Modelling and Optimization of Hybrid Renewable Energy Systems and Applications

A Thesis Submitted in Partial Fulfillment of the Requirements for the Award of the Degree of

DOCTOR OF PHILOSOPHY

Submitted by

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DECLARATION

I hereby certify that the work which is being presented in this thesis entitled **“Modelling and Optimization of Hybrid Renewable Energy Systems and Applications”** submitted in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy in the Department of Electrical Engineering, Delhi Technological University, Delhi. This is an authentic record of my own work carried out under the supervision of Prof. M. Rizwan. The matter presented in this thesis has not been submitted elsewhere for the award of a degree.

Place: Delhi **Upma Singh**

Date: / / **(2K19/PHD/EE/17)**

CERTIFICATE

On the basis of the declaration submitted by Ms. Upma Singh, a student of Ph.D., I hereby certify that the thesis titled **"Modelling and Optimization of Hybrid Renewable Energy Systems and Applications"** which is submitted to the Department of Electrical Engineering, Delhi Technological University**,** Delhi in partial fulfillment of the requirement for the award of the Doctor of Philosophy is an original contribution with existing knowledge and faithful record of research carried out by her under my guidance and supervision.

To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

In the last few years, several countries have accomplished their determined renewable energy targets to achieve their future energy requirements with the foremost aim to encourage sustainable growth with reduced emissions, mainly through the implementation of wind and solar energy. Wind and solar energy is critically important for the social and economic growth of any country. Moreover, reliable and precise wind and solar power prediction is crucial for the dispatch, unit commitment, and stable functioning of power systems. This makes it easier for grid operators of the power system to support uniform power distribution, reduce energy loses, and optimize power output. Consequently, the integration of wind and solar power globally relies on correct wind and solar power forecasting. Current studies typically adopt machine learning algorithms (ML). The foremost contribution of this research is short-term wind power forecasting on the basis of the historical values of wind speed, wind direction, and wind power by using ML algorithms. In this study, regression algorithms such as random forest, k-nearest neighbor (k-NN), gradient boosting machine (GBM), decision tree, and extra tree regression are employed to enhance the forecasting accuracy for wind power production for a Turkish wind farm situated in the west of Turkey. Polar curves have been plotted and the impacts of input variables such as the wind speed and direction on wind energy generation is examined. Scatter curves depicting the relationships between the wind speed and the produced turbine power are plotted for all of the methods here and the predicted average wind power is compared with the real average power from a turbine with the help of the plotted error curves.

The second contribution of this research is short-term solar power forecasting on the basis of the historical values of ambient temperature, irradiation, module temperature and solar power by using ML algorithms. In this study, regression algorithms such as random forest (RF) and k-nearest neighbor (k-NN) regression algorithms are employed to enhance the forecasting

accuracy for solar power production for a Qassim University, KSA. The performance of all algorithms were estimated based on the various statistical indicators.

As renewable energy sources (RES) provide intermittent power and are not available 24 hours a day, it is vital to build hybrid models based on RES to provide an uninterrupted, sustainable, eco-friendly, and cost-efficient power supply. The current research is also devoted to the development and design of an optimal hybrid model using locally accessible RES for selected locations. The evaluation of the potential of locally available RES for selected sites in Uttar Pradesh, India, is carried out to develop the hybrid model. To fulfil the energy demand of the selected site, a hybrid model was constructed using the Hybrid Optimization Model for Electrical Renewable (HOMER) software based on the feasibility analysis of RES at the selected site. To create a hybrid model, the electrical load demand for the specified location is evaluated while taking seasonal fluctuations, current and future power requirements, everyday hourly consumption patterns, living standards, and so on into account. The primary goal of this study is to develop an economic and optimal hybrid PV/Biogas configuration for power production for rural common facilities including one Primary school, Junior school and Panchayat Ghar buildings of Sarai Jairam village in Uttar Pradesh, India. The PV/biogas hybrid configuration was designed utilizing the Hybrid Optimization Model for Electric Renewable (HOMER) and techno-economic analysis is carried out to fulfill the load requirements. The HOMER analysis produced a solution that included total net present cost (NPC) and cost of electricity (COE), and these results were then further improved using sensitivity analysis. Based on the NPC and COE, this analysis evaluates the system performance and demonstrates that it is techno-economically feasible.

In addition, for maximizing the solar power generated from solar photovoltaic system (SPV), the optimization of space and orientation of solar PV system are also done.

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LIST OF ABBREVIATIONS

Abbreviations	
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
BU	Billion Units
CNN	Convolutional Neural Network
COE	Cost of Energy
DT	Decision Tree
ET	Extra Tree
GBM	Gradient Boosting Machine
GDP	Gross Domestic Product
GHG	Greenhouse Gases
HOMER	Hybrid Optimization of Multiple Energy Resources
HRES	Hybrid Renewable Energy System
k-NN	k-Nearest Neighbor
LSTM	Long-Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	Multi-layer Perceptron
MNRE	Ministry of New and Renewable Energy

MSE	Mean Absolute Error
NPC	Net Present Cost
NREL	National Renewable Energy Laboratory
R^2	Coefficient of Determination
RESs	Renewable Energy Sources
RF	Random Forest
RFECV	Recursive Feature Elimination using Cross-validation
RMSE	Root Mean Square Error
SCADA	Supervisory Control and Data Acquisition
SPF	Solar Power Forecasting
SPV	Solar Photovoltaic
SVM	Support Vector Machine
VMD	Varying Mode Decomposition
WNN	Wavelet-based Neural Network

LIST OF SYMBOLS

Parameters/variables

d_g	Availability of cattle dung (kg/day)
DF	Derating factor
E_{PV}	Yearly solar energy potential (kWh/m^2/year)
$E_W\ (t)$	Number of wind turbines
$E_{XPV}\ (t)$	Amount of energy that is left over after the load has been met by the SPV
$E_{XG}\ (t)$	Amount of energy that is left over after the load has been met by the biogas systems
$E_{XM}\ (t)$	Amount of energy that is left over after the load has been met by the biomass generator systems
$E_{XW}\ (t)$	Amount of energy that is left over after the load has been met by the wind based generator systems (kWh)
$E_B\ (t)$	Amount of energy that is stored in the battery in kWh
$E_D(t)$	Hourly load demand" (kWh)
$E_{df}(t)$	Unmet or deficit demand that is not satisfied by Renewable energy source (kWh)
F_G	Calorific value of biogas (kcal/m^3),
FF	Fill factor
M_n	Annual total amount of manure produced
m_j	Manure produced per cattle
N_j	Number of the selected group of animals
n	Overall number of cattle

N_{PV}	Number of SPV modules
$P_{PV}\ (t)$	Power output of the SPV system
Q_{PV}	Average daily solar radiation per year (kWh/m^2/day)
Q_G	Biogas availability per day (m^3/day)
$Q_{PV.STC}$	Solar irradiance incident under STC (1 kW/m^2)
$Q_{PV}\ (t)$	Solar irradiance incident on the SPV array in kW/m^2
R_{PV}	Rated capacity of the SPV array under standard test conditions (STC)
$T_{amb}\ (t)$	Ambient temperature (^{o}C)
$T_{PVnm}\ (t)$	Nominal or rated cell temperature (^{o}C)
$T_{PV}\ (t)$	Operational temperature of the solar cell
Y_G	Biogas yield (m^3/kg)
Vco	cut-out speed of a wind turbine
Vci	cut-in speed of a wind turbine
V_{OC}	Open circuit voltage (V)
V_{mpp}	Voltage at maximum power point
I_{SC}	Short circuit current (A)
I_{mpp}	Current at maximum power point
$\eta_{\ ch}$	Charging efficiency of battery
ς	Short circuit current temperature coefficient (A/^{o}C)
τ	Open circuit voltage temperature coefficient (V/^{o}C).
Δt	Time step of one hour
$\eta_{\ G}$	Overall conversion efficiency from biogas to electrical power production

γ	Self-discharging rate of battery at hour *t*
β	Tilt Angle of the Module
α	Altitude Angle
η	Efficiency

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Power is amongst the most crucial elements of infrastructure, essential for the welfare and economic development of any country. Rapid exhaustion of fossil fuels and tremendous growth in power demand has forced engineers worldwide to consider the utilization of renewable energy sources (RES) [1–2]. The serious consequences of environmental deterioration have also focused universal attention on RES. However, the cost of installation of such RES is higher, but their minimum operational costs and non-polluting nature is intensifying their use worldwide [3]. Wind and solar power generation is a low-cost and profusely available resource. Therefore, various nations are beginning to recognize that wind energy offers a substantial opportunity for future electricity production [4-5]. Consequently, installed wind and solar capacity increases by more than 30% every year. The stimulating and dominating characteristics of wind and solar energy over other resources of energy are the reduction of greenhouse gases emissions, reduction of dependency on fossil fuels, no global warming, low installation cost, less setup time, no fuel cost and low operation and maintenance charges [6-8]. The reliability and stability of power systems depend heavily on the intermittent and unpredictable behaviour of wind and solar energy, which also makes forecasting challenging. Therefore, a precise and efficient short-term forecast technique is essential for the long-term integration of wind power into the power system [9].

The machine learning models produce good forecasting accuracy. There are two significant challenges to using machine learning approaches. To begin, prediction error and reliability must be increased to meet the needs of the energy markets. Second, the required computation times must be decreased to an adequate level [10]. To enhance the economic growth of the nation and the living standard of human’s electricity is very essential.

The majority of the world's population resides in developing nations, with rural areas constituting roughly one-third of these nations. A substantial part of this rural population is completely reliant on bioenergy or fossil fuels to prepare food or meet other electricity needs, yet burning fossil fuels causes environmental pollution and releases greenhouse gases (GHG), which cause global warming, acid rain, and other health hazards [11-12].

In India, around 70% of the population lives in rural areas, and approximately 23% of households do not have access to electricity. Furthermore, the everyday accessibility of power in most rural regions is restricted to a limited number of hours because of a variety of factors such as weak distribution network, electricity stealing, local people’s reluctance to pay electricity bills and so on. In such cases, people utilize diesel generators and kerosene oil, which emit GHGs and cause health problems, among other things [13].

India's installed power generation capacity has grown dramatically during the last four decades. It was 30 GW in 1981 and over 412 GW on February 28, 2023. Despite this expansion, there is a significant gap between load demand and generation demand.

Exploration and utilisation of locally available renewable energy sources (RES) for power generation would be the most viable solution for rural areas in order to address the aforementioned issues and to fulfil Indian Government missions such as "Power to All," "Green and Clean Energy," "Digital India," and so on. The use of renewable energy sources for power production can enhance rural people's living conditions and health, as well as provide them with education and career possibilities, reducing their migration to cities. The chaotic nature of these RES during the year, on the other hand, leads to research toward hybrid systems, which combine two or more sources [14].

Recent research has showed that hybrid systems with multiple sources are more reliable and cost-effective. Because the geographic location and environmental elements influence the performance of a hybrid model, a site-based study is required to determine the size and related capital and operating and maintaining (O&M) costs of components. Furthermore, the initial cost of a renewable energy sources-based system is more costly than that of a conventional energy-based system. As a result, size is one of the requirements for producing power at a low cost.

A lot of research is being done these days in the domain of RE-based hybrid systems. This work is concerned with the design optimization and sizing of components, as well as their economical operations and control. There is still a lot of study to be done in this field. In considering the above discussions, an attempt has been taken to build some hybrid models for the selected site, with the best ones chosen based on reliability, cost and size [15]. Before designing and developing any hybrid system, it is crucial to investigate and utilize the potential of various RES or their ability to generate power.

As a result, one of the objectives has been chosen to be the feasibility analysis of various RES for specified locations. Following the feasibility analysis, the load demand for a specific area must be estimated [16]. Furthermore, it is required to identify and build various feasible configurations that could be used in specific scenarios. An optimal configuration is chosen from among the investigated configurations to achieve cost-effectiveness and reliability. Furthermore, the optimal size is required to use the RES in a cost-effective and efficient manner. As a result, optimization of renewable power based hybrid systems considers the process of selecting the most appropriate components, their suitable size, and operational planning in order to deliver cost-effective, reliable and efficient sustainable power [17-18]. Various researchers use a prominent commercial software called Hybrid optimization model for electric renewable (HOMER) developed by National Renewable Energy Laboratory (NREL) for modelling, sensitivity analysis and optimization to obtain the most optimal and cost efficient hybrid system.

1.2 SCENARIO OF INDIAN ELECTRICITY

Electricity an essential necessity for any country's socioeconomic progress. Furthermore, electrification is one of the most critical demands of remote regions in developing countries such as India in order to achieve economic progress, poverty reduction, creation of jobs, and long-term human growth [19]. With 1.42 billion people, India is the world's first most populous country. Approximately 70% of them live in rural regions. According to published data, around 18452 communities are still without electricity [20, 21].

Furthermore, it has been discovered that electric supply is not always available in the residences in electrified communities. The share of hydroelectric power has been expanded to 90 times in the existing energy system scenario, but the largest portion of the country's generation capacity is still that of thermal power, which is more than 60% and has been grown by around 260 times since Independence of India [20].

In 1974, nuclear power contributed 640 MW to the Indian electricity sector, which has since been grown tenfold to 2023. The share of renewable energy in total installed capacity in India has increased from 0.03% in 1990 to 41.4% (including hydro) as of 31.03.2023. According to the latest data, India has 4,16,058 MW of installed capacity [21]. Renewable energy contributes 30.1% of total installed capacity, second only to thermal energy. Fig. 1.1 depicts the significant share of several conventional and renewable energy-based power production in the nation. Because thermal plants account for 57.02% of total capacity, they contribute to global warming, Greenhouse gases and health issues, among other things. The chart also illustrates that RES account for just 30.1% of total electricity generation, which can be enhanced by harnessing increasing the number of RES [22,23]. Fig. 1.2 shows the renewable energy status of wind, solar, small hydro and biomass as on 31.03.2023. [22]

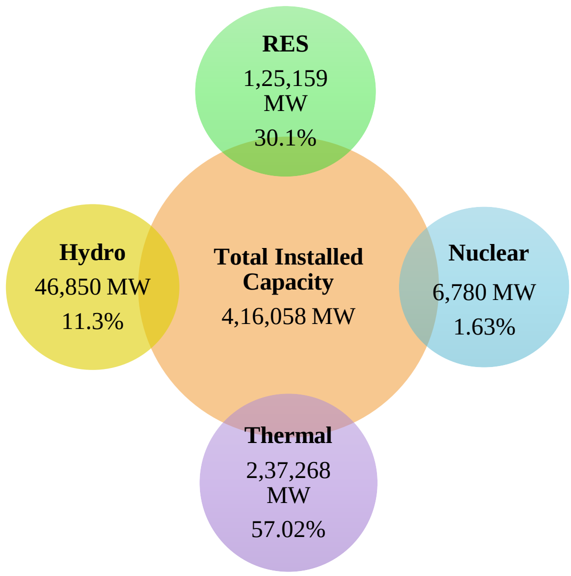


Fig. 1.1: Total installed capacity as on March 31, 2023 (Ref: Ministry of Power) [22]

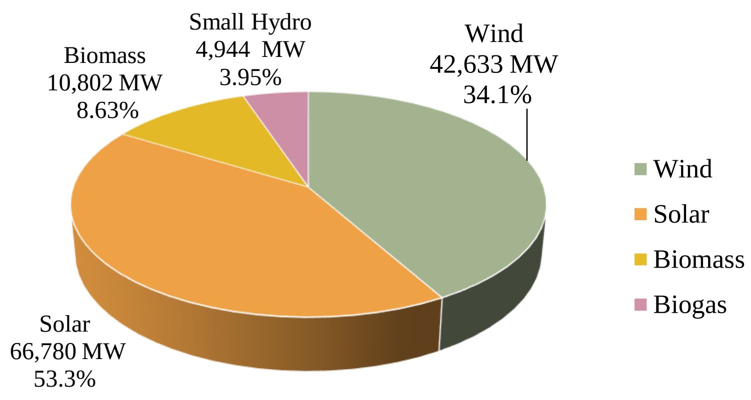


Fig. 1.2: RES status as on March 31, 2023 (Ref: Ministry of Power) [22]

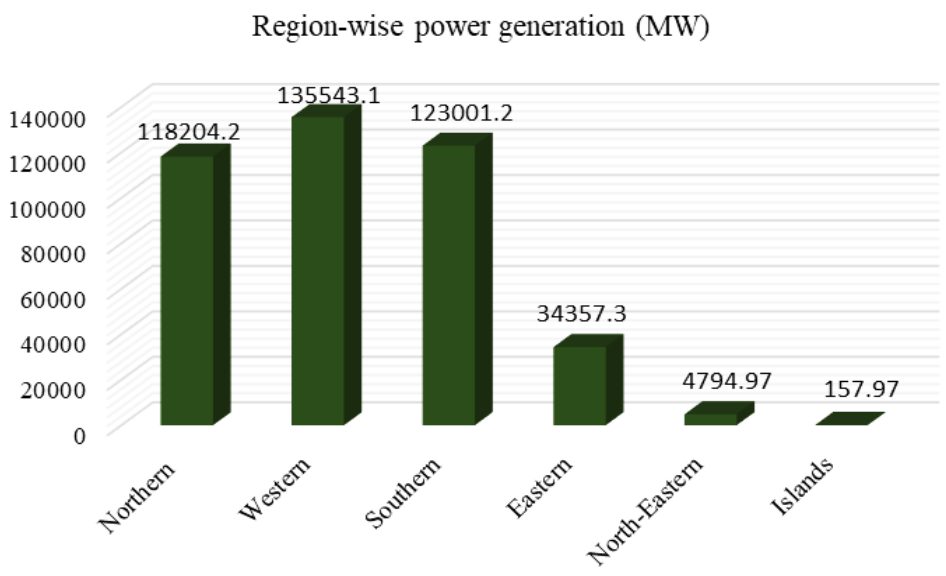


Fig. 1.3: Power generation in India by region as of March 31, 2023 [23]

As shown in Fig. 1.3 electricity production is maximum in the western region, followed by the southern, northern, eastern, north-eastern, and island regions.

Furthermore, Fig. 1.4 presents the sectoral contribution to total installed capacity in the Indian power sector. The private sector contributes approximately 50% of total installed capacity, while the central and state governments contribute 24% and 26%, respectively [23].

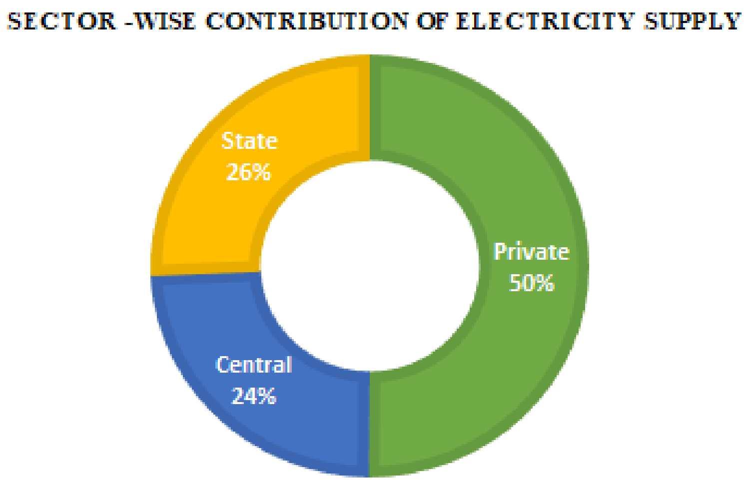


Fig. 1.4. Total installed generation capacity (sector wise) as on February 28, 2023 [23]

1.3 STATUS OF INDIAN RENEWABLE ENERGY

Renewable energy is the foundation for achieving sustainable energy. In the early 1970s, their significance was recognised. India has made significant initiatives to promote renewable power.

A significant amount of research has been conducted in order to reduce the relative cost of renewable energy. India has also enacted a number of price-cutting policies. To meet the energy needs of its emerging economy, India established a separate Ministry of New and Renewable Energy (MNRE) in the early 1980s. Ever since, renewable energy generation in India has been steadily increasing [24-26].

With a population of 1.3 billion, India has a huge demand for power to support its quickly expanding economy. India has been working for more than seven decades to achieve energy independence, despite having a power deficit when it attained independence. With a total installed capacity of over 4 lakh MW, our country now has a surplus of power [27].

India's power generation mix is rapidly changing towards a higher proportion of renewable energy in order to achieve sustainable development [28]. India is now the world's third largest producer of renewable energy, with non-fossil fuels accounting for 40% of installed capacity [29].

Fig. 1.5 depicts the exponential rise in the electricity generation in India from 2005 to 2022 [24]. According to Fig. 1.5, renewable power capacity has grown approximately 9 times over the past 18 years. In addition, the involvement of multiple RES including solar, wind, small hydro, and bio power is displayed in Fig.1.5.

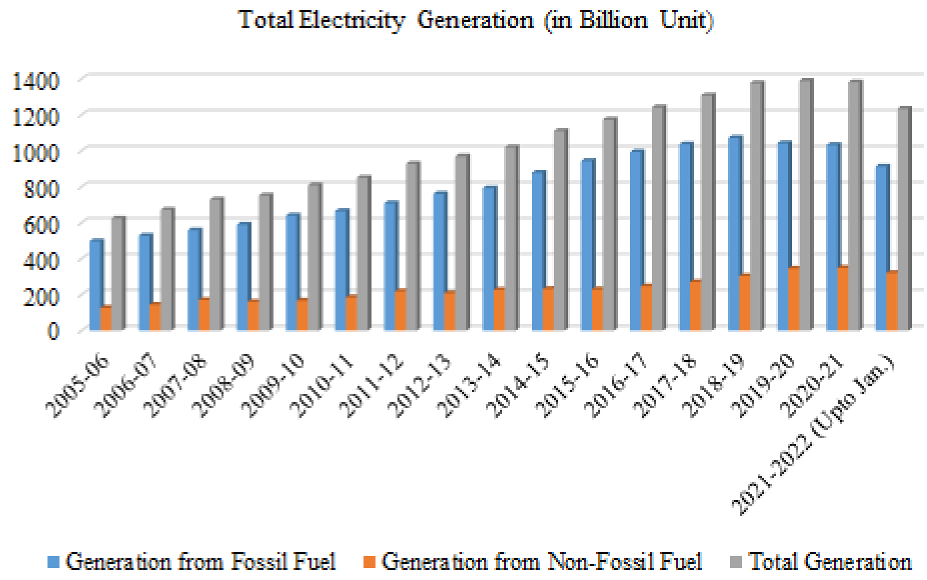


Fig 1.5: Total electricity generation in the country [24]

Total electricity generation, including renewable sources, is expected to be around 1234.298 BU in 2021-22 (up to January 2022), up from 1137.851 BU in the same period last year, representing an 8.5% increase. The country's electricity generation from fossil fuel sources during 2021-22 (up to January 2022) is 913.193 BU, a 9.5% increase over the previous year's generation of 834.109 BU. Coal-based power generation in 2021-22 (up to January 2022) is 850.845 BU, an increase of 11.2% over the previous year's same period. Electricity generation from Renewable Sources (Non Hydro) during 2021-22 (up to January 2022) is 141.280 BU, up 14.5% from the previous year's generation of 123.428 BU. Wind generation is 61.400 BU, up 14.2%, and solar generation is 57.394 BU, up 19.0%. The share of RE Generation (Including Hydro) in Total Generation has been increased to around 22.9% during 2021-22 (up to January 2022), and the share of Non-Fossil Generation in Total Generation has been around 26.0%.[24, 30]. Total electricity generation in the country increased from 624.2 billion units (BU) in 2005-06 to 1234.3 BU in 2021-22. (Upto January 2022). The Pradhan Mantri Sahaj Bijli Har Ghar Yojana - Saubhagya initiative was introduced by the Indian government in October 2017 with the goal of achieving universal household electrification by providing electricity connections to all rural and urban poor families that are not already electrified. Since the beginning of Saubhagya, up until March 14, 2023, 2.86 crore (28.6 million) houses, including 91,80,571 dwellings in Uttar Pradesh, have been electrified. After that, some States stated that 11,83,870 more formerly hesitant homes—including 3,34,652 households in Uttar Pradesh—were now open to electrification. These also received approval. In contrast to this, 4,40,893 families had electricity as of March 15, 2022, according to the ministry's response.

1.4 INDIAN GOVERNMENT INITIATIVES FOR RENEWABLE ENERGY

Energy is the foundation for achieving sustainable energy. In the early 1970s, their significance was recognised. India has made significant initiatives to promote renewable power. A significant amount of research has been conducted in order to reduce the relative cost of renewable energy. India has also enacted a number of price-cutting policies [30, 31]. To meet the energy needs of its emerging economy, India established a separate Ministry of New and Renewable Energy (MNRE) in the early 1980s. Ever since, renewable energy generation in India has been steadily increasing [32-33].

The Government of India started several incentives to tremendously drive the addition of wind capacity, through tax rebates, financial help and subsidies, etc. for supporting market players. In lowering the prices of wind power equipment via large scale manufacturing of equipment, the government has announced new policies through the Make in India scheme [34].

The Indian government made a number of initiatives in recent years, including National Electricity Policy 2005, National Rural Electrification Policy 2006, National Tarrif Policy, and Electricity Act 2003, etc. These initiatives in the wind power field show improved financial incentives, a steady market growth, opportunities in offshore wind power and lowering renewable energy prices [30, 35].

The particulars of the regulatory acts enacted by the state and central governments to enhance clean power are listed as follows.

1.4.1 Electricity Act 2003

The Electricity Act, 2003 was enacted with effect from 10 June 2003. This act covers crucial matters involving transmission and distribution, sales and utility to promote electricity through renewable energies. The following are some of the points included in the 2003 Electricity Act:

1. To deliver improved methods to uplift power via generation and co-generation via RES by giving improved techniques for the integration of grid and trading power to customers, and to mention the terms of service for determining the tariff;
2. To encourage the utilization of RES through distinct sections of 'Electricity Act 2003, the State Commission will have to produce power, grid integration and construct a competitive electricity market in which the sale and purchase of electric power can be accomplished by the RES and also encourage co-generation;
3. To encourage the generation and co-generation of electrical power from RES [30, 36].

1.4.2 National Electricity Policy 2005

National Electricity Policy was set up in discussion with, and taking into consideration, the opinions of the CEA, CERC, state governments and other stakeholders.

The main aim of this policy is to set regulations for faster growth of the power field, delivering power supply to all regions and protection of the interest of stakeholders and consumers by considering the availability of power resources, energy security issues, economics of generation using distinct resources, and the technology available to exploit these resources [30, 37].

1.4.3 National Rural Electrification Polices (NREP), 2006

In 2006 ‘NREP’ Policy was announced by the Ministry of Power, Government of India, for allowing standalone power systems utilizing renewable power. The major objective of NREP is to deliver reliable and sustainable quality of electricity at an appropriate price to all local users. In addition, where grid supply is not possible, off-grid solutions such as a standalone power system can be used to bring electricity to isolated rural locations [30, 38].

1.4.4 National Tariff Policy 2006

The ‘National Tariff Policy was declared in 2006, to expand the utilization of RES under section ’86-1-e’ of the ‘Electricity Act 20030. According to the policy, a suitable commission will set a definite percentage of tariffs having a minimal rate of power purchase from RES, taking into account the accessibility of the RES in the particular area and impacts on production prices [38].

1.4.5 State Level Initiatives

There are several independent state level polices apart from the national policies, whereby wind energy can be promoted as RES. As per the regulations (as of 31 August 2016) of CERC and SERC, they have concluded the electric power cost for their individual states [98]. Therefore, based upon the tariff orders issued by SERC for the financial year 2020–2021, CERC has determined the APPC at the national level to be at Rs 3.85 per unit for the year 2021–2022 [30, 39].

1.4.6 Mechanism of Renewable Energy Certificates (REC)

To encourage renewable power in the electricity market, the REC mechanism is very effective and profitable. In India, the REC mechanism was constituted in 2010 by CERC, under the Electricity ACT (2003). REC acts as a tracking or accounting mechanism for wind, solar and other green energies as they flow into the power grid. Since electric power produced from RES is indistinguishable from that generated by any other RES, some form of tracking is needed.

This accounting and returning power to the grid is essential since electricity is tough and costly to store in batteries [100–102]. Thus, additionally produced renewable power, which is unused by producer, is fed back into the electric grid for utilization by other customers. Hence, the provider of renewable power will then obtain a REC [40].

In order to promote renewable energy in the nation, including wind energy, the government has taken a number of actions. These consist of:

- Allowing 100% of FDI (foreign direct investment) via the automatic route.
- Interstate sales of wind and solar energy without paying ISTS fees are permitted for projects that will be operational by June 30th, 2025.
- Up until 2022, a trajectory for the Renewable Purchase Obligation (RPO) has been declared.
- A trajectory for the Renewable Purchase Obligation (RPO) has been established through 2022.
- Standard Bidding Guidelines for tariff based competitive bidding process for procurement of Power from Grid Connected Solar PV and Wind Projects.

- To ensure prompt payment by distribution licensees to RE generators, the government has issued orders requiring power to be dispatched against a Letter of Credit (LC) or advance payment.
- To develop a pool of skilled workers for the operation, implementation, and upkeep of RE projects through skill development programs.

Along with the aforementioned, the subsequent actions have been specially taken to promote wind power:

- The generation-based incentive (GBI) is given to wind projects that were put into operation on or before March 31, 2017.
- Wind projects that went into operation on or before March 31, 2017, are eligible for the generation-based incentive (GBI) [30, 40].

1.5 THE NEED FOR WIND AND SOLAR POWER FORECASTING

Wind energy is extremely crucial to any country's social and economic development. Given this, accurate and reliable wind power prediction is critical for dispatch, unit commitment, and the stable operation of power systems [41]. This makes it simpler for power system grid operators to support uniform power distribution, reduce energy losses, and optimise power output [42]. Furthermore, without forecasting functionality, wind energy systems that are extremely disorganised can cause irregularities and pose significant challenges to a power system. As a result, the global integration of wind power is dependent on accurate wind power prediction. It is necessary to create dedicated software in this regard, where weather forecast data and wind speed data are model inputs that predict the power that a wind farm or a specific wind turbine could produce on a given day. Forecasted outputs could also be compared to a town's actual per-day power demands [43-44]. When the predicted power is insufficient to meet the town's daily needs, appropriate decisions can be made to arrange for leftover power to be gathered from other sources. If the predicted power exceeds the demand, a sufficient number of wind turbines could be turned off to prevent surplus generation. This method has the potential to reduce frequent power outages and protecting generated power from being wasted. Abundance availability of solar and wind energy. It enables power system entities to maintain lesser operating reserves. To increase grid stability and reliability. A reduction in supply-side uncertainty and an increase in overall preparedness to deal with unforeseen events are two benefits of improved forecasting. Prediction can effectively contain extreme changes in wind and solar generation as well as abrupt changes in the output of power systems. Solar and Wind power forecasts can help system operators make informed choices on power purchasing needs [45].

1.6 THE NEED FOR A HYBRID SYSTEM

Electrical energy demand is rising exponentially as a result of urbanization, fast industrialization, technology advancements, and increased household consumption, among other factors. Moreover, electricity produced from conventional energy sources has become more expensive because of increasing fossil fuel prices and their exhaustion [46]. Furthermore, the non - availability of grid electricity to remote areas, the substantial quantity of Carbon dioxide emission from thermal power plants and the lack of rural electrification, are motivating factors to produce electricity from Renewable sources. Renewable sources would play a crucial role and become good replacement for conventional sources of electricity in the coming years because of their numerous advantages such as environmental friendliness, natural resource, reliable power source, job growth, particularly in rural areas, stabilized fuel costs, managed to improve health concerns, and so on [47]. In light of the aforementioned, renewable energy sources (RES) can play a significant role in achieving a sustainable future. Biomass, small hydro, wind and solar are the most common types of RES; and all have immense capacity to meet future needs for energy. Nevertheless, there are some limitations to Renewable sources, such as their stochastic nature and relying on weather factors, which makes the system layout unreliable and insufficient to meet demand over a long period of time [48]. Energy storage is needed to improve system reliability, which increases system cost that is unwanted. Taking into account the above mentioned, a combination of various Renewable sources like small hydro, biomass, wind energy, solar photovoltaic (SPV), and so on might be possible solutions. "Hybrid Renewable Energy Systems (HRES) are made up of two or more sources of energy, one of which is renewable and is connected with power control equipment and an optional storage system." A hybrid system is a combination of various kinds of systems, and the need for power storage in such systems could be lowered, making the system more economical [49]. A hybrid system based on renewable energy is also a viable solution for electrifying remote regions where the extension of grid is not viable or cost-effective. It may also address, emissions, efficiency, economics, fuel flexibility and reliability issues. The hybrid system can operate either off or on the grid. The system is connected to the power grid when it is in grid connected mode, but not when it is in off grid mode [50]. There are several hybrid system configurations described in the literature, such as , MHP/Biogas/Biomass/SPV/Battery/ Fossil fuel generator, SPV/Wind/Fuel cell (FC)/Electrolyzer, Wind/Biomass, Wind/Biomass , SPV/Wind/DG/Battery, Wind/DG/Battery, SPV/Wind/Battery, Wind/Battery, SPV/Wind, SPV/Battery, SPV/Diesel generator (DG) etc.

1.7 RESEARCH MOTIVATION

To achieve the United Nations Sustainable Development Goals of Sustainable Energy for All and reducing GHG emissions to mitigate climate change, the more utilization of renewables is critical [51]. Small hydro, solar energy, wind energy, and biomass are examples of renewable energy sources. The RES listed above is abundant in India. However, small hydro and wind energy are primarily site dependent, whereas biomass and solar energy are widely available in most areas. India is the 7th, biggest country in terms of its overall land mass area, which provides numerous opportunities for utilizing the commonly accessible potential of renewable energy sources. Approximately 20% of the total population still lacks access to electricity [52].

