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Solar Power Forecasting in Smart Cities using Deep Learning Approaches: A Review

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Abstract: Solar power forecasting is important in smart cities to balance the energy demand with the energy supply. As solar energy is an inexhaustible clean energy source, it can provide sustainability and bulk energy generation economically. The rapid transition of urban cities into smart cities is increasing power demand in many countries. Solar power is a dominant renewable energy source for the success of smart cities. Solar power generation is purely depends on the photovoltaic (PV) panels and sunlight. Hence, the solar panels can also be installed easily on the rooftop. The reliable power is guaranteed by installing solar panels on rooftop in smart cities. The dependability of smart city functions relies on a steady power supply, making accurate solar power forecasting essential. The paper focuses on exploring the research work done in solar power forecasting. It discusses the functioning of smart cities, describes the importance of solar power for the efficient functioning of smart cities, addresses the challenges of solar power forecasting, and presents the applications of deep learning methodologies such as recurrent neural network (RNN), long short-term memory (LSTM), gated recurrent unit (GRU) and hybrid models in solar power forecasting.

Keywords: Electricity demand, Energy forecasting, Photovoltaic panels, Renewable energy, Sustainable Energy

Nomenclature

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
Bi-GRU	Bidirectional GRU
Bi-LSTM	Bidirectional LSTM
CV	Computer Vision
ED-LSTM	Encoder-decoder LSTM
EL	Electroluminescence
EML	Ensemble Machine Learning
ETR	Extra Tree Regression
ETS	Exponential smoothing
FNN	Feed-Forward Neural Network
GBM	Gradient Boosting Machines
GRA	Grey relational analysis
GRU	Gated recurrent unit
ICT	Information and communication technology
KNN	K-nearest neighbor
LSTM	Long short term memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Square Error
nRMSE	Normalized Root Mean Square Error
PV	Photovoltaic
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
RNN	Recurrent neural network
SAM	Self-Attention Mechanism
SARIMA	Seasonal ARIMA
SVM	Support vector machine
SVO-LSTM	Stacked vector output LSTM
SVR	Support Vector Regression
UAV	Unmanned Aerial Vehicle

1. Introduction

In the modern era, a smart city is an essential infrastructural development required for the growth of developing and developed countries. As the population increases problems like maintenance of public facilities, crime, emergency services, and sanitation also increase in society. The fast-growing population in developed and developing countries necessitates the implementation of smart cities in the country. A smart city is developed by utilizing technology and providing services to society to solve such a problem. It is attained by improving the city infrastructure using sensor deployment and developing high connectedness in the city. Processes like monitoring, collecting electronic data, and providing services on time should be automated in smart cities. The goal of smart city is to reduce waste, improve social connection, enhance policy efficiency, and provide a comfortable and good quality of life. The energy requirement is a crucial resource for sustainable development of smart city in the digital age [1].

Rapid digitalization in many countries has led to energy consumption surpassing energy generation. The increase in the worldwide population is also a hindrance to the energy generation. The automation, increase of industrialization, and utilization of electronic items increase the energy demand. It necessitates the energy sector to find a possible source of energy in an eco-friendly and economical way to maintain the smart city for providing good quality life reliably. Due to the high emission of pollution, the traditional way of generating electricity is not an affordable solution for meeting energy demand in smart cities. Even though it is an easy process, these will cause severe health issues to the people and environment. So, the alternate sources for generating electricity mandates. Among the number of sources, renewable energy sources play a key role in energy generation without pollution in an eco-friendly manner [2]. The solar energy source is a vital energy source for generating energy for urban areas. The installation of panels is easy in urban areas as it requires small space that is not on the land. It supports to mound of the panels on the top buildings and the roof. Once the Photovoltaic panels (PV) are installed, the energy generation is free of cost with the free sunlight. It does not pollute the environment in the form of smoke, sound and light. The following section discusses the model of smart city framework, Smart building, and smart energy.

Solar energy sources are suitable for satisfying smart city energy demand. They should be generated enough as required on all days and at all times. For the success of the smart city, the forecasting of energy is important. If the future demand is known in advance, the power sectors can generate the energy as per the demand. Similarly, the possibility of solar energy generation should also be forecasted by considering all the environmental factors supporting to generation of energy and energy demand. It will help to achieve the reliable functioning of smart cities [3]. The machine learning (ML) methodologies effectively analyse the history of solar energy data. It also helps to achieve an accurate forecasting of solar power. The weather data along with solar data can be considered for improving the ML and deep learning (DL) model forecasting performance. The solar energy has a nonlinear, uncertain, and complex nature. It can be forecasted effectively by employing machine learning and deep learning methodologies by the researchers in the literature.

The smart city framework involves many systems like electricity, waste, water, gas and etc. Hence, smart city is a coordinated system of many systems. The smart city framework is shown in Figure 1. The key technologies utilized in smart cities are sensor technology, actuator engineering, and information and communication technology (ICT) [4]. Smart city framework collects electronic data like electricity, water, waste, and gas from different businesses using sensors and ICT techniques. Then it integrates data and provides solutions to the problems in the environment, citizens, administration work, and economy. It addresses the problems with the environment by reducing pollution. The problems with citizens are addressed and the solution by mobile solutions. It identifies the issues with the economy and provides solutions by establishing an optimal infrastructure. It provides the optimal solution for handling administrative problems by defining an accurate advice bureau. Sensor technology utilizes sensor devices which are electronic devices. It can perceive the physical input from its environment and then it converts it into the data which can be easily interpretable by machines and human beings. Different categories of sensors are available now a days. It helps to capture the nature of the environment like light, pressure, heat, moisture, infrared, color, smoke, tilt, touch, proximity, alcohol, level, and motion at a particular state.

