Chapter

A Review of Wind Turbine Icing Prediction Technology

Lidong Zhang, Yimin Xu and Yuze Zhao

Abstract

The global wind energy business has grown considerably in recent years. Wind energy has a bright future as a major component of the renewable energy sector. However, one of the major barriers to the growth of wind energy is the freezing of wind turbine blades. The major solution to overcome the aforementioned problem will be to foresee wind turbine ice using existing anti-icing technologies. As a result, improving wind turbine ice prediction technology can assist wind farms in achieving more precise operation scheduling, avoiding needless shutdowns, and increasing power generation efficiency. Traditional wind turbine icing prediction methods have problems such as misjudgment and omission, while machine learning algorithms have higher accuracy and precision. Because of the rapid advancement of deep learning technology, machine learning algorithms have become an important tool for predicting wind turbine icing. However, in real applications, machine learning algorithms still face obstacles and limits such as inadequate data and poor model interpretability, which require additional study and refinement. This chapter discusses the application of machine learning algorithms in wind turbine icing prediction, provides a comprehensive description of the applicability and accuracy of various machine learning algorithms in wind turbine icing prediction, and summarizes the applications and advantages.

Keywords: wind turbine, icing prediction, machine learning, artificial neural network, forecasting accuracy

1. Introduction

The percentage of total power generation provided by wind has grown continuously as humanity has learned how to utilize wind resources. According to BP's World Energy Outlook 2023 [1], primary energy sources such as wind power would provide 25 to 55% of global primary energy from 2019 to 2050. Renewable and nuclear energy growth is predicted to meet all worldwide electricity demand between 2022 and 2025, according to the International Energy Agency's Electricity Market Report 2023, released in 2022 [2]. Wind resources' improving cost competitiveness, as well as legislative incentives, are driving the rapid spread of wind power [1]. Wind energy resource-rich areas of the world are primarily found in the northern hemisphere [3]. However, icing of wind turbine blades in cold climates [3, 4], single anti-deicing methods [5, 6], and imprecise wind turbine icing forecast are all issues in the growth of wind power generation. Long-term wind turbine operation in cold weather conditions lowers power generation [6]. When icing conditions are met, water droplets in the air, rainfall, drizzle, or wet snow freeze or stick to wind turbine blades, resulting in the formation of ice. Wind turbine ice can shorten the life of components by causing uneven blade mass distribution and higher blade loading [7]. While moderate freezing can have an effect on the aerodynamic qualities of wind turbine blades, significant icing can cause the wind turbine to shut down completely, decreasing the efficiency of wind resource utilization [8]. Wind turbines exposed to mild or moderate ice for 10% of the year can lose 24% of their overall power production, whereas wind turbines exposed to icing for lengthy periods of time can lose up to 50% of their annual power production [9, 10]. Wind turbine shutdowns due to icing can result in not only power production losses, but also in large-scale power outages, as seen on February 14, 2021, in the United States, state of Texas, when cold weather hit Texas with a minimum temperature of −21°C (the average winter temperature in Texas is 1.4°C). Cold weather prompted the closure of 57.3% of wind turbines (about 18,000 MW), affecting nearly 4 million people [11]. Several contributing elements are currently unaccounted for in faulty wind turbine ice prediction models, making it difficult to effectively anticipate wind turbine icing [12, 13]. If historical meteorological data and data from Supervisory Control And Data Acquisition (SCADA) systems are included in classical ice prediction models, and then supervised machine learning methods are applied to forecast icing, the models can anticipate the majority of icing events [14–16].

To summarize, the advancement of wind power generation is a significant step toward a more sustainable energy future. Nonetheless, wind turbine ice continues to be a significant barrier to the effective and dependable use of wind resources. Accurate prediction of wind turbine ice may considerably increase wind turbine performance and assure power supply stability. It is consequently critical to continue researching and improving improved wind turbine ice prediction models.

2. Shallow machine learning-based wind turbine blade icing prediction method

2.1 Neural network

2.1.1 BP neural network

In 1986, Rumelhart et al. developed the error Backpropagation method [17], sometimes known as the BP algorithm, for training neural networks for the first time. The BP neural network is a shallow forward-type neural network that operates using the error backpropagation algorithm [17]. **Figure 1** depicts the basic idea of this neural network computational model, which comprises of an input layer [18, 19]. There is a concealed layer and an output layer. A large number of neurons are connected as network nodes, and each neuron processes the excitation function as the network weights' connection strength signal, and the pattern information contained in the input data is mapped to the output layer by adjusting these connection strengths. The information flow direction of forward propagation is input layer (**Figure 1** Layer1) → hidden layer (**Figure 1** Layer2) → output layer (**Figure 1** Layer3) [18, 19].

In 2019, Cheng et al. developed a BP neural network-based icing prediction model for the problem of wind turbine blade icing [20], which cannot be successfully predicted in advance, and testing results demonstrated that the model could

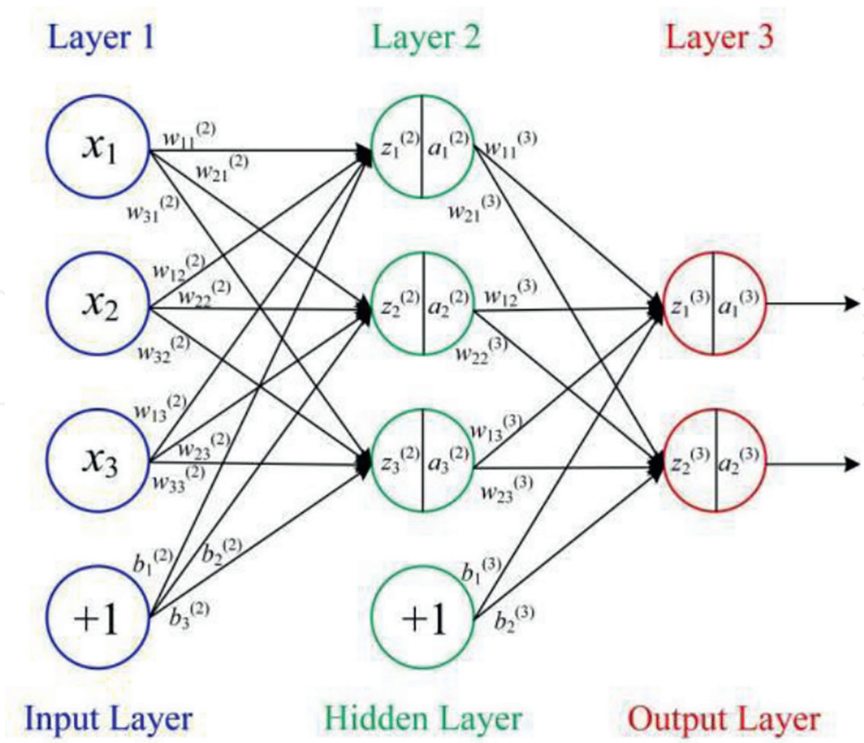

Figure 1.
Principle of BP neural network computational model.

predict blade icing with an accuracy of 0.984 [20]. Li et al. 2022 compared the trained BP neural network to the Radial Basis Function (RBF) neural network for leaf icing prediction in a research on prediction accuracy [21]. The BP neural network's relative percentage error was lower than the RBF network's using 12 sets of processed data, with an average E_{whole} value within 7.5%, indicating superior stability. The findings demonstrated the efficacy and superiority of BP neural networks in forecasting blade icing [21].

2.1.2 Elman neural network

The Elman Neural Network (ENN) is a feedback-based neural network model developed by American Psychologist J. L. Elman in 1990 [22, 23]. It has a simple design and outstanding performance. It works as shown in **Figure 2**. The forward neural network has an input layer (**Figure 2** Input Layer), a hidden layer (**Figure 2** Hidden Layer), and an output layer (**Figure 2** Output Layer), as well as a context layer, which is used to remember the hidden layer's output from the previous moment and calculate the characteristics of time-delayed data, giving it dynamic memory [22]. The Elman neural network can anticipate blade icing in wind turbine blade icing prediction applications by analyzing historical meteorological data such as temperature, humidity, and wind speed. Additionally, the Elman neural network can use blade icing thickness, icing time, and other icing data to reduce bias and thus improve prediction accuracy [20, 22, 23].

Cheng et al. used the trained Elman neural network to predict future values of icing-related characteristics in 2019 [20], and the prediction results revealed that the Elman neural network predicted blade icing defects with a 97.8% accuracy rate [20]. Cheng et al. used processed data to perform icing prediction comparison

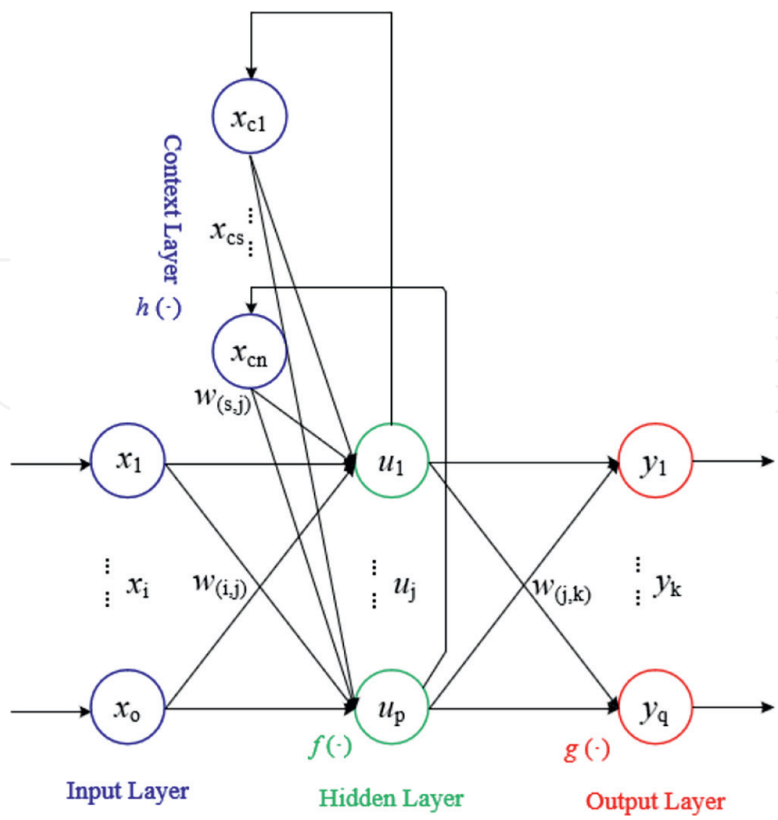

Figure 2.
Principle of Elman neural network computational model.

tests between the Elman neural network and other neural networks in 2020 [24]. According to the testing results, the Elman neural network exhibited reduced deviation and obtained greater accuracy [24].

When the BP and Elman neural networks are compared, it becomes clear that the Elman network sacrifices computational accuracy for greater efficiency, whereas the BP network is better suited for specific complex models. Both networks have distinct benefits in wind turbine icing prediction, and the proper method may be chosen based on the actual scenario to handle the problem.

2.2 Integrated learning

2.2.1 Boosting

The Boosting approach is an ensemble learning method for improving classifier performance by combining a large number of weak classifiers [25, 26]. Two of the most well-known algorithms are AdaBoost and XGBoost. Because of its quick training speed and precise forecasting capabilities, XGBoost is an important tool in wind turbine blade icing prediction [27, 28]. The computational model principle of this method is depicted in **Figure 3**.

In 2019, Wang et al. utilized the XGBoost algorithm to predict the wind turbine blade icing process and compared the prediction results with those of traditional machine learning algorithms and neural networks. The XGBoost algorithm achieved higher accuracy in predicting blade icing, reaching up to 95.18%. In 2021 [29], Guo et al. constructed normal behavior models based on output power and rotor speed using the XGBoost algorithm, and the model error was as low as 0.53% [30].

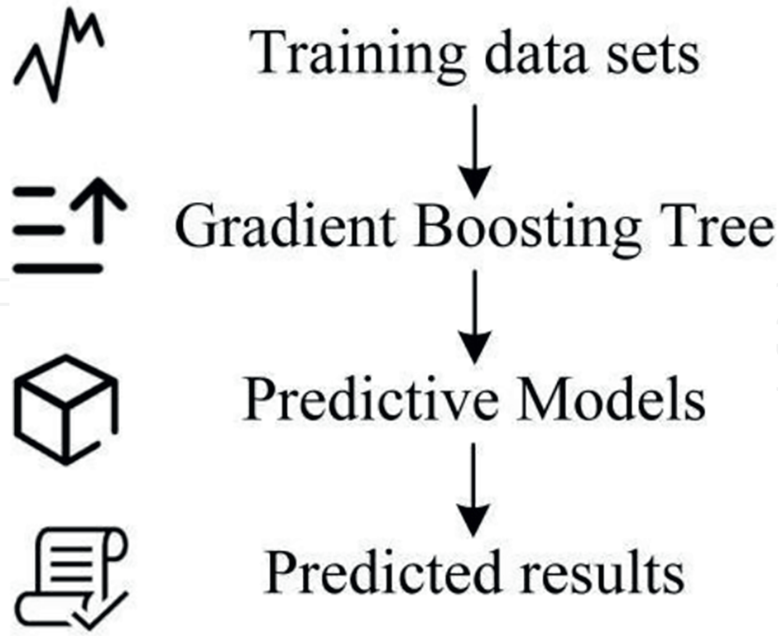

Figure 3.
Computational model principle of XGBoost algorithm.

2.2.2 Stacking

The Stacking method is a machine learning methodology based on model integration that integrates many base models to build a prediction model that outperforms a single model [26]. The computational model principle of this method is depicted in **Figure 4**. The final prediction results are generated by taking the prediction results from the base model as extra features and then training and predicting these features using a meta-model [26, 31].

Li et al. used the Stacking method to anticipate wind turbine blade icing in 2022 by combining Relief and One-Dimensional Convolutional Superposition of Bidirectional Gated Recurrent Units (1D-CNN-SBiGRU). The prediction results reveal that the suggested technique improves the WA (Weighted Accuracy) by 43.08%/34.61%/14.44% when compared to SVM/CNN/BiLSTM, respectively [32].

2.2.3 Bagging

Bagging (Bootstrap Aggregating) is an additional integrated learning method that bootstraps the training set to generate multiple training sets, trains a weak learner based on each training set, and then fuses the prediction results of these weak learners into the final prediction result by voting or averaging to improve the model's accuracy and generalization ability. The computational model principle of this method is depicted in **Figure 5**. Bagging may be used to generate several blade icing prediction models and improve forecast accuracy by fusing the prediction outputs of various models in wind turbine blade icing prediction [28, 33].

Zhang et al. developed a CM technique based on KNN regression and bagging ensemble strategy to detect wind turbine operational conditions in 2022 and tested it with SCADA data gathered in the field [34]. The findings demonstrated that the ensemble model may achieve the anticipated estimate accuracy while also improving operating efficiency by around 30% [34].

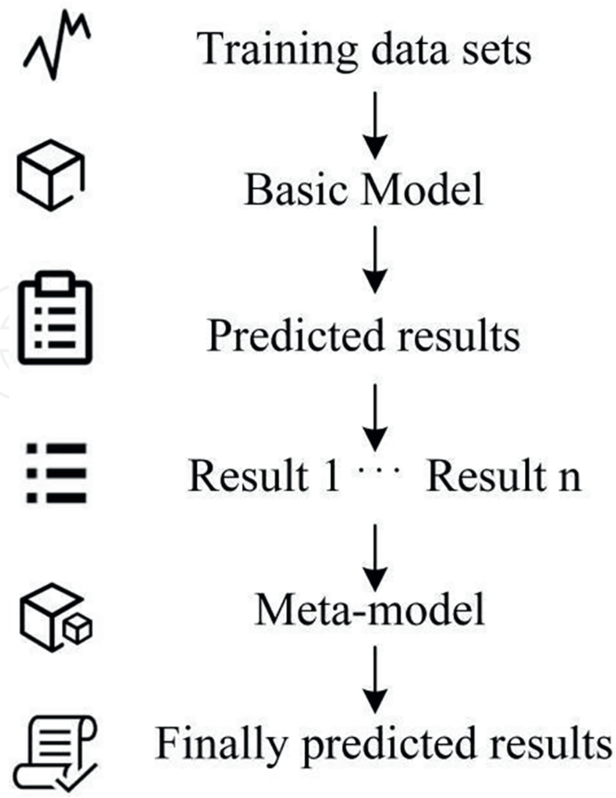

Figure 4.
Computational model principle of stacking algorithm.

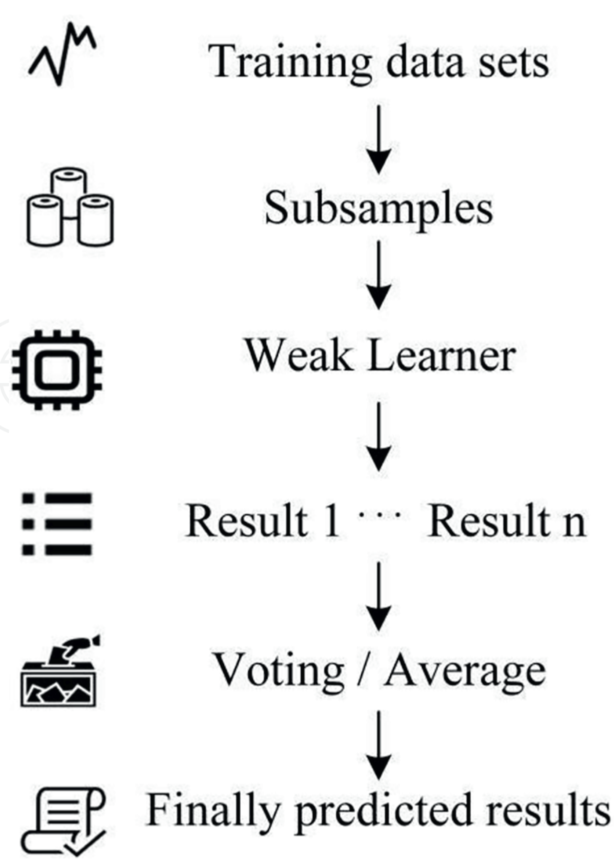

Figure 5.
Computational model principle of bagging algorithm.

By summarizing the applicability and benefits as well as drawbacks of the three prediction algorithms discussed above, it is easy to conclude that the Bagging algorithm is appropriate when we need to predict complex icing conditions; the Boosting algorithm is appropriate when accuracy is required but data is sparse; and the Stacking algorithm may be a better choice when a high-performance prediction model with sufficient computational is required. In real-world applications, the approach must further consider factors like data amount, icing quality, and distribution, and so on.

3. Deep learning

In their 2006 publication "A fast learning algorithm for deep belief nets," Hinton et al. developed the idea and learning algorithm of deep belief networks [35]. Deep learning reached a new stage of growth with the introduction of deep belief networks, and researchers began to investigate more complicated neural network topologies and sophisticated learning algorithms [36]. Deep learning's core idea is to use a multilayer neuron structure to abstract and process data layer by layer, with each layer generating a new set of features for the next layer, so that more advanced features can be gradually acquired, eventually achieving accurate data classification and prediction. Deep learning has also been frequently employed in the prediction of wind turbine blade icing in recent years. Deep learning, as a sophisticated model learning method, can leverage historical data from wind turbine blades to accurately forecast and identify wind turbine blade icing conditions [35–38].

Several classical neural network models have emerged with the development of deep learning, including Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Neural Networks (DNN), and Deep Belief Network (DNN). (DNN), Stacked Autoencoder (SAE), and Transfer Learning (TL). Specific applications of these neural network models to wind turbine blade icing prediction are discussed in this section.

3.1 Convolutional neural networks

In their 1998 study "Gradient-Based Learning Applied to Document Recognition," LeCun et al. established the topology of convolutional neural networks and successfully applied it to handwritten digit recognition [39]. Convolutional Neural Networks (CNN) are deep learning models that have gained popularity due to their excellent accuracy in image recognition applications. CNN's core principle is to employ convolutional operations to extract features from multidimensional input, such as **Figure 6**, and to perform hierarchical feature representation using several convolutional and pooling layers (**Figure 6** Convolutional). Eventually, fully linked layers are used to execute classification, regression, and other tasks [37, 39]. Convolutional neural networks are often used to predict ice on the surface of wind turbine blades because of their high efficiency and prediction accuracy in image recognition task [40].

Kreutz et al. proposed in 2021, a convolutional neural network model with dual inputs and a one-dimensional convolutional filter to predict wind turbine blade icing in the next 24 hours using historical data from wind turbines as well as weather forecasts, and experimented with the model using data from three different wind farms, and the experimental results showed that the model had an average prediction accuracy of 97.9% [41]. Following this, in 2022, Cheng et al. suggested a Temporal Attention-based Convolutional Neural Network (TACNN). TACNN was compared

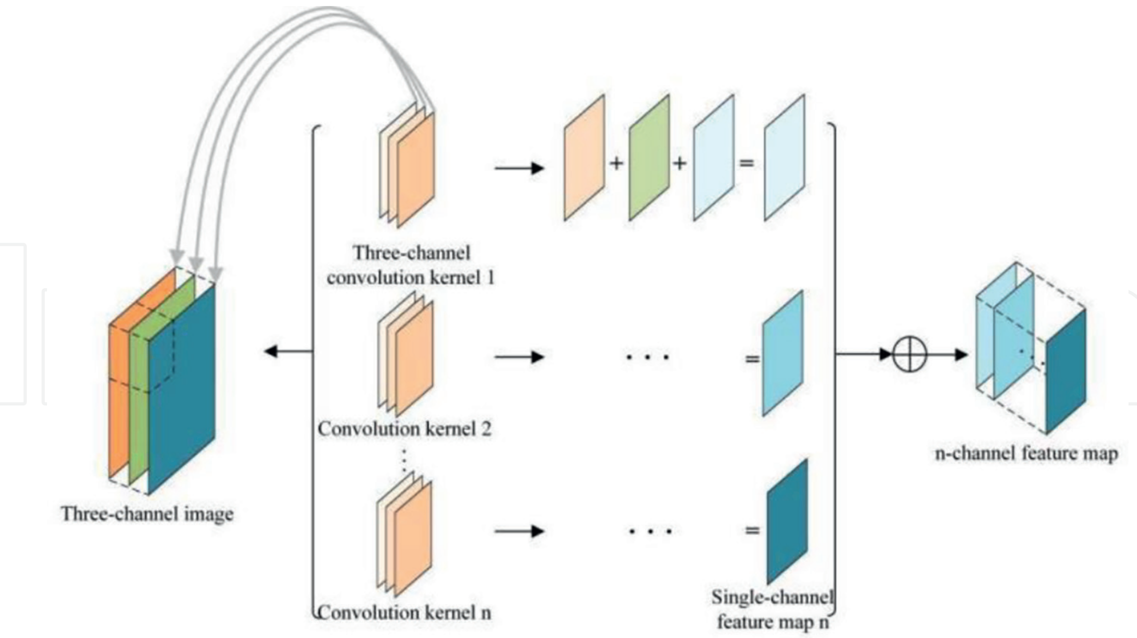

Figure 6.
Principle of convolutional neural network computational model.

to 10 different baseline networks in three data sets in a comparative experiment, and the experimental findings demonstrated that TACNN had considerable benefits over others [42]. In 2022, Xiao et al. combined convolutional neural network (CNN) with recurrent neural network (RNN), Long Short-Term Memory (LSTM), and gated recurrent unit (GRU) to build CNN, CNN-RNN, CNN-LSTM, and CNN-GRU and performed prediction comparison experiments, and the experimental results show that the proposed models outperform single deep learning models in prediction [43].

3.2 Recurrent neural networks

Elman et al. developed the recurrent neural network model in 1986, and recurrent neural network research has progressed greatly since then [23]. The Recurrent Neural Network (RNN) is a type of neural network capable of processing sequential data [44]. Its primary idea is to offer a recurrent structure that allows data to be sent from one-time step to the next. An RNN has an input layer (x), a hidden layer (s), an output layer (o), and parameter matrices (u, v, and w), as shown in **Figure 7**. The connections between hidden layers in recurrent neural networks allow information from the previous instant to be maintained and passed on to the next instant. In the realm of wind turbine blade icing prediction, RNNs can estimate future wind turbine blade icing using input wind turbine historical temperature, humidity, wind speed, and other meteorological data. RNNs may also be used with other deep learning models, such as convolutional neural networks (CNNs), to improve the accuracy and efficiency of hybrid models for forecasting wind turbine blade icing [45, 46].

In 2022, Li et al. integrated the physical information of the underlying wind turbine system into a data-driven model, using the structural properties and linearized representation of the wind turbine system as physical constraints, and applied them to a Deep Residual Recurrent Neural Network (DR-RNN) to form a deep learning model based on physical information, as well as conducted experiments. The experimental findings demonstrate the model's accuracy and effectiveness [47]. In the

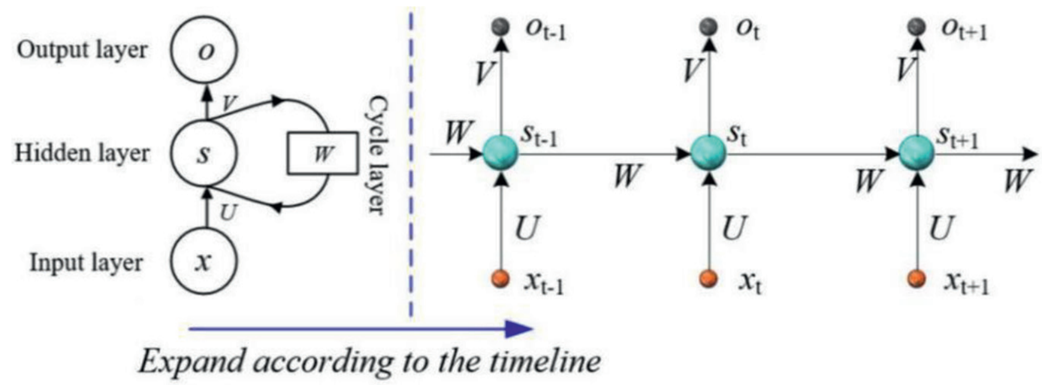

Figure 7.
Principle of recurrent neural network model.

year 2021, Tian et al. presented a Multilayer Convolutional Recurrent Neural Network (MCRNN). On the balanced dataset processed with the data resampling technique, the suggested MCRNN outperforms the ideal baseline by 38.8 and 42.9%, respectively, and by 23.9 and 30.6% on the unbalanced dataset processed with the MCRNN optimized with the equilibrium-like loss function. This model's broad application for icing prediction is demonstrated [48].

3.3 Deep neural networks

Deep Neural Network (DNN) research has improved greatly since Frank Rosenblatt's invention of the model in 1960 [49], and it is currently applied in a wide range of fields [50–53]. The computational model principle of this method is depicted in **Figures 8** and **9**. Deep Neural Networks (DNNs) show high accuracy and generalization capabilities in the prediction of wind turbine blade icing. They can predict icing occurrences by automatically learning characteristics and trends from massive amounts of data.

Li et al. proposed a universal DNN model for assessing prediction accuracy using pre-designed model performance indicators such as the reward function. The technique may relate continuously transmitted features to the binary state of turbine blade icing by using intermediate feature variables. Experiment findings suggest that the integrated metric system outperforms a single accuracy measure when assessing prediction models [54]. Cui et al. performed icing impeller model tests as well as natural world icing trials before recommending a deep neural network-based approach for predicting icing quality in 2022 [55]. In the trials, a mapping relationship between the rate of variation of the icing impeller's natural frequency and its mass was discovered, and the correlation coefficients were all greater than 0.93. The DNN prediction model of impeller icing quality uses the rate of change of the first six orders of natural frequency as one of its input components. The results showed that the MAE and MSE of the trained model were close to zero. For different impeller icing states, the DNN model's average prediction errors were 4.79, 9.35, 3.62, and 1.63% [55]. Using a DNN model, Jeong et al. predicted that freezing of wind turbine blades will occur in 2022. Along with meteorological data, the authors gathered field-based experimental data. The DNN model was created and trained to predict blade icing on wind turbines. The results showed that the DNN model had strong prediction ability under a range of meteorological situations and could accurately anticipate wind turbine blade icing [56].

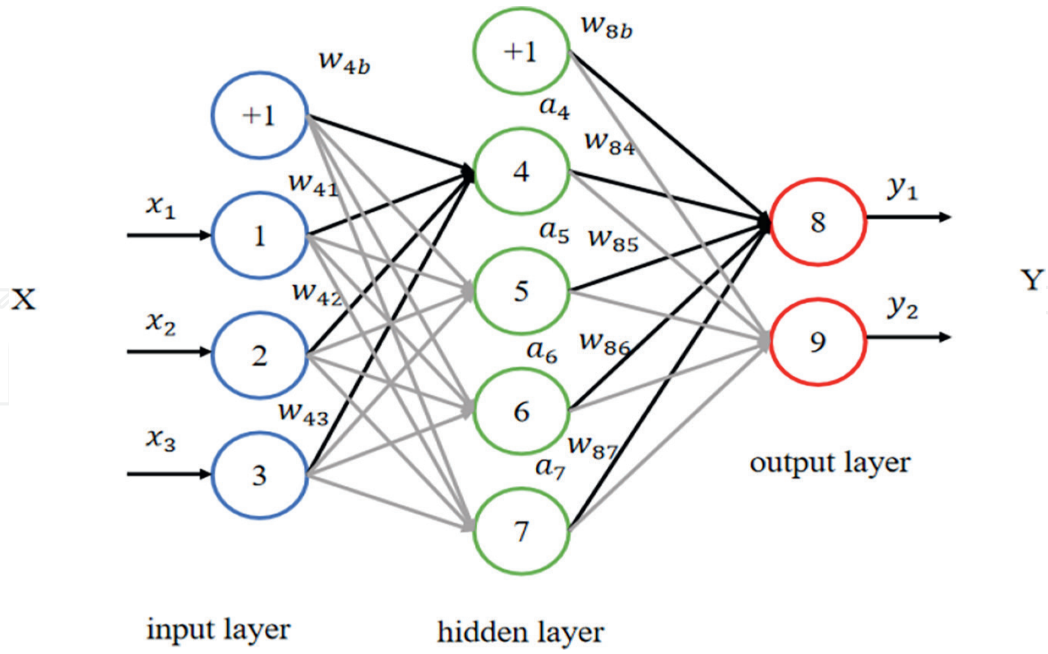

Figure 8.
Schematic diagram of deep neural network model.

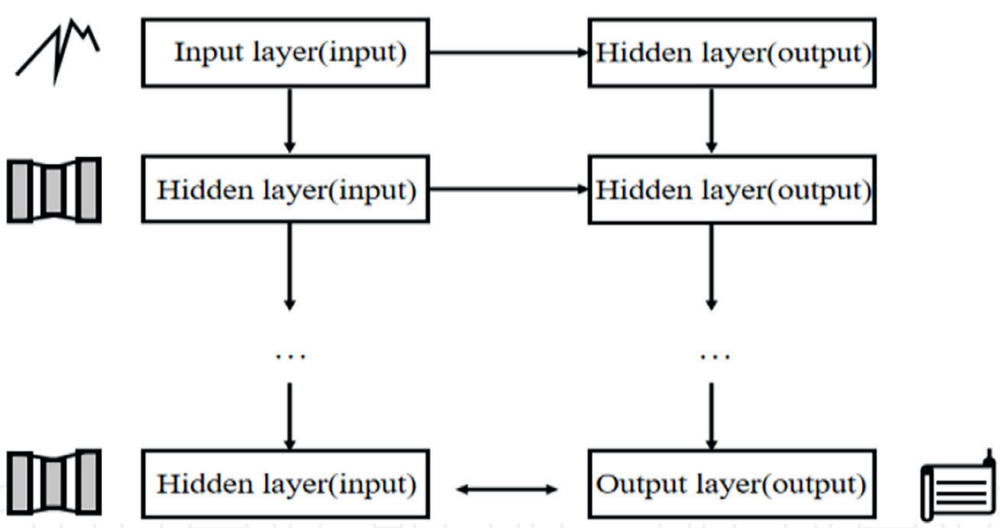

Figure 9.
Deep neural network calculation principle diagram.

3.4 Stacked autoencoder

The Stacked Autoencoder (SAE) is a powerful deep learning model that automatically encodes data via unsupervised learning. In 2006 [35], Hinton and Salakhutdinov introduced the model, which employs numerous non-linear transformations to learn higher-order features of the input data [57]. A stacked autoencoder is composed of multiple autoencoders, each of which receives the output of the previous layer as input and trains on it. The main advantage of SAE is its capacity to autonomously extract significant features from data for supervised learning tasks without the need for labeled data. The computational model principle of this method is depicted in **Figure 10**. SAE is commonly used for feature extraction and data dimensionality reduction in wind turbine blade icing prediction [58].

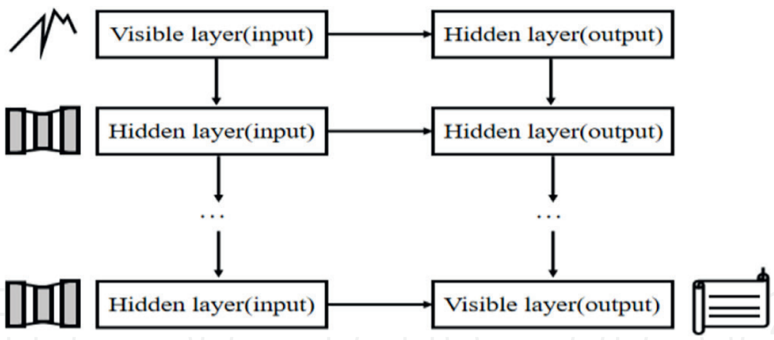

Figure 10.
Schematic diagram of stack self-coding calculation.

In 2020, Lu et al. used stacked self-coding and Fisher Autoencoder (FAE) to extract discriminative wind turbine icing features, which were then input into a hybrid model that combined DFAE with Self-Organizing Map (DFAE-SOM), and the experiments revealed that the hybrid model is more efficient when data with discriminative features is input [59]. Yi et al. published a wind turbine icing data approach based on discriminative feature learning the same year. The approach constructs representations with SAE using normal operation data and time series information, combines original data, SAE-extracted features, and residual vectors for discriminative features, and performs feature selection and dimensionality reduction. The method's practicality and superiority were demonstrated using a benchmark dataset [60].

3.5 Transfer learning

In 1995, Caruana pioneered transfer learning by developing the first transfer learning model. Transfer Learning (TL) is a machine learning technique that applies previously learned knowledge to a new task. Its central concept is to train and reason by transferring a learnt model from one domain to another related domain in order to improve the model's generalization capacity and efficiency [61–63]. **Figure 11** shows how it works. Transfer learning may be used to forecast wind turbine icing utilizing current meteorological datasets (e.g., temperature, humidity, wind speed, precipitation, etc.) in the field of wind turbine ice prediction. Training time may be substantially decreased and prediction accuracy can be increased by pre-training a model on a large meteorological dataset and then transferring it to the wind turbine icing prediction job. Transfer learning may also aid in the prediction of wind turbine ice in various areas or models.

In 2022, Li et al. published a generalized DNN-based model for predicting wind turbine icing situations that is based on data from SCADA systems and has a high

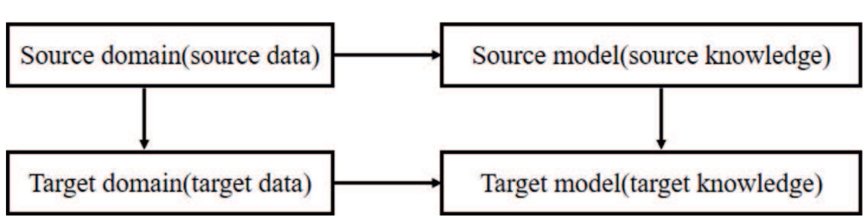

Figure 11.
Principle diagram of migration learning calculation.

combined accuracy [64]. Previously, in 2021, Chen et al. developed TrAdaBoost, a ground-breaking transfer learning algorithm that has been shown to increase performance in dealing with imbalances and varying distributions of wind turbine data [65].

In recent years, deep learning has been actively used and researched in the field of wind turbine blade icing prediction, with the objective of enhancing the operating efficiency and safety of wind generating systems. The most often used deep learning models nowadays include CNN, RNN, DNN, SAE, and TL. Each of these models has advantages and disadvantages, and the most appropriate model must be chosen depending on the unique circumstance in real-world applications [66–69].

4. Conclusion

Overall, the use of deep learning in the prediction of wind turbine blade icing has shown excellent results.

Convolutional Neural Networks (CNNs) are commonly employed in deep learning for extracting spatial information from time series data, allowing them to identify icing spots effectively. For accurate icing time estimates, Recurrent Neural Networks (RNNs) examine serial data and identify temporal correlations. Deep learning algorithms with context adaptation will become more important in wind turbine icing prediction. Future study will concentrate on increasing accuracy, lowering computing complexity, and tackling uncertainty. Furthermore, by incorporating multiple data sources for training and refinement in wind turbine blade icing prediction, federated learning will improve model stability and generalization.

Deep learning is increasingly being used to forecast wind turbine blade ice. As a result of the continuous development and application of machine learning, deep learning, data mining, physical modeling, and data-driven technologies, the performance and accuracy of wind turbine icing prediction methods have significantly improved, providing more effective support and guarantee to ensure the normal operation of wind turbines and promoting the sustainable development and promotion of wind energy.

Author details

Lidong Zhang*, Yimin Xu and Yuze Zhao
Northeast Electric Power University, Jilin, China

*Address all correspondence to: lidongzhang@neepu.edu.cn

References

[1] BP. Energy Outlook 2023 edition. Energy economics. [Internet] 2023 [cited 2023 Apr 1]. Available from: https://www.bp.com/en/global/corporate/energy-economics/energy-outlook.html

[2] IEA. Electricity Market Report 2023 – Analysis. International Energy Agency. [Online]. Available from: https://www.iea.org/reports/electricity-market-report-2023. [Accessed: 10-Apr-2023]

[3] Technical Research Centre of Finland (VTT). Cold climate wind energy showing huge potential. ScienceDaily. 2013. Available from: https://www.sciencedaily.com/releases/2013/05/130528091611.htm [Accessed 7 December, 2017]

[4] Qiuyun M, Guoqiang W, Rongbin G. Wind turbine blade icing condition and anti-ice deicing measures. Science Technology and Engineering. 2022;**22**:09017-09008

[5] Technical Research Centre of Finland (VTT). Cold climate wind energy showing huge potential [DB/OL]. ScienceDaily, 2013 [Accessed 18 December, 2021]. Available from: www.sciencedaily.com/releases/2013/05/130528091611.htm

[6] Contreras M, Leidy T. A review on the estimation of power loss due to icing in wind turbines. Energles. 2022;**15**:1083. DOI: 10.3390/en15031083

[7] Tahir SAR, Virk MS. Vertical axis wind turbine operation in icing conditions: A review study. Wind Engineering. 2021;**46**:0309524X2110618. DOI: 10.1177/0309524X211061828

[8] Clement H, Guy F, Jean P. Wind turbine performance under icing conditions. Wind Energy. 2008;**11**:319-333. DOI: 10.1002/we.258

[9] Yirtici O, Ozgen S, Tuncer IH. Predictions of ice formations on wind turbine blades and power production losses due to icing. Wind Energy. 2019;**22**:909-923. DOI: 10.1002/we.2333

[10] Shakirov VA, Fedyaev AA. Accounting for the impact of blade icing on wind energy production according to Weather Station data. In: 2020 International Multi-Conference on Industrial Engineering and Modern Technologies(FarEastCon) 06-09 October 2020. Vladivostok. Russia: IEEE; 2020

[11] The 2021 power outage in Texas. Available from: https://www.texasmonthly.com/news-politics/texas-blackout-preventable/

[12] Jesus Maria PP, Fausto Pedro GM, Diego RH. Economic viability analysis for icing blades detection in wind turbines. Journal of Cleaner Production. 2016;**135**:1150-1160. DOI: 10.1016/j.jclepro.2016.07.026

[13] Matthew CH, Per JN, Per AS. Ice sensors for wind turbines. Cold Regions Science Technology. 2006;**46**:125-131. DOI: 10.1016/j.coldregions.2006.06.005

[14] Jorge M, Sergio M, Estefanía A, Emilio G. Using SCADA data for wind turbine condition monitoring: A systematic literature review. Energies. 2020;**13**:3132. DOI: 10.3390/en13123132

[15] Michał C, Robert B, Rafał K, Jörg K. Advances and practical applications of deep and shallow machine learning. Journal of Universal Computer Science. 2022;**28**:225-226. DOI: 10.3217/jucs-028-03-0225

[16] Markus K, Abderrahim A, Kamaloddin V, Stephan O. Machine learning-based icing prediction on wind turbines. Elsevier. 2019;**81**:423-428. DOI: 10.1016/j.egypro.2019.03.073

[17] Rumelhart DE, Hinton GE, Williams RJ. Learning internal representations by error propagation. Nature. 1986;**323**:533-536

[18] BP neural network principle and algorithm derivation process. Available from: https://blog.csdn.net/wu740027007/article/details/100884238

[19] Deep Learning -- the New Wave of machine Learning. Available from: https://blog.csdn.net/datoubo/article/details/8577366

[20] Cheng P, Jing H, Hao C, Xinpan Y, Xiaojun D. Icing prediction of Fan blade based on a hybrid model. International Journal of Performability Engineering. 2019;**15**:2882-2890. DOI: 10.23940/ijpe.19.11

[21] Feiyu L, Hongmei C, Hongjie S, Iderchuluun ZM, Yaxiong Z, Yong Z. Icing condition prediction of wind turbine blade by using artificial neural network based on modal frequency. Cold Regions Science and Technology. 2022;**194**:103467. DOI: 10.1016/j.coldregions.2021.103467

[22] Isonguyo JI, James FW, Martin TB. Bilinear modelling, control and stability of directional drilling. Control Engineering Practice. 2019;**82**:161-172. DOI: 10.1016/j.conengprac.2018.10.008

[23] Elman JL. Finding structure in time. Cognitive Modeling. Cognitive Science. 1990;**14**:179-211

[24] Cheng P, Qing C, Xiaohong Z, Songsong W, Zhaohui T. Wind turbine blades icing failure prognosis based on balanced data and improved entropy. International Journal of Sensor Networks. 2020;**34**:126-135. DOI: 10.1504/ijsnet.2020.110467

[25] Ludmila IK. Combining pattern classifiers: Methods and algorithms: Second edition. Technometrics. Technometrics. 1st ed. Chichester: Wiley; 2014. p. 212-234. DOI: 10.1002/0471660264

[26] Ensemble learning. Available from: https://blog.csdn.net/xiao_yi_xiao/article/details/124040296

[27] Breiman L. Bagging predictors. Machine Learning. 1996;**24**:123-140. DOI: 10.1007/BF00058655

[28] Tianqi C, Carlos G. XGBoost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York, United States: IEEE; 13-17 August 2016. p. 785-794 DOI: 10.1145/2939672.2939785

[29] Liwen W, Yanlong Z. Wind turbine blade icing fault prediction based on SCADA data by XGBoost. Academic Journal of Engineering and Technology Science. 2022;**5**:30-35. DOI: 10.25236/AJETS.2022.050206

[30] Peng G, David I. Wind turbine blade icing detection with multi-model collaborative monitoring method. Renewable Energy. 2021;**179**:1098-1105. DOI: 10.1016/j.renene.2021.07.120

[31] Wolpert DH. Stacked generalization. Neural Networks. 1992;**5**:241-259. DOI: 10.1016/S0893-6080(05)80023-1

[32] Yuanyuan L, Lingyu H, Ming T. Prediction of wind turbine blades icing based on feature selection and 1D-CNN-SBiGRU. Multimed Tools

and Applications. 2022;**81**:4365-4385. DOI: 10.1007/s11042-021-11700-7

[33] Mendeleyev SA, Mokhnachev SA. Bagging-based ensemble method for regression problems with low-dimensional data. Journal of Computer and Systems Sciences International. 2019;**58**:186-197. DOI: 10.1134/S1064230719020091

[34] Hongmin Z, Haiming N, Zenghui M, Shuyao Z. Wind turbine condition monitoring based on bagging ensemble strategy and KNN algorithm. IEEE Access. 2022;**10**:1. DOI: 10.1109/ACCESS.2022.3164717

[35] Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. Science. 2006;**313**: 504-507. DOI: 10.1126/science.1127647

[36] Hinton GE, Osindero S, Teh YW. A fast learning algorithm for deep belief nets. Neural computation. 2006;**18**:1527-1554. DOI: 10.1162/neco.2006.18.7.1527

[37] LeCun Y, Bengio Y, Hinton GE. Deep learning. Nature. 2015;**521**:436-444. DOI: 10.1038/nature14539

[38] Deep learning. Available from: https://blog.csdn.net/qq_46458188/article/details/121594693

[39] LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proceedings of the IEEE. 1998;**86**:2278-2324. DOI: 10.1109/9780470544976.ch9

[40] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Communications of the ACM. 2017;**60**:84-90. DOI: 10.1145/3065386

[41] Markus K, Abderrahim A, Kamaloddin V, Jan-Hendrik O, Michael L, Michael F, et al. Convolutional neural network with dual inputs for time series ice prediction on rotor blades of wind turbines. Procedia CIRP. 2021;**104**:446-451. DOI: 10.1016/j.procir.2021.11.075

[42] Xu C, Fan S, Meng Z, Guoyang L, Houxiang Z, Shenyong C. Temporal attention convolutional neural network for estimation of icing probability on wind turbine blades. IEEE Transactions on Industrial Electronics. 2022;**69**:6371-6380. DOI: 10.1109/TIE.2021.3090702

[43] Jin X, Chunyan L, Bo L, Jing H, Ling X. Prediction of wind turbine blade icing fault based on selective deep ensemble model. Knowledge-Based Systems. 2022;**237**:108290. DOI: 10.1016/j.knosys.2022.108290

[44] Recurrent Neural Network. Available from: https://blog.csdn.net/vendetta_gg/article/details/107213295

[45] Cho K, Van Merriënboer B, Gulcehre C, Bahdanau D, Bougares F, Schwenk H, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). 25-29 October 2014. Doha. Qatar: Association for Computational Linguistics; 2014. pp. 1724-1734

[46] RNN/LSTM/GRU. Available from: https://zhuanlan.zhihu.com/p/123211148

[47] Xuan L, Wei Z. Physics-informed deep learning model in wind turbine response prediction. Renewable Energy. 2022;**185**:932-944. DOI: 10.1016/j.renene.2021.12.058

[48] Weiwei T, Xu C, Guoyuan L, Fan S, Shenyong C, Hongxiang Z. A multilevel convolutional recurrent neural network for blade icing detection of wind turbine. IEEE Sensors Journal. 2021;**1**:1. DOI: 10.1109/JSEN.2021.3093726

[49] Rosenblatt F. The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review. 1960;**65**:386-408. DOI: 10.1037/h0042519

[50] Goodfellow I, Bengio Y, Courville A. Deep Learning. The MIT Press; 2016

[51] Deep Neural Networks Available from: https://blog.csdn.net/Yasin0/article/details/86167009

[52] Deep neural network DNN understanding. Available from: https://blog.csdn.net/qq_54432917/article/details/127970677

[53] Wei T, Hao C, Xian D, Yibing L, Zhiyong M, Haihua M. DNN-based approach for fault detection in a direct drive wind turbine. IET Renewable Power Generation. 2018;**12**:1164-1171. DOI: 10.1049/iet-rpg.2017.0867

[54] Tingshun L, Jiaohui X, Zesan L, Dadi W, Wen T. Detecting icing on the blades of a wind turbine using a deep neural network. Computer Modeling In Engineering & Sciences. 2023;**2**:767-782. DOI: 10.32604/cmes.2022.020702

[55] Hongmei C, Zhongyang L, Bingchuan S, Teng F, Yonghao L, Lida L, et al. A new ice quality prediction method of wind turbine impeller based on the deep neural network. Energies. 2022;**15**:8454. DOI: 10.3390/en15228454

[56] Inho J, Haeseong C, Chankyu S, Taeseong K. Sustainable data-driven framework via transfer learning for icing-detection of high aspect ratio blades. Cold Regions Science and Technology. 2022;**201**:103606. DOI: 10.1016/j.coldregions.2022.103606

[57] Schölkopf B, Platt J, Hofmann T. Greedy layer-wise training of deep networks. In: Advances in Neural Information Processing Systems 19: Proceedings of the 2006 Conference;4-7 December 2006. Vancouv. Canada; 2007. pp. 153-160

[58] Vincent P, Larochlle H, Lajoie I. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of Machine Learning Research. 2010;**11**:3371-3408 ISSN: 1532-4435

[59] Weipeng L, Xuefeng Y. Deep fisher autoencoder combined with self-organizing map for visual industrial process monitoring. Journal of Manufacturing Systems. 2020;**56**:241-251. DOI: 10.1016/j.jmsy.2020.05.005

[60] Huaikuan Y, Qinchao J. Discriminative feature learning for blade icing fault detection of wind turbine. Measurement Science and Technology. 2020;**31**:115015. DOI: 10.1088/1361-6501/ab9bb8

[61] Riyad BR, Mark VA. Transfer learning: Leveraging trained models on novel tasks. In: Albert MV et al., editors. Bridging Human Intelligence and Artificial Intelligence, Educational Communications and Technology: Issues and Innovations. Switzerland AG: Springer Nature; 2022. pp. 47-58. DOI: 10.1007/978-3-030-84729-6_4

[62] Transfer learning. Available from: https://blog.csdn.net/houshaolin/article/details/71077705/

[63] Mohammadreza I, Khaled R, Hamid Reza A. A Review of Deep Transfer Learning and Recent Advancements. arXiv. 2022. DOI: 10.48550/arXiv.2201.09679.

[64] Tingshun L, Jiaohui X, Zesan L, Dadi W, Wen T. Detecting icing on the blades of a wind turbine using a deep neural network. Computer Modeling in Engineering & Sciences.

2022;**134**:767-782. DOI: 10.32604/cmes.2022.020702

[65] Wanqiu C, Yingning Q, Yanhui F, Ye L, Andrew K. Diagnosis of wind turbine faults with transfer learning algorithms. Renewable Energy. 2021;**163**:2053-2067. DOI: 10.1016/j.renene.2020.10.121

[66] Haciefendioglu K, Basaga HB, Ayas S, Karimi MT. Automatic detection of icing wind turbine using deep learning method. Wind and Structures. 2022;**34**:511-523. DOI: 10.12989/was.2022.34.6.511

[67] Junqing M, Lixin M, Xincheng T. Wind turbine blade icing prediction based on deep belief network. In: 2019 4th International Conference on Mechanical, Control and Computer Engineering. 24-26 October 2019. Hohhot, China: IEEE; 2019. pp. 26-29

[68] Helbing G, Ritter M. Deep learning for fault detection in wind turbines. Renewable & Sustainable Energy Reviews. 2018;**98**:189-198. DOI: 10.1016/j.rser.2018.09.012

[69] Joyjit C, Nina D. Deep learning with knowledge transfer for explainable anomaly prediction in wind turbines. Wind Energy. 2020;**23**:1693-1710. DOI: 10.1002/we.2510