As of February 28, 2023, India had 412 GW of installed capacity, with fossil fuels accounting for 236.4 GW and renewable energy accounting for about 175.7 GW. As a result, there is an imperative necessity to tap commonly accessible RES for use in electricity production and achieve the goal of "electricity for all." [53].

India has consistently shown that it is willing to lead the fight against climate change [54]. In addition to achieving short-term objectives like increasing renewables capacity to 500 GW by 2030, going to meet 50% of its power needs from energy from renewable sources, decreasing overall emission rates by one billion tonnes by 2030, and reducing India's GDP's emissions intensity by 45% by 2030, the nation's long-term goal is to achieve Net Zero Emissions by 2070. According to demand and commonly accessible RES, an HRES composed of two or more RES may be a more efficient solution for rural electrification because of its versatility in choosing power sources, reliability, sizing, prolonged life cycle, and economic feasibility when compared to utilizing a single energy source [55].

According to the literature, HOMER software is commonly used for hybrid system feasibility analysis. Furthermore, the majority of the work has been done to optimize off-grid hybrid systems. Moreover, size optimization of biogas and biomass generators in hybrid systems was rarely done because most researchers used fixed size bio generators. Additionally, during hybrid system size optimization, only a very limited amount of the seasonal variations in electricity demand for load is taken into account.

1.8 RESEARCH OBJECTIVES

Based on a review of the literature and the growing importance of designing hybrid systems that use commonly accessible RES for electricity production, the primary goal of this work is to design, optimize, and analyze an effective renewable energy-based hybrid system that ensures reliable and economical power supply while emitting less GHG. The following objectives have been set for the research work:

- Artificial Intelligence based approach for short term solar PV and wind power forecasting for smart energy management.
- Feasibility analysis of renewable energy resources based hybrid energy system for remote areas.
- Design and optimization of hybrid energy system for remote areas and applications.
- Optimization of space and orientation of solar PV system for maximizing power generation

The current chapter begins with an overview and background wind and solar power generation, need of forecasting, scenario of Indian electricity, Installed power production capacity from various sources, status of Indian renewable energy,

Indian government initiatives for renewable energy, followed by the need for a hybrid system. This thesis is divided into seven chapters, including an introduction and conclusion. The remaining chapters of the thesis are organized as follows:

Chapter 2 contains a detailed literature review on wind power forecasting, solar power forecasting, and feasibility and techno-economic analysis of hybrid renewable energy systems (HRES) has been presented and discussed in depth.

Chapter 3 presents the comparative study of machine learning models for wind power forecasting with introduction to dataset, data analysis and performance metrics.

Chapter 4 presents the status of global wind power, emission of carbon dioxide renewable power contribution by technology, investment flow of RES, renewable energy jobs, global wind power installed capacity and various achievements and significant information related to worldwide wind energy.

Chapter 5 presents a detailed comparative study of machine learning models for solar power forecasting with introduction to dataset, data analysis and performance metrics.

Chapter 6 introduced the development of off-grid hybrid models utilizing HOMER software to fulfil the electricity requirement of remote applications such as panchayat ghar and primary schools located in remote areas without the availability of grid power. This chapter also discusses the components of HRES, including technical specifications, operating costs, maintenance and operation costs. Furthermore, different models in off-grid modes were chosen based on RES availability and simulated in the HOMER tool for a one-year period utilising economic and technical data as input. Finally, they are compared in terms of various technical and economic parameters to determine the best optimal solution.

Chapter 7 suggests the development of a real-time grid-connected solar photovoltaic (PV) system utilising PVsyst software, with an optimum area solution and a proposed method to enhance power. This chapter also looked at the economic aspects of designing a solar PV system. This chapter thus tends to focus on two primary objectives; one is to use the space in an optimal way in order to get the most benefits in the least amount of space, and the second is to place modules in such a way that the power can be extracted more efficiently without changing the number of solar modules. The results of the simulation were validated and correlated with those of the hardware.

Chapter 8 summarizes the conclusions and key contributions of the thesis work. Finally, the scope of future study has been highlighted.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

This chapter demonstrates general articles about wind and solar power forecasting. Significant time series and machine learning findings for wind and solar power forecasting are also presented. Since the year 2000, a great deal of work has been done in wind speed, wind power and solar power forecasting. Most recent work has focused on artificial intelligence approaches and machine learning models [56]. Wind and solar power forecasts, can be classified into four time scales: very short-term (few seconds - 30 min), short-term (30 min - 6 h), medium-term (6 h - 1 day), and long-term (more than 1 day) [57]. This chapter will review related work using machine learning algorithms for each group, with a focus on short-term forecasts. This chapter also provides a literature review on numerous aspects of renewable energy power systems, such as feasibility analysis, hybrid model design and development, and sizing of renewable power hybrid systems, and so on. Over a hundred research articles on renewable energy-based power systems have been analysed and evaluated. This literature review has been divided into sections, which are discussed in the following sections.

2.2 REVIEW ON WIND POWER FORECAST

With the advent of new technologies and accelerated growth in the world's economy, the power demand increases substantially. Over the recent times, power industries have switched their focus on to the sources of green power in order to minimize the carbon emission during power production [58, 59]. In addition, fossil fuels has a severe influence on the environment such as floods, melting of glaciers, heat waves, droughts and frequent wildfires threatening our earth’s ecosystem. Thus, the growth in renewable energy sources (RES) like solar power, geothermal energy, tidal energy and wind energy have become the long-term goal for the governments throughout the world [60]. Among all power sources, the wind is the source of green power which can replace the utilization of fossil fuels, thereby reducing emission of carbon and efficiently lessening the power crisis [61-63]. Wind has broadly been adopted as power-system alternative because of its easy accessibility, cost-effectiveness and renewable nature. Because of the intermittent nature of power production from wind energy systems, the operators have to operate and control the power plant competently [64, 65]. Therefore, for long-term and short-term planning of power transmission, it is necessary to forecast wind power production. Recently numerous researches have been done on predicting the power production and feasibility analysis by wind system. Few researches have concentrated on direct-power forecasting of RES and some have utilized the methodology to predict the input-variables (wind and solar-irradiance) and estimated the energy produced from hybrid plant utilizing various models [66]. Mostly wind-farms have installed SCADA system to manage the wind turbines for logging on the operational data on and monitoring distinct components. The logged on dataset contains information about speed of wind, direction of wind and produced power etc. It offers the chance to process the time-series data collected for a variety of applications, from operational and maintenance needs to forecasting the amount of power generated by wind turbines [67]. The wind speed, wind direction and time of day are the significant parameters which influence the wind turbine-power production. In the past few years, numerous research papers and review articles have been published that analyzed, in detail, the various wind power forecasting approaches and methods. Hanifi et al. (2020) presented a critical review on various approaches such as statistical, physical and hybrid to forecast the wind power. In this area of research, authors also provide the past and present trends and highlight the future research directions that incorporate a requirement to evolve more cost-effective and advanced forecasting approaches; improvement in data-processing, error post processing and developing specific models for an off-shore wind energy forecasting, as such wind turbines work in distinct weather circumstances. Moreover, their findings show that, among 42 analysed researches 60% utilized wind speed, 25% utilized air temperature and few researches utilized number of generation hours [68]. Delgado and Fahim (2021) evolved long-short term memory (LSTM) based forecasting model for short-term wind energy production [69]. In another research, Extra Trees, ADa- Boost and K-Neighbors Regressors are used to predict power and energy of wind turbine. While manipulations of data are accomplished by recursive-feature-elimination utilizing cross-validation (RFECV) (Qadir et al. 2021) [70]. In another research, a new forecast model using light gradient boosting machine (GBM) and convolutional neural network (CNN) is developed. By examining the characteristics of raw-dataset on the time-series from the surrounding wind field, new feature sets are built, and CNN are utilized to recover the details from the input dataset, and network parameters are updated by comparing the outputs Ju et al (2019) [71]. Chandran et al. (2021) evolved a model that could effectively predict wind energy by using machine algorithms such as recurrent neural network (RNN), long short-term Memory (LSTM) and gated reference unit (GRU) [72]. In other work, to predict the next hour wind power a sparse machine learning technique is utilized (Lv et al. 2021) [73]. Kisvari et al. (2021) evolved a novel data-driven methodology to predict wind energy by incorporating dataset pre-processing, detection of anomalies and treatment, hyper-parameter tuning and feature engineering using gated-recurrent deep-learning models with the help of six features such as gearbox temperature, generator temperature, nacelle orientation, wind speed at hub height, blade pitch angle and rotor speed [74]. In another work, comparison of five optimized robust regression models is done to predict wind turbine output on the basis of wind velocity vector components (Pathak et al. 2021) [75]. González-Sopena et al. (2021) presented a widespread survey of the performance assessment approaches utilized for evaluating the prediction accuracy of short-term wind energy [76]. In another research work, to improve the forecasting accuracy, a hybrid optimization approach is developed that combines varying mode decomposition (VMD) algorithm, long short-term memory neural-network (LSTM) and firefly algorithm (Qin et al. 2021) [77]. Wang et al. (2019) proposed an approach which is the combination of ensemble technique, echo-state-network and wavelet transform, where wavelet transform is utilized to decompose raw wind energy time-series dataset into distinct frequencies with better behaviors and outliers. To automatically learn the input–output non-linear relationship in each frequency and to deal with data noise and model misspecification issues that are common in wind power forecasting problems [78]. Puri and Kumar (2021) used artificial algorithm for wind energy forecasting by utilizing 30 days data of wind speed, air density and temperature in the Himalayan region as input parameters [79].

Noman et al. investigated a support vector machine (SVM)-based regression algorithm for predicting wind power in Estonia one day in advance [80]. Wu et al. suggested a new spatiotemporal correlation model (STCM) for ultra short-term wind power prediction based on convolutional neural networks and long short-term memory (CNN-LSTM). The STCM based on CNN-LSTM has been used for the collection of metrological factors at various places. The outcomes have shown that the proposed STCM based on CNN-LSTM has a superior spatial and temporal characteristic extraction ability than traditional models [81]. Yang et al. developed a fuzzy C-means (FCM) clustering algorithm for the forecasting of wind energy one day in advance to reduce wind energy output differences [82]. Li et al. proposed the combination of a support vector machine (SVM) with an enhanced dragonfly algorithm to predict short-term wind energy. The improved dragonfly algorithm selected the optimal parameters of SVM. The dataset was collected from the La Haute Borne wind farm in France. The developed model showed improved forecasting performance as compared with Gaussian process and back propagation neural networks [83]. Lin et al. constructed a deep learning neural network to forecast wind power based on SCADA data with a sampling rate of 1 s. Initially, eleven input parameters were used, including four wind speeds at varying heights, the ambient temperature, yaw error, nacelle orientation, average blade pitch angle, and three measured pitch angles of each blade. A comparison between various input parameters showed that the ambient temperature, yaw error, and nacelle positioning could be areas for optimization in deep learning models. The simulation outcome showed that the suggested technique could minimize the time and computational costs and provide high accuracy for wind energy prediction [84]. Wang et al. proposed an approach for wind power forecasting using a hybrid Laguerre neural network and singular spectrum analysis [85]. Wang et al. presented a deep belief network (DBN) with a k-means clustering algorithm to better deal with wind and numerical prediction datasets to predict wind power generation. A numerical weather prediction dataset was utilized as an input for the proposed model [86]. Dolara et al. used a feed forward artificial neural network for the accurate forecasting of wind power. Their results were compared with predictions provided by numerical weather prediction (NWP) models [87]. Abhinav et al. presented a wavelet-based neural network (WNN) for forecasting the wind power for all seasons of the year. The results showed better accuracy for the model with less historic data [88]. Yu et al. suggested long- and short-term memory-enriched forget gate network models for wind energy forecasting [89]. Zheng et al. suggested a double-stage hierarchical ANFIS to forecast short-term wind energy. To predict the wind speed and turbine hub height, the ANFIS first stage employs NWP, while the second stage employs actual power and wind speed relationships [90]. Jiang et al. developed an approach to enhance the power prediction capabilities of a traditional ARMA model using a multi-step forecasting approach and a boosting algorithm [91]. Zhang et al. evolved an autoregressive dynamic adaptive (ARDA) model by improving the autoregressive (AR) model. In this approach, a fixed parameter estimation method for the autoregressive model was enhanced to a dynamically adaptive stepwise parameter estimation method. Later on, the results were compared with those of the ARIMA and LSTM models [92]. Qin et al. developed a hybrid optimization technique which combined a firefly algorithm, long short-term memory (LSTM) neural network, minimum redundancy algorithm (MRA), and variational mode decomposition (VMD) to improve wind power forecasting accuracy [93]. Huang et al. used an artificial recurrent neural network for forecasting [94]. Recently, some researchers have developed their own optimization approaches, such as in [95], where the authors developed sequence transfer correction and rolling long short-term memory (R-LSTM) algorithms [96]. Akhtar et al. constructed a fuzzy logic model by taking the air density and wind speed as input parameters for the fuzzy system used for wind power forecasting [97]. Aly et al. developed a model to forecast wind power and speed using various combinations, including a wavelet neural network (WNN), artificial neural network (ANN), Fourier series (FS) and recurrent Kalman filter (RKF) [98]. Bo et al. [99] proposed nonparametric kernel density estimation (NPKDE), least square support vector machine (LSSVM), and whale optimization approaches for predicting short-term wind power. Li et al. developed an ensemble approach consisting of partial least squares regression (PLSR), wavelet transformation, neural networks, and feature selection generation for forecasting at a wind farm [100]. Colak et al. proposed the use of moving average (MA), autoregressive integrated moving average (ARIMA), weighted moving average (WMA), and autoregressive moving average (ARMA) models for the estimation of wind energy generation [101]. Saman et al. proposed six distinct machine heuristic AI-based algorithms to forecast wind speeds by utilizing meteorological variables [102]. Yan et al. investigated a two-step hybrid model which used both data mining and a physical approach to predict wind energy three months in advance for a wind farm [103]. From the literature survey, it is clear that there have been several research studies that have investigated the forecasting of wind energy by employing various analytical approaches across several horizons, among which persistence and statistical approaches have been used. Statistical approaches have not been suitable approaches for forecasting wind power as they have not been able to handle huge datasets, adapt to nonlinear wind dataset, or make long-term predictions [104-105]. Prior to our research, there have been many types of prediction models that have been shaped to predict wind energy, namely, physical models, statistical models, and teaching and learning-based models, which employ machine learning (ML) and artificial intelligence (AI)-based algorithms. Current studies typically adopt machine learning algorithms (ML). In particular, naive Bayes, SVM, logistic regression, and deep learning architectures of long short-term memory networks are typically used [106].

2.3 REVIEW ON SOLAR POWER FORECAST

The rise in prices for fossil fuels and concern about climate change has increased demand for RES, which has numerous advantages, such as being sustainable and environmentally friendly. Solar energy is a renewable energy that converts sunlight into electricity using solar photovoltaic systems. These sources are highly intermittent and chaotic in nature. Solar photovoltaic output is typically highly dependent on the sun's radiation, temperature, and other meteorological conditions. A generative power is typically determined by numerical weather forecasts, also known as a physical model [107]. The reliability of the energy predicting algorithm is heavily dependent on numerical weather prediction, which indicates it degrades with increasing time horizons. Forecasting algorithm horizons range from short-term forecasts in hourly ranges, mid-term forecasts up to some days, to long-term forecasts in the range of some weeks. Different time horizons are of interest to different market participants, which aid in the improvement of various power system applications [108]. There are several models available, including long-term forecasts, mid-term forecasts (e.g., day-ahead forecasts), and short-term forecasts (e.g., hourly-ahead forecasts). Different time horizons, such as extremely short-term, short-term, medium-term, and long-term forecasting, are taken into consideration depending on the users' interest in scheduling to management. Very short-term forecasting, which is useful for quick actions, focuses on an interval of a few seconds to 30 minutes interval. In contrast, load dispatch planning and operational security benefit from short-term forecasting, which is done up to six hours in advance. Long-term forecasting, from one day to a longer time horizon, is taken into consideration. For instance, medium forecasting, starting from a day ahead forecast, is beneficial when achieving considerable operational management and cost optimization. Studies have revealed that sun radiation is essential to the operation of solar energy systems. In comparison to other approaches (such as temperature-based, cloud-based, or other meteorological parameter-based models), solar radiation-based forecasting models offer the highest level of accuracy. However, due to high measuring costs and weather conditions, solar radiation is not always available for various specialized usage objectives (such as short-term, medium-term and long-term). Analysis of solar radiation over a short period of time is significantly more difficult because minute solar radiation is uncommon. Hourly data cannot forecast short-term behaviour, even though they are typically correct when used to assess the total energy delivery of a solar system. Models based on hourly radiation measurements have been utilised despite the fact that it has been known for more than 30 years that they are not an accurate representation of instantaneous or minute radiation. This is because there aren't any detailed radiation data available. Therefore, it is crucial to create a suitable short-term forecasting model that can lessen the restrictions mentioned before. Additionally, voltage fluctuation, poor power quality, and stability concerns are some of the additional issues brought on by the intermittent and uncontrollable nature of solar generation. In brief, the new model is also required for estimating reserves, scheduling the power system, congestion management, optimal management of storage with stochastic production, trading produced power in the electricity market, and, ultimately, to reduce the costs of electricity production.

Meftah et al. forecasted solar power data using a deep learning technique. The LSTM network and Multi-layer Perceptron (MLP) network were compared in terms of performance using the following metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). The prediction outcome demonstrates that for each category of days, the LSTM network provides the best results [107]. Mohamed Abuella et al. used machine learning algorithms to forecast a solar photovoltaic system's solar power output in order to reduce the uncertainty associated with changeable renewable resources. Forecasts are created by support vector machines, and random forest is used to aggregate the forecasts as an ensemble learning technique [108]. Zhang Yue et al. presented the system-level application of three recognised forecasting models to the prediction of solar power over the next 24 hours. In this study, the Least Squares Support Vector Machine (LS-SVM), Radial Basis Function Neural Network (RBFNN) and Auto Regressive Integrated Moving Average (ARIMA), models are all examined [109]. In order to predict monthly solar output power, Kuo-Ping Lin et al. created an evolutionary seasonal decomposition least-square support vector regression (ESDLS-SVR). Seasonal decomposition and least-square support vector regression are used to generate the ESDLS-SVR (LS-SVR). The parameters of the LS-SVR are chosen simultaneously using genetic algorithms (GA). The Taiwan Power Company's monthly solar power output figures are used. Experimental findings show that the proposed forecast model performs better in terms of forecasting accuracy [110]. In order to estimate reliable power generation, Su-Chang Lim et al. suggested a hybrid model that combines a long short-term memory (LSTM) and, a convolutional neural network (CNN). While the LSTM learns power generation patterns depending on weather circumstances, the CNN categorises weather conditions. The PV power output data from a power plant in Busan, Korea, were used to train and test the suggested model [111].Similarly, using deep learning approaches, such as the LSTM algorithm, this Tamer Musha'I AI-Jaafreh et al. investigated the impact of several atmospheric parameters, such as evapotranspiration and soil temperature. According to the results, predicting accuracy increased when new sun irradiation-related features were added [112]. However, the majority of forecasters do not emphasis on the influences of photovoltaic module parameters on the forecasts. Therefore, Yilin Zhou et al. proposed a novel multivariable hybrid prediction system that combines a swarm intelligence optimization technique, deep learning models, artificial intelligence models, and signal decomposition in order to close this gap. To increase the accuracy and effectiveness of solar forecasts, this method completely makes use of independent variable variables, including module temperature [113]. Ying Wang et al. developed a time-series-based solar power forecasting (SPF) model using the local meteorological station's forecasted weather data and the time element. The long short-term memory (LSTM) algorithm is used for short-term SPF in consideration of the data correlation [114]. Yinpeng Qu et al. provided a novel hybrid model to forecast distributed PV electricity production based on Gated Recurrent Units [115]. Using data gathered from a photovoltaic plant in Uruguay, Naylene Fraccanabbia et al. created a forecasting model that uses time series to enable the prediction of electricity energy production. Models (base-learners), pre-processing methods, and models (meta-learners) from the Stacking-Ensemble Learning (STACK) method were used to build the proposal [116]. In this study, we focus on the challenge of daily half-hourly forecasting of the electricity produced by photovoltaic solar systems. Jose F. Torres introduced DL, a deep learning method for huge data time series that breaks the forecasting challenge down into a number of smaller issues. DL is based on feed-forward neural networks. The authors conducted an extensive evaluation using two years' worth of Australian solar data, assessing precision and training time, and contrasting the performance of DL with two other cutting-edge approaches utilizing pattern sequence similarity and neural networks [117]. Using hourly auto-regressive moving average (ARMA) models, Bismark Singh et al. provided a step-by-step methodology to forecast power output from a photovoltaic solar generator [118]. Abinet Tesfaye Eseye et al. used a hybrid forecasting model (Hybrid SVM-PSO-WT) that combines support vector machines, particle swarm optimization, and wavelet transform for the short-term (one-day-ahead) generation power forecasting of a real micro grid PV system [119]. In addition, a thorough error analysis was conducted by Marco Pierro et al. along with the development of deterministic and stochastic models for day-ahead PV production forecasts [120]. Similarly, Irani Majumder et al. mentioned a forecasting technique that depends on a hybrid Extreme Learning Machine (ELM) and empirical mode decomposition (EMD) to predict solar power [121]. In order to create short-term probabilistic solar power forecasts, Simone Sperati et al. applied the Ensemble Prediction System (EPS) of the European Centre for Medium-Range Weather Forecasts (ECMWF) (SPF). The EPS is based on repeatedly running a climatological model from initially disrupted conditions. Estimating the prediction uncertainty is made possible by the distribution of these many runs [122]. Vinayak Sharma et al. developed a method for forecasting photovoltaic (PV) power generation one day in advance without using numerical weather prediction (NWP) data. The proposed method only accepts historical generated PV power data as input and employs a closed loop non-linear autoregressive artificial neural network (CL-NAR-ANN) model [123]. To make short-term predictions of solar irradiation and wind speed and to look into the energy use of micro grids, a novel prediction interval model made up of several sections (modified multi-objective fruit fly optimization algorithm, Group Method of Data Handling neural network, hybrid feature selection and wavelet transform) has been developed [124]. Jie Zhang et al. presented a set of broadly applicable and value-based metrics for solar prediction for a wide range of scenarios (i.e., geographic locations, different time horizons, and applications) that were created as part of the U.S. Department of Energy Sun Shot Initiative's efforts to enhance the precision of solar prediction [125]. A hybrid model of genetic algorithm (GA)/multiverse optimization (MVO), artificial neural networks (ANNs) was used to forecast cell temperature, efficiency and PV output power [126].

2.4 REVIEW ON DEVELOPMENT OF HYBRID SYSTEMS

The unavailability or shortage of electrical networks in remote locations, the excessive cost of grid extension, and the harsh topography frequently lead to the exploration of other alternatives. One of the most promising approaches to meet these areas' need for electrification now involves standalone hybrid systems. Flavio Odoi- Yorke et al. examined the possibility of using a hybrid solar PV/biogas/battery energy system to provide power to distant areas in Ghana. The objective is to employ locally accessible renewable energy sources to reduce greenhouse gas emissions while achieving a Levelized Cost of Electricity (LCOE). The results show that in terms of cost and pollution savings, PV/biogas/battery systems outperform PV/diesel/battery and diesel-only systems [127]. Endeshaw Solomon Bayu et al. conducted a study to incorporate wind turbines, micro-hydro systems, solar photovoltaic (PV) systems, and battery systems to check the feasibility of hybrid systems to electrify the remote place [128]. Paul et al. examined the economic viability and feasibility of utilizing a hybrid-electricity system in rural areas. The findings show that, when compared to PV/Diesel Generator (DG)/B and isolated DG systems, the photovoltaic (PV)/battery (B) system based on renewable energy (RE) has the lowest net profit cost (NPC) and cost of energy (COE). Although the COE and NPC values of the diesel generator (DG) hybrid-electric system (HES) are lower than those of the PV/DG/B system, the DG system still emits the most substantial pollution [129].

Similarly, Nyagong Santino et al. evaluated the viability of a hybrid power system for a remote South Sudanese community without electricity access. Based on the community's energy requirements, average energy consumption profiles were created over the course of a year. The system was configured and optimized using the HOMER pro application, and based on the standalone mode of operation, six potential combinations were modeled and examined technically and economically. Due to the significant solar potential, the Battery/DG/ PV system has the minimum Net Present Cost (NPC) and Cost of Energy (COE) and provides a 22.94% investment return [130]. For the Atacama Desert in Chile, Francisco et al. conducted a cost-benefit analysis of the TEG-HPV system under actual environmental and market circumstances. The economic, electrical, and thermal models of the TEG-HPV system are constructed and examined in MATLAB. With regard to system costs, energy losses, ordinal efficiencies of TEG and PV modules, and their contributions to the economical viability of TEG-HPV systems, five distinct cases are taken into consideration. Payback durations for every scenario are calculated at maximum and minimum PV temperatures for the Atacama Desert, taking into account the industrial and residential prices of electricity [131]. Laetitia et al. conducted a feasibility study with the goal of incorporating renewable energy sources into Popova Island's energy system. It takes an analytical strategy that entails using an energy systems model and the Monte Carlo method before assessing the financial results [132]. Ahmad et al. investigated the feasibility of meeting the load demand with the best system that produces the least amount of CO_2 and net present cost (NPC) emissions. The modeling results demonstrate that the NPC of the proposed grid/PV system is more sufficient than other configurations at the present grid tariff, resulting in a renewable proportion of more than over 50%, a payback period of 17 years, and a 54.3% decrease in CO_2. The outcomes further demonstrate that the integration of a 62 kW PV array with the primary grid is the optimal configuration that results in a minimal COE of 0.0688 $/kWh and sale back power of 9.16% of Al Baha University's total electricity consumption [133]. Mohammad Amin et al. developed the best renewable energy system possible to power a small community using only renewable energy sources. Like many remote Iranian communities, this one experiences regular power shortages. A hybrid stand-alone and on-grid renewable energy system using fuel cells, biogas generators, wind turbines and photovoltaics, is suggested. İn addition to the fuels cells, batteries, a hydrogen tank, an electrolyzer or reformer, and other backup and storage components are employed. The major objective is to identify the best design that can fulfill the demand for power while being acceptable from an environment and an economic standpoint. The findings demonstrate that the cheapest option is to use biogas, wind and solar rather than adding a fuel cell to this design would raise prices by 33-37% while simultaneously increasing the scalability of the system [134].

It is clearly revealed from the literature that a hybrid energy system with a diesel engine has several benefits over one that is solely powered by a diesel engine, including a longer engine lifespan, lower O&M (Operation and Maintenance) costs, lower fuel consumption and less of an adverse impact on the environment [135-137]. Such systems still depend on fossil fuel, which is unfriendly to the environment and necessitates logistical arrangements for delivering the fuel to the community, which is the problem with them [138]. Local fuel availability is frequently poor because of expensive transit expenses and theft danger.

The diesel engine may be totally replaced with a biogas engine to solve the aforemention ed issues, and its fuel can be produced locally in a limited digester. Utilizing locally generated biogas from dung can resolve issues associated with diesel fuel [139-140].

2.5 REVIEW ON OPTIMIZATION OF SPACE AND ORIENTATION OF SOLAR PV MODULE

PV module energy generation is affected by several factors, including solar irradiance intensity, shadowing, pollution, environmental dust, ventilation, module positioning, wind speed and ambient temperature. The total amount of solar energy generated by PV modules is determined by the optimal positioning of the modules under the preferred solar cell efficiency and meteorological factors. PV module positioning is determined by the module's position in relation to the inclination angle (horizontal plane) and the azimuth angle (vertical plane). Standard Test Conditions (STC) determine PV cell efficiency, which usually depends on operating temperature of the cell and type of cell (thin amorphous silicon efficiency is approximately 9.5%, polycrystalline silicon efficiency is 16.0%-18%, and monocrystalline silicon efficiency is approximately 23%). PV increases current while decreasing voltage and electrical power as the temperature rises. Numerous studies have been conducted in order to solve the problem of raising accumulated power by identifying the 'optimised panel positioning' at various geographic locations around the world. The optimum module orientation can be calculated for various periods of time (e.g. annual, semi-annual, seasonal, monthly, daily and hourly) and weather conditions. Using the harmony search (HS) meta-heuristic algorithm, M. Guo et al. [141] finds the azimuth angle and optimum tilt angle of pv systems (PV) panels. In Taiwan, the tilt angle of pv systems (PV) modules is determined using a particle-swarm optimization technique with nonlinear time-varying evolution (PSO-NTVE). The goal is to maximise the modules' output electric power [142]. N. Ur Rehman et al. provided a mathematical model that takes into account the tilt angle of the field as well as the modules and calculates the significant photovoltaic power formation over a specific time frame. The model's validity is determined by comparing the outcomes to measurement taken from a computer-aided 3D model [143]. Q. Hassan et al. evaluated the potential for solar power and identify the optimal tilt angles for maximum solar irradance in Iraq. The optimal south-facing tilt angle has been calculated for eighteen Iraqi cities in order to estimate radiation from the sun. The optimising method is carried out over a period of nineteen years, using hourly experimental solar radiation dataset. The findings indicated that the greatest solar radiation can be collected with a tilt angle ranging from 0° to 64°, with the optimum angle calculated by searching for the maximal hourly-daily solar radiation values with a 1° resolution [144].

2.6 RESEARCH CHALLENGES AND OBJECTIVES

From the aforementioned critical literature review relating to methods that have been used for wind and solar power forecasting as well as for the feasibility analysis and development of the hybrid model the following research challenges are identified:

- Based on the literature, it has been found that several researchers have been working on developing reliable wind power forecast models. Since, most of these techniques have failed to deliver satisfactory outcomes for various wind farm areas when forecasting has been done under irregular and turbulent wind conditions. Due to these factors, there are much more input variables needed.

- Auto-regression and Support vector regression, Linear regression and, among other ML-based regression forecast methods, are widely used nowadays. These methods are employed in wind energy, grid management, solar irradiance prediction for photovoltaic systems, electric load forecasting, and power generation and consumption. The parameters' tuning needs multiple trials and hence takes a long time to get the optimal solution. Moreover, the best solutions achieved by such algorithms cannot be replicated exactly thus several trials should be performed to ensure accuracy and meaningful statistical results.

- Due to the fact that, the methods and algorithms are unable to give satisfactory results with high precision, therefore, for the production of wind and solar power, an accurate and precise forecasting method is necessary. In addition, few researchers have performed exploratory data analysis in polar and Cartesian coordinates system for short-term wind power forecasts rather than long-term forecasts.

- The literature survey also indicates that HRES is a more reliable and cost-effective source of power than conventional grid systems.

- Additionally, the aforesaid research mostly focused on household electrification of rural areas while ignoring the need for power for schools and panchayat ghar. To the author's knowledge, there is no thorough study on the techno-economic analysis of such HRES in using HOMER on the selected location.

- Only a few studies have been reported for India especially North-West i.e Uttar Pradesh state.

- Also, the creation of such models relied on the use of solar and wind energy, and there are only a small number of studies in which biogas and biomass energy sources were regarded as important sources for generating electricity.

- İn this regard, an HRE-based power producing system is suggested for supplying continuous electricity to two schools and Panchayat ghar, located in Sarai Jairam village, district Agra, Uttar Pradesh, India.

- Solar and biogas energy sources have only been used in a small number of research for constructing hybrid power systems.

2.7 SUMMARY

Exploration and use of RES are essential for the sustainable development of humanity. This chapter reviews the literature on wind and solar power forecasting, feasibility studies, hybrid model design and development, and intelligent modelling and sizing approaches for hybrid systems powered by renewable energy sources. Based on the literature survey, research gaps are recognized and research objectives have been framed for the present research work.

CHAPTER 3

WIND ENERGY SCENARIO, SUCCESS AND INITIATIVES TOWARDS RENEWABLE ENERGY IN WORLDWIDE

3.1 INTRODUCTION

Power generation using wind has been extensively utilised, with substantial capacity add-on worldwide, during recent decades. The wind power energy sector is growing, and has turned into a great source of renewable power production [145]. In the past decades of the 21st century, the capacity of installed wind energy has almost doubled every three years. This review paper presents the crucial facets and advancement strategies that were approved and adopted by the Government of various nations for intensifying the country’s own power safety, by the appropriate use of existing power sources. From India’s viewpoint, wind energy is not only utilized for power production but also to provide power in a more economical way. The particulars of India’s total energy production, contributions of numerous renewable sources and their demand are also encompassed in this paper.

After an exhaustive review of the literature, detailed facts have been identified about the present position of wind energy, with an emphasis on government achievements, targets, initiatives, and various strategic advances in the wind power sector. Wind power potential is discussed, which can assist renewable power companies to select efficient and productive locations. All analyses carried out in this paper will be incredibly valuable to future renewable energy investors and researchers. The current scenario of wind power production in India is also paralleled with that of other globally prominent countries.

3.2 STATUS OF GLOBAL WIND POWER

During the 1990s, the price of electrical power produced via wind was six times higher than current prices. Since then, wind power technology has been emerging at a fast rate among all RES with reference to enhanced installed capacity [146]. At the start of 2015, almost 85% of total global new wind power installation has been accomplished by the top ten wind energy leading countries, namely, China, US, Germany, India, Spain, UK, Canada, Italy, France and Denmark. Global new wind energy installations surpassed 90 GW in 2020, which was 53% growth since 2019, increasing total installed capacity to 742.9 GW. A growth of about 14% in comparison with the previous year was observed as shown in Fig. 3.1. The top five marketplaces for new installations were mainly China, US, Brazil, Netherlands and Germany [147-148]. These marketplaces jointly comprised almost 81% of wind installations of the previous year, amounting to about 10% more than in 2019. At the end of 2020 the cumulative installations of the top five marketplaces was the same. These marketplaces were China, US, Germany, India and Spain, which collectively led to about 74% of the total wind energy installations as presented in Fig. 3.2. Wind power installation began in India in 1990 and has significantly increased over the past several years [149-150]. The total installed wind power capacity in 2022 was 40.36 GW, being the fourth highest installed wind-power capacity globally. Due to the reduced price of wind power from onshore wind energy, numerous wind power projects have been instigated.