Actuator engineering is used to make movements by converting the input received. The actuator is a device which is a part of the machine. It receives inputs like electricity, air, and water and then converts these inputs into mechanical movement. Information and communication technology is the infrastructure consisting of resources and technological tools for enabling the generation, collection, storage, and sharing of digital information. It supports the modern computing and automation in smart cities. It improves operational efficiency and helps to share information easily in a smart city. It supports improving the quality of government services and the public welfare. The automated sensing of every functionality and resource status, proper communication to the right authorities, servicing departments on the right time and taking the right actions on the right time automatically or manually, reducing inconvenience and providing a comfortable life is achieved in smart cities with these technologies [5].

The solar power has a significant role in smart city functionalities. The reliable operation of the smart city activities can be attained by providing the reliable electricity economically. Even though there is a number of energy sources are available now a days, the solar energy dominates others in terms of it's environment friendly, less space requirement, easy installation and freely available sun irradiation characteristics. The primary objective of the present study is to focus on discussing the significance of solar energy, smart energy, smart grid, possible energy resources for smart city, machine learning and deep learning methodologies utilized by researchers for an effective forecasting of solar power.

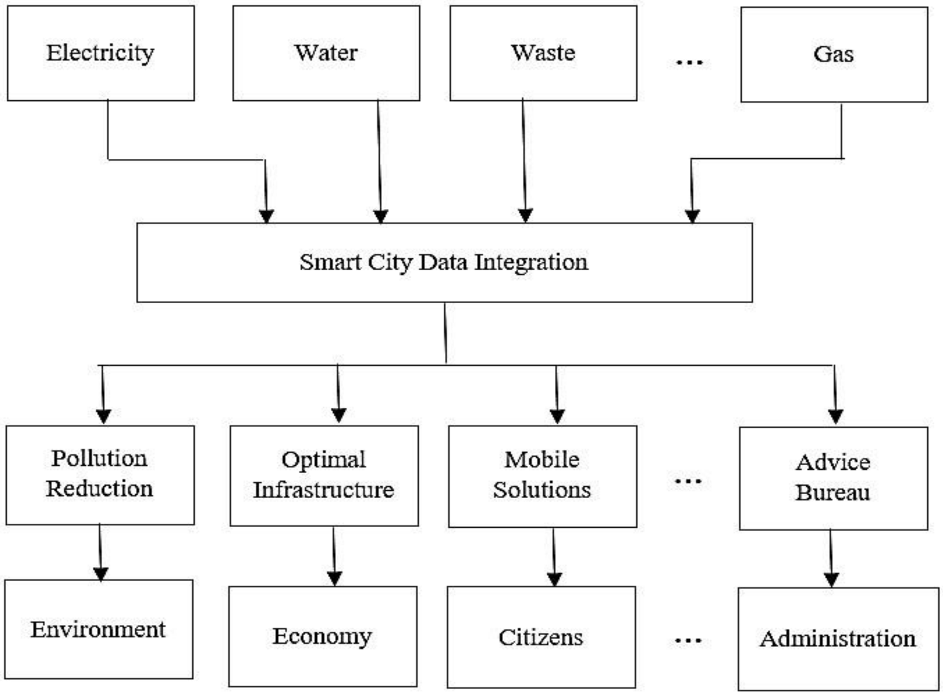

Figure 1. Smart City Framework

This study starts with presenting the framework of smart city and the possible energy sources. Followed by discussing the relevance of smart energy and smart grid with solar energy and smart city. Subsequently, it explores how the solar energy research has been done by researchers, how the ML methodologies helps to forecast the solar energy and how the deep learning methodologies contributes for an accurate solar power forecasting. This study also discusses the challenge of generating and forecasting solar power in smart cities. Finally it discusses the possibilities for the future research in solar power forecasting.

The rest of the study is organized as follows. Section 2 highlights the relationship between solar power and smart energy. It also discusses the role of smart grid with solar energy in smart city functionality. Section 3 describes the challenges of implementing solar plants and generating solar power in smart cities. Section 4 shows the significance and the trend of solar power forecasting. It discusses the research done by researchers from variety of countries on forecasting the solar power. Section 5 presents the applications of machine learning methodologies in forecasting the solar power. Section 6 provides the applications of deep learning methodologies like RNN, LSTM and GRU in forecasting the solar power. Section 7 concludes the present study.

2. Smart Energy

Energy management with innovative modern technology is the smart energy that is achieved in smart cities using smart grid. The smart grid is an important resource for maintaining smart city activities. It provides the required electricity on demand and minimizes the downtime. The traditional way of monitoring the energy utilization of consumers is the installation of mechanical meters and recording the energy utilization every month. It may misguide the energy forecasting process with the missing of timely data. But with the smart meters, it can be implemented effectively. Since the smart meters are digital, they provide the timely monitoring of the consumer's energy utilization and help to find the accurate energy demand. The reliable functioning of the smart city is achieved by supplying the required energy for demand on time. So, the energy should be forecasted accurately to maintain the equilibrium between energy demand and energy supply.

