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Review

# Deep learning for renewable energy forecasting: A taxonomy, and systematic literature review

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ABSTRACT

In order to identify power production and demand in realtime for efficient and dependable management for diverse renewable energy systems, precise and intuitive renewable energy predictions are required. Deep learning can be exploited to handle a variety of operations and maintenance improvement challenges, as well as develop better methods and perspectives for medium- and long-term energy prediction. This paper provides a detailed literature and bibliometric review of deep learning models for effective renewable energy forecasting. To begin, data was gathered via the Web of Science (WoS) library to access a large amount of articles and journals. In WoS, a total of 276 publications were extracted, including five different types, including Articles (261), Reviews (13), Early Access (10), Proceedings Paper (5), Editorial Material (2), and Data Paper (1). Then, literature statistics analyzed top 10 productive country, author, institution, journal. Overall keyword analysis are explored and discussed from various aspects like most frequency keywords, keywords analysis by year, keywords co-occurrence analysis, keywords co-occurrence graph, topic evolution-accumulation, topic evolution weighted. In addition, literature statistics of renewable energy are evaluated for wind energy, solar energy, ocean energy, hydrogen energy. Deep learning models can be leveraged to anticipate underneath a variety of uncertainty arising from renewable energy sources that are fluctuating. Furthermore, the estimated prediction accuracy requirements are given, and the keywords analysis of the deep learning forecasting models iare demonstrated from the perspectives of SAE (Stacked AutoEncoder), DBN(Deep Belief Network), CNN(Convolutional Neural Networks), GAN(Generative Adversarial Networks), and RNN(Recurrent Neural Network). Due to various shifting weather conditions as well as other variables, the forecasting model responds differently by various types of datasets. Deep learning methods offer intriguing potential discoveries in the field of energy forecasting. The relevant aspects and suggestions for future research were highlighted in the conclusion to conquer the projected barriers.

## 1. Introduction

### 1.1. Importance and challenges of renewable energy

As the most promising alternatives to fossil fuels, renewable energy, including wind energy (Zucatelli et al., 2021; Zhu et al., 2019), solar energy (Zhou et al., 2021), ocean energy (Stringari et al., 2021; Shahid et al., 2020), geothermal energy (Pulukool et al., 2020), hydrogen energy (Shams et al., 2021, Prasad et al., 2018), etc, along with the advantages of inexhaustible and green and clean, has attracted extensive attention in recent years. However, the fluctuation, intermittent and randomness nature of renewable energy sources, particularly imbalances between demand and supply, has often limited their direct utilization. Accurate renewable energy prediction can effectively alleviate the problem and remains one of the key focuses in the field.

### 1.2. The meanings for deep learning on renewable energy

Seeing as renewable energy data (Zhou et al., 2021; Zhang et al., 2020) seems to be difficult and complicated, varying weather and climatic variables, such as air temp, pressure, moisture levels, rainfall, wind patterns, and wind velocity, should always be taken into account to

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capture the data relationship from high-dimensional data (Yaprakdal et al., 2020; Yang et al., 2021), resulting in intelligent decision making (Wen et al., 2020). As an essential research direction in the field of machine learning, deep learning-based renewable energy predictions have flourished in recent years (Wei et al., 2019; Wang et al., 2020; Ullah et al., 2021). Deep learning is capable of overcoming the drawbacks of shallow models in extraction of features and hyperparameter over-tuning methods, as well as learning from massive amounts of big data, including imbalanced datasets and heterogeneous data with a large training data set (Prasad et al., 2018; Pramono et al., 2019). By estimating with automatic feature learning (Lu et al., 2021; Kim et al., 2019), the studies aim at determining the correlation of complex and confusing hyperparameters in big data, thus accurately improving the performance of the prediction (Duan and Liu, 2019; Dolatabadi et al., 2020).

### 1.3. Existing reviews and studies

Deep learning's capacity to learn hidden variables gives it potential advantages over conventional machine learning methods. Deep learning outperforms conventional machine learning algorithms due to its hierarchical learning, extraction, and abstraction capabilities. Think about the most recent developments in energy research, such as the rise of Deep Learning applications that are pertinent and the success of boosting algorithms across a variety of domains due to their diversity. As shown in Table 1, the list of reviews on related work has been illustrated with year, author, article title, source journal, and keywords.

The implementation of conventional deep learning techniques to power prediction is still in its initial stages. Most of them are based on the deep learning algorithms of traditional input models, lack input modeling for multi-dimensional spatio-temporally related data mainly NWP data, and the corresponding spatio-temporal correlation between data is insufficient. In addition, for different prediction time scales and prediction types, the applied deep learning algorithm types, network structure, and input elements will all affect the performance of the model.

There have been many similar reports published in recent years, however despite the authors' good analyses of the state and future of the subject from their viewpoints, deep learning literature analysis research on renewable energy forecasting are few and far between. This paper fills this gap by providing a thorough analysis of deep learning-based publications on renewable energy forecasting from the perspectives of literature analysis, summarizing recent developments, and offering a comparative analysis of deep learning-based renewable energy forecasting techniques. In this study, we seek to (a) improve energy researchers' understanding of boosting algorithms and assist scientists and engineers in characterizing various models used for projecting renewable energy sources. (b) Examine the specific benefits of deep learning algorithms and how they might be used to renewable resource research. (c) Determine which hot research areas and models may be applied to enhance their forecasting tools, thereby maximizing the potential of deep learning in forecasting renewable energy. (4) In order to draw potential researchers' attention to the most important unresolved issues, we analyze the difficulties and potential future research areas for deep learning in renewable energy prediction. Therefore, as for the newcomers to have quicker glance about the particular area or topic interested and easy to follow the latest research trend in the study. It would like to give you a broad brush overview of what we're going to be covering in this field and moving deeper into it.

### 1.4. Our contribution

To avoid this problem, we analyze this field from the perspective of bibliometric analysis. Through the scientific measurement statistics, using statistical results to reflect the real research situation, research in recent years and current scholars are focused. The comparative analysis

**Table 1**
List of reviews on related work.

| Year | Author | Article Title | Source journal | Keywords |
|---|---|---|---|---|
| 2018 | Srivastava et al. | A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data | Solar energy | Solar energy forecasting; long short term memory; deep learning; remote sensing data |
| 2019 | Mosavi et al. | State of the Art of Machine Learning Models in Energy Systems, a Systematic Review | Energies | Energy systems; machine learning; artificial neural networks (ann); support vector machines (svm); neuro-fuzzy; anfis; wavelet neural network (wnn); big data; decision tree (dt); ensemble; hybrid models; deep learning; blockchain; renewable energy systems; energy informatics; internet of things (iot); smart sensors; remote sensing; prediction; f 53adorecasting; energy demand |
| 2019 | Liuet al. | Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods | Energy conversion and management | Wind energy forecasting; hybrid intelligent models; artificial intelligence; deep learning; ensemble learning; metaheuristic optimization |
| 2019 | Wang et al. | A review of deep learning for renewable energy forecasting | Energy conversion and management | Deep learning; renewable energy; deterministic forecasting; probabilistic forecasting; machine learning |
| 2019 | Massaoudi et al. | Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects | Ieee access | Forecasting; deep learning; artificial intelligence; smart grids; collaborative work; predictive models; renewable energy sources; smart grid; deep learning; deep neural networks; edge computing; distributed and federated learning; power systems |
| 2020 | Wang et al. | Taxonomy research of artificial intelligence for deterministic solar power forecasting | Energy conversion and management | Artificial intelligence; solar power forecast; taxonomy; photovoltaic power generation |
| 2020 | Rajagukguk | A Review on Deep Learning Models | Energies | Deep learning; time series data; |

(continued on next page)

**Table 1** (*continued*)

| Year | Author | Article Title | Source journal | Keywords |
|---|---|---|---|---|
| | | for Forecasting Time Series Data of Solar Irradiance and Photovoltaic Power | | solar irradiance; pv power; evaluation metric |
| 2020 | Quan | A Survey of Computational Intelligence Techniques for Wind Power Uncertainty Quantification in Smart Grids | Ieee transactions on neural networks and learning systems | Uncertainty; wind power generation; wind speed; wind forecasting; forecasting; stochastic processes; computational intelligence; decision-making; neural network (nn); prediction interval (pi); uncertainty quantification; wind power |
| 2020 | Mishra | Deep learning in electrical utility industry: A comprehensive review of a decade of research | Applied artificial intelligence | Artificial intelligence; deep learning and machine learning electricity demand forecasting; fault detection and classification; power quality; smart-grid and microgrid; solar-photovoltaic and wind forecasting |
| 2020 | Mellit | Advanced Methods for Photovoltaic Output Power Forecasting: A Review | Applied sciences | Photovoltaic plant; power forecasting; artificial intelligence techniques; machine learning; deep learning |
| 2020 | Ahmed | A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization | Renewable & sustainable energy reviews | Solar power; forecasting technique; wavelet transform; deep convolutional neural network; long short term memory; optimization; forecast accuracy |
| 2020 | Basaran | Systematic literature review of photovoltaic output power forecasting | Iet renewable power generation | Learning (artificial intelligence); photovoltaic power systems; renewable energy sources; systematic literature review; photovoltaic output power forecasting; renewable energy resources; potential renewable energy sources; photovoltaic system installations; world-wide; economic contributions; environmental contributions; pv power generation; pv output data; grid systems; pv output power forecasting; pv material; generated outputs |
| 2020 | Aslam | Deep Learning Models for Long-Term Solar Radiation Forecasting Considering Microgrid Installation: A Comparative Study | Energies | Deep learning; microgrid; renewable energy; solar radiation forecasting; gated recurrent unit; long short term memory |
| 2021 | Devaraj et al. | A holistic review on energy forecasting using big data and deep learning models | International journal of energy research | Big data; data preprocessing and feature extraction; deep learning; energy demand forecasting; renewable energy forecasting |
| 2021 | Aslam | A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids | Renewable & sustainable energy reviews | Energy forecasting; renewable energy; deep learning; artificial neural networks; machine learning |

of existing research are conducted, and the future research is point out by the statistic data of several aspects, so as to help researchers have a general understanding of the field in a quicker time and efficiency to further research.

The contribution of this paper is:

(i) Publications output analysis collects the annual publications number and shows the growing trend that the deep learning study on renewable energy has flourished in nearly 3 years and has enjoyed a rapid growth momentum.

(ii) Literature statistics shows the most productive country, author and institution, in which the most productive country is Peoples R China, the most productive author is Liu, Hui (6), and the most productive institution is North China Elect Power Univ (7).

(iii) Besides the search keywords, there are 1142 keywords in related publications, in which prediction, long term memory, and convolutional neural network are the top 3 frequency keywords. Keyword Co-occurrence analysis considers about deep learning, forecasting, and renewable energy. And keywords co-occurrence Graphs depict co-occurrence network diagram of keywords, the density diagram of keyword co-occurrence. The keywords are grouped into 3 clusters, Cluster C0: Deep learning, Cluster C1: Enhanced learning and application, and Cluster C2: Prediction method and model.

(iv) Topic Evolution-accumulation graph shows that the words first appearing in 2021 with deep learning and renewable energy are Correlation, Wind Energy, Task Analysis, Wind Turbine, Time Series Forecasting, Bilstm, Computational Modeling, Data Preprocessing, Smart Meters, Smart Homes, Support Vector Regression. Topic Evolution-weighted graph shows that Keywords occurring from 2019 to 2020 are Convolutional Neural Network, Wind Speed Forecasting, Long Short Term Memory, Recurrent Neural Network, Artificial Intelligence, Forecasting, Load

Forecasting, Machine Learning, Short-Term Forecasting, Renewable Energy, Predictive Models, Neural Networks, Forecasting.

(v) The common evaluated criteria are presented, evaluated criteria of model's accuracy are MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error), SMAPE (Symmetric Mean Absolute Percentage Error), MSLE (Mean Squared Log Error), NRMSE (Normalized Root Mean Square), UMBRAE (Unscaled Mean Bounded Relative Absolute Error), MBRAE (Mean Bounded Relative Absolute Error), inRSE (Independent Cyclic Autoencoder), $R^2$ (R-Squared). And the statistical result are presented of the keyword analysis about deep learning forecasting model including wind energy source keyword analysis, solar energy source keyword analysis, ocean energy source keyword analysis, hydrogen energy source keyword analysis, and other renewable energy sources including hydro-power, biomass energy, geothermal energy and traditional biomass energy. For wind resources, the most frequent keywords are wind forecasting and wind prediction. For the keywords related to solar resources, among which the most frequent keywords are Sloar irradiance, solar forecasting, solar energy, solar radiation. The relevant keywords of ocean energy are bidirectional long short-term-memory (bi-LSTM), neural network, ocean wave energy, forecasting skills, energy absorption, ensemble empirical model decomposition (EEMD), moth-flame optimization, support vector regression (SVR), wave energy control, short-term forecasting, data selection wave energy converter, wave force prediction, boruta random forest optimizer (BRF), significant wave height (HS). For hydrogen energy, the relevant keywords are renewable electricity forecasting, deep-learning algorithms, integrated hydrogen production, optimization, jeju island. And other types of renewable energy do not have relevant studies using deep learning algorithms to make energy prediction for various reasons up to now.

(vi) Deep learning forecasting model-keyword of mainstream deep learning model SAE (Stacked Autoencoders), DBN(Deep Belief Network), CNN(Convolutional Neural Network), GAN(Generative Adversarial Networks) and RNN(Regression Neural Network) research in the filed of renewable energy are proposed. To compare the performance of different models in terms of the results on power prediction. For most publications, the prediction error of LSTM time series is less than that of CNN. DBN is less than SAE on wind speed prediction. CNN tracking accuracy is greater than SAE, and the application of CNN classification accuracy is higher than LSTM(Long Short-Term Memory Neural Network). SAE, DBN, RNN and LSTM can be used to process temporal data, and DBN and LSTM have higher prediction accuracy on time series data.

(v) Three deterministic forecasting structures commonly used in renewable energy forecasting are proposed. The first category is pre-processing technology with deep learning model. The second category, ensemble learning or meta-learning and deep learning models. The third category, hybrid approaches, is employed to accomplish renewable energy sources point predictions. Climatic and environmental variables are commonly used in feature learning.

(vii) Comprehensive analysis of deep learning, including SWOT (Strengths, Weaknesses,Opportunities, Threats) analysis, challenges and future research directions. generalization ability of optimization model. The superiority, weakness, opportunity and challenges of deep learning in research are depicted. The needed conditions for deep learning in RE (Renewable Energy) are analyzed from the aspects of data conditions, mathematical models, and computing resources. And the future research directions suggests challenging and promising issues including interpretability of the algorithm and visualization of the results, improvement of prediction accuracy, parameter optimization and neural network optimization, the long-term forecasting and the multivariate time-series prediction, and deep uncertainty quantification.

## 2. Systematic review of the literature

For the extant research in the field of deep learning for forecasting renewable energy, we employed a systematic literature review (SLR) technique. The systematic approach entails summarizing the results of numerous research projects in a certain field. This approach of reviewing papers is so named because it has a small margin of error, which improves the precision of data analysis. SLR was originally applied in the medical field, and then later in the engineering and social sciences fields. In this research, we conducted a thorough investigation in the field of deep learning for forecasting renewable energy using SLR.

### 2.1. Formulation of questions

This section's goal is to provide research questions on deep learning for projecting renewable energy sources.

RQ (Research question)1:What role does deep learning play in renewable energy forecasting? how long ago did this technology start?

The aim of this inquiry is to learn how many papers have been published online, acknowledging the significance of this topic over time.

RQ2: How many deep learning techniques for renewable energy have succeeded in meeting the primary forecasting objectives?

The objective of this topic is to evaluate the assessment standards currently in place for deep learning for renewable energy methods.

RQ3: How will deep learning be used in future technology for renewable energy?

This inquiry seeks to understand the function of deep learning in anticipating the use of renewable energy sources.

RQ4: What standards are utilized to evaluate the effectiveness of deep learning forecasting techniques for renewable energy?

The goal of this inquiry is to ascertain the performance measuring standards for deep learning forecasting systems for renewable energy.

### 2.2. Selecting search resources

By combining the in Section 2.3 listed keywords with the logical operators and/or. Following IEEE, Elsevier, Springer, Wiley, Taylor, and ACM are the prominent publishers. The Web of Science (WoS) library was used to acquire the data in order to obtain a quantity of academic literature, screen the most significant papers, and lower the repeat rate. Only articles that were published in journals, conferences, and books were chosen after they had undergone technical and scientific peer review.

### 2.3. Literature search strategy

The main concern is a bibliometric study of "deep learning technology applications in renewable energy prediction", Therefore, the keywords used in the search query are: TS= (((renewable energy) OR (wind energy) OR (solar energy) OR (ocean energy) OR (biomass energy) OR (geothermal energy) OR (hydro energy)) AND (deep learning) AND forecast *), Index = SCI-EXPANDED time span = 2010–2021.

### 2.4. Selecting keywords for search

By searching for the terms specified in Section 2.3 in the specified databases, a total of 276 results were obtained, which we saved in an Excel file for later review (see Fig. 1).

We set 2010 as the beginning year of the search, because we intended to get the research in recent 10 years. However, the first paper in the library related to deep learning and renewable energy was published in

2016. The Search query was updated on October 30, 2021. Several tags were retrieved from WoS such as author, title, abstract, country, citation records, author affiliation. As shown in Fig. 2, we performed a search query.

### 2.5. Selection criteria

Additional inclusion and non-inclusion criteria are utilized in order to more effectively choose high-quality papers. These criteria made it simple to distinguish between articles with and without connections.

(i) Inclusion Criteria
- Articles that explicitly state in the title or abstract how to deal with deep learning and forecasting renewable energy.
- Written articles in the field of renewable energy.
- Articles that are only written and published in English.
- Articles that have been printed in journals, publications, and conferences.
- Articles that have been made available through the WoS databases.

(ii) Exclusion Criteria
- Articles published in white papers or technical reports.
- Articles that have been published in the area of renewable forecasting but outside the deep learning domain.

### 2.6. Categorization of selected articles

The items that made it past the filters are grouped in this area. Section 3 provides data on the number of studies published over time, the number of studies published by publishers over time, etc. to address RQ1. As can be observed, deep learning has recently been considered in predicting for renewable energy sources. The chosen articles were carefully taken into consideration in RQ4 in order to respond to RQ2 and RQ3.

### 2.7. Retrieve the results

In WoS, a total of 276 publications were extracted, as shown in Table 2, including five different types, including Articles (261), Reviews (13), Early Access (10), Proceedings Paper (5), Editorial Material (2), and Data Paper (1).

Here, % represents the percentage of a specific publication type. The extracted data were analyzed by the various performance metrics available in the literature for bibliometric analysis.

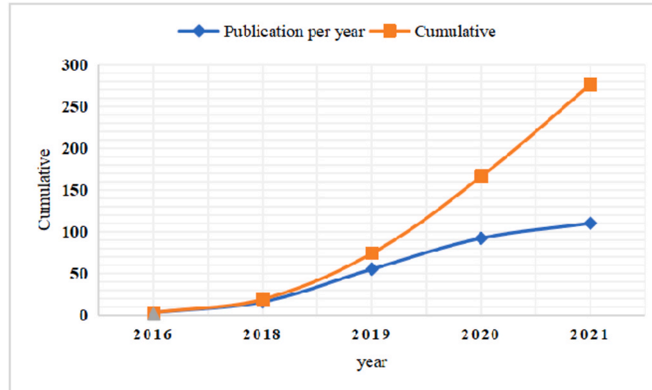



**Fig. 2.** Cumulative publications of output from 2016 to 2021.

**Table 2**
Publication type of statistical publications.

| Publication types | Number | Percentage (%) |
|---|---|---|
| Article | 261 | 94.565 |
| Review | 13 | 4.710 |
| Early Access | 10 | 3.623 |
| Proceedings Paper | 5 | 1.812 |
| Editorial Material | 2 | 0.725 |
| Data Paper | 1 | 0.362 |

As shown in Table 2, the highest proportion of the publication type is Article type, the second is Review type, and some Early Access, Proceedings Paper, Editorial Material and Data Paper.

## 3. Literature statistics

### 3.1. Publications output analysis

As shown in Fig. 2, the annual and cumulative published paper statistics in the deep learning and renewable fields from 2016 to 2021. The publications were accumulated in 2016(1), 2017(0), 2018(16), 2019 (55), 2020(92), 2021(110) by July 30, 2021. The figure shows that the deep learning study on renewable energy has flourished in nearly 3 years and has enjoyed a rapid growth momentum.

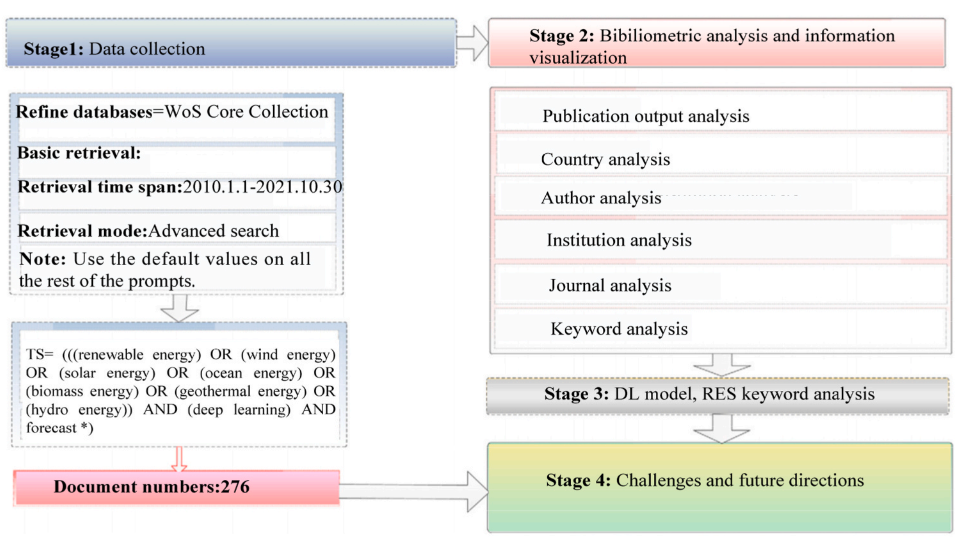



**Fig. 1.** Stages of bibliometric analysis of DL on RE prediction.

### 3.2. Most productive countries, authors, institutions and journals

The Most productive countries are mainly used to obtain information about which countries are more active and leading in current research in the field of adaptation. The most productive author statement is to bring attention to the authors of hot work so that people can follow their work in a timely manner. The most productive institution is a project group that focuses on certain hot topics. Focusing on their movements helps to focus on the work of the group and the hot topics, often the work done by some of the world's leading project groups is a global hot topic. The most productive journal is to help people focus on what are the key journals for this issue when a researcher wants to see the latest directions and articles in the field or wants to submit a manuscript to one of these journals.

(i) Most productive country

In the field of deep learning and renewable energy, the top 20 productive countries of the publications were analyzed. The nation of published papers are analyzed by year Excluding 2016, 2017. The top 10 countries are mentioned and ranked on the basis of total publications. Country statistics included the first author countries and co-author countries. Fig. 3 shows the pie chart for the proportion of countries of the author. We can see that the first and second countries are Peoples R China and USA, respectively, accounting for 29.52% and 20.66%, respectively, and nearly half of the total number of publications in the countries. The third to fifth countries were South Korea, India, England, and the number of publications was 35, 23, 23, respectively, accounting for 6.83%, 6.46% and 4.24%. These three come from Asia, Africa and North America. The sixth to eighth countries were Canada, Pakistan, Australia, with more than 15 publications, representing 4.03%, 3.45%, and 3.07%. The three countries come from Asia, Europe, and 77 countries are published, including the first author, the corresponding author and the remaining co-authors, where 31 countries publishing only one. This suggests that half of the countries have less publications in the field and had just get involved in the field. The ninth to fifteenth countries were over 10 publications, respectively, India, Italy, Pakistan, Canada, Qatar, Saudi Arabia, Japan.

(ii) Most productive author

In the field of deep learning and renewable energy, there has 982 authors. As shown in Fig. 4, the top 20 productive authors are shown. The first was Liu, Hui (6), second is Refaat Shady S. (5). The following five authors have five publications respectively, including Duan, Zhu; Sun, Guoqiang; Wei, Zhinong; Deo, Ravinesh C.; and Chen, Chao.

The remaining authors had three publications, including Cheng, Lilin; Du, Yang; Raj, Nawin; Zhen, Zhao; Yang, Shanlin; Zhou, Kaile; Lee, Jae-Myeong; Ahmadian, Ali; Aslam, Muhammad; Hong, Sugwon, Ding, Tao; Qi, Xiaoxia; Wang, Kejun; Xu, Yan. As can be seen from the author analysis, a large number of publications has been presented in related fields, but the number of publications from one author is still a gap when compared with that of other renewable energy fields with a long development history. This is due to that the field is still an emerging field of renewable energy direction. In the field of deep learning and renewable energy, the authors are analyzed year by year removing year in 2016 and 2017 with fewer published papers. Author statistics included the first author, the corresponding author and the remaining co-authors. Fig. 6 shows the number of publications presented by the top 10 productive authors in different years.

The number of studies given by the authors is seen in Fig. 5, respectively in 2018, The productive author was Liu, Hui (4) in 2019. In 2020, the most productive authors are Aslam, Muhammad (3); Hong, Sugwon (3); Lee Jae-Myeong (3). As of July 30, 2021, the productive author in 2021 were Golkar, Masoud Aliakbar (3); Lin, Zi (3); Ahmadian, Ali(3). Publications with equal number were sorted according to the ID of the exported records from WoS.

(iii) Most productive institution

In the field of deep learning and renewable energy, there are 465 institutions that have publications, including the first and corresponding institution, and the co-institution. Statistical analysis was performed on the top productive 20 institutions.

As shown in Fig. 6, the top 20 productive institutions are shown. From left to right, the number of publications gradually decreased with the top productive 20 publications. The most productive institution were North China Elect Power Univ (7), followed by Hunan Univ (6), Huazhong Univ Sci & Technol (6). The following institutions with 5 publications were Huazhong Univ Sci & Technol (5), Kyung Hee Univ (5), Univ Glasgow (5), Comsats Univ Islamabad (5), Chinese Acad Sci(5), Cent South Univ (5). And institutions with 4 pulications were Cent S Univ (4), Kn Toosi Univ Technol (4), North China Elect Power Univ (4), Nanyang Technol Univ (4), Univ Southern Queensland (4), Hefei Univ Technol (4), Texas A&M Univ (4), Northumbria Univ (4), Xi An Jiao Tong Univ (4), Harbin Engn Univ (4), Univ Liverpool (4), and Univ

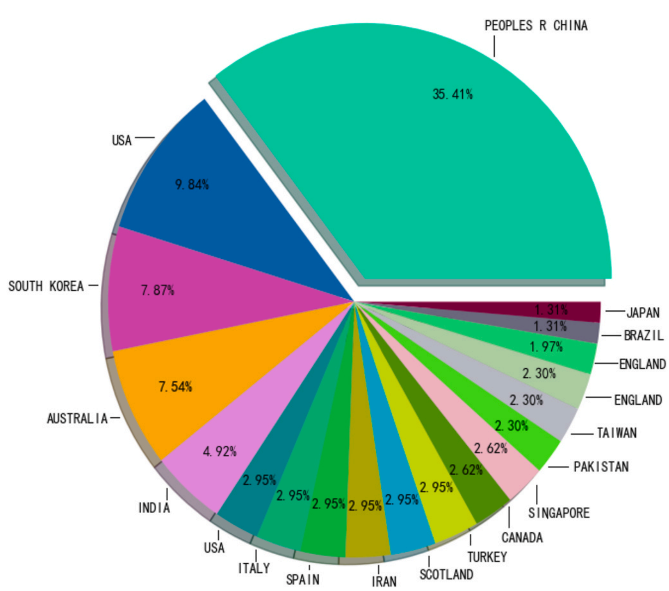



**Fig. 3.** The top 20 productive country.

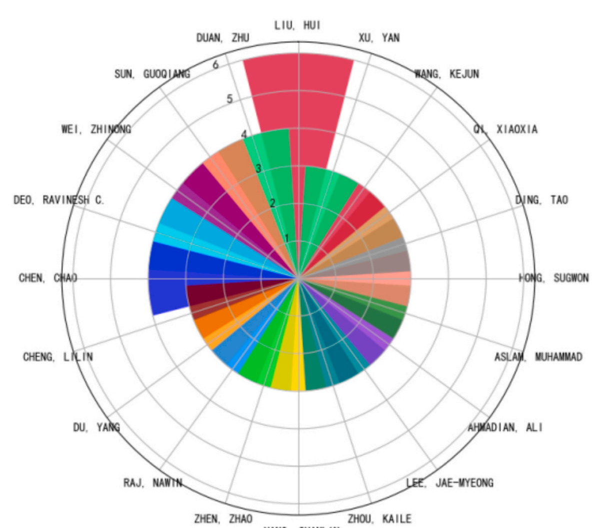



**Fig. 4.** The top 20 productive authors.

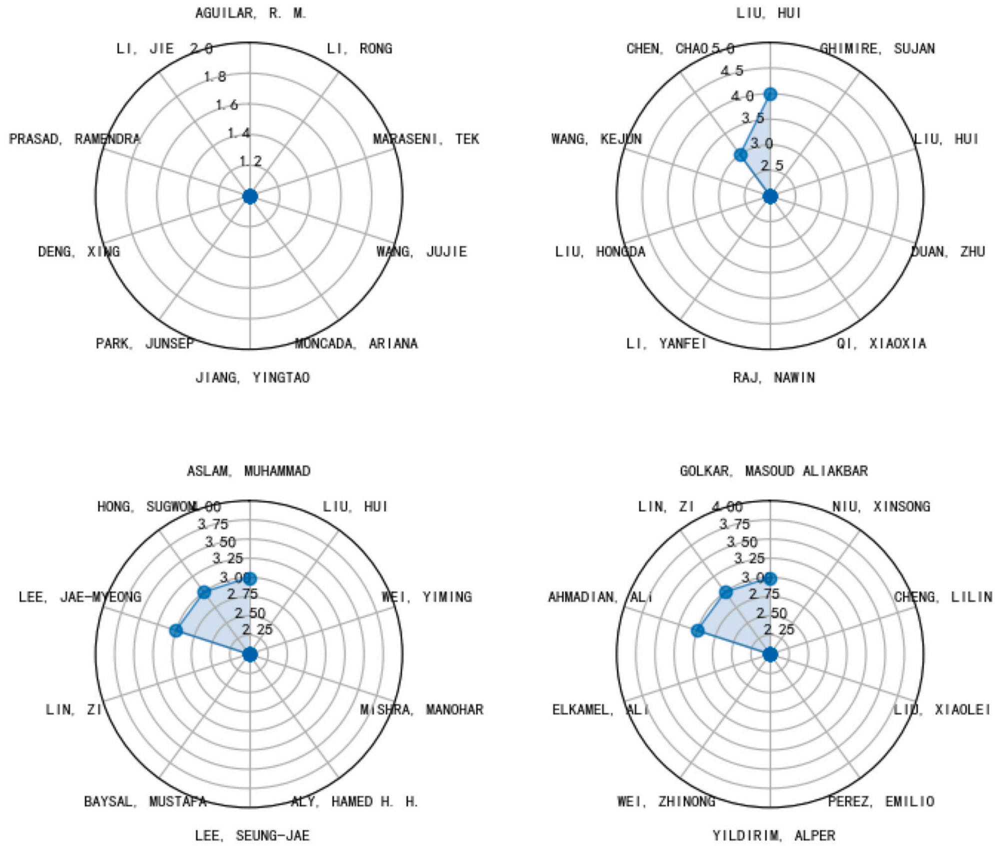



**Fig. 5.** Number of publications for most productive authors in different years.

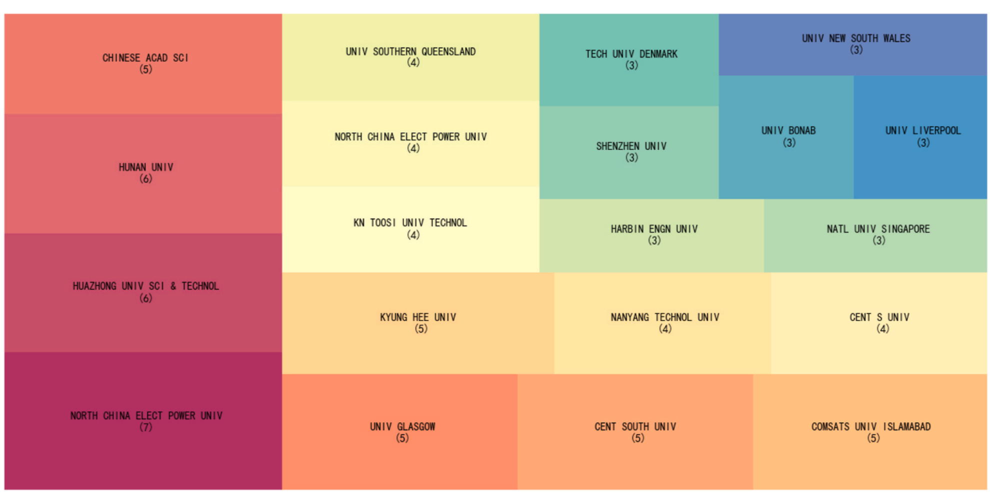



**Fig. 6.** The top 20 productive institution.

Bonab (4).