The MNRE has already set an ambitious target to achieve 450 GW of renewable energy installed capacity by 2030 [151-152]. A total of 42.633 gigawatts of wind power was installed as of March 31st, 2023. In India, the main producers of wind energy have been Adani Green Energy, Alfanar, SembCorp Green Infra and Renew Power [153-155].

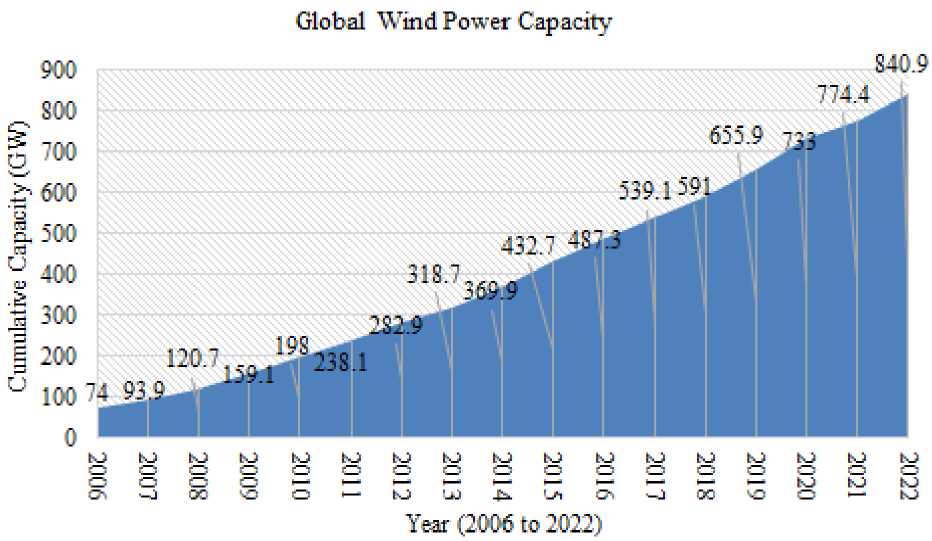


Fig 3.1: Global wind power cumulative capacity (GW) (2006–2022)

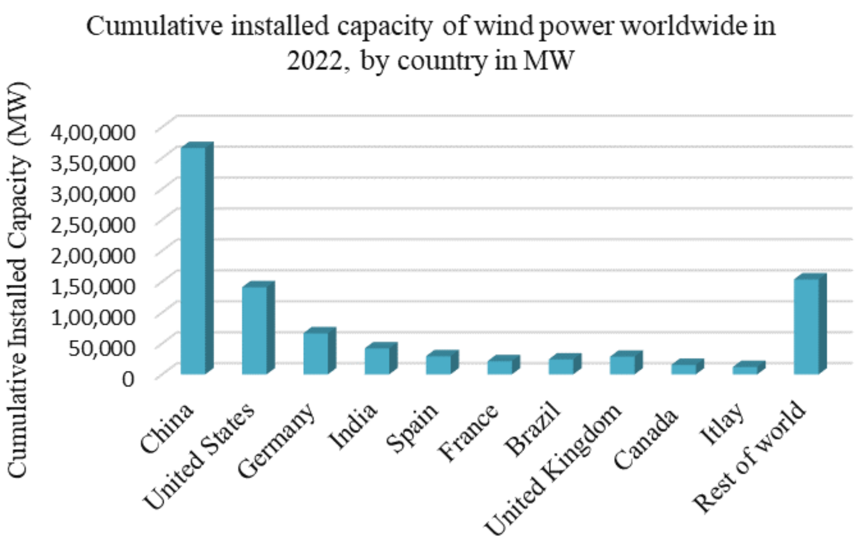


Fig 3.2: Cumulative installed capacity (CIC) of wind power (MW) 2022 [155]

3.3 EMISSION OF CARBON DIOXIDE

Fig. 3.3 shows the CO_2 emission (billion metric tons) produced by the foremost ten countries in the year 2021. It is worth noting that the above-mentioned amount of 742.9 GW of wind power production can reduce carbon dioxide emissions by 1.1 billion tons yearly [156].

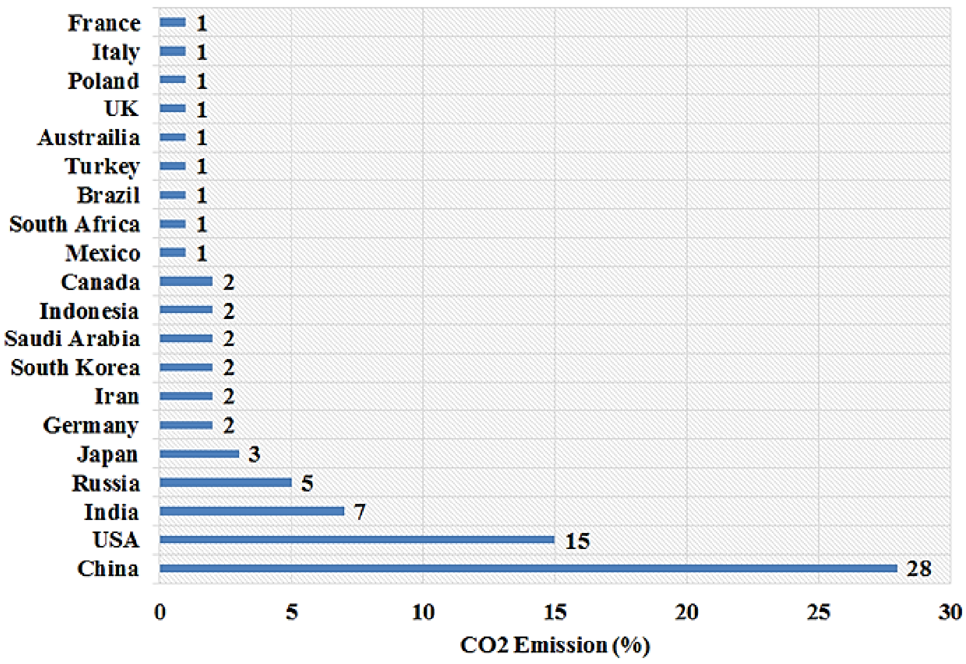


Fig 3.3: CO_2 emission in billion metric tons (as on 27 October 2021) by the foremost countries in the world in the year 2021

As stated in the latest data of the Global Carbon Project, China, the United States, India, Russia, and Japan are the five top nations which generate the most carbon dioxide. Conventional power resources emit approximately half of the total carbon dioxide. Globally, China is the biggest emitter of CO_2, as approximately 58% of the total power supplied in China is derived from coal alone.

Worldwide, India is the third largest emitter of CO_2, although it is still well behind China, the world's largest emitter, and the United States. The global emission of CO_2 totals approximately 33.1 billion metric tons each year [157]. However, due to COVID-19 induced lockdowns, the worldwide carbon dioxide emissions reduced by an estimated 2.5 billion metric tons in 2021.

The Government of India is aware about its adverse impacts and has developed a National Action Plan (NAP) on changing climate.

However, while growing the Indian economy improves the wellbeing level of individuals, it also upsurges the electricity demand. RES has emerged as the best solution for upholding the equilibrium between demand and generation of electricity [158].

In seeking to achieve this, the Government of India has taken numerous initiatives to augment wind energy utilisation, such as (i) no transportation concerns due to finished goods and raw material, (ii) no management and administrative problems for promoting wind energy, (iii) savings from various taxes, (iv) problems associated with sale of energy is no more because various distribution companies and state electricity boards are ready to buy the power, and, (v) easy availability of bank loans for installing wind power plants [159]. The growth of wind energy creates significant problems in areas such as grid integration, inter-connections, network stability, and frequency control, etc.

Therefore, for secure, stable and systematic operation of power systems, various nations have set up new grid codes. The majority of Indian states have gigantic wind power scope and other needed provisions for the steady and secure functioning of wind power plants. For upholding the energy development of any nation, forecasting the potential of future renewable energy is also necessary. Various techniques are being utilised to analyse and forecast the pattern of the future growth of wind power, and also the duration of time for attaining the technical wind power mission [160].

MNRE, Government of India, is outlining policy guidelines and looking towards the promotion of offshore wind projects. An analysis of the Indian shoreline has been conducted, which revealed that approximately 6–8% additional wind potential may occur along the eastern offshore. To select the site, the main steps are to identify several potential sectors following data collection across a large area. Accurate forecasting of wind power density is also necessary for selection of the site.

Various models such as Weibull distribution and extreme learning machine have already been implemented and are being utilised for determining the wind power density [161]. In the last 20 years, the worldwide generation of wind power has been advanced approximately 15 times.

In addition, extensive research has been undertaken to estimate the future potential and current status of renewable power. Several technologies have been developed and implemented by many researchers for enhancing the renewable power potential and technology enhancement behind RESs for improving the system security and quality of power [162].

3.4 RENEWABLE POWER CONTRIBUTION BY TECHNOLOGY

During the past few decades, several nations have become conscious of the harmful impacts of global warming. Hence, to reduce the environmental pollution and harmful impact of greenhouse gases all nations are eager to utilise RES. For the first time, 2015 witnessed an extraordinary growth of the wind industry as yearly installations traversed the historic mark of 60 gigawatts.

Wind turbines with a capacity of more than 63 gigawatts have been installed. The earlier record was set in 2014, when more than 51.7 gigawatts of new capacity was added worldwide [163]. In 2016, 54 gigawatts of wind energy capacity was added around the world.

The rapid development of, and large capacity addition to, the renewable power-sector is mainly delivered by hydro, solar and wind power. However, in the majority of nations, among all the RES, wind farms contribute the most power due to being easily available and having a low maintenance cost [164]. Fig. 3.4 presents the renewable power contribution (in TWh) of the foremost six countries in 2020-21.

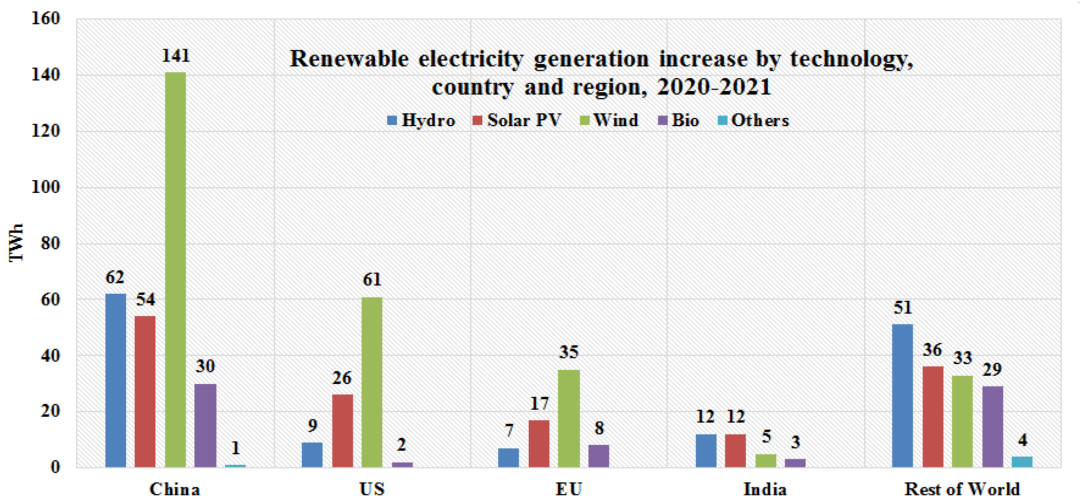


Fig 3.4: Global top countries in the world with renewable power capacities in 2021 (in TWh). Source: REN21 (Renewable Energy Policy Network for the 21st Century) [163].

3.5 INVESTMENT FLOW OF RES

At present, the majority of nations have recognised the necessity of renewable energy and have engaged in innovating for large investment in the renewable power sector, and intend to grow further.

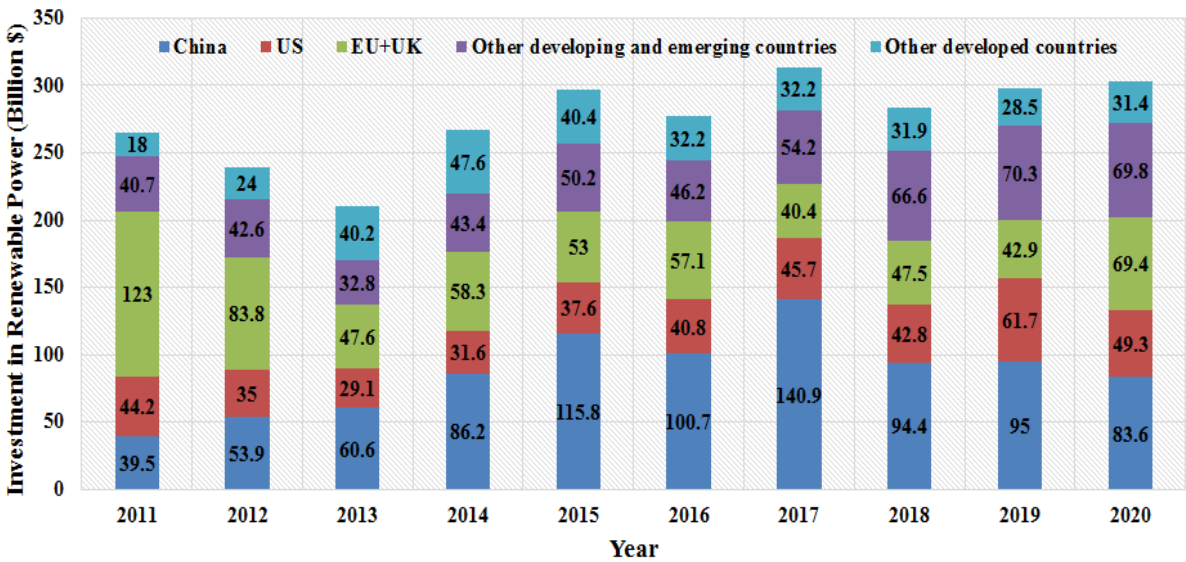


Fig 3.5: Flow of investment in renewable energy in the world from 2011 to 2020 (in billion USD). Source: REN21 (Renewable Energy Policy Network for the 21st Century) [165]

In 2019, global investment was USD 282.2 billion in new RE capacity, and merely 1% higher than the total of the year before. The highest figure of USD 315.1 billion was set in the year 2017, while in the year 2020, global investment in RE capacity increased by 2% to USD 303.5 billion. Fig. 3.5 presents investment flow of RES among developing and developed countries from 2009 to 2019. The data clearly shows that since 2015, overall investment flows in RE among emerging nations have outpaced total investments in developed nations. In 2015, investment in wind power grew by 9% (i.e., USD 107 billion), while solar PV investment grew by 12% (i.e., USD 148.3 billion) in the same year as compared with 2014. Additionally, in 2019 investment was USD 152 billion, or 55% of the global total of USD 282.2 billion [165].

3.6 RENEWABLE ENERGY JOBS

For any energy sector, employment is the major factor; accordingly, the wind power field has the capability of creating employment that grows each year, in various nations. Therefore, the renewable energy field demands the majority of people for research and development, operation, maintenance and expansion. Throughout the world, employment in the renewable energy field is continuously growing.

In 2021, the renewable energy sector directly and indirectly employed 12.7 million people. Over the last decade, the number of jobs in the solar photovoltaic (PV), bioenergy, hydropower, and wind power industries has increased. Fig. 3.6 depicts IRENA's estimates of renewable energy employment since 2014. In 2019, global employment in RE was calculated at 11.5 million jobs, while in 2018 it was estimated at 11 million jobs, as shown in Fig 3.6. Since 2012, global RE employment has been continuously growing. The biggest employers have been solar PV, wind power, hydro, and bio-energy industries. These employment trends are influenced by a wide range of variables, such as prices, expenditures, new and cumulative capacities, as well as a variety of policy strategies to enable the deployment of energy from renewable sources, produce viable supply chains, and develop skilled labour. During 2021, the COVID-19 pandemic continued to have an impact on the global economy, changing both the volume and structure of energy demand [166].

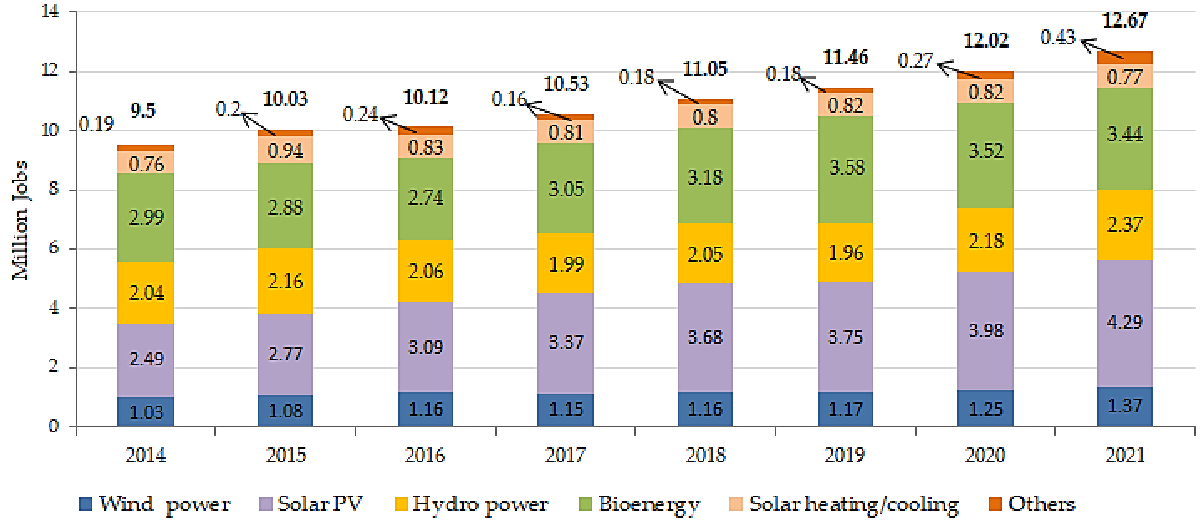


Fig 3.6: Global employment in the field of renewable energy (2014-2021). Source: Renewable Energy and Jobs [166]

Table 3.1: Estimated number of jobs in the renewable energy industry worldwide in 2020-2021. Source: Renewable Energy and Jobs [166]

Renewable Sources (Jobs in Thousands)	China	United States	Brazil	India	European Union	World
Wind power	654	120.2	63.8	35	298	1371
Solar PV	2682	255	115.2	217	235	4291
Solar heating/cooling	636	-	42	19	19	769
Hydro power	872.3	72.4	176.9	414	89	2370
Geothermal energy	78.9	8	-	-	60	196
Solid biomass	190	46.3		58	314	716
Liquid biofuels	51	322.6	874.2	35	142	2421
CSP	59.2	-	-	-	5.2	79
Biogas	145	-	-	85	64	307
Total	4361	923	1272	863	1242	12677

This section also contains employment statistics for a number of leading countries as well as a few other countries. The section also delves into employment in these countries' various states or provinces. As in previous editions, the emphasis is on China, Brazil, India, the United States, and European Union members (Table 3.1), the countries that lead in equipment manufacturing, project engineering, and installations. Overall, Asian countries account for the majority of renewable energy employment, accounting for 63.6% of these jobs in 2021. Table 1 displays global existing status of estimated jobs in 2020-21 in the field of renewable power. United States and China are consistently working in the RE sector and upheld their top places for annual investment, capacity add-on and power production from solar and wind energy [166].

3.7 WIND POWER INSTALLATION CAPACITY

At present, India and China are experiencing large demand for power because of their large populations. Thus, it is necessary to enhance electricity production from RE sources to meet their increasing demand. As a result, numerous countries have established renewable power plants and are deploying cutting-edge technology to increase production capacity. At the end of 2021, worldwide installed wind energy capacity reached a huge level of 824,874 MW, while in 2020, capacity was 733,276 MW [167].

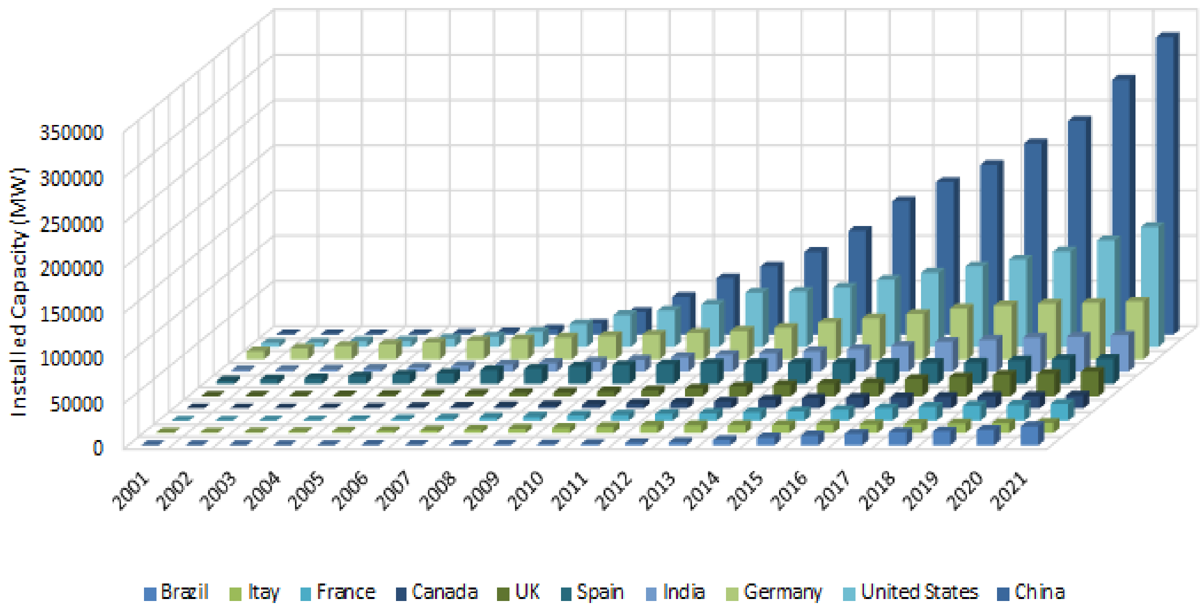


Fig 3.7: Wind power installation capacities of the world's major countries on a year-by-year basis (MW, at the end of 2021) [167]

In 2017, the total renewable power capacity reached 2,179 GW. However, hydro power contributed the biggest part of the world RE, with 1,152 GW installed capacity. Solar and wind power contributed a major portion, with capacities amounting to 397 GW and 514 GW, respectively. Other renewable sources were 500 MW of marine power, 13 GW of geothermal power and 109 GW of bio-power [168].

In 2018, global renewable production capacity was 2,351 GW, where hydropower contributed the biggest share, with an installed capacity of 1,172 GW. Solar and wind power contributed the major portion, providing capacities of 486 GW and 564 GW respectively. Other renewable sources were 500 MW of marine power, 13 GW geothermal power, and 115 GW of bio-power [169].

During 2019, worldwide renewable power capacity was 2,537 GW, where hydropower contributed the major portion with a capacity of 1190 GW. Solar and wind power contributions were 586 GW and 623 GW installed capacities, respectively, while other renewable sources such as marine power, geothermal, and bio-power contributed 500 MW, 14 GW and 124 GW, respectively [170].

During 2020, global renewable power capacity reached 2,799 GW. Hydropower continued to be the major producer of the global total, with a capacity of 1,211 GW. Solar and wind contributed equally to the remainder, with capacities of 714 GW and 733 GW, respectively. However, other renewable-sources, namely, marine power, geothermal power and bio-power capacities were 500 MW, 14 GW and 127 GW, respectively [171].

Global renewable generation capacity was 3 064 GW as of the end of 2021. With a capacity of 1 230 GW, hydropower had the largest share of the global total. With capacities of 849 GW and 825 GW, solar and wind energy accounted for equal shares of the remainder. Other renewables included 143 GW of bioenergy, 16 GW of geothermal energy, and 524 GW of marine energy. Renewable production capacity by various sources of energy from 2017 to 2020 is shown in Fig. 3.8 [172].

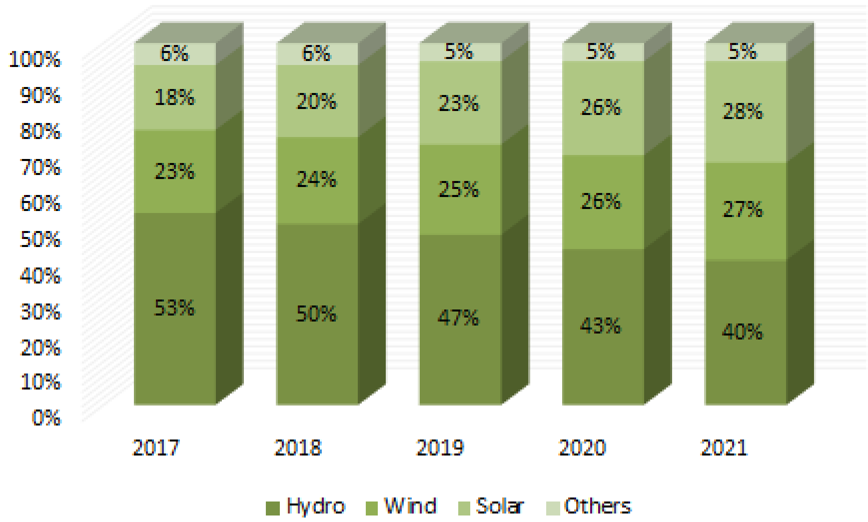


Fig 3.8: Renewable production capacity by energy sources (2017–2021). Source: Global Wind Report [168–172]

3.8 VARIOUS ACHIEVEMENTS AND SIGNIFICANT INFORMATION RELATED TO WORLDWIDE WIND ENERGY

Successes of several nations towards wind-energy production are enumerated as follows:

- At the end 2014, 2.5% of worldwide power was delivered by wind;
- The most powerful offshore wind turbine in the world is Haliade-X, with 14 mega-watts capacity, a 107 m blade, rotor diameter of 220 m, digital capabilities, and lo-cated in Saint-Nazaire, France;
- According to the Global Wind Energy Council (GWEC), at the beginning of 2017, more than 341,000 wind turbines were revolving and generating power;
- Since 2020, China and USA have been two outstanding growth markets of wind energy;

- In the beginning of 2021, worldwide renewable production capacity reached 2,799 GW, with hydropower contributing the major portion (1211 GW) although wind and solar are increasing fast;
- China, already the biggest global marketplace for renewable energy production, added 136 GW in 2020, with the major portion sourced from 49 GW of solar and 72 GW of wind;
- The United States installed 29 GW of renewable capacity in 2020, about 80% more than in 2019, including 14 GW of wind, and around 15 GW of solar;
- The increased share of renewables as a portion of the total energy production is par-tially attributable to the net withdrawal of fossil fuel power in North America, Europe and Turkey, Russia, Georgia, Azerbaijan and Armenia. Total fossil fuel add-on dropped to 60 GW in 2020 from 64 GW the previous year, underlining a continued downward trend of fossil fuel increase;
- Wind power growth nearly doubled in 2020 (111 GW) as compared with 2019 (58 GW);
- Emissions of carbon and sulphur oxides in 2020 reduced by nearly 7%, the biggest drop ever, as nations around the globe enforced lockdowns to restrain the spread of COVID-19. Nearly 743 GW of wind energy capacity could reduce the emission of over 1.1 billion tons of CO2 in 2020, globally;
- India installed new wind capacity of 1119 megawatts in 2020. In addition, the renewable energy target of 175 gigawatts could be achieved by 2022, which includes 60 gigawatts of onshore wind. The Government of India has also shared its dream for a long-term renewable energy target of 450 GW by 2030, including a target of 140 gigawatts of wind capacity;
- India, is the fourth largest power consumer following China, the United States, and the European Union, and the third highest carbon emitter after China and USA;

- For onshore installations, 2020 was a record year. South America, North America and the Asia Pacific jointly installed 74 GW of new onshore wind capacity, 76% more than the previous year. In the offshore market, 6.1 GW was installed globally in 2020, making 2020 a great year;
- As stated in the GWEC report, wind power helped the world reduce emissions of CO2 by more than 637 MT. In addition, 2020 witnessed milestone commitments to carbon neutrality, with South Africa, Canada, South Korea, Japan and EU each pledging to achieve net zero by 2050;
- Incorporating China's net zero intention by 2060 and the United States' target to reach net zero by 2050, nations which have planned net zero target now represent two-thirds of the world economy and 64% of the global greenhouse gases emissions;
- According to IEA and IRENA, to control global warming worldwide it is necessary to install at least 180 gigawatts of new wind energy capacity annually to limit global warming to below 2 °C, and would need to install up to 280 GW annually to con-struct pathway yielding net zero by 2050;
- The Wind Vision Report of the Department of Energy states that wind could poten-tially create more than 600,000 jobs by 2050, and help reduce 12.3 gigatons of green-house gases [173,174].

3.9 CONCLUSION

During the past Presently, India is finally defeating the tremendous challenge of the shortage of electricity, which may lead to lesser utilization of fossil fuels and greater utilization of RES. The Indian Government has taken a number of significant steps to encourage wind power, to build India a vast wind potential nation. The success of initiatives taken by the Indian

Government to encourage wind power projects can be observed with the trend of exponentially growing annual capacity additions. India also plays a significant role in enhancing opportunities for employment, besides minimizing power shortages and carbon emissions. In recent years, several new policies have been introduced in India in the wind power sector that appear to be a sturdy agent in the remarkable development of the wind power markets. In various countries, wind power policies include several benefits such as subsidies, tax exemption, attractive financing options such as lower interest rates, and the involvement of research institutes, etc. Additionally, in several countries (including India), the idea of the Renewable Energy Certificate (REC) has been initiated.

Additionally, renewable power is the best choice for Indian villages that are unable to receive power supply. It also assessed that up to 400,000 megawatts of power could be required by 2022. Therefore, India needs to utilize all existing RESs in order to reach the country's electricity needs. Presently, India has been included among the top five nations worldwide for the creation of job opportunities in the field of renewable power, installations and capacity additions.

Wind power development can be a major tool for reducing import dependence and production cost, and maximizing power security. India has significant wind power potential, and it could be one of the leading sources of power in the near future. For effective execution of various policies, socio-economic, environmental, financial and technical hurdles, along with uncertainties in policy matters, are required to be overcome. In addition, offshore wind projects are the most efficient method of utilizing wind energy in India. However, in India, offshore wind generation remained undeveloped until 2015, and little progress has been made in this area. Therefore, resource assessment and strong policies to commercialize offshore projects must be taken into consideration.

The Indian Government had a target of achieving a wind power capacity of up to 60 gigawatts by 2022. However, according to former trends, the annual capacity addition is not above 4 gigawatts; however it requires almost 6 gigawatts annual capacity addition to achieve the target of 60 gigawatts. This can only be achievable with the superior integration of infrastructure, technology and management in the power sector. Promoting research and development activities, and developing financially stable institutional centers of research in every windy state, could be beneficial. Additionally, regular inspections and monitoring of existing projects should be executed more frequently. To achieve desired targets, the re-powering of projects and an initiative that can assist in achieving the intended goal, an independent policy framework is required. Even while new initiatives implemented by Indian government have long-term consequences, they must be carefully analysed, and policy execution must be ensured by the government in order to achieve the goal of 60 gigawatts by 2022. A well-connected grid network, devoted research centers, modifications in policies and energy prices with ongoing market trends, effective policy implementations and attractive incentives for projects can set wind power markets of India ahead of the other leading nations.

CHAPTER 4

COMPARATIVE STUDY OF MACHINE LEARNING MODELS FOR WIND POWER FORECASTING

4.1 INTRODUCTION

In recent years, renewable energy sources (RES) have become a centre of exploration due to the advantages they are providing to power systems. As the penetration of RES intensifies, the associated challenges in power systems are also escalated. Among various renewable energy resources, wind energy has gathered ample importance due to its sustainability, non-polluting, and free nature [175,176]. Irrespective of the various advantages of wind power, errorless power prediction for wind energy is a very difficult task. Both the climatic and various seasonal effects are not only the factors influencing the generation of wind power, but the intermittent nature of wind itself also makes it increasingly complicated to forecast [177].

Wind energy is critically important for the social and economic growth of any country. Considering this, reliable and precise wind power prediction is crucial for the dispatch, unit commitment, and stable functioning of power systems. This makes it easier for grid operators of the power system to support uniform power distribution, reduce energy loses, and optimize power output [178,179]. Besides this, without the functionality of forecasting, wind energy systems that are extremely disorganized can cause irregularities and brings about great challenges to a power system [180-182]. Consequently, the integration of wind power globally relies on correct wind power prediction. It is necessary to develop dedicated software in this regard, where weather forecast data and wind speed data are model inputs and would predict the power that a wind farm or a particular wind turbine could produce on a particular day [183-185].

Furthermore, forecasted outputs could be analysed in terms of a town's actual per-day power demands [186]. When the forecasted power is not sufficient to meet the daily requirements of the town, then adequate decisions could turned off to prevent surplus generation

4.2 PROBLEM FORMULATION

From the literature survey, it is clear that there have been several research studies that have investigated the forecasting of wind energy by employing various analytical approaches across several horizons, among which persistence and statistical approaches have been used [187-189]. Statistical approaches have not been suitable approaches for forecasting wind power as they have not been able to handle huge datasets, adapt to nonlinear wind datasets, or make long-term predictions of repeated power outages and protecting generated power from being wasted [190-191]. Many of these algorithms have not produced acceptable results for different wind farm locations in which forecasting has been carried out with erratic and turbulent wind conditions. Under these circumstances, the number of required input variables substantially increases [192-194].