The power sector's energy manufacturers generate energy in numerous ways. But these all are not free from the negative impacts like pollution. The technological development permits the power sectors to generate energy easily from renewable energy sources. There are several sources for generating electricity. Renewable energy sources dominate others due to their eco-friendly and pollution-free nature [2, 3]. Though there are many renewable energy sources like wind, biomass, water, marine, and geothermal energies available, solar energy is the suitable energy source for the smart city success.

It can be replenished in a shorter period. Figure 2 shows the types of renewable energy sources.

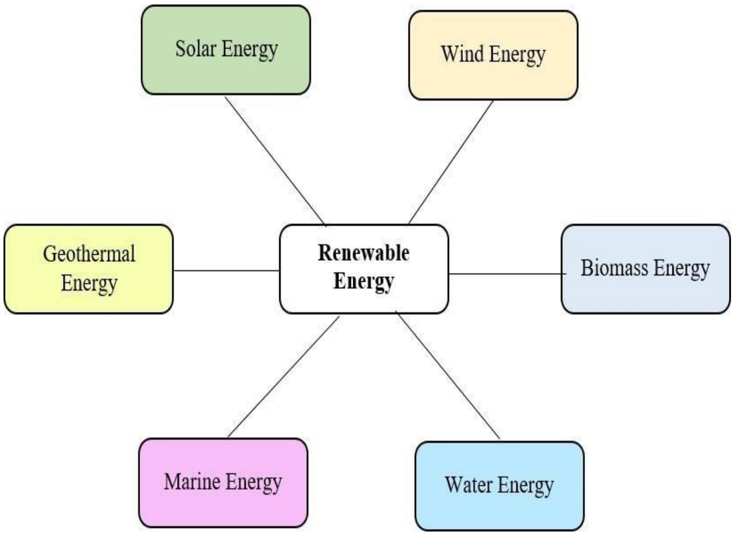

Figure 2. Renewable Energy Resources

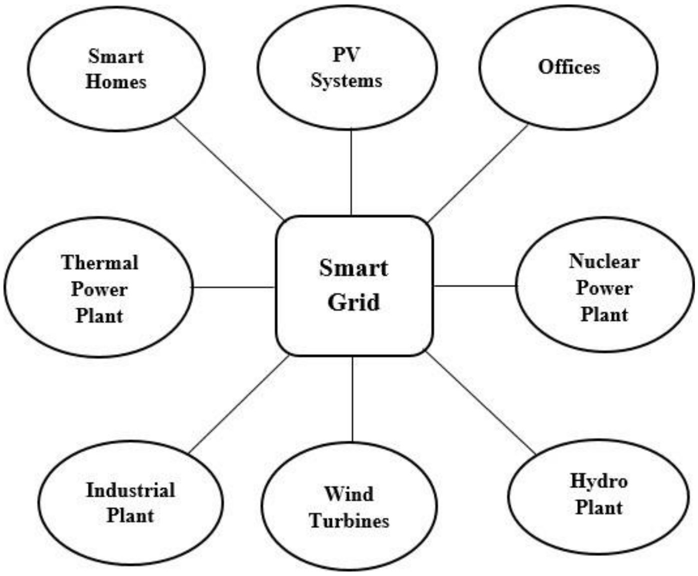

Figure 3. Integral Parts of Smart Grid

Solar plants require minimal space on rooftops and free sunlight for installation and power generation. It is abundant in nature. The development of smart buildings and smart homes can be attained easily by using smart grids. The houses and buildings provide a safe and comfortable life to the occupants. The technological developments and the innovation in the novel materials utilized for the construction fulfil this comfort to occupants. Smart buildings are an integral part of the smart grid [6]. The smart grid is mandatory for integrating the reliable functioning of smart homes, industrial plants, wind turbines, nuclear power plants, thermal power plants, photovoltaic systems, hydropower plants, and offices in cities. A smart city has many dimensions like a smart environment, smart people, smart economy, smart living, and smart governance [7]. The smart grid integration with multiple parts is illustrated in Figure 3.

3. Challenges in Solar Power Forecasting

Solar power generation employing photovoltaic (PV) panels with photovoltaic cells for the transfer of sunshine energy into electricity directly or indirectly. The defect-free PV panels only contribute to solar power generation. So, the maintenance and detection of solar panels is a big challenge for the accurate generation of solar power. A solar cell is a device having electrical properties that converts light energy into power when light falls on it. Singular devices of solar cells are generally used as solar panels.

The defect in solar panels is a great challenge for solar power generation. The solar energy is one of the most frequently used renewable sources of energy for commercial and residential uses in smart cities, is expected to expand at a 15% annual rate. Even though solar energy is commonly used, the one-time installation fee for the panel has not been reduced. Even a small defect in the solar panel will affect greatly the solar power generation. So the solar panel defect detection should be carried out at the earlier stage itself for the economic operation of solar power generation. The management and the maintenance of the solar panels are essential for the effective solar power generation and forecasting. The solar panel defect is a big challenge for the solar power forecasting.

