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An empirical analysis of applications of artificial intelligence algorithms in wind power technology innovation during 1980–2017

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A B S T R A C T

We investigated the applications of artificial intelligence (AI) algorithms in wind power technology changes over time and found that AI accelerates the automation of wind power systems. This study shows evidence of the evolution of wind technology innovation following the advancement in AI algorithms using the patents data issued in four intellectual property (IP) offices from 1980 through 2017. Artificial intelligence and more advanced data analytics can be effectively applied to increase the efficiency of wind power systems and to optimize wind farm operations. This study empirically analyzes the evolution of applications of AI algorithms in wind power technology by employing machine learning-based text mining and network analysis, demonstrating the dynamic changing pattern of applications of AI algorithms in wind power technology innovation.

1. Introduction

Wind energy as a clean and renewable source is widely accepted (Sun et al., 2020) since it is playing an increasing role in reducing greenhouse gas emissions and leading the transition from a fossil fuel-based energy system to a sustainable energy system. Wind energy is considered a promising alternative to conventional fossil fuels and plays an important role in reducing global carbon footprint and (Wang et al., 2018; Dai et al., 2019). Wind turbine installation globally has increased sharply from 24 GW in 2001 to around 651 GW in 2019, which is almost 27 times increased (Global Wind Energy Council, 2020b). The newly installed wind energy capacity reached 60.4 GW in 2019, which marks the largest year in the wind industry history, and the newly installed capacity is expected to reach 76 GW in 2020 (Global Wind Energy Council, 2020a). This remarkable growth has been possible due to technological innovation and a reduction in the costs associated with wind power systems. However, because of the intermittent electricity generation from wind, increasing the use of electricity from wind power and integrating wind systems into power systems bring challenges for the stability, safety, and flexibility of the power system (Evan et al., 2012). Thus, there is increasing attention on controlling and optimizing the performance of wind turbines (Wu et al., 2014; Wang et al., 2020). To expand wind power generation on a large scale, optimizing wind turbine control, operating wind power systems effectively, forecasting wind speed, and wind power generation are crucial. Zhang and Huang (2018) and Ozcanli et al. (2020) argue that artificial intelligence (AI) and data analysis are needed to be applied to wind power systems to increase the performance of wind power.

In recent years, more wind power has been integrated into the power system along with other renewable resources, energy storage systems, and electric vehicle charging systems (Zahraee et al., 2016; Yoldas et al., 2017). As wind energy is a variable renewable energy source, wind turbines are not always driven at rated capacity. Wind turbine producers and manufacturers have sought advanced technologies such as automation, data analysis, robots, artificial intelligence, and machine learning for efficient operation and maintenance (O&M) to minimize manufacturing and O&M costs and optimize wind power generation systems (Stetco et al., 2019). AI predicts wind power generation and power demand and enables smart grids to store and transmit power efficiently (Flores et al., 2005; Barbounis et al., 2006; Bilgili et al., 2007; Jursa

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and Rohrig, 2008; Mabel and Fernandez, 2008). Machine learning aims to develop methods and algorithms to learn from data (Mitchell, 1997; Alpaydin, 2009). The machine learning algorithm is used to describe the behavior of the data set, model input function, expected output and expected output function in relation to the recording. Machine learning algorithms are one of the alternatives to predict wind power based on wind speed data. International Renewable Energy Agency (2019) addresses that innovation in AI and machine learning can improve wind power operations by up to 10 percent by utilizing vast amounts of data and real-time data. AI-based wind turbine technology enables efficient O&M through data analysis. Previous studies (Barambones et al., 2010; Ren and Bao, 2010; Mesemanolis et al., 2012) highlighted that AI technology can detect anomalies early through predictive analysis and can operate smoothly under wind conditions to improve turbine performance. Wind speed prediction can improve the efficiency of wind power systems (Lei et al., 2009) and the operation and maintenance of wind control systems (Li and Shi 2010). Wind power prediction is essential to manage wind power generation due to its intermittence and variability (Qerimi et al., 2020). Colak et al. (2012) addressed that AI can be used for turbine control, power system management, load tracking, and maintenance of wind farms. It is difficult to statistically and mathematically model wind power systems due to complicated architecture and limited knowledge. Wang et al. (2020) argue that traditional methodologies cannot guarantee the best solutions. Hong and Rioflorido (2019) and Lin and Liu (2020) demonstrated that Artificial Neural Network (ANN) could better predict wind power while the physical methods in predicting wind power are too complicated to be explained. Thus, AI can better optimize problems via innovative approaches. Jha et al. (2017) reviewed the current status of research and development of AI approach in renewable systems, including wind and summarized the reports for the application of AI techniques in wind energy, distinguishing wind power prediction and wind speed prediction. The authors presented the application of AI techniques in the optimization of wind systems. However, they did not demonstrate the dynamic change of AI application in wind power technology overtime.

Policy decision-makers need to analyze new and innovative technologies and develop research and development plans regarding renewable energy sources (Borowski, 2020). As AI technology emerges as a critical factor in determining the competitiveness of renewable energy technology, countries and companies are actively pursuing R&D and patent applications for AI technology and the energy technology converging AI technology (Cockburn et al., 2017; Fuji and Magani, 2018). Although it is not a field of wind technology innovation, with stressing the importance of the future direction of recent advances of technologies, Qi et al. (2018) provided insights of technological innovation into the recent advances in emerging 2D metal-halide perovskites and their applications in the fields of optoelectronics and photonics. Patent data provide a variety of valuable information that can demonstrate the evolution of technologies over time (Pilkingtonet et al., 2002). Altuntas et al. (2015) stressed that the patent contains detailed information about developed technologies and is of great significance in identifying past, present, and future technology trends. There have been researches using patent data to identify the evolution of artificial intelligence technology (Tseng and Ting, 2013) and renewable energy technology (Albino et al., 2014; Bointner, 2014), respectively. Previous studies have analyzed AI technology structure and technology trends by utilizing patent data, but there are limitations in these studies as they distinguished and analyzed patent data results based on predefined AI structures. Meanwhile, recently, there has been increasing interest in research on the convergence of AI with other areas. Since the International Patent Classification (IPC) code is assigned to all of each patent, and different classification codes are assigned to the patented technology, network analysis between these patents can be used to identify which technologies are converging with other fields have. Kim and Kim (2012) demonstrated the results of the analysis of the fields that appear simultaneously with AI technology - data processing, image analysis, and financial pricing - based on USPC granted to U.S. patents. They identified the technology convergence phenomenon in AI technology through patents and papers. Through the co-occurrence analysis with the AI technology using USPC Class 706 class, they found a strong technological convergence in data processing, image analysis, and financial pricing. Fujii and Managi (2018) used registered patent data from 2000 to 2016 to identify trends in AI technologies and changes in priorities. Employing a patent decomposition analysis framework, they divided AI technologies into four types-biological-based models, knowledge-based models, specific physical models, and other AI technologies.

Despite these previous studies, there are only limited studies that presented the changes in applications of AI algorithms in wind power technologies over time through patent data analysis. This study empirically analyzes the dynamic pattern of changes of AI application on wind power technology innovation during 1980–2017 by applying text mining and International Patent Classification (IPC) co-occurrence network analysis utilizing patent data documents. This study classifies AI algorithms and then searches patents to analyze the changes of applications of AI algorithms on wind power technology over time to explore answers to the following research questions. i) How the application of AI algorithms on wind power technology innovation has changed over time? ii) What are the main characteristics of each period, iii) How the pattern of convergence of AI and wind power technology has been changed over time?

The novelty and contribution of this study to previous studies lie in the following two aspects:

(i) In the context of the application of AI in wind power technology, as artificial intelligence is expected to improve the performance of wind power and power systems, based on real data and evidence, research and development (R&D) investment policies and appropriate policy combinations for wind power and artificial intelligence innovation should be established. Understanding the impact of AI on wind power innovation and understanding the patterns of convergence effects on technological innovation over the past decades can help predict future technology trajectories. In this regard, it is the first time to identify the changes of applications of AI algorithms in wind power technology overtime for 38 years from 1980 to 2017 through the collected patents for wind power technology using AI algorithm technique issued by four Patent Offices-USPTO, EPO, JPO, and CNIPA (United States Patent and Trademark Office, European Patent Office, Japanese Patent Office, and China National Intellectual Property Administration, respectively).
(ii) In the context of patterns of wind power technology innovation evolved with AI techniques, this is the first study to analyze the convergence pattern of AI technology and wind technology by period, by visualizing the results of patent data analysis using t-SNE algorithm, a machine learning-based technique, and IPC co-occurrence network analysis method that can analyze technology convergence.

The remainder of this paper is organized as follows. Section 2 gives a brief introduction to artificial intelligence algorithms and its' application in wind power. In Section 3, the methodology and the process of data analysis are reported. Section 4 highlight the results and discussion. Section 5 comes to a conclusion.

2. Literature review

2.1. The concept of artificial intelligence

It is becoming increasingly difficult to ignore the effects of AI in analyzing wind power technology innovation. The concepts of artificial intelligence (AI), machine learning (ML), and deep learning (DL) are often used interchangeably, and all three are closely related, but are certainly not the same. Therefore, it is necessary to accurately understand the differences between artificial intelligence, machine learning, and deep learning. Lee (2020) presented their relationship and characteristics of each technique with representative algorithms (Fig. 1.).

Alan Turing is the first person to raise the subject of AI. In 1937, after proposing the concept of a universal machine, in 1950, Turing presented his artificial intelligence issue for the first time in his thesis ‘Computing Machinery and Intelligence’ (Negnevitsky, 2011). Turing is a test to determine whether it is a machine or a person. The test passes if the human judge cannot tell whether the person talking to the judge was a person or a machine after a human judge had a random conversation with one person and one machine. The term artificial intelligence was first mentioned by John Macarthy at the Artificial Intelligence Conference held in Dartmouth in 1956. AI is defined in many ways according to experts’ views. Russell and Norvig (2011) define AI as an intelligent agent that thinks and behaves like a person and argue that it is a generic term for machines capable of perception, logic, and learning. Researchers believe that since the advent of AI in the 1950s, it has had a cycle of boom and fall twice (Mitchell, 1997; Smola and Vishwanathan, 2008; Harrington, 2012; Marsland, 2015; Odaka, 2016; Tada, 2016). Since understanding the technological development of AI by periods allows us to understand the characteristics of each algorithm and to figure out how it has been applied, this section analyzes how AI technology has evolved.