(iv) Most productive journal

In the field of deep learning and renewable energy sources, there were 82 journals that are relatively focused. This also reflects that publications in the field were submitted to journals that meet the subject. As shown in Fig. 7, the top 10 productive journals were depicted. Energies ranked No. 1 with 15.38% in total publications. Applied Energy (11.79%) is the second. The third, ENERGY accounted for 10.77%. The fourth, IEEE Access is 10.26%. Energy Conversion and Management (8.72%) is the fifth. Sixth-to-tenth journals, Renewable Energy, International Journal Of Electrical Power & Energy Systems, Applied Sciences-Basel, IEEE Transactions On Sustainable Energy, IET Renewable Power Generation, accounted for 6.67%, 4.62%, 3.59%, 3.08%, 3.08%.

## 4. Overall KeyWord analysis

### 4.1. Most frequency keywords

There are 1142 keywords in related publications, among which 953 words appeared 1 time, indicating that most of the keywords appeared only once.

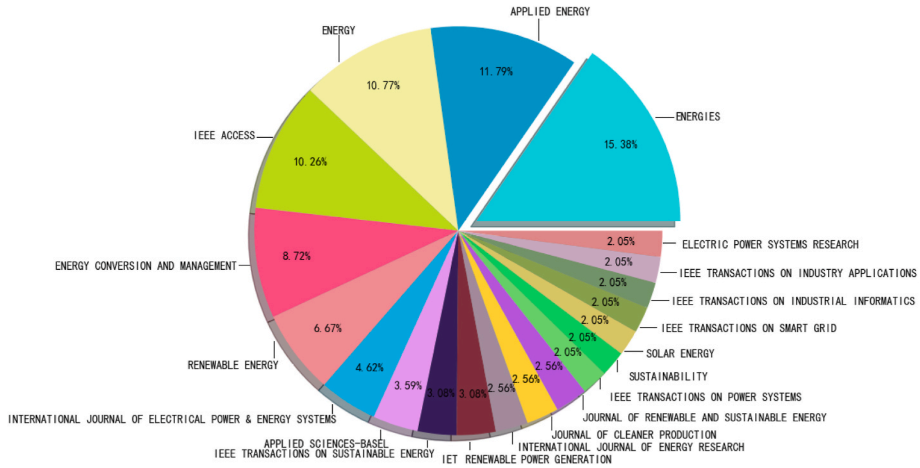



**Fig. 7.** The top 20 productive journal.

Based on the frequency of the keywords, keywords is analyzed in the word-cloud figure. The keywords in the word-cloud figure are displayed according to the number of appearances. In the cloud map figure, the more the keywords are, the larger the font are. Through the keyword-cloud figure, we can have a general understanding of deep learning's work in renewable energy forecasting.

As shown in Fig. 8, you can see the more striking keywords about to the deep learning methods, for instance deep learning, forecasting, prediction, long term memory, convolutional neural network, etc. there are also keywords related to application domains such as renewable energy, power system, wind, solar, photovoltaic, etc.

As shown in Table 3, the top 10 occurrences of keyword are shown in the table and the number ranking the first and third is deep learning (130), forecasting (34)and machine learning (29), which is also the keyword searching for topic words in WoS. Forth to fifth keywords were, predictive models (20), wind speed forecasting (16). Predictive models are the critical parts in deep learning, and using predictive models can effectively help to improve deep learning methods and the accuracy of algorithms. Among the most primary advantages of the power system inside the domain of deep learning is load forecasting, and forecasting is the foundation of deep learning by using a large number of data sets to analyze data characteristics, find valuable data in power big data to process deep learning. They often present simultaneously, and belong to the same classification. The sixth to tenth keywords are convolutional neural network (16), long short-term memory (15), renewable energy (14), load forecasting (12), recurrent neural network (10).

**Table 3**
The top 10 most frequent keywords.

| Publication types | number |
|---|---|
| deep learning | 130 |
| forecasting | 34 |
| machine learning | 29 |
| predictive models | 20 |
| wind speed forecasting | 16 |
| convolutional neural network | 16 |
| long short-term memory | 15 |
| renewable energy | 14 |
| load forecasting | 12 |

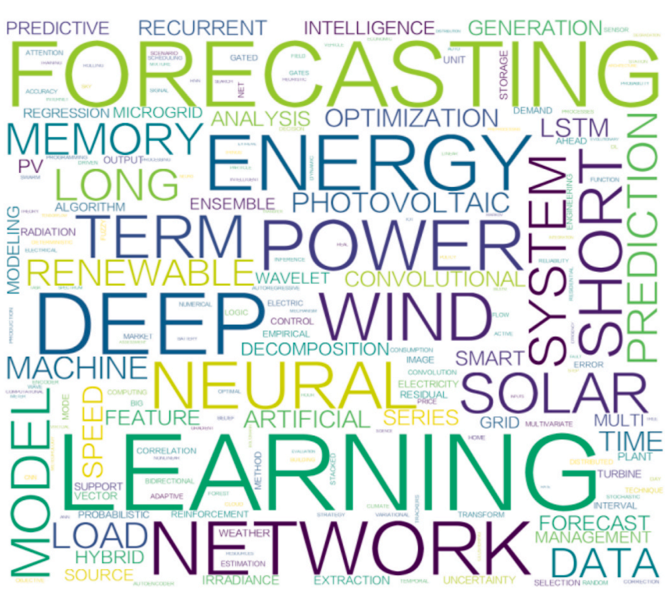



**Fig. 8.** The more striking keywords of deep learning.

Machine learning is the large class of methods to which deep learning belongs, and convolutional neural network and long short-term memory belong to one of the branches of deep learning. It is a commonly used application in smart grid. Its characteristics are suitable for analysis using deep learning methods, which is a critical part for smart distribution network. With the rapid implementation of a considerable number of intelligent sensors monitoring equipment in past few years, the power system are transforming to power, generating a large amount of data, and providing a solid equipment and data foundation for the application of deep learning. Predictive models are a commonly used application in the AI field in recent years. They are often used to integrate deep learning approaches to handle smart grid applications.

### *4.2. Keywords analysis by year*

In the field of deep learning and renewable energy, the keywords are analyzed year by year. Fig. 9 shows different word-cloud figures during 2018–2021, which are depicted based on the frequency of keyword appearances. Keywords are analyzed year by year to show that the differences of keywords in each year.

Deep learning, as the theme word, was the most frequent keyword from 2018 to 2021. In 2018 and 2019, besides the subject words, hot keywords are Long Short-Term Memory, Wind Speed Forecasting, Convolutional Neural Network, Time Series, Machine Learning, Recurrent Neural Network, Forecasting, Renewable Energy Sources, Load Forecasting, Optimization. In 2020, Besides the subject words, hot keywords are Machine Learning, Forecasting, Predictive Models, Wind Speed Forecasting, Long Short-Term Memory, Wind Power Generation, Renewable Energy, Convolutional Neural Network, Load Modeling, Solar Radiation Forecasting. In 2021, Besides the subject words, hot


**Fig. 9.** Keywords wordmap by year.

keywords are Machine Learning, Predictive Models, Neural Networks, Short-Term Forecasting, Data Models, Load Forecasting, Correlation, Logic Gates, Convolutional Neural Network, Feature Extraction, Deep Reinforcement Learning.

### 4.3. Keyword Co-occurrence analysis

Co-occurrence associations between keywords were analyzed in the fields of deep learning and renewable energy. Fig. 10 shows the confusion matrix for the top 10 keywords. The darker color indicates the co-occurrence coefficient bigger, and the lighter color indicates the co-occurrence smaller. If a keyword and other keywords are nonoccurrence, the corresponding item is blank and no color display. Since the subject terms searched in this article are deep learning, renewable energy and forecasting, we focus on the analysis and the co-occurrence of these three keywords.

Keyword 1: deep learning.

By observing the first row in Fig. 10, the blank filling with the deepest color is forecasting (14), indicating that the keywords deep learning and forecasting have appeared simultaneously 14 times. This was followed by predictive models (11), and machine learning (9) ranked third.

The keywords that occurred with deep learning in 7 times are

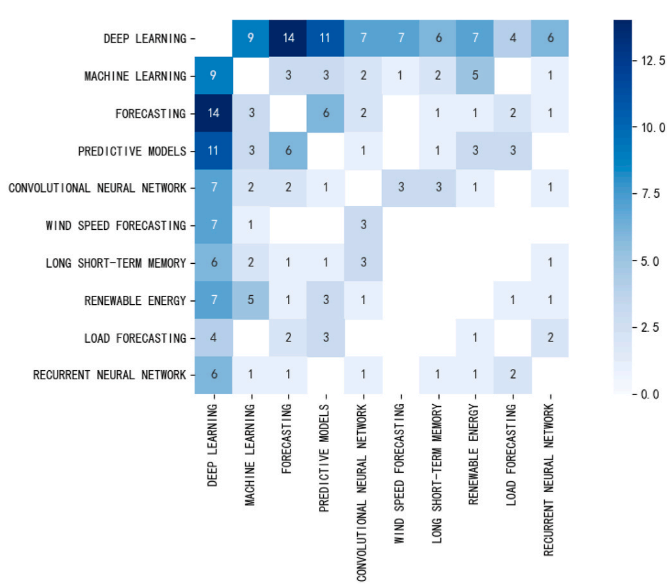



**Fig. 10.** Keywords co-occurrence matrix.

Convolutional Neural Network (7), Wind Speed Forecasting (7), Renewable Energy (7). And other keywords are Long Short-Term Memory (6), Recurrent Neural Network (6), And Load Forecasting (4).

Keyword 2: forecasting.

By observing the third row in Fig. 10, the blank filling with the deepest color is Deep Learning (14). This was followed by Predictive Models (6), Machine Learning (3), Convolutional Neural Network (2), Load Forecasting (2), Long Short-Term Memory (1), Renewable Energy (1), Recurrent Neural Network (1).

Keyword 3: renewable energy.

By observing the eighth row in Fig. 10, the blank filling with the deepest color is Deep Learning (7). This was followed by machine learning (5), predictive models (3), forecasting (1), Convolutional Neural Network (1), Load Forecasting (1), and Recurrent Neural Network (1).

Clustering associations of keywords were analyzed in the fields of deep learning and renewable energy.

During Keyword statistics, the number of keywords reached as high as 1,142, among which 953 keywords appeared only 1 time. In the cluster, as shown in Fig. 11, some keywords were appear repeatedly in several clusters, then these keywords were removed depending on the importance in the different clusters.

For the keyword co-occurrence analysis, the keywords with similar meanings were merged, and the keywords were filtered according to the frequency statistics. Keywords were filtered by the frequency more than 5 times. As a result, 33 keywords were selected. For example, if two keywords have similar meaning and appear in the same cluster, these two keywords will be combined directly and the frequency of occurrence and connection are superimposed. If two keywords have similar meanings and appear in different cluster, the frequency of keywords and connection lines are superimposed, and keywords with low frequency will be deleted from its cluster. The analysis of network and density diagram were performed, as shown in the following.

Fig. 11 shows co-occurrence network diagram of keywords. The network diagram is constructed up of vertices and edges, having vertices represent keywords and edges represent the linkages connecting them. If two keywords are connected by an edge, that means the two keywords appearing in the same publication, so they are more closely related to each other. At the same time, the larger the node is, the more frequency the keyword appears. And according to the degree of correlation, keywords were classified into three categories and identified by different colors by in vosviewer based on the nodes of keywords, where deep Learning is blue, Forecasting is green, and Renewable Energy is red.

Fig. 12 shows the density diagram of keyword co-occurrence. The density diagram of Keyword co-occurrence shows the degree of heat for the keyword, and deeper color indicates that the higher degree of heat

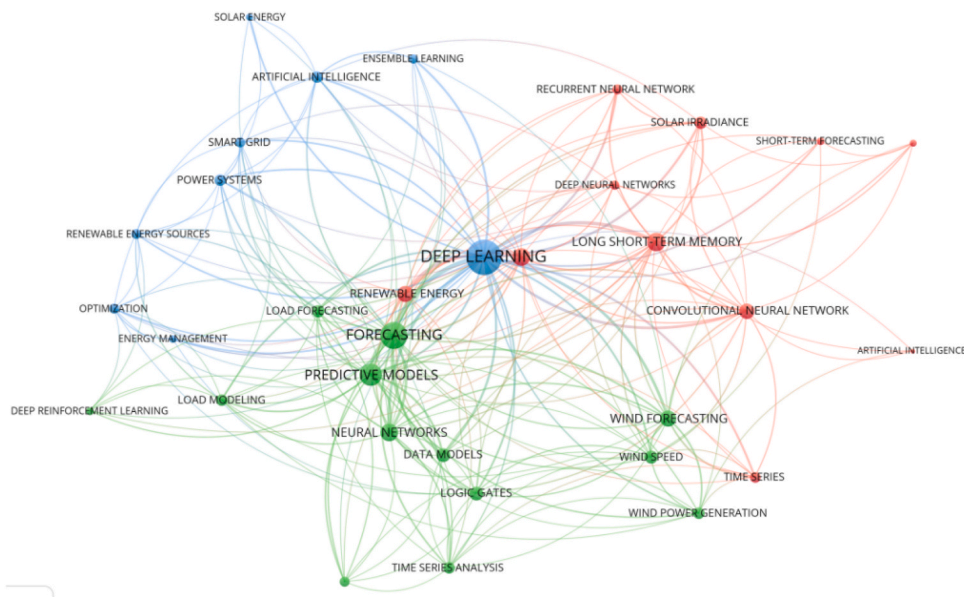



**Fig. 11.** Keyword co-occurrence network map.

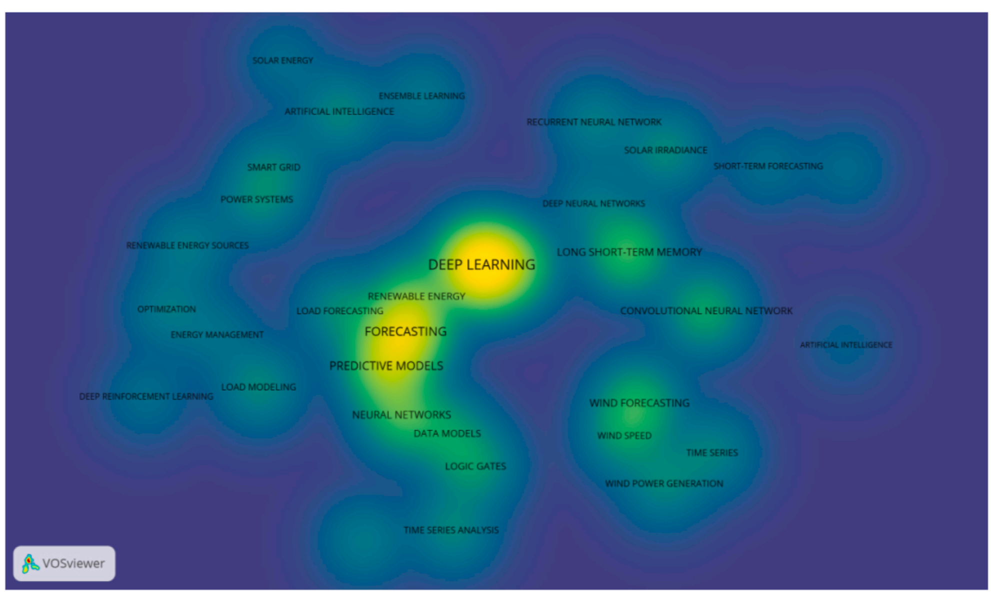



**Fig. 12.** Keyword co-occurrence density network.

and more attention for keyword. The keywords corresponding to the same color means that belong to the same cluster.

Cluster C0: Deep learning.

As shown in Table 4, cluster C0 was ranked according to the weight, and the top 5 keywords are deep learning, artificial intelligence, power systems, smart grid, and renewable energy sources. Therefore, the keywords in cluster C0 mainly focus on the usage of artificial intelligence technology, especially for deep learning technology. These follows by are Optimization, Ensemble Learning, Energy Management. All these technologies are all at the cutting-edge direction of renewable

**Table 4**
Keyword weight analysis for cluster C0.

| Label | cluster | betweenness centrality | closeness centrality | Eigenvector Centrality | Clustering coefficient | degree centrality |
|---|---|---|---|---|---|---|
| Deep Learning | C0 | 0.236788486 | 0.936170213 | 0.321347715 | 0.285365854 | 71 |
| Artificial Intelligence | C0 | 0.01282213 | 0.602739726 | 0.145273885 | 0.533333333 | 15 |
| Power Systems | C0 | 0.005632358 | 0.578947368 | 0.138690315 | 0.653846154 | 13 |
| Smart Grid | C0 | 0.002794316 | 0.578947368 | 0.140744608 | 0.757575758 | 12 |
| Renewable Energy Sources | C0 | 0.001850314 | 0.556962025 | 0.106142549 | 0.777777778 | 10 |
| Optimization | C0 | 0.007750859 | 0.586666667 | 0.133995205 | 0.564102564 | 13 |
| Ensemble Learning | C0 | 0.00159695 | 0.543209877 | 0.094208727 | 0.75 | 8 |
| Energy Management | C0 | 0.000249589 | 0.536585366 | 0.086126957 | 0.904761905 | 7 |

energy research in recent years.

Cluster C1: Enhanced learning and application.

As shown in Table 5, cluster C1 was ranked based on degree centrality, with the top 5 keywords including Machine Learning, Renewable Energy, Convolutional Neural Network, Long Short-Term Memory, and Time Series. Therefore, the keywords in cluster C1 mainly focus on the direction of deep learning and the usage of specific technologies for renewable energy. Keywords ranked 6 to 11 are Recurrent Neural Network, Deep Neural Networks, Solar Irradiance, Short-Term Forecasting, Gated Recurrent Unit, Artificial Intelligence.

In addition, Solar Irradiance is the specific research direction of renewable energy direction applications in recent years. Others are specific cutting-edge technologies.

Cluster C2: Prediction method and model.

As shown in Table 6, cluster C2 was ranked according to degree centrality and the top 5 keywords are Predictive Models, Forecasting, Data Models, Logic Gates, and Neural Networks. Therefore, keywords in cluster C2 mainly focus on the load prediction and prediction model for renewable energy sources, such as load prediction, prediction model, data model, feature extraction, etc. The keywords ranked 6 to 11 are Load Forecasting, Wind Forecasting, Load Modeling, Wind Power Generation, Time Series Analysis, Wind Speed, Feature Extraction, Deep Reinforcement Learning. For example, Time Series Analysis and Feature Extraction technology are key steps in the prediction method.

### 4.4. Topic evolution-accumulation

As shown in Fig. 13, the topic evolution routine was depicted from 2016 to 2021, and topic evolution keywords are analyzed in the field of deep learning and renewable energy sources. Due to no paper was published in 2017, no keywords are shown. The first occurrence time of each keyword was showed, and all statistical frequency of the same keyword were accumulated to the frequency of first occurrence time.

The keywords in the same year were arranged from bottom to top according to the order of statistical frequency. The words first appearing in 2016 are Deep Learning, Deep Neural Networks, Wind Speed Prediciton, Wavelet Transform, Transfer Learning, Wind Speed Forecast, Deep Belief Network, Submarine Earthquake, Quantile Regression, Stacked Denoising Autoencoder. The words first appearing in 2018 are Wind Speed Forecasting, Recurrent Neural Network, Long Short Term Memory, Artificial Intelligence, Wind Power Forecasting, Ensemble, Learning, Neural Network, Solar Irradiance Forecasting, Particle Swarm Optimization. The words first appearing in 2019 are Machine Learning, Forecasting, Renewable Energy, Load Forecasting, Time Series, Short Term Forecasting, Optimization, Renewable Energy Sources, Energy Management, Artificial Neural Networks, Wind Power Generations. The words first appearing in 2020 are Predictive Models, Forecasting, Neural Networks, Data Models, Logic Gates, Load Modeling, Wind Forecasting, Smart Grid, Power Systems, Deep Reinforcement Learning, Time Series Analysis. The words first appearing in 2021 are Correlation, Wind Energy, Task Analysis, Wind Turbine, Time Series Forecasting, Bilstm, Computational Modeling, Data Preprocessing, Smart Meters, Smart Homes, Support Vector Regression (SVR).

### 4.5. Topic evolution-weighted

In the field of deep learning and renewable energy, the evolution of keywords was analyzed year by year. The topic evolution data are showing the average time range of keywords, and remaining keywords with frequency more than 7. Since the keyword Deep Learning appears throughout the process of topic evolution, it is removed. As shown in Fig. 14, keywords occurring from 2019 to 2020 are Convolutional Neural Network, Wind Speed Forecasting, Long Short Term Memory, Recurrent Neural Network, Artificial Intelligence, Forecasting, Load Forecasting, Machine Learning, Short-Term Forecasting, Renewable Energy, Predictive Models, Neural Networks, Forecasting. These keywords are relatively novel, but also the focus of attention in recent years.

## 5. Keyword analysis of renewable energy

### 5.1. Wind energy source

#### 5.1.1. Background

With increasing energy depletion and deterioration of Earth's environment, countries around the world are under great energy pressure (Yang et al., 2020; Wang et al., 2019a,b). In order to ensure the rapid and sustainable development of their own economies, governments around the world are actively looking for alternatives to fossil energy sources and vigorously developing renewable energy sources. The research mainly focuses on two aspects, wind power and wind speed (Wang et al., 2021; Yang et al., 2021). As shown in Fig. 15, the literature introduces the relationship between wind speed and power, including (a)power curves (East-West), (b)Scatter power plots for different directions (see Fig. 16).

The research on wind power prediction is still under research (Wang et al., 2021; Yang et al., 2019), and the problems of wind power prediction mainly come from two aspects. On the one hand, predictions of wind power have a low degree of accuracy. The accuracy of wind power prediction is determined by numerical weather forecasting data, historical wind power data gathered by wind power systems, and the prediction model, as shown in Fig. 15. The prediction research of wind electric power has appeared late, and the monitoring and collection technology for different kinds of data is not mature enough (Ko et al., 2021). The prediction model's input data is of poor quality, which severely restricts the improvement of the prediction accuracy (Jaseena and Kovoor, 2021). In addition, the existing prediction models were mostly based on statistical methods, which requiring a rich supply of historical wind power data as input to accurately predict the real-time fluctuations in the transformation of wind power systems. On the other side, this reduces the wind power grid's forecast power accuracy and thus influences the accurate construction of power grid dispatching plans (Liu and Chen, 2019; Liu et al., 2021; Liu et al., 2020; Lipu et al., 2021).

Generally, the majority of wind power prediction categorization in

**Table 5**
Keyword weight analysis for cluster C1.

| Label | Cluster | Betweenness centrality | Closeness centrality | Eigenvector Centrality | Clustering coefficient | Degree centrality |
|---|---|---|---|---|---|---|
| Machine Learning | C1 | 0.052320286 | 0.6875 | 0.213377209 | 0.402173913 | 24 |
| Renewable Energy | C1 | 0.031965686 | 0.666666667 | 0.214317841 | 0.471861472 | 22 |
| Convolutional Neural Network | C1 | 0.041325567 | 0.656716418 | 0.186138033 | 0.40952381 | 21 |
| Long Short-Term Memory | C1 | 0.01013456 | 0.586666667 | 0.147412636 | 0.582417582 | 14 |
| Time Series | C1 | 0.009956913 | 0.571428571 | 0.12160331 | 0.53030303 | 12 |
| Recurrent Neural Network | C1 | 0.00369437 | 0.564102564 | 0.107352449 | 0.622222222 | 10 |
| Deep Neural Networks | C1 | 0.023049797 | 0.578947368 | 0.113522307 | 0.53030303 | 12 |
| Solar Irradiance | C1 | 0.004566954 | 0.556962025 | 0.107885423 | 0.555555556 | 10 |
| Short-Term Forecasting | C1 | 0.006856065 | 0.543209877 | 0.055526812 | 0.523809524 | 7 |
| Gated Recurrent Unit | C1 | 0.002564461 | 0.536585366 | 0.061229674 | 0.571428571 | 7 |

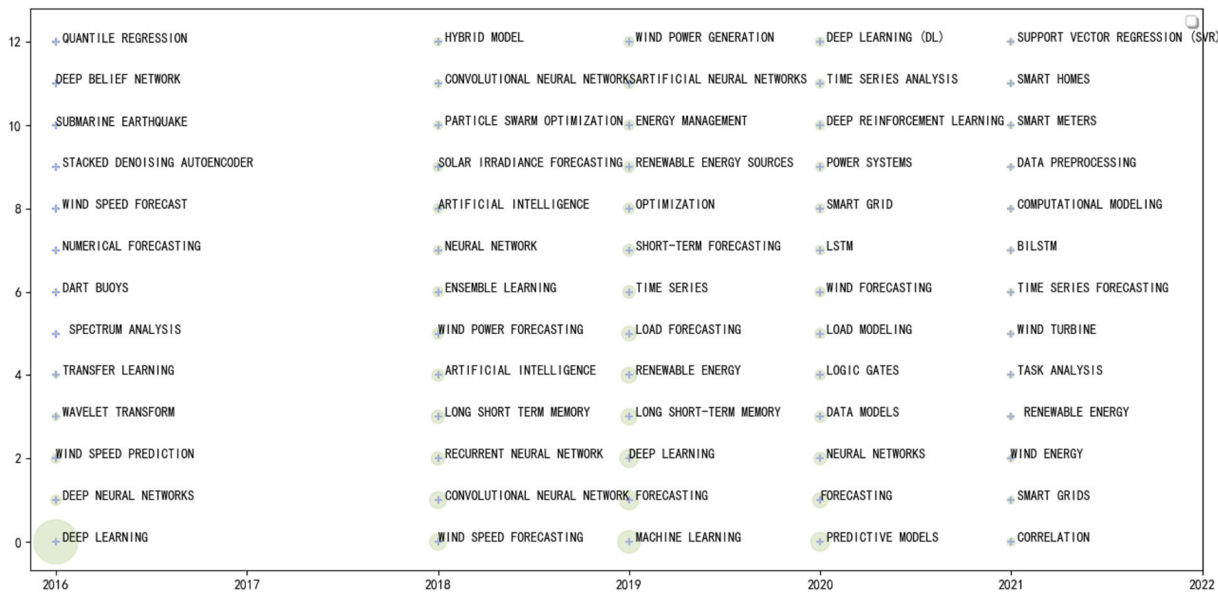



**Fig. 13.** Topic evolution-accumulation.

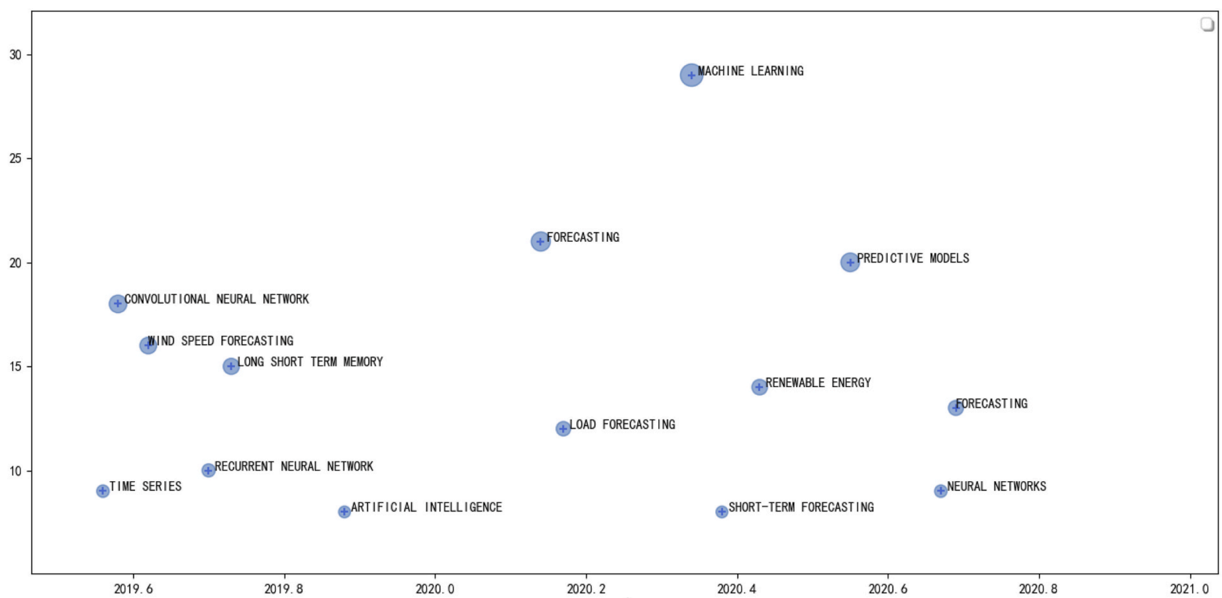



**Fig. 14.** Topic evolution-weighted.

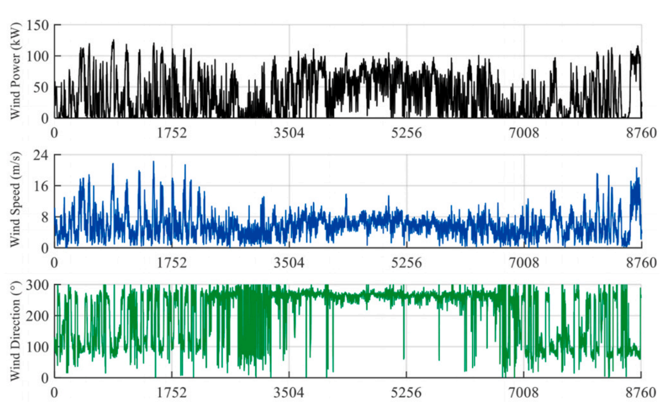



**Fig. 15.** Historical measured dataset. (source:Yildiz et al., 2021).

technology is founded based on time scale of prediction, that could be divided into prediction of ultra-short-term, short-term, medium- and long-term (Khan et al., 2019; Jiao et al., 2018; Jiang et al., 2021) which can be classified into ultra-short-term power prediction, short-term power prediction, medium-and long-term power prediction, etc. (Chen et al., 2018, 2021; Chen and Liu, 2021; Chang and Lu, 2020). The ultra-short-term power prediction has mostly been concentrated on the forecasting of wind energy for a forthcoming load of - hours based on wind power output time series and revealed meteorological parameters, whereas the short-term power prediction is highly depended on the numerical weather forecast as the input, and the short-term (0–72h) wind power is predicted through various algorithms. Studies on medium-and long-term predictions are comparatively limited due to the difficulty of prediction.

### *5.1.2. Keywords analysis*

Analysis the keywords related to wind resources, among which the

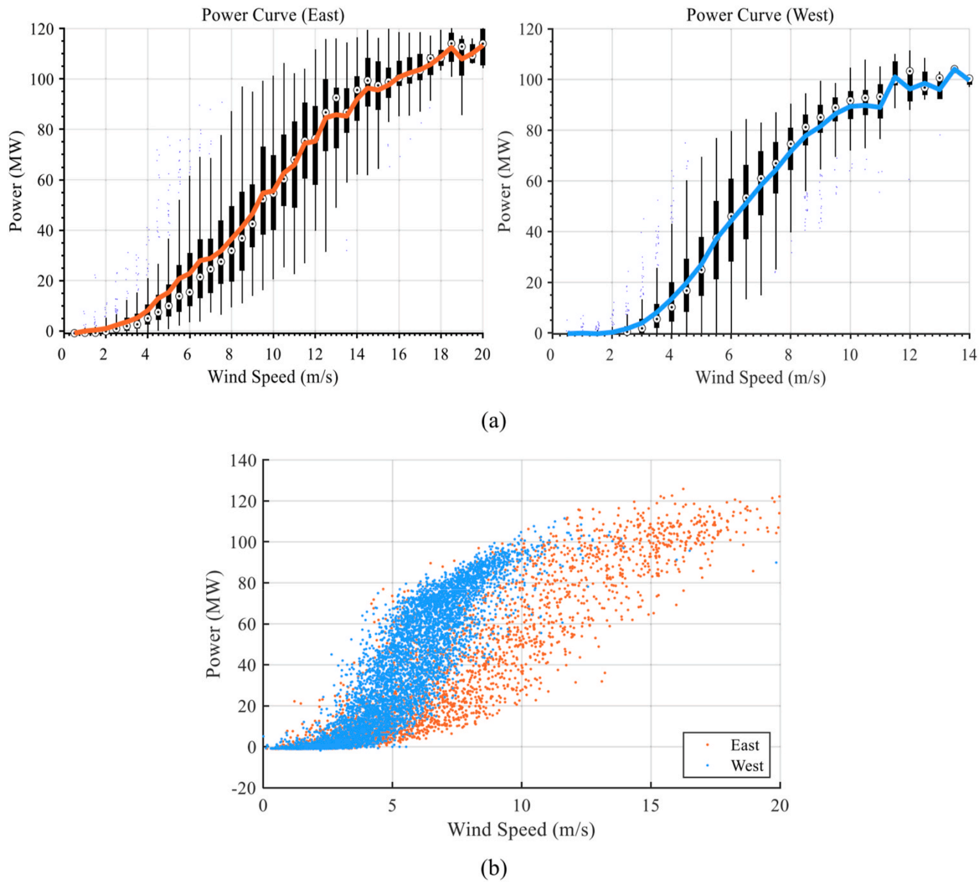



**Fig. 16.** (a)Power curves (East-West), (b)Scatter power plots for different directions. (source: Yildiz et al., 2021).

most frequent keywords are wind forecasting and wind prediction. And the confusion matrix most related to the two keywords are draw to show the occurrence frequency with two keywords and their frequency at the same time.