An effective deep learning methods with pretrained models and transfer learning like techniques can be utilized for the detection and classification of solar panel defects. The incorporation of AI techniques for automating the detection of these defects will improve the solar power forecasting accuracy by detecting the panel issues at the earlier stages itself [8]. Several techniques are used to ensure that the solar PV screens are defect-free. Electroluminescence (EL) examination of solar panels is used by companies. An electricity is transmitted through PV cells during this process, resulting in light output. PV makers will use the EL test to identify and assess any flaws in the model. Artificial Intelligence (AI) is assisting in the answer to the issue. The comparatively new AI and CV techniques of solar panel testing are fast, cost-effective, and precise.

AI-based algorithms are used to identify problems in images autonomously [9, 10]. A drone or Unmanned Aerial Vehicle (UAV) is another way for AI-powered examination. UAVs generate overhead pictures that allow solar field workers to operate in a contactless manner. The pictures gathered by the UAV are processed using deep learning, machine learning, and computer vision techniques. The algorithm's output will inform the standard controller about the state of the solar panels. By surveying the complete facility in a few hours, AI-based techniques for automated defect classification can save money and effort. The choice of location based tagging can quicken the examination and thus increases productivity. With the proper maintenance and management of solar panels the forecasting of solar energy can be accurately performed. Numerous solar panel manufacturers in India are attempting to deliver defect-free goods to market.

4. Research on Solar Power Prediction

The research on solar power has a dominant role in research communities now a days. The transformation of the developed cities into smart cities relies on sufficient power supply. The power demand in smart city can be easily supplied from the solar power generation. As photovoltaic (PV) technology advances, the solar energy contributes a larger share of the global energy mix. However, the solar power is inherently variable in nature, the solar power generation should be forecasted in advance to maintain the reliable supply of solar power to smart cities. An accurate solar power forecasting is also crucial for attaining the reliable energy supply. But it is crucial for optimizing the integration of photovoltaic systems into energy grid. Accurate forecasting of solar PV power generation has an impact on reducing photovoltaic power uncertainty effect. It also improves the system reliability, maintains the power quality, and increases the photovoltaic systems's penetration level [11].

The research on solar power forecasting has been carried out using numerous methodologies and technologies with the aim of enhancing the reliability and accuracy of solar power generation forecast. This forecasting can be categorized into three major types based on the methodology used namely physical methods, statistical methods and hybrid methods. The physical methods like numerical weather predictions rely on the physical parameters like, ambient temperature, cloud coverage, cloud density, cloud thickness, precipitation, solar irradiance, sky conditions, site details, site location, panel orientation, historical data and atmospheric conditions. The statistical methods has been utilized for solar power prediction are time series models like Exponential smoothing (ETS), Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Regression models like Linear regression, Multiplelinear regression, Polynomial regression, machine learning models like support vector machine (SVM), decision tree (DT), Gradient Boosting Machines (GBM), random forest (RF) and deep learning models like RNN, LSTM & GRU. The combination of more than two methods as a hybrid method also utilized for gaining the benefits of all the models and reducing the complexity of forecasting [11].

Based on the time horizon, the solar power forecasting is categorized into four types like very short, short, medium and long term forecasting. The very short term solar power forecasting is done for the time duration which is less than 1 minutes. It is essential for controlling the power distribution. The short term solar power forecasting is done for the time duration which ranges from 1 hour to many hours. It is essential for ensuring the commitment, scheduling and dispatching. The medium term solar power forecasting is carried out for a week to a month. It necessitates for preparing the proper planning and maintenance schedule.

Table 1. Research trend on solar power prediction - Scopus database from 2010 to 2022

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Number of documents	44	58	89	106	135	161	200	239	328	361	397	540	728

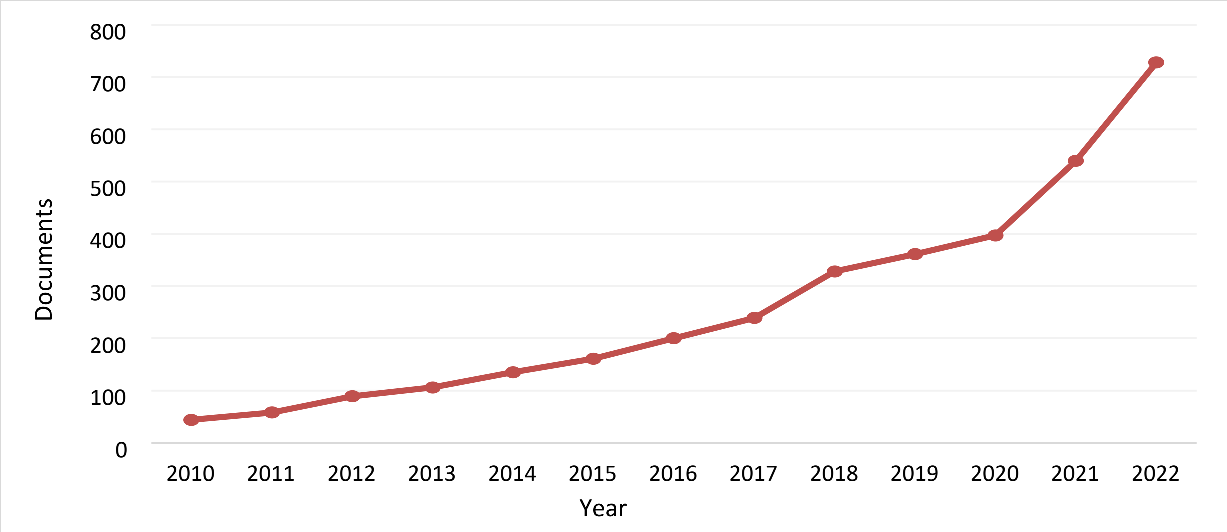

Figure 4. Research growth on solar power prediction: Scopus database from 2010 to 2022