2.1.1. The evolution of artificial intelligence

2.1.1.1. [1960–1980] 1st AI boom. In the 1970s, the first boom of AI occurred as the Expert System, which systematically accumulated professional knowledge and made professional decisions, was developed (Tada, 2016). Minsky designed the Expert System with artificial intelligence based on the theory of symbolism (Tada, 2016). Unlike neural network models, the expert system does not have self-learning systems. Instead, it is based on the expertise of a field and judges it as ‘Do not do this or do it in this situation.’ The expert system extracts the knowledge of human experts and borrows knowledge expressing techniques from logic, etc., and reconstructs information and knowledge in a form that the computer understands; this is called the knowledge base (Russell and Norvig, 2011). The fuzzy theory used in mathematics is critical when expert systems make judgments (Russell and Norvig, 2011). By the 1970s, While Rosenblatt’s simple perceptron model had fallen in popularity, the Expert system continued to evolve and popularize it for use on personal computers in by 1980s (Negnevitsky, 2011). Perceptron is a pattern recognition algorithm using simple perceptron, published by Rosenblatt in 1957 and is a two-layered learning computer network that performs simple addition and subtraction (Russell and Norvig, 2011). Negnevitsky (2011) points out that the expert system has inherent limitations in that it can imitate intellectual abilities only at the level of human experts in narrow and specialized fields, which is not enough to handle the vast and complex social domain. However, as the expert system failed to solve the target problem, interest in the expert system has reduced. The field of AI that has been actively researched so far is the systems that behave like humans’, examples of which include natural language processing, automatic reasoning, knowledge expression, speech recognition, machine learning, computer vision, and robotics (Negnevitsky, 2011). Fuzzy systems and expert systems are AI algorithms that are widely used until recently (Dangeti, 2017). Fuzzy theory is a theory that attempts to express ambiguous human language in computer language, and is a logic dealing with ambiguous objects. It is mainly used in the field of control of production facilities and pattern recognition such as text recognition

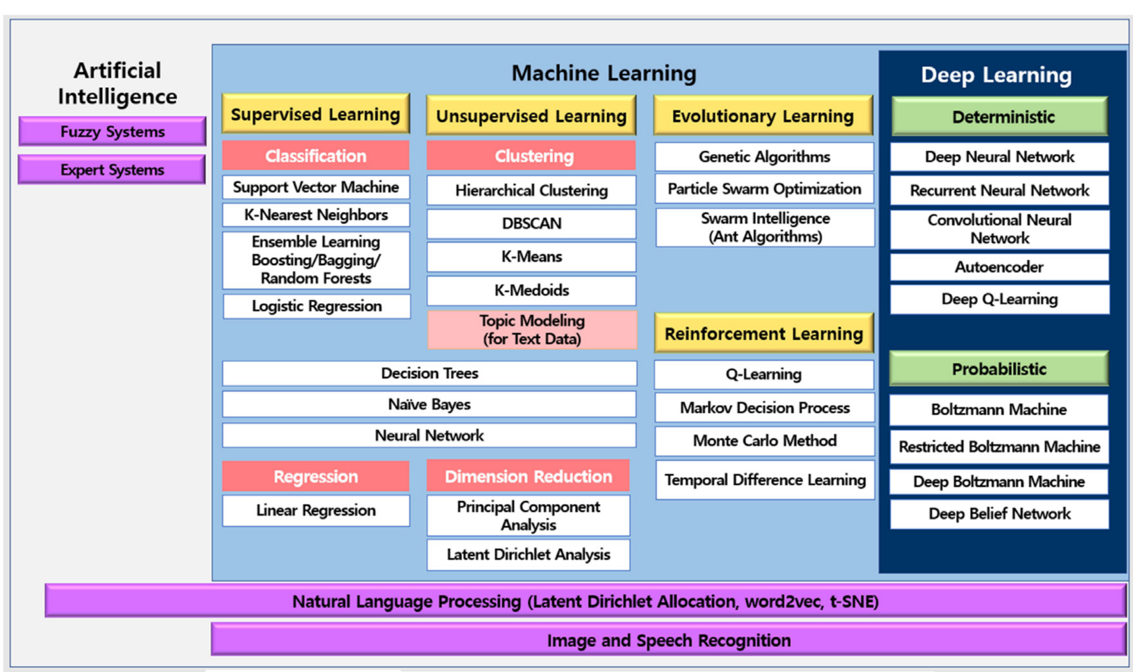


Fig. 1. Classification of artificial intelligence, machine learning, and deep learning. Reprinted from Lee (2020).

and voice recognition.

2.1.1.2. [1980–2000] 2nd AI boom and AI winter. In the 1980s, semiconductor development costs were lowered, enabling large-scale integrated circuits with increased CPU, RAM, and cache memory capacity. These advancements changed the unit of data and speeded up the operation speed. Previous researches (Smola and Vishwanathan, 2008; Harrington, 2012; Odaka, 2016; Tada, 2016) argue that in this period, neural network research was developed with multi-layer perceptron and error-back propagation method, occurring a second AI boom. However, the computational performance of the 1980s has reached the limit that it is difficult to broaden the scope of thinking, and AI research in the 1990s met the dark period (Odaka, 2016).

2.1.1.3. [2000–2010] statistics based machine learning and development of distributed computing. AI research includes a neural network and a machine learning algorithm based on statistical modeling. In the 2000s, machine learning based on statistics was developed and distributed computing that improves computing performance also developed (Tada, 2016). With the development of the Internet and the adoption of information and communication devices, it has become possible to utilize Big Data, and computers have also been developed so that high-performance computation processing technology can be practically used. The high volume of data and advanced computing has supported the evolution of AI.

2.1.1.4. [2011-Present] emergence of deep learning and the prevalence of AI and digital transformation. After deep learning won the 2012 ImageNet Challenge competition with overwhelming performance, algorithms such as DNN/CNN/RNN have developed rapidly and have begun to be utilized in the industry. Since deep learning have emerged and machine learning applied widely after 2011, AI has been regarded to have the potential to transform society and humanity as a revolutionary technology, and its growth has been apparent. Google is one of the most successful companies in developing deep learning. By acquiring DeepMind, a British deep-learning company, it succeeded in learning computers in 2012 and recognizing cats. This was achieved by using various hybrid algorithms and by utilizing 16,000 computer processors and ten million YouTube videos (Hof, 2015). In 2016, Google was able to reduce the energy used to cool the data center by 40% by using DeepMind's machine learning algorithm (Evans and Gao, 2016).

2.1.2. Machine learning

Machine learning is a subset of AI and can be learned without being explicitly programmed. Machine learning can be classified into four categories (Marsland, 2015). Supervised, unsupervised, reinforced and evolved learning. Supervised learning is the most common machine learning technique (Marsland, 2015). Supervised learning provides a training set and target values, and generalizes to give correct answers for all input values through the data set provided. Supervised learning provides training sets and target values, and generalizes them so that the correct answers are given out for all input values through the provided data set. Once the training finishes with the training set, it can be measured how accurately the learned algorithm predicts, using an unspecified test set. There are classification and prediction models in supervised learning. Support Vector Machine (SVM) is the most commonly used supervised learning model (Smola and Vishwanathan, 2008; Harrington, 2012). SVM is an identification method that identifies two groups, and it is a method to find a hyperplane with the maximum margin among the many candidate planes that can separate the two groups. SVM is used when the data to be trained classified into two groups, and it is a model for predicting where the new data will belong to the existing two. Unsupervised learning is a methodology in which the learning data does not have a label, and a computer learns without labeling the data. Unsupervised learning is used to discover hidden features or structures of data. Clustering and dimension reduction are the representative methodology of unsupervised learning (Marsland, 2015; Dangeti, 2017). Reinforcement learning is an intermediate technique between supervised learning and unsupervised learning and is an algorithm that includes data collection in a dynamic environment (Mitchell, 1997). Reinforcement learning is an intermediate technique between supervised learning and unsupervised learning (Harrington, 2012). Mitchell (1997) defines that reinforcement learning is an algorithm that includes data collection in a dynamic environment, and he explains that the agent proceeds to learn by taking action for a given 'state' and obtaining some reward from it; at this point, the agent proceeds to maximize the reward. Representative algorithms for reinforcement learning are Q-Learning, and recently, Q-Learning has been combined with deep learning and used as a Deep-Q-Network (DQN) method (Tada, 2016).

Evolutionary learning is a machine learning method that acquires knowledge by mimicking the evolution of living things (Tada, 2016). It is a learning method that implements the principle of inheritance of living things according to symbol processing (Odaka, 2016). Evolutionary learning has the same belief that learning and intelligence are the same, as nature develops by using natural selection and mutation tools. Typical examples are the genetic algorithm, which uses the characteristics of biological evolution for learning, Particle Swarm Optimization (PSO) and Ant Colony Optimization, which imitate clusters of organisms (Odaka, 2016). Odaka (2016) describes that the genetic algorithm models are the crossover phenomenon where genes are mutually intertwined and mutations that mutate random portions of a gene repeatedly evolve into better genes as the survival of the fittest. PSO is a population-based algorithm for training neural networks and finding neural network architectures and optimizing network weights. The key function of PSO is to get the optimized weights (particle position) where particles are seeking to reach the best solution (Ata, 2015). Genetic algorithms inherit themselves by crossing half of the parent gene in each environment, repeating the process of mutating occasionally. In a genetic algorithm, evolution is learning.

2.1.3. Deep learning

Deep learning is a subfield of machine learning. Deep learning is a kind of neural network, and it consists of large neural networks that were difficult to implement in the past. Deep learning is the result of accumulated machine learning and has been particularly successful in image recognition, speech recognition, and behavioral knowledge acquisition (Odaka, 2016; Tada, 2016). A deep neural network is a multi-layered neural network with a number of units and three or more layers, and learning using deep neural networks is called deep learning. Deep learning classification is not easy to classify according to learning methods or goals, unlike machine learning. This study follows the deep learning classification suggested by Asoh et al. (2015). The authors describe that deep learning has complex relationships, and that classification can also be divided by various criteria. They classify deep learning into a deterministic model and a probabilistic model. Representative algorithms in the deterministic model are a multi-layer neural network, deep neural network, recurrent neural network (RNN), convolution neural network (CNN), and autoencoder. For the probabilistic model, Boltzmann machine, restricted Boltzmann machine (RBM), deep Boltzmann machine (DBM), and deep belief network (DBN) are commonly used. Recurrent Neural Network (RNN) is a neural network that can reflect data by going back a few steps. RNN learns by considering context such as time-series data, so it is used for learning speech data or natural language (Tada, 2016). Convolutional Neural Network (CNN) is mainly used for image recognition, and the basic idea is to abstract an image from a small feature to a complex feature (Odaka, 2016). CNN has recently shown superior performance to image classification and feature detection thanks to algorithm improvement, hardware development, and big data development (Odaka, 2016).

2.2. The application of artificial intelligence in wind power technology

There are three areas where AI algorithms are widely applied to wind power generation: (i) forecasting of wind speed and wind power, (ii) optimization of operation and maintenance (O&M), (iii) optimization of the operation of wind farms. Because wind speed is the most influential variable for the wind turbine at a given size, it is necessary to analyze the wind speed of the wind power plant before forecasting the generation amount. In addition, it is not easy to predict the output because the output of the wind energy varies greatly depending on the weather condition. Because forecasting of wind power generation is applied to the economic evaluation of wind farms, accurate wind power generation forecasting is a critical factor for the successful operation of wind power generation. In addition, since the intermittent output characteristics of wind power generation cause disturbance of the power system, it is essential to predict the amount of wind power generation and to stably connect the power generated from the wind farm to the power system.

AI can contribute to the expansion of a large scale of wind power generation and increase reliability by reducing the uncertainty of variable wind energy as they enable to increase the accuracy of the weather forecast, power generation, and demand prediction (Bechrakis et al., 2004; Monfared et al., 2009; Salcedo-Sanz et al., 2011; Li and Shi, 2010; Ortiz-García et al., 2011). Among other AI algorithms, ANN has been widely used in predicting wind speed and wind power generation. Mabel and Fernandez (2008) studied wind power predictions utilizing ANN based on a 3-year database containing wind speed, relative humidity, and generation hours. The authors concluded that wind speed has a direct effect on power generation. Jafarian and Ranjbar (2010) studied annual power forecasting based on hourly recorded wind speeds from 25 different stations in Netherland by applying fuzzy modeling and ANN. They selected average wind speeds, standard derivation of wind speeds, and air density as input features. Peng et al. (2013) compared ANN algorithm and a hybrid strategy based on physical/statistical models in wind power predictions. The authors concluded that the ANN model could provide the prediction results quickly with a relatively low accuracy while the hybrid predicting method operated slowly with high accuracy. Zameer et al. (2017) developed an integrated model using both ANN and genetic programming for short-term power forecasting based on an hourly sampled database from five wind farms in Europe. The authors concluded that an average root mean squared error of 0.117575 is reached.

AI also can induce cost reduction by optimizing the operation and maintenance (O&M) of wind power, design real-time electricity pricing, and enable efficient power storage/transmission through the smart grid (Zamora and Srivastava, 2010; Ibrahim et al., 2020). Through an extensive literature review, Ata (2015) categorized the main areas of AI application in wind energy systems-wind power/speed prediction, fault diagnosis, pitch control, dynamic modeling, optimal control, maximum power point tracking (MPPT) control, voltage and frequency control, transient stability improvement, sensitivity analysis in wind energy conversion system, and wind turbine power control. Ata (2015) and Heinermann and Kramer (2016) identify algorithms used for wind speed and wind power prediction and concluded that one of the key advantages of AI algorithms compared to other statistical methods is its speed, simplicity, and powerful algorithm enabling modeling multivariable and complex problems. The authors also explain that AI algorithms are powerful to extract non-linear relationships utilizing training data. Table 1 lists the list of previous studies that research the effects of AI in the wind power system and shows each algorithm applied to the areas of prediction of wind power and operation and maintenance. Fig. 2 presents the process of application of AI in wind power systems. The first is to determine the wind speed and direction in advance and predict the amount of electricity produced accordingly. To this end, not only satellite data and meteorological data but also wind direction and wind speed data installed for each wind turbine are used together. GOS (Global Observing System) is an air and ocean survey program of WIGSO (WMO Integrated Global Observing System). GOS observes the atmosphere and the ocean through satellites, ships, and aircraft, and the marine observation field observes and provides sea surface temperature and wave height. It predicts and provides time series of sea wind (wind speed, direction) and wave height, wave height and sea wind by sea area. Numerous weather-only satellites orbit the Earth, tracking cloud patterns, wind, temperature, and meteorological systems, and ground stations constantly collect data in real-time (World Meteorological Organization, 2010). With the advent of the Internet of Things (IoT), as more accurate and new data is provided every day, the weather forecasting process is able to export much more accurate data than before. The wind power generation system consists of a control system, a condition monitoring system, and a SCADA (Supervisory Control and Data Acquisition) system. Among them, the SCADA system enables efficient management of wind farms (Lin and Liu, 2020). The SCADA system monitors the overall operation status of the wind farm in connection with the wind turbine controller. After efficiently analyzing the SCADA data generated every second from the wind turbine, modeling the data in the SCADA system of the wind turbine, the big data platform can predict the amount of electricity produced by using artificial intelligence algorithms.

Recently, as the development of large-scale wind farms has increased significantly, research on AI techniques for optimizing the operation of wind farms composed of dozens of wind turbines is actively developed. Sung et al. (2020) proposed a power prediction model using an artificial neural network and used a genetic algorithm to optimize yaw angles in order to minimize wake effects in wind turbine farms. They introduced the ANN-wake-power model and concluded that ANN-based model showed better performance and higher accuracy rate than the physical models. The ANN-wake-power model they introduced achieved a good performance within the training process of 5000 epochs. The optimization process is effective and can significantly improve the power ratio to 0.96 in all directions involved. They concluded that wind turbines in different positions should adopt different yaw angle control strategies, and that the established ANN-based model has good accuracy and requires little computation cost. Physical models are good for individual turbines but not practical for designing and optimizing the layout of the wind farm (Sung et al., 2020). Recently, deep learning techniques have been used to model wind farms. Li (2003) and Barbounis et al. (2006) used a recurrent neural network (RNN) to predict long-term wind power and wind speed, respectively. In an operating wind farm, upstream wind turbines both generate electricity and cause wakes, resulting in the diminishment of the performance of downstream wind turbines. Wu et al. (2014) estimated the effectiveness of AI techniques in optimizing layouts of the offshore wind farm, using genetic algorithms

Table 1
Summary of research conducted in artificial intelligence algorithms applied in the wind power system.

Type	Function	Algorithms	References
Forecasting wind speed and Prediction of wind power	Short term wind speed forecasting	Neural networks Support vector machine	• Bilgili et al. (2007) • Zhou et al. (2011) • Cheng and Guo (2013)
	Short term wind power prediction	Neural networks with backpropagation	• Flores et al. (2005) • Chang (2014) • Li and Shi (2010)
		Neural networks	• Barbounis et al. (2006) • Mabel and Fernandez (2008)
		Support vector machine	• Heinermann and Kramer (2016) • Treiber et al. (2016) • Mohandes et al. (2004) • Ortiz-García et al. (2011) • Salcedo-Sanz et al. (2011)
		Genetic algorithm and neural networks	• Kolhe et al. (2011)
		Evolutionary optimization	• Jursa and Rohrig (2008)
		Neuro-Fuzzy	• Xia et al. (2010)
		Ensembles	• Hassan et al. (2015)
		Fuzzy and neural networks	• Monfared et al. (2009)
		Random forest	• Demolli et al. (2019)
Wind turbine operation and maintenance (O&M)	Pitch control and prediction	Fuzzy neural networks	• Sakamoto et al. (2006) • Yilmaz and Özer (2009) • Lin et al. (2010)
	MPPT control	Artificial neural networks	• Mesemanolis et al. (2012) • Nouali and Ouali (2011)
	Voltage and frequency control	Artificial neural networks	• Muyeen et al. (2012)
	Wind turbine power control	Artificial neural networks	• Barambones et al. (2010) • Ren and Bao (2010)
	Optimal control	Recurrent neural networks	• Kimura and Kimura (2013)
	Fault diagnosis	Artificial neural networks	• Bangalore and Tjernberg (2013)
Wind farm optimization	Forecasting wind speed at different turbine locations	Convolutional neural networks	• Kou et al. (2020)
		Support vector machine	• Li et al. (2019)
	Layouts of offshore wind farm	Genetic algorithm	• Wu et al. (2014)
	Power generation	Recurrent neural networks	• Li (2003) • Barbounis et al. (2006)

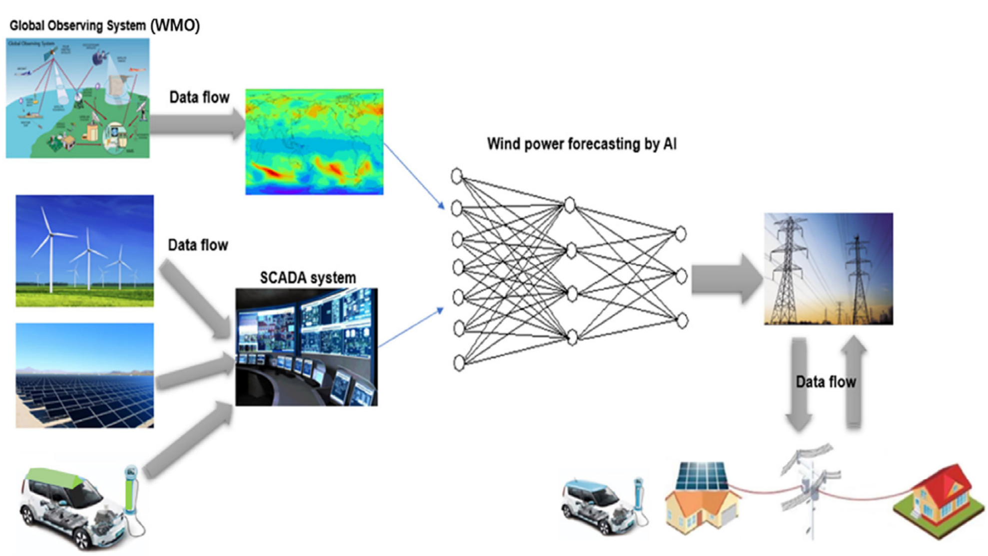


Fig. 2. The process of application of AI in wind power system.

and ant colony system algorithms. They considered the wake effect, wind speed series, and real cable parameters for the research and applied any colony algorithm to optimize the cost of the circuit configuration and genetic algorithm to minimize the loss of wind power in a wind farm. Kou et al. (2020) developed a joint model of convolutional neural network (CNN) and the gated recurrent units (GRU) to forecast the short-term wind speed at turbine locations. They concluded that the deep learning model provides satisfactory forecasting results and has a competitive advantage over existing models. Li et al. (2019) developed a support vector regression model to forecast the wind speed of wind turbines in a wind farm and Knudsen et al. (2011) estimated the effective wind speeds of six turbines in a wind farm using the Kalman estimator.

Besides the application of AI in wind power, Kibaara et al. (2020) summarized different AI techniques for optimization of sizing of hybrid renewable energy systems, introduced by previous authors. For instance, Amer et al. (2013) proposed the cost reduction of HRES using particle swarm optimization (PSO). Bansal et al. (2011) in their simulations of a hybrid wind-solar and battery, used a meta-heuristic particle swarm optimization for cost reduction. Ram et al. (2013), in their design of a standalone solar −wind hybrid with a diesel generator, used PSO to find the optimal sizes of each to meet the existing load. In addition, Trazouei et al. (2013) proposed the use of an imperial competitive algorithm, PSO, to establish the optimal configuration of a hybrid wind-solar and batteries.

3. Methodology

3.1. Patent data collection

Using patent documents represented by technical knowledge (Griliches, 1990; Ernst, 2003), this study performs machine learning-based text mining techniques and IPC co-occurrence network analysis to demonstrate the effects of AI in wind power technology. When collecting patent data, text data including title and abstract, applicant information, filing date, and International Patent Classification (IPC) code was collected for data analysis. First, patent data was collected from the online patent database, the KIPRIS (Korea Intellectual Property Rights Information Service) database. KIPRIS is a free industrial patent information search service agency in Korea managed by the Korean Intellectual Property Office and Korea Institute of Patent Information. They provide domestic and foreign patent information as well as other intellectual property rights including trademark and utility model through the database (DB). The collected patent data are those filed at four Patent Trademark Offices-USPTO (United States Patent Trademark Office), SIPO (Intellectual Property Office of China), JPO (Japan Patent Office), and EPO (European Patent Office), from January 1, 1980, to December 31, 2017. Each AI algorithm was selected based on the literature review on the theory of AI algorithm (Russell and Norvig, 2011; Negnevitsky, 2011; Harrington, 2012; Marsland, 2015; Odaka, 2016; Tada, 2016) and classified each AI algorithm into each category. Fig. 1 presents the classification of selected algorithms. Since this study identifies the effect of AI on wind power technology, a patent search query for this study is a combination of each AI algorithm and the query for wind power; for example, search for 'support vector machine', which a machine learning algorithm and 'wind power' or wind turbine' together. When searching for more than one phrase at the same time, for instance, 'support vector machine'*'wind power', the symbol, '*', that means 'and' can be used. Patent data were analyzed dividing into four periods, i) 1980−1990, ii) 1991−2000, iii) 2001−2010, iv) 2011−2017. Table 2 shows a summary of patent data collection, and Fig. 3 shows the process for patent data analysis.

3.2. Preprocessing

This study proceeded with R library and analyzed the abstract of the patent, which is the unstructured data in text form that provides summarized key information of technology. Natural language processing refers to various techniques for mechanically analyzing language phenomena, changing them into a form that can be understood by a computer, and expressing them in a language that can be understood by humans. Patent documents are unstructured text documents that require text preprocessing; thus, the conversion is required in a form in which information can be extracted. Since this research method uses machine-learning based text mining techniques, text data such as title and abstract were included when collecting patent data, and in addition, IPC code, applicant information, and filing date were also collected. The extracted patent data were analyzed on a 10-year interval. IPC co-occurrence network analysis was performed to identify the pattern of technology convergence of AI and wind power.

3.3. Text mining analysis

Natural language is the language that people speak or the sentence they read. Natural language processing is a machine that analyzes and interprets natural language and gives help or feedback to people as a result of understanding their meaning. Natural language processing divides sentences into words, extracts features, and translates them into other languages (Rajman and Besancon, 1998). The analysis process called Text Mining extracts feature words or sentences from a vast amount of text and graphs them. Text Mining is also part of natural language processing. Usually, the machine is difficult to analyze the sentence itself composed of natural language, so it should be divided into words (Gharehchopogh and Khalifelu, 2011). The primary task is morphological analysis, which is the most fundamental task in natural language processing. Morphological analysis is the task of dividing words and recognizing the parts of words obtained by word segmentation. This study employs Text Mining techniques including word2vec and t-SNE (t-Stochastic Neighbor Embedding) to analyze patent documents. Text mining is a data analysis methodology for analyzing meaningful patterns by extracting information from various documents in the form of unstructured data. The advantage of text mining is that text information, which is unstructured, can be extracted and effectively structured to derive analysis results (Meyer et al., 2008). Previous studies (Du et al., 2020; Ebadi et al., 2020; Ke, 2020) examined the trend of

Table 2
Patent data collection.

Patent data	Patent filed to the ◦ USPTO (United States Patent and Trademark Office) ◦ EPO (European Patent Office) ◦ JPO (Japan Patent Office) ◦ SIPO (Intellectual Property Institutions of China)
Patent filing period	Patent data search: From January 01, 1980 to December 31, 2017
Patent database	KIPRIS (www.kipris.or.kr)
Patent query formulation	◦ AI patent: Each AI algorithm ◦ Wind patent: "wind power" + "wind turbine" * '+' *means 'or* ◦ Wind power technology using AI: Each AI algorithm*("wind power" + "wind turbine") ** '*' *means 'and'*

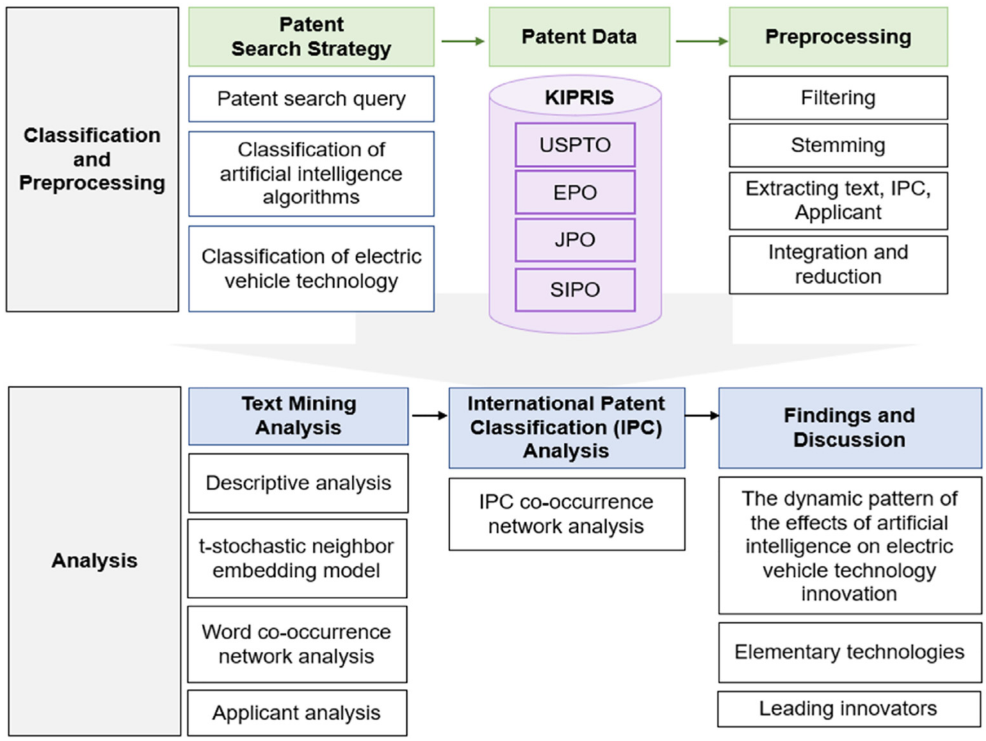


Fig. 3. The flowchart of the analysis process. Edited and Reprinted from Lee (2020).

academic research, the evolution of emergence of different academic areas, or the future technological trajectory by employing text mining analysis from publications and patents. In order to identify the technical characteristics inherent in the patent document, a technique that can cluster texts and visualize the results is required. In this study, the words were vectorized through Word2Vec, a deep learning technique and the vectorized data was visualized through t-SNE. Word2vec is a method of learning word vectors using unsupervised learning, and it is a model that expresses the relationship of words and shows them in a vector space. Word2Vec uses a distributed text representation to grasp the similarity between concepts. In this study, the Word2Vec analysis method, which is a representative method to vectorize the meaning of words, was used to reflect the similarity between texts (words) in a patent document. Mikolov et al. (2013) describe Word2Vec as an embedding method of non-instructional learning. Word2vec identifies and provides a characteristic of data that has a similar relationship within a specific space, and it predicts the next word by converting the term into a number that can be applied to the calculation. Word2Vec explains how to calculate the similarity between texts using word embedding. Word embedding is the technique of expressing words in spatial vectors. When word embedding is used, words with similar meanings appear close to each other, allowing the meaning of words to be included in the vector. The text image is saved in binary code. Using the concept of Bag of Word, characters are vectorized so that machine learning algorithms can understand them. Word2Vec assumes that 'words appearing in similar locations have similar meanings'.

The t-Stocastic Neighbor Embedding (t-SNE) technique was performed to identify and analyze the relationship between words and to visualize the results of the convergence of AI and wind power technology. The t-SNE model is a machine learning-based algorithm that shows data results for low-dimensional space while maintaining neighboring high-dimensional data (Hinton and Lowe, 2003). The t-SNE is an algorithm that diminish the non-linear dimension of data, and can be used to visualize the text embedded in Word2vec by reducing it to two or three dimensions or clustering it. Since t-SNE is output in the form of a graph, it is usually used in two-dimensional shape. In the case of the t-SNE algorithm, similar data are mapped to the closest points, and other data are mapped to distant points. The t-SNE calculates the distance of high-dimensional data with normally distributed probabilities and apply a t-distribution with 1 degree of freedom to identify if the difference is small. Since the t-distribution is longer than the normal distribution and the lower part of the graph is longer than the normal distribution, using the t-distribution to project to a lower dimension keeps the state of the near-distance data closer and makes the state of the distant-data farther away (Maaten and Hinton, 2008) (Fig. 4).

Fig. 5 presented by Maaten and Hinton (2008) demonstrates a visualization of the handwritten number. Not only are cluster created, but similar data like '3' and '8' are located close to each other.

3.4. IPC co-occurrence network analysis

IPC co-occurrences network analysis identifies convergence of technologies (Suzuki et al., 2008; Leydesdorff, 2008; Cho and Sin, 2011). If multiple IPC codes appear in one technology at the same time, this can be seen as a convergence technology (Suzuki et al., 2008). The patent classification code corresponding to the technical field to which the patent belongs is given when applying for the patent. The structure of the international patent classification is divided into eight sections as alphabet A to H, and each section is subdivided into class, subclass, group, and subgroup as follows (Fig. 6.). Multiple classification codes are allocated if the patents are related to several technical fields. Thus, if a single patent is granted multiple IPC codes, it can be understood that various technologies have converged, and this is referred to as IPC co-occurrence. This enables to identify and analyze the flow of technical knowledge

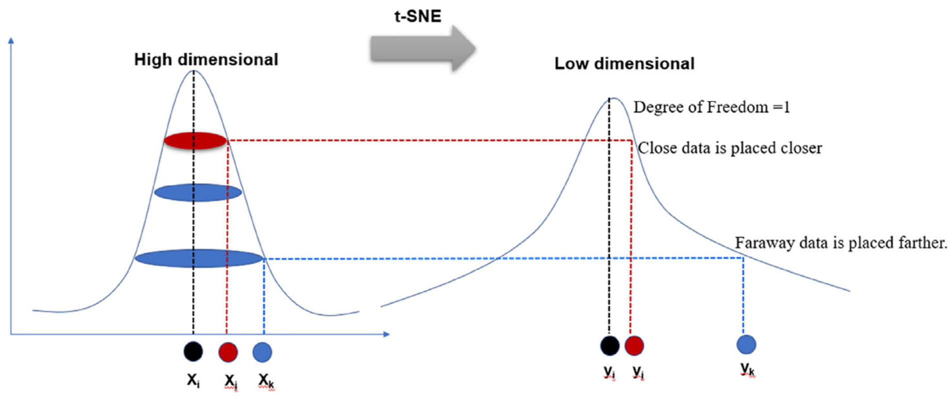


Fig. 4. The t-Stocastic Neighbor Embedding (t-SNE)
Source. Tada (2016).

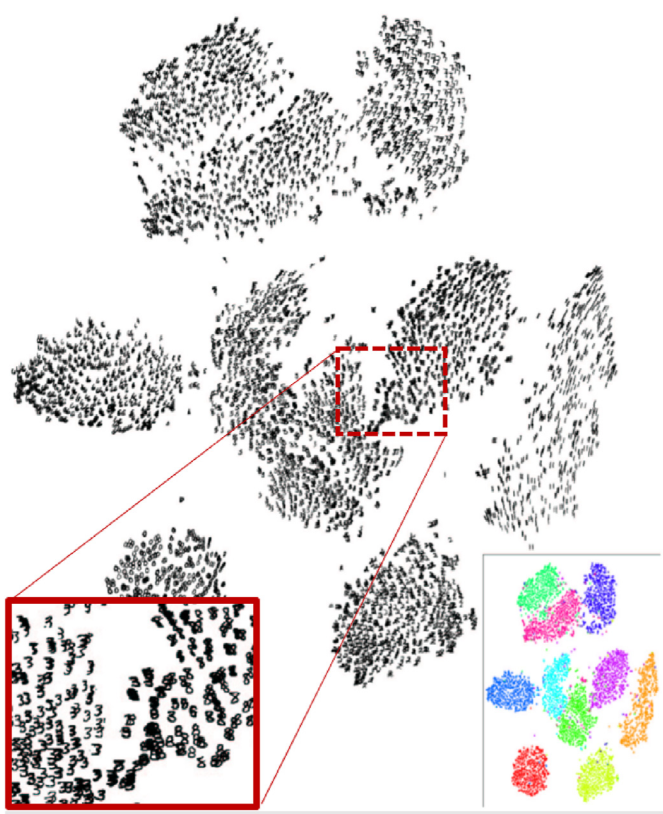


Fig. 5. Visualization of 6000 digits from the MNIST data set produced by the random walk version of t-SNE (employing all 60,000-digit images).
Source. Maaten and Hinton (2008).

based on IPC co-occurrence for individual patents. Suzuki, Junichi, and Jun (2008) explain the IPC co-occurrence as a technology convergence. Lee et al. (2015) applied IPC co-occurrence network analysis to predict the pattern of technology convergence, using patent data during the period from 1955 to 2011. In this study, by performing the IPC co-occurrence network analysis, the dynamic pattern of the convergence of AI and wind power technology is demonstrated, and the patterns of convergences between elementary technology are identified by each period. The IPC co-occurrence network analysis was performed by 10 year basis, but due to the low volume of patent data before 1990, patent data in the period of 1980 and 2000 were analyzed together.

4. Results and discussions

4.1. Descriptive results

A total of 397,340 AI patents were searched for the entire period from 1980 to 2017, and a total of 3621 wind technology patents using AI and a total of 85,054 wind technology were searched, respectively (Table 3). From looking at the number of patents filed at each patent office, the patents filed at the USPTO had the most among all four Patent Offices. Analyzing the trend of the patent applications of wind power technology using AI, the total volume of the patent application cases was not significant before 2001, but since 2001, patent applications have increased and after 2011, the number of patent applications has sharply increased. The number of patents is only 35 in 1980–1990, but increased to 165 in 1991–2000 and to 801 in 2001–2010. The number of patents in 2011–2017 more than tripled from the previous period to 2620. This phenomenon is presumably due to the active convergence and application of AI in wind power technology in conjunction with the

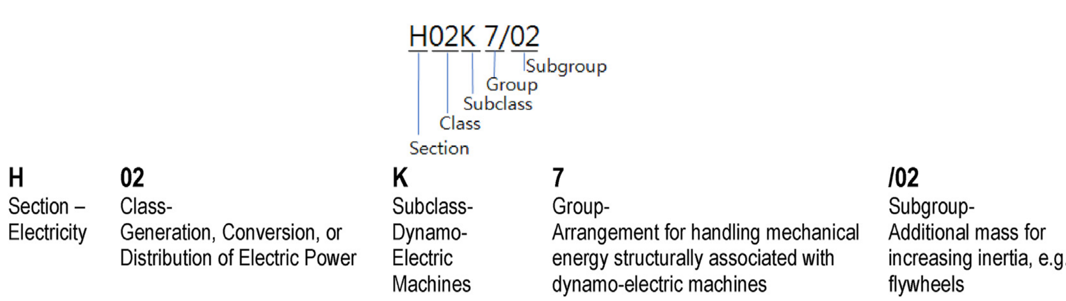


Fig. 6. IPC code classification.

Table 3
The result of patent collection between January 1, 1980 and December 31, 2017.

Patent	Period	USPTO	EPO	JPO	SIPO	Total
Artificial intelligence	1980–1990	2820	1266	5074	28	9188
	1991–2000	22,741	7297	16,530	559	47,127
	2001–2010	92,013	17,397	20,752	6342	136,504
	2011–2017	136,892	13,957	14,440	39,232	204,521
	Total	254,466	39,917	56,796	46,161	397,340
Wind power technology	1980–1990	598	181	415	61	1255
	1991–2000	873	412	1057	182	2524
	2001–2010	10,477	4979	4971	9685	30,112
	2011–2017	18,982	8236	4708	19,237	51,163
	Total	30,930	13,808	11,151	29,165	85,054
Wind power technology using Artificial intelligence	**1980~1990**	**18**	**12**	**5**	**0**	**35**
	1991~2000	**118**	**42**	**5**	**0**	**165**
	2001~2010	**600**	**168**	**27**	**6**	**801**
	2011~2017	**1930**	**392**	**68**	**230**	**2620**
	Total	**2666**	**614**	**105**	**236**	**3621**

IT boom, which began in late 1990 and begun in earnest in early 2000. Also, the global efforts to mitigate greenhouse gases may have affected the increase in the innovation activity in wind power technology. As the Kyoto Protocol was agreed upon at the Third Conference of IPCC held in Kyoto, Japan in 1997 to prevent global warming, and took effect on February 16, 2005, it can be assumed that the development of low-carbon energy technology has been actively developed since 2000. Patents filed at each patent office show the USPTO received the largest number of patents with 2,666, followed by EPO 614, SIPO 236 and JPO 105 (Table 3). The number of patents filed at the USPTO is far higher than the number of patents filed at the other three patent offices combined. Patents filed at SIPO appear to increase sharply since 2012 when deep learning developed. Before 2011, the number of patents filed to JPO was higher than that filed at SIPO, but since 2012, the number of patents filed at SIPO has surpassed that of JPO. Considering that the majority of applicants filing patents in SIPO, as with AI patent, are Chinese companies, it appears that wind technology using AI technology in China has been rapidly increasing as well following the speed at which deep-learning technology evolves. Table 3 and Fig. 7 present the number of patents in each patent office.

Table 4 lists the number of wind power technology patents using AI by the algorithm. The most searched AI algorithms were ‘neural networks’, and a total of 968 were searched, followed by

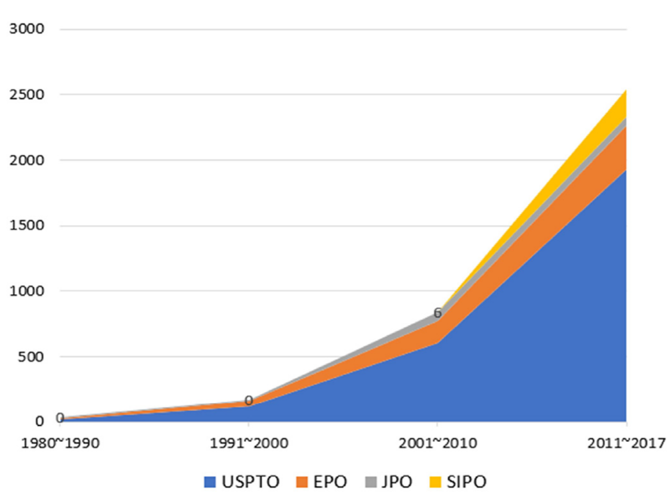


Fig. 7. The trend of issued patents for wind power technology using AI in each Patent Office during 1980–2017.

‘fuzzy systems’ with 881 cases. A total of 300 of the ‘genetic algorithm’ were searched, followed by a total of 299 of ‘bagging’ algorithm. A total of 297 of the ‘expert system’ were searched, followed by 197 of the ‘Monte Carlo’ algorithm. The list of algorithm patents is presented in Table 5. Table 5 presents the results of wind power technology patent data by each AI algorithm. Analyzing patent data by major algorithms on a chronological basis (Fig. 8.), almost all the algorithms have been steadily increasing over time. No algorithms showed a decrease. This suggests that since wind technology using AI technology is in its early stages, there is no algorithm reached a maturity stage. Traditional AI algorithms such as fuzzy, genetic algorithm, and expert systems have been increasing even after deep learning emerged in 2012, and it can be seen that they are still essential and fundamental algorithms among AI algorithms applied in wind power technology. Meanwhile, bagging and PCA algorithm have been increasing rapidly since 2010. The reason why the algorithm growth rate is different for each period can be assumed because the algorithms that are newly developed, emerged, and actively used for each period are different, and the algorithm technology accumulated is widely used after a certain period. For example, the fuzzy system is a representative algorithm of AI that has been used for a long time, but even now, it is actively applied in the fields of automatic control of wind power systems and electric power systems (Xio et al., 2010). Neutral networks and support vector machine are representative algorithms of machine learning, and they have increased significantly since 2000. It might be that these algorithms show high performance in prediction and classification.

4.2. The results of text mining analysis with t-SNE algorithm

The entire word of an abstract of the patents of wind power technology using AI was visualized through the t-SNE algorithm (Figs. 9–11). The model applied student t-distribution to the Stochastic Neigh-dividing algorithm to lower the high-dimensional data into low-dimensional data. Figs. 9–11 show visualizations of the entire word relationship. Word2Vector was extracted and related keywords were made into 100 dimensions and displayed in a two-dimensional graph. The x-axis m[1,1] and y-axis m[2,2] mean that the data has been reduced in two dimensions. A word embedding map visualized through the t-SNE algorithm shows the following results. Fig. 9 presents the technological convergence prior 2000 and can be observed that AI technology and wind power technology convergence are not active. Prior to 2000, AI-related technologies, except for Fuzzy, showed a low relationship with wind power technology. No noticeable clusters were observed, and

Table 4
The patent search result of wind power technology using AI at the four patent offices between January 1, 1980 and December 31, 2017, listed by the algorithm.

AI algorithm used in wind power technology	Abbreviation	Patent Office				Total
		USPTO	EPO	JPO	SIPO	
Neural networks	ANN, NN	732	153	39	44	**968**
Fuzzy	Fuzzy	700	135	13	33	**881**
Genetic algorithm	GA	233	41	5	21	**300**
Bagging	Bagging	228	70	1	0	**299**
Expert system	Expert system	226	46	23	2	**297**
Monte carlo	Monte carlo	123	33	10	31	**197**
Support vector machine	SVP	84	18	4	15	**121**
Principal component analysis	PCA	50	14	33	11	**108**
Evolutionary learning	Evolutionary learning	38	60	0	0	**98**
Decision trees	Decision trees	58	12	0	0	**70**
Particle swarm optimization	PSO	32	3	5	21	**61**
Random forest	RF	47	6	0	1	**54**
Recurrent neural network	RNN	34	8	2	2	**46**
Hierarchical clustering	Hierarchical clustering	13	6	0	2	**21**
K nearest neighbor	KNN	14	0	1	1	**16**
Markov decision process	Markov decision process	12	2	0	0	**14**
Q-learning	Q learning	9	3	0	1	**13**
Deep neural network	DNN	9	0	0	3	**12**
Convolutional neural network	CNN	4	1	0	4	**9**
Deep belief network	DBN	4	2	0	3	**9**
K-means	Kmeans	0	0	8	0	**8**
Ant colony optimization	ACO	5	0	0	0	**5**
Ensemble learning	Ensemble learning	5	0	0	0	**5**
Density-based spatial clustering of applications with noise	DBSCAN	2	1	0	1	**4**
Boltzmann machine	BM	2	0	0	1	**3**
Autoencoder	Autoencoder	2	0	0	0	**2**
Naïve bayes	Naïve bayes	0	0	0	0	**0**
Deep q-learning	Deep q-learning	0	0	0	0	**0**
Deep Boltzmann machine	DBM	0	0	0	0	**0**
Total		**2666**	**614**	**105**	**236**	**3621**

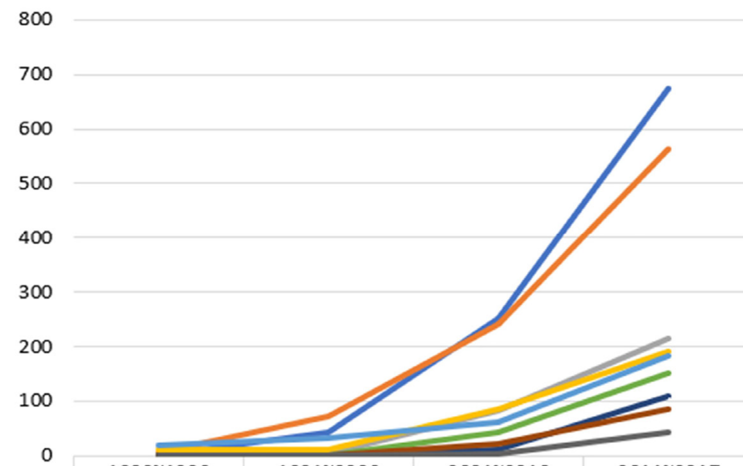
Table 5
IPC code and definition.

IPC	Section	Section definition	Class	Class definition	Subclass	Subclass definition
F02	**F**	Mechanical engineering; Lighting; Heating; Weapons; Blasting	**02**	Combustion engines; Hot-gas or combustion-product engine plants		
H02M	**H**	Electricity	**02**	Generation, conversion, distribution of electric power	**M**	Apparatus for conversion between AC and DC
H04	**H**	Electricity	**04**	Electric communication technique		
H05B	**H**	Electricity	**05**	Electric techniques otherwise provided for	**B**	Electric heating; electric lighting not otherwise provided for
G01M	**G**	Physics	**01**	Measuring; Testing	**M**	Testing static or dynamic balance of machines of structures
G05F	**G**	Physics	**05**	Controlling; Regulating	**F**	Systems for regulating electric or magnetic variables
G06F	**G**	Physics	**06**	Computing; Calculating; Counting	**F**	Electric digital data processing (computer systems based on specific computational models)
G06N	**G**	Physics	**06**	Computing; Calculating; Counting	**N**	Computer systems based on specific computational models

no patterns were observed showing high relationships between technologies. Fig. 10 presents the technology convergence of AI and wind power technologies from 2000 to 2010 and shows that technology convergence patterns had become much more active. Since 2000, artificial neural networks had led prediction and forecasting technology while being applied in wind technology. It is presented that the support vector machine algorithm has led to forecasting ability in wind power along with the neural network. It seems that fuzzy has led the turbine control technology optimized for wind speed and wind direction in relation to yaw, pitch, and blade to optimize wind turbine blades. Fig. 11 is a diagram of AI and wind power technology convergence from 2011 to 2017, and one can observe that technology convergence patterns were much more complex than before in 2010. One interesting finding is that after 2011 two words, 'stability' and 'reliability', appeared nearby 'power supply', 'generation', and 'storage'. The relationship between the words-'wind farm', 'power supply', 'short term', 'stability', and 'reliability'-appeared high. In addition, machine-learning algorithms such as SVM and neural networks have a high relationship with the words 'forecasting', 'training' and 'improved'. This shows that stability and reliability issues and related wind power technologies have become more important while wind power generation is increasing because wind power is dependent on variable winds, and that machine-learning algorithms have developed technology to address these problems by improving the prediction of wind power generation.

4.3. IPC co-occurrence network analysis

In the IPC co-occurrence network map, it can be explained that



	1980~1990	1991~2000	2001~2010	2011~2017
Neural networks	0	43	252	673
Fuzzy	6	73	240	562
Genetic algorithm	0	3	82	215
Baggin	10	12	85	192
Expert system	19	33	61	184
Monte Carlo	0	1	44	152
Support vector machine	0	0	11	110
Principle component analysis	0	0	22	86
Recurrent neural networks	0	0	3	43

Fig. 8. The trend of issued patents for wind power technology using major AI algorithms during 1980–2017.

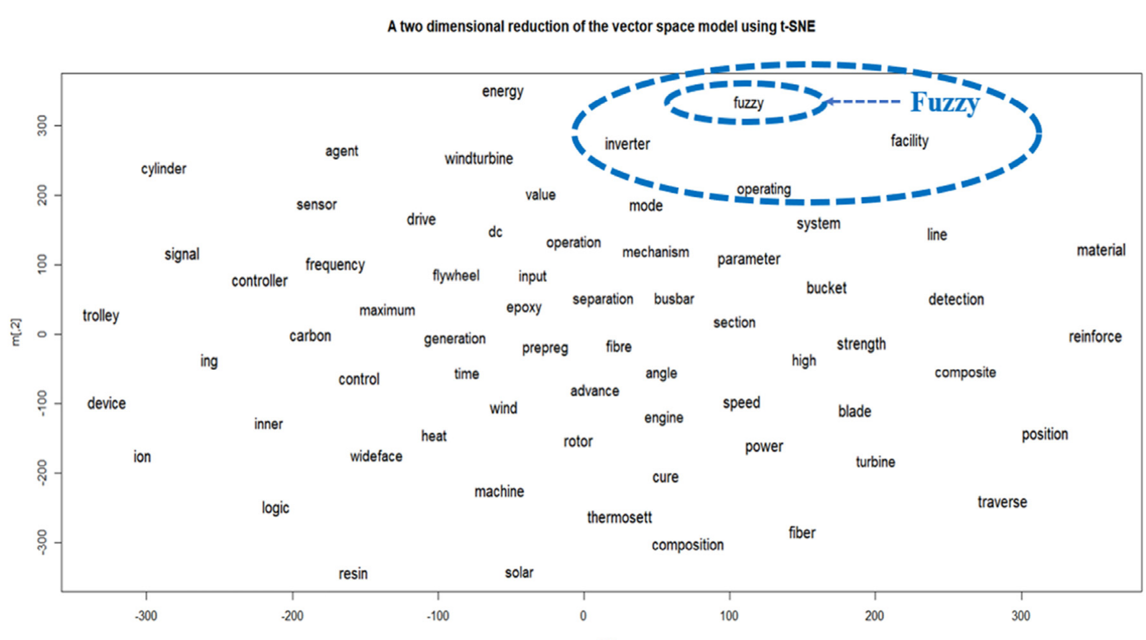


Fig. 9. The result of t-SNE algorithm model (1980–2000).

each cluster is the one resulting from multiple IPC codes appearing in a single patent document and frequent relationships between them. In other words, the coexistence of IPC belonging to different technological areas can explain the form of technology convergence. In analyzing the data for this study, the analysis was performed using only four IPC codes corresponding to the IPC subclass so that the linkage structure of science and technology is not overly subdivided. Drawing upon the outcomes of technology convergence, five classes of codes except for A, C, and E among eight IPC classifications appeared in 1980–2000 (Fig. 12). Although no specific clusters have emerged, it can be seen that convergence between technologies in various areas is underway. In particular, even

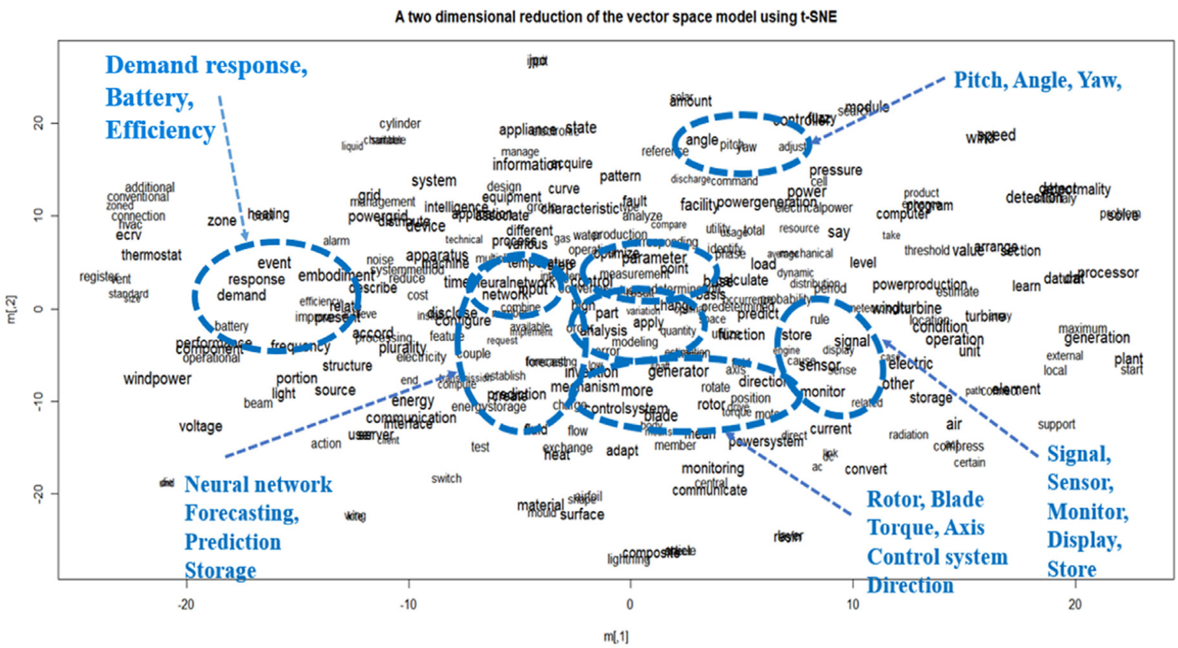


Fig. 10. The result of t-SNE algorithm model (2001–2010).

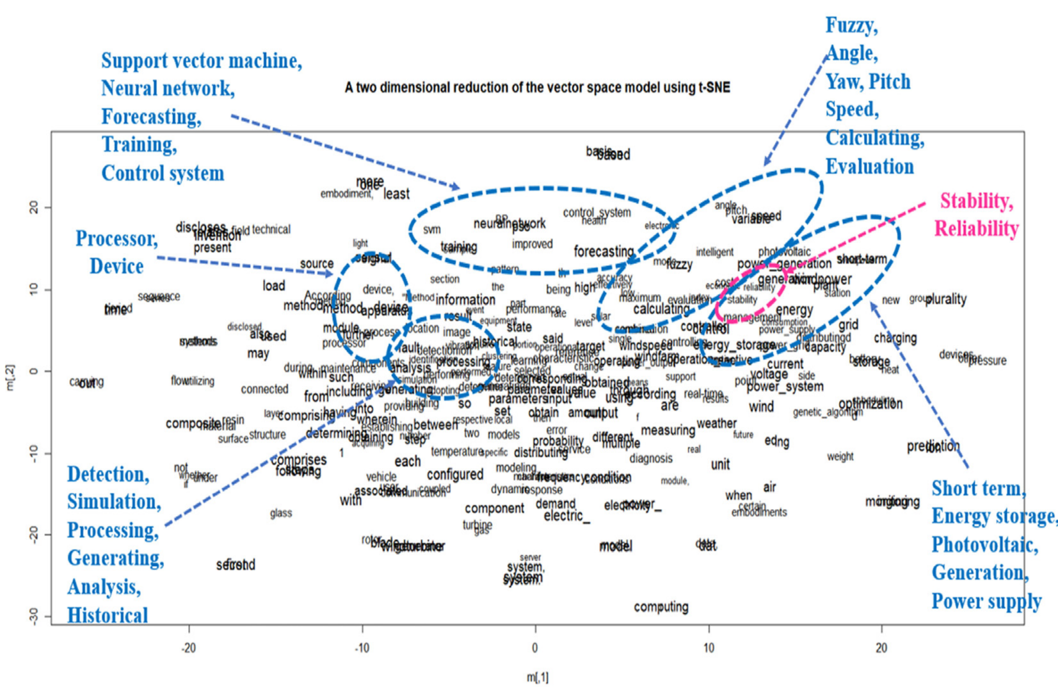


Fig. 11. The result of t-SNE algorithm model (2011–2017).

before 2000, a number of computing-related technologies such as the G6 and G02 appeared. The level of convergence between G05F and H02M appeared to be high. G05F is a technology related to 'systems for regulating electric or magnetic variables', and H02M is related to 'apparatus for conversion between current (AC/DC) or voltage'. Thus, it can be seen that the demand for system-related technologies to control voltage and current has increased. As demonstrated in Fig. 13, the degree centrality of the G06, especially G06F, was high in 2001–2010. G06F corresponds to 'electric digital data processing' and mainly includes data processing devices, equipment, and methods. Thus, from 2001 to 2010, it can be seen that data processing technologies had actively used in wind technology. Compared with the previous period, it appeared that a more diverse field of technologies is emerging and becoming a core technology. Since 2011, the degree of technology convergence of IPC codes such as G06N, H04I, H05B, and G01M has been high (Fig. 14). G01 is a technology related to 'measuring and testing' and F02 is a technology related to 'combustion engines: hot-gas or combustion-product engine plants'. It is interesting to note that in the course of the wind and the AI technology convergence process,

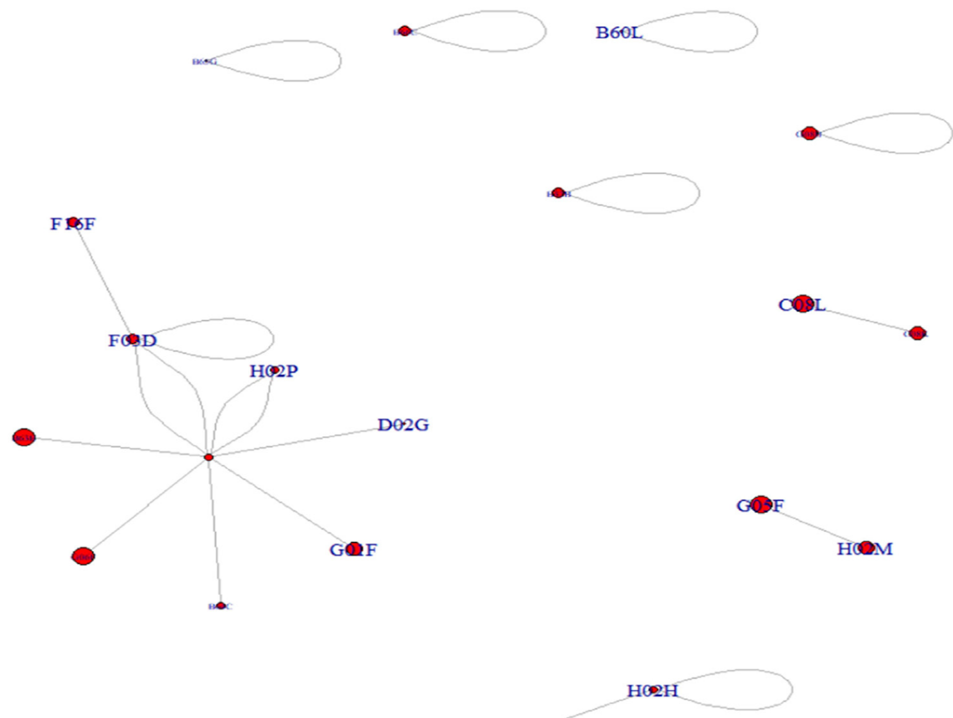


Fig. 12. IPC Co-occurrence network map (1980–2000).

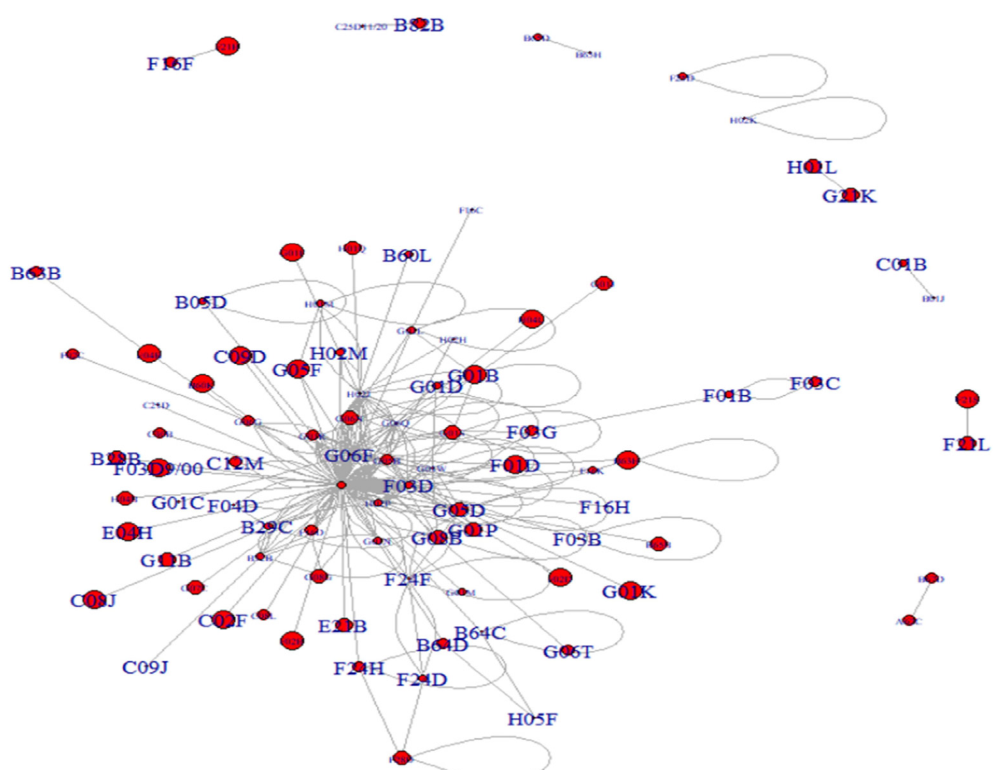


Fig. 13. IPC Co-occurrence network map (2001–2010).

convergence between technology related to combustion engines and technology related to measuring and testing is actively underway. Table 5 shows the description of each section of the IPC code.

5. Summary

This paper proposed a novel approach and methods to analyze the dynamic changes of the application of AI in wind power

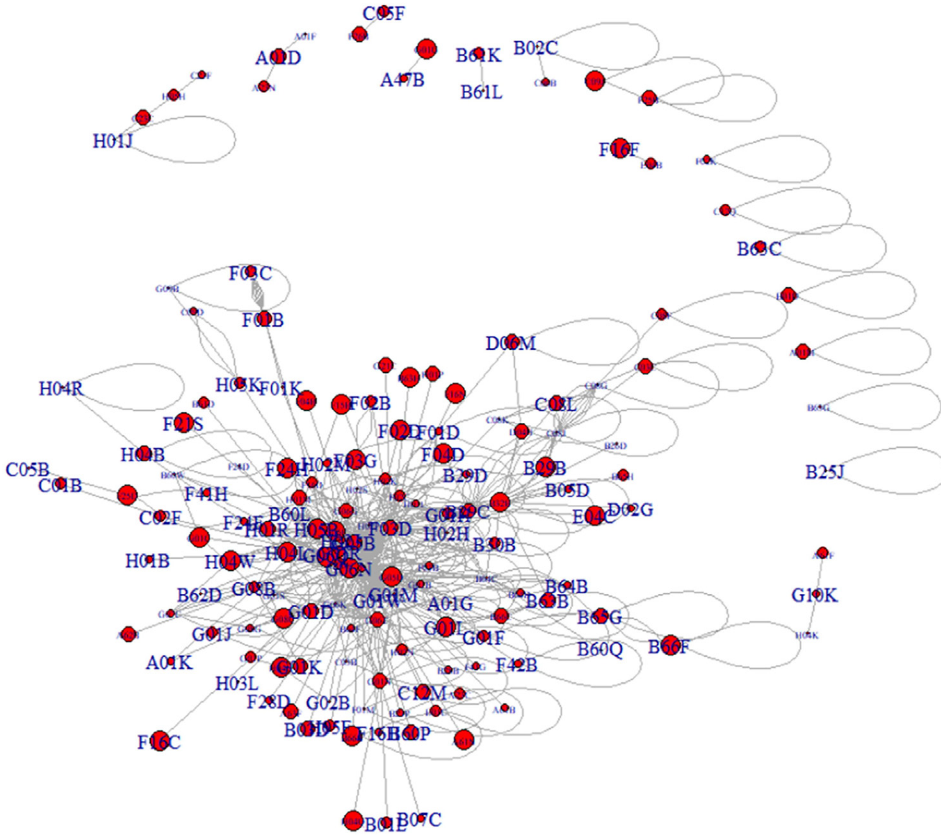


Fig. 14. IPC Co-occurrence network map (2011–2017).

technology overtime during 1980–2017. Through literature review, descriptive statistics, text mining analysis with t-SNE algorithm model, and IPC co-occurrence network analysis, this study revealed the following findings. First, when it comes to AI algorithms used in wind power technology, fuzzy, neural networks, and support vector machine algorithms have been widely used to predict wind speed and wind power and also applied to improve the stability and reliability of wind power systems. Fuzzy has been widely used to optimize the operation and maintenance of wind turbines and to improve the performance of wind turbine operation, and neural networks and support vector machine has been applied to predict wind power. Beginning from 2011, when machine learning has been used widely and deep learning emerged, support vector machine, convolutional neural network (CNN) and recurrent neural network (RNN) algorithms have been applied increasingly in wind power technology. Second, in regard to wind power technology innovation evolved with the advancement of AI, since 2011, material-related technologies and battery technologies, as well as energy storage systems, have emerged as core technology groups in wind power technology. The technology group of energy storage systems has been interrelated with many technologies than any other technologies, showing the highest degree of centrality. This can be inferred that storing variable and excessive wind energy is becoming more important to increase efficiency and maintain a stable wind power system. The material sector, which is an important part of the lightweight and cost reduction of wind turbines, has also emerged as a key technology group. This can be seen that light and solid wind turbine blades improve the performance of wind power generation, and that AI enables more accurate material packages of wind blades. Until 2000, prominent core technology visually did not emerge, but technologies in the area of energy storage systems after the 2000s and material technologies after 2010 appeared a core technology. It can be assumed that this is the result of the development of machine learning algorithms such as support vector machines and neural network algorithms after 2000 and the result of the application of these algorithms to accumulated big data of wind power. Fig. 15 present the evolution of AI application in wind power technology during 1980–2017.

6. Conclusion

AI can better predict the wind speed and direction in advance and predict power production accordingly. AI is also used to predict the fault of wind turbines in advance so that solutions for the fault can be prepared preemptively to reduce the operation costs. By controlling the generator under optimal conditions using past data, AI can maximize the power generation efficiency of wind turbines. AI has been increasingly applied in wind power automation and optimization. These findings suggest that AI promotes low-carbon energy technology innovation by spurring wind technology developing and accelerating energy transition from fossil fuel to green energy. As many countries proclaim carbon neutrality, wind power generation, especially offshore wind power generation, is drawing more attention as a clean energy source for achieving carbon neutrality. As the construction of offshore wind power plants is growing and the wind turbines are also increasing in size, it is important to increase the capacity factor of wind farms to secure economic feasibility. The speed and scope of the technological development of AI are fast and broad, and the application of AI in wind power technology is evolving fast. Thus, to respond to this fast-changing landscape, policy-makers need to understand the changing landscape of AI's role in green technology

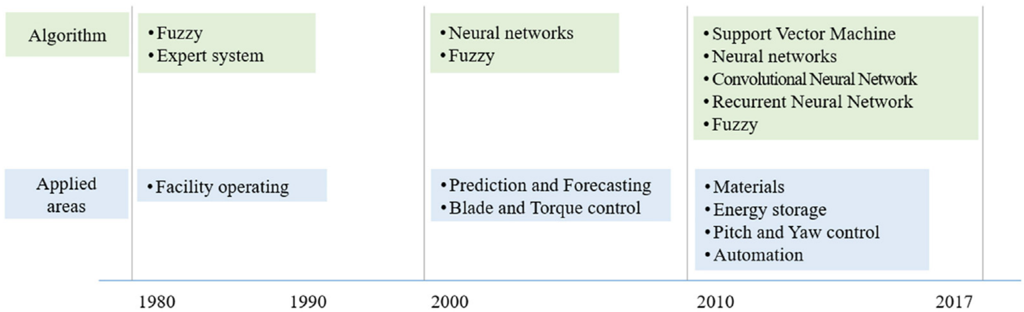


Fig. 15. The evolution of AI application in wind power technology.

advancement and support knowledge diffusion and create an ecosystem for low carbon technology innovation.

CRediT authorship contribution statement

Mekyung Lee: Conceptualization, Methodology, Investigation, Writing, Visualization, Writing – original draft. **Gang He:** Validation, Supervision, Writing – original draft, Writing – review & editing.

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.

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