Nowadays, ML-based regression forecasting techniques such as support vector regression models and auto-regression, among others, are very prominent [195-196]. These techniques are used in power generation and consumption, electric load forecasting, solar irradiance prediction for photovoltaic systems, grid management, and wind energy production [197-198]. Prior to our research, there have been many types of prediction models that have been shaped to predict wind energy, namely, physical models, statistical models, and teaching and learning-based models, which employ machine learning (ML) and artificial intelligence (AI)-based algorithms [199-202]. Current studies typically adopt machine learning algorithms (ML). In particular, naive Bayes, SVM, logistic regression, and deep learning architectures of long short-term memory networks are typically used [203-206]. In the present study, the primary reason for adopting ML algorithms is that they can adapt themselves to changes with regard to the location of wind farms. Varying locations can have more erratic and turbulent trends, and thus generating predictive models on the basis of an input dataset instead of utilizing a generalized model is of importance [207-209]. Therefore, a reliable and accurate forecasting algorithm is essential for wind power production.

4.3 CONTRIBUTION

The foremost contribution of this research is short-term wind power forecasting on the basis of the historical values of wind speed, wind direction, and wind power by using ML algorithms. Furthermore, short-term wind power forecasts are analysed compared to the forecasting of long-term wind power, as the algorithms and methods are unable to deliver satisfying results at high precision with respect to wind speed forecasting in this regard. In this study, regression algorithms such as random forest, k-nearest neighbor (k-NN), gradient boosting machine (GBM), decision tree, and extra tree regression are wind energy generation is examined.

Scatter curves depicting the relationships between the wind speed and the produced turbine power are plotted for all of the methods here and the predicted average wind power is compared with the real average power from a turbine with the help of the plotted error curves. The results demonstrate the superior forecasting performance of gradient boosting machine regression algorithm considered employed to enhance the forecasting accuracy for wind power production for a Turkish wind farm situated in the west of Turkey.

Regression algorithms have been applied because of forecasting problems encountered with continuous wind power values. Polar curves have been plotted and the impacts of input variables such as the wind speed and direction on wind energy generation is examined. Scatter curves depicting the relationships between the wind speed and the produced turbine power are plotted for all of the methods here and the predicted average wind power is compared with the real average power from a turbine with the help of the plotted error curves. The results demonstrate the superior forecasting performance of gradient boosting machine regression algorithm considered here.

4.4 PROPOSED MODEL

4.4.1 Input Metrological Parameters

This section is devoted to estimate suitable input parameters that will affect the active power of wind turbine, considering the wind farm layout. The selected variables are exogenous inputs of machine learning algorithms. The data analysis for forecasting has been accomplished over the freely accessible dataset which has been collected in the north western region of Turkey [210, 219]. The wind farm is onshore Yalova wind farm, having 36 wind turbines, with total capacity of 54,000 kW, according to www.tureb.com.tr/bilgi-bankasi/turkiye-res-durumu (accessed on May, 2020) and has been running since 2016.

4.4.2 Predictive Analysis

The steps involved in predictive analysis are illustrated in Fig 4.1 The Data-Exploration is the initial step in the analysis of data where users explore a large dataset in an unstructured way to un-cover initial-patterns, the points of attention, and characteristics [211].

Data cleaning refers to identifying the irrelevant, inaccurate, incomplete, incorrect, or missing parts of the data and then amending, replacing, and removing data in accordance with the requirements [212-213].

Modelling denotes training the machine learning algorithm to forecast the levels from the structures and then tuning and validating for the holdout data [214]. The performance of machine learning algorithm is evaluated by different performance metrics using training and testing datasets

Fig 4.1: Steps involved in predictive analysis

The proposed model for the data analysis and forecasting is illustrated in Fig 4.2. The supervisory control and data acquisition (SCADA) system has been employed to measure and save wind turbines data-set.

The SCADA system captures speed of wind, wind direction, produced power, and theoretical power on the basis of the turbine's power curve [215-216]. Every new line of data-set is captured at 10 min time intervals and the time period of dataset is one year. The data are accessible in CSV format [217].

Table 4.1 presents dataset information for the wind turbine. The wind turbine technical specifications are given in Table 4.2. Although, there are a quite few gaps and at some points generated output power is absent, which may be due to wind turbine maintenance, malfunction or lower wind speed than the cut-in-speed.

The dataset contains total of 50530 observations whereas 3497 data points were considered as outliers because of zero power production at these timestamps. After removing outliers or missing values, the rest of the dataset i.e. 47033 data points were considered for implementing machine learning models.

The dataset consists of two parts, namely, the training set containing the first 70% of the whole dataset, and the testing set containing the latter 30% of the dataset.

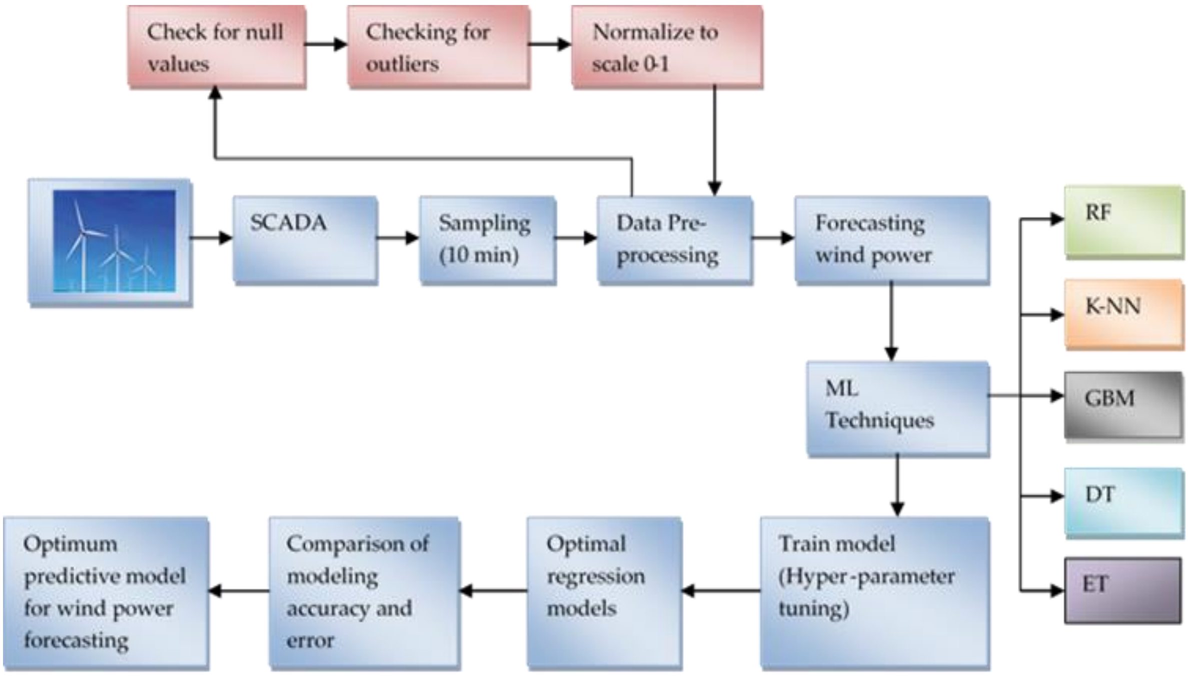


Fig 4.2: Functional block diagram of the proposed model

Table 4.1: Information for the wind turbine (Yalova wind firm, Turkey)

Input Variables	Wind Speed, Wind Direction, Theoretical Power, Active Power
Draft Frequency	10 mins
Start-Period	Jan 1, 2018
End-Period	Dec. 31, 2018

Table 4.2: Wind turbine technical specifications.

Characteristics	**Wind Turbine**
SINOVEL(Turbine manufacturer)	SL1500/90(Turbine model)
Rated power	1.5 MW
Hub height	100 m
Rotor diameter.	90 m
Swept Area	6,362 m^2
blades	3
Cut-in speed of wind	3 m/sec
Rated speed of wind	10 m/sec
Cut-off speed of wind	22 m/sec

As stated in the power curves of a wind turbine, when plotted between the cut-in speed, rated speed and, cut-out speed, can be established by an *n* degree algebraic equation (Equation (4.1)), for forecasting the power output of a wind turbine [218-221].

$$P_i(v)\quad \begin{cases} 0, & v < v_{ci} \\ (a_n v^n + a_{n-1} v^{n-1} + \cdots + a_1 v + a_0), & v_{ci} \le v < v_R \\ P_R, & v_{ci} \le v < v_R \\ 0, & v \ge v_{co} \end{cases} \qquad (4.1)$$

where, $P_i(v)$ is power produced from related wind speed and regression constants are given by $a_n\ a_{n-1}\ a_1 and\ a_0$, v_{ci} is the cut-in-speed, v_R is rated-speed, v_{co} cut-out-speed. The energy output for a considered duration can be calculated by Equation (4.2):

$$E_c = \sum_{i=1}^{N} P(v_i)\Delta t \qquad (4.2)$$

where, *N* denotes the number of hours in the study period and Δt is the time interval [222]. The energy produced with a given wind speed can be appraised by multiplying the power produced by the wind turbine by wind speed *v* and the time period for which the wind speed v prevails at the given site.

The overall energy generated by the turbine over a given period can be assessed by summing the energies corresponding to all possible wind speeds with the related conditions at points where the system is functional.

Fig 4.3 shows a plot of wind speed power scatter curves where the theoretical power generation curve usually fits with the real power generation. It may also be observed that the power generation curve reaches the maximum level and continues in a straight line when the wind speed reaches ~13 m/s. At wind speeds higher than 3 m/s (cut-in speed), there are some points of zero power generation, and this could be due to maintenance, sensor malfunction, degradation, and system processing errors.

Closer examination of the wind turbine power highlighted three anomaly types in the SCADA data of the wind turbine.

Type-1 anomalies are displayed in the scatterplot via a horizontal dense cluster of data where the generation of power is zero at a wind speed higher than the cut-in speed. Such anomalies generally occur due to the turbine downtime that can be cross-referenced when utilizing an operation log [223, 224].

Type-2 anomalies are shown by a dense cluster of data that fall below the ideal power curve of the wind turbine. These anomalies can occur because of wind curtailment, where the turbine output power is controlled by its operator to be lower than its operational capacity. Wind restriction can be executed by operators of a wind farm due to various reasons, such as difficulty in the storage of huge capacities of wind power, a lack of demand for power at several times, and at times where volatile wind conditions cause the produced electricity to be unstable in nature.

Type-3 anomalies are arbitrarily dispersed around the curve and these are generally the result of sensor degradation or malfunction, or they may be due to noise at the time of signal processing [225,126].

It is also worth noting that a segment of type-2 and type-3 anomalies can also be illustrated by the dispersion produced on account of incoherent wind speed measurements taken as a result of turbulence [227].

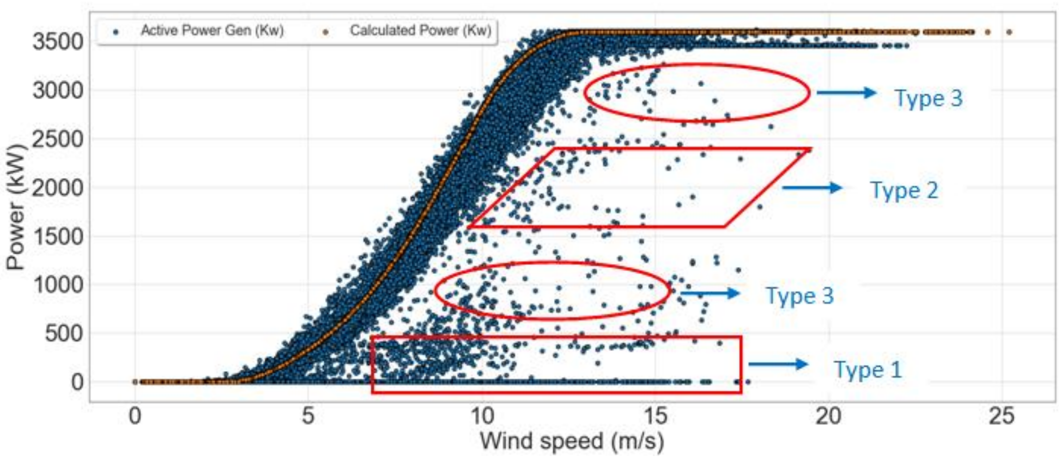


Fig 4.3: Wind speed-power curve of the raw dataset

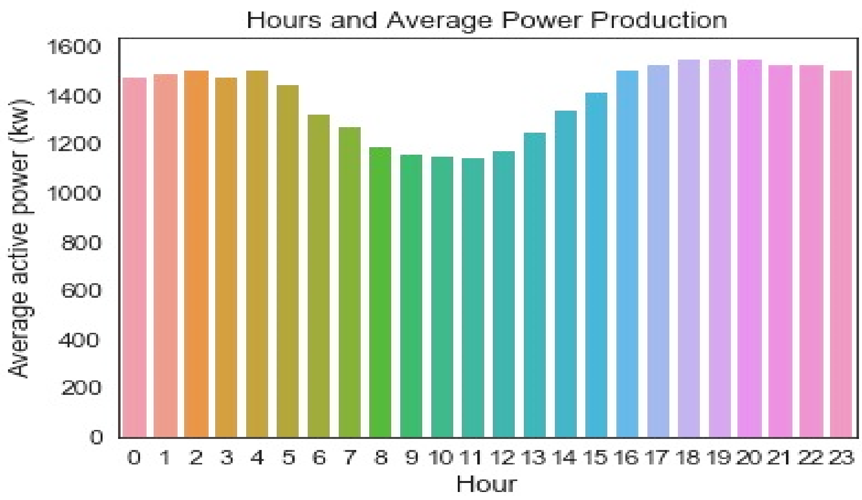


Fig 4.4: Hourly average-power production in a day (kW)

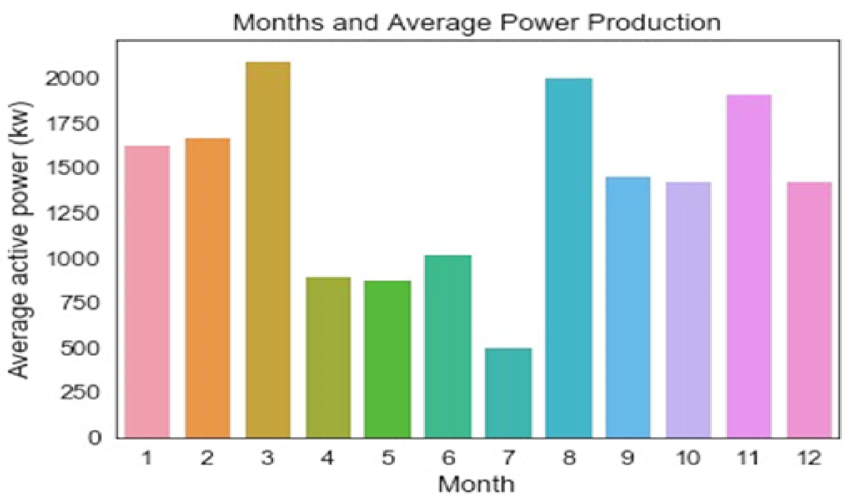


Fig 4.5: Monthly average-power production (kW)

Fig 4.4 shows hourly average power production over a day, while the monthly average power production is shown in Fig 4.5. Fig 4.6 shows paired scatter plots describing the relationship of each feature with each other feature. The plots with a diagonal shape represent histograms showing the probability distribution of each weather feature.

The lower and upper triangles display the scatter plots representing the relationships between the features. It is also seen that each feature demonstrates the distribution with other features. The paired scatter plots show the changes for one feature in comparison to all other features.

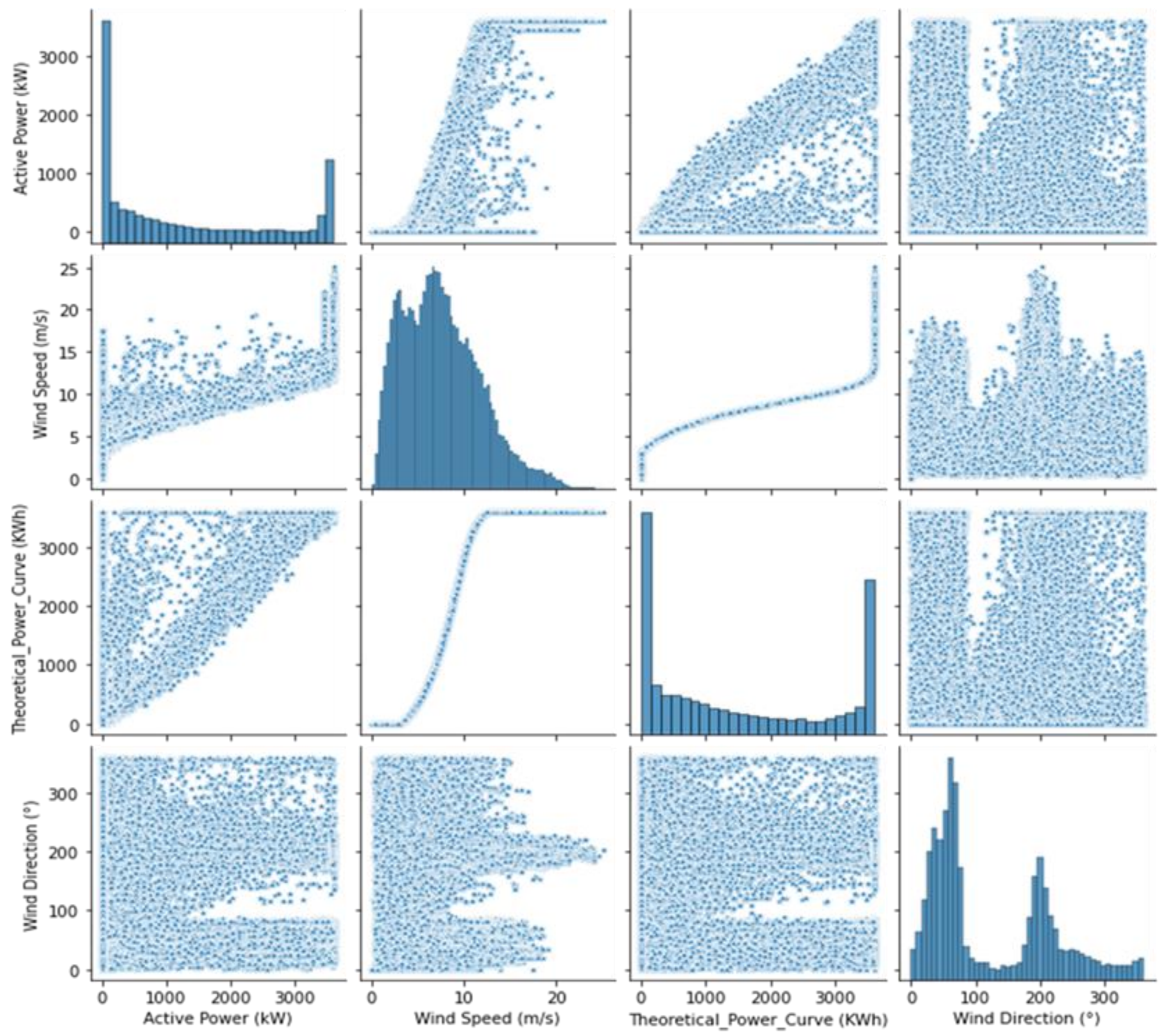


Fig 4.6: Scatter plot demonstrating the relation between input and output parameters

4.4.3 Analysis in Polar Coordinates

Fig 4.7 presents a polar diagram exhibiting the qualitative distribution of power generation with wind speed and wind direction from the sample dataset. It is clear from the polar diagram that the wind speed, wind direction, and power generation are vastly correlated, as wind turbine generates maximum power if the wind blows from a direction between 0–90 or 180–225 degrees.

It is also seen from the polar diagram that there is no power generation beyond the cut-out speed of 22 m/s. Also, from some directions, very low power generation is taking place. The wind direction parameter is denoted by the radius of the polar graph. In the polar graph, light color points represent low power generation when the wind speed is below the cut-in speed (i.e., 3 m/s) of the wind turbine. As the speed of wind increases beyond the cut-in speed, power production increases, as represented by the dark and densely spaced points in the polar diagram.

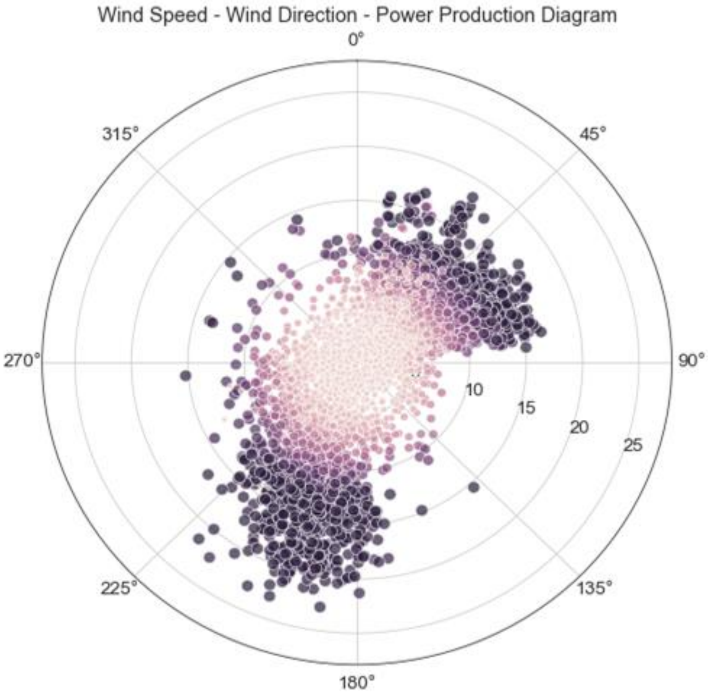


Fig. 4.7: Polar diagram of the wind speed, wind direction, and power generation.

4.4.4 Analysis in Cartesian Coordinates

Fig 4.8 shows a three-dimensional quantitative visualization of the power generation with the wind speed and wind direction in a Cartesian coordinate system for the whole year. In Fig 4.8, it can be seen that the two regions that are dense contribute to the maximum power generation. The first region is observed when the direction of the wind varies from 0◦ to 90◦ and the second region is observed when the wind direction varies from 180◦ to 230◦.

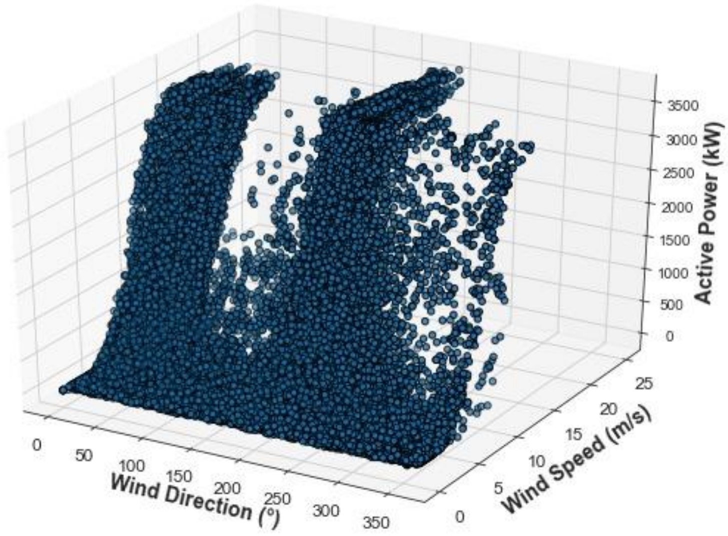


Fig. 4.8: Relationship between wind speed, wind direction, and power generation in a 3D visualization

4.5 SCADA DATA PRE-PROCESSING

1. Outlier removal: The procedure of cleaning and preparing the raw data to make it compatible for training or developing machine learning models is called data pre-processing. To limit the impact of noise and turbulence, a sampling rate of 10 min was used when processing the SCADA data; however, deep analysis of individual parameters identified certain errors in the SCADA data, such as, power production being zero above the cut-in speed (i.e., 3 m/s), negative values of wind speed, or active power and missing data at some timestamps. These results carry no practical significance in terms of the generation of power. As such, to prevent a negative impact on the forecasting, data points belonging to the same timestamp have been removed.

Such erroneous data points are commonly the result of wind farm maintenance, sensor malfunction, degradation, or system processing errors. It is crucial that the SCADA data are pre-processed prior to developing the forecasting models.

2. Normalization of dataset: The input parameters of the wind power forecasting model incorporate the wind speed and wind direction, but their dimensions are not of the same order of magnitude. Hence, it is essential to regulate these input vectors to be within in the same order of magnitude. As such, a min-max approach was used to normalize the input vectors as follows:

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4.3}$$

where the actual data is given by x and x_{min} and x_{max} represent the minimum and maximum values of the dataset. The result $\bar{x}$ remains within the range of [0,1].

4.6 MACHINE LEARNING

Machine learning is a solicitation of AI (artificial intelligence) that offers automatically learning capabilities for systems and the ability to learn from experiences without being explicitly programmed to do so.

Machine learning algorithms exhibit a dataset-based behavior and model input features corresponding to the desired output, thereby forecasting output features by learning from a historic dataset. ML is essential for prediction here due to the following reasons: Firstly, ML gives best performance when the input and output relationship is not clear. It also improves in terms of decision making or predictive accuracy over time. ML algorithms can easily identify changes in the environment and adapt themselves according to the new environment; however, there are several machine algorithms, each of which is specifically utilized for applications or problems. For instance, regression and classification algorithms are mainly used for forecasting problems [228]. ML also has the ability to handle complex systems. We implemented five regression analysis algorithms, namely random forest regression, k-nearest neighbor regression (k-NN), gradient boosting machine regression (GBM), decision tree regression, and extra tree regression. These algorithms were selected based on good performance and extensive usage in the literature. These algorithms have distinct theoretical backgrounds in forecasting problems, where they have provided results successfully.

Additionally, these algorithms have various parameters known as hyper-parameters which affect the runtime, generalization capability, robustness, and predictive performance. We have adopted a trial-and-error approach to select the best parameters for algorithms, and this is known as hyper-parameter tuning. Also, for the best observed outputs, the values of these parameters for each regression algorithm are placed at the bottom of the section for each algorithm.

4.6.1 Random Forest Regression

Random forest (RF) regression is a famous decision tree algorithm where multiple decision trees are produced from a given input dataset. First, the algorithm divides the dataset randomly into several sub-parts and for each subpart it builds multiple decision trees. Then, it merges the predicted output of each decision tree to obtain a more stable and accurate prediction [229].

In RF regression, the output value of any input or subset is a mean of the values predicted by several decision trees. The following process is performed:

1. Produce n tree bootstrap samples from the actual input dataset;
2. For individual bootstrap samples, expand an unpruned regression tree, including subsequent alteration at every node, instead of selecting the best split among all predictors. Arbitrarily sample m_{try} predictors and then select the best split from those variables. ("Bagging" can be considered a special case of RF and where mtry = p predictors. Bagging refers to bootstrap aggregating, i.e., building multiple distinct decision trees from training dataset by frequently utilizing multiple bootstrapped subsets of the dataset after averaging the models);

3. Estimate new data values by averaging the predictions of the n_{tree}, decision trees (i.e., "average" in case of problems of regression and the "majority of votes" for classification problems);
4. Based on the training data, the error rate can be anticipated using the following steps:
    - At each bootstrap iteration, predict data not in the bootstrap sample (as Breiman calls "out of bag" data) by utilizing the tree developed with the bootstrap sample.
    - Averaging the out of bag predictions, on the aggregate, where each data value would be out of bag around 36% of the times and hence averaging those predictions.
    - Compute the error rate and name it the "out of bag" estimate of the error rate.

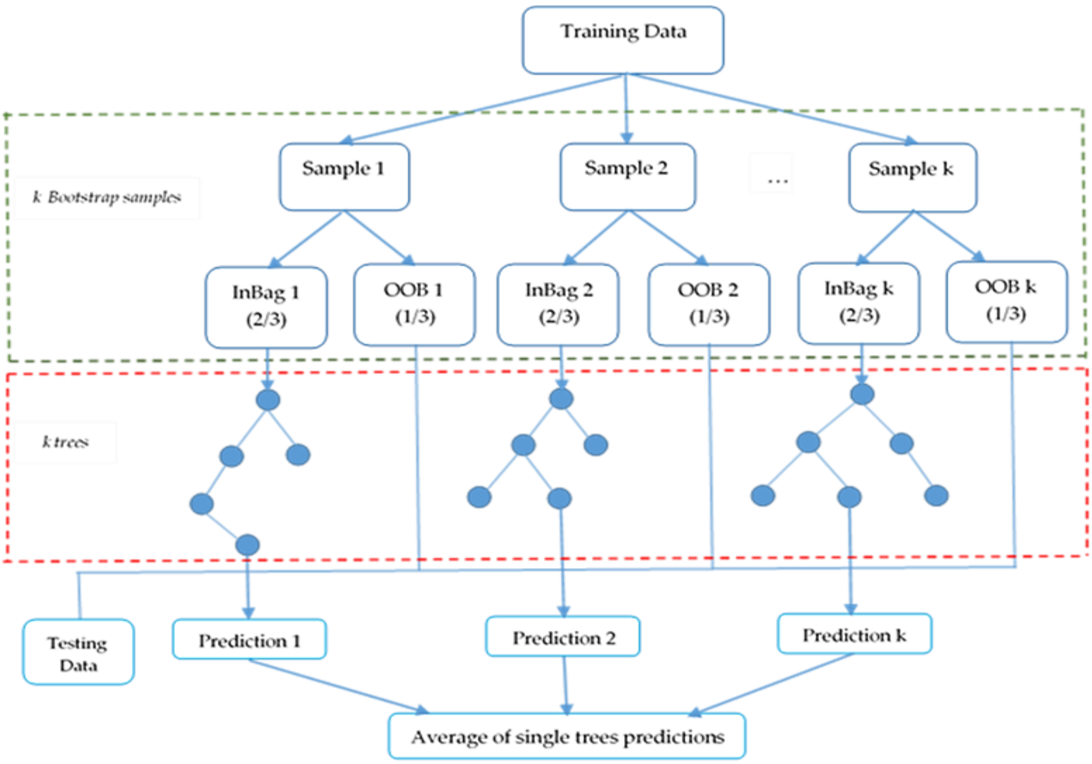
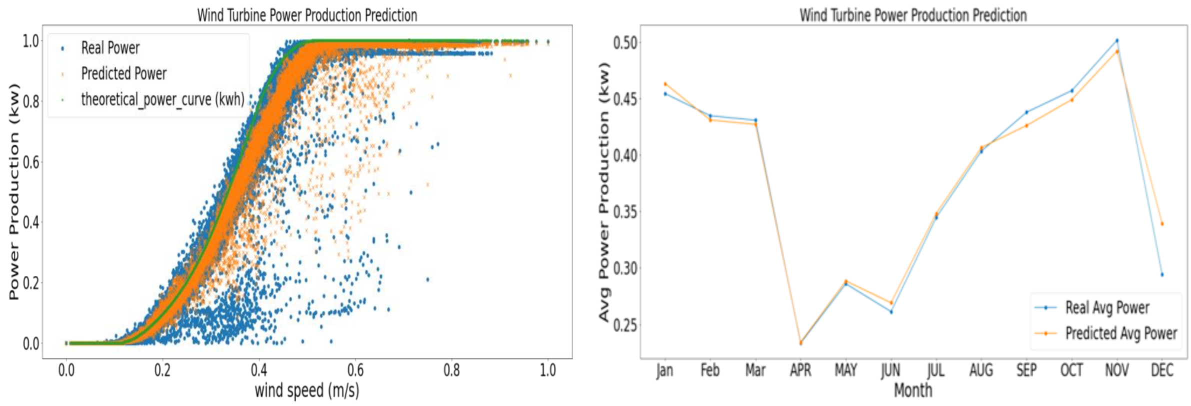


Fig. 4.9: Flowchart of the random forest regression algorithm



. (a) (b)

Fig. 4.10: (a) Scatter plot depicting relation between the wind speed(m/s) and the power produced (kW) from turbine using random forest regression; (b) Predicted average of wind power as compared with real average power from turbine (kW) using random forest regression.

In practice, we have observed that out of bag estimation of the error rate is fairly truthful, provided that large numbers of trees are grown, otherwise the bias condition may occur in the "out of bag" estimate. A complete flowchart for the process can be seen in Fig. 4.9. In this model, the random state was chosen as 40 and the number of trees was selected as 100, as increasing the number of tress to larger than 100 did not significantly improve the forecasting output. Also, an appropriate number of trees is required to be chosen to optimize the forecasting performance and runtime. Fig. 4.10a shows a scatter plot depicting the relationship between the wind speed (m/s) and the power produced (kW) by the turbine when using random forest regression. Fig. 4.10b presents the predicted average of wind power as compared with real average power from turbine (kW) when using random forest regression.

4.6.2 k-Nearest Neighbor Regression

k-Nearest Neighbor (k-NN) regression is one of the most simple, easy to implement, non-parametric regression approaches used in machine learning. The main objective behind k-nearest neighbor regression is that whenever a new data point is to be predicted, the point's k nearest neighbors are nominated from the training-dataset. Accordingly, the prediction of a new data point will be the average of the values of the k-nearest neighbors [227, 230].