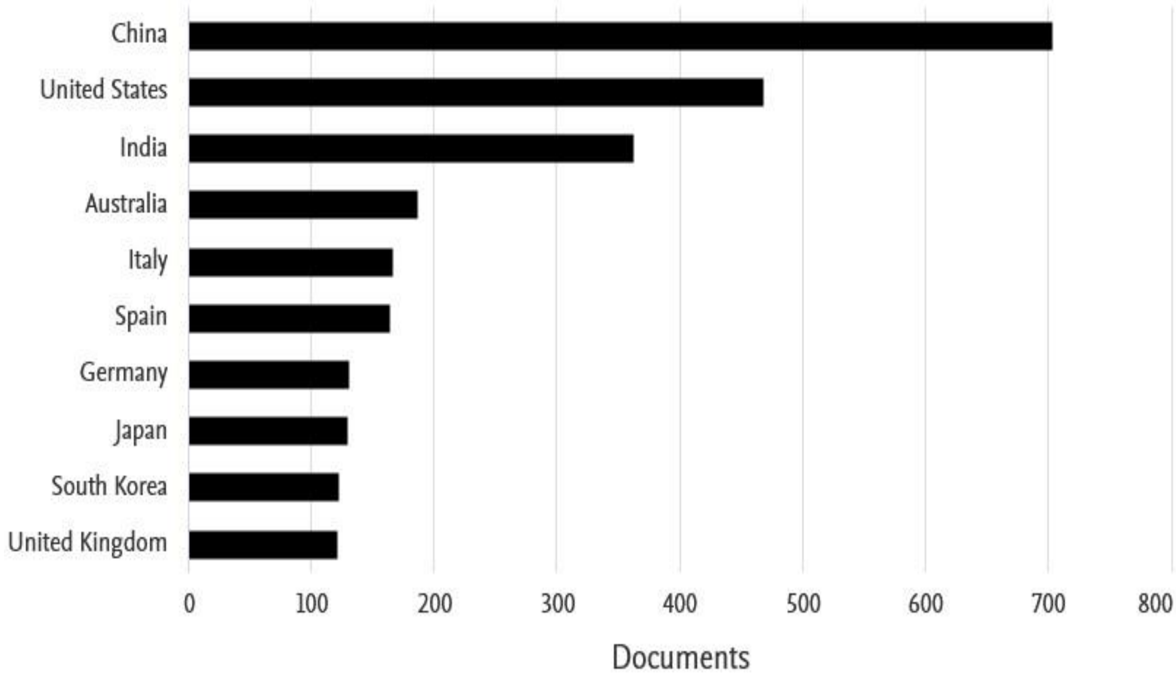

Figure 5. Research on solar power prediction: Scopus database from 2010 to 2022

The long term solar power forecasting is performed for a month to a year duration. It is important for the power generation transmission and also for the distribution [11]. The significance of the solar power forecasting is the predominant research domain in recent years. The Scopus database shows there has been a drastic increase in research in solar power forecasting in the last 10 years. The search in Scopus database as TITLE-ABS-KEY (solar AND energy AND prediction OR solar AND energy AND forecasting OR photovoltaic AND power AND prediction OR photovoltaic AND power AND forecasting) from 2010 to 2022 provides 3386 documents. Table 1 shows the research on solar power prediction increases every year. It also shows that there has been a rapid increase in documents indexed in Scopus in the last two years.

The introduction of automaton and smart city concepts triggered the remarkable growth of research on solar power prediction. The growth of research on solar power prediction based on Scopus database from 2010 to 2022 is shown in Figure 4. This research trend not only increases in India. Almost all developing and developed countries concentrate on solar power prediction. It is graphically shown using bar chart in Figure 5. The top 10 countries indexed the research documents on solar power prediction in Scopus database are China, United States, India, Australia, Italy, Spain, Germany, Japan, South Korea and the United Kingdom.

5. Applications of Machine Learning Methodologies in Solar Power Forecasting

In the modern era, everything is smart. The developed city with automated networks and communication makes the ultra-modern living to the people. Solar power relies an important role in smart cities. The energy requirements of automated and well-connected cities can be effectively fulfilled by using solar energy. As it is a never-ending source of energy from sunlight and requires minimal space on rooftops, it dominates other renewable energy sources in attaining smart city reliability. The solar energy source has numerous benefits like eco-friendly, easy maintenance, easy installation, electricity bill reduction, and easy installation in remote locations. The forecasting of solar power has been done by many researchers using physical methods, heuristic methods, statistical methods, ML and DL methods [12, 13]. The following section discusses the review of related work done for predicting solar energy. The machine learning methods support the better solar power forecast compared to physical and statistical methods [14, 15]. The popular machine learning methods include K-nearest neighbor (KNN), artificial neural network (ANN), light gradient boosting machine, and random forest. The ML methods with feature selection and optimization techniques also guarantee an improvement in solar power forecast [16 - 18]. Table 2 shows the sample of related research work done using machine learning methods.