(i) wind forecasting

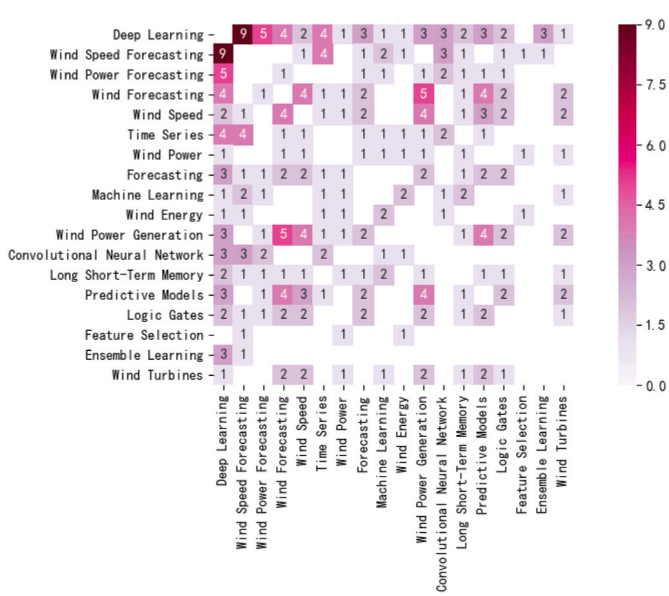



**Fig. 17.** The most relevant keywords of wind forecasting.

As shown in Fig. 17, the most relevant keywords of wind forecasting are deep learning, wind speed forecasting, wind power forecasting, wind forecasting, time series, wind speed, wind power generation, wind energy, convolutional neural network, machine learning, wind power, forecasting, long short-term memory, predictive models, ensemble learning, feature selection, logic gates, wind turbines.

(ii) wind prediction

As shown in Fig. 18, the most relevant keywords of wind prediction are deep learning, wind speed prediction, wind forecasting, wind power forecasting, wind power prediction, predictive models, wind power generation, wind power, ensemble learning, wind power prediction, hybrid model, wind turbines, wind power, numerical weather prediction, feature selection, wind power generation, wind speed.

The analysis for two keywords can be categorized into several aspects:

(i) Wind speed, power, and energy attract the main concerns of the wind forecasting. Forecasting wind behavior is important for energy managers and electricity traders, to overcome the risks of unpredictability when using wind energy. Forecasting wind values can be utilized in various applications, such as evaluating wind energy potential, designing wind farms, performing wind turbine predictive control, and wind power planning.
(ii) Convolutional neural network, long short-term memory, and ensemble learning are most commonly used deep learning algorithm for wind forecasting. The convolution operations in convolutional neural networks extract helpful local features in each mode and the relationships between modes for forecasting. Unlike machine learning (ML) algorithms, the LSTM network avoids

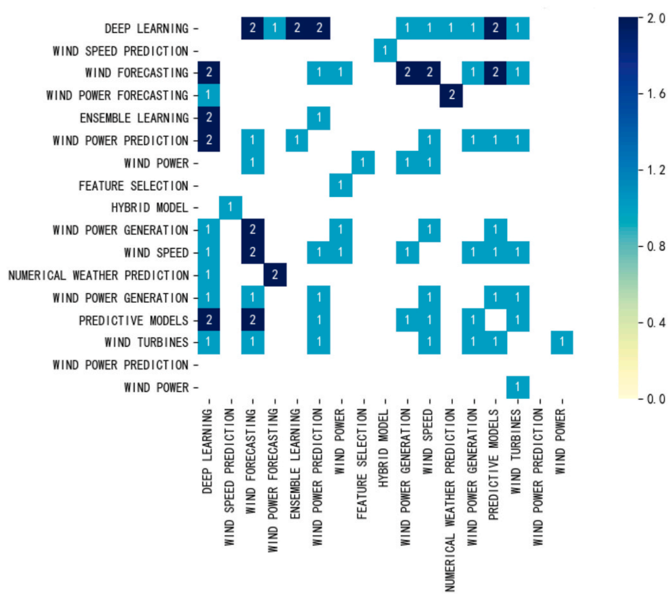



**Fig. 18.** The most relevant keywords of wind prediction.

the need for hand crafted features and learns the long-term temporal dependencies in the gait cycle. The primary advantage of the LSTM network is that it solves the vanishing gradient problem by introducing the memory blocks in place of self-connected hidden units, thereby deciding when to learn new information. Several ensemble models were claimed to have significant advantage over other state-of-the-art models involved in terms of prediction accuracy and stability.

(iii) Predictive models are preferred solution, in which time series, feature selection, logic gate are the crucial parts of them. Data-trained predictive models see widespread use, and they are tools for projecting known patterns or relationships into unknown times or places.

## 5.2. *Solar energy*

### 5.2.1. *Background*

The research of photovoltaic power generation output prediction (Wang et al., 2019a,b; Sharadga et al., 2020; Ryu et al., 2021; Rosato et al., 2021) mainly includes three aspects:

(i) The input of the model is selected based on the effective theoretical basis (Peng et al., 2021), which is the premise of photovoltaic output prediction (Natarajan et al., 2021; Narvaez et al., 2021).
(ii) The analysis of the relationship between environmental factors and photovoltaic output are based on prediction model of the photovoltaic output with variable environmental factors (Moreno et al., 2021).
(iii) Data from diverse time scales are often used to forecast the output of different scales for photovoltaic power generation(Mishra et al., 2020a,b).

There are several ideas and methods for predicting the output of solar power generation that have been developed so far. There are different options for forecasting the output of solar electricity generation: direct prediction and indirect prediction. The direct method is frequently used in conjunction with a forecast model based on historical power and meteorological data. The theory basis of this prediction method is clear, but the selection of model and algorithm is relatively more complex. The indirect method shows different from direct method. For indirect method, first the amount of solar radiation is predicted and took as an intermediate amount, then output power is then determined by using solar power station's power characteristic model.

### 5.2.2. Keywords analysis.

Analysis the keywords related to solar resources, among which the most frequent keywords are Sloar irradiance, solar forecasting, solar energy, solar radiation. And the confusion matrix most related to these keywords are draw to show the occurrence frequency with two keywords and their frequency at the same time.

(i) Sloar irradiance

As shown in Fig. 19, the most relevant keywords of solar irradiance are solar irradiance, deep learning, solar irradiance forecasting, LSTM, convolutional neuarl network, forecasting, predictive models, task analysis, recurrent neural network.

(ii) Solar forecasting

As shown in Fig. 20, the most relevant keywords of solar forecasting are deep learning, LSTM, machine learning forecasting, predictive models, forecasting, solar irradiance forecasting, solar radiation forecasting, deep learning, solar forecasting, convolutional neural network, solar energy, feature extraction, solar energy, data models, recurrent neural network, load forecasting.

(iii) solar energy

As shown in Fig. 21, the most relevant keywords of solar energy are deep learning, machine learning, solar energy, solar radiation forecasting, solar energy, LSTM, deep learning, prediction, renewable energy, convolutional neural network.

(iv) Solar radiation

As depicted in Fig. 22, The most relevant keywords of solar radiation are deep learning, LSTM, machine learning, forecasting, predictive models, forecasting, solar irradiance forecasting, solar radiation forecasting, deep learning, solar forecasting, convolutional neural network, solar energy, feature extraction, solar energy, data models, recurrent neural network, load forecasting.

The keywords analysis for four keywords can be categorized into

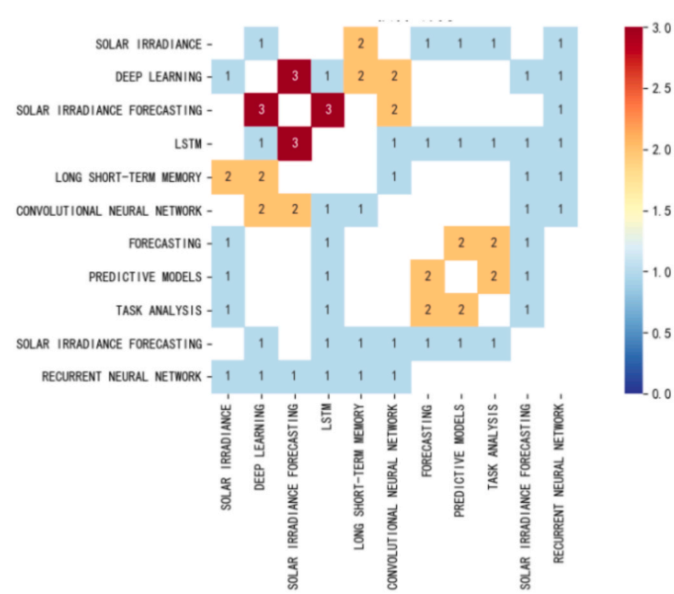



**Fig. 19.** The most relevant keywords of wind forecasting.

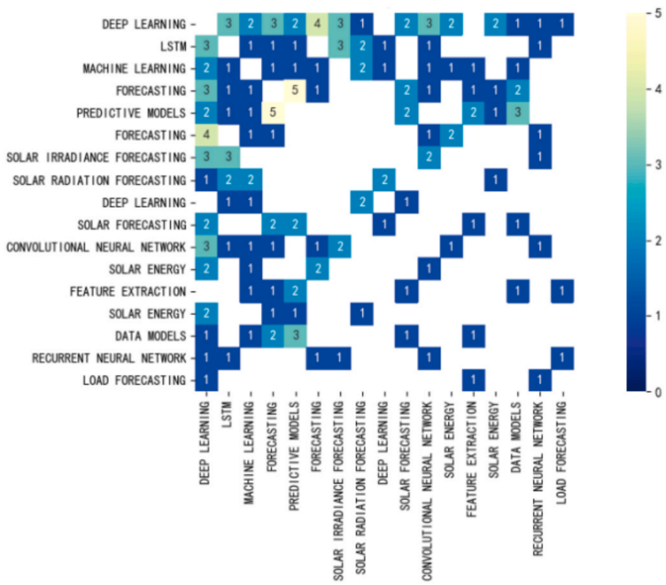



**Fig. 20.** The most relevant keywords of solar forecasting.

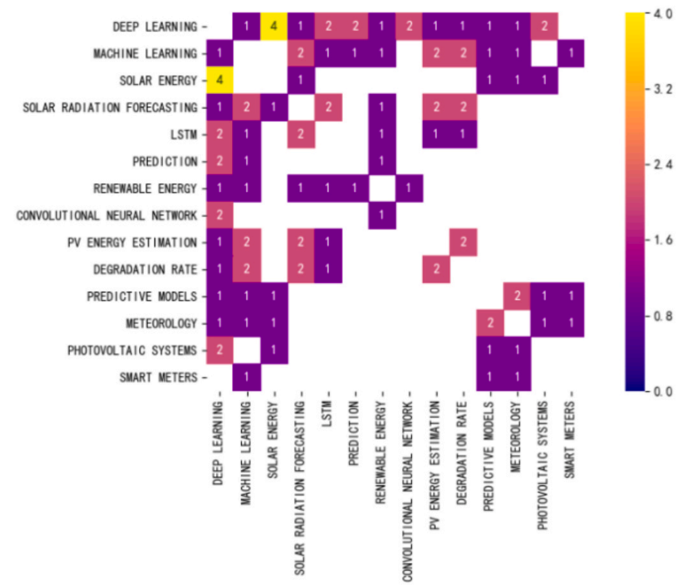



**Fig. 22.** The most relevant keywords of solar energy.

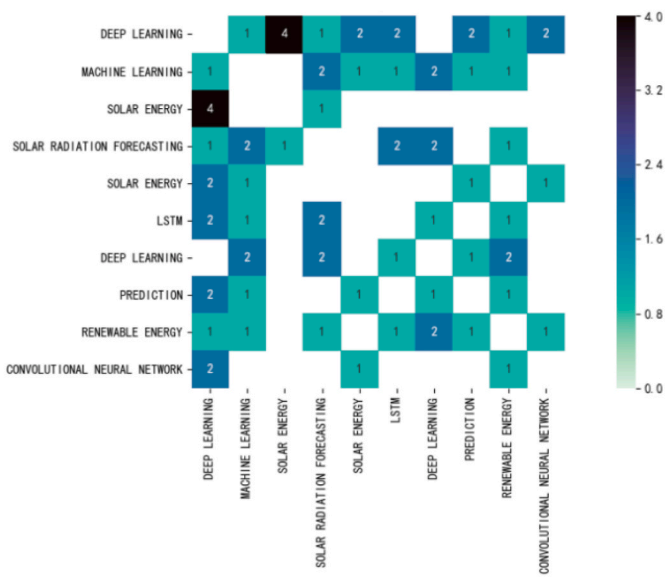



**Fig. 21.** The most relevant keywords of solar energy.

several aspects:

(i) Solar irradiance, radiation and load attract the main concerns of solar forecasting. Solar irradiance is an essential component in solar power applications. The availability of solar irradiance is influenced by several factors, such as forecasting horizon, weather classification, and performance evaluation metrics, which also need consideration. The accurate forecasting of solar irradiance is of utmost importance for the power system designers and grid operators for efficient management of solar energy systems. The intermittent and non-stationary nature of solar irradiance makes many existing statistical and machine learning approaches less competent in providing accurate predictions.

(ii) LSTM, convolutional neural network, recurrent neural network are most frequently used deep learning algorithm for solar forecasting. LSTM has shown good performances in the field of solar forecasting. Taking the advantages of CNN, the researcher can efficiently learn the distinct characteristic of different types of spectrum, and further classify them even more accurate. The non-stationarity characteristic of the solar power renders traditional point forecasting methods to be less useful due to large prediction errors. This results in increased uncertainties in the grid operation, thereby negatively affecting the reliability and increased cost of operation. To solve this issue, the recurrent neural network equipped with additional recurrent connections are adopted.

(iii) Predictive models are useful ploys in solar energy industries to optimize the performance of photovoltaic power systems. And the keywords task analysis, feature extraction, data models get more concerned in the literature. The utilization of new types of predictive models in renewable resource prediction is inclined to compare other AI-based-predictive models because of better accuracy, ease of utilization, less required data, and better performance.

### *5.3. Ocean energy*

#### *5.3.1. Background*

On the earth's surface, Oceans cover more than 70% so that to contribute a massive renewable energy source. Renewable energy derived from the ocean holds great promise. By 2050, it is expected to have a global generating potential of around 337 gigatonnes (GW) of installed capacity, which has the potential to reshape the world's electricity generating balance. For instance, the ocean renewable energy (ORE) resources of Australian coast is greatly outnumber the present electricity consumption. Furthermore, The power output of wave energy is several more times that of wind and solar energy. Ocean energy refers to the renewable energy obtained from the ocean, which includes tidal energy, wave energy, seawater temperature difference energy, seawater salinity difference energy and other different energy forms. Ocean waves are formed by the wind interaction generated by the movement of atmospheric circulation with the ocean surface, which are obviously affected by photovoltaic distribution in the atmosphere.

To exploit such energies, the efforts have concentrated on wave/ocean energy. Wave energy, from the other side, is sporadic and erratic. As with other renewable energy, which may influence stability of power system.

There are several topics that the existing studies concerned.

(i) The study of accurately wave forecasting and oceanographic parameters is crucial and more concerned for the researchers.
(ii) Wave power output and wave height is essential for the forecasting, thus a more comprehensive characterize of power output of wave is a lastlong research direction. Such as, it can be commonly characterized by the set of measurable parameters including mean and peak wave periods, significant wave height, and mean wave direction.
(iii) In considerations of the grid industry, they've been on the search for cost-effective ways of integrating wave energy into the main electricity system, integrating it with wind and solar energy.

Neural network has been adopted to handle the wave forecasting to achieve good results in the approaches of soft-computing and stastical field. And SVM, EML, fuzzy method and ML are also utilized to solve the problems in ocean energy.

To forecast short-term wave forces and operate a heaving point-absorber, a deep machine learning methodology with a multi-layer ANN and forecast manage strategy (Raj and Brown, 2021) was developed. The modeling results indicate that wave forces could also be predicted, and that the validation loss had a deleterious impact on the results, leading to a reduction in energy absorption.

To evaluate the wave energy flux (Bento et al., 2021) and other wave parameters, a platform of machine learning cnns with moth-flame optimizer was designed, as illustrated in Fig. 23. 13 datasets spanning the Pacific and Atlantic coasts, as well as the Gulf of Mexico were used to prove the efficiency of the deep learning network for short-term horizons at all the sites. To strengthen DNN prediction accuracy, the DNN architecture and significant input data selection are tested manually. The DNN is driven by a range of hyperparameters. and its input data are automatically modeled to maximize the potential of the DNN to produce accurate predictions.

### 5.3.2. Keyword

The relevant keywords are bidirectional long short-term-memory (bi-LSTM), neural network, ocean wave energy, forecasting skills, deep machine learning, deep neural networks, energy absorption, ensemble empirical model decomposition, moth-flame optimization, support vector regression, wave energy control, short-term forecasting, data selection wave energy converter, wave force prediction, boruta random forest optimizer, significant wave height, deep learning.

(i) Recurrent neural networks like long short-term memory are important architectures for sequential prediction tasks. long short-term memory model sequences along the forward time direction. Bidirectional LSTMs (Bi-LSTMs) on the other hand model sequences along both forward and backward directions and are generally known to perform better at such tasks because they capture a richer representation of the data. Various deep RNN models have been proposed for renewable energy forecasting. However, deep RNNs may increase the computation complexity, especially when the time series data exhibits long tails. One feasible solution is to adopt recurrent and convolutional operators for model development. Another possible solution attributes to the use of bidirectional calculations that can capture the impacts of both past and future states. Deep RNN can have additional stored state, which are under direct control by the neural network. In addition, the stored states can also be substituted by another neural network with time delays or feedback loops. Such controlled storages are the cornerstone of long short-term memory network and gated recurrent units. They both have unique temporal dynamic behavior and can mitigate the exploding and vanishing gradient problems. Therefore, long short-term memory and gated recurrent network exhibit promising performance for renewable energy forecasting.
(ii) As with other sources of renewables, however, wave energy has an intermittent and irregular nature, which is a major concern for power system stability. Consequently, in order to integrate wave energy into power grids, it must be forecasted. A controller is usually used to maximize the energy absorption of wave energy converter. Despite the development of various control strategies, the practical implementation of wave energy control is still difficult since the control inputs are the future wave forces. The main inspiration of Moth-Flame Optimization (MFO) algorithm is the navigation method of moths in nature called transverse orientation and is able to provide very promising and competitive

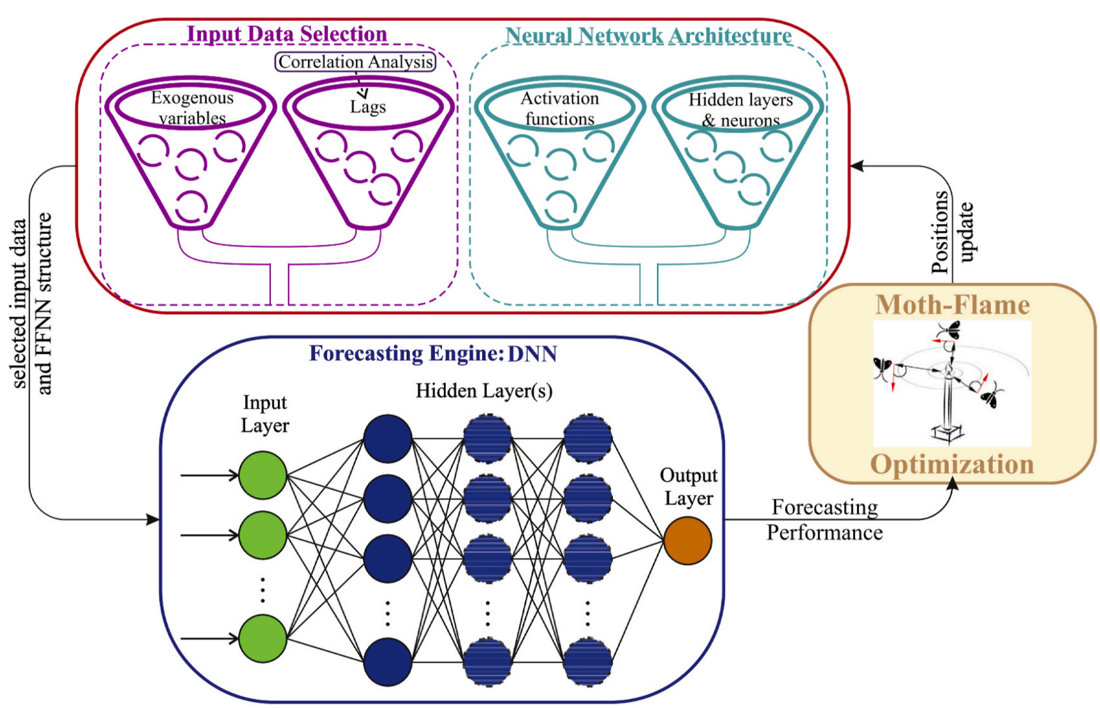



**Fig. 23.** The framework of deep learning neural networks with moth-flame optimization algorithm (source: Bento et al., 2021).

results. Compared with other marine energy resources, wave energy is a kind of resource with high power density and all-day availability. Owing to these advantages, wave energy is regarded as a prospective solution to the sustainable generation of power. The device used to harvest energy from ocean waves is called the wave energy converter. Wave force prediction is necessary for the implementation of real-time control. As proved in previous studies, the prediction deviation will reduce the efficiency of real-time control and thereby an accurate wave force prediction method is essential. In addition to these hyperparameters, a befitting input data selection for the forecasting engine should not be underestimated, given its potential to improve the performance.

### 5.4. Hydrogen energy

#### 5.4.1. Background

Hydrogen is synthesized by a multi-step process involving extra renewable energy. To compensate for the lack of renewable energy, the hydrogen can be transformed into electric energy using energy storage. The effectiveness of the optimal or near - optimal innovation is hindered by many of the prediction models in renewable energy, which are site-specific and influenced by variations in prediction time windows. How to use hydrogen as energy carrier for efficient power generation with renewable energy has become a hot topic. Using the intelligent hydrogen balance technology, the renewable energy supply and demand prediction model can be used to realize the self-sustaining power grid of the system. One of the most fundamental hydrogen-based activities is steam methane reforming (SMR). It works as part of a full hydrogen generation process, which must be stable in terms of preparing for a long-term deficit of renewable energy.

There are limited studies on renewable energy model prediction and renewable hydrogen system. Using the renewable energy power supply and demand prediction model and DL algorithm, a hydrogen-based self-sustaining holistic clean energy architecture has been constructed, allowing EMD and DL models to be used to predict wind power source, solar power demand, and renewable generation supply. The extra clean energy will be readily distinguished by comparing the expected the supply and demand of clean energy supply and demand. The hybrid emd-dl model is based on the forecasting model and is used to evaluate the supply and demand of renewable energy power.

The supply and demand prediction model and the DL method had been used to create a theoretical formulation of a hydrogen-based power network named as HySIREN (Hwangbo et al., 2019). Fig. 24 depicts the general framework. Forecasting was performed using the hybrid model with EMD-DL and historical data.

#### 5.4.2. Keyword

The relevant keywords are renewable electricity forecasting, deep-learning algorithms, integrated hydrogen production, optimization, jeju island.

Many researchers have been constructing renewable electricity forecasting models based on machine learning and artificial intelligence to improve the accuracy of renewable electricity generation forecasts while trying to enhance the flexibility of generating systems by using hydrogen to store energy. Hydrogen from the integrated hydrogen production process is compressed and transferred to a storage tank. The total amounts of hydrogen production are identical to the sum of the total hydrogen amounts from the integrated hydrogen production process underpinned by the optimized process.

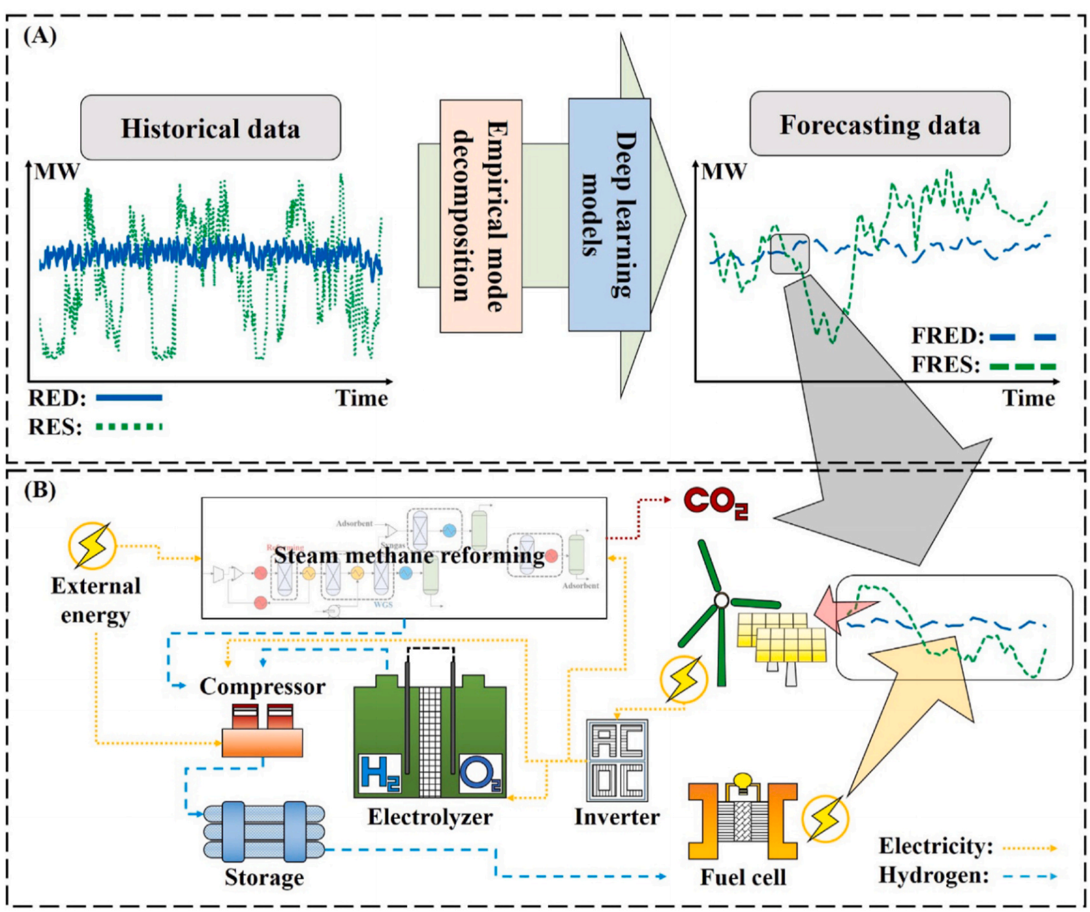



**Fig. 24.** The framework of the HySIREN model (source:Hwangbo et al., 2019).

### 5.5. Other renewable energy

Other renewable energy sources including hydro-power, biomass energy, geothermal energy and traditional biomass energy.

(i) Small hydro-power

Small hydro-power usually refers to the small hydro-power stations and its supporting small power grid.

(ii) Biomass energy

Biomass energy is the energy contained in the biomass. It is the energy stored in the biomass of the green power stations by converting the solar energy into chemical energy via the chloroplasts.

(iii) Geothermal energy

Geothermal resources refer to the thermal energy of the rock in the crust and the energy of geothermal fluids by utilizing the current technical economy and geological environment.

Unfortunately, as far as we know, these types of renewable energy do not have relevant studies using deep learning algorithms to make energy prediction for various reasons up to now.

## 6. Keyword analysis of deep learning forecasting model

In the field of solar energy forecasting, which has become a research hotspot in recent years, deep learning has gained prominence. These five common deep learning algorithms — Generative Adversarial Networks, Recurrent Neural Network, Convolutional Neural Network, Stacked Auto-Encoder, and Deep Belief Network — will be examined in the next section for their merits, limitations, and potential uses (DBN). In solar energy prediction, RNN and CNN are widely used. There have been a number of publications on SAE and DBN, despite the fact that they are both typical deep learning algorithms. Less is known about solar power generation predictions based on GANs.

### 6.1. Evaluated criteria

In Table 6, scale-independent measure of model's accuracy are mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentile error (MAPE), symmetric mean absolute percentile error (SMAPE), Mean squared log error (MSLE), normalized root mean squared error (NRMSE), unscaled mean bounded relative absolute error (UMBRAE), mean bounded relative absolute error (MBRAE), inRSE, $R^2$.

Analyzing MAE is based on the difference between the expected and actual values. Larger faults don't break this function as easily as they do the other ones. The distribution of models is also reflected in the MSE and RMSE. When compared to MAE, they are more susceptible to big errors since the errors are squared and hence amplified. It is the difference between erroneous data and the actual data. An error function can be applied to it. When the wind speed is low, a minor error can have a big influence, but when the wind speed is high, a large error can have little impact. Large errors aren't punished if both the actual and forecast values are large numbers, hence MSLE takes this into account. If you want to compare different datasets and models, NRMSE is a better option than RMSE.

These formulas can then be used to evaluate a forecasting application's efficiency from several perspectives. Using naive prediction outcomes as a baseline, the unscaled mean bounded relative absolute error (UMBRAE) and the mean bounded relative absolute error (MBRAE) can also be used to verify the efficiency of various models.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |x_i|$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{n=1}^{N} (x_i - \widetilde{x}_i)^2$$

$$\mathrm{RMSE} = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n} (x_i - \widetilde{x}_i)^2}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{\widetilde{x}_i - x_i}{x_i}\right|$$

$$\mathrm{SMAPE} = \frac{2}{n}\sum_{i=1}^{n} \frac{|\widetilde{x}_i - x_i|}{|x_i| + |\widetilde{x}_i|}$$

$$\mathrm{MSLE} = \frac{1}{n}\sum_{i=1}^{n} \log\left(\frac{x_i + 1}{\widetilde{x}_i + 1}\right)$$

$$\mathrm{NRMSE} = \frac{\sqrt[2]{\frac{1}{n}\sum_{i=1}^{n} (x_i - \widetilde{x}_i)^2}}{x_{max} - x_{min}}$$

$$\mathrm{UMBRAE} = \frac{\mathrm{MBRAE}}{1 - \mathrm{MBRAE}}$$

$$\mathrm{MBRAE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|x_i - \widetilde{x}_i|}{|x_i - \widetilde{x}_i| + |x_i - \widetilde{x}_i^*|}$$

### 6.2. Stacked auto-encoder

#### 6.2.1. Introduction to SAE

Autoencoders could be used in a variety of deep learning-based models for wind predictions. Deeper predictors can be built by stacking the AE (autoencoder), denoising autoencoder (DAE), and stacked

**Table 6**
Keyword weight analysis for cluster C2.

| Label | Cluster | Betweenness centrality | Closeness centrality | Eigenvector Centrality | Clustering coefficient | Degree centrality |
|---|---|---|---|---|---|---|
| Predictive Models | C2 | 0.072661188 | 0.785714286 | 0.290026927 | 0.393145161 | 32 |
| Forecasting | C2 | 0.050468999 | 0.733333333 | 0.270362427 | 0.418719212 | 29 |
| Data Models | C2 | 0.00441049 | 0.586666667 | 0.163919025 | 0.714285714 | 14 |
| Logic Gates | C2 | 0.012177212 | 0.61971831 | 0.190792591 | 0.594771242 | 18 |
| Neural Networks | C2 | 0.00910923 | 0.611111111 | 0.17245449 | 0.625 | 16 |
| Load Forecasting | C2 | 0.006958045 | 0.586666667 | 0.153270287 | 0.615384615 | 14 |
| Wind Forecasting | C2 | 0.001511452 | 0.571428571 | 0.140536299 | 0.818181818 | 12 |
| Load Modeling | C2 | 0.008031624 | 0.594594595 | 0.157534917 | 0.6 | 15 |
| Wind Power Generation | C2 | 0.006366202 | 0.578947368 | 0.143027878 | 0.705128205 | 13 |
| Time Series Analysis | C2 | 0.007635158 | 0.602739726 | 0.173210292 | 0.641666667 | 16 |
| Wind Speed | C2 | 0.002616916 | 0.571428571 | 0.132552405 | 0.742424242 | 12 |
| Feature Extraction | C2 | 0.002049184 | 0.536585366 | 0.126504669 | 0.727272727 | 11 |
| Deep Reinforcement Learning | C2 | 0.000848497 | 0.55 | 0.093854917 | 0.821428571 | 8 |

autoencoder (SAE), which are referred to as stacked autoencoder (SAE), stacked denoising autoencoder (SDAE), and stacked sparse autoencoder (SSAE). Some academics combined the theory of transfer learning alongside AE-based prediction model in their research.

The AE's structure contains an encoding layer and a decoding layer, as can be seen in Fig. 25, and the goal of training the AE is to map the input data into a hidden layer expression through the activation function, and then to be decoded to match the training model with the generation process of real world data. The loss function was minimized on the training set to determine the weights and errors, while the optimization, regularization and other techniques were used to avoid model overfitting during the training process. The output of either the hidden layer of the final AE is often used as an input to the classifier, and then the first AE subsequently initialized layer by layer throughout the SAE training procedure. and the parameters of the classifier is trained in a supervised method. The basic structure of the AE and the SAE training procedure are shown. The purpose of SAE is to extract higher-order features of input data layer by layer, during which the dimension of input data is reduced, a complex input data is converted into a simple series of higher-order features, and then higher-order features are input into a classifier or cluster for classification or clustering.

Whereas if amount of hidden layer nodes for SAE is insufficient, or the input sequence is random, the implied node will compress the original data, which will become difficult to extract the input data features. The way to solve the problem is to add sparse constraints on the hidden layer. In addition to the self-coding model described above, the structural units of the SAE can also use the AE deformation, such as the independent cyclic autoencoder (IRAE) and the two-layer stack sparse autoencoder (SSAE). SAE also employed an unsupervised training approach layer by layer.

### 6.2.2. SAE research in the field of renewable energy sources

In the field of renewable research, the main research in SAE are focusing on load demand forecasting, probability forecasting, and wind power forecasting, and aiming to minimize the power input to wind speed prediction, accurate wind power prediction with 15 min interval for photovoltaic output forecast, short-term wind power forecast, establish accurate large-scale wind power penetration prediction model, and predict long-term solar radiation.

The major publications of SAE models throughout the field of renewable energy are included in Table 7 and the author, titles, problem solving, inputs, algorithmic models, and outputs are introduced.

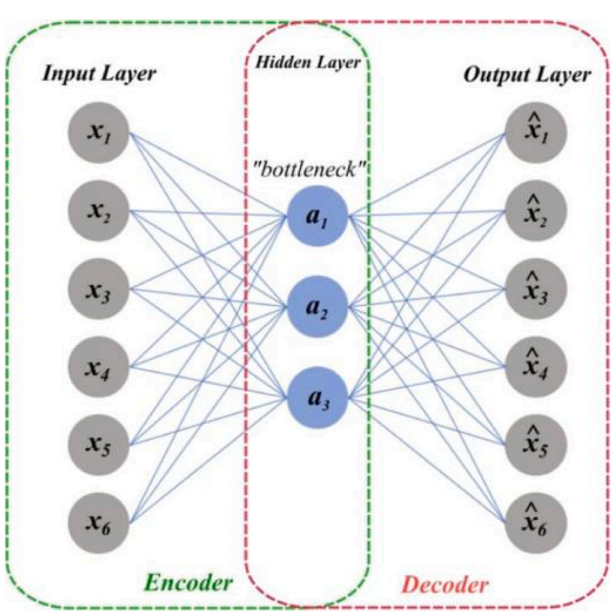



**Fig. 25.** The structure of Auto-encoder.

Phan et al. (2021) established a hybrid prediction model with numerical weather forecast (NWP) models and XGBoost training models for forecasting wind power in the short term. The proposed prediction algorithm includes data preprocessing, in which an autoencoder model is used to reduce 20 dimensions of NWP integration. Based on the prediction results, the proposed model produces better performance and prediction accuracy in other predictive models, revealing the importance of using autoencoders as well as deep learning models in deterministic or probabilistic predictions.

Suresh et al. (2020) introduces the energy management system of the University of Technology. It consists of three components: prediction system, optimizer, and optimized electricity velocity charging stations as independent loads of the system. The methods and approach is based on a fundamental learning model that employs an autoencoder-based long, short-term memory (LSTM) framework. The research describes a quantitative models of its efficiency across various datasets and explains in detail of validity and computation time, constructing a trial for its implementation.

Liu et al. (2019) launched a separate combination multi-step wind turbine forecasting model. that includes dense extraction of features, 2 different learning techniques, multi-objective optimization, and adaptive error detection and correction. A hidden model of the underlying high-resolution wind speed data was identified that used a two-layer stack sparse autoencoder (SSAE) in Fig. 26 and Fig. 27. A series of experiments showed that the proposed model was well trained and had strong convergence to reasonably integrate the base predictors, as shown in Table 8.

A unique deep learning network layered by an independent cyclic autoencoder (IRAE) was created by Wang et al. (2021). In Fig. 28, those IRAE were packed into *SIRAE*, and supervised training was used to set the parameters for each layer of SIRAE. The SIRAE model provides more reliable popular models, according to the results of two contrast studies. RMS errors grew by 18.46%, 31.16%, 9.06%, and 34.24% in March, June, September, and December, respectively. With its effective and reliable predictive ability, SIRAE seems to have become an effective technique of ultra-short-term wind electric power forecasting.

For 15-min intervals, Zhang et al. (2020) developed a hybrid deep learning model driven by external meteorological data. Fig. 29 illustrates the suggested model, which is based on recent breakthroughs in extended short-term memory networks and autoencoders, which evaluates uncertainty in order while forecasting complicated weather circumstances. The consistency model was developed to estimate the weather on successive sunny days. As can be seen in Fig. 30, the accuracy of the predictions was confirmed by information gathered from various sources.

Jiao et al. (2018) designed a new forecasting method. A back-propagation technique with three hidden layers and stacked auto-encoders is used to automatically extract from a baseline data series. In order to fine-tune the weighting of the stacked autoencoder network, BP and PSO algorithms are now used to measure the amount of neurons in the hidden layer as well as the learning rate of each Autoencoder. Table 9 illustrates that the suggested method outperformed conventional BP neural networks and SVMs in terms of stability and efficiency.

After training the DNN on data from farms, Hu et al. (2016) fine-tuned the mapping of wind speed patterns utilizing data from newly created farms. As a result, well-trained networks are able to send data from one farm to another. According to experiments, the proposed method greatly minimizes the forecast error when used.

For the predictive model of long-term solar irradiance, Aslam et al. (2020) have used AE-LSTM (autoencoder-long short-term memory) long-term deep learning method. A long, short-term memory was used to fine-tune the autoencoder (AE) to produce the final prediction. The experiments showed that the PV system's energy potential will be impacted by degradation rates (DR) in 3 years based on the estimated

**Table 7**
The publication information of SAE models in the renewable energy field.

| Time | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|
| Phan et al. (2021) | Accurate wind power prediction | The NWP includes point wind speed from WRFD, RWRF, and ensemble wind speed from WEPS | NWP + XGBoost | Wind power PI validity | The proposed model yields better performance and prediction accuracy in other prediction models |
| Suresh et al. (2020) | Minimimize power input to the autonomous grid | Electric vehicle charging stations | AE-LSTM | RMSE,MAE, MBE,BIAS | Improve renewable energy utilization within the facilities |
| Liu et al. (2019) | Wind speed prediction | Raw 3s high-resolution wind speed data | stacked sparse autoencoder (SSAE + bidirectional LSTM | RMSE,MAE, MAPE | The average R M S E for the 10-step prediction of 0.2618 m/s, outperforms other existing models in all experimental sites and prediction steps, the multi-objective optimization algorithm can reasonably integrate base predictors and the proposed residue correction model can yield over 78% of RMSE improvements. |
| Wang et al. (2021) | Accurate wind-electric power prediction | Wind power data | independent cyclic autoencoder (IRAE) | MAPE, nMAE, NRMSE | In extended applications, SIRAE increased 18.46%, 31.16%, 9.06% and 34 mean square error in March, June, September, and 34.24% in December, compared to the persistence model, respectively. |
| Zhang et al. (2020) | Pre-day photovoltaic output predictions were made at 15-min intervals | Photovoltaic data | AE-LSTM | nRMSE, nMAE | Improve the estimation accuracy of photovoltaic power generation |
| Jiao et al. (2018) | Short-term wind electric power forecast | Wind power | SAE + BP | MAPE,MAE, RMSE | Accuracy was improved on average by 12% at different time steps. |
| Hu et al. (2016) | Establish an accurate large-scale wind power penetration prediction model | Data for the different wind farms | Stacked denoising autoencoders (SDE)+ Shared-hidden layer DNN | MAE,MSE, RMSE, MAPE | The use of the proposed technique significantly reduces the prediction error |
| Aslam et al. (2020) | Long-term solar radiation prediction | Clear sky global horizontal irradiance (GHI) and historical solar radiation | AE-LSTM | RMSE,MAE, R2 | Energy estimation methods for solar radiation prediction and DR effects are compared with conventional methods to show the efficiency of the proposed method. |

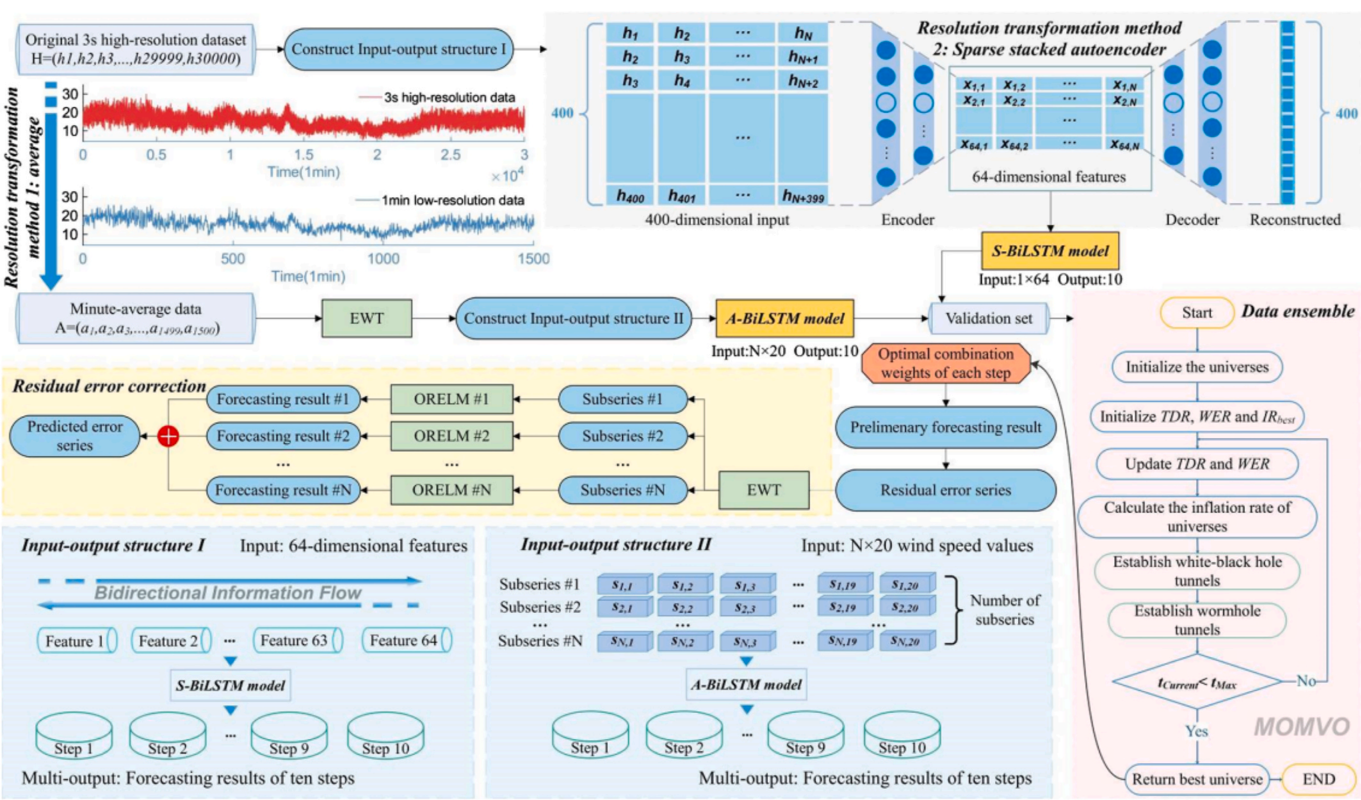



**Fig. 26.** Framework of proposed hybrid forecasting model (source: Liu et al., 2019a,b).

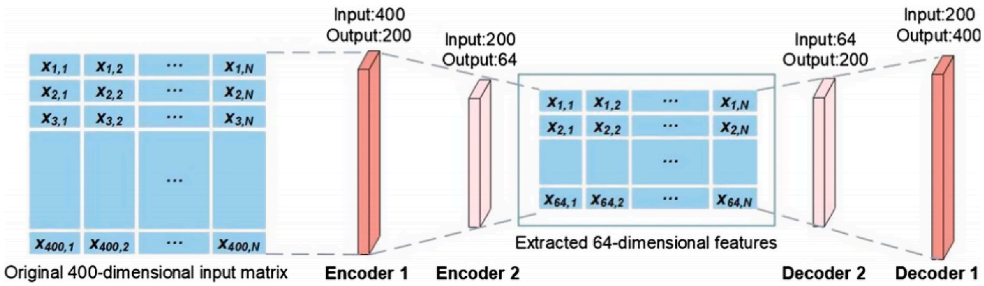



**Fig. 27.** The structure of the proposed two-layer SSAE (source: Liu et al., 2019a,b).

**Table 8**
Forecasting performance of forecasting models (source: Liu et al., 2019a,b).

| Indicator | Model | Forecasting step | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| MAPE (%) | S-BiLSTM | 7.3049 | 7.095 | 7.3265 | 7.3163 | 7.6784 | 7.7856 | 7.7991 | 8.2027 | 8.1248 | 8.0553 |
| | A-BiLSTM | 3.4741 | 5.3241 | 7.1947 | 7.5771 | 7.8122 | 8.512 | 8.7344 | 9.1338 | 9.8241 | 10.4566 |
| | SA-Bil5TM-MOMVO | **3.2243** | **4.6549** | **5.6822** | **6.0144** | **6.2883** | **6.6583** | **6.7748** | **7.0156** | **7.1057** | **7.2S18** |
| MAE (m/s) | S-BiLSTM | 1.1558 | 1.0948 | 1.121 | 1.1264 | 1.1983 | 1.2215 | 1.2192 | 1.25 | 1.2441 | 1.2397 |
| | A-BilSTM | 0.5446 | 0.8267 | 1.1101 | 1.1584 | 1.197 | 1.2952 | 1.3278 | 1.3901 | 1.488 | 1.5852 |
| | SA-BiLSTM-MOMVO | **0.5064** | **0.7163** | **0.8633** | **0.9169** | **0.9698** | **1.028** | **1.0414** | **1.0569** | **1.0724** | **1.1018** |
| RMSE (m/s) | S-BiLSTM | 1.4712 | 1.4079 | 1.4327 | 1–4459 | 1.523 | 1.5801 | 1.5953 | 1.6291 | 1.6352 | 1.6397 |
| | A-BilSTM | 0.6804 | 1.0497 | 1.4077 | 1–4818 | 1.5249 | 1–651 | 1.6978 | 1.7707 | 1.8786 | 2.0263 |
| | SA-BiLSTM-MOMVO | **0.6302** | **0.8874** | **1.1019** | **1.1735** | **1.2171** | **1.2921** | **1.3187** | **1.363** | **1.3965** | **1.4419** |

Note: Bold values indicate the best performance.

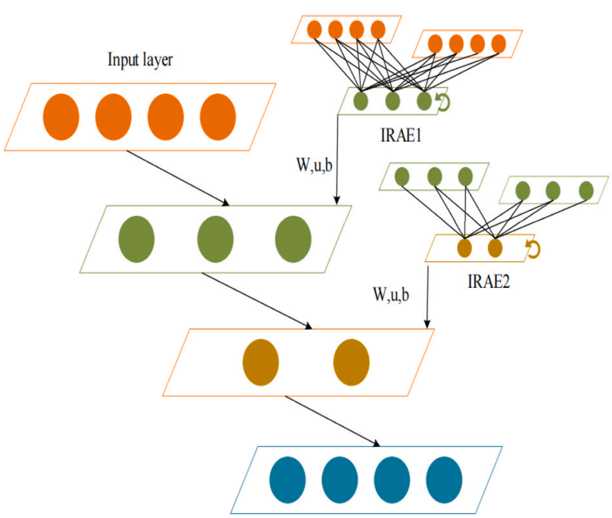



**Fig. 28.** The structure of SIRAE (source: Wang et al., 2021).

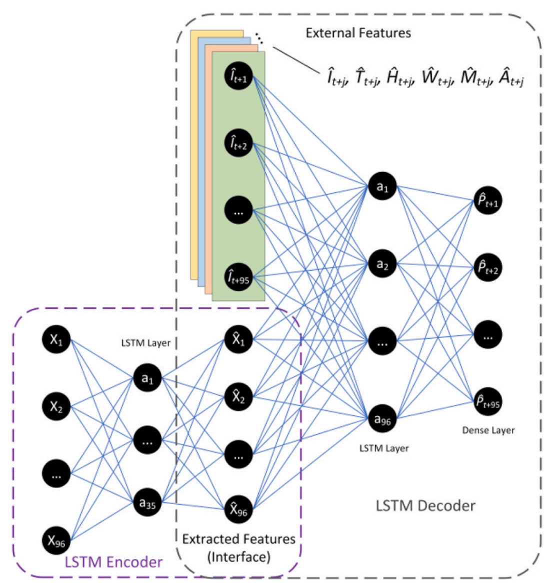



**Fig. 29.** The architecture of AE-LSTM network (source: Zhang et al., 2020).

solar radiation.

### 6.2.3. SAE research in the field of renewable energy sources

SAE are stacked by autocoder and restricted Boltzmann machine (RBM). AE and RBM can be trained with label-free data to obtain the feature representation of input data through nonlinear transformation, with flexible structure, simple algorithm and less training difficulty. They are easy to expand in practice, and SAE is suitable for modeling and feature extraction of unrelated data.

Through analysis, the existing research in the renewable field mainly has the following characteristics in SAE:

(i) In terms of application fields, SAE is mainly used in the field of wind energy and solar energy, and more is used in the research of wind energy.
(ii) In terms of use purpose, it mainly extracts and reduces the dimension of data features through SAE and SAE optimization algorithm for specific data.
(iii) In terms of application methods, wind or solar energy prediction is usually studied in combination with other basic algorithms or optimization algorithms of machine learning or deep learning, including LSTM, BP(Back Propagation), PSO(Particle Swarm Optimization), etc.
(iv) Evaluation criteria of SAE were MAPE, MASE.
(v) The advantages of SAE in renewable energy can be concluded as, a. It is common to conduct unsupervised performance extraction, b. The algorithm is easy to complete, c. The unlabeled data is not

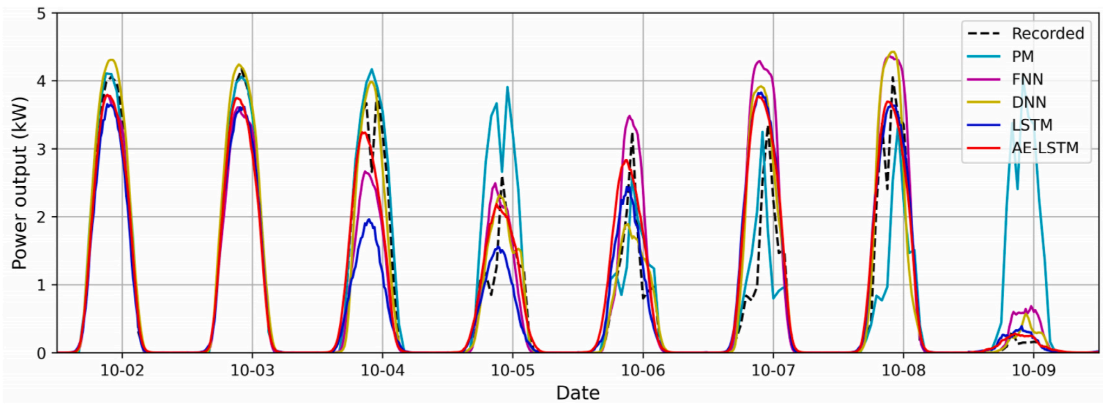



**Fig. 30.** Forecast output comparison at Catania from October 2 to October 9 (source: Zhang et al., 2020).

**Table 9**
Comparison of forecasting performance for multi-step wind power forecasting (source: Jiao et al., 2018).

| | 1-step | 2-step | 3-step | 4-step | 5-step | 6-stcp | 9-step | average |
|---|---|---|---|---|---|---|---|---|
| RMSE (MW) | | | | | | | | |
| BP | 42.5541 | 318.43 | 509.5931 | 552.618 | 4997061 | 6645697 | 591.7251 | 454.17 |
| SVM | 281785 | 663899 | 120.554 | 1717443 | 2247633 | 270.0486 | 584321 | 209.43 |
| SAE BP | 28.3197 | 449789 | 88.0719 | 108.9562 | 1431312 | 353.7017 | 220.7056 | 141.12 |
| MAE (MW) | | | | | | | | |
| BP | 303281 | 246016 | 3222614 | 4358386 | 4210345 | 495.5854 | 472.6068 | 346.24 |
| SVM | 19887 | 520355 | 98.4002 | 1473712 | 1973102 | 2390523 | 490.0291 | 177.73 |
| SAE BP | 20.5644 | 33.322 | 70.5791 | 819918 | 116.3902 | 286.1584 | 166.1055 | 110.73 |
| MAPE (%) | | | | | | | | |
| BP | 4.654 | 34.3 | 46.696 | 56.067 | 71.512 | 59.189 | 58.873 | 47.33 |
| SVM | 339 | 8768 | 165 | 25.102 | 33925 | 41145 | 6636 | 2788 |
| SAE BP | 3.472 | 5.639 | 10.94 | 12.164 | 19.008 | 36.859 | 23.604 | 15.96 |

required for training, d. It has Excellent performance on feature extraction of renewable energy.

(vi) The disadvantages of SAE can be concluded as, a. The SAE network is difficult to optimize, b. The SAE network need Extensive processing time and fine-tuning, c. Training may be affected by the disappearance of the error.

### 6.3. Deep belief network

#### 6.3.1. Introduction to DBN

Essentially, the DBN is a restricted Boltzmann machine containing hyperparameters initialized layer-by-layer without supervision. Since characteristic features throughout the input could be recognized, the DBN would be used to forecast renewables.

Restricted Boltzmann Machines are the basic building blocks of DBN, as shown in Fig. 31. RBM typically consists of two layers of neural network models, one for the feature map and one for the hidden layer. However, there is no relationship between the units in any one layer and those in other layers. The RBM uses the network objective functions to characterize the probability distribution of such input data. The partial derivative of the energy function cannot be settled directly, and needs to be estimated by statistical methods. Pre-training and fine-tuning are the different stages of RBM training: An unsupervised pre-training methodology guarantees that as much feature data as possible may be extracted from a feature vector if it maps to a new feature space, and a final BP network receives the RBM's output feature vector as its input feature vector. Due to this, each RBM network can only assure that its own layer's weights approach the ideal feature vector mapping of such a layer, but not the entire DBN. The BP network additionally distributes error to each RBM layer and fine-tunes the entire DBN network in either a supervised training manner. During the pre-training phase for DBN networks, the weight parameters for deep BP networks are established. Due to unpredictable starting weight values, BP networks are susceptible to local optimality and extended training times. DBN can alleviate these issues.

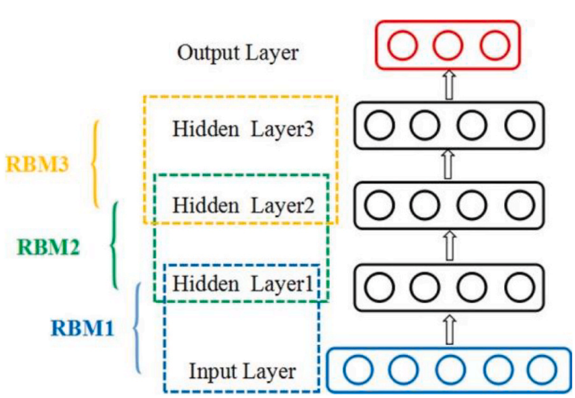



**Fig. 31.** The structure of DBN.

#### 6.3.2. DBN research in the field of renewable energy sources

As shown in Table 10, main publications of DBN in the field of renewable field of research keywords are analyzed. The research objective are the risk of wind energy supplier bidding strategy, solar radiation, accurate prediction of wind speed, wind power prediction, wind speed time series, photovoltaic output power prediction, short-term electricity price prediction, etc.

Zhang et al. (2021) presented a new bidding strategy (BS), in which DBN were used to account for WP in order to enhance the validity of the forecasting predictions. The suggested case studies had revealed that the proposed methodology and the previously implemented bidding tactics are more beneficial than previous approaches that had not been included in the investigations.

**Table 10**
The publication information of SAE models in the renewable energy field.

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| Zhang et al. (2021) | A Wind Energy Supplier Bidding Strategy Using Combined Ega-Inspired Hpsoifa Optimizer And Deep Learning Predictor | Risk Of The Wind Energy Supplier Bidding Strategy | wind production data obtained from Shangchuan Island wind farm in Guangdong Province from January 2013 to October 2013 in 1-h intervals | PSO + Firefly + DBN | MAPE,PI (prediction interval),SV (shapley value) | The Proposed Algorithm And Established Bidding Strategies Are Verified To Show Higher Effectiveness. |
| Ghimire et al. (2019) | Deep Learning Neural Networks Trained With Modis Satellite-Derived Predictors For Long-Term Global Solar Radiation Prediction | Solar Radiation | Mid-Resolution Imaging Spectrometer (Modis) Satellite Data, In Solar Cities In Australia | DBN + deep neural network | MAE,RRMSE,r, RMSE, high correlation coefficient | During The Test Phase, The Deep Learning Model Produced a Significantly Lower Absolute Percentage Deviation (3%) And a High Kling-Gupta Efficiency (97.5%) Values When Compared To The Single-Hidden Layer And Ensemble Models. |
| Liu et al. (2019) | Deep Belief Networks with Genetic Algorithms in Forecasting Wind Speed | Accurate Prediction Of wind speed with various weather attributes. | Wind speed and weather-related data are collected from Taiwan's central weather bureau | DBN + Genetic Algorithms | MAPE, RMSE | A Feasible And Effective Method For Wind Speed Prediction |
| Wang et al. (2018) | Deep Belief Network Based K-Means Cluster Approach For Short-Term Wind Power Forecasting | Wind Power Forecast | Numerical Weather Forecast (Nwp) Data Of the Sotavento wind farm | K-Means + DBN | NMAE, NRMSE | The Prediction Error Of The Dbn Model Is Mostly At Small Levels, And The Prediction Accuracy Of The Proposed Method Is Better Than Above Bp And Mwnn44% |
| Wang et al. (2016) | Deep Belief Network Based Deterministic And Probabilistic Wind Speed Forecasting Approach | wind speed forecasting | Real Wind Farm Data From China And Australia | Wavelet Transform (Wt)+ Deep Belief Network (Dbn)+ Spinal Quantile Regression (QR) | MAE,RMSE, MAPE,ACE (Average converage error), Interval sharpness (IS), | Advanced Nonlinear And Nonstationary Features In The Wind Speed Sequences Can Be Better Learned |
| Jza et al. (2020) | An Adaptive Hybrid Model For Day-Ahead Photovoltaic Output Power Prediction | Indirect, Randomness, And Fluctuation Of Solar Power, Accurate And Stable Photovoltaic Output Power Prediction | Raw Pv Output Power | Ivmd + Arima + Idbn | MAE,MAPE, RMSE,SDE (standard deviration of error) | The Proposed Model Can Improve The Predictive Performance Of The Photovoltaic Output Power. |
| Zhang et al. (2020) | An Adaptive Hybrid Model For Short Term Electricity Price Forecasting | Short-Term Electricity Price Forecast | Data From Australia, Pennsylvania-New Jersey-Maryland (Pjm), And The Spanish Power Markets | Variational Mode Decomposition (Vmd)+ Adaptive Particle Swarm Optimization (SAPSO)+ Seasonal Autoregressive Integrated Mobile Average (SARIMA)+Deep Belief Network (DBN) | MAE,MAPE, RMSE | The accuracy and stability of the prediction can be significantly improved |

Ghimire et al. (2019) designed the algorithms based on deep belief networks to predict medium-resolution Imaging Spectrometer (MODIS) satellite data. They had a reduced fraction error (3%), as well as an efficiency of 97.5 percent, comparing to the one hidden layer and ensemble models, respectively.

A model for predicting wind speed was developed by Lin et al. a Deep Belief Network with a genetic algorithm (DBNGA) Genetic algorithms are used to determine the parameters of deep belief networks. Empirical results show that the DBNGA model predicts wind speed over other prediction models in terms of prediction accuracy.

Deep belief networks were designed by Wang et al. (2018) for wind power prediction. Many NWP samples with a large impact on the prediction accuracy were selected as input to the DBN model to improve the model efficiency. The Sotavento power station in Spain proved the DBN model accurate. Table 11 revealed that the DBN model's error values was predominantly at minor levels, and the suggested technique's generalization ability was superior than above BP 44 percent.

**Table 11**
Wind power forecasting error at Sotavento (source:Wang et al., 2018).

| | error | BPNN | MWNN | DBN |
|---|---|---|---|---|
| spring | NMAE | 0.0432 | 0.0686 | 0.0389 |
| | NRMSE | 0.0551 | 0.0734 | 0.0475 |
| summer | NMAE | 0.0250 | 0.0369 | 0.0155 |
| | NRMSE | 0.0291 | 0.0415 | 0.0246 |
| fall | NMAE | 0.0283 | 0.0435 | 0.0208 |
| | NRMSE | 0.0370 | 0.0628 | 0.0307 |
| winter | NMAE | 0.0819 | 0.0340 | 0.0193 |
| | NRMSE | 0.1109 | 0.0650 | 0.0258 |
| average | NMAE | 0.0446 | 0.0458 | 0.0236 |
| | NRMSE | 0.0580 | 0.0607 | 0.0322 |

It was hypothesized by Wang et al. (2016) that a new deep learning based methodology for wind speed prediction (WSF) may be used. Spinal quantile regression was combined with wavelet transform (WT),

**Table 12**
Deterministic 1-h ahead forecasting error (source:Wang et al., 2016).

| Season | Error | ARMA | BPNN | MWNN | Proposed method |
|---|---|---|---|---|---|
| Spring | MAE | 0.7957 | 0.8426 | 0.9086 | **0.4097** |
| | RMSE | 1.0170 | 1.0834 | 1.1395 | **0.5510** |
| | MAPE | 11.94% | 0.1265 | 13.64% | **6.15%** |
| Summer | MAE | 0.6714 | 0.9036 | 0.7426 | **0.3987** |
| | RMSE | 0.9251 | 1.1662 | 0.9799 | **0.5200** |
| | MAPE | 10.99% | 0.1479 | 12.15% | **6.53%** |
| Fall | MAE | 0.7323 | 0.8062 | 0.8584 | **0.5397** |
| | RMSE | 0.9748 | 1.0424 | 1.1083 | **0.7061** |
| | MAPE | 7.18% | 0.0790 | 8.41% | **5.29%** |
| Winter | MAE | 1.0526 | 1.3597 | 1.1552 | **0.6222** |
| | RMSE | 1.4675 | 1.8815 | 1.5467 | **0.7829** |
| | MAPE | 17.27% | 0.2230 | 18.95% | **10.21%** |
| Average | MAE | 0.8130 | 0.9780 | 0.9162 | **0.4926** |
| | RMSE | 1.0961 | 1.2934 | 1.1936 | **0.6400** |
| | MAPE | 0.1184 | 0.1441 | 0.1329 | **0.0704** |

deep belief network. Table 12 compares real wind farm dataset from China and Australia and demonstrates as higher-level nonlinear and non-stationary features can be effectively trained to attain competing results in comparison.

Improved variational pattern decomposition (IVMD), the autoregressive integrated mobile average (ARIMA), and the improved deep belief network (IDBN) were all used in conjunction by Jza et al.(2020) to develop an adaptive combination model for predicting solar irradiance power. Table 13 shows that the suggested model is capable of predicting the output of a solar system more accurately under different weather condition.

SARIMA (Seasonal Autoregressive Integrated Moving Average), VMDVariational Pattern Decomposition (), and a Deep Belief Network (DBN) were used by Zhang et al. (2020) to devise a unique dynamic combination method for estimating short-term electricity prices Using data from Australia, Pennsylvania-New Jersey-Maryland (PJM), and the Spanish power markets, the usefulness of the suggested model was demonstrated in Table 14. The new proposal can noticeably enhance the precision and reliability of the forecasting, according to experimental evidences.

### *6.3.3. DBN summary in renewable fields*

The DBN is stacked by a restricted Boltzmann machine, which can be trained with label-free data, where the sampling distribution of the training dataset would be used to retrieve higher-order features of the data. A joint cumulative probability of function P (X,Y) for the input is calculated, without focusing on the classification boundaries of the data. DBN has characteristics of flexible structure, simple algorithm and less difficult to train, and they are easy to expand in practical applications.

Through analysis, the existing research in the renewable field mainly has the following characteristics in DBN:

(i) In terms of application fields, DBN is mainly used in the study of wind energy, solar energy and price forecasting, and more publications are used in wind speed/power forecasting.
(ii) In terms of use purpose, it is mainly used directly as an independent model to predict solar radiance or wind speed prediction.
(iii) In terms of application methods, DBN can not only be used alone to forecast energy, but also be integrated with other algorithms or optimization algorithms of machine learning or deep learning, including DNN, genetic algorithm, etc. Dimensionality reduction algorithms, such as wavelet transform and variational mode decomposition are usually used before performing DNN.
(iv) Evaluation criteria of DBN were MAPE, MASE.

**Table 13**
Comparison results of different models under different weather condition (source:Jza et al., 2020).

(a)sunny days

| Model | October 17 (Spring) | | | February 8 (Summer) | | | April 14 (Autumn) | | | August 17 (Winter) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA | 23.51 | 3.86% | 44.00 | 68.6 | 7.89% | 108.52 | 52.65 | 13.73% | 92.09 | 36.06 | 8.08% | 63.59 |
| LSSVM | 111.46 | 17.91% | 136.84 | 160.7 | 17.23% | 191.78 | 85.01 | 33.09% | 128.35 | 59.15 | 18.27% | 98.39 |
| WNN | 88.35 | 12.66% | 115.19 | 83.02 | 9.18% | 112.16 | 67.65 | 25.59% | 119.43 | 31.77 | 7.16% | 60.12 |
| WPS | 41.21 | 4.12% | 50.08 | 43.12 | 4.35% | 56.43 | 46.73 | 5.01% | 60.41 | 52.21 | 4.47% | 59.43 |
| GAS | 38.54 | 3.67% | 47.22 | 39.41 | 4.04% | 51.02 | 42.22 | 4.31% | 57.54 | 49.32 | 4.12% | 53.21 |
| ESE | 31.37 | 3.47% | 33.76 | 36.53 | 3.98% | 39.23 | 39.43 | 4.23% | 45.45 | 37.56 | 4.03% | 42.12 |
| Presented | 4.84 | 0.67% | 7.54 | 11.73 | 1.32% | 16.61 | 6.52 | 1.64% | 10.12 | 6.97 | 1.35% | 10.94 |

(b)cloudy days

| Model | September 30 (Spring) | | | December 19 (Summer) | | | May 27 (Autumn) | | | June 28 (Winter) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA | 45.93 | 24.31% | 66.42 | 40.19 | 6.08% | 63.51 | 44.35 | 15.87% | 88.34 | 80.17 | 23.51% | 111.99 |
| LSSVM | 53.21 | 26.34% | 70.21 | 213.2 | 25.42% | 228.44 | 53.12 | 21.34% | 93.43 | 97.65 | 26.54% | 143.23 |
| WNN | 46.28 | 21.73% | 63.57 | 52.78 | 8.10% | 80.44 | 41.76 | 12.91% | 82.81 | 81.27 | 22.43% | 111.38 |
| WPS | 42.39 | 5.52% | 50.76 | 42.28 | 4.88% | 43.79 | 40.21 | 5.02% | 41.24 | 62.32 | 7.32% | 73.63 |
| GAS | 39.43 | 4.93% | 45.31 | 36.39 | 3.65% | 40.21 | 34.31 | 4.31% | 39.08 | 48.32 | 6.88% | 49.93 |
| ESE | 37.65 | 4.87% | 41.23 | 31.45 | 3.54% | 36.54 | 33.27 | 4.24% | 38.43 | 46.54 | 6.43% | 47.65 |
| Presented | 6.39 | 3.60% | 8.38 | 5.28 | 0.72% | 7.49 | 8.13 | 2.73% | 11.45 | 13.71 | 4.97% | 19.08 |

(c)Rainy days

| Model | October 17 (Spring) | | | February 8 (Summer) | | | April 14 (Autumn) | | | August 17 (Winter) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE |
| ARIMA | 23.51 | 3.86% | 44.00 | 68.6 | 7.89% | 108.52 | 52.65 | 13.73% | 92.09 | 36.06 | 8.08% | 63.59 |
| LSSVM | 111.46 | 17.91% | 136.84 | 160.7 | 17.23% | 191.78 | 85.01 | 33.09% | 128.35 | 59.15 | 18.27% | 98.39 |
| WNN | 88.35 | 12.66% | 115.19 | 83.02 | 9.18% | 112.16 | 67.65 | 25.59% | 119.43 | 31.77 | 7.16% | 60.12 |
| WPS | 41.21 | 4.12% | 50.08 | 43.12 | 4.35% | 56.43 | 46.73 | 5.01% | 60.41 | 52.21 | 4.47% | 59.43 |
| GAS | 38.54 | 3.67% | 47.22 | 39.41 | 4.04% | 51.02 | 42.22 | 4.31% | 57.54 | 49.32 | 4.12% | 53.21 |
| ESE | 31.37 | 3.47% | 33.76 | 36.53 | 3.98% | 39.23 | 39.43 | 4.23% | 45.45 | 37.56 | 4.03% | 42.12 |
| Presented | 4.84 | 0.67% | 7.54 | 11.73 | 1.32% | 16.61 | 6.52 | 1.64% | 10.12 | 6.97 | 1.35% | 10.94 |

**Table 14**
Evaluation results of different models for all cases (%) (source:Zhang et al., 2020).

| Model | Feb.12-Feb.18 | | | Mar.19-Mar.25 | | | Jul. 23-Jul. 29 | | | Sep.10-Sep.16 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pmae | Pmape | Prmse | Pmae | Pmape | Prmse | Pmae | Pmape | Prmse | Pmae | Pmape | Prmse |
| Australian market | | | | | | | | | | | | |
| LSSVM | 86.12 | 85.94 | 85.56 | 90.29 | 90.82 | 90.13 | 77.52 | 77.14 | 76.95 | 88.01 | 85.75 | 88.38 |
| WNN | 71.77 | 70.49 | 73.04 | 77.69 | 77.77 | 79.68 | 75.32 | 73.41 | 76.45 | 85.89 | 85.77 | 86.38 |
| ARIMA | 70.21 | 69.51 | 71.71 | 76.38 | 76.14 | 78.67 | 77.52 | 74.70 | 79.30 | 84.76 | 82.70 | 86.94 |
| SAA | 35.47 | 26.89 | 17.01 | 55.72 | 35.54 | 41.70 | 15.51 | 13.70 | 6.81 | 29.17 | 23.77 | 25.43 |
| IAA | 24.87 | 24.31 | 10.31 | 55.02 | 33.98 | 39.58 | 12.28 | 7.35 | 5.20 | 24.63 | 18.87 | 13.36 |
| MAH | 22.16 | 24.01 | 18.36 | 54.54 | 33.33 | 38.94 | 11.53 | 7.04 | 4.37 | 22.72 | 17.55 | 12.65 |
| PJM market | | | | | | | | | | | | |
| LSSVM | 93.23 | 93.96 | 94.33 | 93.23 | 91.85 | 96.04 | 84.48 | 84.02 | 89.79 | 83.33 | 83.68 | 87.93 |
| WNN | 93.10 | 93.20 | 94.26 | 88.48 | 87.14 | 93.07 | 82.23 | 81.83 | 87.92 | 84.72 | 84.54 | 89.55 |
| ARIMA | 84.61 | 84.21 | 89.65 | 87.09 | 85.85 | 92.14 | 84.02 | 83.55 | 89.53 | 84.50 | 84.12 | 89.06 |
| SAA | 66.66 | 62.14 | 67.85 | 50.76 | 48.64 | 56.71 | 61.97 | 58.54 | 65.75 | 54.41 | 45.33 | 62.16 |
| IAA | 60.00 | 59.70 | 61.70 | 37.25 | 45.97 | 45.28 | 57.14 | 56.50 | 62.12 | 44.64 | 42.79 | 54.09 |
| MAH | 51.35 | 58.67 | 53.84 | 31.91 | 44.92 | 43.13 | 51.78 | 54.03 | 56.89 | 42.59 | 42.25 | 51.72 |
| Spanish market | | | | | | | | | | | | |
| LSSVM | 90.64 | 90.59 | 92.60 | 83.55 | 87.32 | 88.59 | 63.98 | 63.98 | 67.58 | 93.42 | 93.15 | 92.10 |
| WNN | 81.33 | 81.08 | 88.21 | 74.58 | 75.25 | 81.87 | 47.17 | 14.36 | 30.26 | 85.61 | 85.49 | 84.84 |
| ARIMA | 82.27 | 81.96 | 89.09 | 74.15 | 72.65 | 82.90 | 41.14 | 12.50 | 43.61 | 82.45 | 82.38 | 82.45 |
| SAA | 68.29 | 68.31 | 77.56 | 63.03 | 35.49 | 65.31 | 34.39 | 35.85 | 31.16 | 75.61 | 85.03 | 69.07 |
| IAA | 64.86 | 67.09 | 75.17 | 59.06 | 34.24 | 62.96 | 26.95 | 33.74 | 28.37 | 71.83 | 82.05 | 62.96 |
| MAH | 66.38 | 67.37 | 75.86 | 60.89 | 36.23 | 63.63 | 27.46 | 34.28 | 28.85 | 74.35 | 81.81 | 64.28 |

(v) The advantages of DBN in renewable energy can be concluded as, a)It is common to conduct unsupervised performance extraction, b)It has efficient computational performance.

(vi) The disadvantages of DBN can be concluded as, a)The process of training is slow and inefficient, b) Multidimensional renewable energy data cannot be handled by it. c)The characteristics of the renewable energy data cannot be identified.

### 6.4. Convolutional neural network

#### 6.4.1. CNN brief introduction

Fig. 32 shows an example of a CNN, which is a prototypical back-propagation neural network required for the extraction of input features, prior to the data being convolved and pooled layer by layer as illustrated. Increasing the hidden layers allows for a more abstraction of the extracted features and the continuous feature representation of input data. Using sparse connections, weight sharing, temporal or spatial subsampling and other methods to boost the model's learning capabilities from large data sets, thus CNN has a remarkable productivity feature. 2D features or raw data maps were input into CNN networks, which is mapped to the hidden layer through the weight matrix of neurons, and what distinguished from other networks is that CNN does not need to vectorize these data. The output layer is directly coupled to the previous layer, allowing the softmax classifier to handle the multi-level classification issue. Since the CNN is ready to comprehend data characteristics in concurrently, it drastically leads to fewer of variables that might go wrong, which enabling the formation of deep models and learning more features.

#### 6.4.2. CNN research in the field of renewable energy sources

As shown in Table 15, in the field of renewable research keywords, CNN has 30 papers, and the main research aims to reduce the supply power, solar irradiance prediction, data prediction of time series, deep learning solar flares prediction model and its relationship with physical parameters of solar activity region, short-term wind power prediction, hourly solar irradiance prediction, solar irradiance forecasting, photovoltaic instability fluctuations, wind speed randomness, etc.

Reverse osmosis (RO) desalination methods were reported by Soleimanzade et al. (2021), which consisted of PV, PRO, and rechargeable batteries. As depicted in Table 16, the effects of predictor errors were explored by using actual PV power replicate simulations.

To accurately forecast measurements of solar irradiation at a particular location, Brahma et al. (2021) created an artificial neural network (ANN) using deep learning. Convolutional layers are used to extract feature representation for time series data of solar irradance as well as an attention-based LSTM network to identify time dependence as illustrated in Fig. 33. From the studies conducted, models, optimizer, and range all have an impact on the results., thus they are analyzed to determine the final prediction results which indicates strong predictive accuracy, as seen in Table 17.

In 2021, Rosato et al. (2021) suggested an unique deep learning scheme to overcome the prediction problem of energy time series. In Fig. 34, the model implementation is based on the superposition of the network layers using LSTM and CNN, thus forming a stacked deep neural architecture. The algorithm has been tested on real-world energy concerns to verify its reliability and accuracy.

Solar irradiation forecasting models have been developed by Choi

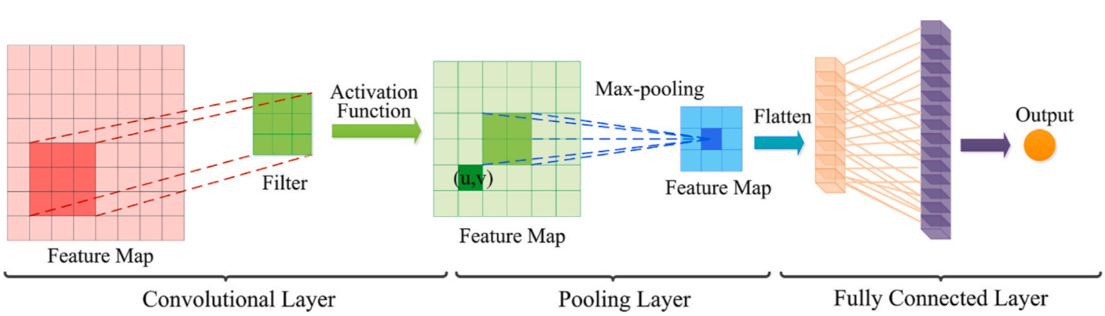



**Fig. 32.** The basic structure of CNN model.

**Table 15**
The publication information of CNN models in the renewable energy field.

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| Soleimanzade et al. (2021) | Deep learning-based energy management of a hybrid photovoltaic-reverse osmosis-pressure retarded osmosis system | Reduce the power of the grid | Photovoltaic Power Prediction | LSTM + CNN | MAE,RMSE, inRSE | Photovoltaic power prediction was made 5 h in advance, and the model with minimal error was selected |
| Brahma et al. (2021) | Visualizing solar irradiance data in arcgis and forecasting based on a novel deep neural network mechanism | Solar irradiance prediction | Made over 36 years from solar datasets from both sites, taken from the NASA Global Energy Resources (POWER) Renewable Energy Project Archive | LSTM | MAE,MSE, RMSE,R2, SSE | The proposed model performs a R2 score of more than 50%, indicating excellent predictive performance. The deviation and variance components also show the superior performance of the proposed model. |
| Rosato et al. (2021) | 2-d convolutional deep neural network for the multivariate prediction of photovoltaic time series | Energy time-series prediction problem | Interdependencies between several different time series | LSTM + CNN | RMSE | It is tested on energy issues, demonstrating the accuracy and robustness of the proposed method |
| Choi et al. (2021) | Short-term solar irradiance forecasting using convolutional neural networks and cloud imagery | Accurate, generalizable, and scalable solar irradiance predictions are obtained | Solar irradiance across different predicted time ranges at 12 different locations in the United States | CNN | RMSE, MAPE,R2, nRMSE | The model produced up to 24% improvement in the prediction an hour ago, and a 26% improvement in the previous prediction |
| Yi et al. (2021) | Visual explanation of a deep learning solar flare forecast model and its relationship to physical parameters | The deep learning prediction model of the solar flare and its relation to the physical parameters of the solar active region (AR) are intuitively explained | The 00:00 UT total magnetogram of the Solar and Solar Daylamheric Observatory/Michelson Doppler Imager and Solar Dynamics Observatory/ helioseismic and Magnetic Imager, as well as physical parameters from the spatial weather HMI active area patch (SHARP), and geostationary operating environment satellite X-ray flare data | CNN | R,RMSE, SMAPE, MAPE | Our deep learning model was successfully applied to the predictions of daily solar flare occurrence, TSS = 0.65, without any preprocessing to extract features from the data. |
| Yildiz et al. (2021) | An improved residual-based convolutional neural network for very short-term wind power forecasting | Short-term wind power forecast | Weather wind speed, wind direction, and wind power data | Variational Pattern decomposition (VMD)+ CNN | RMSE,MAE | , Show promising results in the very short-term wind power forecasts |
| Gao et al. (2020) | Hourly forecasting of solar irradiance based on ceemdan and multi-strategy cnn-lstm neural networks | Solar hourly irradiance is predicted | Four real-world datasets of different climate types | CNN + LSTM | RMSE, nRMSE,MAE | With a relatively stable prediction performance under different climatic conditions |
| Brahma et al. (2021) | Solar irradiance forecasting based on deep learning methodologies and multi-site data | Prediction solar irradiance | The 36-year Solar irradiance data (1983–2019) data obtained from the NASA POWER project repository | LSTM, GRU, bidirectional LSTM, CNN LSTM, attention LSTM | MSE,RMSE, R2 | Multi-site data with historical solar irradiance data improves the predictive performance of single-unit univariate solar data |
| SHIVAM et al. (2020) | Multi-step short-term wind speed prediction using a residual dilated causal convolutional network with nonlinear attention | wind speed prediction | Six real-world wind speed datasets with different probability distributions | CNN + residual expansion causal convolutional neural network (Res-DCCNN) | RMSE,MAE, MAPE, SMAPE, MSLE, NRMSE | Multiple error metrics demonstrate that our proposed model is robust, accurate, and applicable to practical situations |
| SUCCETTI et al. (2020) | Deep neural networks for multivariate prediction of photovoltaic power time series | Multivariate prediction of the energy time series, predicting the photovoltaic energy output | All different time orders were combined and filtered in the case of available information | Four different deep neural models are proposed, all based on long and short-term memory networks, a recurrent neural network that handles long-term dependencies, and also uses convolutional neural networks to obtain a higher level of abstraction | | Once trained, the proposed deep neural network ensures that it is applicable to real online scenarios characterized by high variability in the data without retraining |

(continued on next page)

**Table 15** (*continued*)

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| RAY et al. (2020) | A new data driven long - term solar yield analysis model of photovoltaic power plants | Output forecast of Australian Solar PV Systems (i. e., proposed PV Systems) | Historical dataset of solar photovoltaic systems from 1990 to 2013 (e. g., North Queensland | LSTM + CNN | MAE, average time, system complexity | Power generation planning and reserve estimates in power systems with high solar photovoltaic (PV) or other renewable energy sources (RES) permeability |
| WANG et al. (2019) | Photovoltaic power forecasting based lstm-convolutional network | Photovoltaic power prediction | Photovoltaic time series | LSTM + CNN | RMSE, NRMSE, MAPE,MAE, RMSE,SDE | The results of eight error evaluation metrics show that a mixed prediction model is better predictive than a single prediction model |
| GHIMIRE et al. (2019) | Deep solar radiation forecasting with convolutional neural network and long short-term memory network algorithms | half-hour Global Solar Radiation (GSR) prediction | Extract the half-hour GSR of Alice Springs (Australia: January 1, 2006 to August 31, 2018) | CNN + LSTM | R, MAE, RMAE, RMSE, RRMSE, MAPE,APB, KGE | The hybrid model recorded excellent results with over 70% prediction error below ± 10 Wm (−2), and low 1-day half-hour GSR prediction for the benchmark mean model (about 1.515%)), mean absolute% error (about 4.672%) and absolute% deviation (about 1.233%). |
| LIU et al. (2019) | A novel two-stage deep learning wind speed forecasting method with adaptive multiple error corrections and bivariate dirichlet process mixture model | wind speed prediction | The wind speed sequence is divided into two components: predictable and unpredictable components | wavelet packet decomposition + CNN + adaptive multiple error correction | MAE, MAPE, RMSE | Three practical wind speed sequences were used to verify the effectiveness of the proposed model. |
| AFRASIABI et al. (2019) | Multi-agent microgrid energy management based on deep learning forecaster | Minimize the agent's energy loss and operating costs | Conventional distributed generators, wind turbines, photovoltaic, requirements, battery storage systems, and microgrid aggregation agents | CNN + GRU | RMSE, NRMSE, MAPE | The proposed framework is tested on a realistic test system. |
| WANG et al. (2019) | A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network | Accurate prediction of photovoltaic power prediction becomes very difficult due to the instability, intermittent and randomness of solar energy | Applied to the data obtained in the DKASC, Alice Springs photovoltaic systems | CNN + LSTM | RMSE,MAE, MAPE | The model accuracy was also improved when the input sequence increased, and the hybrid model predicted the best |
| YANG et al. (2019) | Deterministic and probabilistic wind power forecasting based on bi-level convolutional neural network and particle swarm optimization | wind power probability interval prediction | Wind power data from Chinese wind farms and simulated wind power data provided by the US Renewable Energy Laboratory | deep learning + particle group optimization (PSO) | NMAE, NRSME, MAPE | The proposed method has a competitive advantage in wind electric power prediction based on point and probability intervals. |
| Chen et al. (2018) | Multifactor spatio-temporal correlation model based on a combination of convolutional neural network and long short-term memory neural network for wind speed forecasting | The inherent intermittency of the wind makes achieving high-precision wind speed prediction challenging | Datasets collected from the Texas National Wind Energy Institute | CNN + LSTM | SSE,MAE, RMSE,SDE, UI,IA,DA, PCC | Fourteen baseline models, eight evaluation metrics, one percent performance improvement, and hypothesis testing show that the proposed model outperforms the other baseline models in terms of prediction accuracy and generalization power. |
| MI et al. (2019) | Wind speed prediction model using singular spectrum analysis, empirical mode decomposition and convolutional support vector machine | Wind speed prediction | Four datasets of 10-min average wind speed time series gathered from a wind farm in xinjiang | SSA + EMD + CNN SVM | MAPE,MAE, RMSE | |
| WANG et al. (2018) | Wavelet decomposition and convolutional lstm | solar irradiance prediction | In four general solar irradiance types (i. e., sunny, | WD + CNN + LSTM solar | RMSE,MAE,R | |

(continued on next page)

**Table 15** (*continued*)

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| | networks based improved deep learning model for solar irradiance forecasting | | cloudy, rainy and heavy rain), the raw solar irradiance sequence | | | Final solar irradiance forecast results for a specific weather type |
| Lee et al. (2018) | Forecasting solar power using long-short term memory and convolutional neural networks | Estimate the future short-term or long-term solar power generation | Time-series data in the deep-learning community | CNN + LSTM | MAPE, RMSE,MAE | Solar power generation forecast |
| Kuo and Huang (2018) | A high precision artificial neural networks model for short-term energy load forecasting | Short term load prediction | he USA District public consumption dataset and electric load dataset from 2016 provided by the Electric Reliability Council of Texas | CNN | MAPE,CV-RMSE | The proposed algorithm for MAPE and CV-RMSE is 9.77% and 11.66%, respectively, with a high prediction accuracy. |

**Table 16**
The performance of the methods (source: Soleimanzade et al., 2021).

| Weather | Method | $P_{Grid}$ $[kWh]$ | $Q_P$ $[m^3]$ | $PI_1$ $[kWh/m^3]$ | $PI_2$ $[kWh/m^3]$ | $PI_3$ | $PI_4$ |
|---|---|---|---|---|---|---|---|
| Sunny | IEMS | 14.1126 | 27.4719 | 0.5137 | 3.1325 | 0.3147 | 0.9692 |
| | First benchmark | 29.7902 | 32.7280 | 0.9102 | 3.1500 | 0.0072 | 0.9718 |
| | Second benchmark | – | – | 0 | 2.2303 | – | 0.993 |
| Cloudy | IEMS | 31.1664 | 17.1401 | 1.8183 | 2.5866 | 0.1136 | 0.9513 |
| | First benchmark | 38.3672 | 20.0779 | 1.9109 | 2.5532 | 0.0182 | 0.9549 |
| | Second benchmark | – | – | 0 | 2.2303 | – | 0.993 |
| 10 days | IEMS | 88.8643 | 106.4353 | 0.8349 | 2.8387 | 0.3257 | 0.9608 |
| | First benchmark | 164.3552 | 132.9860 | 1.2359 | 2.8896 | 0.0020 | 0.9657 |
| | Second benchmark | - | - | 0 | 2.2303 | - | *0.993* |

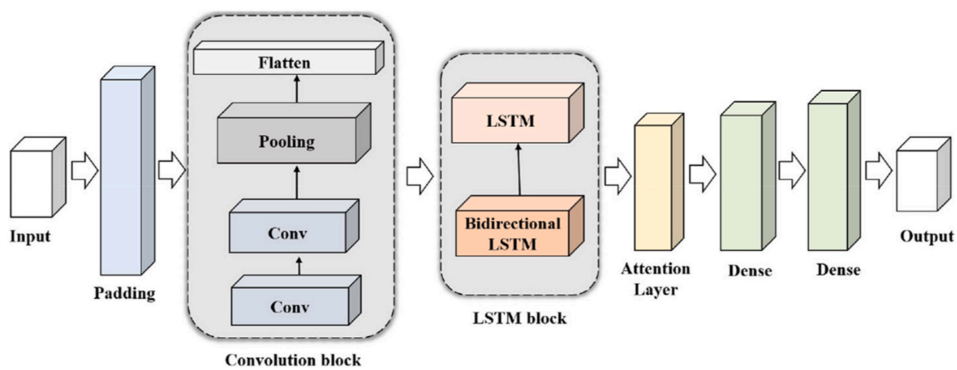



**Fig. 33.** Proposed method architecture (source:Brahma et al., 2021).

**Table 17**
Performance evaluation for 1 horizon on location 1 (source: Brahma et al., 2021).

| Model | MSE | RMSE | R2 |
|---|---|---|---|
| RNN | 9.765 | 9.8818 | 68.4786 |
| LSTM | 9.656 | 9.8267 | 68.8298 |
| GRU | 9.653 | 9.8253 | 68.8381 |
| Bidir-LSTM | 9.560 | 9.7780 | 69.1378 |
| CNN-LSTM | 9.558 | 9.7769 | 69.1446 |
| Attention LSTM | 9.558 | 9.7765 | 69.1469 |
| Proposed | 9.531 | 9.7627 | 69.2339 |

et al. (2021), in which solar irradiance may be predicted with the assistance of cnn and modeling techniques. across different predicted time ranges at 12 different locations in the United States. The prediction model yielded up to 24% improvement in the pre-prediction 1-h ahead prediction and a 26% improvement in the previous prediction.

Using CNNs, Yi et al. (2021) introduced two prediction models

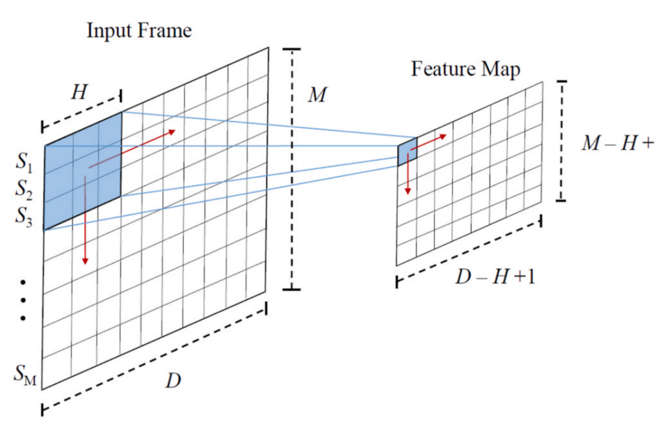



**Fig. 34.** Application of 2-D convolutional filters to extract feature maps (source:Rosato et al., 2021).

depending on bootstrap backpropagatio gradient-weighted class activation mapping (Grad-CAM)n with gradient-weighted class activation mapping (Grad-CAM). They were used to explain the model that provide quantitative information, without any preprocessing to extract features from the data.

Two-step deep methodology for renewable power prediction was proposed by Yildiz et al., in 2021. Variational pattern decomposition (VMD) and image conversion are the first steps in the process outlined in Fig. 35. Wind power is predicted in the second stage using an upgraded residual-based CNN. SqueezeNet, GoogLeNet, and ResNet −18, AlexNet −16, and VGG-16, are all used to verify the proposed technique's outcomes. For very short-term wind energy estimates, the suggested technique performs better than existing systems (Fig. 36).

Regarding hourly irradiance estimation, a hybrid CEEMDAN–CNN–LSTM framework has been proposed by Gao et al. (2020). First, the original historical data After data features extracting, solar irradiance was predicted for the following hour using CNN and LSTM. As Table 18 shows, multiple comparative experiments with four real-world datasets showed that solar irradiance can be predicted with greater accuracy using the model than can any other alternative solution.

Brahma et al. (2021) designed develop predictive models based on CNN and LSTM method to forecast solar irradiance with multi-site solar irradiance data based on the 36 years obtained from the NASA POWER project repository (1983 to from 2019). Table 19 shows that irradiance data may be predicted using LSTM models of two-directional and attention-based.

Res-DCCNN was proposed by SHIVAM et al. (2020) for multi-step wind prediction involving nonlinear attention. An forecasting model that uses testing scheme for sliding window could exceed LSTMs, gated recurrent units (GRU). Six real-world wind datasets were used to assess the proposed effectiveness of the algorithm, as shown in Table 20, to prove the robustness, accuracy, and applicability in practical situations.

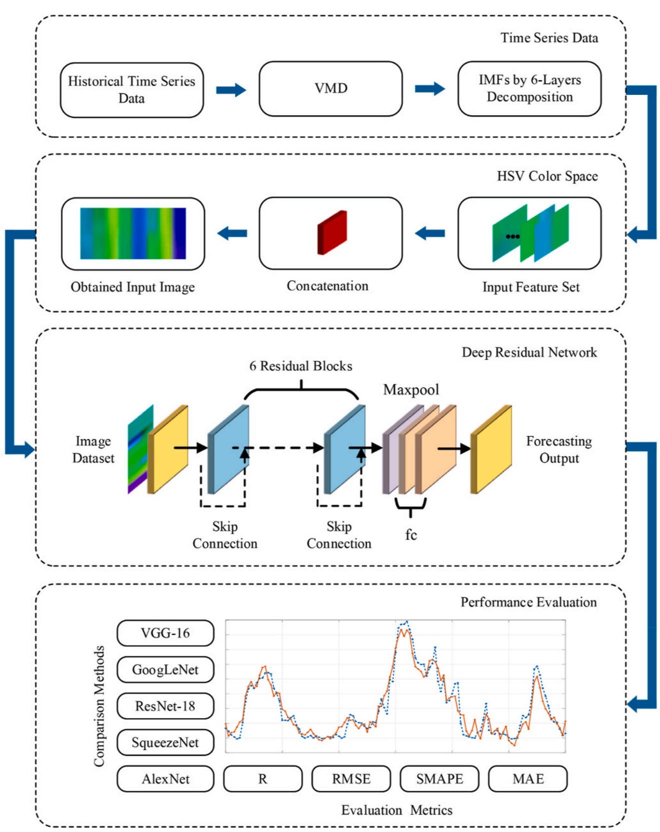



**Fig. 35.** Overall architecture of residual CNN-based forecasting method (source:Yildiz et al., 2021).

As shown in Table 21, the models can ensure their applicability and high data variability for real online scenarios without retraining and end-user techniques.

RAY et al. (2020) proposed output prediction of Australian solar PV systems based on hybrid deep learning framework. The frameworks were validated using historical datasets from 1990 to 2013 (North Queensland). In order to achieve specific goals, the proposed framework was compared to random forests, statistical analysis, and ANN-based methodologies.

WANG et al. (2019) proposed a LSTM-Convolutional Network to predict photovoltaic power as shown in Figs. 37 and 38. And then the spatial features was extracted a convolutional neural network model. The results are evaluated by eight error assessment metrics in Table 22.

GHIMIRE et al. (2019) created a combined cnn model for pattern recognition with lstm for short term GSR prediction. When used in conjunction with low-latency LSTM, the half-hour data of Alice Springs (Australia: January 1, 2006 to August 31, 2018) was derived, and it was discovered that the models can reliably determine and constantly monitor energy supplies over a multi-step range in Table 23.

To manage the two major components individually, LIU et al. (2019) suggested an alternative two-stage prediction model. To forecast predictable components, a new model based on WPD(Wavelet Packet Decomposition), CNN, and error correction is proposed in the first step. A hybrid model is presented in the second stage to replicate the heterovariasticity of the erratic residuals by bivariate Dirichlet. Three practical wind speed sequences were trained to verify, and the results show in Table 24.

AFRASIABI et al. (2019) presented a multi-agent recent microgrid energy management framework, which may result in minimizing the energy loss and operating costs of agents. The proposed framework is tested on a realistic test system as shown in Table 25.

WANG et al. (2019) established hybrid models based on cnn and models of LSTM. and applied the models to deal with the data obtained from DKASC in Alice Springs photovoltaic systems in Fig. 39. Table 26 shows that the model has the optimum predictive accuracy.

YANG et al. (2019) proposed a two-layer cnn and PSO technique for determining wind power probabilistic intervals. To extract extra information and expose hidden knowledge mostly in raw data of wind energy, researchers utilized VMD and phase space reconstruction. Wind power data provided by the US Renewable Energy Laboratory was used to thoroughly test the suggested approach. The findings revealed that the proposed solution has a strategic advantage in the wind electric power prediction based on point and probability intervals.

Chen et al. (2018) proposed a novel multivariate spatiotemporal correlation model for wind speed prediction as shown in Fig. 40.

Mi et al. (2019) designed a novel multi-step prediction model of wind speed as shown in Fig. 41, the MAE significantly outperformed the seven comparison models by comparing the SVM models, the CNNSVM models, the EMD-BP(Empirical Mode Decomposition-Back Propagation) models and so on.

WANG et al. (2018) proposed an improved deep learning model in which uses a CNN-based spatial feature extraction technique to dynamically learn feature representation of the data and then constructed the subseries prediction model in LSTM by performing a wavelet reconstruction of these predicted subsequences as depicted in Fig. 42.

LEE et al. (2018) presented a solar prediction technique by using recently developed cnn model.

Kuo and Huang (2018) introduced an exact algorithm for short-term load prediction (STLF). As seen in Table 27, Table 28, The results of the experiments demonstrate that the suggested method's MAPE and CV-RMSE (Coefficient Of Variation-Root Mean Square Error) are 9.77% and 11.66%, correspondingly, with superior predictive precision.

### *6.4.3. CNN summary in renewable fields*

The CNN directly learns the information from the decision function

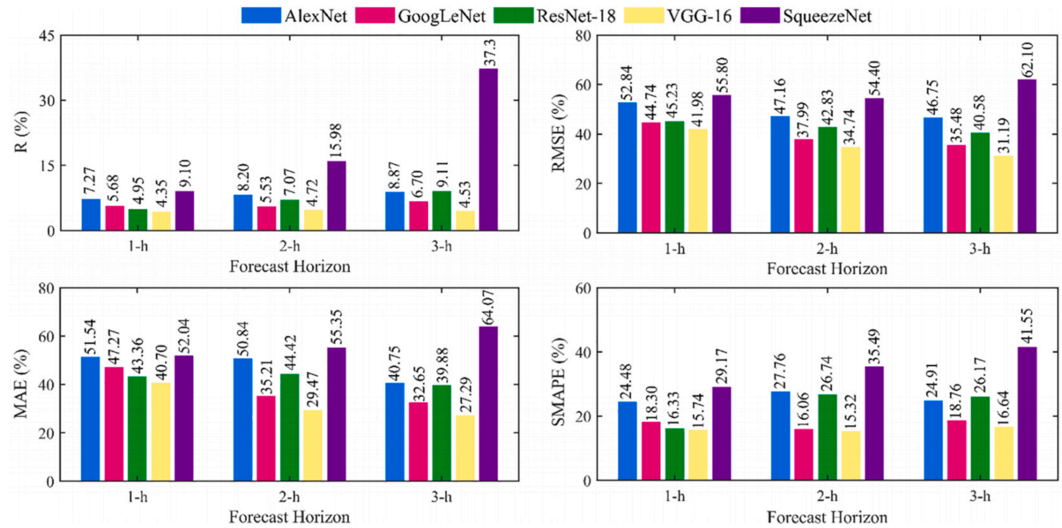



**Fig. 36.** Improvement percentages of proposed method compared to other models (source:Yildiz et al., 2021).

**Table 18**
The annual FS of CEEMDAN–CNN–LSTM(source:Gao et al., 2020).

| C–C-Lvs. | Los Angeles | | Denver | | The big island of Hawaii | | Tamanrasset | |
|---|---|---|---|---|---|---|---|---|
| | $FS_{RMSE}$ (%) | $FS_{MAE}$ (%) | $FS_{RMSE}$ (%) | $FS_{MAE}$ (%) | $FS_{RMSE}$ (%) | $FS_{M}AE$ (%) | $FS_{RMSE}$ (%) | FSMAE (%) |
| C-L | **9.97** | 30.42 | 16.83 | 21.83 | 11.81 | 26.87 | 20.52 | **21.01** |
| C–S | 29.45 | 40.72 | 30.82 | 45.63 | 20.18 | 28.87 | 39.94 | 54.58 |
| C–B | 25.76 | 21.40 | 34.56 | 40.33 | 22.94 | 38.78 | 37.53 | 40.19 |
| C-A | 51.25 | 48.41 | 44.49 | 42.05 | 38.68 | 37.08 | 52.13 | 44.35 |
| LSTM | 34.07 | 24.92 | 44.76 | 44.99 | 29.58 | 28.32 | 47.15 | 42.39 |
| SVM | 44.47 | 52.88 | 50.11 | 62.35 | 36.20 | 43.57 | 53.33 | 60.63 |
| BP | 35.54 | 27.37 | 46.08 | 48.73 | 32.93 | 27.76 | 48.84 | 45.40 |
| ARIMA | 58.72 | 57.91 | 58.47 | 60.10 | 57.14 | 60.17 | 61.90 | 64.29 |
| Per | **73.06** | **75.89** | 63.13 | 67.32 | 61.88 | 69.08 | 70.92 | 74.84 |

C–C-L: CEEMDAN–CNN–LSTM; C-L: CNN-LSTM; C–S: CNN-SVM; C–B: CNN-BPNN. C-A:CEEMDAN-ARIMA; Per: Persistence.

**Table 19**
Forecast performance of Location 2 data set for horizon length of 10 (source: Brahma et al., 2021).

| Model | Single-Location | | | Multi-Location | | |
|---|---|---|---|---|---|---|
| | MSE | RMSE | $R^2$ | MSE | RMSE | $R^2$ |
| LSTM | 12.51 | 11.18 | 56.34 | 12.61 | 11.23 | 55.89 |
| GRU | 13.07 | 11.43 | 54.38 | 12.98 | 11.39 | 54.59 |
| CNN | 13.40 | 11.57 | 53.25 | 15.12 | 12.29 | 47.11 |
| Bidir | 12.83 | 11.32 | 55.23 | 12.54 | 11.19 | 56.14 |
| Attention | 12.65 | 11.25 | 55.84 | 12.45 | 11.16 | 56.44 |

Y = f(X) or the conditional probability distribution P (X|Y), which cannot reflect the properties of the data. However, it looks for an optimal interface between different categories of data, reflecting differences between abnormal data. CNN has high distortion tolerance for input data and more accurately expresses data characteristics, and utilizes local receptive field methods. This substantially decreases the number of parameters and the connectivity model's sophistication.

Through analysis, the existing research in the renewable field mainly has the following characteristics in CNN:

(i) In terms of application fields, CNN is mainly used in the subject of wind energy forecasting, solar energy forecasting and mining agent energy loss and operating costs, and more publications are used in the research of solar irradiance/power/flare and photovoltaic power prediction.
(ii) In terms of use purpose, it mainly extract internal representations.
(iii) In terms of application methods, CNN can not only be used in original or deformation way to predict the solar/wind power, but also often be integrated with the algorithms LSTM, in which CNN was utilized to consistently obtain required data features from predictive factors, whereas LSTM was employed to produce predictions. And wavelet decomposition methods were used to handle with the prediction result in some publications.
(iv) Evaluation criteria of CNN were MAPE, RMSE, MAE, inRSE, $R^2$, nRMSE, RMSE, RRMSE, R and SMAPE.
(v) The advantages of CNN in renewable energy can be concluded as, a. It is good at to processing image data and strong abstract characteristics, b. It has ability to capture the spatial correlation. c. It has high generalization potential.
(vi) The disadvantages of DBN can be concluded as, a. Computational performance is inefficient and the feature selection requirement is high, b. it may result in high computational overhead, c. The adjustments different parameter may affect prediction result. d) The renewable energy data needs to be image data for CNN.

### 6.5. Generative adversarial network

#### 6.5.1. Introduction to the GAN

GAN initiatively uses adversarial training mechanism to train two neural networks and optimizes by stochastic gradient descent, which improves the application efficiency without variational lower limit and approximate inference. The framework of GAN incorporates two conflicting models: discriminators and generators. The discriminator's

**Table 20**
Error metrics of different models on six site's wind speed data (source:SHIVAM et al., 2020).

| Wind Data | Models | MAE (m/s) | RMSE (m/s) | MSLE (m/s) | MAPE (X100%) | SMAPE (X100%) | NRMSE (1) | UMBRAE (1) |
|---|---|---|---|---|---|---|---|---|
| Site 1 | Naive | 1.683 | 2.068 | 0.092 | 0.298 | 0.274 | 0.192 | 1.000 |
| | GRU | 1.359 | 1.694 | 0.063 | 0.259 | 0.218 | 0.157 | 0.843 |
| | LSTM | 1.356 | 1.688 | 0.063 | 0.262 | 0.220 | 0.157 | 0.853 |
| | SeriesNet | 1.304 | 1.618 | 0.058 | 0.248 | 0.211 | 0.15 | 0.804 |
| | ResUnet | 1.306 | 1.624 | 0.058 | 0.249 | 0.211 | 0.151 | 0.805 |
| | ResAUnet | **1.254** | **1.583** | **0.055** | **0.237** | **0.202** | **0.147** | **0.768** |
| Site 2 | Naive | 2.631 | 3.171 | 0.328 | 0.767 | 0.529 | 0.306 | 1.000 |
| | GRU | 1.745 | 2.138 | 0.155 | 0.515 | 0.359 | 0.206 | 0.705 |
| | LSTM | 1.629 | 2.016 | 0.142 | 0.483 | 0.340 | 0.194 | 0.698 |
| | SeriesNet | 1.482 | 1.868 | 0.119 | 0.414 | 0.312 | 0.180 | 0.618 |
| | ResUnet | 1.504 | 1.879 | 0.125 | 0.423 | 0.323 | 0.181 | 0.632 |
| | ResAUnet | **1.353** | **1.707** | **0.107** | **0.389** | **0.296** | **0.165** | **0.584** |
| Site 3 | Naive | 2.935 | 3.504 | 0.312 | 0.668 | 0.505 | 0.323 | 1.000 |
| | GRU | 1.839 | 2.235 | 0.136 | 0.456 | 0.322 | 0.206 | 0.657 |
| | LSTM | 1.773 | 2.151 | 0.129 | 0.443 | 0.312 | 0.198 | 0.679 |
| | SeriesNet | 1.527 | 1.916 | 0.104 | 0.375 | 0.278 | 0.177 | 0.575 |
| | ResUnet | 1.470 | 1.858 | 0.098 | 0.356 | 0.269 | 0.171 | 0.554 |
| | ResAUnet | **1.271** | **1.641** | **0.079** | **0.310** | **0.236** | **0.151** | **0.486** |
| Site 4 | Naive | 1.710 | 2.194 | 0.158 | 0.438 | 0.357 | 0.198 | 1.000 |
| | GRU | 1.422 | 1.761 | 0.099 | 0.388 | 0.296 | 0.159 | 0.896 |
| | LSTM | 1.417 | 1.746 | 0.101 | 0.400 | 0.299 | 0.157 | 0.837 |
| | SeriesNet | 1.378 | 1.708 | 0.094 | 0.373 | 0.288 | 0.154 | 0.864 |
| | ResUnet | 1.390 | 1.717 | 0.095 | 0.375 | 0.290 | 0.155 | 0.873 |
| | ResAUnet | **1.288** | **1.624** | **0.085** | **0.350** | **0.268** | **0.146** | **0.810** |
| Site 5 | Naive | 1.453 | 1.88 | 0.105 | 0.359 | 0.264 | 0.176 | 1.000 |
| | GRU | 1.073 | 1.402 | 0.061 | 0.287 | 0.193 | 0.131 | 0.779 |
| | LSTM | 1.081 | 1.408 | 0.062 | 0.290 | 0.195 | 0.131 | 0.803 |
| | SeriesNet | 1.059 | 1.374 | 0.060 | 0.282 | 0.192 | 0.128 | 0.773 |
| | ResUnet | 1.070 | 1.388 | 0.062 | 0.283 | 0.195 | 0.130 | 0.779 |
| | ResAUnet | **1.035** | **1.342** | **0.056** | **0.272** | **0.187** | **0.125** | **0.762** |
| Site 6 | Naive | 1.731 | 2.138 | 0.085 | 0.28 | 0.257 | 0.204 | 1.000 |
| | GRU | 1.319 | 1.658 | 0.053 | 0.231 | 0.195 | 0.158 | 0.794 |
| | LSTM | 1.315 | 1.662 | 0.054 | 0.234 | 0.195 | 0.159 | 0.833 |
| | SeriesNet | **1.292** | 1.625 | 0.051 | 0.225 | **0.191** | 0.155 | **0.768** |
| | ResUnet | 1.295 | 1.630 | 0.052 | 0.226 | 0.192 | 0.156 | 0.771 |
| | ResAUnet | 1.295 | **1.617** | **0.050** | **0.223** | 0.192 | **0.154** | 0.781 |

**Table 21**
Average MAE (kW) for 1-day and 3-days test sets considering both univariate and multivariate approaches (source:SHIVAM et al., 2020).

| Model | Input Data | May 1-day | May 3-days | Oct. 1-day | Oct. 3-days |
|---|---|---|---|---|---|
| Basic LSTM (with embedding) | S1 | 1.445 | 1.744 | **1.844** | 2.502 |
| Basic LSTM (without embedding) | S1 | 5.335 | 2.961 | 6.167 | 4.085 |
| C-LSTM | S1,S2 | 2.222 | 1.962 | 2.563 | 3.506 |
| | S1, S3 | 4.729 | 4.912 | 4.170 | 3.576 |
| | *S1,S2, S3* | 2.250 | 1.988 | 2.438 | 3.520 |
| Conv-LSTM | *S1,S2* | 1.381 | 1.943 | 2.792 | 3.117 |
| | S1, S3 | 3.943 | 3.171 | 2.340 | 2.614 |
| | *S1,S2, S3* | 4.994 | 4.252 | 1.873 | 3.379 |
| Multi-LSTM | *S1,S2* | **1.089** | **1.524** | 2.148 | 2.439 |
| | S1,S3 | 1.625 | 1.806 | 2.225 | 2.372 |
| | *S1,S2, S3* | 1.334 | 1.539 | 2.273 | **2.360** |
| Stacked-LSTM | *S1,S2* | 4.048 | 2.841 | 5.737 | 3.937 |
| | S1, S3 | 5.317 | 3.091 | 5.512 | 3.899 |
| | S1, S2, S3 | 5.058 | 2.962 | 5.973 | 4.214 |

objective is to accurately identify real data from generated data in order to maximize discriminant validity; the generator's purpose is to resemble the real data's potential distribution as closely as feasible. They must constantly enhance abilities of discriminative and generative abilities in order to achieve competitive advantages, and the purpose of optimization is to achieve a Nash equilibrium between them. GAN has had a lot of success in the field of picture and video generation in recent years, and its popularity has grown significantly.

### *6.5.2. GAN research in the field of renewable energy sources*

As shown in Table 29, in the research keywords of the renewable field, GAN has fewer publication, and its main research goal is to automatically perform building energy prediction, etc (see Table 30).

Qiao et al. (2021) implemented the architecture for ctrl-GAN used for renewable scenario generation, including a fully connected autoencoder, a convolutional autoencoder, and generates adversarial networks in Fig. 43. The principal component analysis (PCA) technique was used, and an automatic feature engineering based on deep learning was completed. Residential data for Hong Kong in 2015 were used with a sampling interval of 30 min, and it had 17,040 observations. The GAN-based function was utilized in CV-RMSE (kW), MLR (26.4%), SVR (21.3%), ANN (20.1%), XGB (Extreme Gradient Boosting) (17.7%). Different types of data were used for testing and validating that the model can automatically make building energy prediction.

### *6.5.3. GAN summary in renewable fields*

The GAN represents the data distribution by learning the joint probability density distribution P (X,Y) of the data statistically, and does not focus on the classification boundaries of the data. GAN avoids

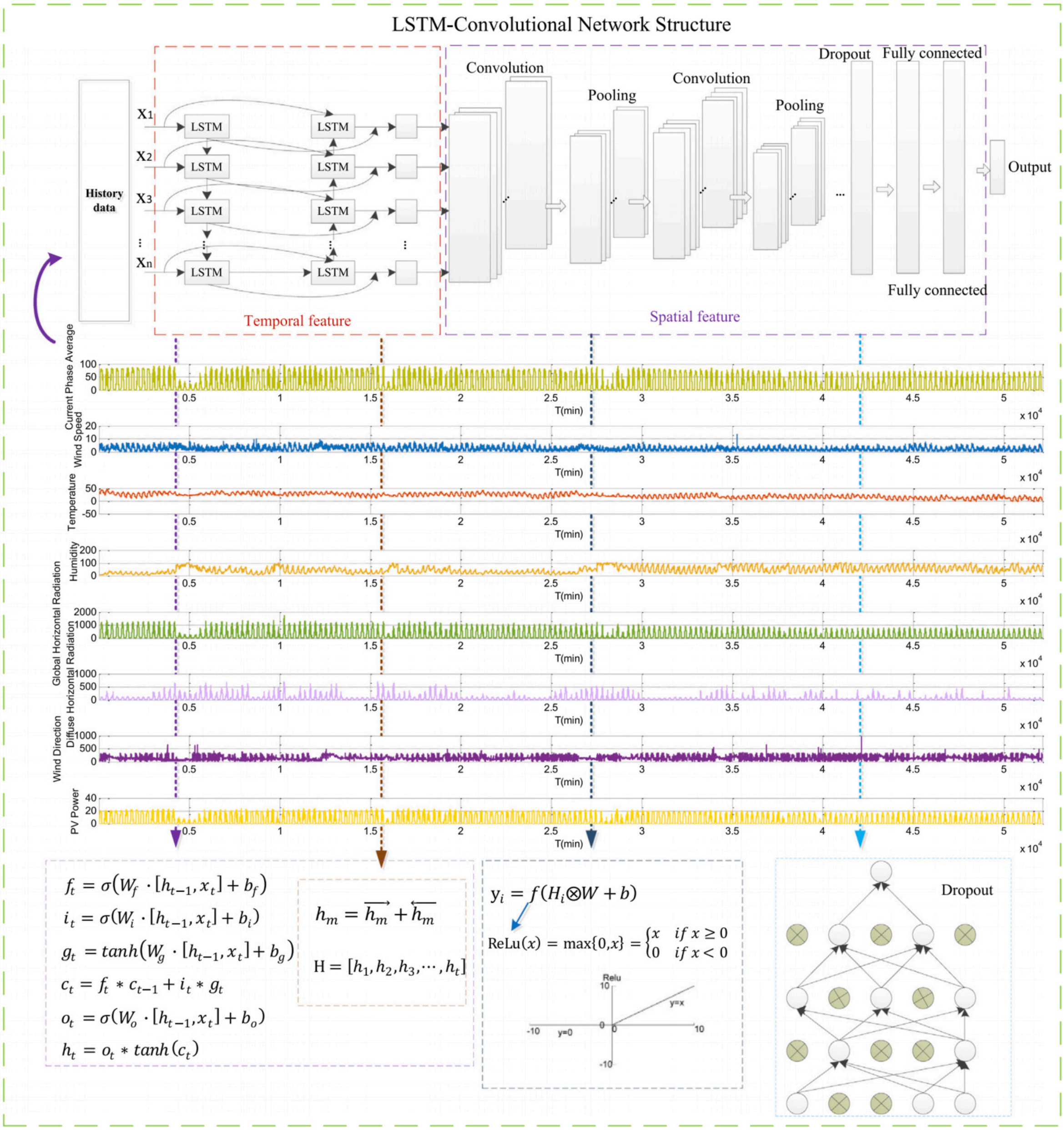



**Fig. 37.** The LSTM-Convolutional network structure (source:Wang et al., 2019).

Markov-chain learning mechanism and improves application efficiency. Its design is flexible framework to integrate different types of loss functions.

Through analysis, the existing research in the renewable field mainly has the following characteristics in GAN:

(i) In terms of application fields, GAN is used in the field of wind and solar energy.
(ii) In terms of use purpose, it captured the nonlinear and dynamic renewable patterns without the need for modeling assumptions and complicated sampling techniques and generated realistic time series data of wind and photovoltaic power.
(iii) In terms of application methods, orthogonal regularization and spectral normalization are adopted to strengthen the training stability of the GAN model.
(iv) Evaluation criteria of GAN were error, MMD Score, Frechet Inception Distance, 1-Nearest Neighbor score.
(v) The advantages of GAN in renewable energy can be concluded as that it is capable of producing fresh data that has the same distribution as the raw data.
(vi) The disadvantages of GAN can be concluded as, a)characteristics of the input renewable data cannot be effectively described, b) if renewable energy data has missing data, it is hard to handle for GAN.

### 6.6. Recurrent neural network

#### 6.6.1. Introduction to the RNN

As shown in Fig. 44, the RNN is proposed for time series data. The output of RNN is the result of the current input together with all moment states in history, with some advantages for temporal data processing. However, the gradient diffusion effect on the timeline may causes the RNN to be unsuitable for processing longer sequence data. RNN networks became increasingly popular due to the advancement of network design and increased computational power on graphics processing units.

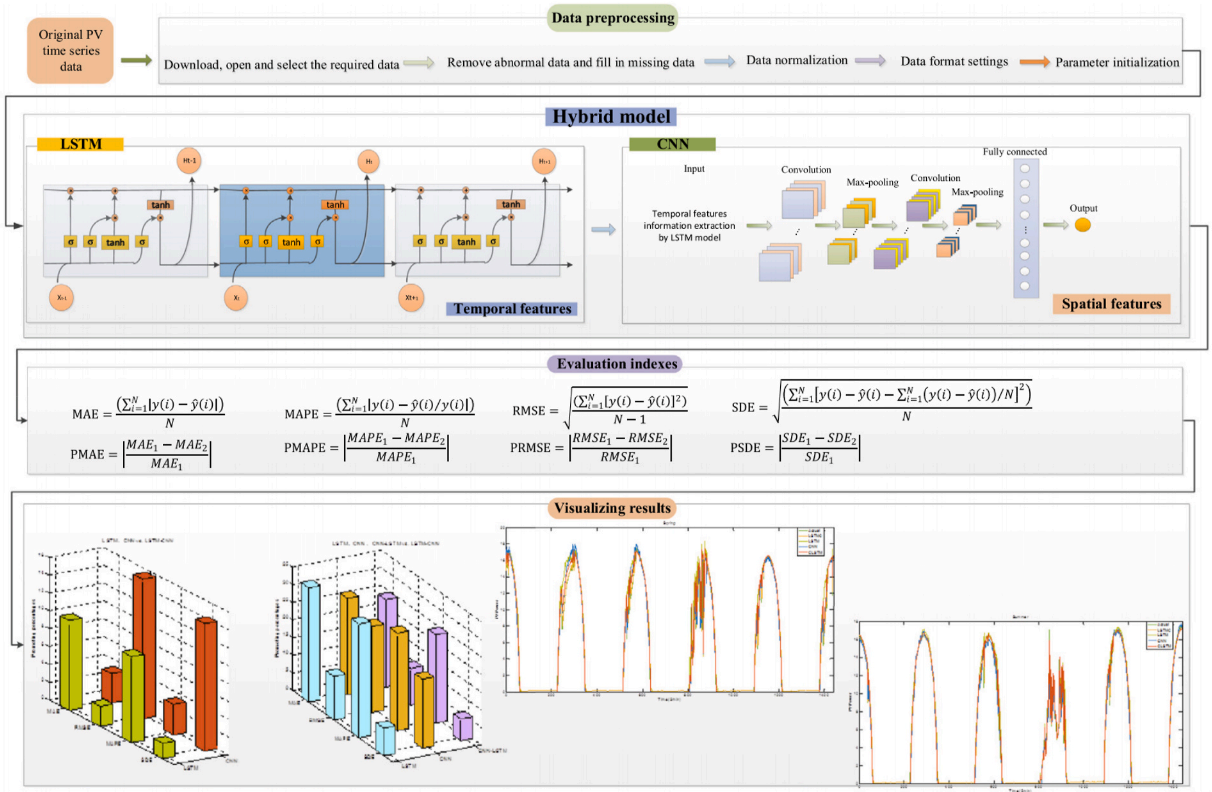



**Fig. 38.** The block-diagram for the framework (source:Wang et al., 2019).

**Table 22**
The comparison of promotion percentages between different models (source: WANG et al., 2019).

| | LSTM vs. CNN-LSTM | CNN vs. CNN-LSTM | LSTM vs. LSTM-CNN | CNN vs. LSTM-CNN | CNN-LSTM vs. LSTM-CNN |
|---|---|---|---|---|---|
| PMAE | 10.09% | 3.29% | 32.416% | 27.303% | 24.830% |
| PRMSE | 2.26% | 15.69% | 12.412% | 24.453% | 10.390% |
| PMAPE | 9.68% | 3.45% | 32.258% | 27.586% | 25.000% |
| PSDE | 1.74% | 14.30% | 7.837% | 19.620% | 6.204% |

This network is particularly useful for time series data, because each neuron or cell can use its internal store relevant information from its previous input.

The network can be trained the modification regulations in between sequence analysis due to the obvious neural connections with in RNN layer, as well as the intrinsic temporal regulations of sequence analysis are trivial to extract. RNN is commonly utilized in applications like voice recognition and language processing that deal with sequence data. However, such a structure also produces some problems, which is inevitably prone to occurring gradient disappearance or gradient explosion problems in the backward data transmission. In Fig. 45, by incorporating many specific computational components to the RNN hidden layer, the RNN-derived LSTM network modifies the way gradients are sent during backpropagation.

### 6.6.2. RNN research in the field of renewable energy sources

It can be seen in Fig. 30 that, in the field of renewable research keywords, main publication of RNN are analyzed, and the research goal are Microgrid Energy Management, Wind Power Prediction, Online Adaptive RNN, Solar Irradiance, Weather Forecasting, Photovoltaic Power Systems, 24-Hour-Ahead Prediction Problem, Short-Term Net Energy Forecasting.

In Fig. 46, a new mechanism based on LSTM was provided to forecast the renewable power of a cost-effective wave energy converter by Mousavi et al. (2021). Simulations were carried out using Flow-3D software, and the LSTM network predicted power in terms of height more accurately and faster than the numerical solution in a field of predicting.

**Table 23**
Evaluation of CLSTM hybrid predictive model over multiple forecast horizons for 1-Day (1D), 1-Week (1W), 2-Week (2W) and 1-Month (1 M) periods (source: GHIMIRE et al., 2019).

| Predictive models | | *r* | | | | RMSE (Wm-2) | | | | MAE (Wm-2) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1D | 1W | 2W | 1M | 1D | 1W | 2W | 1M | 1D | 1W | 2W | 1M |
| 2-Phase Hybrid Predictive models | CLSTM | 1 | 0.999 | 0.999 | 0.993 | 8.189 | 16.011 | 14.295 | 32.872 | 6.666 | 9.804 | 8.238 | 13.131 |
| | CNN | 0.999 | 0.998 | 0.998 | 0.992 | 9.991 | 16.827 | 16.985 | 36.465 | 7.526 | 10.834 | 11.122 | 14.165 |
| | LSTM | 0.999 | 0.998 | 0.999 | 0.993 | 21.055 | 18.879 | 16.327 | 33.387 | 18.339 | 11.275 | 10.75 | 14.307 |
| | GRU | 0.999 | 0.998 | 0.998 | 0.979 | 14.289 | 21.464 | 19.207 | 57.589 | 11.32 | 15.658 | 14.005 | 39.716 |
| | RNN | 0.998 | 0.998 | 0.999 | 0.993 | 20.177 | 18.113 | 15.494 | 41.511 | 18.206 | 11.387 | 10.492 | 26.858 |
| | DNN | 0.999 | 0.997 | 0.999 | 0.991 | 16.167 | 25.974 | 14.413 | 39.754 | 13.442 | 19.934 | 8.572 | 21.816 |
| | MLP | 1.00 | 0.998 | 0.999 | 0.992 | 12.929 | 20.525 | 16.379 | 35.261 | 10.862 | 15.027 | 10.631 | 14.317 |
| | DT | 0.998 | 0.995 | 0.995 | 0.988 | 19.758 | 33.427 | 31.61 | 44.283 | 15.95 | 24.328 | 24.763 | 28.442 |

**Table 24**
The deterministic forecasting performance of the proposed models and the existing models (source: LIU et al., 2019).

| Series | Forecasting step | MAE (m/s) | MAPE (%) | RMSE (m/s) | MAE (m/s) | MAPE (%) | RMSE (m/s) |
|---|---|---|---|---|---|---|---|
| #1 | | WCA | | | Liu's model | | |
| | 1-step | **0.1069** | **3.8991** | **0.1334** | 0.1270 | 4.6880 | 0.1659 |
| | 2-step | **0.1190** | **4.2572** | **0.1566** | 0.1841 | 7.5572 | 0.2328 |
| | 3-step | **0.1539** | **5.5702** | **0.1961** | 0.2339 | 7.5519 | 0.3163 |
| | | Li's model | | | Qu's model | | |
| | 1-step | 0.2224 | 8.3723 | 0.2961 | 0.3091 | 11.9560 | 0.4039 |
| | 2-step | 0.2745 | **11.1890** | 0.3490 | 0.3621 | 14.6242 | 0.4586 |
| | 3-step | 0.3079 | 9.9834 | 0.4320 | 0.3194 | 12.3850 | 0.4147 |
| | | ARMA | | | ELM | | |
| | 1-step | 0.4174 | 15.2625 | 0.5503 | 0.6350 | 27.3011 | 0.7640 |
| | 2-setp | 0.4843 | 18.4199 | 0.6305 | 0.6902 | 29.8389 | 0.8383 |
| | 3-step | 0.5184 ENN | 20.0742 | 0.6682 | 0.7891 | 34.3622 | 0.9420 |
| | 1-step | 0.9293 | 40.8435 | 1.0793 | | | |
| | 2-step | 1.0811 | 47.3950 | 1.2405 | | | |
| | 3-step | 1.0828 | 47.4828 | 1.2434 | | | |
| #2 | | WCA | | | Liu's model | | |
| | 1-step | **0.3125** | **2.9411** | **0.3964** | 0.4933 | 4.5648 | 0.6207 |
| | 2-step | **0.3324** | **3.1443** | **0.4189** | 0.4885 | 4.5557 | 0.6242 |
| | 3-step | **0.4560** | **4.3122** | **0.5776** | 0.6835 | 6.2874 | 0.9053 |
| | | Li's model | | | Qu's model | | |
| | 1-step | 0.7274 | 6.6619 | 0.9271 | 1.0067 | 9.3602 | 1.2795 |
| | 2-step | 0.7419 | 6.8648 | 0.9480 | 1.0029 | 9.3945 | 1.2804 |
| | 3-step | 1.2657 | 11.7752 | 1.5535 | 1.2717 | 11.9835 | 1.5791 |
| | | ARMA | | | ELM | | |
| | 1-step | 1.6549 | 15.9934 | 2.0534 | 1.8040 | 18.1057 | 2.2206 |
| | 2-step | 1.6763 | 16.4067 | 2.0790 | 1.8451 | 18.5578 | 2.2616 |
| | 3-step | 1.7349 ENN | 17.1364 | 2.1307 | 1.8854 | 19.0276 | 2.3095 |
| | 1-step | 1.9006 | 19.2591 | 2.3428 | | | |
| | 2-step | 1.9932 | 20.2417 | 2.4371 | | | |
| | 3-step | 2.0301 | 20.6645 | 2.4777 | | | |
| #3 | | WCA | | | Liu's model | | |
| | 1-step | **0.4402** | **2.1506** | **0.5595** | 0.6152 | 3.0155 | 0.7848 |
| | 2-step | **0.5556** | **2.7396** | **0.6922** | 0.6432 | 3.1430 | 0.8163 |
| | 3-step | **0.6771** | **3.3321** | **0.8521** | 0.9815 | 4.9186 | 1.2594 |
| | | Li's model | | | Qu's model | | |
| | 1-step | 1.0325 | 5.0621 | 1.3168 | 1.5213 | 7.4881 | 1.8940 |
| | 2-setp | 1.0565 | 5.1747 | 1.3376 | 1.4911 | 7.2877 | 1.8684 |
| | 3-step | 1.5761 | 7.8188 | 1.9315 | 1.7226 | 8.7671 | 2.1119 |
| | | ARMA | | | ELM | | |
| | 1-step | 2.1690 | 10.2715 | 2.7771 | 2.1848 | 10.3268 | 2.7981 |
| | 2-step | 2.3073 | 10.9893 | 2.9156 | 2.3302 | 11.0708 | 2.9476 |
| | 3-step | 2.3746 | 11.3329 | 2.9756 | 2.3801 | 11.3152 | 2.9974 |
| | 1-step | 2.1749 | 10.3075 | 2.7877 | | | |
| | 2-step | 2.2976 | 10.9300 | 2.9287 | | | |
| | 3-step | 2.3739 | 11.3227 | 2.9891 | | | |

**Table 25**
Performance of forecasting methods for wind speed (source:AFRASIABI et al., 2019).

| Forecasting methods | MAPE (%) | RMSE | NRMSE |
|---|---|---|---|
| CNN-GRU | 3.5875 | 0.21578 | 0.021758 |
| CNN-LSTM | 5.4813 | 0.34515 | 0.034515 |
| 2D-CNN | 8.1056 | 0.33372 | 0.044556 |
| GRU | 10.218 | 0.45985 | 0.062843 |
| LSTM | 10.37 | 0.48 | 0.065322 |
| ARIMA | 21.546 | 0.983 | 0.0783 |
| KNN | 28.910 | 1.037 | 0.0860 |
| NNE | 19.773 | 0.8412 | 0.08254 |

Ji et al. (2021) RNN was used to provide a data-driven online appointment scheduling solution for microgrid power management. by utilizing RNN with Markov decision process (MDP), a network based on the gated cycle unit (GRU) and proximal policy optimization (PPO) to develop data-driven neural network-based methods as shown in Fig. 47.

Regarding wind power prediction, Liu et al. (2021) presented a Stacked Recursive Neural Network (SRNN) incorporating a Parametric Susoidal Active Function (PSAF) algorithm, as shown in Fig. 48. And the result of wind power forecasting and comparison of different evaluation metrics are presented in Fig. 49 and Table 31 respectively.

Wang et al. (2021) designed a framework stacked by an independent recurrent autoencoder (IRAE), SIRAE (staking Independent recurrent Autoencoder).

Fekri et al. (2021) presented online adaptive RNN that can continuously learned from new arrived data. The proposed method were evaluated by using data from five independent smart meter, and the results showed in Fig. 50.

Brahma et al. (2020) developed predictive models based on LSTM by using multi-site data based on 36 years (1983–2019) solar irradiance data obtained from the NASA POWER project repository.

Carrera et al. (2020) presented a hybrid network called PVHybNet, including a deep feedforward network using weather forecast data and a recurrent neural network using recent weather observations to exploit 24-h ahead prediction of photovoltaic power. When predicting solar power generation in Korea, the final model yielded an R square value of 92.7%.

Pang et al. (2020) presented a case study of solar radiation prediction, and the performance evaluation of RNN model with different sampling frequencies is shown in Table 32.

Wen et al. (2020) proposed a deep learning framework to forecast the load requirements of residential buildings at an hour resolution, while considering its complexity and variability. Hourly data on residential loads in Austin, Texas, USA were used to demonstrated the effectiveness,

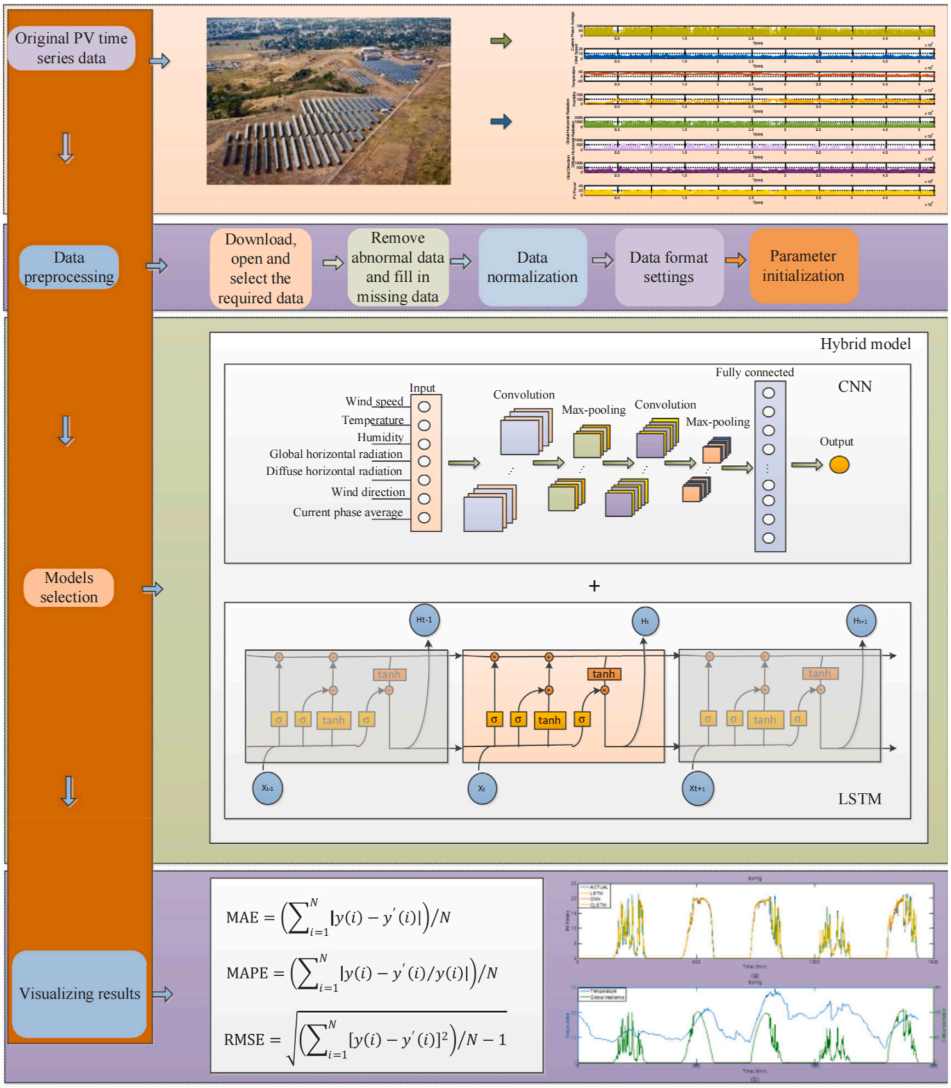



**Fig. 39.** The structure of the proposed model (source:Wang et al., 2019a,b).

**Table 26**
The forecasting results in different input sequence and different models (source:WANG et al., 2019).

| Models Input sequence | LSTM | | | CNN | | | CLSTM | | |
|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAE | MAPE | RMSE | MAE | MAPE | RMSE | MAE | MAPE |
| 0.5Y | 1.244 | 0.654 | 0.131 | 1.128 | 0.566 | 0.114 | 1.161 | 0.559 | 0.112 |
| 1Y | 1.393 | 0.616 | 0.103 | 1.563 | 0.640 | 0.111 | 1.434 | 0.628 | 0.105 |
| 1.5Y | 1.533 | 0.599 | 0.101 | 1.411 | 0.567 | 0.095 | 1.248 | 0.529 | 0.095 |
| 2Y | 1.320 | 0.457 | 0.068 | 0.983 | 0.452 | 0.059 | 0.941 | 0.397 | 0.052 |
| 2.5Y | 0.945 | 0.389 | 0.051 | 0.447 | 0.231 | 0.041 | 0.426 | 0.198 | 0.035 |
| 3Y | 0.398 | 0.181 | 0.032 | 0.367 | 0.140 | 0.025 | 0.343 | 0.126 | 0.022 |
| 3.5Y | 1.150 | 0.455 | 0.083 | 1.136 | 0.412 | 0.077 | 0.991 | 0.384 | 0.070 |
| 4Y | 1.465 | 0.565 | 0.089 | 0.971 | 0.478 | 0.083 | 0.886 | 0.405 | 0.080 |

and the findings revealed that the proposed paradigm is viable, as shown in Table 33.

Razavi et al. (2020) presented a multi-input single-output (MISO) model based on LSTM, through which different household energy conditions contribute to provide more accurate predictions for other household or overall energy conditions.

Ray et al. (2020) built a hybrid deep learning-based solution for output prediction of Australian solar PV systems using a combination of multivariate, LSTM, and CNN to achieve a balance between precision and efficiency.

Zeng et al. (2019) developed a new dynamic energy management system (EMS) to incorporate Markov decision process (MDP), and approximations to a sample day's optimal value function are shown. By deep RNN and shallow RNN in Fig. 51.

Kim et al. (2019) proposed a recurrent initial convolutional neural network (RICNN) that combines both RNN and one-dimensional CNN (1-D CNN). The proposed RICNN model has been validated in electricity data for three large distribution complexes in Korea, Table 34 indicates

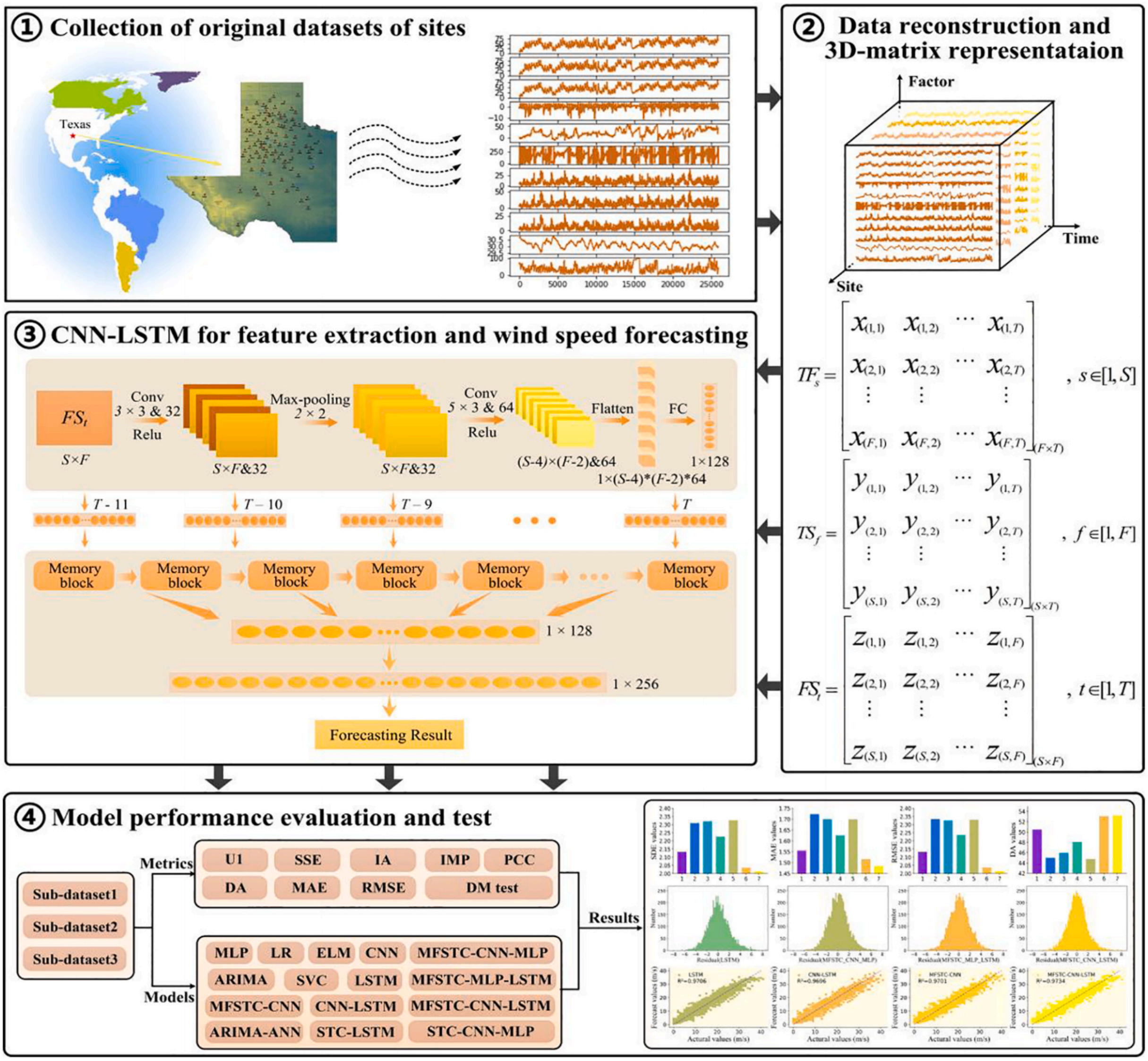



**Fig. 40.** Process of proposed wind speed forecasting model (source: Chen et al., 2018).

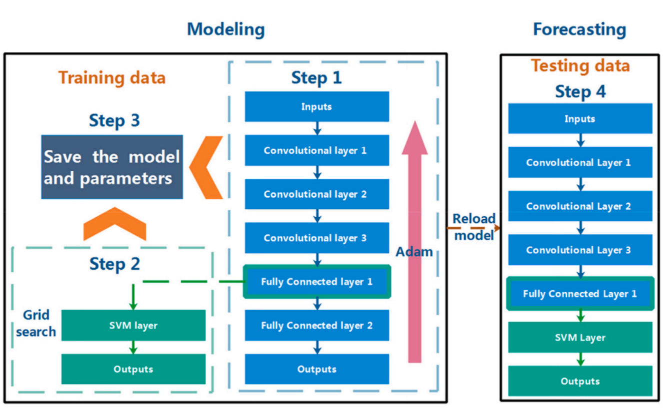



**Fig. 41.** Computational steps of CNNSVM(source:Mi et al., 2019).

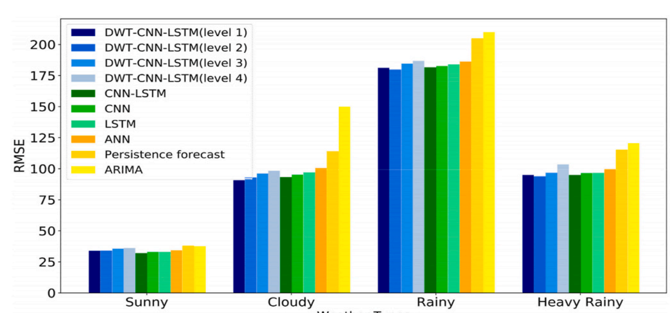



**Fig. 42.** The RMSE of several prediction model with different weather (source: WANG et al., 2018).

also that RICNN model is superior the benchmark multi-layer perception model in experiments.

Husein et al. (2019) developed a LSTM-RNN to predict hourly anterior solar irradiance in Fig. 52. As shown in Table 35, Six experiments using measurements from German, US, Swiss and Korean weather stations were compared, and the developed model is more effective, thus according test findings.

Kong et al. (2019) presented a framework based on LSTM and RNN to address residential load forecasting problem. The proposed framework is tested on a set of real-residential smart meter data, and the proposed LSTM method outperforms the other listed competitor algorithms.

**Table 27**
The experimental results in terms of MAPE in percentages (source:Kuo and Huang, 2018).

| Test | SVM | RF | DT | MLP | LSTM | DeepEnergy |
|---|---|---|---|---|---|---|
| #1 | 7.327408 | 7.639133 | 8.46043 | 9.164315 | 10.40804813 | 7.226127 |
| #2 | 7.550818 | 8.196129 | 10.23476 | 11.14954 | 9.970662683 | 8.244051 |
| #3 | 13.07929 | 10.11102 | 12.14039 | 19.99848 | 14.85568499 | 11.00656 |
| #4 | 16.15765 | 17.27957 | 19.86511 | 22.45493 | 12.83487893 | 12.17574 |
| #5 | 5.183255 | 6.570061 | 8.50582 | 15.01856 | 5.479091542 | 5.41808 |
| #6 | 10.33686 | 9.944028 | 11.11948 | 10.94331 | 11.7681534 | 9.070998 |
| #7 | 8.934657 | 6.698508 | 8.634132 | 7.722149 | 7.583802292 | 9.275215 |
| #8 | 18.5432 | 16.09926 | 17.17215 | 16.93843 | 15.6574951 | 13.2776 |
| #9 | 49.97551 | 17.9049 | 21.29354 | 29.06767 | 16.31443679 | 11.18214 |
| #10 | 11.20804 | 8.221766 | 10.68665 | 12.20551 | 8.390061493 | 10.80571 |
| Average | 14.82967 | 10.86644 | 12.81125 | 15.46629 | 11.32623153 | 9.768222 |

**Table 28**
The experimental results in terms of CV-RMSE given in percentages (source:Kuo and Huang, 2018).

| Test | SVM | RF | DT | MLP | LSTM | DeepEnergy |
|---|---|---|---|---|---|---|
| #1 | 9.058992 | 9.423908 | 10.57686 | 10.65546 | 12.16246177 | 8.948922 |
| #2 | 10.14701 | 10.63412 | 12.99834 | 13.91199 | 12.19377007 | 10.46165 |
| #3 | 17.02552 | 12.42314 | 14.58249 | 23.2753 | 16.9291218 | 13.30116 |
| #4 | 21.22162 | 21.1038 | 24.48298 | 23.63544 | 14.13596516 | 14.63439 |
| #5 | 6.690527 | 7.942747 | 10.10017 | 15.44461 | 6.334195125 | 6.653999 |
| #6 | 11.88856 | 11.6989 | 13.39033 | 12.20149 | 12.96057349 | 10.74021 |
| #7 | 10.77881 | 7.871596 | 10.35254 | 8.716806 | 8.681353107 | 10.85454 |
| #8 | 19.49707 | 17.09079 | 18.95726 | 17.73124 | 16.55737557 | 14.51027 |
| #9 | 54.58171 | 19.91185 | 24.84425 | 29.37466 | 17.66342548 | 13.01906 |
| #10 | 13.80167 | 10.15117 | 13.06351 | 13.39278 | 10.20235927 | 13.47003 |
| Average | 17.46915 | 12.8252 | 15.33487 | 16.83398 | 12.78206008 | 11.65942 |

**Table 29**
The publication information of GAN models in the renewable energy field.

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| QIAO et al. (2021) | renewable scenario generation using controllable generative adversarial networks with transparent latent space | Automate building energy prediction | The datasets obtained from NREL Wind and Solar | Controllable GAN | CV-RMSE (kW) | Error |
| | | | | | MLR (26.4%) | autocorrelation coefficient MMD Score |
| | | | | | SVR (21.3%) | Frechet Inception Distance 1-Nearest Neighbor score |
| | | | | | ANN(20.1%) | the ramp value Δx |
| | | | Integration Datasets | | XGB (17.7%) | Pearson correlation |

Wang et al. (2018) proposed a more efficient DL model is developed based on WD, CNN and LSTM to predict solar irradiance, the proposed model was built separately under four different sorts of weather.

### 6.6.3. Summary of the RNN in the renewable domain

RNN is connected by feedback between neurons, considering the association between samples, and RNN is unable to handle long sequence data. The most common transformation mode of RNN are LSTM and GRU.

Through analysis, the existing research in the renewable field mainly has the following characteristics in RNN:

(i) In terms of application fields, RNN and RNN with different architectures, such as LSTM, were used in the field of wind, solar and wave energy.
(ii) In terms of use purpose, it generated realistic time series data of wind and photovoltaic power, trained on the denoised datasets and used as a sub-model of point wind speed prediction, and predict power loads for individual energy users.
(iii) In terms of application methods, RNN can not only be used in orginial or deformation way to predcit the wind/solar/wave power, but also often be integrated with other algorithms, such as CNN, ANN, GRU, deepforward network, MDP, and WD to improve the prediction accuracy.
(iv) Evaluation criteria of RNN were MAE, RMSE, $R^2$, NMBE (Normalize Mean Bias Error), NRMSE (Normalized Root Mean Square), R value.
(v) The advantages of RNN in renewable energy can be concluded as that time-series data was processed and the computational efficiency was high. .
(vii) The disadvantages of RNN can be concluded as, a)Characteristics of the input data cannot be effectively described, b) Renewable energy data need to be time-series data when RNN is used.

## 6.7. Comparison of different deep learning algorithm

After analysis in the previous section, SAE and DBN are more used in wind power forecasting, CNN is more used in photovoltaic forecasting, GAN is very rarely used in both types of forecasting, and RNN is used more in both types of forecasting. Five common deep learning algorithms are discussed, along with their benefits, drawbacks, and application scenarios. including GAN, RNN, CNN, SAE, and DBN, are summarized in Table 36. As shown in Table 36, in the case of solar data or information, RNN and CNN are especially prominent. Although SAE and DBN are typical deep learning algorithms, so far, either 8 and 7

**Table 30**
The publication information of RNN models in the renewable energy field.

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| Mousavi et al. (2021) | Deep Learning For Wave Energy Converter Modeling Using Long Short-Term Memory | Accurate prediction of the wave energy | Experimental data from another study and applied data from Searaser numerical simulations were provided | LSTM | RMSE | Numerical solutions in the prediction field predict height power more accurately and faster. |
| Ji et al. (2021) | Data-Driven Online Energy Scheduling Of A Microgrid Based On Deep Reinforcement Learning | The increase in uncertain RES, traditional online scheduling methods that rely on accurate predictions become difficult to implement | Real-world power system data for the California Independent System Operator (CAISO) | GRU + feedward network + output layer | Total operating cost, optimization error | The effectiveness of the proposed method is demonstrated. |
| Liu et al. (2021) | Short-Term Wind Power Forecasting By Stacked Recurrent Neural Networks With Parametric Sine Activation Function | Wind energy resources have inevitable intermittent, complex fluctuations and high fluctuation, and short-term wind electric power prediction is a challenging problem | Based on the National Renewable Energy Laboratory (NREL) wind power data | A Stacked Recursive Neural Network (S R N N) +parametric sinusoidal activation function (PSAF) | MAE,MAPE,MSE | High power in retrieving the manifold features in wind power. |
| Wang et al. (2021) | Effective Wind Power Prediction Using Novel Deep Learning Network: Stacked Independently Recurrent Autoencoder | Accurate wind-electric power prediction | Massive wind power data | independent cyclic autoencoder (IRAE)+ VMD | RMAE, R2 score | The SIRAE model outperforms the existing popular models. In extended applications, SIRAE increased 18.46%, 31.16%, 9.06% and 34 mean square error in March, June, September, and 34.24% in December, compared to the persistence model, respectively. |
| Fekri et al. (2021) | Deep Learning For Load Forecasting With Smart Meter Data: Online Adaptive Recurrent Neural Network | The recurrent neural networks are trained offline and are not suitable for new data scene changes | Smart meter data from five independent homes | Online adaptive RNN | NAME, NRMSE, MAE,RMSE | The proposed method achieves higher accuracy than an independent offline, long, short-term memory network and five other online algorithms. |
| Brahma et al. (2020) | Solar Irradiance Forecasting Based On Deep Learning Methodologies And Multi-Site Data | Predictive modeling of the solar irradiance data | Solar irradiance data from two Indian sites (1983–2019) obtained from the NASA POWER project repository | Bi-directional LSTM + attention-based LSTM | MSE,RMSE,R2 | Multi-site data with historical solar irradiance data improves the predictive performance of unit univariate solar data, the accuracy, performance, and reliability of the model |
| Carrera et al. (2020) | Pvhybnet: A Hybrid Framework For Predicting Photovoltaic Power Generation Using Both Weather Forecast And Observation Data | Energy instability resulting from a strong dependence on the weather | Solar power generation from the Lingyan power station in South Korea | Deepforward network + RNN | RMSE,MAE,R2 | The final model yielded a R square value of 92.7%. The hybrid model outperforms several machine learning models. |
| Pang et al. (2020) | Solar Radiation Prediction Using Recurrent Neural Network And Artificial Neural Network: A Case Study With Comparisons | Sun radiation prediction | | ANN + RNN | R2,RMSE,CV (RMSE),NMABE | |
| Wen et al. (2020) | Load Demand Forecasting Of Residential Buildings Using A Deep Learning Model | , Predicting the load requirements for residential buildings at a 1-h resolution | Residential load data measured hourly in Austin, Texas, USA | DRNN + GRU | RMSE,MAE,MAPE | The validity of the proposed model, and the prediction error was assessed quantitatively using multiple metrics. |
| Razavi et al. (2020) | From Load To Net Energy Forecasting: Short-Term Residential Forecasting For The Blend Of Load And Pv Behind The Meter | Residential Solar PV (P V) at single-household and low overall levels | Two real Ausgrid and Solar Analytics case studies in Australia | multi-input single output (M I S O) model + LSTM | MAAPE | Online LSTM is more resilient to sudden changes at the individual family level, while MISO LSTM is more effective at the overall level. |
| Ray et al. (2020) | A New Data Driven Long-Term Solar Yield Analysis Model Of Photovoltaic Power Stations | Output forecast of the solar PV system (i. e., the proposed PV system) | Historical datasets from 1990 to 2013 (e. g. North Queensland) | LSTM + CNN | RMSE, NRMSE, MAPE, RVALUE | The proposed hybrid deep learning (LSTM-CNN) is compared with existing techniques to evaluate the performance. |
| | Dynamic Energy Management Of A | The dynamic energy management | Real power grid data from the Independent System | MDP (Markov decision process)+ | | Detailed simulation studies were performed to verify |

(continued on next page)

**Table 30** (*continued*)

| Time | Title | solve the problem | Input | Algorithm model | Evaluation criteria | Output |
|---|---|---|---|---|---|---|
| Zeng et al. (2019) | Microgrid Using Approximate Dynamic Programming And Deep Recurrent Neural Network Learning | mechanisms developed do not require allocation knowledge of long-term prediction and optimization or uncertainty | Operator of California (CAISO) | ADP (Approximate dynamic programming)+RNN | AVERAGE COMMULATIVE COST | the effectiveness of the proposed method. |
| Kim et al. (2019) | Recurrent Inception Convolution Neural Network For Multi Short-Term Load Forecasting | Prediction of a specific time of power load | Prediction of a specific time of power load | RNN+1-D CNN | RMSE, MAPE | The RICNN model outperforms the benchmark multi-layer perception, R N N, and 1 D C N N in terms of daily power load prediction (48 time steps, 30 min intervals). |
| Husein et al. (2019) | Day-Ahead Solar Irradiance Forecasting For Microgrids Using A Long Short-Term Memory Recurrent Neural Network: A Deep Learning Approach | Predicting solar output is critical for optimizing operation and reducing the impact of uncertainty. | Measurements from Germany, USA, Switzerland, and Korea weather stations were conducted in six experiments, using widely available weather data, namely dry ball temperature, dew point temperature, and relative humidity | LSTM-RNN | RMSE,MAE | The proposed method is more accurate than FFNN, with an accuracy of 60.31W/m$^2$ in terms of root mean square error (RMSE). |
| Kong et al. (2019) | Short-Term Residential Load Forecasting Based On Lstm Recurrent Neural Network | The high fluctuation and uncertainty involved, predicting the power load for individual energy users is quite challenging | A set of publicly available real-residential smart meter data | LSTM-RNN | MAPE | The proposed LSTM method outperforms the other listed competitor algorithms in the short-term load prediction task for individual residential families. |
| Wang et al. (2018) | Wavelet Decomposition And Convolutional Lstm Networks Based Improved Deep Learning Model For Solar Irradiance Forecasting | Solar irradiance prediction | Established under four general weather types (i. e. sunny, cloudy, rainy and heavy rain). | WD + CNN + LSTM | MAE,RMSE,R | Final solar irradiance forecast results for a specific weather type |

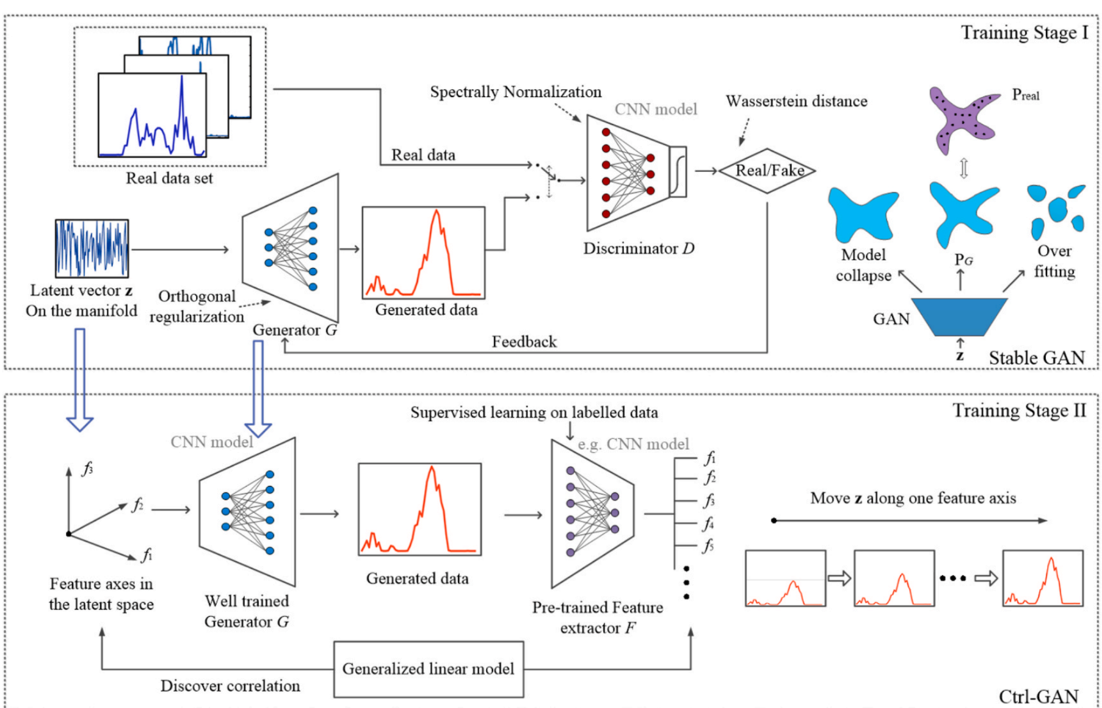



**Fig. 43.** The architecture of ctrl-GAN used for renewable scenario generation (source:Qiao et al. 2021).

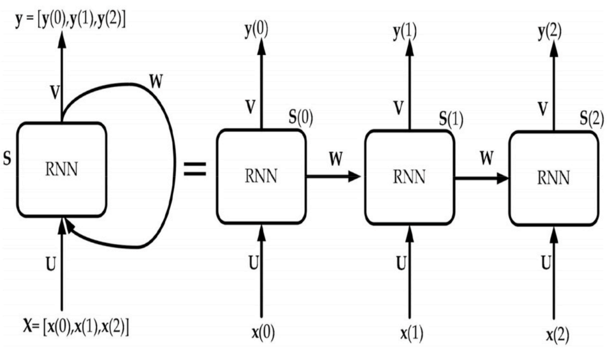



**Fig. 44.** The structure of recurrent neural network.

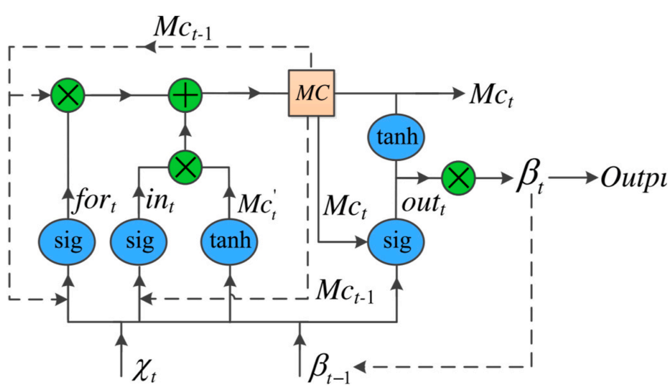



**Fig. 45.** Basic structure of LSTM memory block.

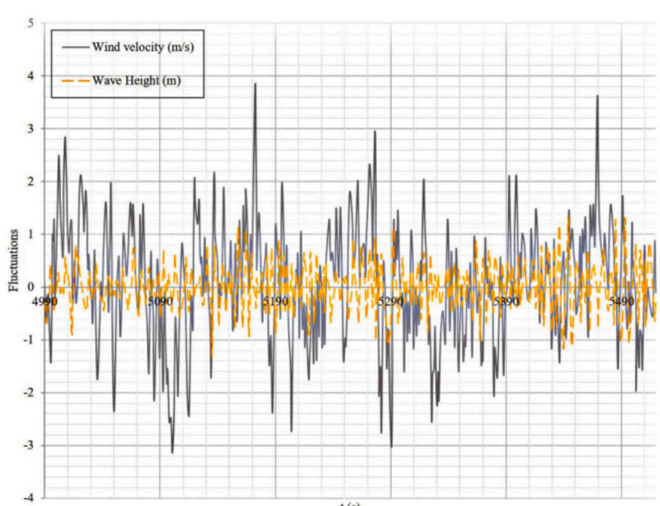



**Fig. 46.** The wind speed and wave height fluctuation in simulation time (source:Mousavi et al., 2021).

papers have already been discovered. Furthermore, there is limited studies on GAN derived photovoltaic solar forecasting.

The differences between several deep learning models are shown as follows:

(i) SAE and DBN are stacked by AE and RBM, AE and RBM can be trained with label-free data, and supervised CNN training.

(ii) The SAE obtains the feature representation of the input data through the nonlinear transformation, while the DBN extracts the higher-order features of the data through the probability distribution of the input data.

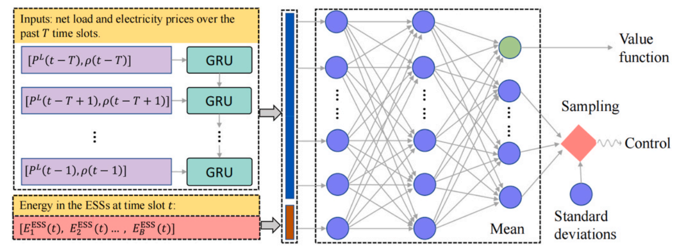



**Fig. 47.** The architecture of the designed policy and value network (source:Ji et al., 2021).

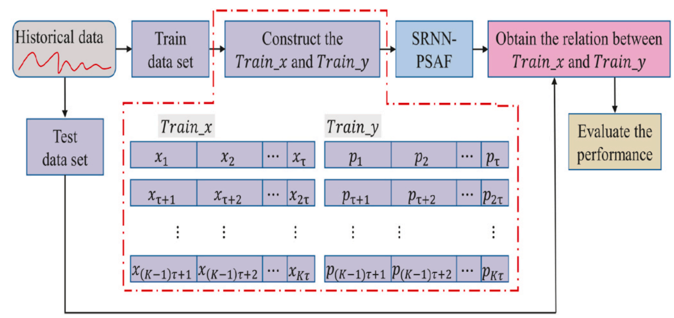



**Fig. 48.** Algorithm framework of SRNN-PSAF-based forecasting (source:Liu et al., 2021.).

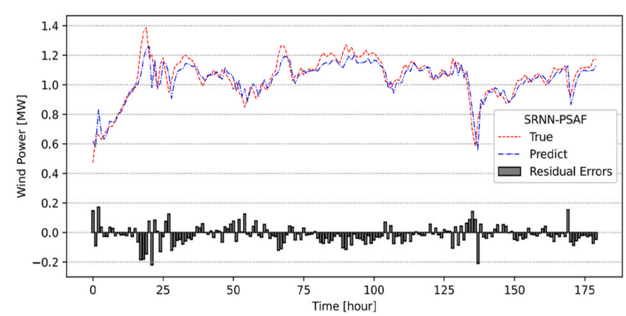



**Fig. 49.** Wind power forecasting with SRNN-PSAF (source:Liu et al., 2021).

(iii) GAN, RNN, SAE, and DBN are the generative model, while CNN is the discriminant model. The combined cumulative probability of data distribution is acquired by GAN and DBN, representing the distribution of the data, without focusing on the classification boundaries of the data. The judgement function Y = f(X) or the probabilistic model distribution P (X|Y) are explicitly learned by CNN. which cannot reflect the characteristics of the data itself, but it looks for the optimal partition interface between different categories of data, reflecting the differences between anomalous data.

(iv) The largest difference between RNN and DBN, SAE, and CNN lies in its feedback connection between neurons, and inter-sample associations can be considered.

