybrid forecasting model, leveraging CNN-LSTM, has been developed to predict irradiance and temperature for PV power generation. The results indicate that this hybrid model achieves superior accuracy, demonstrating its effectiveness in addressing the complexities of PV power forecasting. Leveraging the forecasting outcomes of PV generation, the utility has the flexibility to determine the execution time of the DR program. The precision of the forecasts enables strategic decision-making regarding when to implement the DR program for optimal energy management. This integration of proposed hybrid forecasting method with DR program combines the benefits of both aspects results in the increased reliability of the overall system makes the study unique.

For the cost minimization problem, three distinct cases have been discussed in this study. Case I is referenced as a base case in which the consumer has opted for self-scheduling for its appliances. It has been observed that as the consumer used HEMC to schedule the appliance, the electricity bill was reduced upto 37.35 percent, which was reduced upto 53.5 percent after employing a solar PV module as a distributed generator, as shown in Fig. 13. By implementing the peak limiting strategy, it has been further observed that compared to case I, the peak demand drawn from the grid upto 52.19 percent in case III, and PAR is also reduced upto 30.27 perccent, which affect the requirement of power reserves by the utility.

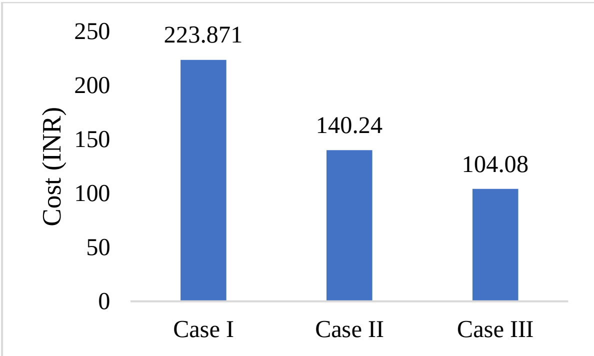

Fig. 13: Cost comparison of cases.

The sensitivity and uncertainty analysis also have been done in the study to see the impact of variation in input parameters on the performance of the PV plant. From the economic point of view, the payback period is calculated as 5.112 years, which means that after approximately five years, the plant will be able to generate revenue for the consumer.

Combining a DR program with PV helps lower carbon emissions, cut energy costs, and improve grid reliability. It gives communities access to cleaner, more affordable energy, boosting overall well-being. Together, these efforts create a more sustainable and resilient future for everyone.

Although this work includes forecasting of weather parameters that later affect the renewable power generation and energy management of household load, it did not include emission analysis, which can be fulfilled in future work.

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