The basis of the k-nearest neighbor algorithm can be outlined in three major steps: 1. Compute the predefined distance between the testing dataset and training dataset; 2. Select k-nearest neighbors with k-minimum distances from the training dataset; 3. Predict the final renewable energy output based on a weighted averaging approach.

A distance measure is needed to distinguish the similarity between two instances. The Manhattan and Euclidean distances are widely used distance metrics in this regard [230]. In the present study, the actual Manhattan distance was improved by the use of weighting. The weighted Manhattan distance is determined by the following:

$$\boldsymbol{D}[\boldsymbol{X^i}, \boldsymbol{X^j}] = \sum_{\boldsymbol{n=1}}^{\boldsymbol{r}} \boldsymbol{w_n} \left| \boldsymbol{x_n^{(i)}} - \boldsymbol{x_n^{(j)}} \right| \qquad (\mathbf{4.4})$$

Where X^i and X^j are two instances and there are r attributions for each instances i.e $X = [x_1, \dots, x_n, \dots, x_r]$ and w_n is the weight allocated to nth attribution. The weight w_n equals to '1' in original Manhattan-distance that means equal contribution of each attribute to the distance 'D'. Although, the significance of each attribution is quite distinct in renewable power generation forecasts. The w_n weight considers the contribution of every variable to the distance, and would be computed by the process of optimization.

So, Prediction is done based on the target values linked with them, once the value of k nearest neighbors is determined. Consider $X^1, \dots, X^K$indicate k nearest instances that are nearest to testing instance$X$, and their power outputs are shown by $p^1, \dots, p^K$. The distance between k nearest neighbor and X follows the ascending order$d^1 \leq \cdots \leq d^K$, where d^K=D[X, X^k](k=1,..., K). So, renewable power production, point prediction is estimated with an average weighed through exponential function.

$$\tilde{p} = \sum_{k=1}^{K} \delta^k p^k = \frac{\sum_{k=1}^{K} e^{-d^k} . p^k}{\sum_{k=1}^{K} e^{-d^k}} \tag{4.5}$$

where d^k and p^k are distance associated with the instance X^k and the renewable power output, correspondingly. Fig. 4.11 presents the flowchart of k-Nearest Neighbors Regression method. In this paper, k is selected as 7 and Manhatten-distance was chosen as distance measure. Fig. 4.12a shows a scatter plot depicting the relationship between the wind speed (m/s) and the power produced (kW) and Fig. 4.12b presents the error curves, showing the comparison of forecasted average power with the real average power (kW) when using k-nearest neighbor regression.

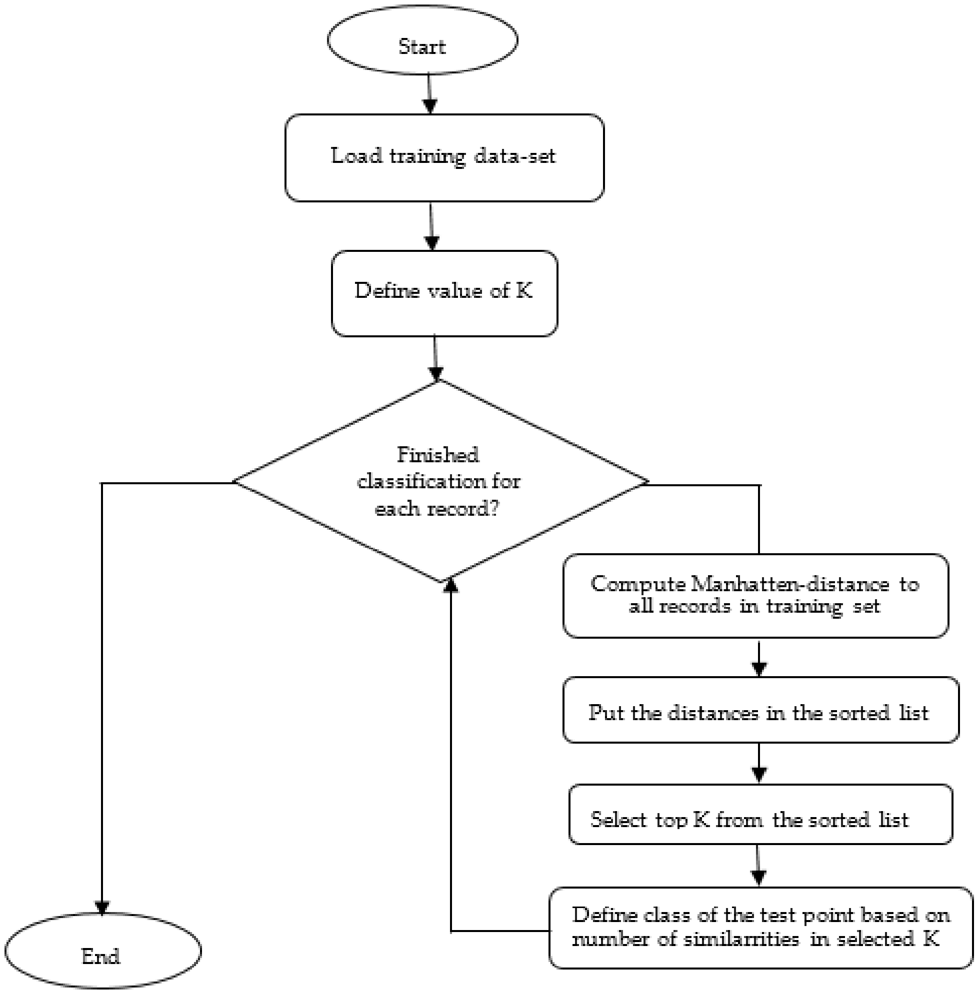
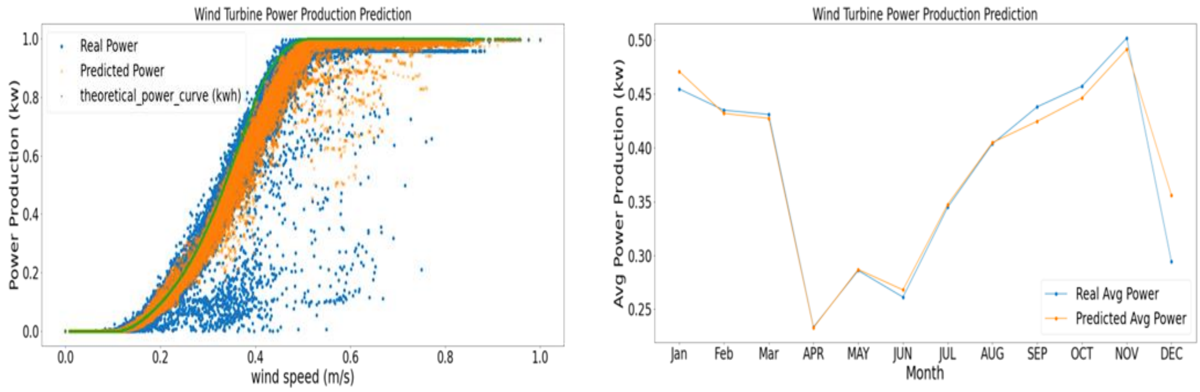


Fig. 4.11: The k-nearest neighbor flowchart regressor procedure



(**a**) (**b**)

Fig. 4.12: (a) Scatter plot depicting relation between the wind-speed (m/s) and the power produced (kW) from turbine using k- nearest neighbor regression; (b) Predicted average power in comparison with real average power from turbine (kW) using k- nearest neighbor regression.

4.6.3 Gradient Boosting Trees

Gradient boosting regression tree algorithms involve an ensemble learning approach where robust forecasting models are formed by integrating several individual regression trees (decision trees) that are referred to as weak learners. Such an algorithm reduces the error rate of weakly learned models (regressors or classifiers). Weakly learned models are those which have a high bias regarding the training dataset, with low variance and regularization, and whose outputs are considered only somewhat improved when compared with arbitrary guesses. Generally, boosting algorithms contains three components, namely, an additive model, weak learners, and a loss function.

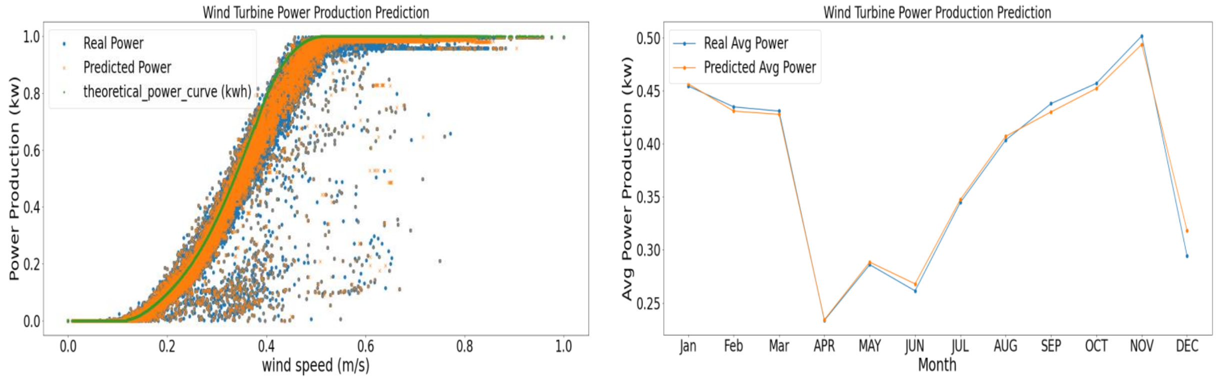
The algorithm can represent non-linear relationships like wind power curves and uses a range of differentiable loss functions and can inherently learn during iterations between input features [231]. GBM (gradient boosting machines) operate by identifying the limitations of weak models via gradients. This is attained with the help of an iterative approach, where the task is to finally join base learners to decrease forecast errors, where decision trees are combined by means of an additive model while reducing the loss function via gradient descent. The GBT (gradient boosting tree) $\mathrm{F_n}(\mathrm{X_t})$ can be defined as the summation of n regression-trees.

$$F_n(x_t) = \sum_{i=1}^{n} f_i(x_t) \tag{4.6}$$

where, every $f_i(x_t)$ is a decision tree (regression-tree). The ensemble of trees are constructed sequentially by estimating the new decision tree $f_{n+1}(x_t)$ with the help of given equation,

$$argmin \sum_{t} L\big(y_t . F_n(x_t) + f_{n+1}(x_t)\big) \tag{4.7}$$

For, some loss-function L(·), where L(·) is differentiable. This optimization is solved by steepest-descent method. In this study, leaning rate 0.2 and estimators were selected as 100. The smaller learning rate makes it easier to stop prior to over fitting.



(**a**) (**b**)

Fig. 4.13. (a) Scatter plot depicting relationship between the wind-speed(m/s) and the power production(kW) from turbine using gradient boosting regression; (b) Predicted average power in comparison with real average power from turbine (kW) using gradient boosting regression

Fig. 4.13a presents a scatter plot depicting the relationship between the wind speed (m/s) and the power production (kW) of the turbine, and Fig. 4.13b presents the error curves of the predicted average power in comparison with the real average power of the turbine (kW) when using gradient boosting regression.

4.6.4 Decision Regression Trees

A decision tree algorithm is an efficacious algorithm in machine learning which is utilized in supervised learning. This algorithm can be used to solve both regression and classification tasks. In decision analysis, it can be employed to explicitly and visually show both decisions and decision making. The foremost objective of using the algorithm is to produce a training model which can be used to forecast the value of the target variable with the help of learning modest judgment principles inferred from the training data [230, 231]. As the name goes, it has a simple tree-like structure of decisions. In a decision tree, each node depicts a conditional statement and the branches of it show the outcome of the statement shown by the nodes. The algorithm iterates from the root node (highest node) to leaf nodes (bottom-most nodes). After executing all attributes in the nodes above, the leaf node (terminal node) shows the decision formed. This approach is considerably more accurate than SVM and ANN techniques.

The input to the algorithm includes training record E and attribute set F. The algorithm functions by recursively selecting the best feature in order to split the data and increases the leaf nodes of the tree until the ending criterion is encountered (Algorithm 1).

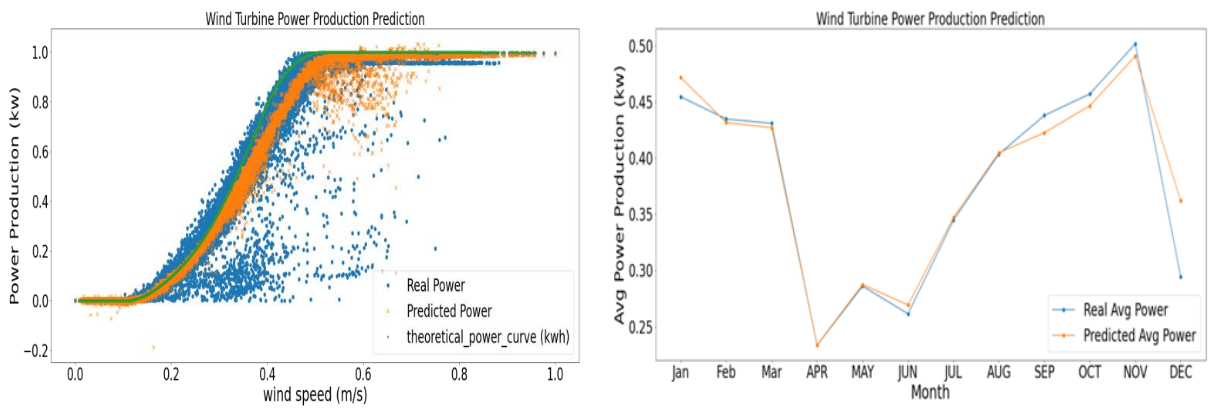
Tree Growth (E, F)

1. if stopping _cond(E, F) = $true$ then
2. leaf = createNode()
3. $leaf.label$ = Classify(E)
4. return $leaf$
5. else
6. $root$ = create Node()
7. $root.test\_cond$ = find_best_split(E, F)

let$V = \{ v | v$ is a possible outcome of $root.test\_cond$
for each $v \in V$ do
$E_v = \{e \mid root.test\_cond(e) = v \; and \; e \in E\}$
$child$ = TreeGrowth(E_v F)
add $child$ as descendent of $root$ and label the edge ($root \rightarrow child$) as v
end for
end if
return root

In this study, the decision tree depth was selected as 17. In general, if the decision tree depth is greater, then the complexity of the model increases as the number of splits increases and contains more information about the dataset.

This is the main reason for overfitting with DTs, where the model is perfectly fit with the training dataset and will not be able to generalize well with the testing dataset. In addition, a very low depth causes model under-fitting. Fig. 4.14a presents a scatter plot depicting the relationship between the wind speed (m/s) and the power production (kW) of the turbine and Fig 4.14b shows the predicted average power in comparison with real average power of the turbine (kW) when using decision tree regression.



(a) (b)

Fig. 4.14. (a) Scatter plot depicting relation between the wind-speed(m/s) and the power-production(kW) from turbine using decision tree regression; (b) Predicted average power in comparison with real average power from turbine (kW) using decision tree regression.

4.6.5 Extra Tree Regression

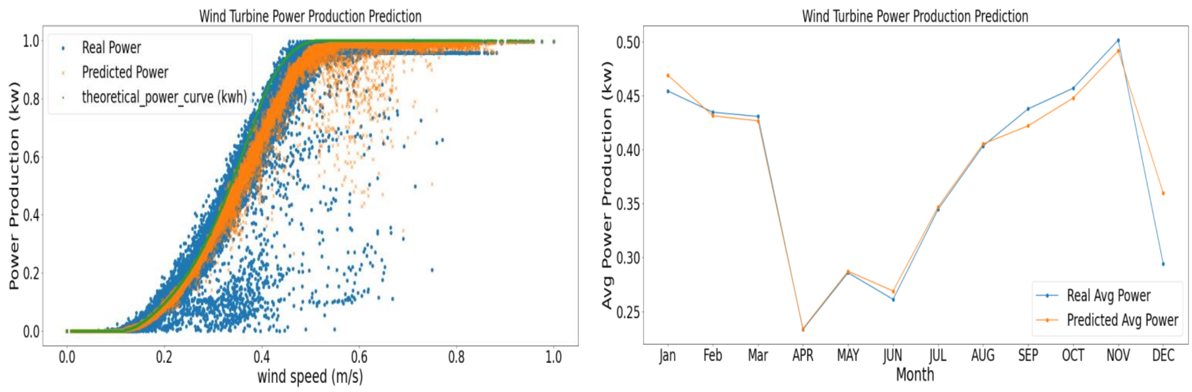
Extra tree or extremely randomized tree regression algorithms involve an ensemble machine learning technique. The algorithm has been evolved as an expansion of random forest algorithm, but the main difference is that it randomly chooses cut points partly or completely, with individual attributes, and selects splits.

Extra tree regression utilizes the same rule as the RF algorithm and uses a random subset of topographies to train each base estimator. The nodes above the leaf node (the terminal node) show the decision that is formed. This approach is considerably more accurate than SVM and ANN techniques [230].

This algorithm randomly selects the paramount features, along with the consistent value for splitting a node; however, rather than selecting the most discriminative split in each mode [232], the extra tree approach utilizes the whole training dataset to train each regression tree. On the other hand, the RF algorithm utilizes a bootstrap replica to train the forecast model. These significant differences makes extra tree regression less likely to over-fit a dataset, as there is better reported performance in the nodes above the leaf node (terminal node).

In the present study, the number of trees was selected as 90 and the maximum depth of trees was selected as 14. Generally, deeper tree sizes result in better performance. For extra tree regression, trees deeper than 14 started to depreciate the model performance. A maximum depth of six did not perform significantly better as the performance metrics were approximately equal.

At a maximum depth of two, the model became under-fitted, resulting in lower R^2 values and higher values for performance matrices. Fig 4.15a presents a scatter plot depicting the relationship between the wind speed (m/s) and the power production (kW) of the turbine and Fig 4.15b shows the predicted average power in comparison with the real power of the turbine from turbine (kW) when using extra tree regression.



(a) (b)

Fig 4.15. (a) Scatter plot depicting relation between the wind-speed(m/s) and the power-production(kW) from turbine using extra tree regression; (b) Predicted average power in comparison with real average power from turbine (kW) using extra tree regression

4.7 RESULTS AND DISCUSSIONS

Based on the study performed in the above sections, the present section scrutinizes the outcomes and the key observations accomplished from the performances of the various regression models after programming for the forecasting of wind power. All models mentioned and explained above were trained and tested on a machine featuring 12 GB of 16 MHz DDR3 RAM and a 1.6 GHz Intel Core i5 processor running in a Jupiter notebook (Python 3.9.5 version) development environment.

Several hyper-parameters, such as the learning rate, size of trees (depth), and regularization parameters stated with the various regression models were empirically selected by a stepwise searching approach to find the optimal hyper-parameters for the regression models. The performances of all algorithms were estimated based on the mean absolute error (MAE), mean absolute percent error (MAPE), root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R^2). Algorithms with minimum errors indicate the most desirable and accurate method. The MAE reflects the sum of absolute differences between the actual and predicted variables. The MAPE estimates accuracy in terms of the differences in the actual and predicted values. The RMSE is the standard deviation of the prediction errors, and practically it can be generalized that the lower the value of the RMSE, the better is the model considered to be. A model is considered to be good and without over-fitting if the RMSE values of the training and testing samples are within a close range. The MSE is average square of the errors, and R^2 checks how well-the observed outputs are reproduced by the model. Among the five performance indices estimated here, we are certain that we can suggest that the RMSE may be viewed as the metric of primary focus, where the errors are squared prior to being averaged and impose a high weight for large errors. As such, the minimum value of the RMSE inferred the minimum error rate in reality. The values of the root mean square, being adjacent to the mean absolute error, would imply that there is no significant variation between the magnitudes of error, in turn signifying the effectiveness and generalization of the model. Table 4.3 shows the MAE, MAPE, RMSE, MSE, and R^2 results for the training and testing dataset values for forecasting wind power. Generally, errors in the training dataset present the suitability of the developed model, while errors in the testing data present the generalization capabilities of the developed model. For optimizing model accuracy and performance, the ML model parameters were tested using hundreds of runs for the individual algorithms on the basis of the learning rate, number of trees, value of k, distance measure, and random state, etc.

The various machine learning performances can be analysed through the overlapping scatter plots that depicts the relationships between the wind speed and power produced by the turbine and from the graph between the forecasted average power values of the wind power in comparison with actual average power produced by the wind turbine, which graphically demonstrates the individual regression model performances as depicted in Figures 10 and 12–15. Fig. 4.10a represents the results of the RF regression. It is evident from the figure that the RF algorithm could predict values of power positively; however, its performance was better than the DT regression model, although, at high values of wind speed, this algorithm could not produce correct forecasts. From Fig. 4.10b, most of the forecasted or predicted values are overlapping or close to the real average power values and the model has a high R^2 value. As such, the overall performance of the RF regression model was better.

Fig. 4.12 depicts the results of the k-NN regression model. As can be seen from Fig. 4.12a, the k-NN model could be seen to be more successful at predicting both high and low values of wind speed with a lower training time and better handling of higher values of wind speed in contrast with both the DT and RF models. As is clear from Fig. 4.12b, the majority of the values of predicted power are overlapping and close to the real average power or active power. As such, it can be seen that the k-NN regression model also performed satisfactorily. Fig. 4.13 presents the outputs of the GBM regression model. As is clear in Fig. 4.13a, the GBM algorithm gave the best results for forecasting both low and large values of wind speed and was successful at handling high values of wind speed, which is in contrast to the other regression models.

Moreover, as can be seen from Fig. 4.13b, the prediction curve successfully fits or completely overlaps with the real average power curve. Hence, the performance of the GBM algorithm can be observed to have the best performance when compared with the other algorithms. Fig. 4.14 shows the results of the DT regression model. As can be clearly observed in Fig 3.14a, this algorithm could not predict correct power values. Among the five regression algorithms, the DT algorithm exhibited poor performance and had a high forecasting error, as is clearly visible from the given performance indices shown in Table 4.3. In addition, this algorithm also had a lower R^2 value than the other regression algorithm. Fig 4.15 represents the results of the ET regression algorithm. As can be seen in Fig. 4.15a , the ET algorithm performed well with both low and high values of wind speed and the algorithm resulted in lower values for the MAE, RMSE, MSE, and MAPE, but with a higher value of R^2, though still demonstrating the good performance of ET regression model. The model performances based on the MAE, MAPE, RMSE, MSE, and R^2 metrics are given in Table 4.3.

Table 4.3: Model performance based on the MAE, MAPE, RMSE, MSE and R^2 metrics. Italic and bold parameter indicate better performance.

Regression Models	Performance evaluation on Training Dataset					Performance evaluation on Testing Dataset					Training Time (sec.)
	MAE	MAPE	RMSE	MSE	R^2	MAE	MAPE	RMSE	MSE	R^2	
Random Forest	0.0186	0.2966	0.0588	0.0040	0.9888	0.0277	0.3310	0.0672	0.0045	0.9651	11.9
K-NN	0.0278	0.2960	0.0580	0.0036	0.9742	0.0286	0.3248	0.0667	0.0044	0.9656	0.08
GBM	***0.0260***	***0.0555***	***0.0228***	***0.0031***	***0.9897***	***0.0264***	***0.3012***	***0.0634***	***0.0040***	***0.9690***	***5.83***
Decision Tree	0.0325	0.3213	0.0592	0.0055	0.9660	0.0336	0.3349	0.0884	0.0078	0.9497	0.22
Extra Tree	0.0274	0.2915	0.0522	0.0036	0.9782	0.0276	0.3243	0.0655	0.0041	0.9678	3.05

4.8 CONCLUSION

As the world is increasingly utilizing renewable energy sources like wind and solar energy, forecasting such energy sources is becoming a crucial role, particularly when considering smart electrical grids and integrating these resources into the main power grid. At present, wind energy is being utilized on a massive scale as an alternate source of energy. Because of the fluctuating nature of wind energy, forecasting is not an easier task and consequently integration into primary power grids represents a big challenge.

As forecasting can never be considered free from error, this provokes us to create advanced models to mitigate such errors. In this study, comparative analysis of various machine learning methods has been carried out to forecast wind power based on wind speed and wind direction data. To achieve this objective, Yalova wind farm, located in the west of Turkey, was utilized as a case study. A SCADA system was used to collect experimental data over the period of January 2018 through to December 2018 at a sampling rate of 10 min for training and testing

ML models. To appraise the forecasting performance of the ML models, different statistical measures were employed.

The results show that the random forest (RF), k-nearest neighbor (k-NN), gradient boosting machine (GBM), decision tree (DT), and extra tree (ET) regression algorithms are powerful techniques for forecasting short-term wind power. Among these algorithms, the capability of the gradient boosting regression (GBM)-based ensemble algorithm, with a MAE value of 0.0264, MAPE value of 0.3012, RMSE value of 0.0634, MSE value of 0.0040 and R^2 value of 0.9690 for forecasting of wind power, has been verified with better accuracy in comparison with the RF, k-NN, DT and ET algorithms. The performance of the DT algorithm was not satisfactory, with a MAE of 0.0336, MAPE of 0.3349, RMSE of 0.0884, and MSE of 0.0078, although the R^2 (0.9497) values of the DT algorithm were relatively acceptable, with a training time 0.22s.

In gradient boosting, an ensemble of weak learners is used to improve the performance of a machine learning model. The weak learners are usually decision trees. Combined, their output results in better models. In the case of regression, the final results are generated from the average of all weak learners. In gradient boosting, weak learners work sequentially, where each model tries to improve upon the error from the previous model. Furthermore, decision trees are structurally unstable and not robust, and thus small changes in the training dataset can lead to significant changes in the structures of the trees and different predictions for the same validation examples.

The developed tree-based ensemble models can provide reliable and accurate hourly forecasting and could be used for sustainable balancing and integration in power grids. As described previously, it is extremely beneficial to provide predictions for wind power that can be produced in a day on the basis of input parameters (wind speed and wind direction), and our machine learning models have been proven to be quite accurate for such purposes. Future research areas for further analysis may be comprised of the exploration of other deep learning methods, the improvement of machine learning algorithms for point forecasts, forecasting combinations, forecast interval formation, and the amalgamation of wind power for speed forecasting.

CHAPTER 5

COMPARATIVE STUDY OF MACHINE LEARNING MODELS FOR SOLAR POWER FORECASTING

5.1 INTRODUCTION

Photovoltaic (PV) systems are used worldwide to produce solar power. Solar power sources are unpredictable in nature because their output power is alternating and heavily reliant on the external environment [233-234]. These variables include things like irradiance, PV surface temperature, humidity and wind speed. Since solar power forecasting is necessary for the electric grid, it is essential to plan ahead for solar power generation due to the unpredictable nature of photovoltaic generation [235].

The production of solar energy is weather-dependent and erratic; the forecast is tough and complex [236]. The effects of various environmental factors on a PV system's production are discussed in this chapter. With weather variables as model inputs, machine learning (ML) algorithms have demonstrated excellent results in time series forecasting and can be used to predict power [237].

The forecasting of solar power using a variety of machine learning, artificial neural network, deep learning techniques. Here, regression models using machine learning methods such as random forest, k-nearest neighbor, gradient boosting, decision tree and extra tree regression models were used. The random forest regressor outperformed the other four regression models in terms of accuracy by a wide margin.

5.2 THEORY AND MATHEMETICAL BACKGROUND

In this section, we will discuss the theory related to solar power and describe the mathematical theory of machine learning. We have a dataset that displays the ambient temperature, irradiation, module temperature and followed by the amount of power produced.

5.2.1 Solar Power

Solar power is the direct or indirect conversion of sunlight energy into electricity using photovoltaic (PV) or concentrated solar power. Using the photovoltaic effect, photovoltaic cells convert light into an electric current.

5.2.1.1 Photovoltaic Cell

A PV cell is a non-mechanical device that converts sunlight directly into electricity. The system contains no mechanical moving devices, unlike hydroelectric power plants, steam power plants, thermal power plants, and nuclear power plants. A PV cell is a semiconductor diode with a sun-exposed p-n junction. Photons of solar energy make up sunlight. These photons contain varying amounts of energy that correspond to the solar spectrum's various wavelengths. When photons strike a PV cell, they have three options: they can reflect off the cell, they can pass through the cell, or they can be absorbed by the semiconductor material. Absorbed photons are in charge of generating electricity. When enough sunlight is absorbed by the semiconductor material, electrons are emitted from the material's atom. Only photons with energies greater than the PV cell's band gap are useful for generating electricity; the rest of the energy is dissipated as heat energy in the PV cell [237-238].

5.2.1.2 The Nature of Light Energy:

Light is made up of energy. The light from the sun appears white because it is composed of many different colors that, when combined, produce white light. Each visible and invisible radiation in the sun's spectrum has a different amount of energy. Within the visible spectrum (red to violet), red has the lowest energy and violet has the highest.

Light in the infrared spectrum has less energy than light in the visible spectrum. The ultraviolet region of light has more energy than the visible region. Visible light is only a small part of the vast radiation spectrum. Light and similar radiation studies indicate that how one light ray interacts with another or with other physical objects can often be explained as if light is moving as a wave.

Every wave has a set distance between its peaks (called the wavelength). This wavelength is also known as a frequency. The wavelength-frequency relationship is inverse [239].

The energy associated with light waves enhances as the frequency is increased (wavelength decreases). Red light has a wavelength of about 3×10^{-24} kWh per photon, while violet light possesses 4.5×10^{-24} kWh.

5.2.1.3 Global Horizontal Irradiance

The global horizontal irradiance that strikes the earth's surface is made up of two components: diffuse horizontal irradiance and direct normal irradiance.

The geometric relationship between GHI, DNI, and DHI is as follows:

$$GHI = DNI.cos\theta_z + DHI \tag{5.1}$$

where z denotes the zenith angle. The zenith angle is the angle formed by the zenith and the centre of the Sun's disc. Watts per square metre is the unit of global horizontal irradiance.

Fig. 5.1 depicts the relationship between altitude (α), zenith angle (θ_Z), and azimuthal angle (A_Z) [240].

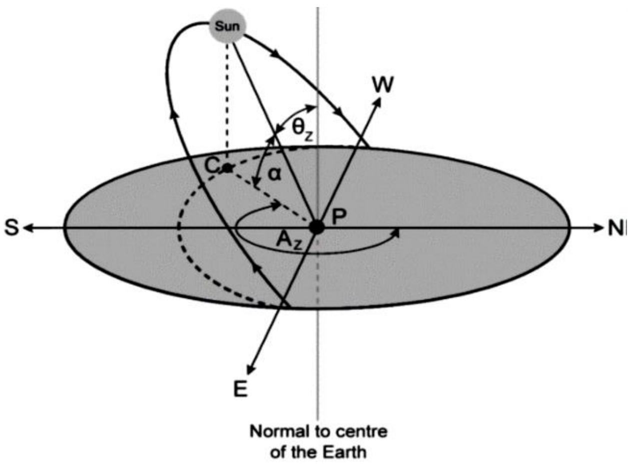


Fig. 5.1: The solar locus

5.2.1.4 Modeling of Photovoltaic Devices

A PV cell can be mathematically modelled as shown in Fig. 5.2.

$$I = I_{pv} - I_d \tag{5.2}$$

where Ipv is the incident light current and Id is the Shockley diode equation, that can be expressed as;

$$I_d = I_o \left[e^{\left(\frac{qV}{akT}\right)} - 1 \right] \tag{5.3}$$

Equation (5.2) can now be rewritten as,

$$I = I_{pv} - I_o \left[e^{\left(\frac{qV}{akT}\right)} - 1 \right] \tag{5.4}$$

where I_o is the diode's reverse saturation or leakage current, q is the electron charge ($1.60217646 \times 10^{-19} C$), k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T is the pn junction temperature (T), and a is the diode ideality constant. Because ideal PV cell modelling is no longer valid for practical PV arrays, the following equation can be approximated:

$$I = I_{pv} - I_o \left[e^{\left(\frac{V + R_S I}{V_t a}\right)} - 1 \right] - \frac{V + R_s I}{R_p} \tag{5.5}$$

where, I_o and I_{pv} are the saturation and photovoltaic currents, respectively and $V_t = \frac{N_S K T}{q}$ is the thermal voltage of the array with N_s cells connected in series. If N_p number of cells were connected in parallel, then $I_o = I_{o,cell} N_p$ and $I_{pv} = I_{pv,cell} N_p$.

Furthermore, R_p is the equivalent parallel resistance of the array and R_s is the equivalent series resistance [241-242].

As shown in Fig. 5.3, the equation generates the I-V curve with three distinct points: short circuit (0, I_{sc}), maximum power point ($V_{mp,}I_{mp}$), and open circuit ($V_{oc}, 0$) .

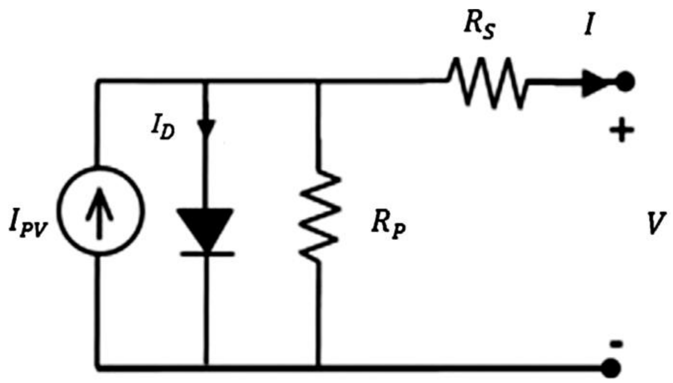


Fig. 5.2: Equivalent circuit of single-diode model of PV cell

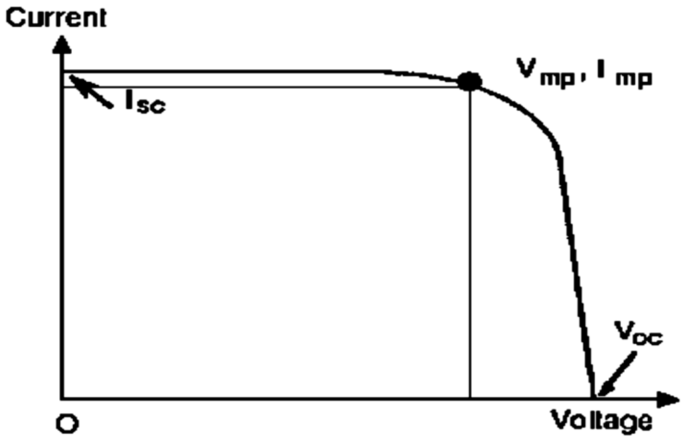


Fig. 5.3: Practical PV cell I-V curve

5.3 SOLAR POWER DATASET

The solar power dataset utilized in this thesis is an actual data gathered from the Qassim University, KSA. It is a 6300 W_P solar photovoltaic system (SPV). This system consists of fourteen 450 W_P SPV modules arranged in a 7 × 2 configuration on the roof of the building of Qassim University in KSA. This assessment is carried out by gathering data from the installed SPV system. This data includes incident irradiance (W/m^2), module temperature, ambient temperature and power produced by the system. This information is gathered using a wattmeter, an irradiance metre, voltage sensors, and current sensors. Every new line of the dataset is captured at a 5 min time interval and the time period of the dataset is one year (September 2021- August 2022). The data are accessible in the Excel format.

5.4 METHODOLOGY

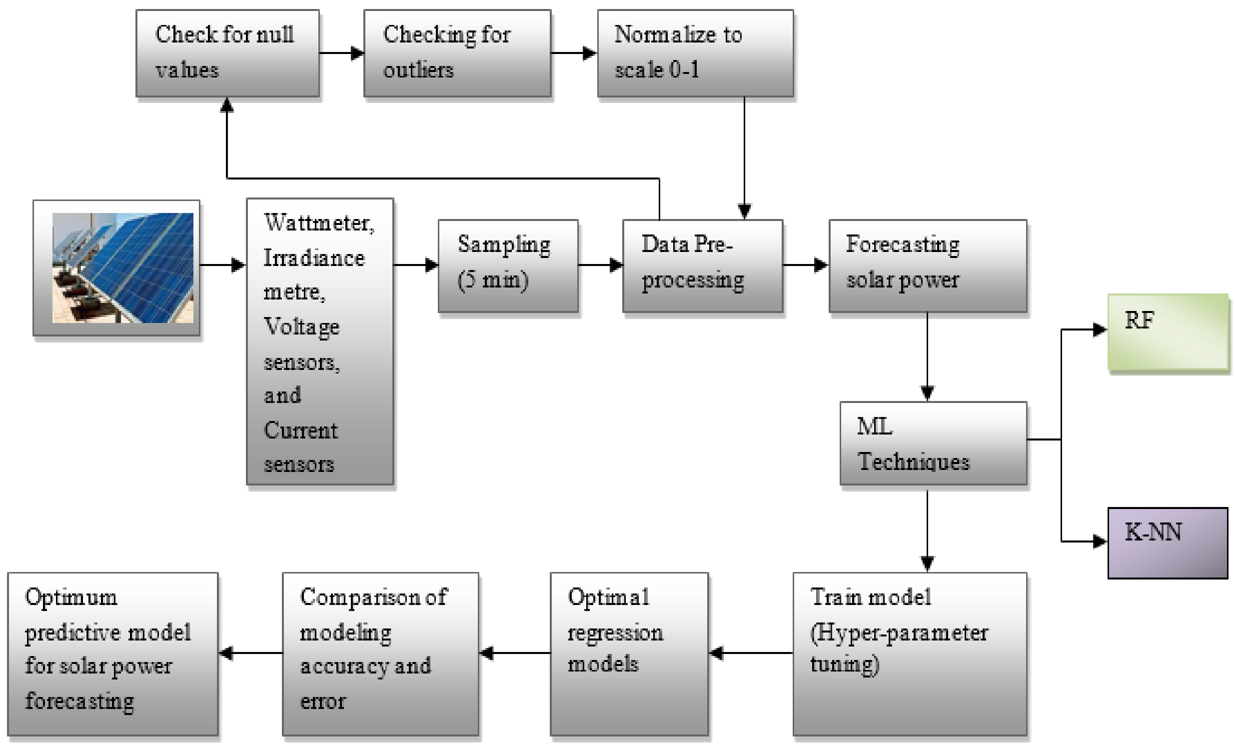


Fig. 5.4: Solar power forecast methodology

The explained process is shown in a flow diagram in Fig. 5.4 Inputs included historical ambient temperature, Irradiation, module temperature and output is solar power data. A wattmeter, an irradiance meter, voltage sensors, and current sensors are used to collect this data. The dataset's new lines are recorded every 5 minutes. There after data-preprocessing has been done for cleaning the dataset and making it suitable for a ML model which also enhances the efficiency and accuracy of a ML model. As the data points in the dataset are not of the same order of magnitude so, it is required to bring the data-points in the same order of magnitude. Hence, the given dataset is normalized using the relation.

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5.6}$$

where, actual data is specified by x, x_{max} (maximum value of the dataset), x_{min} (minimum value of the dataset) and x is the scaled data specified within the range 0–1. Later the dataset were used to develop the ML Models. The dataset is separated into two portions: first 75% of the dataset is considered for training and the rest 25% dataset is considered for testing purpose.

5.5 DATA PREPROCESSING

Data preprocessing in machine learning is the process of getting the raw data ready (organizing and cleaning it) so that it can be used to create and train machine learning models. It is the first and crucial step while creating a machine learning model. In the raw dataset, there were some timestamp where dataset values were negative or missing. These negative and null values in the raw dataset indicate noticeable outliers. As a result, these evident outliers, as well as the related variables under the same time stamps, would be deleted. This could be due to irregular maintenance of solar panel or malfunction. The dataset contains 50,420 observations in total, with 2,496 data points considered outliers due to zero power production. After removing outliers and missing values, the remaining dataset, 47,924 data points, was considered for machine learning model implementation.

5.6 MACHINE LEARNING MODELS FOR SOLAR POWER FORECASTING

5.6.1 Random Forest

Random Forest Regression is an ensemble supervised learning approach, which involves fitting numerous regression trees on random selections of the training dataset. Initially, the algorithm randomly divides the dataset into numerous subparts and then generates various decision trees for each subpart. All trees are utilized for prediction, and their forecasts are averaged to produce a more reliable and precise forecast. Also, it is capable of effectively handling huge datasets.

This approach also manages variables quickly, which makes it suitable for complex tasks. The random forest cannot forecast values that are not in the training dataset target range [242]. We utilized scikit-learn for random forest regression implementation. In RF, a random vector of k is generated, which is a subset of the dataset's feature space, and each tree is built utilizing k and the training data. In a random forest, margin function and the generalization error are stated in Equation (5.7).

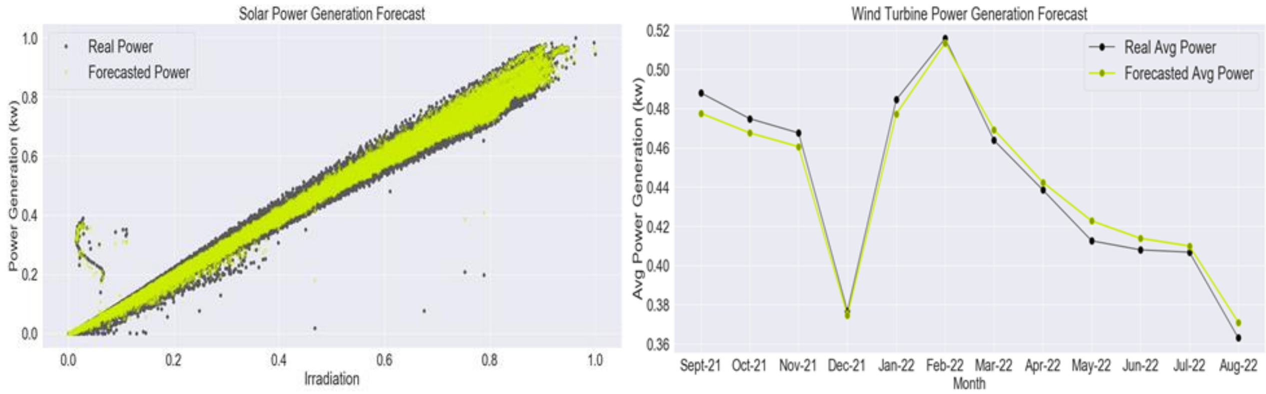
$$PE^{*} = P_{X,Y}(mg(X,Y) < 0) \tag{5.7}$$

$$where, \qquad mg(X,Y) = av_k I(h_k(X) = Y) - max_{j \neq Y} av_k I(h_k(X) = j)$$

where h_k are the classifiers, $I\,(.)$ is the indicator function, mg is the margin function which governs the average votes at random vectors for the right output as compared to any other output, $PE^{*}$is the generalization error and X,Y are random vectors.

In RF algorithm, the random state is set to 35, and the number of trees is set to 100, because raising the number of trees to more than 100 did not substantially increase the forecast outcome. In order to improve runtime and forecast performance, an adequate number of trees must be determined.

Fig. 5.5(a) depicts the scatter plot employing RF regression showing the relationship between Irradiation (w/m^2) and SPV power generation (kW) and Fig. 5.5(b) compares the forecast average power with the actual average power (kW) produced from the solar panels.



(a) (b)

Fig. 5.5: (a) Scatter plot depicting relation between the Irradiation(w/m^2) and the power generation (kW) from SPV using random forest regression; (b) Predicted average of solar power as compared with real average power from SPV (kW) using random forest regression

5.6.2 K-Nearest Neighbors

The K-Nearest Neighbors (KNN) technique is a non-parametric approximation approach that may be used to solve problems like classification and regression. The assumption behind KNN is that an item belongs to the same class as its nearest neighbors. The approach demands the input of a positive integer k at initially. For every sample, the method finds the k points on the dataset that have a similar pattern to that of the sample. The distance between all of the samples in the dataset and the newly analysed sample is needed for this selection procedure

[242]. It has an algorithmic framework that is simple to understand and implement, and it does not involve any model fitting or function estimation.

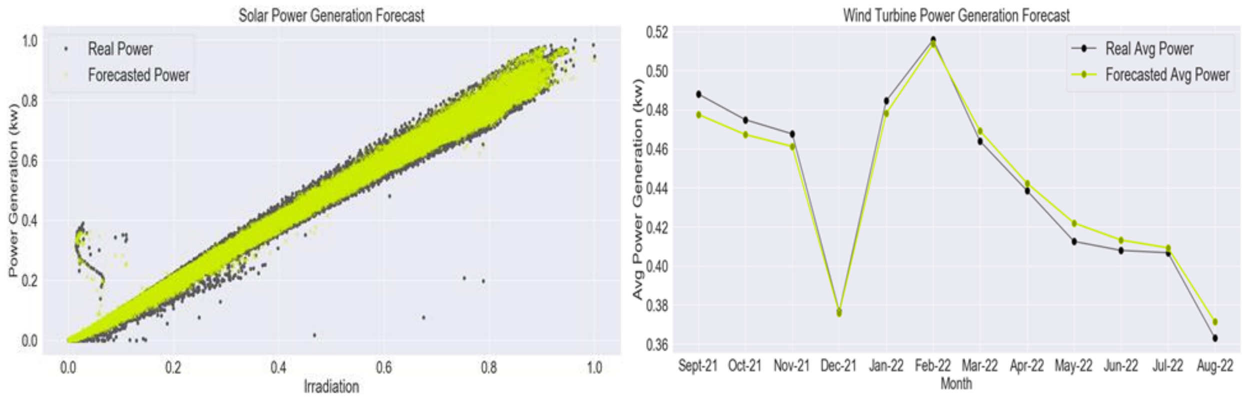
The KNN regressor is widely considered as one of the most prominent data mining algorithms in the area of research due to its sophisticated capabilities. The KNN approach, when applied in forecasting applications, determines the neighbors: components from the training set that meet the reference conditions based on certain pre-set criteria.

The past data on wind power, wind direction and speed are the significant features of this study. These data are organized in a matrix X_{ij}, where each row represents a feature vector for a certain estimate period. The nearest neighbor for a new data point at time t, as defined by the feature vector y_j, is compared to all of the rows in X_{ij}, and the result is recorded in the Euclidean distances vector d_i:

$$d_i = \sqrt{\sum_i (X_{ij} - y_j)^2} \tag{5.8}$$

The first k matches are obtained after sorting the distance values in increasing order. The numerical value for y_j is the average of all the ‘K’ nearest neighbors variable numerical values. In this algorithm, the Euclidean distance was used as the distance metric and the number of neighbors for the kNN algorithm was determined to be 5.

Fig. 5.6(a) depicts a scatter plot employing KNN regression which shows the relationship between Irradiation (w/m^2) and SPV power production (kW) whereas Fig. 5.6(b) depicts the forecast average power compared to the actual average power (kW) employing KNN regression.



(a) (b)

Fig. 5.6: (a) Scatter plot depicting relation between the Irradiation(w/m^2) and the power generation (kW) from SPV using k- nearest neighbor regression ; (b) Predicted average of solar power as compared with real average power from SPV (kW) using k- nearest neighbor regression.

5.7 RESULTS AND DISCUSSION

This segment discusses the findings and significant observations obtained from the final outcomes of wind power forecast models. All of the algorithms presented and detailed above were trained and tested on a Jupiter notebook (Python 3.9.5 version) equipped with 12 GB of 16 MHz DDR3 RAM and a 1.6 GHz Intel Core i3 processor. This assessment is carried out by gathering data from the installed SPV system. All the models are trained by utilizing the selected input parameters incident irradiance, module temperature, ambient temperature, and generated power, produced by the system. Following that, the model is given a testing/ validation dataset depending on which it provides production forecasts (active power). The forecast accuracy of all machine learning models is evaluated by utilizing the statistical indicators R^2, MAE, MSE, RMSE, and MAPE. In general, errors in the train set demonstrate the applicability of the generated model, whereas errors in the test set demonstrate the model's prediction performance. Algorithms with minimal errors represent the most accurate and acceptable method. The statistical indicator, R^2 indicates how efficiently the model reproduces the measured outputs. The MSE represents the average square of the errors. The RMSE is the standard deviation of the forecast errors; the lower the RMSE, the superior the model is regarded to be. Moreover, a model is deemed good and free of over-fitting if the RMSE values of the testing and training sets fall within a restricted range. The MAE is calculated by adding the absolute differences between the real and forecast values. The MAPE determines accuracy by comparing the real and forecast data points. Amongst the five evaluation criteria assessed here, RMSE should be seen as the key focus, with errors squared before being averaged and a significant weight assigned to significant errors. As a result, the smallest value of the RMSE deduced the actual error rate. The fact that the values of the root mean square are comparable to the mean absolute error implies that there is no considerable variance in the magnitudes of error, indicating the model's efficacy and generality. The forecast model parameters have been evaluated utilizing numbers of runs for the separate algorithms based on the random state, value of k, distance measure, number of trees, learning rate and booster parameter among other things, in order to optimize the model performance and accuracy. The performance of all forecast models can be assessed utilizing the overlapping scatter plots which indicate the correlations between the power developed (kW) by the solar photovoltaic panel and Irradiation (w/m^2), as well as the plot between the forecast average power values in comparison to the actual average power generated by the solar photovoltaic panel, that pictorially reveals the performances of regression models, as can be seen in Figures 5.5 and 5.6. The RF regression model's outcomes are shown in Fig. 5.5. As seen in Fig. 5.5a and 5.5b, this approach was able to anticipate accurate power values. The RF method performed good and had a high accuracy rate and small predicting error, as demonstrated by the performance measures presented in Table 5.1. as compared to the KNN method. Additionally, the R^2 value of this algorithm was higher than that of the other model with longer execution times. The majority of the forecast values are found overlapping or near to the actual average power levels, as illustrated in Fig. 5.5b

The KNN regression results are shown in Fig. 5.6. The KNN method could forecast power values favourably, as shown in the graph; nonetheless, its performance was not better than the RF regression model, despite the fact that this algorithm could not make proper forecasts as shown in Fig. 5.6b. Also the model has a small R^2 value than that of the RF regression model. As a result, the overall performance of the RF regression model was found to be very good.

Table 5.1: Model performance based on the MAE, MAPE, RMSE, MSE and R^2 metrics. Italic and bold parameter indicate better performance.

Regression Models	Performance evaluation on Training Dataset					Performance evaluation on Testing Dataset					Training Time (sec.)
	MAE	MAPE	RMSE	MSE	R^2	MAE	MAPE	RMSE	MSE	R^2	
Random Forest	**0.0091**	**0.2708**	**0.0126**	**0.0001**	**0.9979**	**0.0132**	**0.7674**	**0.0191**	**0.0003**	**0.9953**	0.65
K-NN	0.0108	0.5834	0.0158	0.0002	0.9967	0.0134	1.2703	0.0196	0.0003	0.9950	0.18

5.8 CONCLUSION

Forecasting the solar power output is necessary for the proper functionality of the power grid. Machine learning regression models are used to estimate solar photovoltaic (SPV) panel output, which overcomes the drawbacks of traditional models. In this chapter, we have compared two ML regression models (RF and K-NN) with real-world data gathered from Qassim University, KSA. In the practical application, our research demonstrates the superiority of using Random Forest Regression model over K-NN method with MAPE, RMSE, MAE, MSE and R^2 is 0.7674, 0.0191, 0.0132, 0.0003 and 0.65 respectively.

CHAPTER 6

A FEASIBILITY STUDY AND COST-BENEFIT ANALYSIS OF AN OFF-GRID HYBRID SYSTEM FOR A REMOTE AREA ELECTRIFICATION

6.1 INTRODUCTION

Prior to the development of any model based on RES, it is critical to accurately estimate their potential. The proposed research aims to create a hybrid model based on RES like wind energy, solar energy, biogas, biomass, etc [243]. To examine the viability of the available RES for the creation of a hybrid model, the potential of these sources has thus been estimated in this chapter. The Sarai Jairam village, district Agra, Uttar Pradesh, India has been chosen as study area, in the present chapter. The potential of various RES at the chosen places has also been calculated using the data gathered. According to this evaluation, study area has adequate supplies of solar energy, biomass, and biogas. The mathematical modelling of various RES and system components used in the creation of the hybrid model has also been provided.

6.2 METHOD OF MODELING HYBRID SYSTEMS

For the design and construction of an optimum hybrid system for a rural region, a systematized modelling technique is an integral step since it ensures that the rural population has reliable, consistent and dependable access to electricity. The HOMER pro software has been utilized as a tool to identify the set of optimum systems that meet the load demand under specific system restrictions and input assumptions. HOMER pro is a distributed power optimization tool designed by the National Renewable Energy Laboratory in the United States [243]. Due to the uncertainties, a sensitivity analysis is conducted to investigate the influence of input assumptions on the optimization outcomes. Fig. 6.1 depicts the process and proposed framework for system modelling and analysis. In the current study, a modelling technique that is shown in the following sections includes a description of the selected location, assessment of renewable energy sources potential, electrical load estimation and system design and optimization procedure.

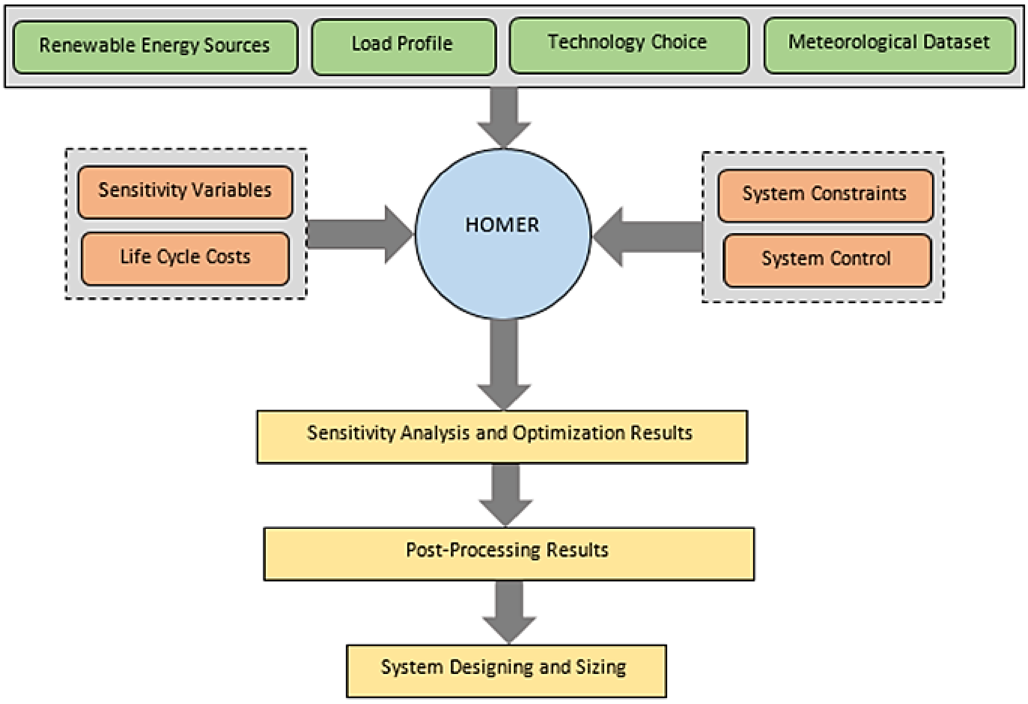


Fig. 6.1: Process and proposed framework for system modelling and analysis

6.3 LOCATION DISCRIPTION

It is crucial to choose the right location for the development of the hybrid model. For the proposed work, sites with a significant potential for many RES have therefore been taken into consideration. Based on the lack of grid power to homes or other essential facilities like panchayat ghar and primary schools, etc., two separate sites in Sarai Jairam village, district

Agra, Uttar Pradesh, India have been taken into consideration for creating hybrid models. Uttar Pradesh is situated between 23°52'N and 31°28'N latitudes and 77°3'E and 84°39'E longitudes. Uttar Pradesh has a total land area of 240,928 square kilometres (93,023 sq mi) and is the fourth largest state in the country in terms of area, and the first in terms of population. There is a 3,000 MW shortfall in Uttar Pradesh. Only 20,000 MW are available to meet the roughly 23,000 MW demand, which forces load shedding in rural and smaller communities. According to data made available by the state power agency, energy is currently provided in rural areas on average for 15 hours and 7 minutes instead of the 18 hours that are scheduled. In the same way, electricity is delivered on average in towns at 19 hours 3 minutes as opposed to the scheduled 21 hours 30 minutes, and in tehsil headquarters in 19 hours 50 minutes as opposed to 21 hours 30 minutes.

The site for this study is Sarai Jairam village in Uttar Pradesh, India. The abundance of renewable energy and the region's strategic significance was taken into consideration while choosing the location. The location is identified by the coordinates at the longitude of 78° 10.7’E and latitude of 27° 20.2’N and time zone (GMT+05:30) from NASA meteorological data. Fig. 6.2 shows the geographic view of the research location.

Fig. 6.2: The geographic view of the research location

6.4 ASSESSMENT OF WIND AND SOLAR RESOURCES POTENTIAL AT THE SELECTED SITE

From NASA meteorological data, the solar and wind energy data for Sarai Jairam village have been extracted, and the data are shown in Table 6.1 with their latitude and longitude (27° 20.2'N, 78° 10.7'E), and time stamp (GMT+05:30). Fig. 6.3 and Fig. 6.4 provide graphical representations of the specifics of solar radiation throughout the course of the year and wind data over the same period. Table 6.1 provides data on the selected site's annual average daily radiation (kWh/m^2/day), clearness index and wind speed (m/s).

Table 6.1: Average monthly daily radiation, clearness index and wind speed

Month	Solar Energy (SE) (kWh/m^2/day)	Clearness Index	Wind Speed (WS) (m/s)
Jan	3.670	0.578	4.230
Feb	4.690	0.623	4.690
March	5.590	0.620	5.020
April	6.080	0.589	5.100
May	6.360	0.574	5.250
June	6.010	0.531	5.180
July	4.960	0.444	4.740
Aug	4.540	0.430	4.410
Sept	4.750	0.503	4.150
Oct	4.730	0.595	3.450
Nov	4.030	0.611	3.360
Dec	3.490	0.585	3.700
Average	4.908	0.5569	4.44

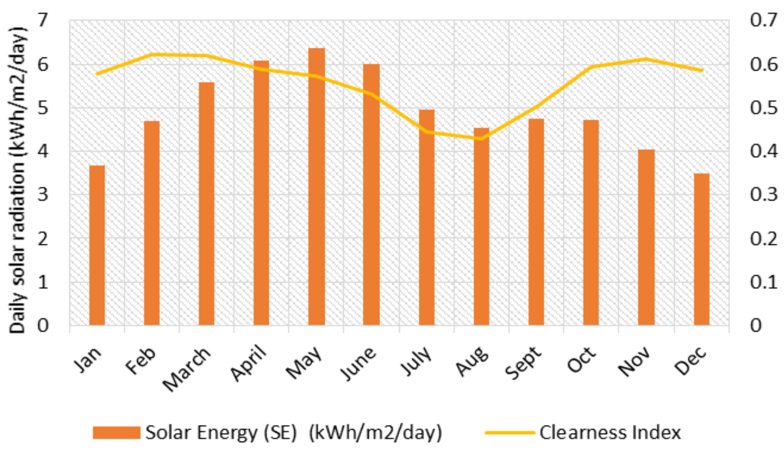


Fig. 6.3: Monthly average solar irradiance throughout the year

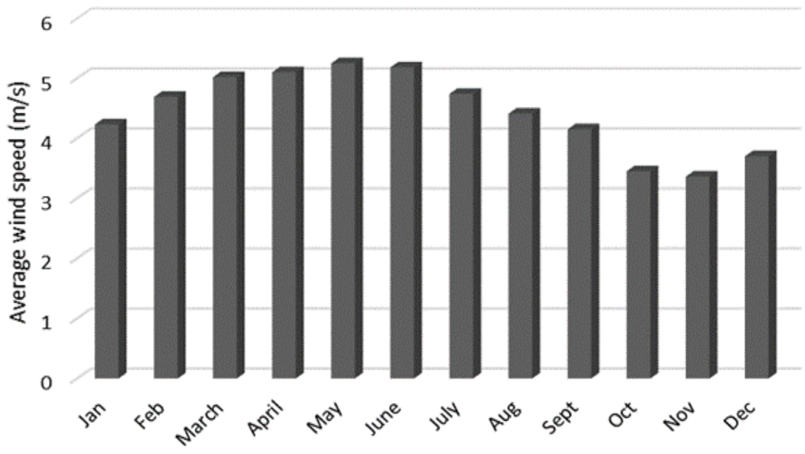


Fig. 6.4: Monthly average wind speed throughout the year

6.4.1 Solar energy

The sun provides an improbable amount of solar energy to the planet, which can be used to produce electricity. The database of the Indian meteorological service reveals that India has between 250 and 300 bright days each year, which suggests that the nation can readily use solar energy. Historically, only things like pickles, jam, and clothes were dried using solar energy [244-245]. In addition, a solar water heater uses solar energy to heat water, and a solar cooker uses solar energy to prepare food. However, modern solar thermal and photovoltaic (PV) technology also uses it to produce energy. PV cells made of a thin layer of semiconductor material are used in SPV technology to convert solar energy into electrical energy [246]. One PV cell typically produces relatively little voltage between 0.5 and 0.8 volts. Therefore, PV cells are connected in series to create a PV module, which may then be connected in series or parallel to create a PV panel or array, in order to take advantage of this technology and increase the voltage level [247]. Therefore, when exposed to solar radiation, PV panels or arrays produce high voltages and currents at their output terminal that can be used to provide our electricity needs. PV panels, however, are unable to produce power when there is a lack of solar radiation, such as at night or in overcast conditions [248]. In order to store energy that can be used at night or in cloudy weather, a storage device like a battery is needed.

DC power is produced by PV panels. The majority of electrical gadgets, however, need AC power. Therefore, a device that can convert DC power to AC power is required. An inverter is able to achieve this [249-250]. Consequently, the SPV system is made up of PV panels, batteries, an inverter, and a charge controller. The charge controller is a crucial component of the SPV system because it controls the energy flow from the renewable energy source via the battery bank and the load demand [251]. The SPV system can be operated in grid-connected or off-grid modes. While it is not connected to the grid when in off-grid mode, the SPV system is connected to the utility grid when in grid connected mode.

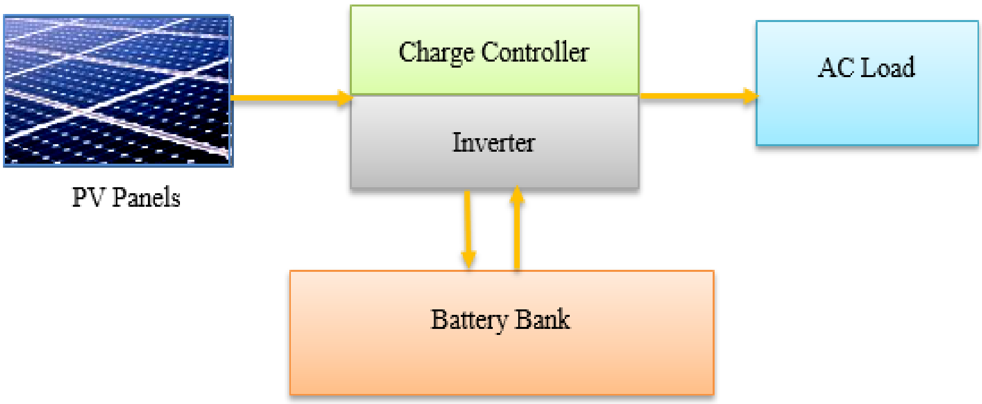


Fig. 6.5: PV System Schematic Diagram

Additionally, Fig. 6.5 depicts the schematic diagram of the SPV system. The amount of solar radiation, or irradiance, in a chosen area must be estimated in order to build and construct an SPV system [252]. In order to collect the solar radiation data for the various months of the year, the HOMER software was given the longitude, latitude, and time zone of the study location. The results are shown in Table 6.1. The Sarai Jairam village has higher annual average solar daily radiation of 5.26 kWh/m2/day, as can be seen in Table 6.1. Due to its best solar energy potential, the village of Sarai Jairam has been chosen. The chosen site's 4.91 kWh/m^2/day of yearly average global solar radiation is sufficient to produce electricity effectively. Further observation reveals that the solar radiation reaches its peak in May (6.36 kWh/m^2/day) and reaches its minimum (3.49 kWh/m^2/day) in December as can be seen in Fig. 6.2. Additionally, using the following calculation, the yearly solar energy potential (E_{PV}) of the chosen site was calculated to be 1792.15 kWh/m^2/year.

$$E_{PV} = Q_{PV} \times 365 \tag{6.1}$$

Where, Q_{PV} is the average daily solar radiation per year (4.91 kWh/m^2/day) [253].

6.4.2 Wind energy

Electricity is generated by a wind turbine using the kinetic energy of the wind. Small wind turbines in India called aero generators are made to withstand winds of up to or close to 10 m/s [254]. According to Fig. 6.6, it consists of the wind turbine rotor, inverter, charge controller, and battery bank.

The wind turbine's output is collected by the charge controller, which also charges the battery bank [255-256]. To power an AC load, an inverter converts DC electricity to AC. The chosen area's 4.44 m/s average annual wind speed is somewhat low for the production of electricity, as seen in Table 6.1. As a result, wind energy has not been considered as a source of electricity production for the indicated site in this study.

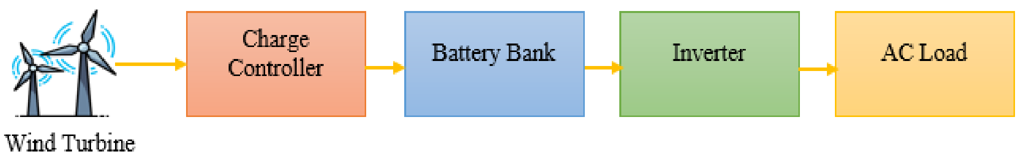


Fig. 6.6: Small-scale aero-generator schematic diagram

6.4.3 Bio Gas

A biogas system generates biogas by using a biological agent such as bacteria to break down organic waste like animal dung, food scraps, or human sewage. Anaerobic digestion is the term for this process [257]. The biogas that is produced includes some solid wastes as well as 50–60% CH_4 and 30–40% CO_2. A biogas collecting tank, an anaerobic digester, and an IC engine with a generator make up the biogas-based power generation system [258, 259]. Additionally, the evaluation of biogas generation in the study area is done using animal manure from various animals, such as buffaloes, cows, sheep, and goats. It is predicted that the study area I has a total of 310 buffaloes, 175 cows, and 25 goats based on the thorough survey and data collection. The chosen area's biogas potential is assessed as follows:

$$Q_G = d_g \times Y_G \tag{6.2}$$

Where Q_G is the biogas availability per day (m^3/day), Y_G is the biogas yield (m^3/kg) and d_g is the availability of cattle dung (kg/day) [260, 262]. Additionally, Table 6.2 provides an evaluation of the biogas and energy potential at the chosen site. Around 1750 kg of cow manure are available daily in Study Area.

It is predicted that 1 kg of cow and buffalo dung can produce 0.036 m^3 of biogas, but sheep and goat produce 0.070 m^3 and 0.078 m^3 respectively. The evaluation of biogas output is based on the cattle dung acquired from various species [261]. The research area's available biogas is calculated to be 116.175 m^3/day using a 50% collection efficiency assumption. Additionally, it is thought that 0.5 m^3 of biogas can generate 1 kWh of energy [262]. The computed annual energy potential of the chosen site is 84,807.75 kWh/year. According to Table 6.2, the main source of biogas generation comes from buffaloes (72.04%) followed by cows (27.1%), and goats (0.84%), respectively. As a result, the total annual energy potential of various RES at the chosen site is estimated and shown in Table 6.3.

Table 6.2: Biogas and energy potential assessment in the study area

Description	**Buffaloes**	**Cow**	**Goat**
No. of animals	310	175	25
Dung per cattle (kg/day/cattle)	15	10	1
Dung from different animals (kg/day*no. of cattle)	4650	1750	25
Availability of cattle dung at 50% collection efficiency (kg/day)	2325	875	12.5
Biogas yield rate (m^3/kg)	0.036	0.036	0.078
Biogas yield from different animals (m^3/day)	83.7	31.5	0.975
Total biogas from all animals (m^3/day)	116.175		
Annual energy potential (kWh/year)	84,807.75 kWh/year		

Table 6.3: Potential estimates for various RES in the study region

S. No.	**Renewable energy sources (RESs)**	**Annual energy potential**
1	Solar energy	1792.15 kWh/m^2/year
2	Biogas	84,807.75 kWh/year

Table 6.3 shows that the selected area has a large potential for various RES that can be used to meet the energy needs of the rural people in the given area. Furthermore, biogas has the greatest potential, followed by solar energy. As a result, this village has been selected for the configuration of a renewable energy-based system for power production

6.5 ASSESSMENT OF BIOMASS ENERGY RESOURCE POTENTIAL AT THE SELECTED LOCATİON

In Sarai Jairam village animal dung may be simply used to produce biogas through the digestion and combustion processes, respectively. Anaerobic digesters are used to treat the manure produced by cattle and produce power. The total dung produced annually from the community is calculated by equation (6.3);

$$M_n = \sum_{n=1}^{j} N_j m_j \tag{6.3}$$

where, M_n is the annual total amount of manure produced, N_j is the number of the selected group of animals, n is the overall number of cattle and m_j shows manure produced per cattle [263, 272].

Table 6.2 lists the number of animals and the availability of animal manure in the village of Sarai Jairam. The total amount of manure produced by all the animals is estimated to be 6.425 tons/day, which may be used to produce 84,807.75 kWh/year of power annually. The total potential of biomass is shown in Fig. 6.7.

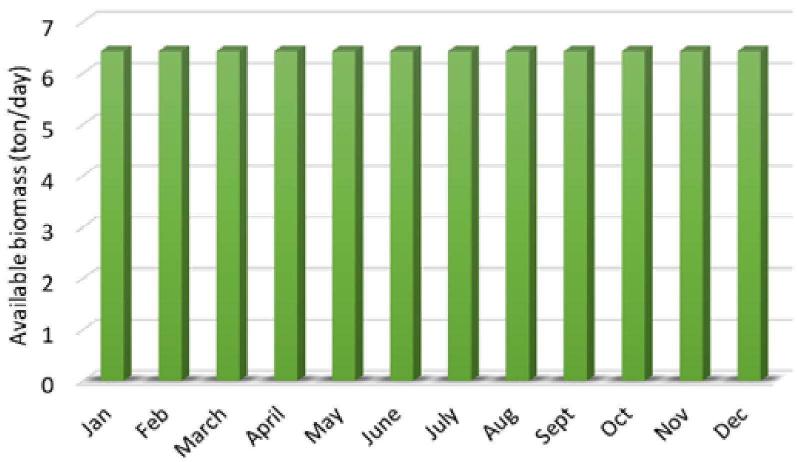


Fig. 6.7: Technical potential of biomass (animal manure)

6.6 FEASIBILITY ANALYSIS

Electrical load assessment and data on various RES have also been done in order to do the feasibility analysis of the chosen sites [164].

6.6.1 Assessment of Electrical Load

In this work, a hybrid system that employs energy from solar and biogas has been designed to meet the electrical demands of one Primary school, Junior school and Panchayat ghar. The panchayat ghar has two rooms with two fans and four tube lights. The primary school contains six rooms with twelve fans, twelve tube lights, two computers and one submersible pump, while, five rooms, ten fans, ten tube lights, two computers and one submersible pump make up the junior high school. Table 6.4 provides the quantity, power ratings and power consumption for each load. Fig. 6.8 depicts the electricity load of the proposed region taking into account future expansion. The data has been gathered from the school and panchayat ghar employees.

Table 6.4: Electricity load calculation for the selected communities

S.No.		1	2	3	4
Load		Fan	Tube light	Computer	Water pump
Power rating (watts)		60	30	100	500
Panchayat ghar	No. in use	2	4	0	0
	Utilization hours	10	10	0	0
Primary school	No. in use	12	12	2	1
	Utilization hours	8	8	8	1
Junior school	No. in use	10	10	2	1
	Utilization hours	8	8	8	1
Total energy Consumed (Watt)		11760	6480	3200	1000
Total load		22.440kWh			

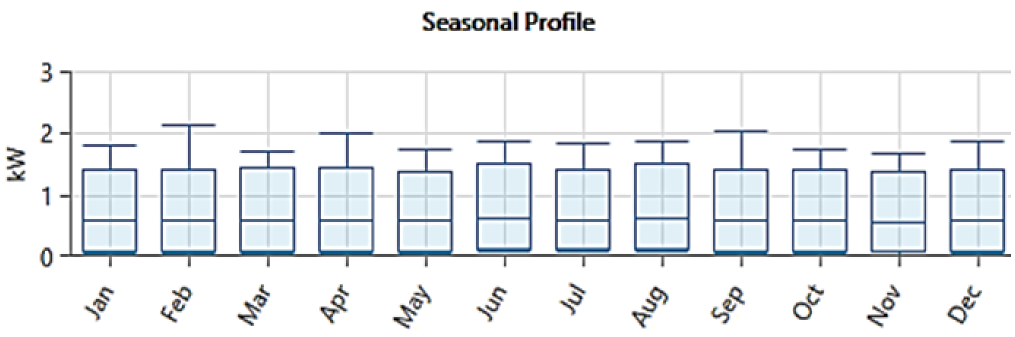


Fig. 6.8: Monthly load profile during the whole year

The proposed location is not yet connected to the grid, a DG set, or any other type of power source. As a result, connected load and the data supplied by the proposed Primary school, Junior school and Panchayat ghar were used to determine the hourly load assessment.

6.7 INTRODUCTION OF HOMER SOFTWARE

The National Renewable Energy Laboratory (NREL) produced the well-known software called Hybrid Optimization Model for Electrical Renewables (HOMER) [265, 272]. For the design of various off-grid and grid-connected RES-based hybrid systems, it runs simulations. This software initially determines if the system can technically meet the energy demand given the various techno-economic data inputs and constraints provided by the modeler [266, 273]. Following that, it runs hourly-based simulation for a year, calculates the net present costs (NPC) of all possible system configurations, and then ranks them according to which has the lowest NPC. NPC of a hybrid system is essentially the algebraic total of all costs and revenues over the lifespan of the system. Various costs include capital investment, operating and maintenance costs, replacement costs, fuel prices, grid power purchases, penalties, etc [267]. Different revenues take into account the salvage value of a biomass generator, a battery, the amount of power sent to the grid, etc [268]. The initial investment cost of the component is its capital cost. Operation and maintenance (O&M) cost is the annual cost incurred for operating and maintaining the components, whereas replacement cost is the cost of replacing that component with a new one at the end of the old one's lifetime [269, 270]. Additionally, sensitivity analysis can be carried out with this tool to evaluate the system's performance in ambiguous situations [271]. Fig. 6.9 shows the flowchart for the design and development of the hybrid system utilizing the HOMER tool.

The system components that will be employed in the HOMER softwere are explained in section 6.8 for the estimate of power and energy potential of RES. Furthermore, equation 6.4

can be used to determine the power output of the SPV system (PV P (t)) in HOMER software.

$$P_{PV}\ (t) = \ R_{PV}\ \times DF\ \times \frac{Q_{PV}\ (t)}{Q_{PV.STC}} \tag{6.4}$$

Where: $Q_{PV}\ (t)$ is the solar irradiance incident on the SPV array in kW/m^2; R_{PV} is the rated capacity of the SPV array under standard test conditions (STC); and $Q_{PV.STC}$ is the solar irradiance incident under STC (1 kW/m^2). The SPV array's derating factor, or DF, is utilized to account for output reduction under real-world environmental factors includes shadow, dust etc.

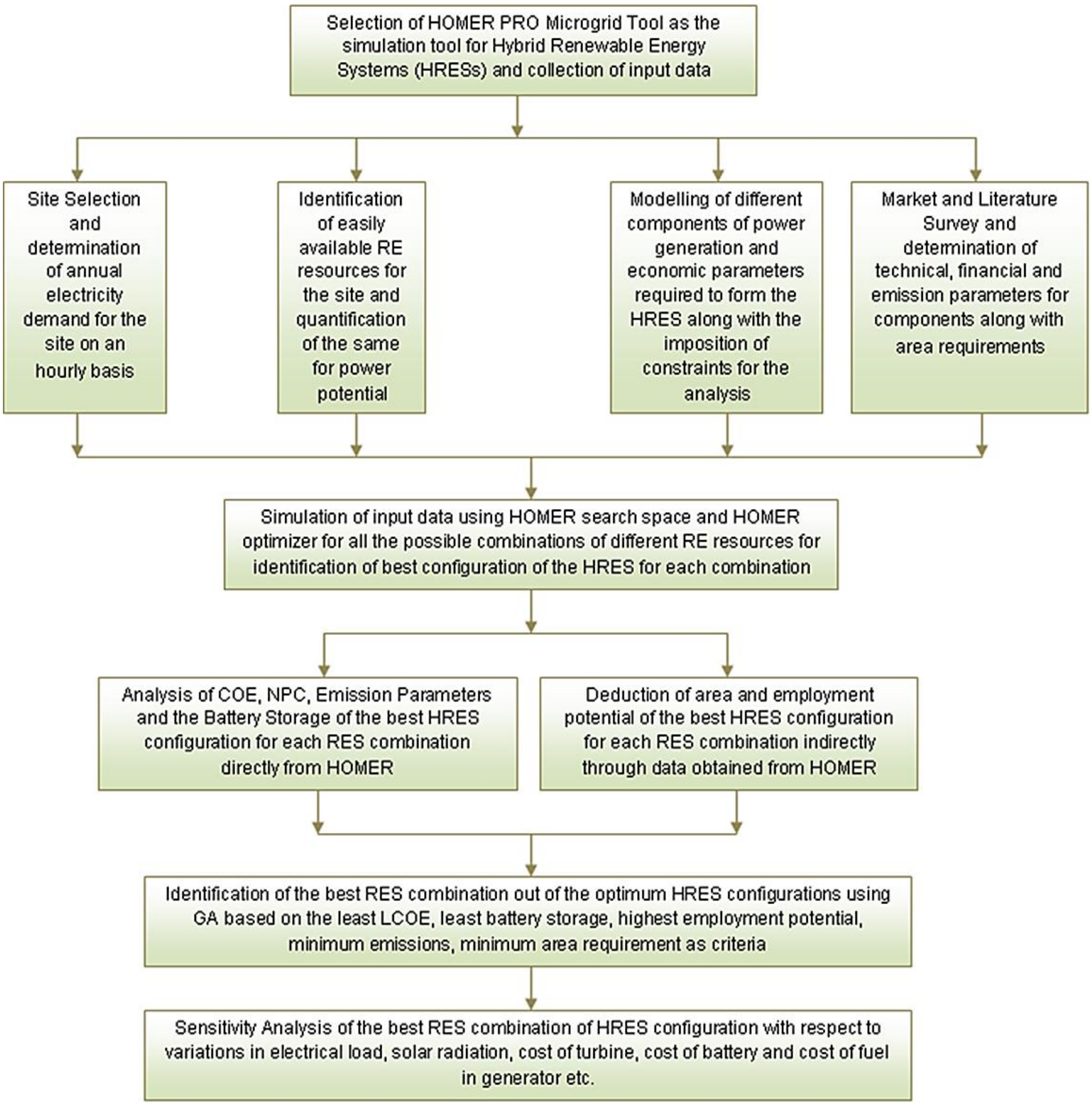


Fig. 6.9: Flow chart of design and development of hybrid model

6.8 VARIOUS RENEWABLE ENERGY SYSTEM COMPONENTS MATHEMATICAL MODEL

Mathematical modelling is an important step in designing a renewable energy-based model because it provides knowledge about the operation and performance of system components under various circumstances [272, 273]. The following sections discuss the mathematical modelling of each component of various RESs for power potential evaluation:

6.8.1 Solar Photovoltaic (SPV) System

PV modules are connected in series and parallel in an SPV system. The output power (P_{PV} (t)) of an SPV system is calculated as follows [272-274]:

$$P_{PV}(t) = N_{PV} \times V_{OC}(t) \times I_{SC}(t) \times FF \tag{6.5}$$

Where N_{PV} denotes the number of SPV modules, FF denotes the fill factor, $I_{SC}(t)$ and $V_{OC}(t)$ denote the short circuit current (A) and open circuit voltage (V) of the S_{PV} module, respectively, and A SPV module's $I_{SC}(t)$ and $V_{OC}(t)$ can be calculated as follows:

$$V_{OC}(t) = V_{OCS} - \tau \times (T_{PV}(t) - 25^o) \tag{6.6}$$

$$I_{SC}(t) = [I_{SCS} + \tau\, (T_{PV}(t) - 25^o)] \times \frac{Q_{PV}(t)}{1000} \tag{6.7}$$

$$T_{PV}(t) = T_{amb}(t) + \frac{T_{PVnm}(t) - 20^o)}{800} \times Q_{PV}(t) \tag{6.8}$$

Under standard test conditions (STC), I_{SCS} and V_{OCS} are short circuit current (A) and open circuit voltage (V) respectively. $T_{amb}(t)$ is the ambient temperature (^oC). $T_{PVnm}(t)$ is the nominal or rated cell temperature in ^oC, $T_{PV}(t)$ is the operational temperature of the solar cell, $Q_{PV}(t$ is the global solar irradiance (W/m^2) incident on the SPV module, ς is the short circuit current temperature coefficient (A/^oC) and τ is the open circuit voltage temperature coefficient (V/^oC).

Furthermore, the fill factor (FF) of an SPV module is calculated as the product of the voltage at maximum power point (V_{mpp}) and corresponding current (I_{mpp}) divided by the product of short circuit current (I_{SC}) and open circuit voltage (V_{OC}) utilising equation (6.9) as:

$$\text{Fill Factor} = \frac{V_{mpp} \times I_{mpp}}{V_{OC} \times I_{SC}} \tag{6.9}$$

The energy generated $E_{PV}(t)$ by the SPV system (kWh) at hour "t" was calculated using equation (6.10) as follows:

$$E_{PV}(t) = P_{PV}(t) \times \Delta t \tag{6.10}$$

where, Δt is a time step of one hour in the current study.

6.8.2 Biogas Generator (BG) System

The BG system's output power $P_G(t)$ is computed as follows:

$$P_G(t) = \frac{Q_G \times F_G \times \eta_G}{860 \times H_G} \tag{6.11}$$

Where η_G and F_G are assumed to be 28% and 4700 kcal/m^3 respectively, H_G represents the number of operating hours of the biogas generator per day. η_G is the overall conversion efficiency from biogas to electrical power production, F_G is the calorific value of biogas (kcal/m^3), which is divided by 860 to convert kcal to kWh, and Q_G is the availability of biogas per day (m^3/day).

6.8.3 Wind Energy Generator System

The manufacturer's actual power-wind speed chart is used to curve-fit the mathematical model of the wind energy generator. According to the following equations, the power output of a chosen wind energy system at hour "t" can be calculated:

$$P_W(t) = \begin{cases} 0, & \text{when } V < V_{ci} \text{ and } V > V_{co} \\ (x_1V^2 + y_1V + \cdots + z_1), & V_{ci} \le V < V_1 \\ (x_2V^2 + y_2V + \cdots + z_2), & V_1 \le V < V_2 \\ (x_3V^2 + y_3V + \cdots + z_3) & V_2 \le V < V_{co} \end{cases} \quad (6.12)$$

Where Vco and Vci and stand for the cut-out and cut-in speeds of a wind turbine, V indicates wind speed in m/s. The quadratic equation's coefficients are denoted as x, y, and z. The energy produced by a wind energy system $E_W\ (t)$ is calculated as follows:

$$E_W\ (t) = N_W \times P_W\ (t) \times \Delta t \quad (6.13)$$

where $E_W\ (t)$ stands for the number of wind turbines.

6.8.4 Battery System

The product of power capacity (kW) and step size can be used to determine the hourly energy production of renewable generators (kWh) (1 hour). Battery operation consists of two states: charging and discharging, depending on supply and demand. The generation from RES exceeds the hourly load demand in the charging state. In contrast, in the discharging condition, the hourly load demand exceeds RES generation. Equations (6.14-6.16) have been used to calculate the battery capacity at hour t during the charging and discharging states as shown in:

$$E_B\ (t) = E_B\ (t-1) + [E_{XW}\ (t) + E_{XM}\ (t) + E_{XG}\ (t) + E_{XPV}\ (t)] \times \eta_{ch} \quad (6.14)$$

Where η_{ch} is the charging efficiency, E_{XPV} *(t)*, E_{XG} *(t)*, E_{XM} *(t)*, and E_{XW} *(t)* are the amount of energy that is left over after the load has been met by the SPV, biogas, biomass, and wind based generator systems, respectively (kWh), E_B *(t)* is the amount of energy that is stored in the battery in kWh.

$$E_B(t) = (1 - \gamma) \times E_B(t-1) - \frac{E_{df}(t)}{\eta_{inv} \times \eta_{dh}} \quad (6.15)$$

$$E_{df}(t) = E_D(t) - [E_W(t) + E_M(t) + E_G(t)] - [E_{PV}(t) \times \eta_{inv} \tag{6.16}$$

where, the term $E_D(t)$ is "hourly load demand" (kWh), $E_{df}(t)$ is unmet or deficit demand that is not satisfied by Renewable energy source (kWh), η_{inv} and η_{dh} shows inverter efficiency and discharging efficiency of battery and γ indicates self-discharging rate of battery at hour t [273, 274].

6.9 SYSTEM DESIGN AND ASSESSMENT

The system configuration shown in Fig. 6.10 includes a PV panel, biogas engine generator, and battery storage with a bidirectional converter. An electric load and biogas generator are connected to the AC bus. The battery storage and PV module are connected to the DC bus. Additionally, the converter is coupled with the AC and DC buses. Table 6.5 shows the technical specifications and capital costs of components.

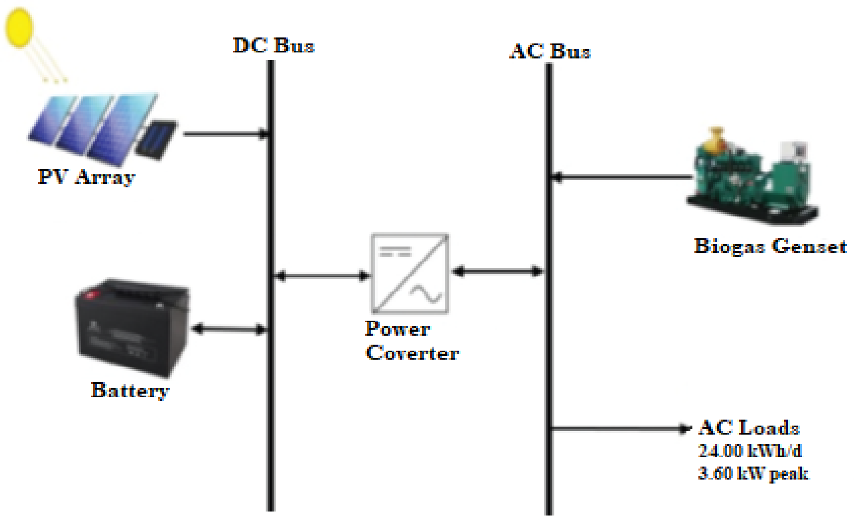


Fig. 6.10: Configuration of off-grid hybrid PV-biogas system

Table 6.5: Technical specifications and cost of components

Hybrid system components	Specifications	Value
Solar PV	Capital cost	650$/kW
	O&M cost	1$/kW
	Replacement cost	0$/kW
	Sizes	0,1,1.5,2,2.5,3,3.5,4,4.5,5,6,7,7.5,8,9,10
	Tracking system	No
	Ground reflectance	20%
	Derating factor	80%
	Life span	25 years
	Azimuth,Slope	0
Converter	Capital cost	190$/kW
	Replacement cost	190$/kW
	Sizes	0,1,1.5,2,2.5,3,3.5,4,4.5,5
	Rectifier efficiency	85%
	Capaicity relative to inverter	100%
	Inverter efficiency	95%
	Life span	20 years
	Annual rate of interest	0%
Battery	Capital cost	150$/kW
	Replacement cost	30$/kW
	Nominal capacity	1kWh
	Float life	5 years
	Round trip efficiency	80%
	Mninmum state of charge	40%
	Lifetime throughput	917kWh
Biogas generator	Capital cost	250$/kW
	O&M cost	0.08$/kW
	Sizes	0, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5
	Replacement cost	150$/kW
	Biomass cost	$3.75/tone
	Lowest load ratio	30%
	Life span	20000 hours

6.10 RESULTS AND DISCUSSION

6.10.1 System sensitivity analysis outcomes

For technical and economical assessment purposes, the system must be designed with certain constraints or control variables that have an impact on the operating costs and output of the HRES system. Because the developed system is sustainable and the possibilities like the changes in solar radiations and biomass supply were taken into account for the sensitivity analysis. Since animal dung is a free source of biomass, hence, the biomass price was not considered in the system design. It enables planners and designers in selecting a very efficient and cost-effective method for the specified design parameters. To find out how variations in solar radiation and biomass supply might affect the system economy, both variables were varied. As the supplied biomass was 6.43 tonnes per day, it varied between 6.43-6.50 tonnes per day for the sensitivity analysis, and the solar radiation varied between 4.91-4.99 kWh/m2/day. The sensitivity analysis outcomes of the HRE system are displayed in Table 6.6, which highlights how changes in the supply of biomass and solar radiation affect the NPC, COE, and operating costs. The findings reveal that as biomass is increased and solar radiation changes are taken into account, net present and operating costs also rise.

Table 6.6: Sensitivity outcomes for the hybrid PV/biogas system

Sensitivity		**Architecture**				**Cost**			
Solar Scaled Average (kWh/mÂ^2/day)	Biomass Scaled Average (t/d)	PV (kW)	Bio (kW)	1kWh LA	Converter (kW)	NPC ($)	COE ($)	Operating cost ($/yr)	Initial capital ($)
4.91	6.43	5	1.5	30	3.25	57283	0.614	4547	8743
4.92	6.44	5	1.5	32	3.25	56901	0.610	4483	9043
4.95	6.46	5	1.5	32	3.25	55964	0.600	4396	9043
4.97	6.48	5	1.5	32	3.26	55345	0.594	4337	9044
4.99	6.5	5	1.5	32	3.25	54762	0.587	4283	9043

6.10.2 System optimization outcomes

The developed hybrid Photovoltaic/biogas system with sensitivity inputs was modelled in HOMER Pro software by ranging the potential of the biogas generator and solar radiance in order to determine the most efficient, optimized, and cost-effective system for the Primary school, Junior school, and Panchayat ghar in rural areas.

To maximize the system's ability to meet the electricity demand, the capacity range of the biomass generator varied between 1kW to 5 kW, while the capacity range of the PV system varied between 4kW to 6 kW. In this study, a 1.50 kW biogas generator, a 5 kW PV array, a

3.25 kW converter, and 30 storage batteries were the optimal and most economically viable configurations evaluated for the hybrid system. This configuration is depicted in Fig 6.10. As NPC, COE, and beginning capital investment are used to sort HOMER's optimum results. The total capital cost, NPC and COE for the best optimized PV-Biogas configuration are, respectively $8,743, $57,283, and $0.614. Other designs with varying equipment sizing that can meet the same energy load have low initial capital costs but high NPC, COE, and operating costs over the lifetime of the project.

Table 6.7: Various different optimized system configurations with economic parameters

Various Configuration	NPC ($)	COE ($)	Operating Cost ($)	Initial Cost ($)
PV/Biogas/Battery/Converter	57283	0.6145	4547	8743
PV/Biogas/Converter	169188	1.8107	15458	4178
Biogas/Battery/Converter	213798	2.3475	19884	1539
Biogas	260688	2.8009	24362	625

Table 6.8: Electricity generation of different feasible system designs

Parameters	PV/Biogas/Battery/Converter	PV/Biogas/Converter	Biogas/Battery/Converter	Biogas
PV array (kWh/year)	7,868 (81.1%)	7,868 (56.2%)	-	-
Biogas generator (kWh/year)	1,830 (18.9%)	6,128 (43.8%)	9,013 (100%)	10,185 (100%)
Total electricity generation (kWh/year)	9,698 (100%)	13,996 (100%)	9,013 (100%)	10,185 (100%)
Renewable fraction (%)	100	100	100	0
Capacity shortage (kWh/year)	0.212 (0%)	143 (1.63%)	2.11 (0.1%)	111 (1.27%)
Excess electricity (kWh/year)	65.0 (0.67%)	5,055 (36.1%)	0	1,466 (14.4%)
Unmet electric load (kWh/year)	0.0000267 (0%)	6.77 (0.0773%)	1.10 (0%)	41.0 (0.468%)

The various system designs with their significant economic parameters are shown in Table 6.7. Table 6.8 also depicts the share of power production of each configuration throughout a year, total electricity production, renewable percentage, and excess electricity with unmet load for all different system designs.

Fig. 6.11 depicts the average monthly electricity production from a hybrid PV-Biogas system, where orange bars show the power supplied by the photovoltaic panel and green bars show the power generated by bio gas generator.

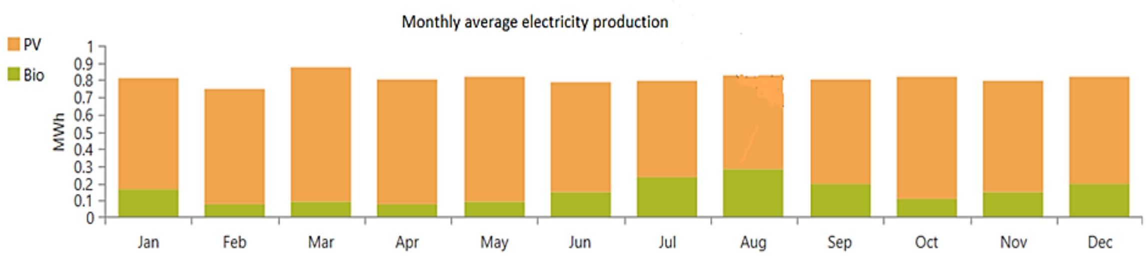


Fig. 6.11: Monthly average electricity generation from the hybrid system

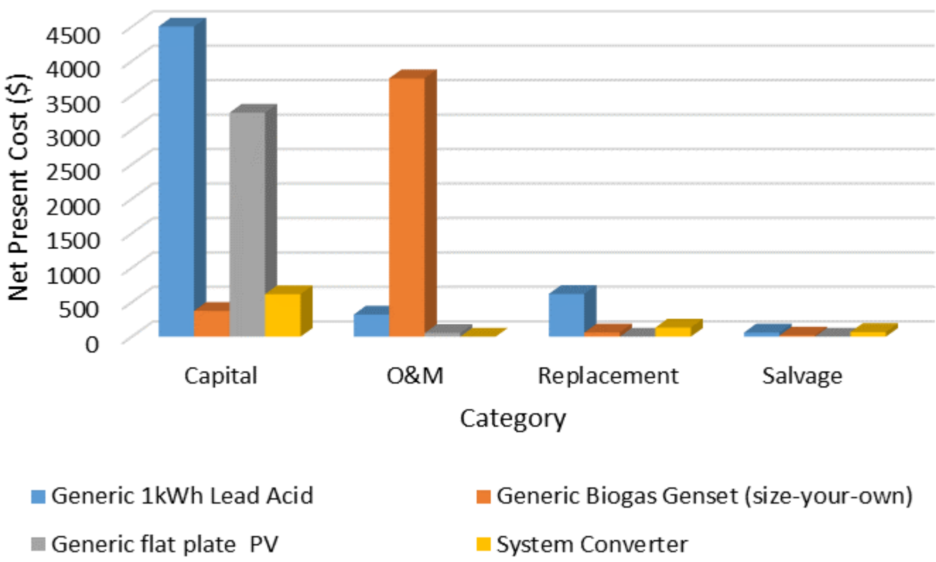


Fig. 6.12: Cost summary of the hybrid PV/Biogas system

The total initial cost is calculated at $8,743 as shown in Table 6.7. This is the first investment needed to start the project. The initial cost of Lead acid battery and photovoltaic panels are more as compared to other components as shown in Fig. 6.12. This higher cost is a result of the substantial battery storage capacity, which is intended to offer reliable electricity dispatch when the electricity produced by the power systems is not enough to fulfill the load. In addition, the photovoltaic panels, which are less expensive once installed than a biogas generator, as biomass is available for free, which is why the fuel category has not been presented. Fig. 6.13 displays the power generated by each component and the total electrical load served is represented in the above plot while the lower plot shows the unmet electrical load, total renewable power output, ac primary load served, input power and state of chage of battery over the course of July 9 to July 18 to help with a better understanding of how the system operates.

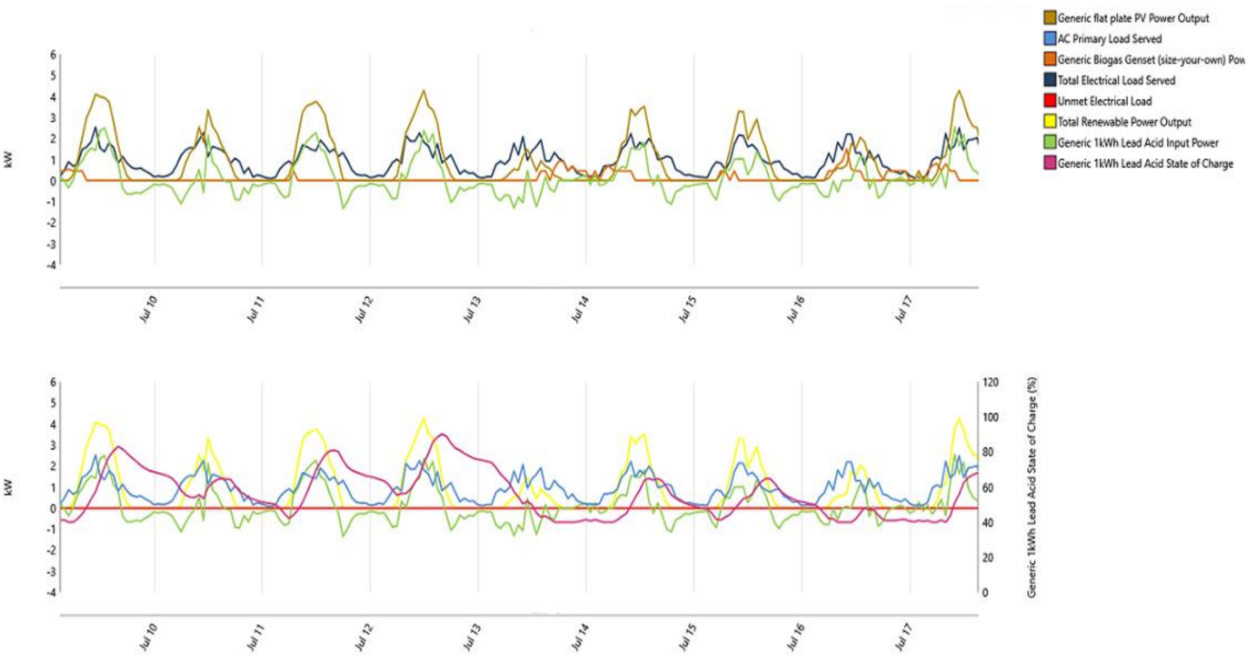


Fig. 6.13: Total electrical load served, unmet electrical load, total renewable power output, state of charge of the battery, ac primary load served and generated power by each component during July 9 to July 18.

Table 6.9: Annual generation and consumption of electricity by a hybrid system

Generation	kWh/year	%	Consumption	kWh/year	%
PV Modules	7,868	81.1	AC primary load	8,733	100
Biogas Generator	1,830	18.9	DC primary load	0	0
Total	9,698	100	Total	8,733	100

Table 6.9 and Fig. 6.11 make it clear that the photovoltaic system consistently outperforms biogas in terms of electricity production. Being off the grid, the system uses solar and biogas as resources to meet the load demands because our maximum demand hours are during the daytime for

community load (schools and panchayat ghar) purposes. The capacity factor of the PV modules is about 81.1%, and it operates throughout the year depending on load requirements, producing about 7,868 kWh/year, compared to 1,830 kWh/year from the biomass generator having a capacity factor of 18.9%. Due to the lack of biomass availability throughout the day, biogas power generation is reduced. Furthermore, the system is producing more power than it needs to satisfy its annual power usage of 8,733 kWh, which can be saved or used for other productive purposes.

6.11 Conclusion

This chapter offers a technical and economical assessment of different stand-alone solutions for Primary school, Junior school and Panchayat Ghar buildings of Sarai Jairam village in Uttar Pradesh, India. HOMER pro analysed several hybrid PV-biogas system configurations by modelling a dynamic hybrid model.

An ideal solution was suggested based on the cost analysis after these hybrid designs underwent sensitivity analysis using variables such as solar radiation, biomass resource, and system sizing. In this study, the combination of a 1.50 kW biogas generator, 5 kW PV array, a 3.25 kW converter and 30 storage batteries was found to be the most cost-effective option with a total capital cost of $8,743, Net Present Cost (NPC) of $57,283 and Cost of Energy (COE) $0.61, respectively. This hybrid renewable energy system produces roughly 9,698 kWh per year, with an additional 965 kWh per year being generated to make the study area grid-independent. Additionally, the system has an estimated payback period of 0.41 years and a favourable net current cost for a projection timeframe of 25 years. By providing rural areas with these hybrid renewable energy systems, the Indian government may significantly contribute to resolving the country's current energy crisis.

Additionally, the existing legislation that supports the use of such systems only offers tax breaks or reductions, which is insufficient to allow low-income populations to make use of these systems. The government may alter its supporting policies, offer rewards for system employment, and launch a national electrification campaign. Similar studies could be undertaken for other rural places in order to electrify them, which would also help the Indian government achieve its goal of "Power to all."

CHAPTER 7

SOLAR PV SYSTEM PARAMETERS OPTIMIZATION TO EXTRACT MAXIMUM POWER

7.1 INTRODUCTION

An optimal and cost-effective system that works in sync with the existing grid must be developed to meet the immense electricity demand with solar energy. In developing countries such as India, the government is creating fantastic opportunities and schemes to promote RESs such as solar power generation [175]. This chapter aims to investigate the economic and efficient production of electricity using solar photovoltaic (PV) systems, as developing an economical and efficient solar PV system is always a challenge for the design engineer. Aside from technical problems, structural factors influence PV module power production. This chapter presents an innovative architecture of a non-movable tracking system that improves PV module energy production by simply providing two grooves in the mounting structure instead of the tracking system.

7.2 PVsyst MODELLING

Scientists and researchers must focus on issues such as generating power economically, minimization of losses and optimal space utilisation from PV solar systems. Several researchers have developed new topologies for inverters as well as DC-DC converters in order to reduce losses and increase production [276]. However, aside from optimum space utilisation, technical features for PV system placement is one of the most important factor for all developers [277]. The research is primarily concerned with generating the most energy possible within the available space. The tracking system has been subjected to research, so as to collect the maximal solar radiation by the Photovoltaic panels. Commercially available trackers include dual axis, single axis, and seasonal tracking, but they have drawbacks in terms of maintenance and initial investment [278-279]. To address these issues and capture the maximal irradiance, this work proposes the module tilt angle (MTA) strategy, which is explained below. Another possible solution to the problem of optimal space utilisation by designers is optimal module placement (OMP). This study demonstrates that the system can be enhanced in efficiency and technically viable by performing a few simple steps during the setup process.

7.2.1 Tilt angle of module

In most cases, when designing a photovoltaic solar power system, the tilt angle of the module should be nearly equal to the latitude of the site or area. To track as much energy and consequently enhance solar power generation, designers preferred dual axis or single axis trackers. However, the placing of trackers is also an issue.

First, the tracking system adds a cost to the project, and second, it requires regular maintenance. Even though companies are working on maintenance-free trackers, this adds to the overall project cost. As a result, the PVsyst report results were investigated in order to analyse this issue and its potential solutions. After accounting for all possible losses, a case study was done using a 5 kW solar photovoltaic system considering a location in New Delhi, India, is modelled utilizing PVsyst software. The details of the case study is presented in Table 7.1 which contains the relevant data. Several intriguing facts were discovered after a close study of the generation pattern over the course of the year. Currently, 2 different tilt angles are taken into account, the first at 30 degrees, which is roughly identical to the latitude of New Delhi, and a second at zero degrees, which keeps the sun right angles to the flat plane. It has been discovered that from April to August, the irradiance collected is greater if the module is at 0°, or horizontal or flat to the surface, while production is greater at 30° slanted module. Thereby, if a space is provided in the mounting structure with only two grooves, one at the identical angle as the latitude and a second at zero degrees to the surface, the irradiance and thus the production of the PV system can be increased by not employing a tracking system.

Table 7.1: Irradiance comparison analysis with various configurations.

Month	Irradiance at 0° tilt obtained based on PVSYST data (in kWh/m^2)	Irradiance at 30° tilt obtained based on PVSYST data (in kWh/m^2)	Irradiance obtained with the proposed configuration based on PVSYST data (in kWh/m^2)
Jan	117.0	167.8	167.8
Feb	138.0	177.2	177.4
March	187.0	214.5	214.5
April	208.0	206.4	207.0
May	221.0	199.7	222.0
June	198.0	171.0	197.0
July	166.0	149.0	167.0
Aug	161.0	151.7	160.0
Sept	170.0	182.4	182.4
Oct	166.0	205.9	205.7
Nov	128.0	184.5	184.7
Dec	116.0	174.3	174.1
Total	1976.0	2184.4	2259.6

Table 7.1 reveals how the proposed method improves the irradiance received by the Photovoltaic system, which leads to increased solar energy generation. The power produced from the 5 kW solar photovoltaic system by PVsyst software has been analysed and validated by comparing the outcomes with the hardware configuration mounted on the rooftop. Fig. 7.1 depicts the experimental setup for the 5 kW system. The following are the specifics of the inverter and solar PV module utilized in the hardware:

Solar Photovoltaic Module Datasheet:

- Number of cells per module = 60
- Module efficiency (η) = 15.2%

- V_{mpp} = 30.72 V
- I_{mpp} = 8.15 A
- V_{oc} = 37.05 V
- I_{sc} = 8.58 A
- Model: PM-250

Inverter Datasheet:

- Efficiency (η) = 98.1%
- Absolute max. PV voltage = 1000 V
- MPP voltage range = 200-900 V
- Max input current = d.c. 2×11A
- ISC PV(absolute maximum) = d.c. 2×16.5A
- Rated grid voltage = ~380/400V
- Max. continuous output current = a.c. 3×8.5A
- Max. AC output apparent power = 5500VA
- Max. AC output active power = 5500W
- Rated grid frequency = 50/60Hz
- Operating temperature range = -25…+60oC
- Model: Evershine TLC5000

Fig. 7.1: Hardware implementation of GCPV system

The results obtained from the software and hardware depicts that energy injected into the grid with 30^o tilt from the hardware setup (in kWh) is less as compared to the energy injected into the grid with 30^o tilt from PVsyst data (in kWh). However, this variation could be owing to environmental parameters like heat and smog. Throughout the analysis of the power produced by the hardware configuration, the level of pollution in Delhi was very high, especially from November to February, and thus the smog in Delhi was too substantial. This explains why there are more differences in the results obtained using hardware and software throughout these months. With no additional financial burden on the project, a simple alteration can produce upto 5% more power per year from the solar photovoltaic (PV) system. In general, the Photovoltaic system is considered for a 25-year period. As a result, with a minor change in the structure, approximately 2000 more units can be produced. In the mounting structure, a groove with two slots must be provided, one with a defined tilt angle based on the area specific and the other parallel to the surface or ground where it is installed.

Based on the results obtained and the data provided in Table I, it can be indicated that the module can be positioned parallel to the surface from April to August, and in the remaining months of the year, panels can be placed at 30^o or latitude angle of the area. This chapter focuses on the two grooves that must be altered only twice a year. As a result, it is an easy approach with no extra cost or labour. The regular maintenance team is capable of carrying out the same. Even so, end users of this technique may use other grooves for greater conversion while saving on labor and maintenance costs.

7.2.2 Optimal module positioning (OMP)

Another important consideration in the design of a solar PV system is optimal space utilisation. By orienting the modules correctly, the area can be maximised. There are primarily two orientations available, vertical and landscape, and the designer must select one of the two.

However, no such guidelines are available. Based on the size and shape of the land, the designer may consider any orientation. This section discusses an investigation that suggests the most efficient manner to place modules in order to maximise production from a limited land area. Furthermore, the number of modules used in parallel-series combinations to establish the array is determined by the calculation of voltage and current. However, no such techniques exist to illuminate the module combination in an array. Combining modules to frame an array remains a tough problem for a product designer because the whole shadow computation or distance between the rows is totally reliant on the size of the array, which has a significant impact on the PV system design calculation. This research analysed various combinations along with the area requirement and shadow calculation, which enables the design team to design photovoltaic (PV) systems with optimum usage of space. The calculation of the PV array row spacing is a crucial task prior determining the required area. Here are the exact PV array row spacing or inter-row space calculations. The several solar Photovoltaic designers use the inter-row distance formula in Equation (7.1) that is correct yet fails to offer an accurate calculation.

$$Shadow\ Lenght = w\ \times (\cos\beta + \frac{sin\ \beta}{\tan\beta}) \tag{7.1}$$

where α = $90^o - (\phi + 23.45)$, β is module tilt angle, ϕ is the latitute of the area, w is module width. This work has proposed a generalised Eq. (7.2) for calculating the inter-row area and shadow length, where β is the tilt angle, w is the module width and θ is the azimuth angle at December 21. The date of December 21 is chosen because the sun's altitude angle is greatest on this day, and thus the shadow length is greatest. A represents the area's altitude angle on December 21. Fig. 7.2 depicts the shadow length calculation quite clearly. This work considers the Delhi site. As a result, the altitude angle (α) and azimuth angle (θ) are assumed to be 28^o and 143.5^o, respectively.

$$Shadow\ Lenght\ (D) = w\ \times\ \frac{sin\beta\ \times \cos(180^o -\ \theta\ )}{\tan\alpha} \quad (7.2)$$

The following parameter calculations are taken into account when designing the experimental setup:

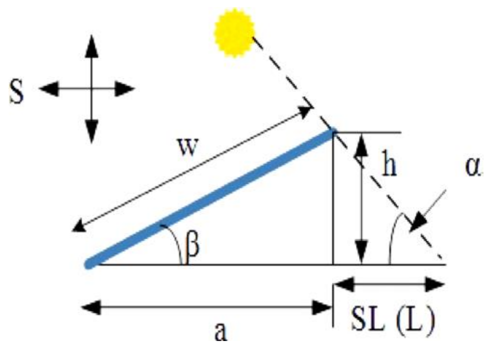


Fig. 7.2: Shadow length calculation

7.2.2.1 Thermal Parameters

Thermal loss factor U = U_C + U_V × Wind velocity, where Uv is the wind loss factor (taken to be 0W/m^2k m s) and Uc is the constant loss factor (taken to be 29 W/m^2k). The module mounting structure is designed as a free-standing module with proper ventilation.

7.2.2.2 Ohmic loss

The 5 kW system is made up of 2 strings of 10 modules each. So every module is rated at 250Wp. Each module's I_{mpp} (current at maximum power point) and V_{mpp} (voltage at maximum power point) and are 8.15 A and 30.72 V, respectively. As a result, the wire's cross-sectional area is computed as

$$A_{DC} = \frac{2\ \times\ L_{DC}\ \times\ I_{DC}\ \times\ \rho}{Loss\ \times\ V_{mpstring}} \quad (7.3)$$

We chose copper wire for the DC side because it has less loss. As a result, the corresponding constant values for copper wire are used here as well. We also factored in a 0.5% voltage drop. $V_{mpstring}$ is the total voltage of the string at MPP. $V_{mpstring}$ is the voltage of the entire string at MPP. In this case, V_{mpp} per module is 30.72 V. As a result, $V_{mpstring}$ = 30.72 × 10 = 307.2 V because a string contains 10 modules.

The unit of ρ is Ω /m mm^2. With the help of equation (7.3), the cross-section of the wire with ohmic losses from the array to the array junction box (AJB) and from the AJB to the inverter for the DC side can be calculated. The losses on the AC side are calculated using standard equations.

7.2.2.3 Mismatch or Module quality loss

The module quality or mismatch loss is entirely dependent on the module manufacturer. The module's datasheet may be useful in this regard. However, the proposed study considers the standard or average module mismatch loss to be 1.5%. Furthermore, loss when running at fixed voltage is assumed to be 4% and power loss at MPP is assumed to be 2%.

7.2.2.4 Soiling loss

If soil or other dust particles are spread over the modules, their efficiency decreases and they do not produce the expected power. This loss is entirely determined by the area. Rajasthan, India, has a sandy terrain, so soiling loss is higher there. In regions such as Delhi, the soil loss are significantly low. This study assumed a soiling loss of 2% per year on average.

This loss can be reduced if a proper PV plant module cleaning schedule is planned and implemented. After calculating the inter-row spacing or shadow calculation, the total optimised precised area (OPA) required is proposed as;

$$OPA\ (in\ m^2) = \left[\left\{w\cos\beta + \left(\frac{w\sin\beta \times \cos(180^0 - \vartheta)}{\tan\alpha}\right)\right\} \times n_r\right] \times [n_h \times l + (n_h - 1) \times d_m + d_a \times (n_a - 1)], \quad (7.4)$$

where n_a denotes the number of array tables, d_a denotes the distance between arrays (in m), d_m denotes the distance between modules for air circulation (in m), l denotes the length of each module (in m), n_h denotes the total number of modules connected horizontally and n_r denotes the number of rows.

The optimized area for a 5 kW test system in Delhi, India, is calculated utilizing the proposed formula. Fig. 7.3 depicts the module dimensions taken for the experimental setup as well as the two different module orientations; vertical orientation and landscape orientation. The test system is 5 kW in size, with every module rated at 250 Wp.

As a result, the proposed system necessitates the use of 20 such modules. These 20 modules were placed in various positions and configurations so that the area requirement could be calculated using the same number and dimensions of modules.

Various module placements have been analysed with these two orientations in mind to figure out the optimal area requirement for setting up the solar photo voltaic plant. Fig. 7.4 and Fig. 7.5 show the distinct layout of modules with vertical and landscape orientation.

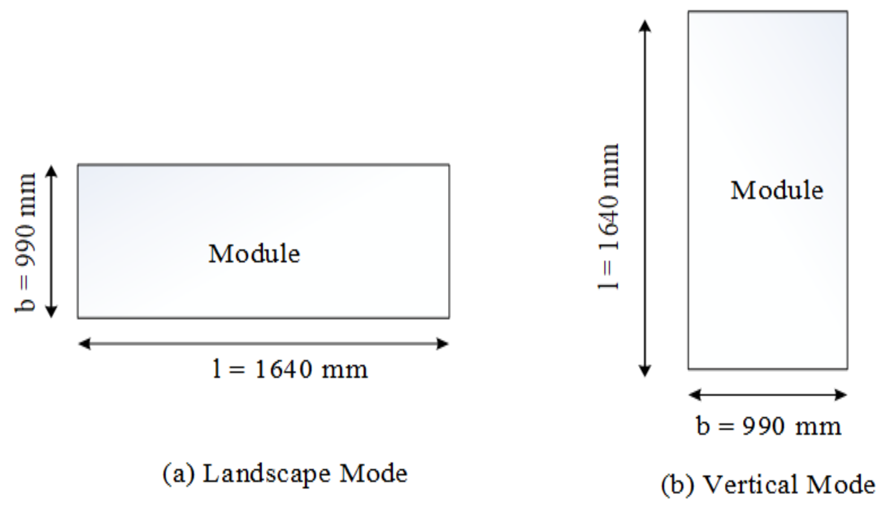


Fig. 7.3: Dimensions and orientation of the test system module

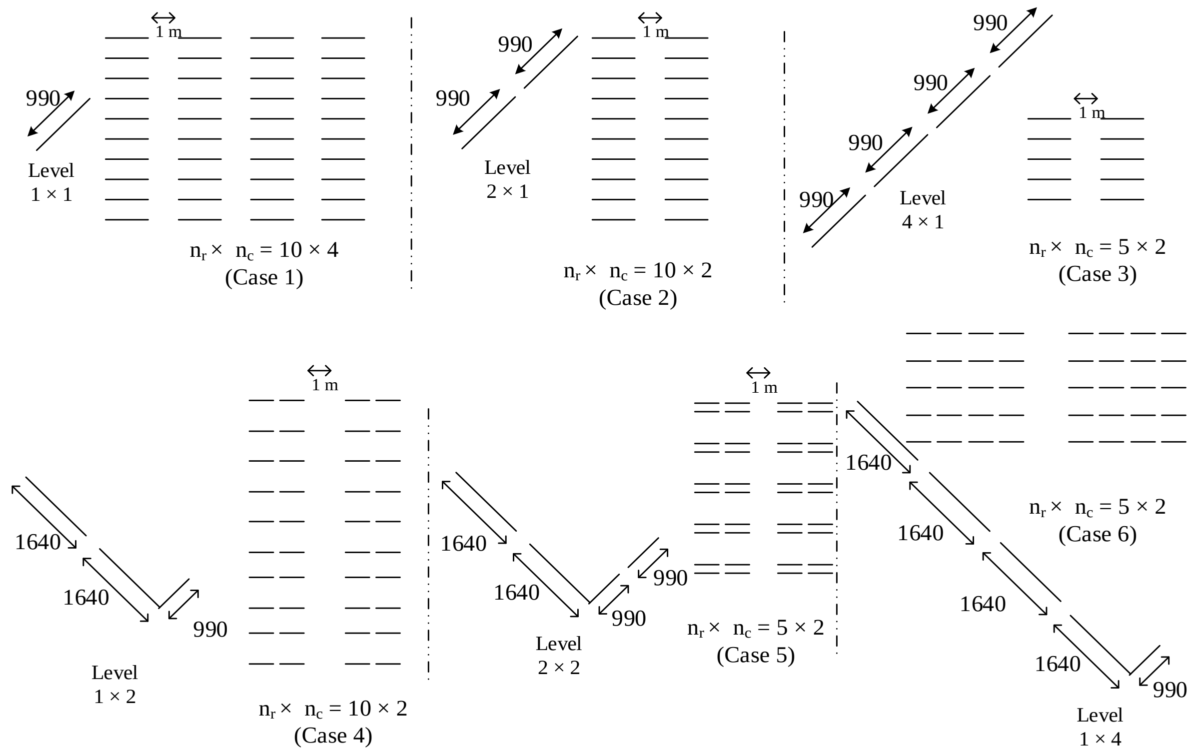


Fig. 7.4: Different module configurations in landscape orientation

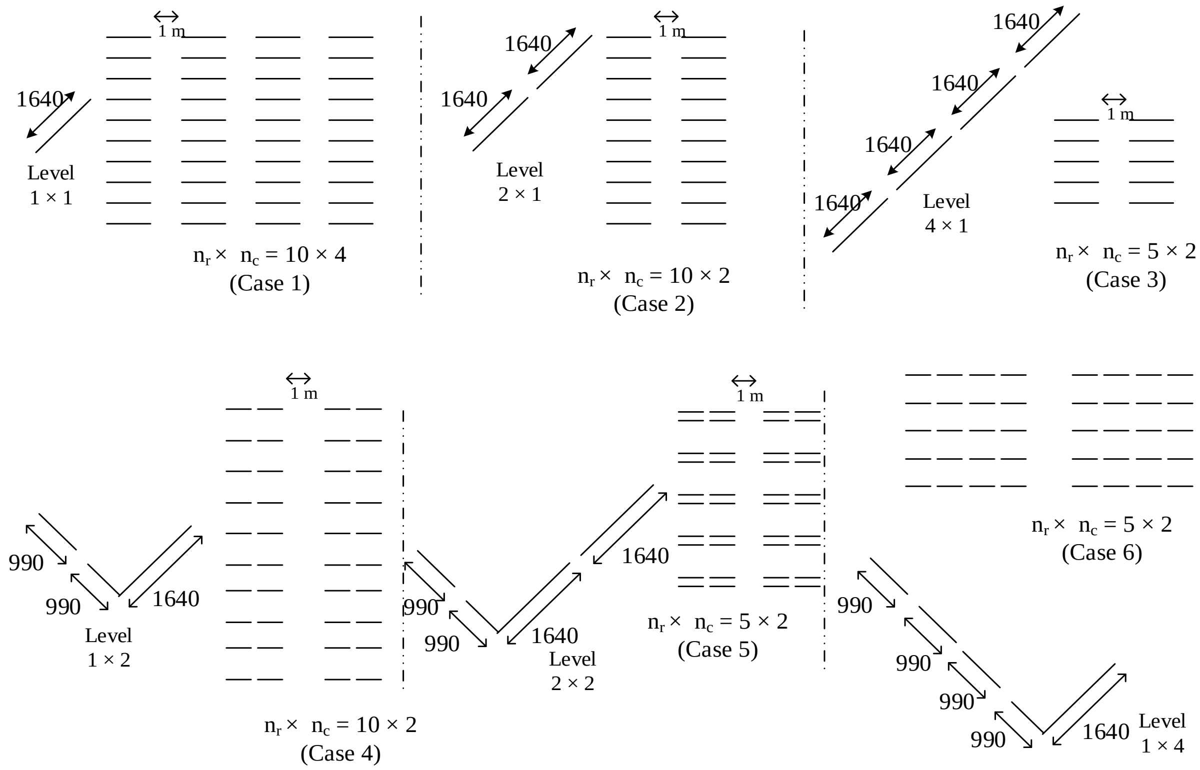


Fig. 7.5: Different module configurations in vertical orientation

It is clearly evident from Fig. 7.4 and Fig 7.5, that area required varies with the placement and orientation of the photovoltaic modules. If the modules are arranged vertically, they will take up more space than if they are arranged horizontally.

It has been discovered that the area requirement varies depending on module configuration. The space required to form a 5 kW solar PV system with the same number and size of modules significantly increases without affecting Photovoltaic systems output generation.

Here, equation (7.4) is proposed to determine the optimised precised area requirement for setting up the solar photovoltaic (PV) system, and then the module placement can be carried out on the field. This will aid in calculating the optimal area requirement and making better use of the available area.

7.3 CONCLUSION

Because of rapid population growth, the need for space or land for power plant installation has become a significant issue nowadays. A solar photovoltaic system is an excellent alternative because it can be installed on the top of buildings and other available waste areas. Even in such cases, optimal space must be used to produce peak energy. In this work, efforts were made to enhance power. In this research, a test system of 5 kWp has been simulated utilising PVsyst software for observation of solar power at different angles of orientation of the photovoltaic panel, and the results have been evaluated by comparing with the hardware configuration. The results obtained for solar energy generation are nearly precise by assessing real-time losses, taking into account the specified geographic area, and using adequate shading computation. In this analysis, two models were proposed: Module Tilt Angle (MTA) and Optimal Module Placement (OMP). The MTA technique increases energy generation upto 5% by modifying the module mounting structure to allow for different module tilt angles.

Furthermore, in the MTA module, distinct case studies with two distinct orientations of the module were conducted, and a formula for calculating space requirements was derived based on their results, hence, the area requirements for the same dimensions and number of modules have been significantly reduced depending on module orientation and arrangement.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

8.1 INTRODUCTION

This chapter describes the most important findings from the research that is carried out in this thesis, as well as some brief suggestions for potential future research tasks. The important original contributions are discussed and listed below.

8.2 CONCLUSIONS OF THE PRESENT RESEARCH

Good prediction models are required to integrate the rapidly expanding wind and solar power sectors and ensure that the electrical grid is always balanced. Based on prior research, this work focuses on short-term power forecasting for Turkish wind farm which is located in the north-western region of Turkey. Renewable power forecasting is crucial when we deal with the smart-grid and integrating renewable sources into the grid to meet the increasing demand of electricity. Based on the past data power requirements can be forecasted and it is most significant to improve power saving strategies and for managing power production, transmission as well as distribution. In addition, advances in RE power technology have created a slew of new obstacles, and the only way to anticipate the proper power generation is to use new machine learning approaches. Currently, power generated from wind turbine is being used on an immense scale as an alternative source of power. Wind power forecasting is difficult due to the intermittent nature of wind. As a result, integrating wind energy into the main grid is a challenging task. Since wind power forecast can never be accomplished error free, so this provokes the researchers to develop intelligent forecasting models. Based on the data of speed of wind and its direction, a comparative analysis of two regression algorithms is done for wind power prediction. To accomplish the desired aim, the SCADA system data from the Yalova wind-farm which is situated in west Turkey, was collected for the time period 1 January to 31 December 2018 (1 year dataset) at 10-min sampling rate to train and test the regression models. The performance evaluation of regression models has been done using various statistical metrics (MSE, RMSE, MAPE, MAE and R^2). The results show that the random forest (RF), k-nearest neighbor (k-NN), gradient boosting machine (GBM), decision tree (DT), and extra tree (ET) regression algorithms are powerful techniques for forecasting short-term wind power. Among these algorithms, the capability of the gradient boosting regression (GBM)-based ensemble algorithm, with a MAE value of 0.0264, MAPE value of 0.3012, RMSE value of 0.0634, MSE value of 0.0040 and R^2 value of 0.9690 for forecasting of wind power, has been verified with better accuracy in comparison with the RF, k-NN, DT and ET algorithms. The performance of the DT algorithm was not satisfactory, with a MAE of 0.0336, MAPE of 0.3309, RMSE of 0.0884, and MSE of 0.0078, although the R^2 (0.9497) values of the DT algorithm were relatively acceptable, with a training time 0.22 sec. The model performances based on the MAE, MAPE, RMSE, MSE, and R^2 metrics are given in Table 4.3. Hence the developed ensemble models are accurate and reliable for hourly forecasts and can be utilized for sustainable balancing and grid integration.

In chapter 5, various forecasting techniques based on ML algorithms was presented to forecast photovoltaic power and the dataset from the Qassim University, KSA, was used to evaluate the proposed models. After analysing the performance metrics of both regression techniques i.e. Random Forest (RF) and K-Nearest Neighbor, it was determined that Random Forest (RF) regression outperformed the other technique in terms of all statistical indicators (MAE 0.0132, MAPE 0.7674, RMSE 0.0191, MSE 0.0003, R^2 0.9953) considered with training time 0.65.

In this thesis, we have introduced high-accuracy machine learning models and demonstrate their effectiveness in forecasting wind and solar power generation. We anticipate that our methodology will provide decision-makers, system operators, engineers and practitioners, in the wind and solar power industry with an efficient method for making decisions using reliable forecasts.

The research area for developing hybrid power systems based on renewable energy have been determined based on the data gathered of un-electrified Primary school, Junior school and Panchayat Ghar buildings of Sarai Jairam village in the Indian state of Uttar Pradesh. In addition, the selected study area has significant potential for solar radiation and biogas that can be used for power generation, according to estimates of their RES potential. The feasibility research has been done in order to determine the most cost-effective and feasible hybrid system, and the generated models are used for applications in schools and Panchayat Ghar buildings. The simulation and comparison of various potential models has been done. According to the NPC and COE data, the PV/Biogas/Battery/Converter hybrid system is the best option for study area. One of the most important considerations is the optimal design or sizing of each hybrid system component because it influences the cost and power security of the system. In this study, the combination of a 1.50 kW biogas generator, 5 kW PV array, a 3.25 kW converter and 30 storage batteries was found to be the most cost-effective option with a total capital cost of $8,743, Net Present Cost (NPC) of $57,283 and Cost of Energy (COE) $0.61, respectively. This hybrid renewable energy system produces roughly 9,698 kWh per year, with an additional 965 kWh per year being generated to make the study area grid-independent. Additionally, the system has an estimated payback period of 0.41 years and a favourable net current cost for a projection timeframe of 25 years. By providing rural areas with these hybrid renewable energy systems, the Indian government may significantly contribute to resolving the country's current energy crisis. In chapter 6, Fig. 6.11 and Table 6.9 make it clear that the photovoltaic system consistently outperforms biogas in terms of electricity production. Being off the grid, the system uses solar and biogas as resources to meet the load demands because our maximum demand hours are during the daytime for community load (schools and panchayat ghar) purposes. The capacity factor of the PV modules is about 81.1%, and it operates throughout the year depending on load requirements, producing about 7,868 kWh/year, compared to 1,830 kWh/year from the biomass generator having a capacity factor of 18.9%. Due to the lack of biomass availability throughout the day, biogas power generation is reduced. Furthermore, the system is producing more power than it needs to satisfy its annual power usage of 8,733 kWh, which can be saved or used for other productive purposes. Although HOMER software gives the size of each component, it has some drawbacks, such as black box coding, longer computing times, calculation and algorithm not evident, lack of hourly variability, and immutable simulation models for system components.

On the current research, it can be concluded that hybrid energy systems, particularly in developing nations like India, are capable of resolving the demand and generation imbalance problems.

The small-scale SPV system is primarily installed on the roof. However, the space issue is always linked to the roof-top system. The investigation was conducted to discuss the two main issues associated with rooftop solar photovoltaic systems: optimum area utilization and increasing the energy output from the prearranged solar system. In this study, two methods were suggested: Optimum Module Placement (OMP) and other is Module Tilt Angle (MTA). MTA technique increases power production upto 5% using the same array of solar photovoltaic modules by making a simple modification to the module mounting structure by introducing special grooves for changing MTA in two fixed positions. Furthermore, in the OMP model, distinct case analyses with 2 distinct module orientations were conducted, and based on the results, a formula to calculate space requirements was developed. The area requirements for the same number of modules and dimensions have been significantly reduced depending on module orientation and arrangement. And hence, the optimal area required by the proposed formula results in significant reduction in space requirement, which can be used for other purposes or to increase the capacity of the solar power plant. The proposed structure was mathematically calculated and designed to simulate. A test system of 5 kWp has been simulated utilizing software for analysis of solar power at several angles of inclination of solar modules, and the outcomes have been satisfactorily compared with the hardware configuration. Results for solar power generation are nearly precise when real-time losses, specified geographic locations, and adequate shading measurements are considered.

8.3 RESEARCH AREA OF FUTURE WORK

The forecast for wind power has been the focus of extensive research. This study has demonstrated its impact on short-term forecasting of wind power produced by turbines in the north western region of Turkey. To increase the forecasting of wind power produced by turbines, more research is necessary. Firstly, machine learning algorithms using wind speed and wind direction as input parameters have produced satisfactory results.

The process of research and development is never-ending. Each end of a study effort marks the beginning of an opportunity for new possibilities for future research. For future study, the following suggestions have been made. These additional tasks can be added to the current work:

- While employing the same input parameters, alternative forecasting models like recurrent neural networks and other machine learning algorithms such as, support vector machines, logistic regression and linear regression should be taken into account or improvement of machine learning algorithms for point forecasts.

- In addition, more meteorological factors should be considered for future studies for more in-depth assessments.
- The forecast accuracy could also be improved in future study, and more machine learning algorithms will be tested using the suggested approaches.
- It is possible to study more areas across several villages, districts, states, etc.
- The analysis may also take into account minor hydroelectric power plants.
- In the current study, every effort has been made to develop the most practical solution for study area that is also the least expensive. Moreover, intelligent techniques or hybrid optimization methods can be investigated, like the School of Fish, the Ant Lion Optimizer (ALO), the Moth Flame Optimizer (MFO), the hybrid PSO-GWO, the hybrid HS-Random Search, etc.

LIST OF RESEARCH PUBLICATIONS

List of papers (s) published in peer reviewed referred international journals:

1. Upma Singh and M. Rizwan, “Analysis of wind turbine dataset and machine learning based forecasting in SCADA-system,” *Journal of Ambient Intelligence and Humanized Computing*, 2022, pp.1-10. DOI: https://doi.org/10.1007/s12652-022-03878-x

2. Upma Singh and M. Rizwan, “Enhancing wind power forecasting from meteorological parameters using machine learning models,” *Journal of Renewable and Sustainable Energy*, vol. 14, 063302, 2022, pp.1-10. DOI: https://doi.org/10.1063/5.0117662

3. Upma Singh, Mohammad Rizwan, Hasmat Malik, and Fausto Pedro García Márquez, "Wind energy scenario, success and initiatives towards renewable energy in India—A review," *Energies* 15, no. 6 (2022): 2291. DOI: https://doi.org/10.3390/en15062291

4. Upma Singh and Mohammad Rizwan, MuhannadAlaraj, and Ibrahim Alsaidan, "A machine learning-based gradient boosting regression approach for wind power production forecasting: a step towards smart grid environments," *Energies* 14, no. 16 (2021): 5196. DOI: https://doi.org/10.3390/en14165196

5. Upma Singh and Mohammad Rizwan, “SCADA system dataset exploration and machine learning based forecast for wind turbines,” *Results in Engineering*, 2022, p.100640. DOI: https://doi.org/10.1016/j.rineng.2022.100640

6. Upma Singh and Mohammad Rizwan, "A Systematic Review on Selected Applications and Approaches of Wind Energy Forecasting and Integration," *Springer, Journal of The Institution of Engineers (India): Series B*, vol. 102, no. 5 (2021): 1061-1078. DOI: https://doi.org/10.1007/s40031-021-00618-1

7. Upma Singh and M. Rizwan, "A feasibility study and cost benefit analysis of an off-grid hybrid system for a rural area electrification," *Solar Compass*, vol. 3 (2022): 100031. DOI: https://doi.org/10.1016/j.solcom.2022.100031

List of paper(s) published in international/national conferences:

1. Upma Singh and M. Rizwan, "Error Evaluation of Short-Term Wind Power Forecasting Models," 3rd International Conference on Inventive Computation and Information Technologies (ICICIT-2021) 12-13 August 2021, pp. 541-559. Springer, Singapore, 2022. DOI: https://doi.org/10.1007/978-981-16-6723-7_41

2. Upma Singh and M. Rizwan, "Comparative Study of Machine Learning Techniques to Forecast Short-Term Wind Power," 2nd International Conference on Smart Data Intelligence (ICSMDI 2022), Trichy, Tamil Nadu, India, 11-12th April 2022, pp. 1-11. Springer, Book: Smart Data Intelligence. DOI : 10.1007/978-981-19-3311-0

3. Upma Singh and M. Rizwan, "Analysis of Fuzzy Logic, ANN and ANFIS based Models for the Forecasting of Wind Power," Proceedings of 2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), October 22-24, 2018, IEEE xplore, pp. 1-7, IEEE, 2018. DOI: https://doi.org/10.1109/ICPEICES.2018.8897445

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