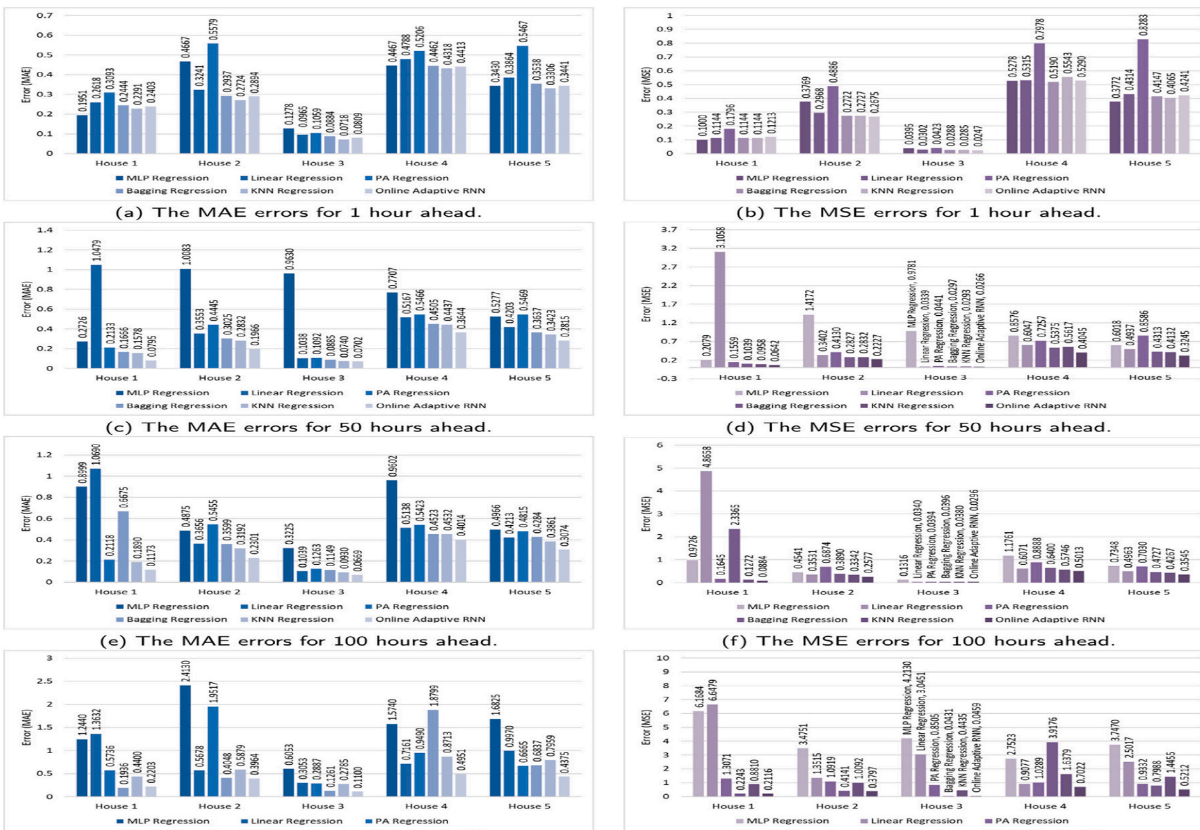
Different models at the application level have the following characteristics.

(i) SAE and DBN are flexible in structure, simple in algorithm, and less difficult in training, and they are easy to expand in practical applications. SAE is more suitable for modeling and feature extraction than DBN.

(ii) CNN has higher distortion tolerance for input data and more accurately expresses data characteristics, which uses local

**Table 31**
Comparison of different evaluation metrics (source:Liu et al., 2021).

| Model | MAE | MAPE | MSE | RMSE | R2 score | *Ui* |
|---|---|---|---|---|---|---|
| SVR | 0.070982 | 1.567991 | 0.01712 | 0.130842 | 0.741673 | 0.120656 |
| ANN | 0.063223 | 1.300913 | 0.016503 | 0.128464 | 0.750977 | 0.11772 |
| RNN-tanh | 0.0676 | 1.3256 | 0.0166 | 0.1289 | 0.7493 | 0.1194 |
| RNN-sin | 0.068482 | 1.232654 | 0.017072 | 0.130658 | 0.742399 | 0.120906 |
| RNN-PASF | 0.064304 | 0.702422 | 0.015813 | 0.125748 | 0.761396 | 0.116423 |
| LSTM | 0.0654 | 0.8718 | 0.0161 | 0.1269 | 0.7572 | 0.1182 |
| GRU | 0.0669 | 1.2540 | 0.0163 | 0.1278 | 0.7537 | 0.1164 |
| SRNN-PSAF | 0.0602 | 0.9360 | 0.0143 | 0.1195 | 0.7847 | 0.1112 |




(a) The MAE errors for 1 hour ahead.
(b) The MSE errors for 1 hour ahead.
(c) The MAE errors for 50 hours ahead.
(d) The MSE errors for 50 hours ahead.
(e) The MAE errors for 100 hours ahead.
(f) The MSE errors for 100 hours ahead.
(g) The MAE errors for 200 hours ahead.
(h) The MSE errors for 200 hours ahead.

**Fig. 50.** Comparison of online adaptive RNN with five online regression algorithms (source:Fekri et al., 2019).

**Table 32**
Performance evaluation of RNN model with different sampling frequencies (source:Pang et al., 2020).

| | RNN (Ten minutes) | RNN (Half an hour) | RNN (An Hour) |
|---|---|---|---|
| $R^2$ | 0.983 | 0.977 | 0.97 |
| RMSE | 41.2 | 53.3 | 58.1 |
| (CV)RMSE (%) | 7.64 | 9.27 | 9.83 |
| NMBE (%) | 0.92 | 4.62 | 3.02 |

receptive field methods. This substantially decreases the variety of parameters as well as the network model's intricacy. (iii)GAN avoids Markov chain learning mechanism and improves application efficiency. Its design is a flexible framework to integrate different types of loss functions.

(iv) The RNN's incapacity is compensated for by LSTM to handle long-sequence data through unique gate units.

In comparison with the results of several models with different of the results on power prediction. For most publications, the prediction error of LSTM time series is less than that of CNN. DBN is less than SAE on wind speed prediction. CNN tracking accuracy is greater than SAE, and the application of CNN classification accuracy is higher than LSTM. SAE, DBN, RNN and LSTM can be used to process temporal data, and DBN and LSTM have higher prediction accuracy on time series data.

**Table 33**
Evaluation metric values of the DRNN-GRU and other investigated methods (source:Wenet al., 2020).

| Models | RMSE | MAE | P | MAPE |
|---|---|---|---|---|
| DRNN-GRU | **0.510** | **0.345** | **0.991** | **3.504%** |
| DRNN-LSTM | 0.562 | 0.398 | 0.989 | 3.640% |
| Deep RNN | 1.113 | 0.945 | 0.974 | 8.599% |
| MLP | 2.206 | 1.672 | 0.810 | 14.496% |
| ARIMA | 2.259 | 1.707 | 0.792 | 15.089% |
| SVM | 2.844 | 2.147 | 0.670 | 32.735% |
| MLR | 6.078 | 4.608 | 0.347 | 37.740% |

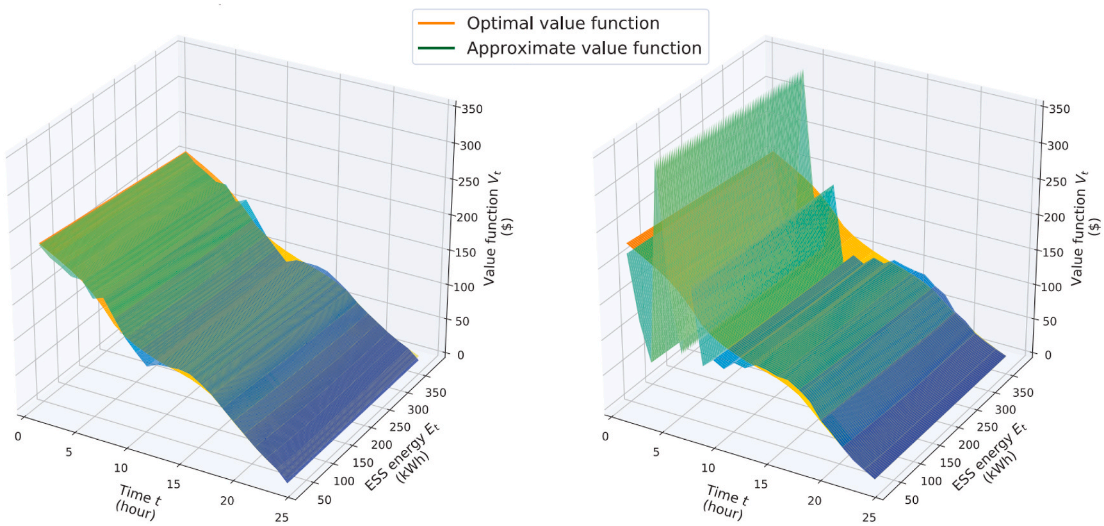



**Fig. 51.** Approximations to the optimal value function of a sample day (source:Zeng et al., 2019).

**Table 34**
Total average RMSE and MAPE results (source:Kim et al., 2019).

| Area | Algorithm | 3 Days | 5 Days | 7 Days |
|---|---|---|---|---|
| Incheon | MLP | 103.117 (6.623) | 105.825 (6.849) | 112.188 (7.298) |
| | 1-D CNN | 92.657 (5.820) | 95.719 (6.095) | 96.361 (6.074) |
| | RNN | 92.523 (4.976) | 82.939 (5.177) | 87.592 (5.343) |
| | RICNN | **83.333 (4.622)** | **74.919 (4.590)** | **71.245 (4.481)** |
| Gwangju | MLP | 72.623 (6.689) | 75.141 (6.914) | 84.771 (7.905) |
| | 1-D CNN | 69.746 (6.337) | 76.339 (6.888) | 75.929 (6.813) |
| | RNN | 61.677 (5.017) | 66.420 (5.471) | 71.313 (5.689) |
| | RICNN | **57.685 (4.719)** | **61.300 (5.167)** | **63.569 (5.286)** |
| Shihwa | MLP | 66.589 (10.226) | 67.959 (10.489) | 73.641 (11.088) |
| | 1-D CNN | 64.996 (10.134) | 64.431 (10.327) | 69.106 (11.012) |
| | RNN | 57.576 (8.556) | 58.623 (8.717) | 61.261 (9.062) |
| | RICNN | **55.144 (8.479)** | **57.552 (8.889)** | **57.476 (8.789)** |

## 7. Comprehensive analysis of deep learning in RE prediction

### 7.1. SWOT analysis

The SWOT stands for the strengths, the weaknesses, the opportunities, and the threats for the deep learning in RE prediction. The strengths of deep learning in RE prediction are: Strong feature learning ability, strong fault tolerance ability, wide applicability, breakthrough validation in multiple fields. The weaknesses of deep learning in RE prediction are:Learning requires a large number of samples, weak interpretability, computation increases rapidly with scale, reliability is difficult to guarantee, complex training may bring over-fitting and weak generalization ability. The opportunities of deep learning in RE prediction are:broad potential application scenarios in the field, there are few practical applications, some scenarios are expected to quickly produce breakthroughs. The threats, which also means the challenges of deep learning in RE prediction are: controlled of black box methods, improve interpretability of results, reliability guarantee, computing and storage capacity need to keep up with the needs of large-scale neural network applications.

### 7.2. Needed conditions

To use deep learning to solve problems for RE prediction, it is required to judge whether there are data conditions for deep learning application, and whether the problem is suitable to solve with deep learning by converting the practical engineering problem into a mathematical model.

The needed conditions for deep learning in RE:

In terms of data conditions, deep learning needs to measure the size and quality of sample data in RE, clarify the correlation between the target and the data, and eliminate the noise data. If the open source model is used to train, it should estimate the similarity between the sample data of the current conditions and the open source model training data.

In terms of mathematical models, different from shallow learning depending on manual experience in the analysis and selection of features, the applicability of deep learning to RE prediction problems depends on the feature selection mechanism of sample data and model complexity.

In terms of computing resources, the model training of deep learning requires a lot of floating-point calculation and matrix operation. Without efficient computing environment and data storage capabilities, efficient deep learning methods should not be adopted.

### 7.3. Challenges

Deep learning applications are expanding quickly as a result of their capacity for handling large amounts of data and powerful high performance computation. The use of deep learning for forecasting renewable energy is already the subject of a sizable body of literature. The primary issue with renewable energy systems is the unpredictable and irregular nature of power production as a result of weather patterns and environmental variables including solar radiation, wind direction and speed, cloud cover, and time of day (day and night). Overcoming these difficulties will aid in increasing the precision of deep learning prediction models. Even though numerous studies on projecting renewable energy have been published, certain crucial problems have still not been adequately resolved.

(i) Forecasting for renewable energy is really difficult.

The results of an analysis of the already available literature indicate that weather and environmental factors are just as important to prediction outcomes as current operational conditions. One of the major scientific issues that needs to be resolved in the future is how to effectively connect the physical models of batteries, weather, and environmental elements.

(ii) The renewable energy projection challenge is currently described in almost all papers as a "black box model." Not all of the

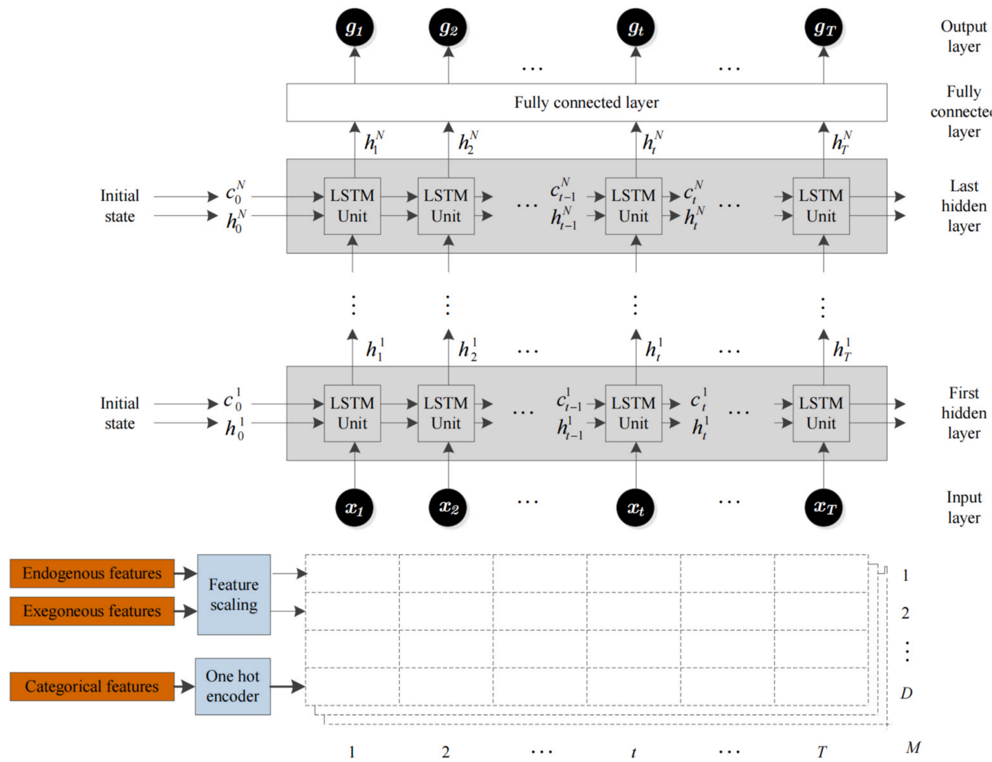



**Fig. 52.** The proposed deep learning framework (source: Husein et al., 2019).

**Table 35**
Performance evaluation of the proposed model (source: Husein et al., 2019).

| Location | RMSE (W/m2) | | | MAE (W/m2) | | | Forecast Skill (%) | |
|---|---|---|---|---|---|---|---|---|
| | LSTM | FFNN | Persis. | LSTM | FFNN | Persis. | LSTM | FFNN |
| Jena | 65.76 | 84.54 | 142.75 | 38.65 | 54.23 | 80.61 | 53.93 | 40.77 |
| Golden | 60.31 | 108.08 | 193.92 | 36.90 | 72.45 | 108.11 | 68.89 | 44.26 |
| Basel | 71.17 | 91.88 | 144.25 | 42.52 | 49.79 | 75.81 | 50.66 | 36.30 |
| Jeju | 108.52 | 113.83 | 194.66 | 64.36 | 70.54 | 111.86 | 44.24 | 41.51 |
| Busan | 82.52 | 86.76 | 171.96 | 47.87 | 51.74 | 93.33 | 52.01 | 49.54 |
| Incheon | 92.15 | 107.91 | 143.25 | 54.54 | 64.13 | 76.73 | 35.67 | 24.67 |

mathematical connections between the input and output are made clear.

Furthermore, it is unclear which input parameter has the greatest influence on the accuracy of the prediction. In conclusion, understanding how to interpret the forecasting model for renewable energy is a significant difficulty.

(iii) Probabilistic forecasting of renewable energy hasn't gotten enough attention up to this point. Probabilistic forecasting can offer a variety of renewable energy variations in power and energy systems and so quantify the uncertainty involved. This aids in preparing power systems for unknowable operating situations in the future. Thus, probabilistic forecasting of renewable energy sources is an important area of study in the future.
(iv) There are various subproblems in forecasting renewable energy.

Such as point forecasting, multi-step forecasting, day-ahead forecasting, and probabilistic forecasting, for PV forecasting, as an illustration, these forecasting subproblems have not been economically and independently resolved in the existing research. The key issue that needs to be moderately addressed in academics is how to train cooperatively on various forecasting jobs.

(v) Theoretical problems.

When predicting renewable energy, it is important to comprehend the complexity of the prediction samples, the number of training samples required to build deep learning networks, and the amount of CPU power required to train these samples. It is also challenging for deep learning to train deep networks and optimize their parameters since deep learning models are typically non-convex functions. Calculating the complexity of the prediction samples is necessary in order to employ deep learning-based prediction models in the production of renewable energy. The quantity of training samples and the computing power required to train the model must also be determined.

(vi) Modeling problems.

It has been researched in the literature that when the amount of data is large, complex models are better equipped to utilize the information properties in those large volumes of data. Features and other data extracted from large-scale prediction samples typically grow more valuable as deep learning becomes more potent. Through layer-by-layer feature learning, deep learning makes it simpler to study time series data for renewable energy sources. It might be very difficult to select the best network topology and learning algorithm to anticipate the results of a specific dataset.

**Table 36**
The analysis of five typical deep learning algorithms.

| | Application | Purpose | application methods | Evaluation criteria | advantages | disadvantages | Application scenario needs |
|---|---|---|---|---|---|---|---|
| SAE | Wind energy and solar energy, more in wind energy | extracts and reduces the dimension of data features | Combine with LSTM, BP, PSO | MAPE, MASE | - Network is difficult to optimize<br>- Extensive processing time and fine-tuning<br>- Training may be affected by the disappearance of the error | - Renewable energy data need dimensionality reduction | - Network is difficult to optimize<br>- Extensive processing time and fine-tuning<br>- Training may be affected by the disappearance of the error |
| DBN | Wind energy and solar energy, more in wind energy | used directly as an indepent model | integrated with DNN, genetic algorithm or Dimensionality reduction algorithms | MAPE, MASE | - Cannot process multidimensional renewable energy data<br>- Training is slow and inefficient | The characteristics of the renewable energy data cannot be identified | - Cannot process multidimensional renewable energy data<br>- Training is slow and inefficient |
| CNN | Wind energy and solar energy, more in solar energy | extract internal representations | integrated with the algorithms LSTM | MAPE, RMSE, MAE, inRSE, $R^2$, nRMSE, RMSE, RRMSE,APB,KGE, R,SDE,SMAPE | Computational performance is inefficient and the feature selection requirement is high<br>High computational overhead<br>Different parameter adjustments | Renewable energy data needs to be image data | Computational performance is inefficient and the feature selection requirement is high<br>High computational overhead<br>Different parameter adjustments |
| GAN | Wind energy and solar energy | captured the nonlinear and dynamic renewable patterns | The orthogonal regularization and spectral normalization are adopted | Error, MMD Score, Frechet Inception Distance,1-Nearest Neighbor score | Characteristics of the input data cannot be effectively described | Renewable energy data has missing data | Characteristics of the input data cannot be effectively described |
| RNN | wind, solar and wave energy | generated realistic time series data and predict power loads | CNN, ANN, GRU, deepforward network, MDP, and WD | MAE, RMSE, R2, NAME, NMBE, NRMSE, Rvalue, and time consumption | - Network is difficult to optimize<br>- Extensive processing time and fine-tuning<br>- Training may be affected by the disappearance of the error | - Renewable energy data need dimensionality reduction | - Network is difficult to optimize<br>- Extensive processing time and fine-tuning<br>- Training may be affected by the disappearance of the error |

### 7.4. Future research directions

It is evident from the above analysis that deep learning-based forecasting of renewable energy has attracted a lot of interest and has seen the publication of numerous studies recently. On the one hand, it is necessary to use recently developed DL algorithms to address the current problems with renewable energy projection. On the other hand, system upgrades for renewable energy sources will undoubtedly create new issues or present fresh opportunities.

The suggested future directions of deep learning-based renewable energy prediction models are primarily included in sections 5 and 6, which analyze the year-by-year trends of the top keywords and keywords used in existing literature.

(i) Forecasting for renewable energy sources like geothermal and waves.

The analysis of applications for renewable energy in the literature reveals that the primary uses of the existing deep learning algorithms are for day-ahead and real-time predictions of wind and solar energy. Deep learning for predicting wave energy has received relatively little research. Deep learning has also not been used to anticipate geothermal energy in real time. As a result, the forecasting of additional renewable energy sources has tremendous research value and aids in the investigation of the potential for use of various renewable energy sources.

(ii) Prediction based on probability.

It can be observed from the analysis and statistics of the hot keywords in the deep learning methods portion of the literature that a lot of publications have been published and that the research on deterministic prediction of renewable energy has existed for a while. Although it has been demonstrated that probabilistic prediction models can quantify the uncertainty present in renewable energy time series data, deep learning-based probabilistic prediction models have just recently begun to appear. In some cases, it also has a stronger predictive effect, although it hasn't gotten enough attention yet. The analysis of probabilistic predictions of renewable energy is therefore the next step, which is crucial for the practical management of power and energy systems as well as their economic operation.

(iii) The creation of fresh deep learning methods.

It is evident from the model comparison in the section on deep learning approaches that there are a variety of widely used DL techniques that can be applied to the prediction of renewable energy sources. DL approaches have certain drawbacks in addition to their benefits. To get over these issues, it is not a terrible idea to create a new DL approach or improve an existing DL technique. To increase the accuracy of DL approaches, more study is required.

(iv) A unified paradigm of prediction.

Due to the many deep features of renewable energy data in various seasons, climates, and topographic circumstances, it is known from the data inputs used in the part of deep learning methods that the renewable energy datasets utilized in the existing literature differ from one another. As a result, determining how well the prediction models fit various datasets is challenging. It is vital to provide universal forecasting methodologies and standards in order to assess the current renewable energy forecasting models. Future research will focus heavily on the creation of integrated forecast models for renewable energy based on topographic, meteorological, and seasonal data.

(v) generalization ability of optimization model.

For renewable energy, the prediction conducted by deep learning model has high complexity and is prone to overfitting. In response to the overfitting problem of deep learning, the main processing methods of existing literature include early termination of training, regularization, dropout, or enrich training dataset, etc. The generalization ability of the model is also closely related to the completeness of the training set. The deep learning generally adopts the mode of offline training and online application, so the generalization ability of the model is particularly important.

There are several common solutions. One is optimizing the model hidden layer nodes and parameters by utilizing the gray correlation analysis, genetic algorithm, particle group optimization and other algorithms, as well as transforming the deep learning characteristics into the constraints of the deep learning network. Another is combining various learning algorithms to analyze prediction problem of renewable energy, such as deep learning, reinforcement learning and transfer learning, etc. For instance, deep learning is used to extract features based on operation information of power grid system firstly, then reinforcement learning makes decisions on the basis of former analysis result, and migration learning migrates deep models to new sample data of renewable energy lastly. Therefore, combining them could enhance the model's innovative learning capabilities and generalization ability.

(6) Interpretability of the algorithm and visualization of the results.

The deep learning model is essentially a black-box model, and the learner's mapping of the input and output is often not interpretable, so the guidance effect on the power system production practice is limited. If the physical expression or visualization of the high-dimensional features obtained from deep learning can be reasonable, it is of some significance to enhance its practicability. a. Deep learning has deficiency in robustness, and slight perturbation against the sample can cause wrong result or a fatal problem for security -critical systems. b. Deep learning algorithm is not interpretable, which means it is hard to establish accurate formal model and attribute characterization. c. Infinite input space, large neurons, nonlinear activation function of deep learning may cause state space explosion during verification. As a result, the black box strategy is critical for problems requires extensive investigation.

(7) Improvement of prediction accuracy.

Deep learning adopts multi-layer structure, and without insufficient data, the generalization ability of the model will be greatly reduced, and so it is not applicable to insufficient data volume. The prediction accuracy methods could increase from several aspects: a. big data with good-quality, b. Preprocessing and cleaning the data to missing data and identify outliers, c. Taking account of hybrid models.

(8) Parameter optimization and neural network optimization.

The model of deep learning has a complex structure and multiple parameters, and the training speed is slower compared to the shallow learning methods. The research should take into account the costs of deployment, the motivations for choosing DL architectures for such specific problem, and minimizing powerful cryptographic.

(9) The long-term forecasting and the multivariate time-series prediction.

The majority of previous research focused on short-term horizons and linear time series prediction.

(10) Deep Uncertainty Quantification

Wind and solar involve a high level of uncertainties with intermittency and variability. And prediction result of DL models have uncertainty due to data diversity, parameter diversity, and predictor diversity. These uncertainties provide significant issues for infrastructure management and administration. a. how such deep uncertainty assessments can be directly obtained using procedures, b. whether their reliability may be improved, and c. if they could be obtained in real time with the smallest substantial computational effort.

## 8. Conclusion

Recent years have seen a rise in the popularity of renewable energy systems due to environmental and sustainability concerns. By 2030, the EU's (European Union) total energy consumption (and output) will be at least 35% renewable, according to the European Parliament. Some nations have more ambitious goals (Germany, for instance, wants to use 55% renewable energy by the year 2030). In order to ensure the smooth and stable operation of complex energy systems, intelligent and precise energy forecasting is crucial for detecting energy production and demand in advance. The best systems for forecasting renewable energy sources must be designed using deep learning techniques.

This study examines modern deep learning-based prediction models for renewable energy. A multilayer perceptron with many hidden layers is what deep learning is. It either classifies classes of attributes to find the innate characteristics of the input data or combines low-level features to create more abstract high-level features. For the first time, a thorough and methodical investigation of deep learning-based predictions for renewable energy from the standpoints of SLR and literature analysis is offered. It presents a thorough statistical analysis of current research hotspots and areas of interest in projecting renewable energy. Deep learning techniques and SLR are used to examine data, and hot keywords and literature as well as research trends are described using literature analysis. The effect of deep learning on various renewable energy sources is first carefully examined. The efficiency of several DL model categories is then investigated. The models are assessed based on the types of deep learning, the input data, and the outcomes of the predictions. The analysis demonstrates that every deep learning technique, optimization technique, and prediction structure has unique benefits and drawbacks. The difficulties and potential paths for future study in deep learning-based renewable prediction are suggested in light of the analysis's findings. Future research in additional types of renewable energy forecasting, including tidal, biomass, hydrodynamics, wave energy, and geothermal energy, seems promising. Due to changes in the environment and other variables, prediction models behave differently for various types of data sets. One promising area for future research is the creation of uniform prediction models that excel in a range of seasonal and climatic situations. Future research will pay particular attention to explainable deep learning algorithms in order to highlight the enormous prospects that explainable deep learning presents for transparent and comprehensible learning paradigms.

In this paper, an extensive literature review of the recent applications of DL techniques to renewable energy forecasting, is presented:

(i) The theme terms of renewable energy and deep learning are explored in the WoS core library, and statistics for publication outputs, such most productive and high influential nation, authors, institutions and source journals.
(ii) Keywords in deep learning and renewable energy were analyzed to convey keyword pattern of existing literature, including concurrence network, hot research, emerging trends, and theme evolution.
(iii) On the basis of analysis of related keywords, existing renewable energy prediction models based on deep learning algorithms are classified and analyzed. The characteristics of various renewable energy prediction models are summarized by comparative analysis.

(iv) The challenges and potential future research directions in renewable energy prediction are proposed.

This paper fills a gap in the literature, and these analyses and numerical demonstrations can assist the practitioners in the renewable energy industry, such as scientists and engineers, in determining which specialized intelligent algorithms and forecasting structures can enhance their specific forecasting tools, assisting in the investigation of the potential of deep learning in renewable energy forecasting. The research will provide a useful guideline for scholars and practitioners who are interested in deep learning for renewable energy technology and seek cooperation opportunities with other scholars and research institutions by systematically collecting, characterizing, and analyzing research papers related to renewable energy. Moreover, the predictions based on the bibliometric analysis can also provide ideas for future research.

## Declaration of competing interest

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

## Data availability

Data will be made available on request.

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## Glossary

*AE:* Absolute Error
*AE:* Auto-Encoder
*AE-LSTM:* Autoencoder-Long Short-Term Memory
*AI:* Artificial Intelligence
*ANN:* Artificial Neural Network
*ARIMA:* Autoregressive Integrated Moving Average Model
*Bi–CNN:* Bi-Convolutional Neural Network
*bi-LSTM:* Bidirectional Long Short-Term-Memory
*BP:* Back Propagation
*BPNN:* Back Propagation Neural Network
*BRF:* Boruta Random Forest Optimizer
*BS:* Bidding Strategy
*CEEMDAN:* Complete Ensemble Empirical Mode Decomposition With Adaptive Noise
*CNN:* Convolutional Neural Network
*CNNLSTM:* Convolutional Long Short-Term Memory Network
*DAE:* Denoising Autoencoder
*DBM:* Deep Boltzmann Machine
*CV-RMSE:* Coefficient Of Variation-Root Mean Square Error
*DBN:* Deep Belief Network
*DBNGA:* Deep Belief Network With a Genetic Algorithm
*DCNN:* Deep Convolution Neural Networks
*DL:* Deep Learning
*DNN:* Deep Neural Networks
*DNN-LSTM:* Deep Neural Network-Long Short-Term Memory
*DR:* Degradation Rates
*DRBM:* Discriminative Restricted Boltzmann Machine
*DSCN:* Deep Sparse Coded Network
*EMD:* Empirical Mode Decomposition
*EMD-BP:* Empirical Mode Decomposition-Back Propagation
*EMS:* Energy Management System
*EEMD:* Ensemble Empirical Mode Decomposition
*EML:* Extreme Machine Learning
*EWT:* Empirical Wavelet Transform
*FL:* Fuzzy Logic
*GAN:* Generative Adversarial Networks
*GCNN:* Gated Convolution Neural Networks
*GMM:* Gaussian Mixture Model
*Grad-CAM:* Gradient-Weighted Class Activation Mapping
*GRNN:* Gated Recurrent Neural Networks
*GRU:* Gated Recurrent Unit
*HS:* Significant Wave Height
*IDBN:* Interval Deep Belief Network
*inRSE:* The Improved Deep Belief Network
*IRAE:* The Independent Cyclic Autoencoder
*IVMD:* Improved Variational Pattern Decomposition
*KNN:* k-Nearest Neighbor
*LSSVR:* Least Square Support Vector Regression
*LSTM:* Long Short-Term Memory Neural Network
*MAE:* Mean Absolute Error
*MAPE:* Mean Absolute Percentage Error
*MASE:* Mean Absolute Scaled Error
*MBRAE:* Mean Bounded Relative Absolute Error
*MDBN:* Multitask Deep Belief Network
*MLP:* Multi-Layer Perceptron
*MODIS:* Medium-Resolution Imaging Spectrometer
*MSE:* Mean Squared Error
*MSLE:* Mean Squared Log Error
*KELM:* Kernel-Based Extreme Learning Machine
*KF:* Kalman filter
*MISO:* Multi-Input Single-Output
*NMBE:* Normalize Mean Bias Error
*NN:* Neural Network
*NRMSE:* Normalized Root Mean Square
*NWP:* Numerical Weather Prediction
*PCA:* Principal Component Analysis
*PSO:* Particle Swarm Optimization
*PV:* Photovoltaic
*PSAF:* Parametric Susoidal Active Function
*R:* Related Coefficient
*$R^2$:* R-Squared
*RBM:* Restricted Boltzmann Machine
*RE:* Renewable Energy
*RICNN:* Recurrent Initial Convolutional Neural Network
*RMSE:* Root Mean Squared Error
*RNN:* Regression Neural Network
*RO:* Reverse Osmosis
*RQ:* Research question
*RRMSE:* Relative Root Mean-Squared Error
*SAE:* Stacked Autoencoders
*SARIMA:* Seasonal Autoregressive Integrated Moving Average
*SDE:* Stacked Denoising Autoencoders
*SDAE:* Stacked Denoising Autoencoder
*SELM:* Stacked Extreme Learning Machine
*SIRAE:* Staked Independently Recurrent Autoencoder
*SLR:* Systematic Literature Review
*SMAPE:* Symmetric Mean Absolute Percentage Error
*SRNN:* Stacked Recursive Neural Network
*SSAE:* Stacked Sparse Autoencoders
*STLF:* Short-Term Load Forecasting
*SVM:* Support Vector Machine
*SVR:* Support Vector Regression
*SWOT:* Strengths, Weaknesses,Opportunities, Threats
*UMBRAE:* Unscaled Mean Bounded Relative Absolute Error
*VMD:* Variational Pattern Decomposition
*WoS:* Web 0f Science
*WPD:* Wavelet Packet Decomposition
*WT:* Wavelet Transform
*XGB:* Extreme Gradient Boosting

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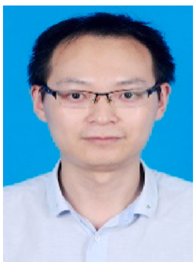

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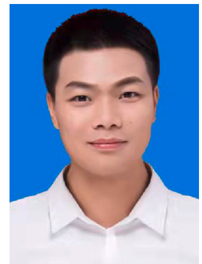

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