Almadhor *et al.* [19] introduced ML based prediction model for solar power by integrating statistical analysis methodologies with ML methodologies. The model provided a useful suggestion to Mashhad and Iran for forecasting the generation of electricity power. The power requirement is calculated by measuring the mean sun irradiance at a particular spot. The artificial neural network (ANN) using linear regression is utilized to forecast solar power.

Table 2. Research on solar energy forecasting using machine learning methodologies

Sl. No	Author & References	Methodologies	Performance metrics	Remarks
1	Almadhor et al. [19]	ANN using linear regression	Root Mean Square Error (RMSE)	Achieved 99.9% reliability rate for the summer and winter seasons solar power forecast
2	Mubarak et al. [21]	ETR, SVM, DT, KNN, FFN	RMSE,Mean Square Error (MSE), Mean Absolute Error (MAE), R^2	ETRs outperformed other ML algorithms. ETR; RMSE = 59.17 MAE= 39.07
3	Chakraborty et al. [20]	ML models: KNN, Linear regression, ElasticNet, Bayesian ridge regression, Ensemble ML models (EML): Voting regressor, light gradient boosted machine, Histogram gradient boosting regressor, Gradient boosting regressor, XGBoost regressor, AdaBoost regressor, ETR and Stacking regressor	RMSE, R-Squared (R^2)	Most of the ensemble methods guaranteed a precise prediction result by considering the impact of weather parameters
4	Mantri et al. [22]	Logistic Regression, RF, LR, DT, SVR	RMSE, MSE, MAE	Random forest achieved better forecast than others with an accuracy of 88.28%
5	Sun et al. [23]	DEMSE: Dynamic ensemble model for solar energy	MSE, MAE	DEMSE achieved better results than static ensemble model and other methods

The forecast result shows that the model achieved a 99.9% reliability rate for the summer and winter seasons. Chakraborty *et al.* [20] presented a prediction model for solar power generation that considered the meteorological parameters as an additional input for the ensemble learning methodologies. The prediction was done by using machine learning like linear regression, Bayesian ridge regression, KNN & ElasticNet regression, and also ensemble machine learning methods like voting regressor, light gradient boosted machine, gradient boosting regressor, XGBoost regressor, AdaBoost regressor, extra-tree regressor & histogram gradient boosting. The results represent many of the EML methods performed well compared to machine learning methods.

Mubarak *et al.* [21] presented a prediction model for solar photovoltaic energy using machine learning models with thin film technology. The methodology used is Extra Tree Regression (ETR) and it is compared with methodologies like support vector machine (SVM), DT, K-nearest neighbor (KNN), and feed-forward neural network (FNN). Mantri *et al.* [22] suggested a model for the prediction of solar energy. The methodology used is random forest regression and compared with methodologies such as SVR, logistic regression, decision tree, and linear regression. Sun *et al*. [23] designed a model to predict the solar power generation. The dynamic ensemble model is utilized for forecasting solar energy generation and it is compared with support vector regression and decision tree. The dynamic ensemble model outperformed the static ensemble model for solar energy and state-of-the-art methods.

6. Applications of Deep Learning Methodologies in Solar Power Forecasting

The uncertain, non-linear, and dependence of many climate factors complicates and pulls down the solar power forecasting performance. But the deep learning methods can analyse effectively the dataset with these characteristics [6, 14, 24, 25]. The deep learning methods with feature selection also guarantee an improvement in solar power forecasting. The dominant deep learning methods that proved the improvement in solar power forecasting are RNN, LSTM, GRU, and the combinations of multiple methodologies and techniques. The following section discusses the related works done using these methodologies.

6.1 Research on Solar Power Forecasting using Recurrent Neural Network

The RNN is a type of deep neural network suitable for sequence modelling. It can analyse effectively the sequence dependency that exists in time series data. Unlike feed-forward neural networks, RNN is designed to handle the input data with some sequence dependency characteristics. As the solar power irradiance and the related weather data are time series in nature, the sequence dependence pattern hidden in the historical data provides an efficient input for an accurate prediction of future solar power generation. The RNN based forecasting models can retain the sequence dependence data from the input for the future computation. Hence it guides the prediction process in the positive direction to achieve better accuracy. Li et al. [26] developed a photovoltaic power forecasting model which is based on recurrent neural networks. The model prepared an intra-day and interday data by dividing the input time series data. Then it discovered the non-linear features and the invariant structures from that using RNN. This model's performance was compared against the persistence model, SVM, back propagation neural network, LSTM and radial basis function. The simulation result showed that the RNN outperformed others. Khan *et al.* [27] performed an analysis of photovoltaic power forecast using Seasonal autoregressive integrated moving average (SARIMA), recurrent neural network-based LSTM, and bidirectional LSTM. The results proved that the RNN is the best method for photovoltaic power forecast. Hence it proved that the Bi-LSTM is the suitable method for the photovoltaic power forecast with the cloudy dataset.

