International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** IX **Month of publication:** September 2023

DOI: https://doi.org/10.22214/ijraset.2023.55780

Day Ahead Solar Generation Forecasting inSmart Grids to Minimize Electricity Bill

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***Abstract:** In order to meet the increasing growth of energy demand, integration of renewable resources into residential applications appears to be a viable solution. In the proposed model,a residential house is considered where the consumer is able to generate his own energy from a microgrid consisting of solar panels and wind turbines. In this study, an optimization method is employed to minimize the overall electricity bill of a residential home over a periodof 24 hours. In smart grids, energy management is imperative in reducing the electricity cost of consumers under a real time pricing approach. Nowadays, learning-based modeling methods are utilized to build a precise forecast model for renewable power sources. In this paper, we propose a long short-term memory (LSTM) recurrent neural network-based framework, which is one of the most popular techniques of deep learning. This technique predicts day ahead solar irradiation and wind speed data. We also consider an energy storage system (ESS) for efficient energy utilization. Optimization is done and from the obtained results a substantial reduction in electricity bill is observed.*

I. INTRODUCTION

A. Background

Energy and environmental issues are two key roadblocks in the pursuit of global sustainable development. In most nations, power supply still mainly relies on the combustion of traditional fossil fuels which has brought serious environmental problems. At the same time, electricity consumption has increased significantly with the explosive growth of population and the rapid development of the economy, especially for residential electricity consumption. Renewable energy generation is the more sustainable alternative for sustaining the energy demands of our society. alternative energy and wind energy are both unlimited in supply and eco-friendly when utilized for energy generation. In a trial to cut back the nationwide carbon footp1rint, they played a considerable role in energy generation in recent years, with governments worldwide installing said units individually and collectively.

Smart grids are power grids with advanced communication and control technologies between consumers and generating stations, delivering optimized power usage, clean energy at reduced cost, and improving the standard of energy and efficiency of the facility grid. With microgrids, evolution dependence on fossil fuels is reduced, and the excess carbon emission problem is resolve d. Furthermore, the microgrid relates to smart homes in modes like grid-connected and islanded. In island mode, microgrids and commercial grids couldn't initiate the purchase/sell mechanism of energy. On the opposite hand, in grid-connected mode, the microgrid purchases and sells electricity from/to the external grid. The microgrid includes renewable energy sources (RES) like solar, wind to come up with electricity, contributing to electricity bill minimization. Furthermore, RES are intermittent in nature; thus, one cannot depend on them. Therefore, ESSs (Energy storage system) are used with RES to unravel this problem.

In the recent past, a major form of forecasts has been employed. The choice of a forecasting model is usually dependent on the available data , the model network mechanism's aims, and also the energy planning operation. Throughout this paper, we examine renewable energy and power forecast models used as an energy planning tool. Machine learning mode ls handle enormous data while also providing precise predictive analyses. By integrating various models, we may improve forecasting accuracy. Machine learning models, when utilized correctly, can help one make the better decision because they will extract and model previously unknown correlations and characteristics. Machine learning subtypes, like Artificial Neural Networks (ANNs), operate by extracting high dimensional complex nonlinear features to map input and output variables. Deep learning subtypes, like Long Short Term Memory (LSTM), operate by solving complex problems with multiple layers of knowledge. Despite their differences, they're both capable of predicting the information. during this paper, forecasting is finished using LSTM for more accurate results.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IX Sep 2023- Available at www.ijraset.com

The main issue to be catered within smart grid/smart house is energy management, whose main purpose is to provide good control to the user over the power usage to push the efficient use of electricity, which is done with the implementation of demand response (DR). The DR is classed in 2 classes, namely: direct DR program, in this the electrical utility company (EUC) operator interrupts or disconnects the load as per the contract signed with the consumer; indirect DR program, in this user changes/adapts their demand in response to the offered pricing signaled by the EUC operator. The second DR program is the ma in focus of this work. The indirect DR program plays an important role in reliable and cost efficient, installation operations. The price can be reduced using scheduling smart home appliances using an indirect DR program.

B. Objectives

1) Develop the optimal artificial intelligence (AI) model for the short-termforecasting of solar irradiance.
2) Apply the predicted values of PV power and Wind power output for loadscheduling and battery operations.
3) Minimize the electricity bill.

C. Summary

Taking all these factors into consideration this work proposes an optimized management scheduling method to user activities by considering RTP prices with the main aim to minimize the user's electricity bill. In addition, we investigate a smart home connected to microgrid equipped with PV panels and WT connected to the power grid. We also use static storage (ESSs) to take care for uncertainties in the generated power from RES's and ensure the reliable management of electricity. Moreover, a LSTM prediction model is developed and is used to predict day ahead solar irradiance and wind speed for accurate. prediction. Results show that the newly developed model based on the LSTM technique isaccurate and effective, which also considerably reduces the user's electricity bill.

D. Outline of the report

IN SECTION 2: We discussed about the literature survey done
IN SECTION 3: We explained the methodology used in this report
IN SECTION 4: Results are explained, and the related discussions are presentedIN SECTION 5: The report is concluded.

II. LITERATURE REVIEW

A. Previous Research

M.F. Khan et al. [1] led a reenactment based study to evaluate the variety of inverter yield with the variety of sun powered light. A relationship was found between inverter yield and sun powered irradiance, with a major expansion in inverter yield in late spring months like July contrasted with cold weather months like December. Cloud-prompted change in sun based irradiance, it likewise changes the PV yield. At long last, we've to discover that when irradiance diminishes radically, the change detaches the heap from the inverter yield.

Shakya et al. [2] conducted a trade sun oriented irradiance gauging technique for remote microgrids upheld the Markov Exchanging Model (MSM), by involving locally accessible information to conjecture sunlight-based irradiance for the next day. this is frequently done to plan energy assets in remote microgrids by utilizing past sun oriented irradiance information, Clear Sky Irradiance (CSI), and Fourier premise developments to shape straight models for 3 systems or states: high, medium, and low energy systems for a really long time identical to radiant, somewhat overcast, and exceptionally shady days, separately. Other than collected private burden during an enormous scope, determining an electrical heap of one energy client is reasonably provoking thanks to the high instability and vulnerability included.

To limit the transmission and appropriation misfortunes inside the influence network, powerplants are require d that are nearby utilization regions. This alludes to the greener energy sources like a microgrid. Whenever a most extreme piece of power utilization is created fromthe microgrid, the high fossil fuel byproduct issue is consequently tackled, where roughly, 41% carbon impression is radiated by the energy area and transport area produces 23% of all out ozone harming substances all over the planet.

To handle this issue, Sheraz Aslam et al. [3] proposed a home energy the board plan to relieve the energy cost of the private family, expanding upon a reasonable home with a few savvy machines. The shrewd house is additionally incorporated with a matrix associated microgridthat is engaged by RESs. A verifiable information-based EDE-ANN model was created for exact day-ahead energy forecast.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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S.Q. Ali et al. [4] planned a heap booking issue as a combinatorial advancement issue obliged by the most extreme interest (MD) limit on a microgrid. This paper zeroed in on the cost based request reaction (PBDR) plans with a two section duty upheld when of Purpose Valuing (ToUP) calculation. Such duties might be utilized as an instrument by the utilities to spur thecustomers to move their heaps to low-cost periods a large number of days.
Rocha et al. [5] nitty gritty a roundabout interest reaction (DR) program concentrate on that would help clients in decreasing expenses and further developing their solace level by planning shrewd home apparatuses. "Essentially, the DR program is utilized to plan various homes' heaps with the indistinguishable residing designs in Kim et al. [6]. Be that as it may, the suspicions made by the creators appear to be unreasonable in light of the fact that, typically, numerous homes don't have the indistinguishable gadgets with the indistinguishable activity time and power rating. A totally remarkable energy the executives plan can make an ideal timetable of apparatuses power use, which represents the indistinguishable profile on the grounds that the power created by a microgrid." The clients lessen power cost and import a second measure of energy from the business establishment by embracing the ideal timetable.In that capacity, energy the executives is integral to dependable microgrid activity.
D. Hadjout et al. [7] fostered a totally exceptional gathering calculation upheld profound figuring out how to accomplish exceptionally exact long-medium-term power utilization determining. Three particular AI models - LSTM, GRU and TCN - were joined to be informed the development of power consumption.[8] The n, the creators utilized a weighting technique to get a definitive weight incorporation. to see the ideal weight coefficients of each and every model, a GS system is utilized. In this way, a definitive power utilization gauging results are accomplished by the total of three anticipating consequences of different profound learning models with the ideal weight coefficients got by the GS calculation.
Aslam et al. [9] proposed an effective energy the board strategy to methodically deal with the energy utilization inside the domain to reduce the level to average proportion and moderate power cost along with client solace boost. We fostered an effective energy the executives plot utilizing blended number applied arithmetic (MILP), which timetables shrewd machines and charging/releasing of electrical vehicles (EVs) ideally to relieve energy costs. To confirm and approve the significant time ways of behaving of the model, advancement results are contrasted, and the power levies and an extensive expense decrease is noticed.
Doroudchi et al. [10] applied Blended Whole number Direct Programming (MILP) to improve the energy cost of a solitary family house with battery energy capacity for four unique situations of introducing sun powered chargers. A network associated homegrown PV framework with battery capacity reinforcement (PV/stockpiling framework) framework, which essentially affects diminishing energy costs and adds to meet the necessities of an almost net-zero energy building., was utilized. The mathematical outcomes demonstrated that it is for sure practical to coordinate capacity frameworks in network associated PV frameworks in private applications, other than showing the effect of battery size on month-to-month energy cost.
Gopinath et al. [11] looked into the specialized appraisal strategies for a framework associated sunlight based photovoltaic (PV) — battery capacity framework — concerning most extreme interest shaving. The reasoning lies in that a successful battery stockpiling framework can give the additional energy required during the pinnacle energy utilization periods, as well aswhen sustainable power (RE) sources go disconnected. The survey demonstrated that greatest interest shaving with great Return-of-Venture (return for capital invested) can be accomplished by considering the genuine burden profile, specialized, and financial parts of the sun-oriented PV-battery framework.

B. Machine Learning Models

1) Linear Regression

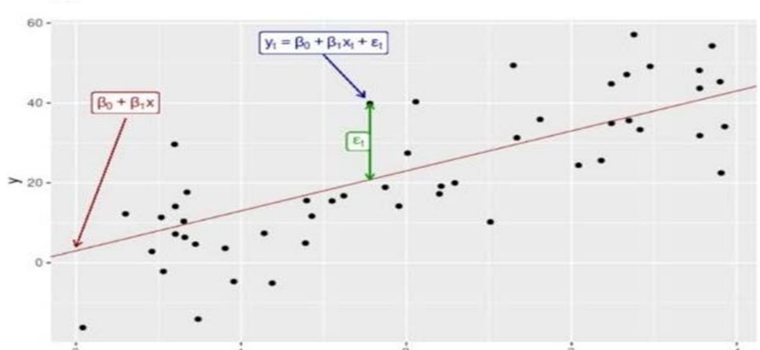

Fig. 2.1: An example of data from a simple linear regression model [18]

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue IX Sep 2023- Available at www.ijraset.com

Linear regression analysis is a statistical technique for forecasting the value of one variable on this basis of another's. The dependent variable is the variable you want to predict. The independent variable is the one you're using to predict the value of the second variable.

One input variable refers to simple linear regression, whereas more than one renders multiple linear regression.

Simple linear regression is expressed by the equation:

$$y = mx + c \qquad (1)$$

where 'y' indicates the Y coordinate, 'm' indicates the slope, 'x' indicates the x coordinate and 'c' indicates the y intercept.

2) Artificial Neural Networks

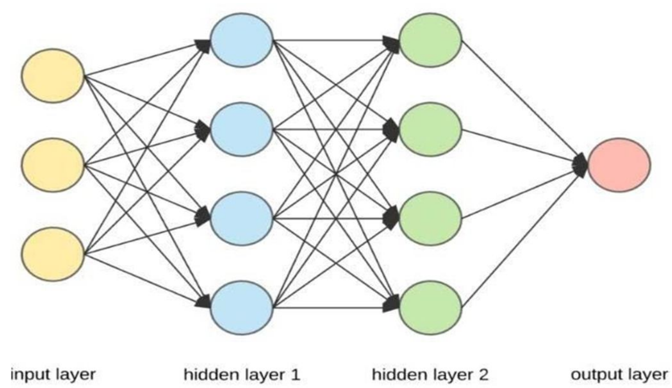

Figure 2.2: Example of an artificial neural network [19]

Artificial Neural Networks (ANN) are multi-layer fully connected neural nets that appear as in the figure provided above. A typica l ANN contains one input layer, multiple hidden layers, and one output layer. Every node in one layer is connected to every other node within the next layer. The depth of the network can be increased by increasing the number of hidden layers. If we focus on one of the hidden or output nodes, we come across a figure that looks like the one below.

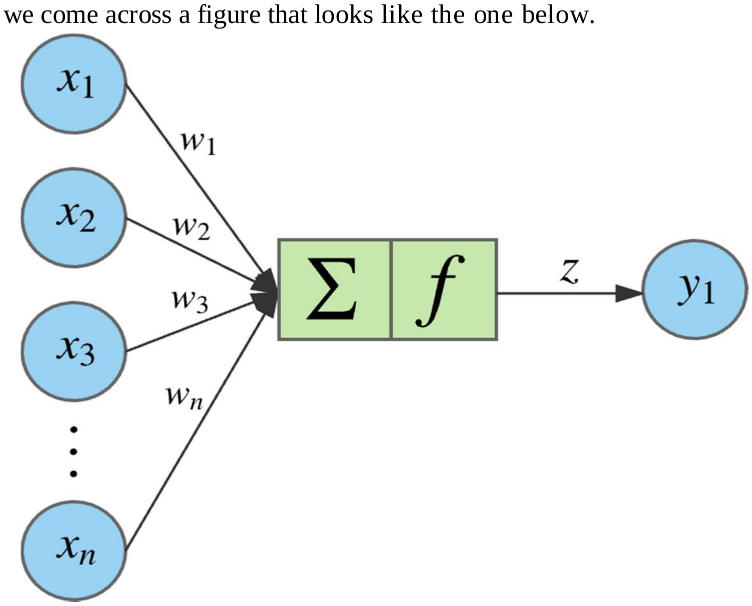

Figure 2.3: Illustration of linear activation function [20]

A given node takes the weighted sum of its inputs, and passes it through a non-linear activation function. This is the output of the node, which then becomes the input of another node in the next layer. The signal flows from left to right, and the final output is calculated by performing this procedure for all the nodes. Training this deep neural network means learning the weights associated with all the edges. The equation for a given node looks as follows.

The weighted sum of its inputs passed through a non-linear activation function. It can be represented as a vector dot product, where n is the number of inputs for the node.

We first need to train our model to actually learn the weights, and the training procedure works as follows:

a) Randomly initialize the weights for all the nodes. There are smart initialization methodswhich we will explore in another article.
b) For every training example, perform a forward pass using the current weights, and calculate
c) the output of each node going from left to right. The final output is the value of the last node.
d) Compare the final output with the actual target in the training data and measure the errorusing a loss function.
e) Perform a backwards pass from right to left and propagate the error to every individual node using back propagation. Calculate each weight's contribution to the error and adjust the weights accordingly using gradient descent. Propagate the error gradients back starting fromthe last layer.

3) Recurrent Neural Networks

Recurrent neural networks are networks with loops in them, allowing information to persist.

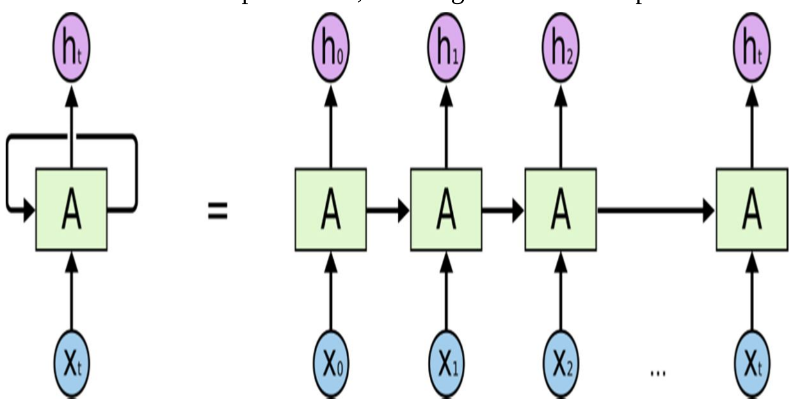

Figure 2.4: An unrolled recurrent neural network (RNN)[20]

In the above chart, a piece of brain organization, A, sees some info xt and results a worth ht.A circ le permits data to be passed starting with one stage of the organization then onto the next.

These circles cause repetitive brain organizations to appear to be somewhat secretive. In anycase, assuming you think a touch more, incidentally, they aren't exactly unique in relation to an ordinary brain organization. An intermittent brain organization can be considered numerous duplicates of a similar organization, each passing a message to a replacement. Think about what occurs on the off chance that we unroll the circle, additionally given in Figure 2.4. This cha in-like nature uncovers that intermittent brain networks are personally connected with successions and records. They're the normal engineering for brain organizations to use for such information.

4) The Problem Of Long Term Dependencies

One of the allures of RNNs is the possibility that they could possibly associate past data to thecurrent undertaking, for example, utilizing past video casings could illuminate the comprehension regarding the current edge. On the off chance that RNNs could do this, they'dbe incredibly helpful. Yet, they aren't generally ready.

Once in a while, we just have to take a gander at ongoing data to play out the current errand. In such cases, where the hole between the pertinent data and the spot that it's required is little, RNNs can figure out how to utilize the previous data. Be that as it may, there are additionally situations where we want additional background info. It's not difficult to imagine for the hole between the important data and where turning out to be exceptionally large is required. Sadly, as that hole develops, RNNs become incapable to figure out how to interface the data.

Hypothetically, RNNs are totally e quipped for dealing with such "long haul conditions." Basically, notwithstanding, RNNs don't appear to be ready to learn them. The issue was investigated inside and out by Hochreiter [12] and Bengio, et al. [13], who revealed pragmatic troubles have been accounted for in preparing intermittent brain organizations to perform assignments in which the fleeting possibilities present in the info/yield groupings range long stretches. Luckily, LSTM beats this obstacle.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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5) Brief overview of Long Short Term Memory (LSTM)

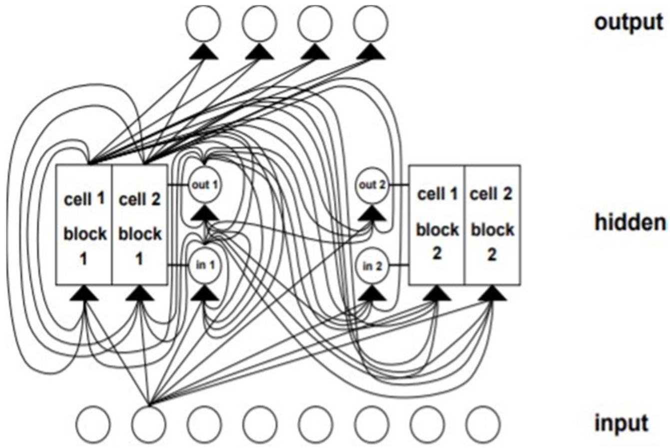

Fig 2.5: Example of a network with 8 input units, 4 output units and 2 memory blocks of size two [21]

LSTM is a unique kind of Repetitive Brain Organizations (RNNs) that is equipped for learning long haul conditions in the gave information. The LSTM model was first presented by Hochreiter et al. [12] yet was along these lines transformed by different analysts. It has been utilized in the writing for energy market, securities exchange expectation, hydrology estimating, GSR forecast, etc. LSTMs have been created to keep away from long haul reliance issues unequivocally. As found in the figure beneath, the LSTM model utilized for sun powered irradiance anticipating has a chain-like design. Notwithstanding, the rehashing module has an alternate design. Rather than having a solitary brain network layer, a few layers are associating in a special way. With a contribution of xt once, a secret condition of st and W being the result of the past hub, the RNN memory can is communicated with the equation:

$$S_t = f(U_{xt} + W_{st-1}) \qquad (2)$$

LSTM is a period subordinate RNN, with the distinctive component being its remarkable activity within cells. The thought is to condition the brain network on past data and tie the loads at each time step. In learning the drawn-out reliance of data, LSTM tackles the disadvantages of angle evaporating and inclination detonating intrinsic to conventional RNNs. As initially portrayed in Hochreiter et al. [12], a LSTM unit contains:

a) An input gate, to update cells
b) A forget gate, to selectively retain information
c) An output gate, to decide the next hidden state

As for its applications, Y. Yu et al. [14] detailed a calculation of global horizontal irradiance (GHI) one hour in advance and one day in advance. To improve prediction accuracy on cloudy days, the clearness-index was introduced as an input data.

C. Identifying The Optimal Model For The Project

S. Gbémou et al. [15] led a relative investigation of AI techniques for GHI estimating, using two years of information with a period step of 10 minutes to prepare the models and gauge GHI at different time skylines. The three measures utilized for execution assessment were: standardized root mean square mistake (nRMSE), dynamic mean outright blunder (DMAE) and inclusion width-based rule (CWC). While taking a gander at the nRMSE upsides of the AI models for all skylines, the LSTM model outflanked the others as the gauge skyline expanded. A comparable pattern of more prominent precision on account of LSTM models was noticed for the other two basis (CWC and DMAE), particularly during overcast days. This can be credited to the innate capacity of LSTM models in recognizing long haul conditions in information.

W. Kong et al. [16] nitty gritty a long transient memory (LSTM) intermittent brain network-based system, which is the most recent and one of the most famous methods of profound learning, to handle this interesting issue. "Numerous benchmarks are extensively tried and contrasted with the proposed LSTM load gauging structure on a genuine world dataset. Incidentally, many burden estimating approaches which are effective for matrix or substation load gauging battle in the single-meter load determining issues. The proposed LSTM system accomplishes commonly the best determining execution in the dataset.

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Additionally, albeit individual burden anticipating is nowhere near exact", conglomerating all singular figures yields better gauge for the total le vel, contrasted with the regular procedure of straightforwardly estimating the amassed loa d.
In February of the year, López et al. [17] fostered a forecaster to anticipate sun-oriented light in the extremely present moment (10 min ahead). Two instruments were createdin light of ANNs, in particular LSTM and CNN. The instrument was tried with root mean square mistake as the measuring stick and brought about an improvement of 8.16%
Moreover, for the 82% of the tried days it has given an under 4% mistake between the anticipated and the real energy age. All in all, they avowed the suitability of their calculation in the execution of a PV age plan-working on their mix into the electrical lattice for power age.

D. Selection Of Performance Evaluation Criteria

Mean square error is defined as the averaged square difference between model outputsand the target. It is expressed with the equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2 \qquad (2)$$

MSE stands for Mean Squared Error.
y_i is the actual output
y'_i *is the* observation of y_i
n is the total observations considered
As a rule of thumb, the lower the value of MSE, the lesser the number of false classifications
The above concept is applied when different models are trained using an optimization technique to determine the minimum MSE of the model. The model with the least MSE is taken as the optimizable mode l.

Table 1: A summary of the literature with MSE as performance selection criteria

	AUTHORS	OBJECTIVE	PROCEDURE
Linear Regression	Sakallioglu, Sadullah & Kaciranlar, Selahattin & Akdeniz, Fikri.[18].	Mean squared error comparisons of linear regression models	The direct relapse assessor was contrasted and the Liu assessor in the network type of mean square blunder sense.
Artificial Neural Network (ANN)	Sharma, Sanjay & Kaur, Tarlochan.[19]	Development of ANN Based Model for Solar Potential Assessment Using Various Meteorological Parameters	To acquire the best presentation, the organization is run various times. Execution plot - > as the quantity of emphases continue to build the MSE becomes least.