Alzahrani *et al*. [28] presented a prediction model for solar irradiance using RNN. The deep learning-based RNN accurately predicts solar irradiance by effectively extracting the relevant and needed features from the input. The performance of the Deep RNN outperformed the FNN and SVR. Mishra and Palanisamy [29] suggested a model for solar forecasting with a multi-time horizon using RNN. The suggested unified architecture outperformed a model for each time horizon. Jaihuni et al. [30] designed a deep model for forecasting 5-minute interval solar irradiance. The author developed three unidirectional deep learning methods such as RNN, LSTM, and GRU. The author also developed two bidirectional deep learning models such as Bidirectional-LSTM and Bidirectional-GRU. The results of the experiment highlights the bidirectional models BI-LSTM and Bi-GRU provided better accuracy than unidirectional methods. Among these bidirectional methods, the Bi-GRU outperformed Bi-LSTM by producing less MAPE of 46.1 and a high R^2 of 0.958. Table 3 presents some samples of related research works done using recurrent neural network.

6.2 Research on Solar Power Forecasting using Long Short Term Memory

The deep learning method RNN can keep the past computation in each cell of the RNN network. But this information can be kept for a short-term period only. So the variant of RNN named long short-term memory was introduced. It overcomes the difficulties of maintaining the past computational results in each cell by maintaining it for a long period in that cell [31].

Many researchers utilized LSTM for solar power forecasts, solar radiance forecasts, solar power generation forecasts, and photovoltaic power forecasts. Table 4 presents a sample of related research work done using LSTM. Singh *et al.* [32] suggested a model for solar energy prediction using GRU and LSTM. The comparative analysis of these methods against random forest, SVM, and K-nearest neighbor was done. The performance metrics used are Mean Square Error and mean absolute error. Deep learning models GRU and LSTM outperformed machine learning algorithms RF, KNN, and SVM in terms of MSE, RMSE, and MAE. Thus, deep learning algorithms are more preferable. Sultanuddin *et al.* [33] suggested a model to forecast the solar power generation. The hybrid deep learning is employed which combines the concepts of clustering, CNN, LSTM, and attention mechanism. Model performance is evaluated by comparing it with DNN-based deep learning algorithms. The suggested hybrid model achieved an improved performance than other models.

Table 3. Research on solar energy forecasting using deep learning based recurrent neural network

Sl. No	Author & References	Methodologies	Performance metrics	Remarks
1	Li *et al.* [26]	RNN	MAE, RMSE, MAPE	RNN discovered the non-linear features and also discovers invariant structures in an intraday and inter day data efficiently
2	Khan *et al.* [27]	RNN Bi-LSTM	RMSE, R^2, coefficient of variation of RMSE (Cv RMSE)	Photovoltaic power forecast using RNN proved the better accuracy. Bi-LSTM with the cloudy weather data provides a remarkable accuracy of Photovoltaic power forecast.
3	Alzahrani *et al.* [28]	Deep RNN	MSE, RMSE, Mean Bias Error (MBE)	Deep RNN extracts high level features from the input and accurately predicts the solar irradiance compared to SVR and FNN
4	Mishra and Palanisamy [29]	RNN	MSE	RNN achieved better performance for multi time horizon solar forecasting with unified architecture compared to one model for each time horizon.
5	Jaihuni *et al.* [30]	RNN, Bi-RNN	RMSE, R^2	RNN and bidirectional RNN works well for solar irradiance forecast with less data and high variability. Bi-GRU & Bi-LSTM works better than its unidirectional networks. RMSE = 46.1 R^2 = 0.958

Table 4. Research on solar energy forecasting using deep learning based long short term memory

Sl. No	Author & References	Methodologies	Performance metrics	Remarks
1	Singh et al. [32]	LSTM, GRU	MSE, MAE, RMSE	GRU and LSTM outperformed in forecasting the solar photovoltaic power compared to RF, KNN and SVM.
2	Hamberg [34]	Encoder-decoder LSTM (ED-LSTM), Stacked vector output LSTM (SVO-LSTM)	RMSE	ED-LSTM produced 26.63% extra accuracy in solar PV power forecast and 44.96% extra accuracy in solar PV power forecast with meteorological factors than persistence model.
3	Sharma *et al.* [35]	LSTM with Nadam optimizer	RMSE, MSE	LSTM achieved better performance with Nadam optimizer than other optimizers, ARIMA and SARIMA.

4	Chen and Chang [36]	LSTM with Pearson coefficient	MAE, RMSE	Prediction model LSTM with Pearson coefficient feature selection reduced the noise of PV power and produced an accurate forecast.
5	Leelavathi and Suresh Kumar [37]	LSTM	MAE, MSE, RMSE	LSTM network reduced the overfitting issues and achieved an accurate solar power forecast.
6	Zafar *et al.* [38]	LSTM-RNN with k-means clustering	RMSE, NRMSE, MAE, NMAE	Hybrid LSTM-RNN with clustering achieved accurate solar irradiance forecasting than conventional LSTN-RNN, SVM, FNN and persistence model.
7	Jailani *et al.* [39]	CNN-LSTM	MAE, RMSE, nRMSE, MAPE	Hybrid model achieved better forecast accuracy than standalone and machine learning models.
8	Chen *et al*. [40]	GRA-LSTM: Grey relational analysis long short term memory	RMSE, MAPE, R^2	Similar hours from the input historical data is selected by GRA. The mapping of non-linearity between weather and power data is done by LSTM. As a result GRA-LSTM outperformed GRA-BPNN, GRA-RBNNF and GRA-Elman