Recurrent Neural Network (RNN)	Rasheed, Nadia & Amin, S.H.M. & Sultana, Umbrin &Bhatti, Abdul & Asghar, Mamoona.[20].	Extension of grounding mechanism for abstract words - computational methods insights	Two neuro-advanced mechanics models in light of feed forward brain organization and repetitive brain network are introduced to see theupsides and downsides ofconnectionist approach
Long Short Term Memory (LSTM)	B Brahma, R Wadhwahi [21]	Solar Irradiance Forecasting Based on DeepLearning Methodologiesand Multi-Site Data.	For checking the approval and steadiness of the recreation results,the decency of attack ofthe mode tried utilizing MSE.

The results of the aforementioned studies have demonstrated the capability of the proposedmethodology in providing accurate daily prediction of solar irradiance.

III. MODELING

A. Data Processing

Available variables in the data are explored, visualized, and pre-processed before being passed to the machine learning algorithms.

1) Data Gathering

To predict the solar irradiance and wind speed for 24 hours, the meteorological data of Chennai from 2007 to 2020 has been collected from solcast.com. This data has 122,640 rows and 10 columns.

2) Data preprocessing

The acquired data is preprocessed by adding extra parameters like Hour sine etc. and some parameters which are not useful are not considered like date, wind direction, wind speed while predicting solar irradiance whereas GTI, surface pressure etc. are not considered while predicting wind speed. Previous 2 days data of GTI and wind speeds are added while predicting Solar irradiance andWind speeds respectively.

3) Data Types Available In This Literature

a) Data types considered while predicting solar irradiance:

There are 3 major parameters which are considered

- Air temperature
- Precipitation
- Relative humidity

There are 7 minor parameters which are considered

- Hour sine
- Hour cosine
- Month sine
- Month cosine
- Year
- Solar irradiance of one day prior
- Solar irradiance of two days prior

b) Data Types Considered While Predicting Wind Speed

There are 3 major parameters which are considered:

- Air temperature

- Wind direction
- Relative humidity

There are 7 minor parameters which are considered:

- Hour sine
- Hour cosine
- Month sine
- Month cosine
- Year
- Wind speed of one day prior
- Wind speed of two days prior

4) Data normalization

The data is converted in a cyclic manner to streamline the prediction process for models. The value of each feature is normalized to fit in the range of -1 and +1, in order to optimize the accuracy and speed.

5) Data Splitting

The entire dataset is split into 70% training data and 30% test data. The test data is held out and unseen throughout the training of the different models. The test data then further split into 22.5% and 7.5% for validation and testing. The model is first trained with the training data and validates with the cross-validation data. Finally, the data is tested with the test data.

B. Comparing Machine Learning Models:

1) Overview

All models were developed using Keras, TensorFlow the open-source deep learningAPI of Python programming language. In brief, the steps involved were:

a) The models developed are

- LSTM model
- RNN model
- ANN model
- Linear regression model

b) Verify model predictions with actual values.

c) Comparison between LSTM vs RNN vs ANN vs Linear Regression using MSE values.

d) Determine the optima l number of hidden layers re quired for the LSTM model to be most accurate.

2) Comparing ML Models

a) Four models i.e., LSTM, RNN, ANN, Linear regression models are created and are used to predict the day-ahead values of solar irradiance.

b) By comparing MSE values from the equation (2) , it is found out that the LSTM model is the most accurate model.

3) Optimized LSTM Model Structure

To find out the LSTM model with the most accurate prediction, 4 different LSTM models with different numbers of hidden layers are used and compared with each other and LSTM model with 3 hidden layers is found out to be most accurate.

In our project, the LSTM model consists of:

a) Input layer

- Taken in the form of (x, y)
- X indicates the number of hours in a day. It holds the value 24.
- Y indicates the number of features considered for the model. It holds the value10.

b) Hidden layers

- We've taken 3 hidden layers.
- Each hidden layer contains 48 cells.

c) Output layer

- It indicates the number of hours between 12 am and 11 pm.
- It yields 24 values which are the day-ahead predictions.

A LSTM model without the inclusion of prior 2 days data is plotted and its accuracy iscompared to that of the used model.

C. Procedure Followed

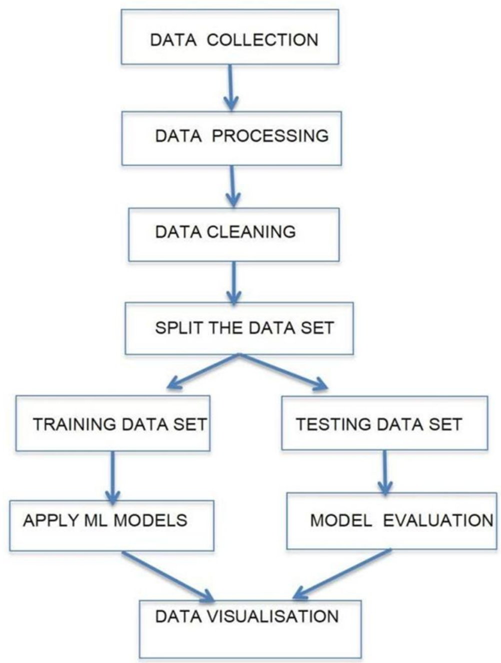
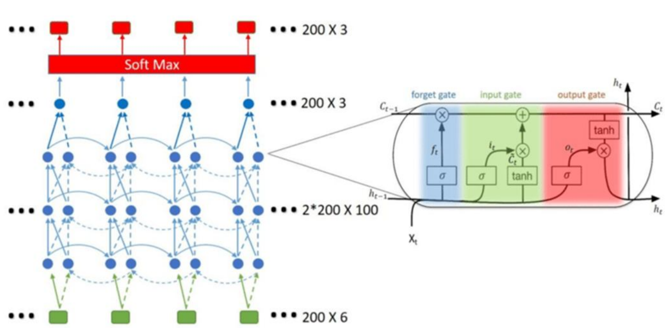


Figure 3.1: Flowchart of the technical procedure

1) *Training:* In order to train the weights in the model, the training data with a batch sizeof 16 is sent into the model.
2) *Assigning:* The epoch is set to 100 so that the model runs a total of 100 times eachwith the same training data and the weights are updated each time.
3) *Calculating:* Mean square error (MSE) values between the actual and predicted data for the next 24-hour period are calculated and plotted.



Each dot represents an LSTM unit. SoftMax layer is added to scale the output value with a sum of 1 so that they can be interpreted as probabilities.

D. Modeling Of A Grid-Connected System

1) Overview

The micro-grid considered in this work is connected with PV panels, WT and ESS for electricity optimization. The net energy generated from the sources connected with micro-grid is the sum of energies from both pv panels and wind turbines.

As the micro-grid is equipped with RESs which are unpredictive in nature, thus the LSTM prediction model is implemented to predict solar irradiation and wind speed for next day for accurate future electricity generation estimation. The detailed explanation of generating sources equipped with micro-grid is given as follows:

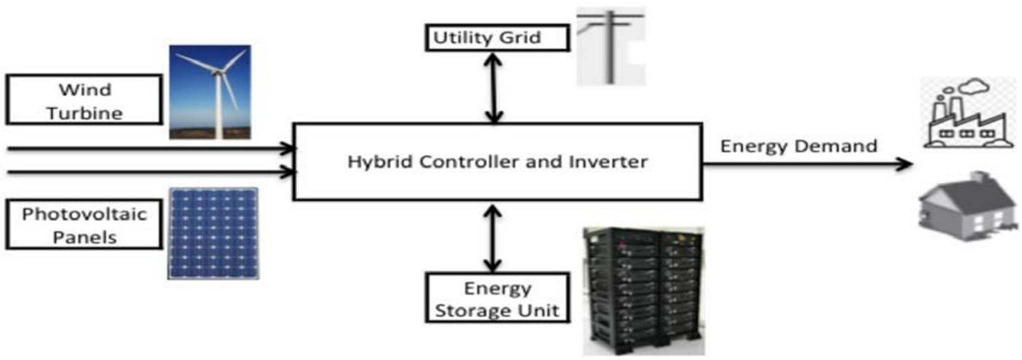


FIG. 5. Investigated microgrid system.

Figure 3.2 Microgrid connected system [16]

2) PV Panels

PV panels are used to generate electricity from the sunlight, which is mathematicallycalculated in Equation (3) as follows.

The solar irradiance predicted is converted to solar power using the formula:

$$P_t^{pv} = \eta^{pv} \times A^{pv} \times Irr(t) \times [1 - 0.005 \times (Temp(t) - 25) \quad (3)$$

Where, P_t^{pv} shows amount of electricity produced from PV panels.

The symbols A^{pv} and η^{pv} show area and efficiency of PV panel, respectively.

The Irr(t) and Temp(t) indicate amount of solar irradiation and the outside temperature.

3) Wind Turbine

The WT is totally dependent on wind speed for generation of electricity, which ismathematically calculated in Equation (4) as follows.

The wind speed predicted is converted to wind power using the formula:

$$P^{wt}(t) = \frac{1}{2} \times (\mu) \times \rho \times A \times (V_t^{wt})^3 \quad (4)$$

Where P^{wt} represents WT electricity generation at timeslot t,

A is the area swept by turbine blades through which WT generates power, V_t^{wt} denotes wind speed and air density is ρ.

The generation of electricity from WT is directly proportional to wind speed, i.e., thehigher the wind speed, the higher the electricity generation, as presented in Equation (4).

4) Energy Storage System

ESSs includes storage that are equipped with Energy sources connected to the microgrid to store energy during excess energy production (act as a load) and discharge energy to load in high low demand (act as a source).

The house considered in this work is integrated with ESS with a storage capacity of 5 kWh, the same as is discussed in [10,11].

The ESS is subjected to various conditions such as ESS (min) and ESS(max), which represent minimum and maximum charge limit, respectively.

The minimum charge limit is set to 20% and maximum charge limit is set to 90%.

E. Electricity Bill Minimization

This model is run using Keras, an open-source software library exclusive to Python, using OR tools with the objective to minimize the cost.

More cost optimization is done by considering 15% of the peak load as schedulable loadwhere it is shifted from peak hours to off-peak hours.

This model considers time-of-use tariff (TOUE) prices during optimization.

Table 2 The electricity prices per unit on a normal working day.

	DURING PEAK HOURS	NORMAL HOURS	OFF-PEAK HOURS
COST OF POWER TAKEN	8 Rs	6 Rs	4 Rs
COST OF POWER SOLD	5 Rs	3 Rs	2 Rs

Cost Minimization function:

$$\min\left(\sum_{t=1}^{n} P_{grid}(t)C_{cost}(n)\ \sum_{t=1}^{n} P_{grid}(t)C_{sold}(n)\right)$$

Where, $P_{grid}(t)$ is the power taken or sent to the grid at time slot t, $C_{cost}(n)$ is the cost ofpower taken from the grid at time t and $C_{sold}(n)$ is the cost of power sold to the grid at time t.

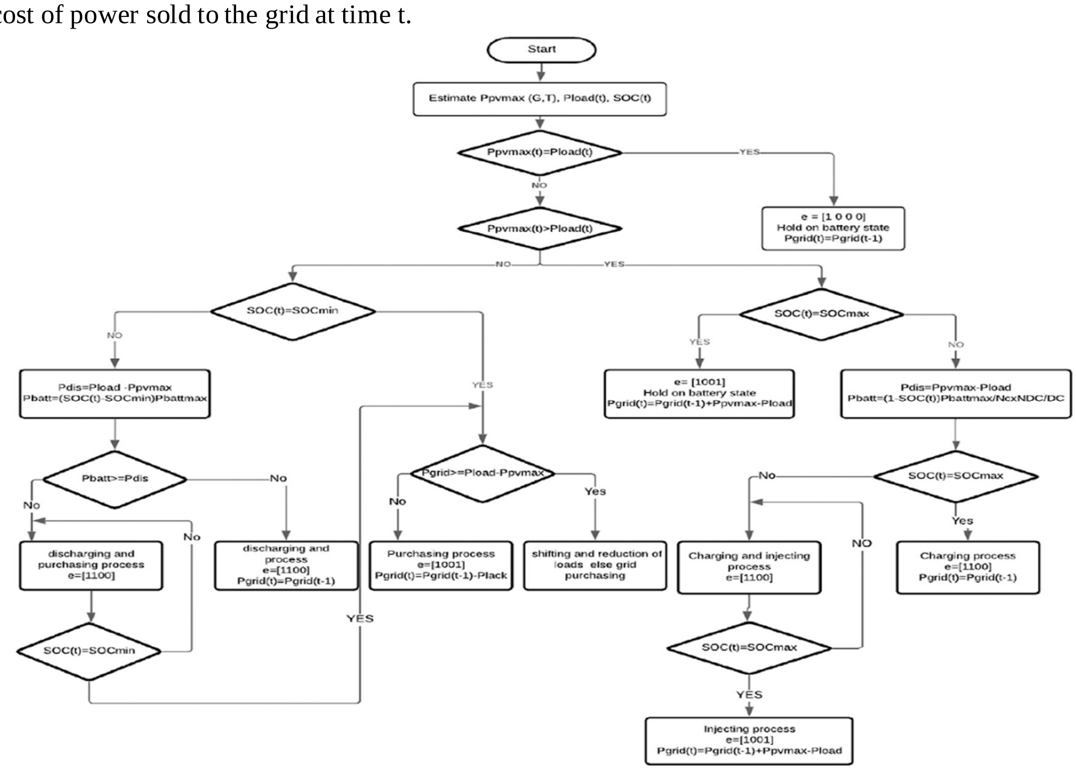


Fig. 3.3 represents the process followed by the model during cost optimization [11]

F. Microgrid Model Comparing

Three different types of microgrid models with different RES are considered in this paper.

Case 1: The microgrid is only connected to solar panels and the power generated from this panels is calculated, and the optimization function is run to find out the monthly electricity bill. After that 5kWh battery is integrated into the microgrid, this is used to store the excess power and to further decrease the electricity bill.

Case 2: The microgrid is only connected to wind turbine and the power generated from this turbine is calculated and the optimization function is run to find out the monthly electricity bill. After that 5kWh battery is integrated into the microgrid and the electricity bill is calculated again.

Case 3:The microgrid in this case, is connected to both solar panels and wind turbine and the hybrid power generated from both these is calculated by adding the powers and the optimization function is run to find out the monthly electricity bill. After that 5kWh battery and 3kWh battery are integrated into the microgrid separately to find out the optima l capacityof the battery to be used.

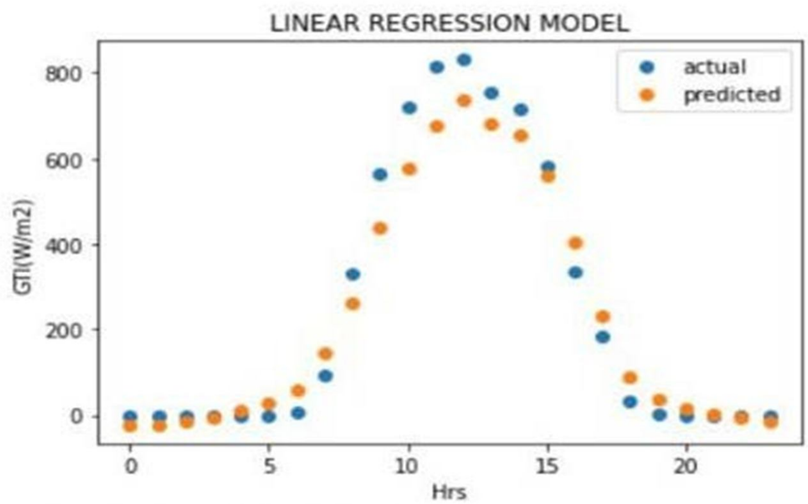
It is found out that using hybrid power with 5kWh battery minimizes the electricity bill more when compared to any other case.

IV. RESULTS & DISCUSSIONS

A. Determining Accurate Forecasting Model

1) Comparing different Machine Learning models

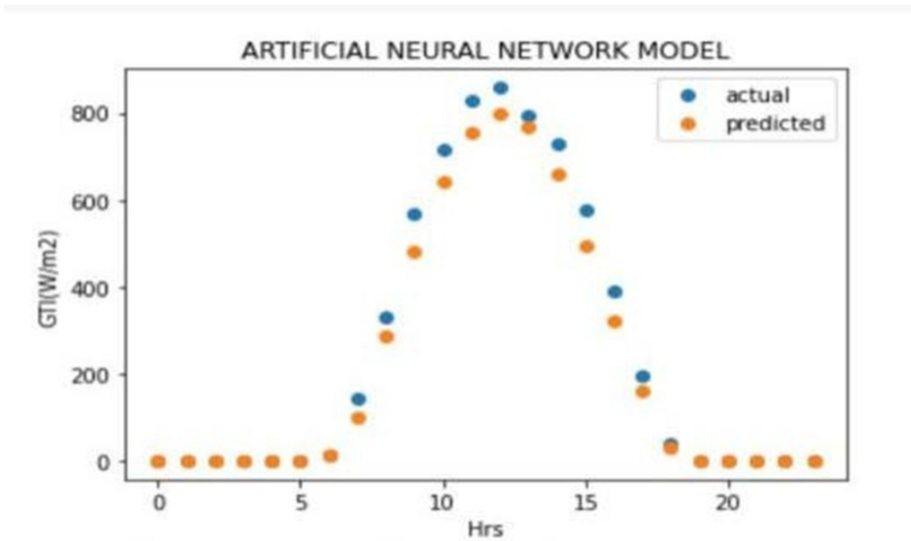
Actual and predicted data of solar irradiance for 24 hours is plotted for the Linear Regressionmodel.



MEAN SQUARE ERROR: 4102.367557864939

Figure 4.1 Actual vs Predicted values of solar irradiance for a linear regression model

Actual and predicted data of solar irradiance for 24 hours is plotted for the Artificial NeuralNetwork model.



MEAN SQUARE ERROR: 1829.6030268949692

Figure 4.2 Actual vs Predicted values of solar irradiance for the Artificial Neural Network(ANN) model

Actual and predicted data of solar irradiance for 24 hours is plotted for the Recurrent NeuralNetwork model.

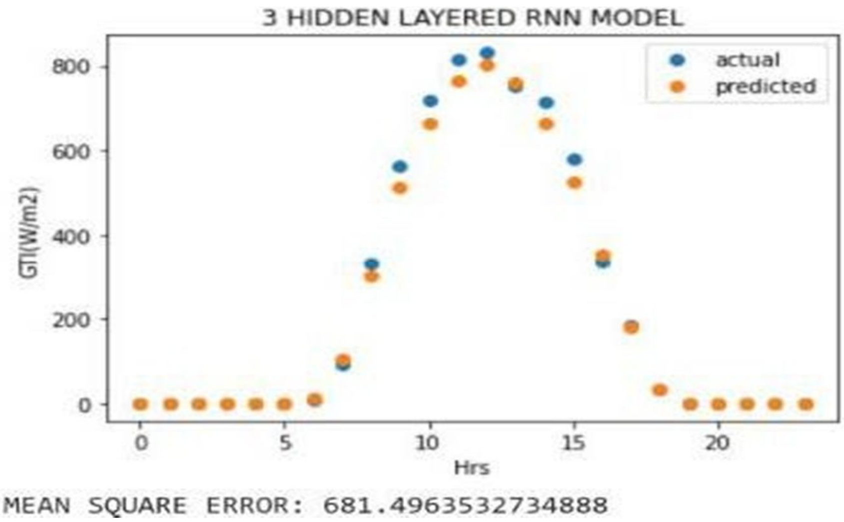


Figure 4.3 Actual vs Predicted values of solar irradiance for the Recurrent Neural Network(RNN) model

Actual and predicted data of solar irradiance for 24 hours is plotted for the LSTM model.

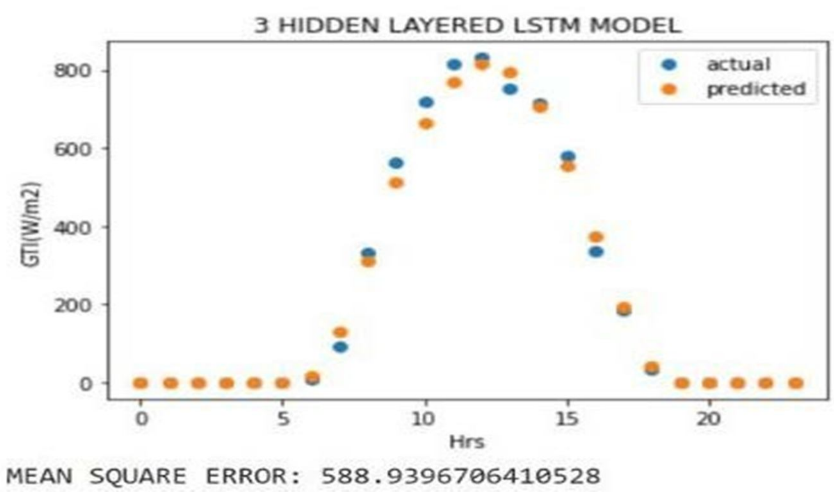


Figure 4.4 Actual vs Predicted values of solar irradiance for the LSTM model

2) Mean Square Error Calculation For Each Prediction Model

Table 2 MSE values of different Machine learning models

S.NO	MODEL	MEAN SQUARE ERROR(MSE)
1)	LINEAR REGRESSION MODEL	4102.3675
2)	ANN MODEL	1829.6030
3)	RNN MODEL	681.4963
4)	LSTM MODEL	588.9396

From table 2, it can be seen that the MSE is lowest for LSTM model which indicates that it has the most accuracy. Hence, the LSTM model is taken into reference and now LSTM models with different hidden layers are compared to finalize the model to be used.

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3) Comparing Lstm Models With Different Hidden Layers

a) The actual and predicted value graphs are plotted for 4 different LSTM models, eachwith different numbers of hidden layers.

b) Then, their MSEs are compared.

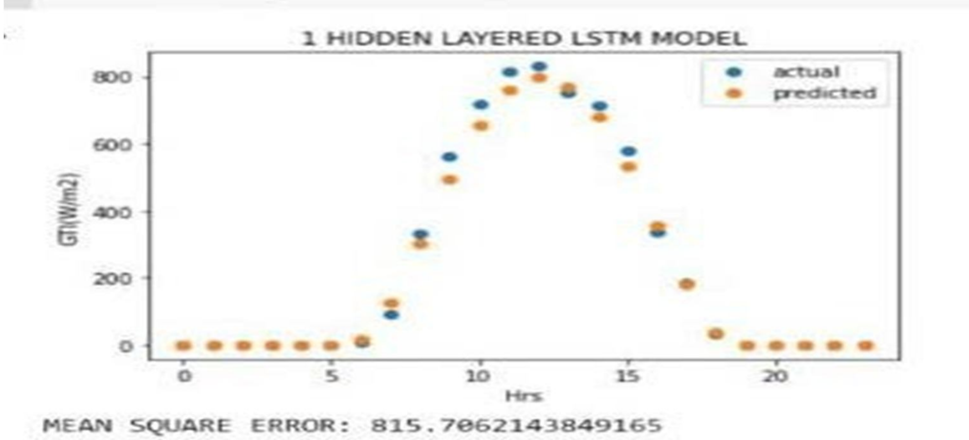

Figure 4.5 Actual vs Predicted values of solar irradiance for the LSTM model with 1 hiddenlayer

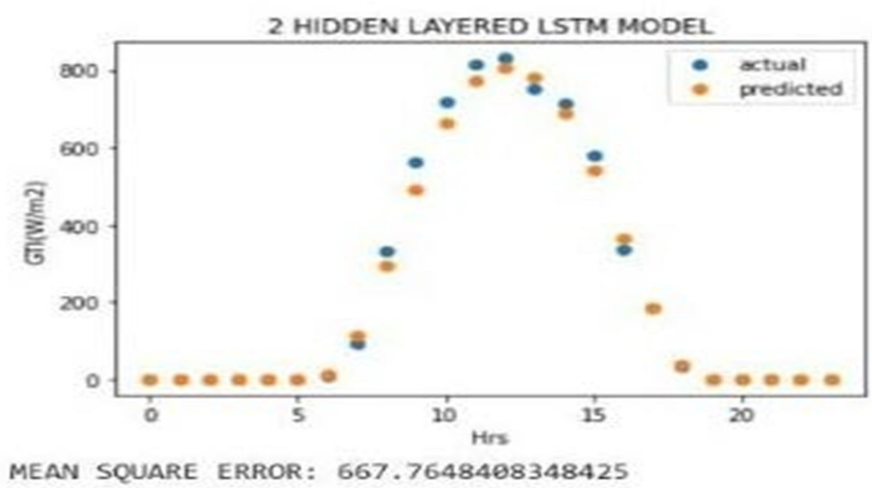

Figure 4.6 Actual vs Predicted values of solar irradiance for the LSTM model with 2 hiddenlayers

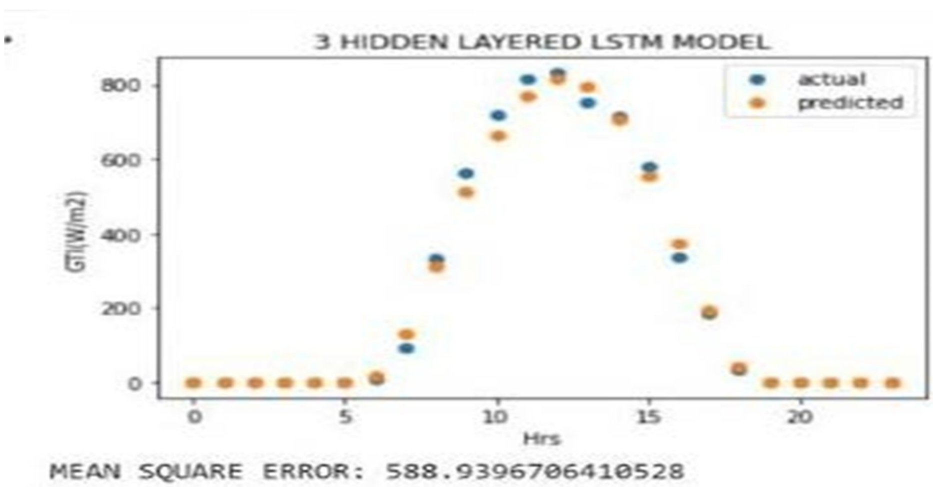

Figure 4.7 Actual vs Predicted values of solar irradiance for the LSTM model with 3 hiddenlayers

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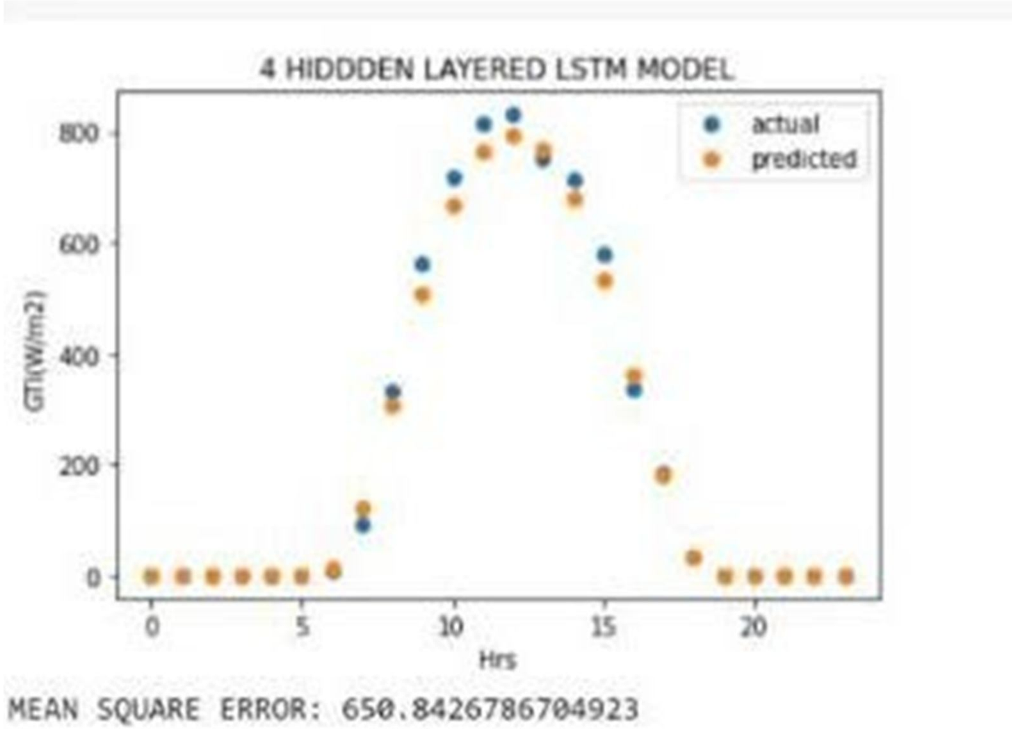

igure 4.8 Actual vs Predicted values of solar irradiance for the LSTM model with 4 hiddenlayers

c) The MSE is lowest for LSTM model with 3 hidden layers, which indicates that it has the most accuracy. Hence, the LSTM model with 3 hidden layers is our final model.

d) These results indicated that the simple structure models were less accurate, whereas problems such as over-fitting occur in more complex models.

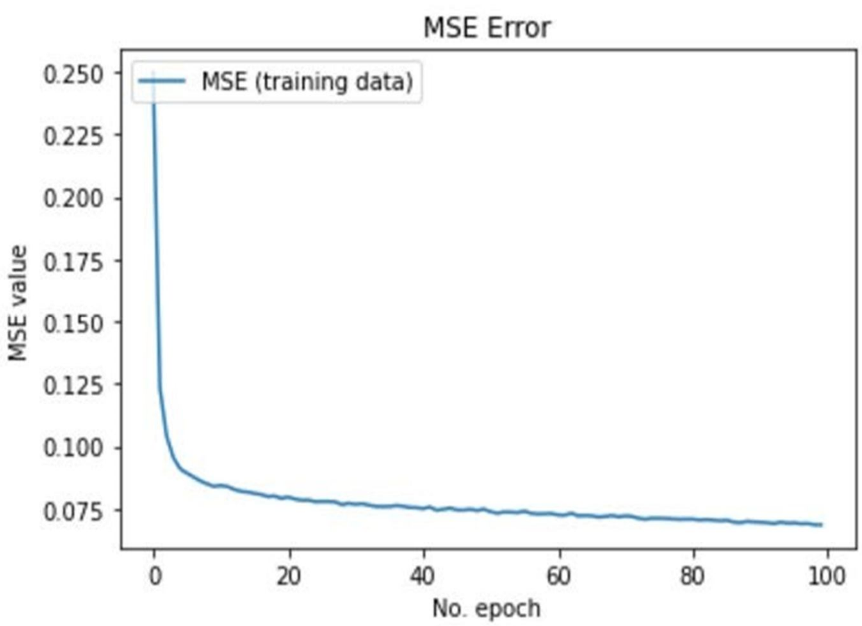

Figure 4.9 The graph depicting MSE values between actual and predicted values of trainingdata

From figure 4.9, it can be seen that the MSE values keeps decreasing after each epoch as aconsequence of the weights being updated each time in the LSTM model.

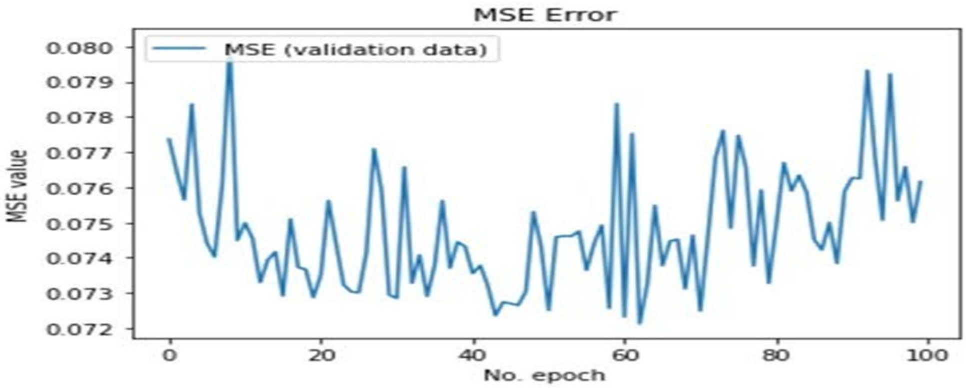

Figure 4.10 The graph depicting MSE values between actual and predicted values ofvalidation data

e) From figure 4.10, it can be seen that the MSE value decreases during the initial state and, then starts to increase. This is due to the over fitting of data after each epoch inducing an increase in error.

4) LSTM model without the inclusion of the GTI from the previous two days

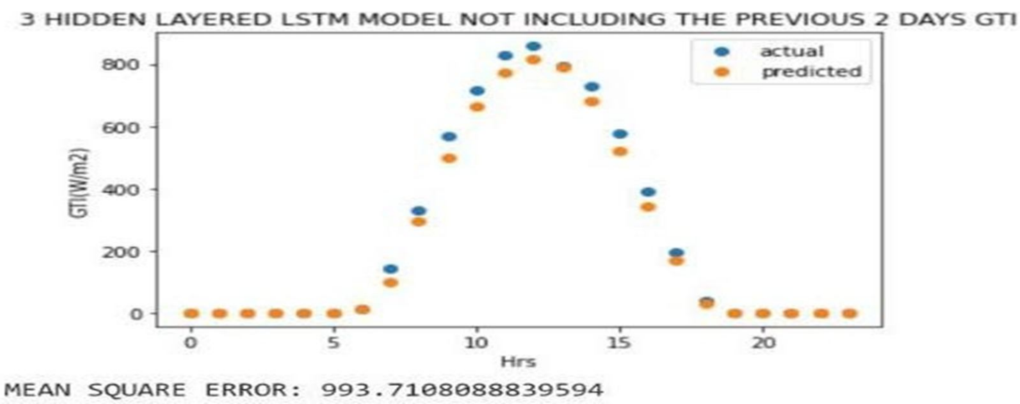

Figure 4.11 Actual vs Predicted values of solar irradiance for the LSTM model not includingthe previous 2 days GTI.

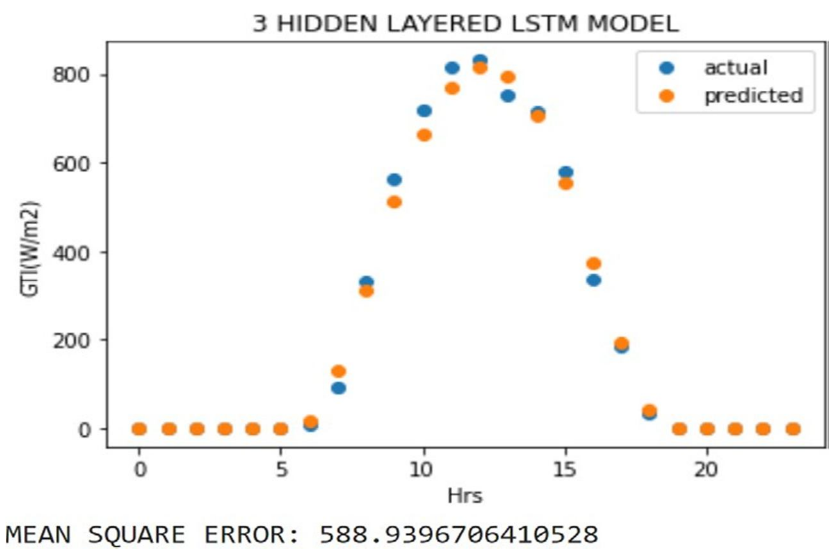

Figure 4.12 Actual vs Predicted values of solar irradiance for the LSTM model including theprevious 2 days GTI.

The above figure 4.12, shows us that the inclusion of data from the previous 2 dayshas increased the accuracy of the model as the mean square error is decreased. This is the final model which is used for prediction of solar irradiance.

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B. Load Demand For The House

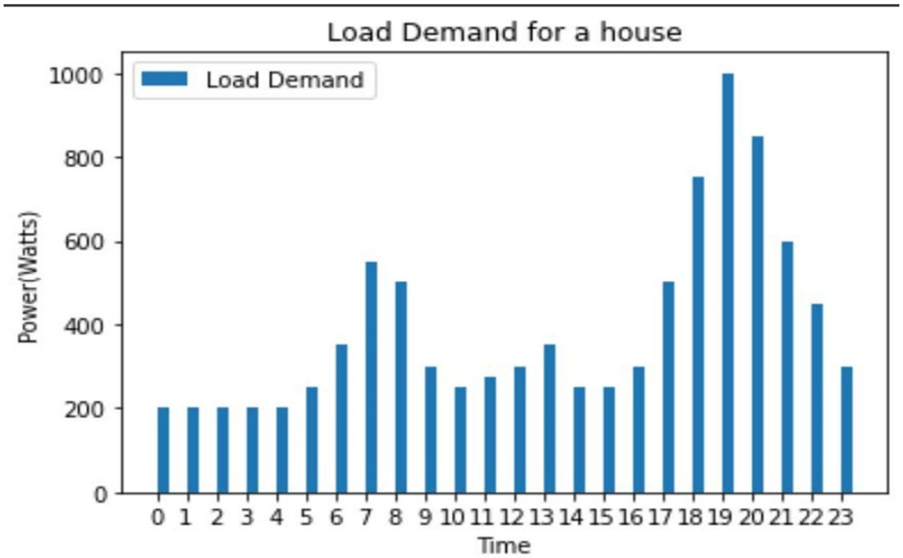

Figure 4.13 Load Demand for a house

1) The total load demand for the house in 1 day is 9375 watts
2) According to this the total load demand for the house for 1 month is 281.25 units
3) From the table 3, the price for 1 unit of electricity is 7.2 rupees
4) Therefore, the monthly electricity bill for the house is 2025 rupees.

Table 3 Cost for 1 unit of electricity per month [15]

Up to 100 units		101-200 units		Above 200 units	
0-50	Rs. 1.45	0-100	Rs. 3.3	0-200	Rs. 5
51-100	Rs. 2.6	101-200	Rs. 4.3	201-300	Rs. 7.2
				301-400	Rs. 8.5
				401-800	Rs. 9
				>800	Rs. 9.5

C. Using Only Solar Panels For Energy Generation

1) The solar irradiance is converted to pv power with the help of solar panels installed onthe roof of the house.
2) The solar panels are considered to have an efficiency of 15% and six 330W powerrating solar panels are installed to meet the load demand.
3) The total power generated from these solar panels per day is 9432.85W.
4) PV Power vs Load demand is plotted for better visualization.

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a) PV Power vs Load Demand

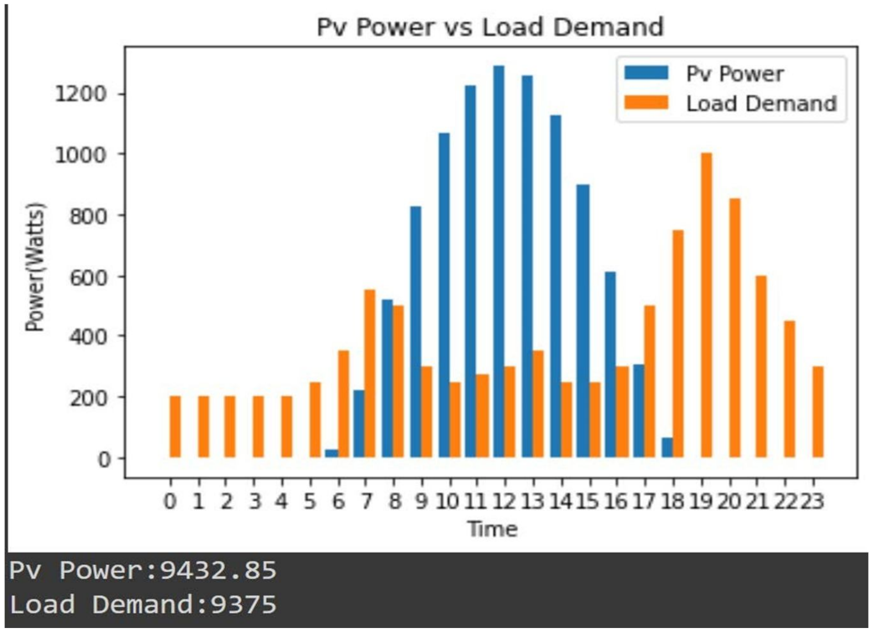

Figure 4.14 PV Power vs Load Demand

- From the above figure 4.14, the power is taken from the grid when the difference between load demand and solar power generated is greater than zero and only for thatpower bill is calculated.
- Here, the RTU pricing is used to calculate the monthly electricity bill and it is found to be 380.72 rupees.
- As, we have predicted this day ahead solar power we can reschedule some part of the peak load to use generated energy in an efficient way instead of letting it get wasted.
- So, we take 15% of the peak load as schedulable load and reschedule it to minimize the monthly electricity bill.

b) PV Power vs Load Demand after rescheduling

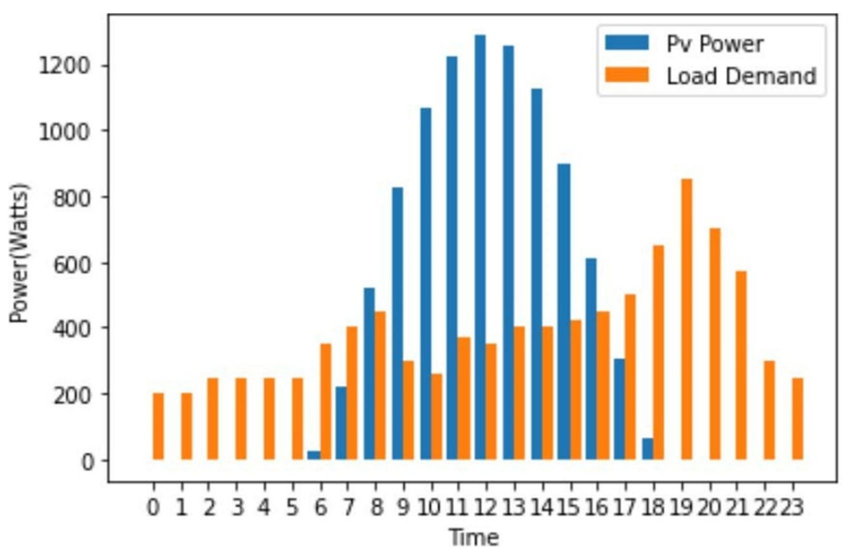

Figure 4.15 PV Power vs Load Demand after rescheduling

- The monthly electricity bill is found out to be 316.64 rupees after rescheduling.

From the above figure 4.15, it can be seen that Pv power is getting wasted in the cases where generated Pv power is greater than load demand. To utilize this energy a 5kWh battery (ESS) is connected to the microgrid.

c) Energy stored in Battery using only PV Power

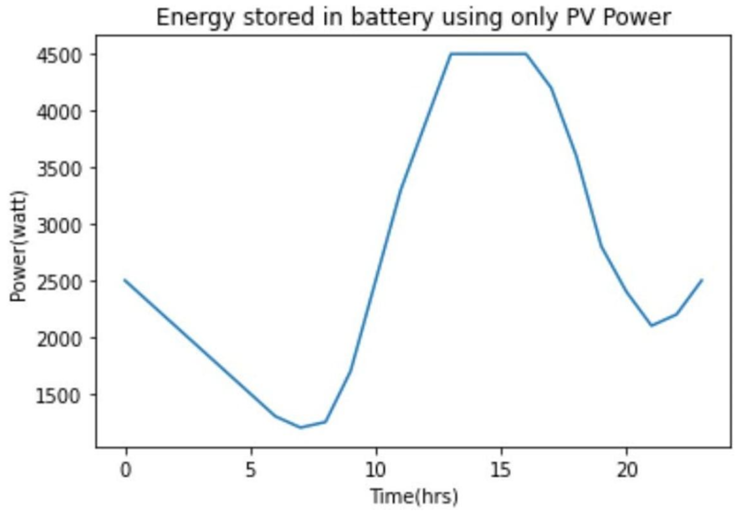

Figure 4.16 Energy stored in 5kWh battery using only Pv Power

- After connecting the battery, the monthly electricity bill is found out to be 98.24 rupees.
- The battery is taken at 50% i.e. 2.5kWh capacity at the beginning of the day and the optimization process is carried out by charging and discharging of the battery.
- The ESS is subjected to various constraints such as ESS min and ESS max, which represent minimum and maximum charge limit, respectively.
- Every ESS has a pre-defined charging and discharging limit, namely higher charging limit, which is set at 90% i.e. 4.5kwh capacity and lower discharginglimit, which is set at 20% i.e. 1kWh capacity.
- The charging and discharging rate of battery is also set to a maximum limit of1kWh while carrying out the operations.

D. Using only Wind Turbine for energy generation

Using the same LSTM 3 hidden layered model, wind speeds for the next 24 hours arepredicted and the MSE and R2 values are calculated.

1) Wind Speed Actual vs Predicted

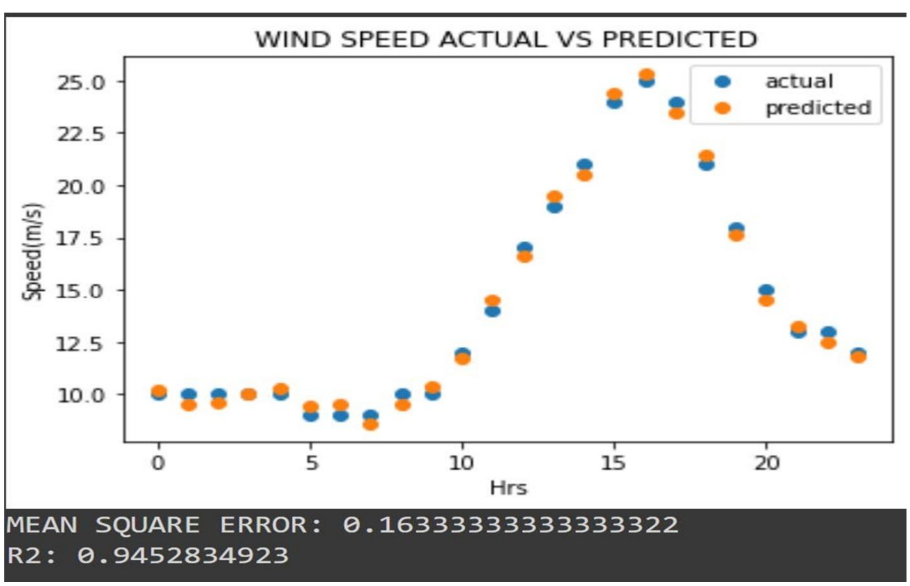

Figure 4.17 Wind Speed Actual vs Predicted

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a) The wind speed is converted to wind power with the help of wind turbine installed onthe roof of the house.
b) The wind turbine is considered to have an efficiency of 45% and 2kW power ratingwind turbine is installed to meet the load demand.
c) The total power generated from the wind turbine per day is 9415.25W.
d) Wind Power vs Load demand is plotted for better visualization.

2) Wind Power vs Load Demand

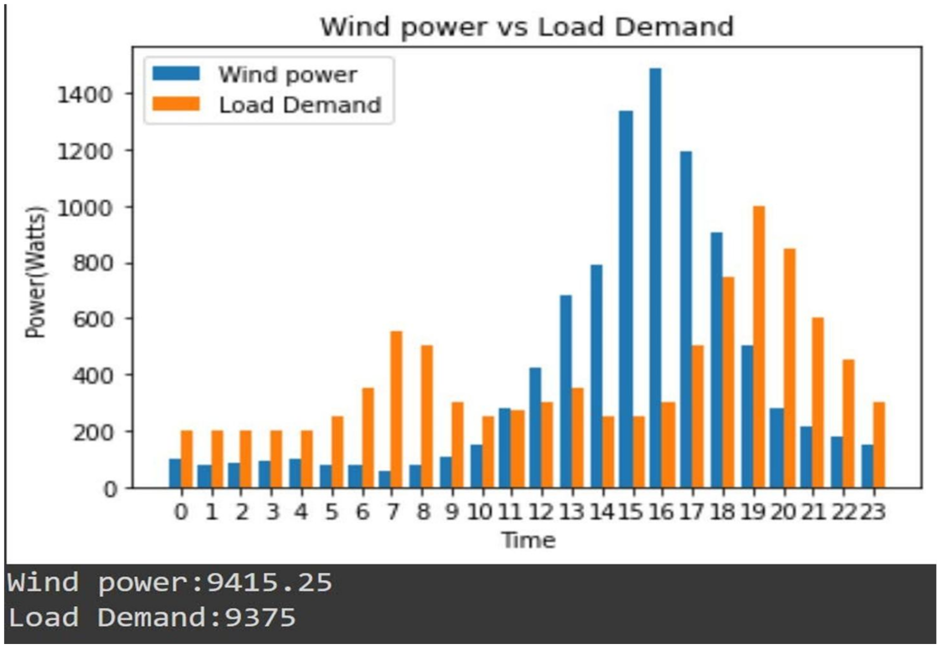

Figure 4.18 Wind power vs Load Demand

a) Here, the RTU pricing is used to calculate the monthly electricity bill and it is found tobe 346.42 rupees.
b) As, we have predicted this day ahead wind power we can reschedule some part of thepeak load to use generated energy in an efficient way instead of letting it get wasted.
c) So, we take 15% of the peak load as schedulable load and reschedule it to minimizethe monthly electricity bill.

3) Wind Power vs Load demand after rescheduling

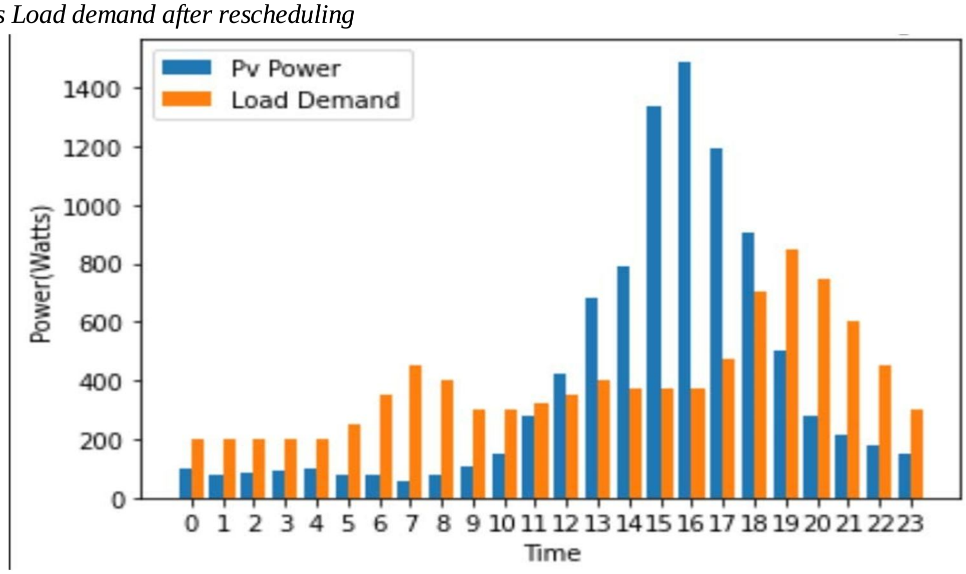

Figure 4.19 Wind power vs Load demand after rescheduling

a) The monthly electricity bill is found out to be 276.84 rupees after rescheduling. From the above graph, it can be seen that wind power is getting wasted in the cases where generated wind power is greater than load demand. To utilize this energy a 5kWh battery (ESS) is connected to the microgrid.

4) Energy stored in 5kWh battery using only Wind Power

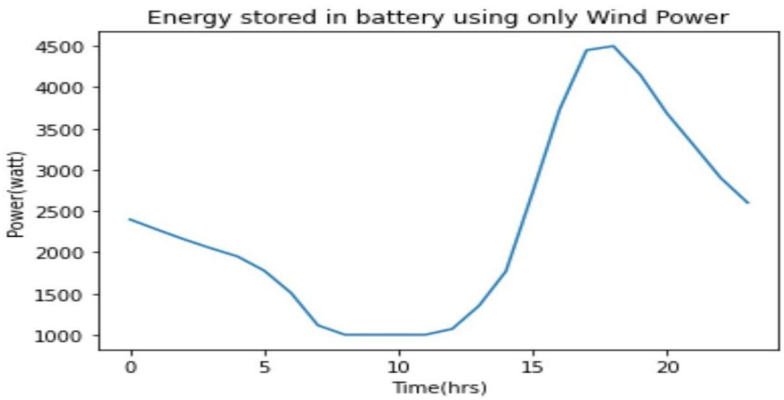

Figure 4.20 Energy stored in 5kWh battery using only Wind Power

- After connecting the 5kWh battery the monthly electricity bill is found out to be 74.82rupees.

E. Considering Both Solar Panels And Wind Turbine For Energy Generation

Now, instead of de pending only on solar power or wind power both are taken together and connected to the microgrid and the power generated is called hybrid power.

It is useful to take both solar panels and wind turbine together as in the case of cloudy days there is a less generation of power from pv panels, but wind turbine balances it by generatingmore power because of high wind speeds.

1) The solar irradiance and wind speed is converted to solar power and wind power withthe help of solar panels and wind turbine installed on the roof of the house.
2) The solar panel is considered to have an efficiency of 15% and three 330W powerrating solar panels are used and they generate 4.76kW per day.
3) The wind turbine is considered to have an efficiency of 45% and 1kW power rating wind turbine is installed and it generates 4.65kW per day.
4) Total power generated from both solar panels and wind turbine is 9419.99W per day.
5) Hybrid Power vs Load demand is plotted for better visualization.

a) Hybrid power vs Load demand

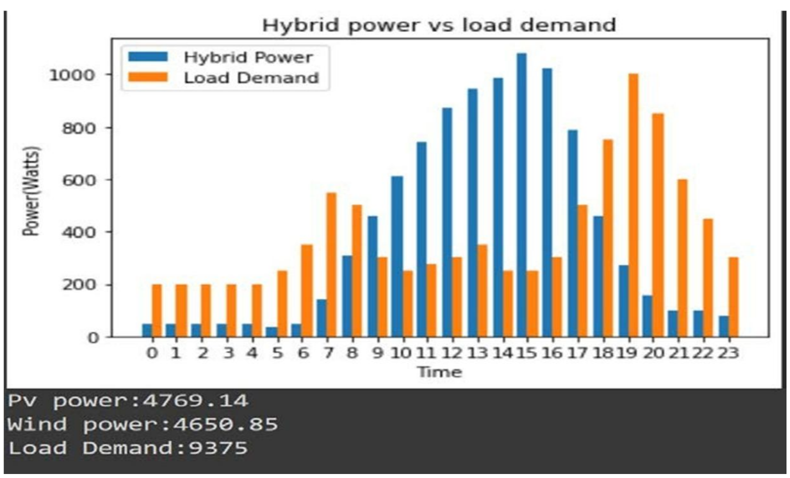

Figure 4.21 Hybrid Power vs Load demand

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- Here, the RTU pricing is used to calculate the monthly electricity bill and it is found tobe 304.82 rupees.
- As, we have predicted this day ahead wind power we can reschedule some part of thepeak load to use generated energy in an efficient way instead of letting it get wasted.
- So, we take 15% of the peak load as schedulable load and reschedule it to minimizethe monthly electricity bill.

b) Hybrid Power Vs Load Demand After Rescheduling

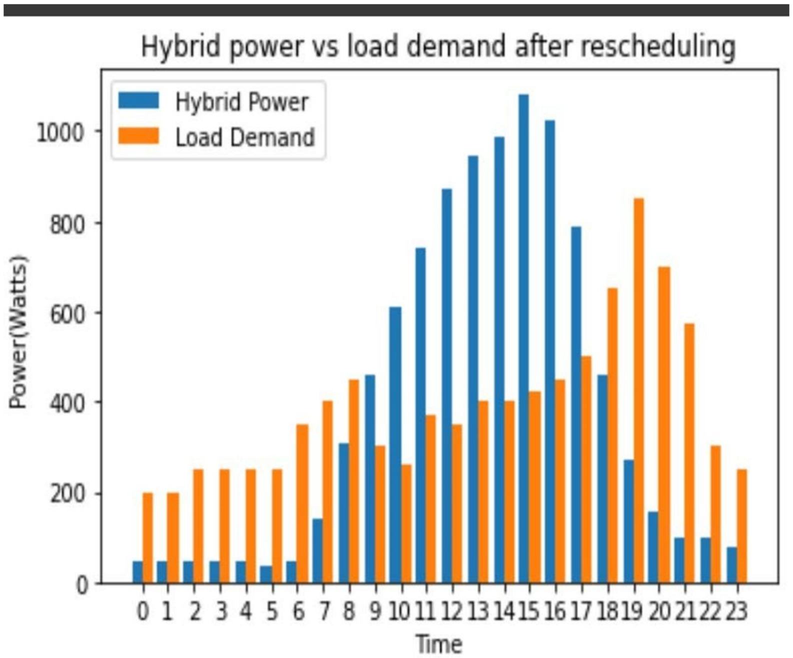

Figure 4.22 Hybrid power vs Load demand after rescheduling

- The monthly electricity bill is found out to be 236.90 rupees after rescheduling.

From the above figure 4. 22, it can be seen that hybrid power is getting wasted in the cases where generated hybrid power is greater than load demand. To utilize this energy a 5kWh battery (ESS) is connected to the microgrid.

c) Energy Stored In 5kwh Battery Using Hybrid Power

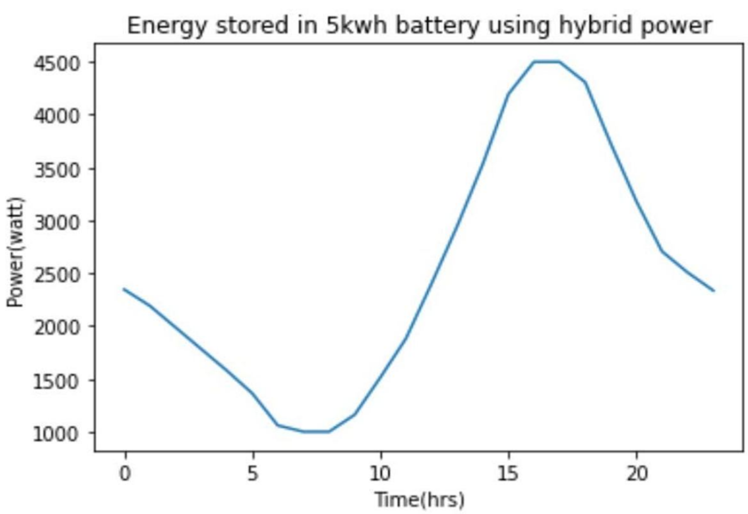

Figure 4.23 Energy stored in 5kWh battery using Hybrid power

- After connecting the 5kWh battery the monthly electricity bill is found out to be 15.36rupees.

d) Power sold VS Power taken from the grid

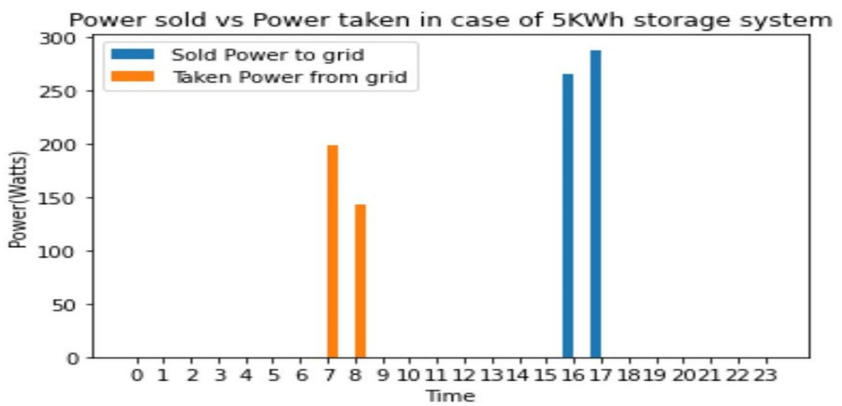

Figure 4.24 Power sold vs power taken from the grid in case of 5kWh battery

- The hybrid power model costs approximately 2 lakhs as the battery costs around 1lakh rupees.
- The size of the battery is reduced to 3kWh battery to decrease the initial investment ofthe system from 2 lakhs to 1.5 lakhs.

e) Energy stored in 3kWh battery using Hybrid power

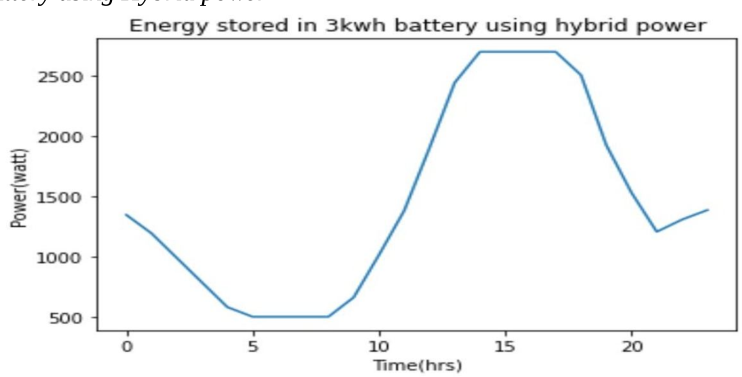

Figure 4.25 Energy stored in 3kWh battery using Hybrid power

- After connecting the 3kWh battery the monthly electricity bill is found out to be 93.46rupees.
- From this it can be said that using 3kWh battery is not as much profitable as using5kWh battery.

f) Power sold VS Power taken from the grid

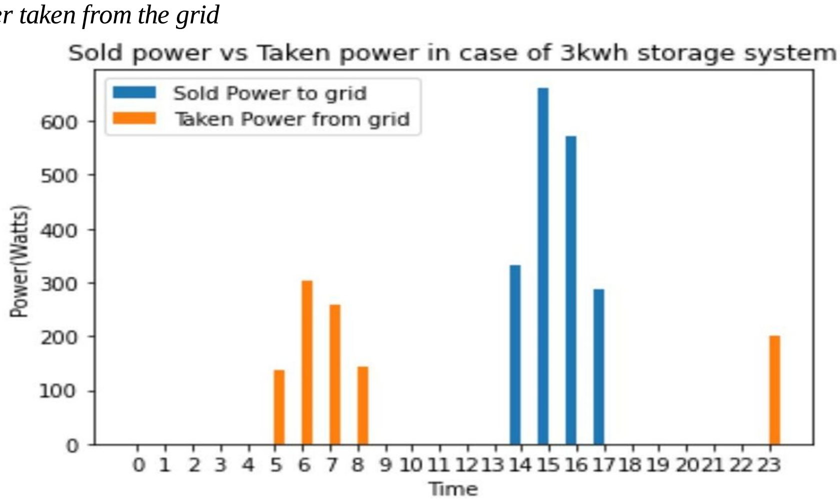

Figure 4.26 Power sold vs power taken from the grid in case of 3kWh battery

F. Time Taken To Pay Back The Initial Investment

1) While calculating number of years to return the initial investment the money saved ineach month is considered as payment.
2) Also, the Indian government provides a subsidy of 30% for installation of any RES inhouseholds. So the initial investment becomes 1,40,000 rupees.
3) The rate of interest is taken as 10% and also while calculating the rate of return theload is considered to increase by 10% for every 2 years.
4) So, the load becomes 10,312 after 2 years, 11,343 after another 2 years etc.
5) The monthly electricity bill also changes as the load changes. The monthly electricity bill becomes 2227.34 rupees after 2 years, 2450.08 after another 2 years etc.
6) The monthly electricity bill after integrating the hybrid model is 75. 12 after 2 years, 145.23 rupees after another 2 years etc.
7) The monthly payment back by the user is the savings made from using the model so, 2025-15.36 rupees i.e.. 2009.64 rupees per month during the first 2 years, in the same way 2227.34-75. 12 rupees i.e.. 2153.22 rupees per month during the next 2 years etc.
8) Finally taking all these factors into consideration, no of years it takes to pay back theinitial investment is 6.94 years.

V. CONCLUSIONS

A. Determination Of Optimal Machine Learning Model

LSTM model prediction results were compared against those of the RNN model as wellas conventional ML models like ANN and linear regression approaches.

B. Determination of optimal LSTM structure

1) To improve the accuracy of the LSTM model, this study examined 4 different LSTM structures, each with a different depth.
2) The three-layer LSTM model was found to be the most accurate and hence is used topredict solar irradiance.

C. Determination Of Optimal Input Dataset

1) We also found out that inclusion of previous 2 days data increased the accuracy of the LSTM model.
2) Upon training and arriving at the best model (the LSTM model with 3 hidden layers), it was able to predict day-ahead solar irradiance with a 6% error.
3) The same model is again used to determine the day-ahead wind speed with a error of7%.

D. Determination Of Optimal Microgrid Model

1) The three electricity bills from the microgrid models using three powers: Solar power, Wind power and Hybrid power are compared and it is shown that using the Hybrid model the electricity bill is minimized more.
2) Load rescheduling is also done to minimize the power drawn during peak time.

E. Determination Of Optimal Battery Size

1) Two batteries with different capacities i.e. 3kWh and 5kWh are connected to the Hybrid model and it is found that using 5kWh battery is more advantageous during long term.
2) The monthly electricity bill for the house is decreased from 2025 rupees to 15. 36 rupees after connecting hybrid model with a 5kWh battery.
3) So, this model decreases the monthly electricity cost by 99.24%.

F. Determination Of Payback Period

1) The initial investment for the hybrid model is calculated out to be 1,40,000 rupees with a rate of 10% interest per annum.
2) The load is considered to increase with a rate of 10% for every 2 years.
3) So, considering all these factors the number of years taken to return the initialinvestment is found out to be 6.94 years.

G. Future Scope

1) The accuracy of the LSTM model can be further increased if data like cloud cover can be obtained from the weather stations.
2) Further components like EVs, Micro gas turbines etc. can also be integrated into themicrogrid.
3) This model can be extended from the range of a single house to a community.

VI. ACKNOWLEDGEMENT

We whole heartedly thank our guide Dr. Ram Krishnan, Assistant Professor, Department of Electrical Engineering, for being a constant source of motivation, supervision and encouragement, which in hindsight has proven to be invaluable to this project report.

We are grateful to Dr. Sailaja Kumari, Professor and Head of Electrical Engineering Department, for providing us with all the facilities to carry out this project work. We are immensely thankful to her for her mora l support during the total span of this Project.

We are also very thankful to the Project Evaluation Committee, for their strenuous efforts to evaluate our projects.

We consider it as a great privilege to express our deep gratitude to many respected personalities who guided, inspired and helped us in the successful completion of the project.

We are also thankful to all our friends who have given valuable suggestions and help in all stages of the development of the project.

Finally, we would like to dedicate this work to our parents who have provided support and encouragement during every part of our life.

Onwards and upwards, now and forever.

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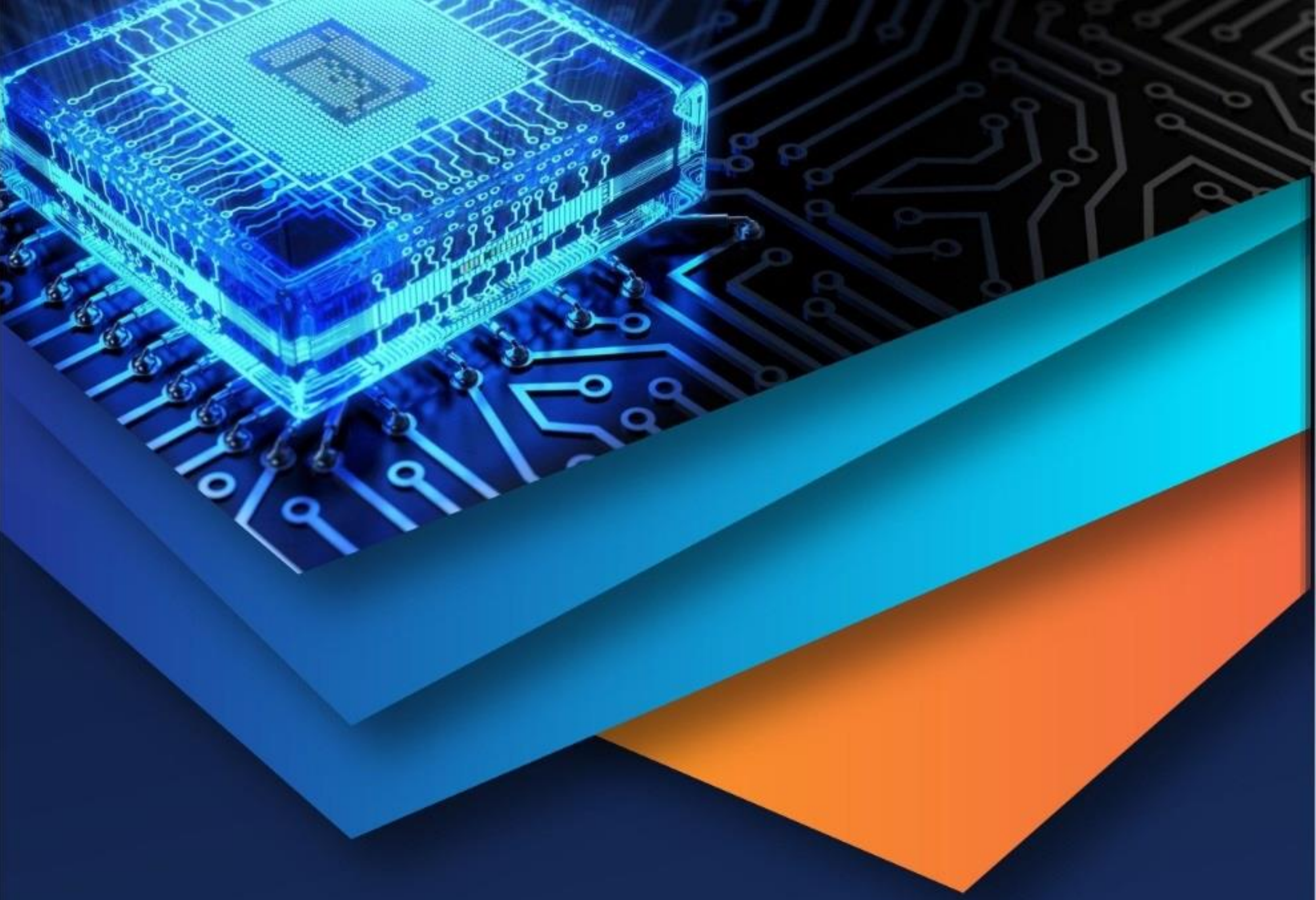

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