Hamberg [34] developed an LSTM-based model namely encoder-decoder LSTM and stacked vector output LSTM for solar PV power forecasting. This hybrid methodology is the combination of multiple methodologies. It is designed to avail the benefits of all the methods in a single model. The forecast models accuracy can be easily improved by employing hybrid models compared to standalone models. The LSTM used as a part of the hybrid model outperformed the standalone LSTM. Zafar et al. [38] presented a hybrid model for solar irradiance forecasting. The model combines the k-means clustering for grouping sunny day and cloudy day samples. Then the LSTM-RNN is utilized to forecast the solar irradiance at the day ahead level. For this forecast, the developed neural network is trained with exogenous features such as relative humidity, dry-bulb temperature, and dew point temperature. As a result, LSTM-RNN with clustering attained better forecasts than SVM, FNN, and persistence model. Jailani et al. [39] analyzed the accuracy of LSTM as a standalone and also as a hybrid model in solar power and solar irradiance forecast. The hybrid model takes little extra training time than the standalone LSTM. The analysis result shows that the hybrid model guarantees better accuracy of forecast than standalone and other machine learning models.

6.3 Research on Solar Power Forecasting using Gated Recurrent Unit

GRU is a type of deep RNN that provides a better forecast than simple RNN and provides the same accuracy as LSTM. But it differs in its architecture [41]. In each unit, LSTM has three gates to keep required information, delete unwanted information, and compute and transfer the result to the next cell. But GRU performs these all tasks by using only two gates [42]. Thus the GRU works well with time series sequence data and provides better forecast results with high accuracy and less time. Many researchers utilized GRU, bidirectional GRU, and hybrid versions of GRU networks for forecasting solar power. Table 5 presents a sample of related research work done using a gated recurrent unit. Khatib *et al.* [43] presented a solar PV power prediction model using GRU. The model achieved a better performance compared to long short-term memory by producing the photovoltaic power forecast with 0.27 RMSE. Faisal *et al.* [44] presented a solar radiance prediction model by considering weather data collected from different cities in Bangladesh as additional data. The powerful deep learning methods RNN, LSTM, and GRU are designed and the solar radiance is forecasted. Among all the gated recurrent unit (GRU) achieved better accuracy with a MAPE of 19.28%.

Bendali *et al.* [45] designed a hybrid model for solar radiance prediction. The combination of principal component analysis and gated recurrent unit with grid search optimization is introduced as a hybrid model. It experimented with multivariate datasets and proved better forecast results than other standalone deep learning models such as multilayer perceptron (MLP), RNN, LSTM, and GRU.

Wang *et al.* [46] introduced a novel hybrid model which is a combination of GRU with Pearson coefficient and k-means clustering. The introduced hybrid model achieved an accurate photovoltaic power forecast compared to ARIMA, BP, LSTM, and SVM by forming a similar group of samples and identifying the relationship between time steps effectively.

Table 5. Research on solar energy forecasting using deep learning based gated recurrent unit

Sl. No	Author & References	Methodologies	Performance metrics	Remarks
1	Khatib *et al.* [43]	GRU	RMSE, MAE, MBE, R^2	GRU produced better photovoltaic power prediction with 0.27 RMSE compared to LSTM.
2	Faisal *et al.* [44]	GRU	MAPE	GRU produced better solar radiation forecasting results with less MAPE of 19.28% compared to RNN and LSTM.
3	Bendali *et al.* [45]	PCA-GRU with Grid search optimization	MSE, MAE	Hybrid PCA-GRU tuned with hyper parameter optimization by Grid search and produced accurate solar radiance forecast than MLP, RNN, LSTM and GRU.
4	Wang *et al.* [46]	GRU with Pearson coefficient and k-means clustering	MAE, RMSE	Model attained accurate photovoltaic power forecast by forming similar group of samples and identifying relationship between time steps compared to ARIMA, BP, LSTM and SVM.
5	Khan *et al.* [47]	Dual Stream network (DSN): CNN-GRU-Self-Attention Mechanism (CNN-GRU-SAM)	RMSE, MBE, MSE, NRMSE, MAE	DSN extracts spatial features using CNN and temporal features using GRU. The SAM identifies the optimal features.

Khan *et al.* [47] developed a hybrid model named dual stream network (DSN). It combined a model of a convolution neural network, GRU, and a self-attention mechanism. It improved the accuracy of the forecast by extracting the spatial features using CNN, temporal features using GRU, and optimal features using the self-attention mechanism.

7. Conclusion

Solar energy is the vital renewable energy resource for the successful establishment of smart city development projects globally. Many countries released a plan for providing a good quality of life to the people living in urban areas. The rapid growth of the population in recent years imposes a great challenge to the governments and power sectors in fulfilling the energy requirements in urban cities. As the solar plant setup and installation is easy in highly populated and industrialized urban areas, it helps a lot for the success of smart cities compared to other energy sources. The comfortable lives of people depend on the reliability of the interconnected networks in smart cities. Power plays an important role in maintaining the reliability of all functions in a smart city. It influences the green and clean renewable solar power to be forecasted. The economic and pollution-free solar power forecasting has been done accurately in literature by many researchers using machine learning and deep learning methods. The study shows that accurate solar power can be forecasted using deep learning methods like RNN, LSTM, GRU, Bi-LSTM, Bi-GRU, and its hybrid versions. In the future, the performance of the deep learning methods can also be enhanced by considering weather data, sky imager data, feature selection, transfer learnng and hyperparameter optimization techniques.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes