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Machine Learning based Wind Power Forecasting for Operational Decision Support

School of Technology and Innovations
Industrial Management
Licentiate of Technology

Vaasa 2022

UNIVERSITY OF VAASA
School of Technology and Innovations

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Title of the thesis:	Machine Learning based Wind Power Forecasting for Operational Decision Support
Degree:	Licentiate of Technology
Discipline:	Industrial Management
Supervisor:	Iivari Kunttu, Heidi Kuusniemi
Year:	2022 **Pages:** 195

ABSTRACT :
To utilize renewable energy efficiently to meet the needs of mankind's living demands becomes an extremely hot topic since global warming is the most serious global environmental problem that human beings are facing today. Burning of fossil fuels, such as coal and oil directly for generating electricity leads to environment pollution and exacerbates global warning. However, large-scale development of hydropower increases greenhouse gas emissions and greenhouse effects.

This research is related to knowledge of wind power forecasting (WPF) and machine learning (ML). This research is built around one central research question: How to improve the accuracy of WPF by using AI methods? A pilot conceptual system combining meteorological information and operations management has been formulated. The main contribution is visualized in a proposed new framework, named Meteorological Information Service Decision Support System, consisting of a meteorological information module, wind power prediction module and operations management module. This conceptual framework has been verified by quantitative analysis in empirical cases. This system utilizes meteorological information for decision-making based on condition-based maintenance in operations and management for the purpose of optimizing energy management. It aims to analyze and predict the variation of wind power for the next day or the following week to develop scheduling planning services for WPEs based on predicting wind speed for every six hours, which is short-term wind speed prediction, through training, validating, and testing dataset.

Accurate prediction of wind speed is crucial for weather forecasting service and WPF. This study presents a carefully designed wind speed prediction model which combines fully-connected neural network (FCNN), long short-term memory (LSTM) algorithm with eXtreme Gradient Boosting (XGBoost) technique, to predict wind speed. The performance of each model is tested by using reanalysis data from European Center for Medium-Range Weather Forecasts (ECMWF) for Meteorological observatory located in Vaasa in Finland. The results show that XGBoost algorithm has similar improved prediction performance as LSTM algorithm, in terms of RMSE, MAE and R2 compared to the commonly used traditional FCNN model. On the other hand, the XGBoost algorithm has a significant advantage on training time while comparing to the other algorithms in this case study. Additionally, this sensitivity analysis indicates great potential of the optimized deep learning (DL) method, which is a subset of machine learning (ML), in improving local weather forecast on the coding platform of Python.

The results indicate that, by using Meteorological Information Service Decision Support System, it is possible to support effective decision-making and create timely actions within the WPEs. Findings from this research contribute to WPF in WPEs. The main contribution of this research is achieving decision optimization on a decision support system by using ML. It was concluded that the proposed system is very promising for potential applications in wind (power) energy management.

KEYWORDS: Decision-making, Deep learning, Energy management, Machine learning, Operations management, Strategic management, Wind power forecasting, XGBoost.

Acknowledgement

Firstly, I would like to thank Dr. Iivari Kunttu at Häme University of Applied Sciences as my first supervisor. He is very supportable and patient all the time.

Thanks for Prof. Heidi Kuusniemi at University of Vaasa being as my second supervisor. She gave guidance from key perspectives.

Dr. Ari Venäläinen from Ilmatieteen Laitos (Finnish Meteorological Institute) guided me. He is a rigorous and amiable expert, and he provided me with the guidance from the domain of meteorology.

Prof. Yang Liu from the Department of Management and Engineering in Linköping University gave me support and lit up a lamp for me when I got confused.

I would like to express my sincere gratitude to Prof. Donald Huisingh at University of Tennessee and for the invaluable comments during the writing phases.

The dean of Technology and Innovation Management Unit in University of Vaasa, Dr. Raine Hermans, led and contributed to my graduation process much. Mrs. Ulla Laakkonen is an experienced administration staff member, and I got a lot of help from her for the past few years. Prof. Marja Naaranoja always has constructive opinions and she made me more confident. Thanks to Mrs. Juuli Honko for doing lots of paperwork and job related. Tobias Glocker made important comments and supported me most of the time.

I extend this warm Thank You to all researchers and staff at University of Vaasa and University of Twente who made my learning experience in Finland and The Netherlands memorable. Besides these, my colleagues are always very supportive and encouraging. My best friend Mei Sun-Simonen stands by me, beieves in me and it never could be another.

Finally, I would like to thank my parents, my husband, and my little lovely princess. My parents are the teachers of my life and they taught me how to become the best version of myself. Although my husband devotes all to his work and dream, then I need to devote more to my family, job, and study. I also got too much, for example, sharing every exciting moment with my husband, joining every second of happiness with my small sweetheart, enjoying the warm and sweet family atmosphere. Thanks for their unconditional support, forever love and companion to me all through the way, especially during the most difficult time in doing this research.

Meanwhile, the most important thing is that I am on the way to get the doctoral degree at the same time. My dearest father would be extremely proud of this. The ending of this study may be a new start for the research journey.

Expecting nothing and appreciating everything is my life attitude. Doing is everything while saying is nothing. I believe life is preparing a gift for everyone!

Kiitos, tack, bedankt, danke, thank you, 谢谢(謝謝) , 감사합니다, ขอบคุณ!

Linköping and Vaasa, May 2022

Wenshan Yang

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Abbreviations

AI	Artificial intelligence
ANN	Artificial neutral network
CBM	Condition-based maintenance
CDR	Climate data record
DL	Deep learning
EWEs	Extreme weather events
KF	Kalman filters
LSTM	Long short-term memory
MAE	Mean absolute error
ML	Machine learning
NWP	Numerical weather prediction
RERs	Renewable energy resources
RMSE	Root mean square error
SDE	Standard deviation of error
SVM	Support vector machine
TBM	Time-based maintenance
WERs	Wind energy resources
WPD	Wind power density
WPEs	Wind power enterprises

WPF	Wind power forecasting
WPP	Wind power potential
XGBoost	Extreme gradient boost

Appendix 1.
Yang, W., Liu, Y., and Yang, G. (2014): A review of innovation in wind power forecast. *Proceedings of the 11th International conference on Innovation & Management*.

Appendix 2.
Yang, W., Liu, Y., and Yang, G. (2014): The impact of climate change on wind power enterprises. *Proceedings of the 11th International conference on Innovation & Management*.

Appendix 3.
Liu, Y. and Yang, W. (2015): Meteorological information service support system in wind park application. *International journal of production economics*, no. 2, pp. 222-237.

Appendix 4.
Yang, W. and Liu, Y. (2015): A study on renewable energy potential based on the global atmospheric data. *Global Cleaner Production & Sustainable Consumption Conference.*

1 Introduction

1.1 Background

With the deterioration of the global environment and the exhaustion of fossil energy, the mineral energy resources consumed in the future will gradually be replaced by renewable energy resources. The development and utilization of ecological energy is very important for environmental protection and has become a global issue. Renewable energy does not pollute the environment at the point of energy generation, and generally has a much lower pollution footprint than traditional energy from installing to decommissioning and can diversify the power generation technology (He et al., 2021). Increasing population growth requires more sustainable development of energy.

Wind energy stands out when compared with other energy because it is free, clean, inexhaustible, has the capacity to generate greater power, and has lower energy costs. Hence, wind power plays an important role as a source of energy supply (Adeyeye, Ijumba, & Colton, 2020; Bórawski, Bełdycka-Bórawska, Jankowski, Dubis, & Dunn, 2020). Wind energy resource is becoming a leader in the current energy transition process as the most significant characteristics of wind energy are, clean, ecological, and inexhaustible (Gil-García, García-Cascales, Fernández-Guillamón, & Molina-García, 2019; Saleh Asheghabadi, Sahafnia, Bahadori, & Bakhshayeshi, 2019).

Excessive consumption of traditional fossil energy, hydrocarbon fuel for energy production has led to a severe global air pollution and climate change. However, wind energy is widely considered to be a qualified renewable as it can mitigate climate change impacts and achieve low-carbon transformation (Cui, Liu, Ali, Gao, & Chen, 2020; Saeed, Ahmed, & Zhang, 2020; N. Shen, Wang, Peng, & Hou, 2020).

1.2 Wind Power around the World

According to Renewables 2021 Global Status Report from REN21, the estimated share of renewables in global electricity generation was more than 29% by the end of 2020. Figure 1 shows wind power global capacity and annual additions during 2020-2020. China and the United States accounted for a bit more than three quarters of the global electricity production rise in 2020. Wind power capacity and additions of top 10 countries in 2020 can be seen in Figure 2. Demand of renewable energy resources (RERs) is growing as the global population grows continuously and on the other hand fulfilling the climate change mitigation aims agreed in UNFCC COP 21 Paris 2015 require that an even larger and larger share of energy production be based on renewable energy. According to Renewables 2016 Global Status Report, developed and developing countries have had increased investment in solar power by 12% and wind power by 4% while biomass and waste to energy, ocean, biofuels, small hydro, geothermal power reduced respectively by 42%, 42%, 35%, 29%, 23% in 2015. Global Wind Energy Council claimed that global installed wind power capacity has increased by 63,467 MW in 2015, representing annual market growth of 22%. Although world electricity generation produced by wind power is still low, it is growing rapidly. Wind power capacity is 743 megawatts and ranked secondly among renewable power capacity while the hydropower capacity is 1,170 megawatts by the end of 2020. As well, U. S. Energy Information Administration data show that particularly some European countries had the largest portion of their electricity generation from wind: Denmark (48%), Portugal (25%), Spain (22%), Ireland (38%), Germany (27%). So far, the most important wind gross electricity producers in the EU are Germany and Spain. The highest increase of wind cumulative installed capacity in 2022 will be in Croatia (Bórawski et al., 2020).

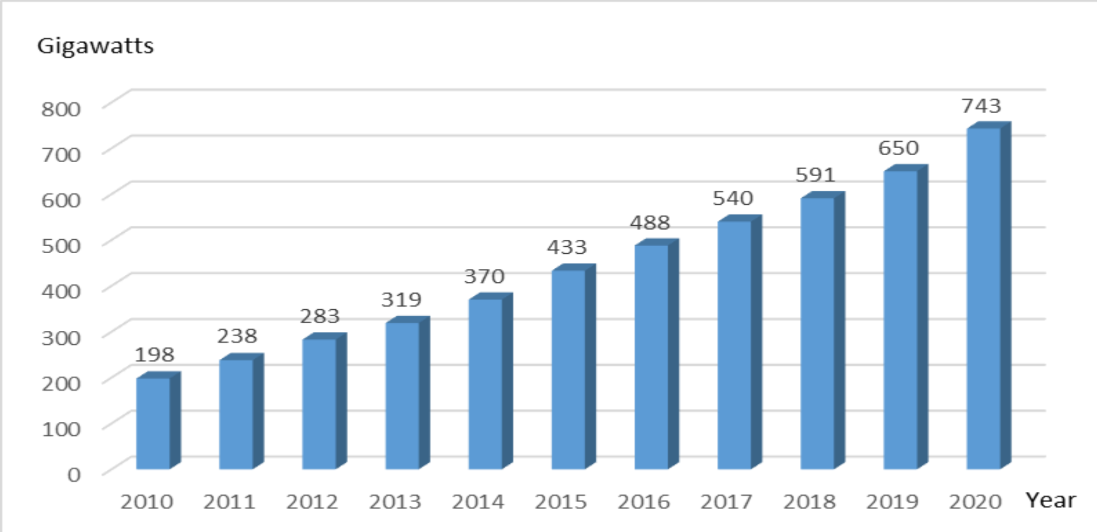

Figure 1. Wind power global capacity and annual additions, 2010-2020. adopted from REN21, 2021

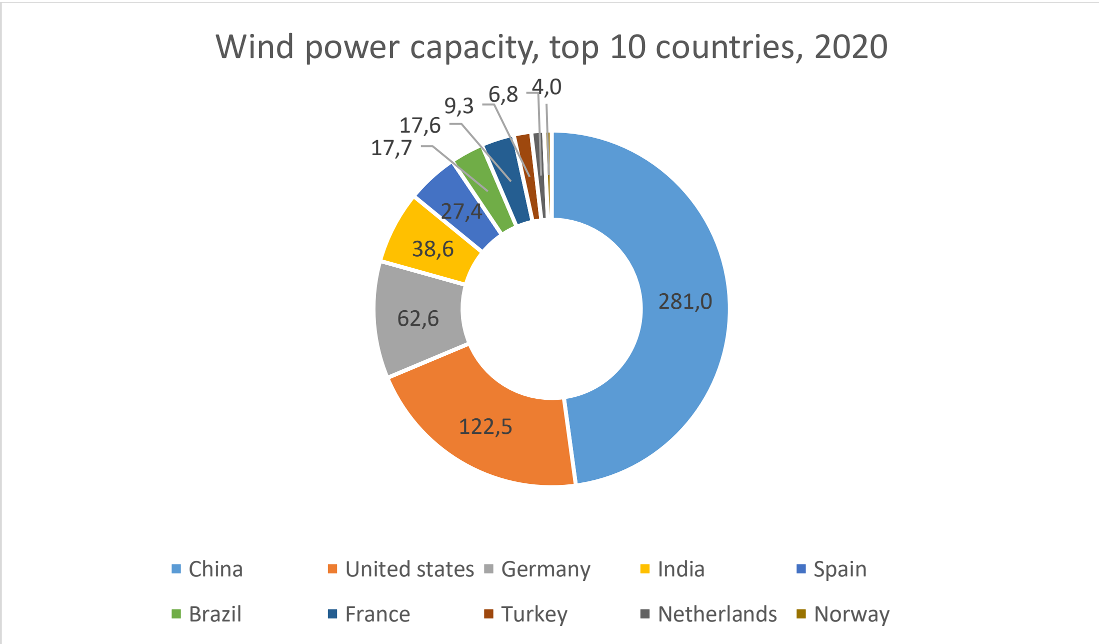

Figure 2. Wind power capacity, top 10 countries, 2020. adopted from REN21, 2021

Changes in temperature, precipitation, sea level, and the frequency and severity of extreme events will likely affect how much wind power generation is produced, delivered, and consumed. For example, various weather phenomena, such as rainstorm, hail, thunderstorm, and tornado, can generate damage more or less to wind turbines.

Despite the challenges the production of wind power is the foreseen trend (Kandpal & Broman, 2014).

The wind power construction In Finland began later than in many other European countries. However, from 2012 to 2013, wind power construction has gained momentum and national construction and production statistics have been broken year after year. In Finland, the wind turbine capacity in offshore parks will increase to be over 7MW instead of the largest turbines currently 5MW in the future.

According to Finnish wind power statistics 2021 from Suomen Tuulivoimayhdistys, at the end of 2021, there were 962 installed wind turbine generators, with a combined capacity of 3257 MW. They generated 11,7% of Finland’s electricity consumption in 2021. 141 new wind farms were built in Finland in 2021, but annual wind power production increased by 26 % comparing with previous year. They generated 9,3 % of Finland’s electricity consumption in 2021. Wind power production for the whole year was 8,061 TWh, or 11,7 % of all electricity production in Finland. Wind power covered 9,3 % of Finland’s electricity consumption and the amount is expected to increase to 25 % by 2025 at the latest.

Suomen Tuulivoimayhdistys also pointed out that Finland has the potential to increase wind power capacity considerably. The objective of the wind power industry is to achieve at least 30 TWh of annual wind power production in Finland in 2030, which corresponds to approximately 30% of Finland's electricity consumption at that time. This means there is great potential in Finland’s wind power development.

1.3 Meteorological Source

Wind is a type of meteorological phenomena and wind energy is one kind of natural resource which is obtained from the wind. It is one of the oldest-exploited energy sources by humans and today is the most seasoned and efficient energy of all renewable energies. Wind energy results from horizontal air pressure differences, which means air movement, have regional differences, and are affected by surrounding terrain. Wind power generation is the most efficient technology to produce energy in a safe and environmentally sustainable manner. It is a process of converting the energy produced by the movement of wind turbine blades driven by the wind, namely as kinetic energy of the air, into electric energy (Emeis, 2018).

Wind generated when the pressure gradient force, the Coriolis force and friction are combined. The greater pressure gradient force, the greater the wind force. The higher the latitude, the greater the Coriolis force. The rougher the underlying surface, the greater the friction and the smaller the wind force. Among them, the Coriolis force influences wind direction, friction influences wind speed while the pressure gradient force influences both wind speed and wind direction.

There are many factors that affect wind speed, such as, topography, meteorological factors. Topography includes geomorphology, surface obstacles, and so on. For meteorological factors, temperature, humidity, pressure, etc. have a greater impact on the changes in wind speed, making the daily variation regularity of wind speed not good, and the prediction accuracy is not high.

Wind farms, namely wind parks, where planted groups of wind turbines, are located on open land, on mountain ridges, or offshore in lakes or the ocean. Wind farms can be either onshore or offshore.

According to the 8th edition of WMO Guide to Meteorological Instructions and Methods of Observation from World Meteorology Organization (WMO) in 2014, the measurement of wind speed should be taken from a site that is well exposed to the wind, and not in the lee of obstructions such as buildings, trees, and hillocks. If it is possible, the measurement site should be a good distance from obstructions, namely at least 10 times of the obstructions’ height and upwind or sideways by at least twice of the obstruction’s height. Direction should be estimated from a vane (or banner) mounted on a pole that has pointers indicating the principal points of the compass. The vane is observed from below, and wind direction may be estimated to the nearest of the 16 points of the compass.

There are advantages and disadvantages of developing wind power generation based on its own natural characteristics of wind energy.

a. Environment friendly:

Wind energy is a source of renewable energy. Wind turbines do not release emissions that can pollute the air or water. Wind turbines may also reduce the amount of electricity generation from fossil fuels (Tong, Cheng, & Tong, 2021).

b. Inexhaustible:

Wind power provides energy from air movement and has the capacity to generate greater power. This process will continue as long as there is weather on planet Earth, meaning that energy can be gained from air movement forever (Oñederra, Asensio, Saldaña, Martín, & Zamora, 2020).

c. Unstable:

As the wind power is proportional to the cubic wind speed, even small errors in estimation of wind speed can have large effects on the energy.

d. Unpredictable

Renewable energy sources, such as wind energy, solar energy, are innately unpredictable, owing to the uncertain nature of themselves and bring about more challenges in the distribution networks (Rezaeian-Marjani, Masoumzadehasl, Galvani, & Talavat, 2020). Even wind energy is variable but intermittent, but not completely random and unpredictable.

1.4 Decision Support

To ensure the proper operation of renewable energy-based hybrid systems, and ensure demand and increase system performance, energy management techniques and a decision support element is needed for efficient management of energy. The strategic management process should be turned into a management tool with a decision support element in terms of sustainability. A robust energy management strategy allows the system to meet demand, to increase the lifetime of the components, increasing operating costs and, to ensure maximum use of renewable sources, to reduce energy costs output, to protect components from overload damage and enhance the reliability of the power system as a result, to optimize system performance (Ammari, Belatrache, Touhami, & Makhloufi, 2021; Çetin & Ziya Sogut, 2021).

To establish an assessment model, find crucial solutions, support industrial decision-makers highlighting specific actions, some models with proposed energy management strategy were designed, the energy management strategy was optimized, proved effective for intelligent energy systems (X. Huang, Zhang, & Zhang, 2021; Trianni, Cagno, Bertolotti, Thollander, & Andersson, 2019). The tool may serve as a point of reference for energy and environmental decision support aids in communities where important cultural resources, values, and traditions are potentially impacted by energy management decisions (Necefer, Wong-Parodi, Small, & Begay-Campbell, 2018).

A powerful reliability management tool, to deal with the risk assessment, is indispensable in decision-making. Common requirements for an effective decision support platform include credibility, relevance, legitimacy, model accessibility, end-user satisfaction, timeliness, and costs for maintenance and computing. Among these, accurate identification of the risks and timely quality management of the risks play an important role in improving the quality, safety, and reducing loss costs. Strategic decision-making on long-term drought risk management can be supported by integrated assessment models to explore uncertain future conditions and potential policy actions (Hamilton et al., 2019; P. Liu & Li, 2021; Mens, Minnema, Overmars, & van den Hurk, 2021).

Deep learning (DL) algorithms train data longer than ML algorithms since training big data, so it is meaningless of decision-making in some cases of requiring results in a limited time. Results are only valuable if they can be obtained within a specified time-period. By reviewing articles which related to relevant topics, it is found that lots of articles related to decision support and ML are linked to the domain of clinics and medicine, such as, surgical decisions, triage for patients, emerging decision support, and diagnostic Decision Support in Radiology. Compared to those topics, fewer articles are relevant to the topic of WPF.

The main objective of this research is to support grid dispatchers and decision-makers in electricity transition towards climate friendly economies by giving them suggestions and options in planning and designing low carbon solutions. To do so, Meteorological Information Service Decision Support System integrates artificial intelligence (AI) algorithms with meteorological information decision support platform while it develops optimal operational planning via predicting wind speed to optimize energy management decision-making. It is an AI decision support system that considers the uncertainty of wind power output and proves that the machine learning (ML)-based system can optimize the prediction results while comparing with some other traditional algorithms for wind power enterprises (WPEs).

This decision support system consists of a meteorological information module, wind power prediction module and operations management module. It utilizes meteorological information for decision-making based on condition-based maintenance in operations and management for the purpose of optimizing energy management. This research attempts to make full use of distributed new energy and rationalize the energy management strategy of grid dispatching companies. In this research, decision maker refers to the level of person who is involved in the operational decision-making process, focuses on more strategic decisions, and makes the final decision organizationally to adopt the practice.

The expected result is that, by using Meteorological Information Service Decision Support System, it is possible to support effective decision-making and create timely actions within the WPEs. Besides this, findings from this research contribute to WPF in

WPEs. The main contribution of this research is to achieve decision optimization on a decision support system by using ML algorithms.

1.5 Research Questions

The main research objective of this research is to improve wind power prediction through increasing wind speed accuracy by using AI algorithm as the key research method. To achieve its objectives, decision support platform of Meteorological Information Service Decision Support System answers the following questions.

Judging from the background and research objectives, the central research question (RQ) is as follows.

Central RQ: *How to improve the accuracy of wind power forecasting by using artificial intelligence methods?*

The five sub-questions can be formulated:

Sub-question 1. *What is the innovation in the development process of WPF among so much relevant research?*

Sub-question 2. *How climate change influences WPEs and what factors affect wind power output?*

Sub-question 3. *Can there be a general framework to help forecasting wind speed and wind power more effectively in decision-making?*

Sub-question 4. *How to use the global atmospheric reanalysis data to analyze the potential of WERs in Finland?*

Sub-question 5. *What is the sufficient ML algorithm to improve the accuracy of wind speed prediction?*

The five sub-questions are depicted as above and developed from the main research objective. The sub-question 1, 2, 3 and 4 are responded respectively by paper 1, 2, 3 and 4 while sub-question 5 is answered in chapter 3. These four related papers are attached in the appendix. The structure of the research method used is presented in figure 3.

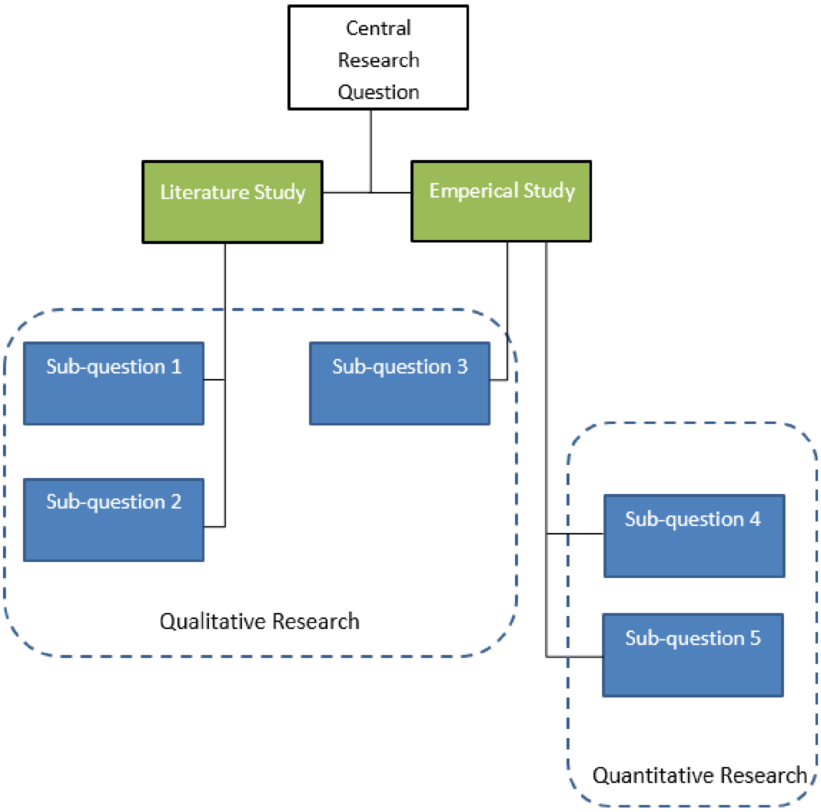

Figure 3. Research method for research questions.

1.6 Opportunities and Challenges

RERs are one of the solutions to solve the challenges related to energy production and mitigation of climate change. It is possible to replace fossil fuels by developing a variety of renewable energy, including hydro, wind, solar, wave and biomass, geothermal and ocean. Making strategies for converting present energy systems into a 100% sustainable renewable energy system is crucial (Dincer, 2000; Lund, 2007). As an example, since the early 1980s, Denmark has been one of the leading countries in the world in the field of wind energy utilization based on the management of development and diffusion of sustainable technologies (Christensen & Lund, 1998). One research predicted that global energy demand in 2040 will be approximately 30% higher than it was in 2010. Because the typical characteristics of wind energy are stochastic and intermittent, it is important to know and use appropriate renewable energy technologies in the whole process of producing wind power generation (Dashwood, 2012). Another research in China showed developing green energy business in emerging economies, with the aim being long term sustainability of a healthy level of overall flexibility of the wind power industry chain, pay special attention to competition flexibility, technology flexibility, and intellectual property and talent flexibility (Z.-Y. Zhao, Zhu, & Zuo, 2014). In one word, the future development of wind power presents a significant opportunity in terms of providing low carbon energy.

As it known to everyone, challenges always go with opportunities. Wind power is fluctuating, intermittent as wind has the characteristics of volatility, intermittent, and low energy density. These features do not have a significant impact on the grid when wind power accounts for a small proportion of the grid. However, as wind power develops rapidly in this decade, wind power production will face serious problems which are electrical system safety, operations stability. Meanwhile, there exist also environmental challenges and technical challenges.

1.7 Structure of the Study

This study is published as articles based. The structure of this study is divided into six chapters as follows.

Chapter one presents an introduction and background of this research. After describing the opportunities and challenges, depicting the function of strategic decision support in risk management, it also displays the central research question, five sub-questions, opportunities, and challenges.

Chapter two firstly reviews, makes a statistic and analysis on the relevant articles, and presents circumstances of mainstream research towards relevant topics. Then it describes the research gap of this research.
Chapter three presents the research methodology. It includes research philosophy, research approach, research strategy, research methods, research design and data collection. Research process is described also.

Chapter four depicts the results and findings of the case study.

Chapter five provides the summary of the publications. This section interprets the logic connections and depicts the main content of each article.

Chapter six makes conclusions for this study, provides contribution, managerial implications, and research limitations, gives some final remarks, and proposes for the future research.

The Appendix consists of four original articles (paper 1-4) and author's role in the whole research.

2 Literature Review

This chapter firstly makes a statistic of related articles, and then classifies them into different categories by time-period, research methodologies and research topics. Chapter 2 also summarizes and reviews state-of-art articles on wind energy resources (WERs), wind power prediction, commonly used wind power forecast (WPF) algorithms, energy storage system, wind turbine control system, errors, and risk management. Research gap is depicted after reviewing literatures.

2.1 Focused Literatures

There exist large number of issues in aspects of wind energy that must be examined. For example, studies may focus on installed capacity, mathematical models, optimization of energy output, facility maintenance, or excessive energy storage. On the other hand, there also exist many literature reviews investigated in the same areas. For instance, review on forecasting wind speed, wind power density (WPD) and generated power, review wind energy resources (WERs) in the urban environment, review on wind power short-time prediction, specific wind power forecasting (WPF) models, local energy plans and policies. Besides reviewing papers, this study also reviews the state of the art of wind energy conversion systems and technologies, wind energy status in a specific year, global renewable electricity scenario, wind speed probability distributions in application, etc. This research gives a comprehensive review on the WERs, WPF, whole developing process, innovative technologies, and the related areas in Chapter 2.

Based on more than 500 selected articles, the main objectives of this review work can be formulated as follows: (i) a summary of the previous studies, (ii) a construction framework of related research topics, and (iii) the identification of the future research. These articles were mainly chosen from SCOPUS (Elsevier), ScienceDirect (Elsevier), Web of Science (ISI Web of Knowledge) and Google Scholar, classified by Mendeley, and analyzed by Microsoft Excel statistical function. The earlier publications may not be displayed on the Internet, and this may have a small influence on the reviewed literature work.

2.2 Description of Material Reviewed

2.2.1 Distribution across time-period

After searching by relevant keywords, the number of reviewed papers is 506. The temporal variation of reviewed publications during the period 1976-2021 is shown in Figure 4. These are incomplete statistics since the papers produced in 2020 continue to be published. Thus, high numbers of publications are found for the time-period between 2011 and 2021. In general, the total number of papers increases steadily year by year during 2014-2020. The review of publications was based on articles from SCOPUS (Elsevier), ScienceDirect (Elsevier), Web of Science (ISI Web of Knowledge), Google Scholar, national and international renewable energy reports.

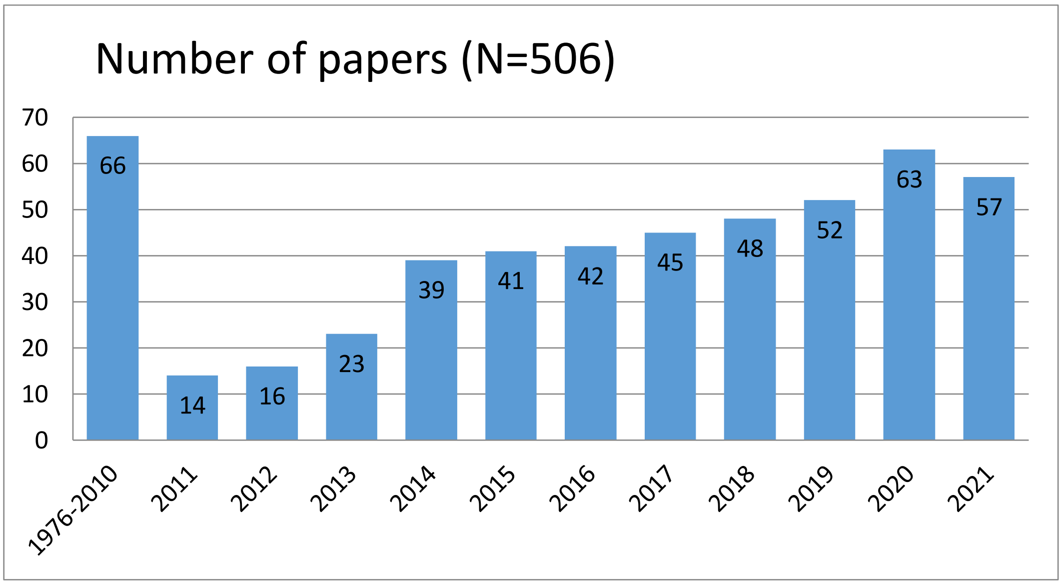

Figure 4. Distribution of publications per year across the period studied.

2.2.2 Distribution of research methodologies

Five research methodologies were differentiated in this research: (1) theoretical and conceptual papers; (2) empirical papers and case studies; (3) surveys and review papers; and (4) books. It shows the classification of publications according to the research methodologies. Among them, the number of empirical papers was the largest group is 421 while the number of theoretical papers is 33 and the number of review papers is 42, and the number of books is 10.

2.2.3 Classification of research topics

While reviewing the research publications, it ended up with classifying the publications into seven categories. The seven main topics include: (1) Wind resource assessment; (2) Wind speed prediction, numerical weather forecast, climate changes; (3) Wind power prediction methods; (4) Wind-solar complementary; (5) Wind energy storage; (6) Wind turbine control and service; and (7) Wind power forecast errors and risk management. Figure 6 shows the framework and classification of the framework of the publications, which based on the inductive analysis approach, revealed that there is a cluster of innovative technologies pertaining to wind power generation.

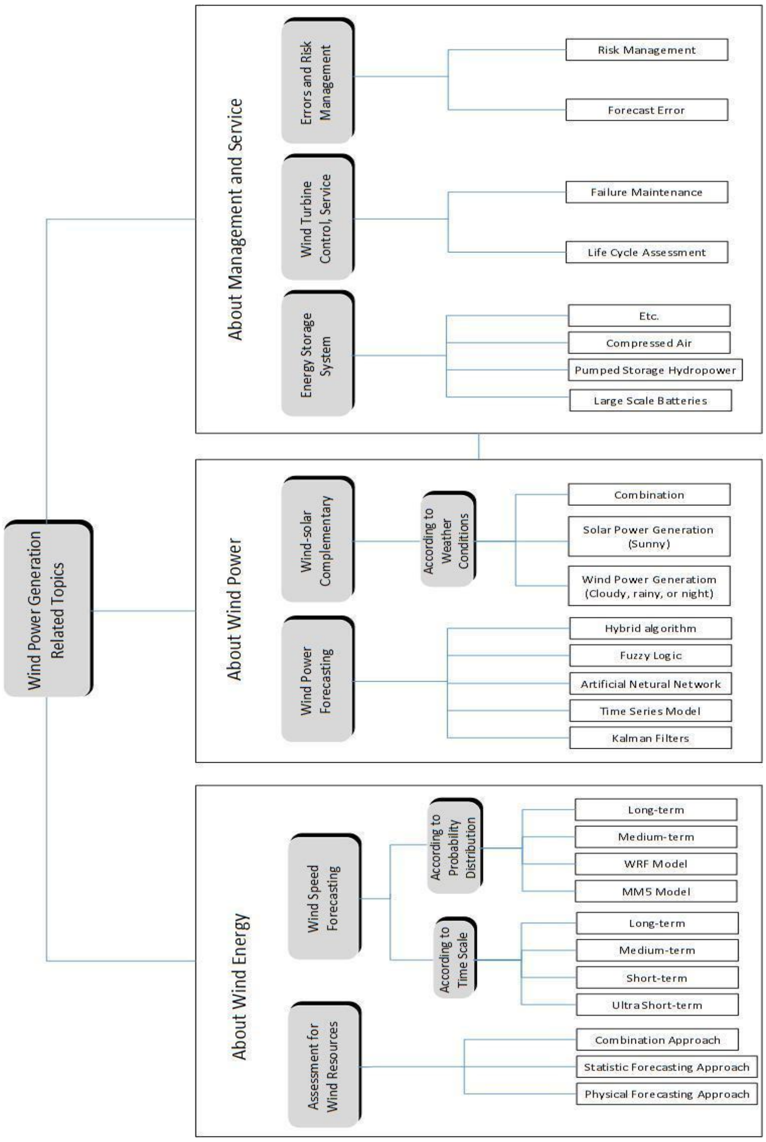

Figure 5. Mind map of related research topics for this article based upon variation of research field. adopted from Liu & Yang, 2015 (Paper 3)

2.3 Circumstances of Mainly Research

2.3.1 Assessment for wind resources

Previous research has been done on assessing the potential WERs all around the world. Various geographic characteristics also cause a wide variety of temperature and climate differences. Among the publications identified in the related searching, some evaluated the installed wind capacity, some interpreted wind power assessment metrics, while some reviewed the global renewable resources.

The capacity of installed wind turbines is increasing in many wind farms all around the world. Through statistical methods, Staid and Guikema (Staid & Guikema, 2013) had investigated the factors that influence the installed wind capacity in each state of U. S. are the physical and geographic characteristics of the state. Flora, Marques, & Fuinhas (2014) studied the wind idle capacity during the year of 1998-2011 among 18 European countries to help policymakers when adjusting energy policy. In China, there existed a large discrepancy between installed capacity and wind power generation even with the dramatic increasing installed wind capacity (M. Yang, Patiño-Echeverri, & Yang, 2012). Turkey had an extremely low installed wind power capacity 0.22% of the total economy power capacity (Güler, 2009).

Chadee and Clarke (Chadee & Clarke, 2014) assessed regional wind resources through comparing statistical wind power density (WPD). They used reanalysis wind data for the period 1979–2010. The results show that although the prevailing winds are from the east-north-east over the eastern Caribbean islands, their wind direction distributions are bimodal. Moreover, other papers (Carta & Mentado, 2007; Hennessey, 1977; Lu, Yang, & Burnett, 2002; Sedefian, 1980; Shamshirband et al., 2016) also estimated the WPD distribution function in different districts.

J. Zhang, Chowdhury, & Messac (2014) proposed to use a more comprehensive metric named Wind Power Potential (WPP). Compared to WPD, WPP is more credible because it not only accounts for wind speed information but also considers the joint distribution of wind speed and direction. The results from four sites of North Dakota, that WPD and WPP follow different trends, and that the realistic resource potential measure was not captured by WPD. Additionally, Ucar & Balo, 2010; W. Zhou, Yang, & Fang (2006) measured the wind energy resource via WPP.

2.3.2 Wind power forecasting

In practice, ultra-short-term, short-term, medium-term, and long-term time scales are used to predict wind power in WPEs (Soman, Zareipour, Malik, & Mandal, 2010). There are different timescales when classifying WPF species according to time periods and one example is as follows (Colak, Sagiroglu, & Yesilbudak, 2012; De Giorgi, Ficarella, & Tarantino, 2011).

a. Long-term forecasting

It predicts from one day to one week ahead and aims to optimize maintenance and repair of wind turbines. It is usually used for planning and designing wind farms.

b. Medium-term forecasting

It predicts from six hours to one day ahead and aims to optimize power system management and energy trading. It is usually used for dispatching the electricity grid rationally.

c. Short-term forecasting

It predicts from thirty minutes to six hours ahead and aims to optimize pre-load sharing. It is usually used for repairing and debugging.

d. Ultra-short-term forecasting

It predicts from a few seconds to thirty minutes ahead and aims to optimize turbine control and load tracking. It is usually used for controlling wind turbines and stabilizing electrical energy.

The methods of wind power prediction are mainly divided into the following three groups (González-Mingueza & Muñoz-Gutiérrez, 2014; Jung & Broadwater, 2014; Lei, Shiyan, Chuanwen, Hongling, & Yan, 2009):

- Physical forecasting approach:

In contrast to statistic approach, the physical approach is based on the use of physical considerations. It needs detailed physical descriptions of the wind farm and their surroundings, including description of the wind farm (wind farm layout and wind turbine power curve, etc.) and description of the terrain (orography, roughness, obstacles, etc.). This approach aims to get the optimized predicting wind speed and direction in different hub height of wind turbine generator system.

- Statistic forecasting approach:

The statistical approach is based on mathematical statistics analysis of the main variables associated with the relationship between energy generation and meteorological information. The meteorological data, obtained from historical data or output of Numerical Weather Forecast (NWP), mostly used as input. For example, wind speed, wind direction, temperature, and atmospheric pressure in the wind farm.

- Combination approach:

The hybrid method is a useful predicting way as it can improve the WPF accuracy by offsetting random error with one method from each other. In some models, a combined approach is used to integrate advantages of both approaches.

2.3.3 Commonly used wind power forecasting algorithms

Based on different input data, which means whether to use NWF, the WPF can be divided into NWF forecasting method and historical meteorological data forecasting method. From 1977 until now, many articles described different algorithms of WPF. Some of the representative models are reviewed in this section.

a. Kalman filters

Kalman filters (KF) is an optimal recursive data processing algorithm, and it has been firstly achieved by Stanley Schmidt in 1958. Some papers regarded the KF model as an algorithm which applied to wind speed numerical prediction to improve prediction accuracy. Cassola and Burlando (Cassola & Burlando, 2012) reported that meteorological models are usually unable to provide reliable surface wind speed forecasts due to the shortcomings in horizontal resolution, physical parameterizations, initial and boundary conditions. Thus, they used KF wind speed data to forecast the wind energy output, and the percentage error between simulated and measured wind energy values was still very low and showed a stable evolution. (Louka et al., 2008) developed a wind speed forecasts method, which includes two limited-area atmospheric models based on KF, efficiently eliminating systematic errors, even in the lower resolution cases, and contributing further to the significant reduction of the required CPU time. To improve the performance of KF models, (Poncela, Poncela, & Perán, 2013) substituted the traditional way of setting the values of the model parameters by estimating them by quasi maximum likelihood methods for a certain forecast horizon. They showed that the improved model is close to an optimum for all the horizons and provides more accurate predictions, with up to 60% of improvement for the RMSE.

b. Time series model

Commonly used time series models include auto regressive (AR), moving average (MA), auto regressive moving-average model (ARMA) and auto regressive integrated moving average (ARIMA).

Among these, one ARIMA model established by Box and Jenkins (Box & Jenkins, 1976) have been widely used for the purpose of time series forecasting. Meanwhile, this book is extremely comprehensive because it interprets each kind of time series model in detail and gives examples. Huang and Chalabi (Z. Huang & Chalabi, 1995) used AR model to forecast wind speed from one hour to a few hours ahead because it takes into account the non-stationary nature of wind speed. Based on multidimensional ARMA series, Soder (Kavasseri & Seetharaman, 2009) provided a method that can simulate possible outcomes of wind speeds based on available forecasts. This method was established based on the assumption that wind speed forecasts are available in several regions and that the forecast errors in different regions are correlated. Kavasseri and Seetharaman (Kavasseri & Seetharaman, 2009) forecasted wind speeds on the day-ahead (24 h) and two-days-ahead (48 h) by using a fractional-ARIMA model. The results showed that significant improvements in forecasting accuracy are obtained with the proposed models compared to the persistence method. (Kamal & Jafri, 1997) found the ARMA model is suitable for predicting intervals and probability forecasts.

c. Artificial neural network

Various Artificial neural network (ANN) models are widely used, such as back propagation (BP) and radial basis function (RBF) neural networks. The ANN is an information-processing method, which works like a human brain processes to find an algorithmic solution to select the structure from the existing data (Kavasseri & Seetharaman, 2009; Olaofe, 2014). Based on the original BP network, one new wind power prediction model which optimized the tabu search algorithm with memory function was developed by Han, Li, & Liu (2011). Guo, Wu, Lu, & Wang (2011) proposed a new hybrid wind speed forecasting method based on a BP neural network and the idea of eliminating seasonal effects from actual wind speed datasets using seasonal exponential adjustment then get lower mean absolute errors. By investigating the use of weather ensemble predictions in the application of ANNs, Taylor and Buizza (Taylor & Buizza, 2002) found that the average of the load scenarios is a more accurate load forecast than that produced using traditional weather forecasts. Alexiadis, Dokopoulos, & Sahsamanoglou (1999) developed an ANN algorithm that significantly improved forecasting accuracy compared to the persistence forecasting model. Salcedo-Sanz (Salcedo-Sanz, Ortiz-García, Portilla-Figueras, Prieto, & Paredes, 2009) presented the hybridization of the fifth-generation mesoscale model (MM5) with ANN to address a problem of short-term wind speed prediction. The adopted strategies were individual ANN and hybrid strategy based on the physical and the statistical methods. Peng, Liu, & Yang (2013) comprehensively compared the performance of two prediction methods and his calculated results showed that the individual ANN prediction method can quickly produce the prediction results.

d. Support vector machine (SVM)

Support Vector Machine (SVM) was firstly developed by Corinna Cortes and Vapnik in 1995. The most apparent difference between SVM and ANN is that the former focuses on mathematical methods and optimization mechanisms even though they are similar.

(Mohandes, Halawani, Rehman, & Hussain, 2004) introduced SVM, the latest neural network algorithm, to wind speed prediction. The result indicated that SVM compared to multilayer perceptron (MLP) neural networks is closer to the actual wind speed. Ortiz-García et al. (Ortiz-García et al., 2011) proposed an improvement to an existing wind speed prediction system, using banks of regression Support Vector Machines (SVMr) to manage the diversity in input data arising from the use of different global forecasting models and several parameterizations of a mesoscale model. They showed that the system implementing SVMr banks outperforms the basic system without taking diversity into account in the input data. (Q. Hu, Zhang, Xie, Mi, & Wan, 2014) developed a technique of the uniform model of v-support vector regression for the general noise model (N-SVR). The existing studies on using SVM for wind speed prediction are very limited as these studies usually only use one particular kernel function and a specific combination of parameters. J. Zhou, Shi, & Li (2011) applied Least-squares Support Vector Machines (LS-SVM) with linear, Gaussian, and polynomial kernels to perform short-term wind speed forecasting.

e. Fuzzy logic

Initially, one approach draws definite conclusions from vague, ambiguous, or imprecise information, however it is not widely used because of the low accuracy as low ability of fuzzy logic prediction is low when studying (Klir & Folger, 1988). Metternicht developed a useful and practical technique for modelling complex phenomena that may not yet be fully understood owing to its ability to deal with imprecise, uncertain data, or ambiguous relationships among data sets (Metternicht, 2001). Fuzzy logic is a new and logical approach, which when applied in the field of engineering, a fuzzy logic model is useful for predicting wind speed, electrical power, or rotor's speed. There are few up-to-date literature reviews about this algorithm for predicting wind power. Therefore, this is a promising research gap.

f. Fuzzy logic control

The Fuzzy logic controller (FLC) approach, which tracks the generator speed with the wind velocity to extract the maximum power, takes into account the grid demands and power generation predictions, are used for efficiency optimization and performance enhancement control in wind generation systems (Sarrias-Mena, Fernández-Ramírez, García-Vázquez, & Jurado, 2014; Simoes, Bose, & Spiegel, 1997a, 1997b). Mohamed, Eskander, & Ghali (2001) designed the tracking controller of the wind energy conversion system based upon fuzzy logic control (FLC) technique and this system has been tested to have robustness and effectiveness by simulation. Kamel, Chaouachi, & Nagasaka (2010) proposed and developed a new fuzzy logic pitch controller and an energy storage ultra-capacitor to smooth the output power of wind turbines and enhance Micro-Grid (MG)'s performance in islanding mode, and the results proved that the proposed strategies are effective.

g. Hybrid algorithm

A combined, nonlinear hybrid KF-ANN model was found to be a better way of forecasting wind speed than KF and ANN separately, to solve the inaccuracy wind power forecasting of linear ARIMA (Shukur & Lee, 2015). A hybrid wind speed forecasting model consists of ARIMA model and ANN model, predicted the wind velocities with a higher accuracy than the ARIMA and ANN model separately (Cadenas & Rivera, 2010). Two hybrid methods namely ARIMA-ANN model and ARIMA-Kalman model, which were based on single time series model, ANN model and KF model, had good forecasting accuracy and were suitable for the jumping wind samplings. One hybrid model named PMERNN and PAERNN, combine SVM with seasonal index adjustment (SIA) and Elman recurrent neural network (ERNN) methods, forecasted the daily wind velocities with a higher degree of accuracy over the prediction horizon (J. Wang, Qin, Zhou, & Jiang, 2015).

Two hybrid models, namely, ARIMA–ANN and ARIMA–SVM, were selected to compare with the single ARIMA, ANN, and SVM forecasting models, showed that the hybrid methodology does not always outperform the individual forecasting models based on ARIMA, ANN, or SVM (Shi, Guo, & Zheng, 2012).

A novel hybrid modelling method named SVR–UKF was proposed for integrating unscented Kalman filter (UKF) with SVR to precisely update the short-term estimation of wind speed sequence. With this method, the prediction errors were closer to zero with significantly smaller variations, whereas the prediction errors of the other methods were widely scattered (K. Chen & Yu, 2014).

According to Guo et al. (2011), there is no single best forecasting algorithm that can be applied to any wind farm since wind speed patterns can be very different between wind farms and are usually influenced by many factors that are location-specific and difficult to control. Each of the physical models, statistical models, spatial correlation models and artificial intelligence models has advantages and disadvantages. For example, the time series model is one kind of statistical model, and it is popular because its computation is simple. But ANN and KF are more widely used for their good nonlinear performance.

2.3.4 State-of-art of machine learning

DL has higher recognition accuracy on large sample data sets Comparing with traditional machine learning (ML), such as SVM, convolutional neural network (CNN) has a better solution and effect on recognizing objects (P. Wang, Fan, & Wang, 2021).

One new research proposed by Jiang et al develops a short-term wind speed forecasting method which combines statistical method, ANN, and DL. This system consists of four parts: optimal sub-model selection, point prediction based on a modified multi-objective optimization algorithm, interval forecasting based on distribution fitting, and forecasting system evaluation (Jiang, Liu, Niu, & Zhang, 2021).

In a photovoltaic power generation system, Shin et al. demonstrate that RNN and LSTM are more suitable for the time series data structures compared with dynamic neural networks to achieve the best prediction results (D. Shin, Ha, Kim, & Kim, 2021).

Accurate wind speed forecasting. This study proposes a hybrid model named VMD-DE-ESN incorporating variational mode decomposition (VMD) and differential evolution (DE) and echo state network (ESN) for wind speed forecasting. This hybrid model was validated, mean absolute percentage errors (MAE) are 2.0161%, 3.4153%, 2.1544%, and 2.8478% respectively, which are much lower than several others (H. Hu, Wang, & Tao, 2021).

By combining AI methods with statistical knowledge, Zhang et al. proposes a new interval prediction model based on the Fast Correlation Based Filter (FCBF) algorithm, the optimized Radial Basis Function (RBF) model and Fourier distribution for wind speed. The results show that the maximum and average value of the prediction error are only 0.8430 m/s, 0.1749 m/s, which are significantly better than several others (Y. Zhang, Pan, Zhao, Li, & Wang, 2020).

2.3.5 Wind-solar complementary

The site selection plays an important role in wind power farms, photovoltaic power farms, and wind-solar hybrid power stations. Matlab, Simulink Software are commonly used to evaluate the performance of hybrid systems (Akyuz, Oktay, & Dincer, 2012; Dihrab & Sopian, 2010).

In March 1995, Kimura, Onai, & Ushiyama (1996) documented complementary relationships between solar energy and wind energy in a small-scale wind-solar hybrid power system. Ma, Yang, Lu, & Peng, 2014; H. Yang, Lu, & Zhou (2007) utilized the model of Loss of Power Supply Probability (LPSP) to minimize the cost of energy and help reduce the size of energy storage based on a techno-economic evaluation. Q. Huang, Shi, Wang, Lu, & Cui (2015) proposed an approach which used multiple small wind turbines instead of one bigger one. The results showed that at low wind speed, the former one has more power production.

(Chávez-Ramírez et al., 2013) focused on the integration of photovoltaic (PV) system, micro-wind turbine (WT), Polymeric Exchange Membrane Fuel Cell (PEM-FC) stack and PEM water electrolyzer (PEM-WE), for a sustained power generation system. Bhattacharjee and Acharya (Bhattacharjee & Acharya, 2015) performed a small-scale application of wind-solar hybrid simulation model in an educational building to alleviate grid dependence. Maouedj's (Maouedj, Mammeri, Draou, & Benyoucef, 2014) hybrid system consists of PV and wind subsystems, battery energy storage, load and a hybrid system, controller for battery charging and discharging condition. The experimental results showed that the photovoltaic panel group constituted the primary energy supplier of the system; while the wind turbine was the secondary supplier since the contribution of the wind turbine was small compared to the share of the photovoltaic subsystem.

To evaluate system efficiency, Xydis (Xydis, 2013) identified the overall Exergetic Capacity Factor (ExCF) for a wind-solar power generation complementary system. ExCF is a new parameter which can be used for better classification and evaluation of RESs. One research (Y. Shin, Koo, Kim, Jung, & Kim, 2015) presented one PV-wind-battery-diesel power generation system which optimizes power generation by sparse matrices and the linear programming algorithm.

2.3.6 Energy storage system

Zahedi (Ahmad Zahedi, 2014) interpreted several benefits of integrating intermittent sources of energy such as solar and wind with energy storage has several benefits for the electricity grid. (Wu et al., 2014) identified the distribution of probabilistic methods to determine the optimal size of the Energy storage system ESS for a wind farm in electricity markets. Maleki and Askarzadeh (Maleki & Askarzadeh, 2014) used a discrete version of harmony search (HS) to optimize the size. The decision variables (number of PV panels, wind turbines, and batteries) are optimized by use of HS for having a cost-effective system.

- Battery storage

In 2010, Khalid and Savkin (Khalid & Savkin, 2010) designed a controller which was based on model predictive control (MPC) to smooth the wind power output. The proposed controller is capable of smoothing wind power by utilizing inputs from our prediction system, optimizes the maximum ramp rate requirement and the state of the charge of the battery under practical constraints. Four years later, they proposed a new semi-distributed battery energy storage system (BESS) scheme to minimize the capacity of BESS to ensure the lower cost of the system (Khalid & Savkin, 2014).

Ge et al. (2013) used a dynamic mathematical model of Vanadium redox flow battery (VRB) in an energy storage system (ESS) to provide a stable and smooth power flow injected into the grid though the wind power fluctuated. X. Y. Wang, Mahinda Vilathgamuwa, & Choi (2008) illustrated using the proposed design method, a BESS in a buffer scheme, to attenuate the effects of unsteady input power from wind farms. Jannati, Hosseinian, Vahidi, & Li (2016) reduced the cost of BESS by using Smart Parking Lots (SPLs).

Two researchers explored the benefit of optimally integrating wind power with pumped hydro storage (PHS) because the daily wind speed patterns do not match the average daily load pattern. The results of the survey revealed that PHS, in conjunction with the wind farm, can reduce the system's total power output shortage and increase the expected daily revenue (Gao et al., 2014; Murage & Anderson, 2014).

Kaldellis, Kapsali, & Kavadias (2010) used an integrated computational algorithm for sizing of PHS systems that exploit the excess wind energy produced by local wind farms, the contribution to the electrification of the remote islands becomes evident.

- Wind-compressed air energy storage

Wind-compressed air energy storage (Wind-CAES) is an inexpensive way to store massive amounts of energy for long periods of time. Satkin, Noorollahi, Abbaspour, & Yousefi (2014) developed a site selection method for wind-CAES power plants to identify the wind energy potential for wind-CAES sites. The case study from Fertigand and Apt (Fertig & Apt, 2011) in the U.S. showed CAES brought social benefits including avoiding construction of new generation capacity, improving air quality during peak times, and increasing economic surplus. In Germany, a stochastic electricity market model has been applied to estimate the effects of significant wind power generation on system operation and on economic value of investments in CAES. This case showed that CAES can be economically beneficial in the case of large-scale wind power deployment (Swider, 2007).

- Flywheels

Flywheel based energy storage systems (FESSs) are designed to smooth the net power flow injected to the grid by a variable speed wind turbine. In a wind diesel power system (Sebastián & Peña-Alzola, 2015), the main components of FESS include electrical machine, flywheel, grid converter and electrical machine converter, improving the power quality of the isolated micro-grid. According to the intermittency of the wind, researchers integrated and validated the energy storage systems. For instance, Zhao et al. developed one hybrid energy storage system, which was based on adiabatic compressed air energy storage and flywheel energy storage system, to deal with the wind power fluctuations (P. Zhao, Dai, & Wang, 2014; P. Zhao, Wang, Wang, & Dai, 2015).

More RESs will be integrated into the electricity grid worldwide in future. Taking the limited storage unit to find a more effective solution to handle the reliability and stability for the hybrid energy storage system is important.

2.3.7 Wind turbine control system

Eriksson and Bernhoff (Eriksson, Bernhoff, & Leijon, 2008) compared three different wind turbines through a case study. The vertical axis wind turbine appears to be advantageous to the horizontal axis wind turbine in several aspects. Uddin and Kumar found out that life cycle assessment (LCA) study varied from location to location due to industrial performance, countries energy mix and related issues (Uddin & Kumar, 2014). Demir and Taşkın thought that environmental impacts are low for the turbines with high hub heights due to increase in electricity production of those turbines (Demir & Taşkın, 2013). Novak, Ekelund, Jovik, & Schmidtbauer (1995) proposed a model to design and evaluate the number of linear and nonlinear control schemes for wind-turbine speed regulation.

Normally, wind turbines will reach the end of their service lives after 20-40 years. Ortegon, Nies, & Sutherland (2013) considered the management of end-of-service (-) life of wind turbines (EOSLWTs) should also be considered by the wind power industry. According to ISO 14040 standard, which allows us to make an LCA study quantifying the overall impact of a wind turbine and each of its components, Martínez et al. (Martínez, Sanz, Pellegrini, Jiménez, & Blanco, 2009) analyzed the wind turbine during all the phases of its life cycle, from cradle to grave, with regard to the manufacture of its key components (through the incorporation of cut-off criteria), transport to the wind farm, subsequent installation, start-up, maintenance and final dismantling and stripping down into waste materials and their treatment. Schleisner developed a model to assess the life cycle of the production and manufacture of materials in a wind farm in Denmark (Schleisner, 2000). Bonou, Skelton, & Olsen (2016) proposed an eco-design framework which was based on LCA to drive sustainable innovations in components, product systems, technologies, and business models.

2.3.8 Errors and risk management

The stochastic electricity market is influenced not only by the uncertainty of nature's wind resources but also wind power forecast errors, as forecasting plays a crucial role in the renewable wind energy market. Holttinen outlined the forecast errors of wind power producers in the electricity market, pointing out shorter times between bids and delivery of production is to handle the forecast error (Holttinen, 2006). Two research (Díaz-González, Hau, Sumper, & Gomis-Bellmunt, 2015; Taraft, Rekioua, & Aouzellag, 2013) found out that the measurements of the power output and reduction of the ensemble wind power forecast error depends on the size of the region. Pinson and Kariniotakis introduced a new methodology for assessing the prediction risk of short-term wind power forecasts. Their purpose was to find a linear relation between the Meteo-risk Index (MRI) and the resulting prediction errors (Pinson & Kariniotakis, 2004).

Considering the wind power fluctuations under extreme weather conditions, Lin et al. proposed a model in the frequency domain to assess the wind power reduction under extremely high wind speed conditions. This model was validated and demonstrated to be valuable for both power system planning and operation with high wind penetration under extreme wind conditions (Lin, Sun, Cheng, & Gao, 2012). Hosseini-Firouz used the conditional value-at-risk methodology based on stochastic programming to optimally solve the wind power problem faced by the uncertainty issues, derived from wind availability, market prices, and balancing energy needs (Hosseini-Firouz, 2013). Soukissian and Papadopoulos used the Error-In-Variables approach to find the effects of alternative wind data sources on the wind climate analysis by examining the offshore WPD (Soukissian & Papadopoulos, 2015).

González-Aparicio and A. Zucker used the stochastic scenario extensions of dispatch models to take the value of flexibility into account to combine with the nature of forecast uncertainties. It applied clustering techniques to reduce the range of uncertainty, and regressive techniques to forecast the probability density functions of the intra-day price. (González-Aparicio & Zucker, 2015).

2.4 Research Gap

Even though many published articles refer to topics which are classified as above, the trend is more and more publications are mainly about using AI in the science of WPF in WPEs. Many recent studies show that AI technology can improve the accuracy of wind speed prediction. Table 1 shows the searching methodologies used for this research.

Table 1. Summary of searching methodologies used for this study.

Literature search strings	Search field	Numbers of documents results	Limit to
(“wind” and “speed” and “prediction”)	Article title, Abstract, Keywords	8911	Search field Documents,
(“wind” and “speed” and “prediction”) AND (“artificial” and “intelligence”)	Article title, Abstract, Keywords	144	Documents, English
(“wind” and “speed” and “prediction”) AND (“machine” and “learning”)	English	215	Documents, English
(“wind” and “speed” and “prediction”) AND (“artificial” and “intelligence”) AND (“machine” and “learning”)	Article title, Abstract, Keywords	39	Documents, English
(“wind” and “speed” and “prediction”) AND (“artificial” and “intelligence”) AND (“machine” and “learning”) AND (“deep” and “learning”)	English	4	Documents, English
(“wind” and “speed” and “prediction”) AND (“artificial” and “intelligence”) AND (“machine” and “learning”) AND (“deep” and “learning”) AND (“xgboost”)	Article title, Abstract, Keywords	39	Documents,
(“wind” and “speed” and “prediction”) AND (“machine” and “learning”) AND (“xgboost”)	English	0	Documents, English
(“wind” and “speed” and “prediction”) AND (“machine” and “learning”) AND (“deep” and “learning”) AND (“xgboost”)	Article title, Abstract, Keywords	3	Documents, English
(“wind” and “speed” and “prediction”)	English	2	Documents, English
(“wind” and “speed” and “prediction”) AND (“artificial” and “intelligence”)	Article title, Abstract, Keywords	0	Documents, English

From the angle of artificial intelligence (AI) algorithm, there are 144 journal papers searched within article title, abstract, keywords with “artificial intelligence” among 8911 papers with “wind speed prediction” in SCOPUS (Elsevier) database. After exploring with narrow down, only 2 document results display. In other words, there only existed two published articles which show in figure 6 are specifically related to wind speed prediction, machine learning (ML), deep learning (DL) and eXtreme Gradient Boosting (XGBoost) technique.

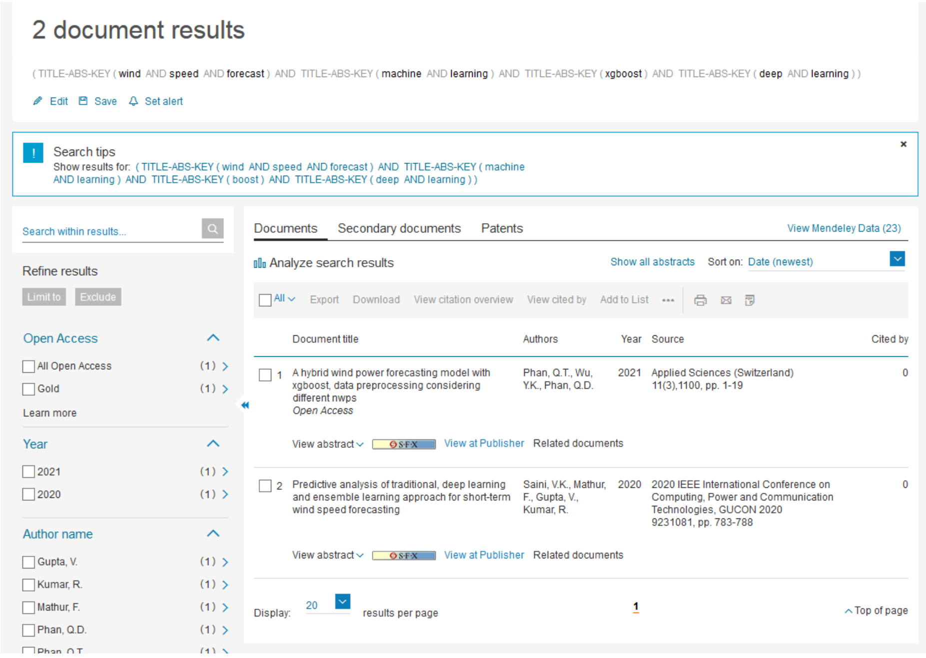

Figure 6. Literature search results. adopted from screenshot of SCOPUS (Elsevier) database

The research uses Uncertainties in Ensembles of Regional Reanalysis (UERRA) database which contains a big amount of data but not big data. Using these reanalysis data can solve the problem of lacking real measured data. From the aspect of AI technology, noise refers to unreal data or wrong data and not all of them can be seen from human beings. The noise may come from sensor failures or inaccurate measurement. Noise is a problem for analyzing data by AI method since AI algorithms cannot recognize which are real useful data, and which are noise. In this circumstance, there is a need to do data cleaning to get a good result. However, manually cleaning data is a heavy work-load and it cannot be done by manpower as this massive data brings burden to working stations, even some computers. On the other hand, machine learning (ML) cannot recognize right or wrong data and treat all wrong data as right data, so if training real measured data from meteorological observatory directly then the result can have errors. Deep learning is more suitable for predicting wind speed in a very long term by training massive amounts of data without noise.

The main innovation of the research is to develop an effective machine learning (ML) algorithm which is based on LSTM algorithm and XGBoost and the final goal is to improve the accuracy and save the model running time of wind speed prediction base as the decision-making time is limited. These two newly published journal papers which is described in figure 7 has been listed above sets a benchmarking for researchers who explore the topic of optimizing algorithms in WPF area using AI technology through reanalyzing meteorological reanalysis data. This research develops a neural network algorithm, which is based on LSTM and XGBoost, and this algorithm is validated to show better performance when compared with traditional ones. XGBoost is the optimal choice as it needs no big data and operates quickly. Searching for these predictions, high accuracy requirement with limited data and the computational time of XGBoost must be reasonably low.

More attention has been paid to utilize renewable energy to produce electricity, but the random input does not always match the demand. Therefore, a set of management policies with different levels of participation of the decision maker can optimize processes in energy management (Azcárate, Blanco, Mallor, Garde, & Aguado, 2012). Besides this, effective information could be provided to support decision-making toward appropriate energy models and systems for isolated areas with different scales and demands (Y. Liu, Yu, Zhu, Wang, & Liu, 2018). Effective wind energy potential analysis and accurate forecasting can reduce the operating cost of wind parks. A wind energy decision system which combines these two can not only provide an effective wind energy assessment but can also satisfactorily approximate the actual wind speed forecasting rather than poor decisions (X. Zhao, Wang, Su, & Wang, 2019).

3 Methodology

This chapter covers the research philosophy, approach, strategy, and method where methodological choice is described as following based on the theory of Research Onion developed by Sauders et al. firstly in 2007. This is interdisciplinary research that combines the knowledge of Industrial Management, Artificial Intelligence and Meteorology. The main method is quantitative analysis and Python is the programming tool. This chapter also depicts research strategy, research design, data collection and results, data analyzes and application and managerial implications.

3.1 Research Strategy

3.1.1 Research philosophy

This research is a positivism one based on it is quantitative research which aims to predict wind speed and explain the whole process. The results are verified and depicted in chapter 4. The science used in this research can be judged by logic rather than common sense.

Positivism adopts a clear quantitative approach to investigating phenomena, as opposed to post-positivist approaches, which aim to describe and explore in-depth phenomena from a qualitative perspective (Crossan, 2003).

The five main principles of positivism research philosophy can be summarized as the following (Dudovskiy, 2018):

1. There are no differences in the logic of inquiry across sciences.
2. The research should aim to explain and predict.
3. Research should be empirically observable via human senses. Inductive reasoning should be used to develop statements (hypotheses) to be tested during the research process.

4. Science is not the same as common sense. Common sense should not be allowed to bias the research findings.
5. Science must be value - free and it should be judged only by logic.

3.1.2 Research approach

The logical sequence of deduction is from rule to case to result, and induction is from case to result to rule, whereas abduction follows another process – from rule to result to case (Taylor, Fisher & Dufresne 2002; Danermark 2001). This research uses both inductive and deductive approaches to develop theory. This research uses mainly deduction to test and evaluate the data-driven model in empirical research by carrying out three different algorithms. In paper 4, it also uses some induction to build theory from case study research, for example the integration of individual models of meteorological information, wind power prediction module and operations management module to construct a holistic model, named Meteorological Information Service Decision Support System.

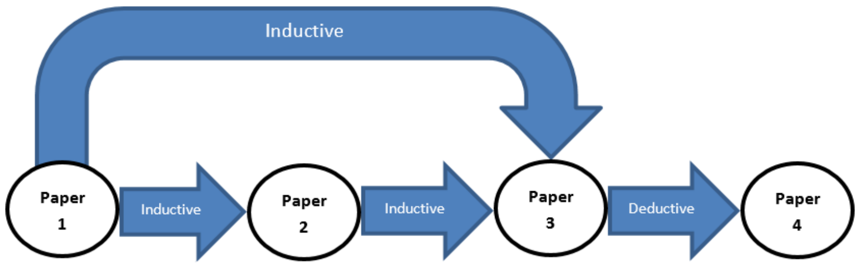

Figure 7. Approach to theory development.

Figure 7 depicts the logic relationship of research approach among four papers. Paper 1 made a literature review about state-of-art from related articles. This research uses an inductive approach to indicate and display the core content in paper 3 by finding and observing the universality or commonality both from paper 1 and paper 2, to summarize the theory and framework. Paper 4 used a deductive method to test the proposed framework and system from paper 3.

Figure 8 describes the process to build a dataset for machine learning. It mainly includes training dataset and test dataset by using different algorithms.

Data driven approaches include machine learning, deep learning, parameter tuning, training, validation, and test.

Training: to train the models.

Validation: to make sure the models are not overfitting.

Test: to determine the accuracy of the models.

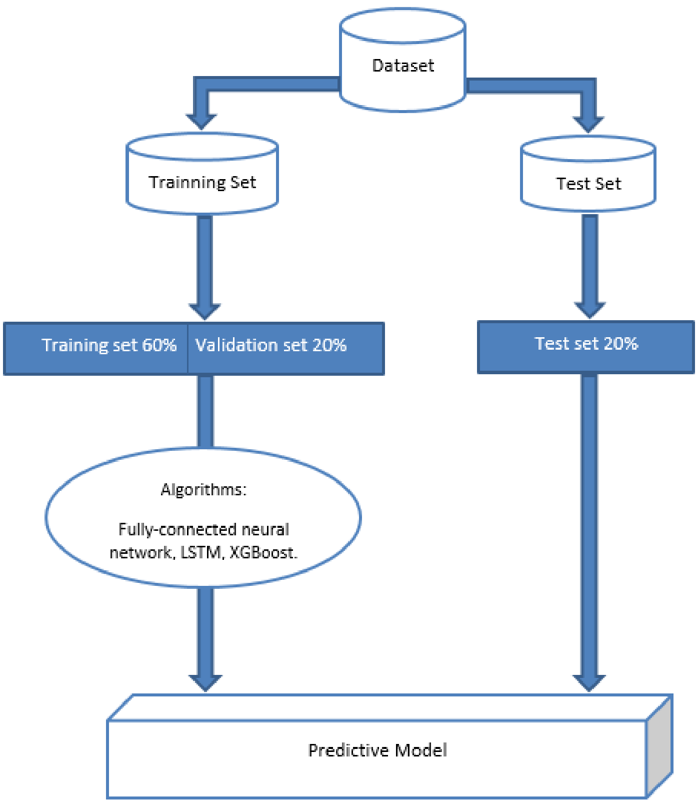

Figure 8. To build a dataset for machine learning.

3.1.3 Research strategy

This is empirical research which draws conclusions strictly from concretely empirical and verifiable evidence. The empirical evidence can be gathered using both quantitative market research and qualitative market research methods. This research chooses a quantitative method to carry out research. It uses case study and archival research as research strategies.

This research chooses Vaasa wind farm as research site (63.05641° N， 21.55187 °E) since the fourth related paper has done data analysis there. Besides this, this research obtained the collected reanalysis data of 2015-2018 from open sources to predict wind speed of 2019 then compared them with reanalysis data itself to get the comparison difference.

Overall plan is to predict wind speed and wind power density in 2019 by analyzing meteorological reanalysis data 2015-2018 in the way of traditional commonly used wind power forecasting methods, ML and DL mathematical modelling, combined with XGBoost technique in a real case study. After comparing the performance and accuracy from them, it can be shown which algorithm makes the strategy reliable.

The whole procedures and action include start, establishing research topic, reviewing literature, and exploring, defining research questions, mathematical modeling, collecting data, analyzing data, results, validating and end. There are several steps taken to complete the study.

3.2 Research Methodology

3.2.1 Main research methodology

There are two basic approaches to research, qualitative and quantitative approaches. The quantitative approach can be sub-classified into inferential, experimental and simulation approaches to research (Kothari, 2004). This is applied, quantitative, and empirical research. The preferred main research methods are quantitative ones.

To be specific, this research firstly gives deeper literature review by using systematic review, association analysis and cluster analysis method to find out the research gap.

After summarizing and classifying innovative topics, it explores the research content and describes the research questions.

The case study in Vaasa region in Finland has been studied by analyzing reanalysis data. Meanwhile, the core part of this research depicts machine learning (ML), deep learning (DP) algorithms through mathematical modelling which needs quantitative analysis methods including time series analysis, regression analysis, decision tree, ML.
In general, this is interdisciplinary research and uses an interdisciplinary approach.

Attached are four papers and this study uses a variety of research approaches which are shown as below.
Paper 1 uses qualitative analysis methods including literature review and descriptive research.
Paper 2 uses qualitative analysis methods including literature review, descriptive research, and contingency approach.
Paper 3 uses qualitative analysis methods including literature review, descriptive research, exploratory research, and interdisciplinary approach.
Paper 4 is the starting of quantitative research and it is exactly a case study to get into the core part of this research. This paper uses mathematical modeling and quantitative analysis, such as, time series analysis, regression analysis, to improve algorithms.

3.2.2 Programming platform

MATLAB is a high-level language and interactive environment that enables it to perform computationally intensive tasks faster than with traditional programming languages such as C, C++, and Fortran. It is designed for the way of analyzing data, developing algorithms, or creating models. Python is an interpreted, high-level, general-purpose programming language and aims to help programmers write clear, logical code for small and large-scale projects. Python is more productive when compared with other programming languages, such as, C++ and JAVA. This research adapts Python to execute quantitative analysis since Python can be used to make decisions involving big data while Matlab can be used to teach introductory mathematics such as calculus and statistics.

3.3 Method Design

3.3.1 Artificial intelligence, machine learning and deep learning

Artificial intelligence (AI) refers to any technique that enables computers or other devices to mimic human behavior. Machine learning (ML), a subset of AI, aims to make predictions or decisions by building mathematical models to train datasets. As a branch of ML, Deep learning (DL) underlying features a great amount of data using deep neural networks. Figure 9 shows the relationship among AI, ML and DL. In general, DL is a subset of ML while ML is a subset of AI.

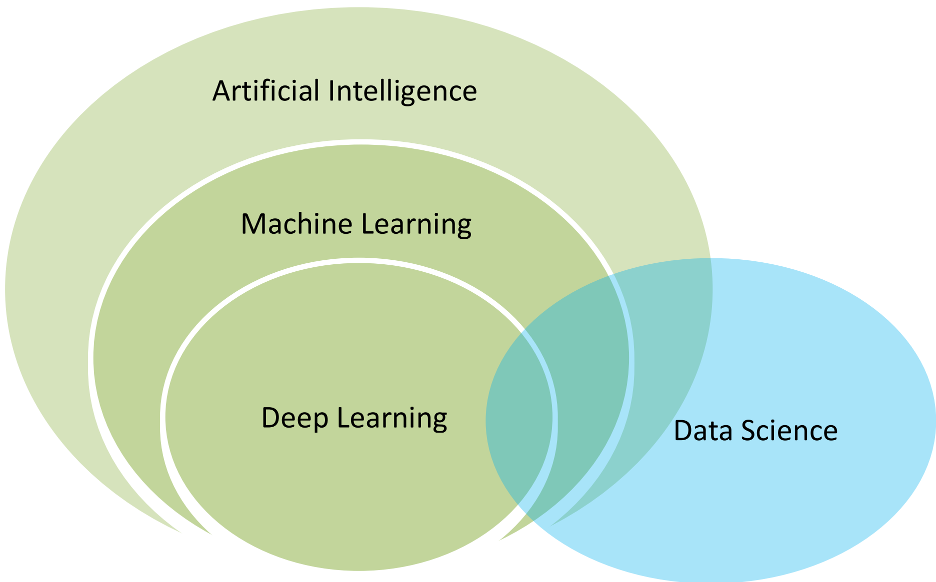

Figure 9. Structure chart of artificial intelligence.

ML are commonly used in image and video recognition, face recognition, picture description, image style conversion, automatic speech recognition and synthesis, text classification, machine translation, image, and poetic creation and so on in daily life over the past several years and now. ML is an interdisciplinary technique which tries training computers or other devices to forecast the unknown features by describing the behavior of the dataset, inputting models with features regards to the expected output, forecasting output with features regards to historical data by feature extraction (Alpaydin, 2019; Griffith, 1974). Figure 10 depicts the differences of the mode between ML and human thought. ML algorithms are one of the alternatives to forecast wind power based on wind speed data as it can increase productivity, quality, and profit levels by predicting effectively in academia as well as industry (Lee, Yoo, Kim, Lee, & Hong, 2019). Deep learning (DL) is a subset of ML and pushes ML technology to be one of the essential enablers for the renewed AI success with a great process (Duan, Edwards, & Dwivedi, 2019).

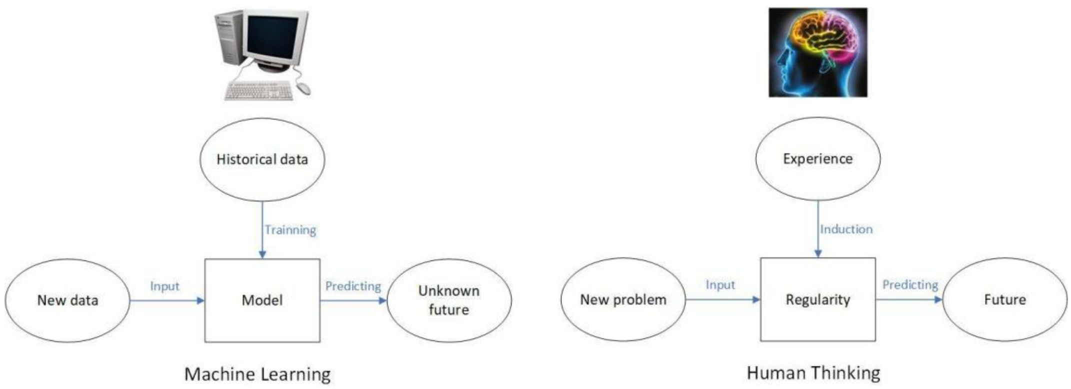

Figure 10. Machine learning and human thinking mode.

The traditional ML approaches have unavoidable limitations while producing satisfactory accuracy. Firstly, the traditional ML methods lack capability to analyze and derive full value from large volumes of data. Another limitation is that the performance of the traditional ML methods highly depends on how the undergoing trend of the data could be represented by the extracted characteristic features (S. Shen, Sadoughi, Chen, Hong, & Hu, 2019; Sheng Shen, Mohammadkazem Sadoughi, Xiangyi Chen, Mingyi Hong, 2019). In other words, DL is large neural networks due to DP dealing with big data compared with extracting features of ML. However, it is very hard to identify appropriate characteristic features when establishing ML models.

DL, as a kind of supervised learning technique, has acquired growing attention and it has become more popular in recent years. It is well known for its capacity for learning hidden patterns in data (LeCun, Bengio, & Hinton, 2015). Moreover, the performance of DL models tends to be better when the dataset size grows, and DL techniques have become useful tools in data analytics (Le Cun et al., 2015). However, when the data size is small, the performance of DL tends to be jeopardized (C. Chen, Liu, Kumar, Qin, & Ren, 2019). Figure 11 shows the performance level of DP, traditional ML and human thinking. Traditional ML methods perform stable and better with a minimum intake of data. However, after crossing the threshold point, DL methods performance increases with increasing the amount of data. (Sharma, Sharma, & Jindal, 2021).

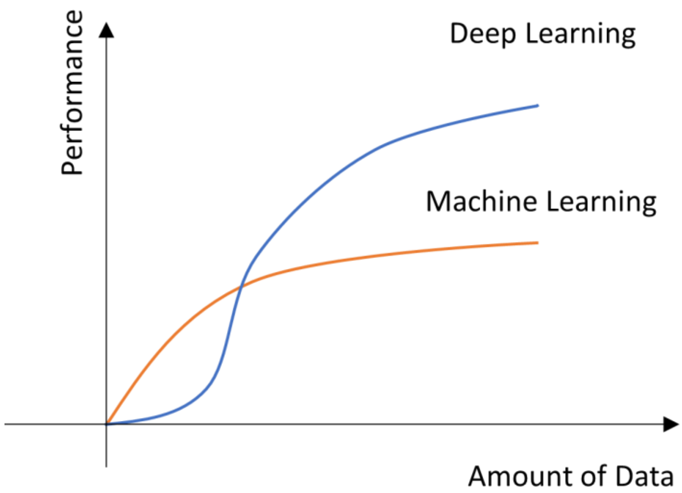

Figure 11. Deep learning performance. adopted from Bhardwaj & Di, 2018

3.3.2 Fully-connected neural network, long short time memory, XGBoost

Fully-connected neural networks (FCNNs) are a classic type of artificial neural network architecture, in which all the nodes or neurons in one layer are connected to the neurons in the next layer. A fully connected layer offers learning features from all the combinations of the features of the previous layer, but they are incredibly computationally expensive. Usually, FCNNs are only used to combine the upper layer features (Fiesler, Caulfield, Choudry, & Ryan, 1990). Figure 12 shows the network structure of FCNNs.

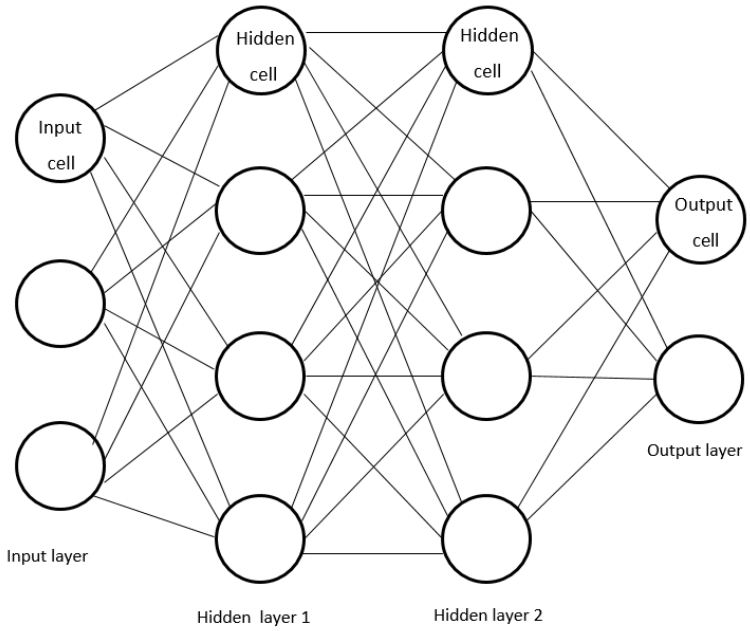

Figure 12. Fully-connected neural network.

Long Short-Term Memory networks (LSTMs) were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in the following work. LSTMs inspired mostly by circuitry, not so much biology, try to combat the vanishing / exploding gradient problem by introducing gates and an explicitly defined memory cell. LSTMs are explicitly designed to avoid the long-term dependency problem. The biggest advantage of LSTMs is that remembering information for long periods of time is practically their default behavior rather than struggling to learn. Figure 13 shows the network structure of LSTMs (Hochreiter & Schmidhuber, 1997).

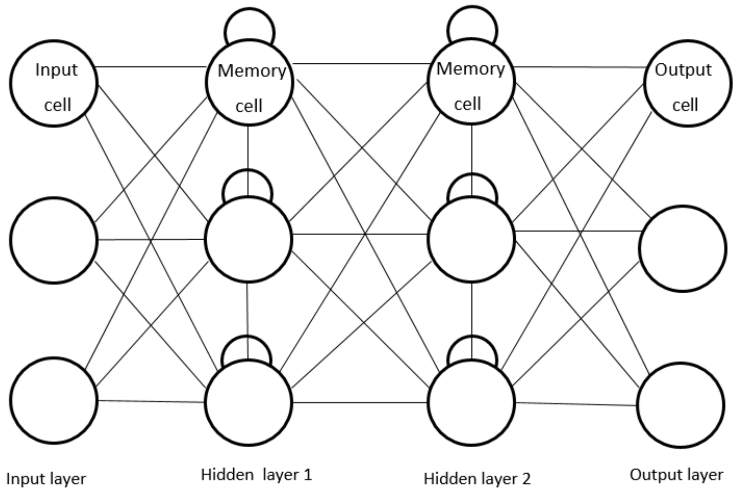

Figure 13. Long short-term memory network.

Extreme gradient boosting (XGBoost) is an efficient and scalable implementation of gradient boosting framework by Friedman in 2001. (Friedmanet, 2001). XGBoost package includes an efficient linear model solver and tree learning algorithm. It supports various objective functions, including regression, classification, and ranking. XGBoost has emerged as a robust ML technique that has been applied in several areas (Lim & Chi, 2019; D. Zhang et al., 2018)

XGBoost is a decision-tree-based ensemble ML algorithm that was developed for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models. When a decision tree is the weak learner, the resulting algorithm is called gradient boosted trees, which usually outperforms random forest (Friedman, 2001).

3.3.3 Research design

WPF uses wind farm historical power, historical wind speed, topography and terrain, and wind turbine operating status to establish a wind farm output power prediction model. Wind speed, power, or numerical weather forecast data are used as input for the model. Equipment status and operating conditions to get the future output power of the wind farm. The real-time operation of a WPF system needs NWF data, real anemometer tower data, real wind power output data, wind turbine generators, and wind farm running status.

This is a prediction method which uses NWP rather than historical data. NWP cannot be used for predicting wind power directly, so the power of wind farms is calculated by NWP models. As it is depicted in Chapter 2 Literature Review part, WPF usually proceeds by physical forecasting approach or statistical forecasting approach. This research chooses the former approach to predict wind speed, wind direction and air density in the selected wind farm. It is important to do horizontal extrapolation from measurement height to hub height, from meteorological observatory site to wind farm.

This research uses reanalysis data of 2015-2018 from Public Datasets in European Centre for Medium-Range Weather Forecasts to predict wind speed of 2019 then compare them with historical data. The reanalysis data in this research uses short term forecasting and picks up wind speed data every six hours. Some related information of the selected wind farm is listed as follows.

Kunta (Municipality):Vaasa site

Sijainti (Location):（63.05641° N，21.55187° E）

Vuosi (Year):2012

Kokonaisteho (Total power):4 MW

Turbiineja (Turbines):1

Omistaja (Owner):Wasa Wind Oy

Laitevalmistaja (Equipment manufacturer): Mervento

Located area: Kronvik

Wind power station code: 6741

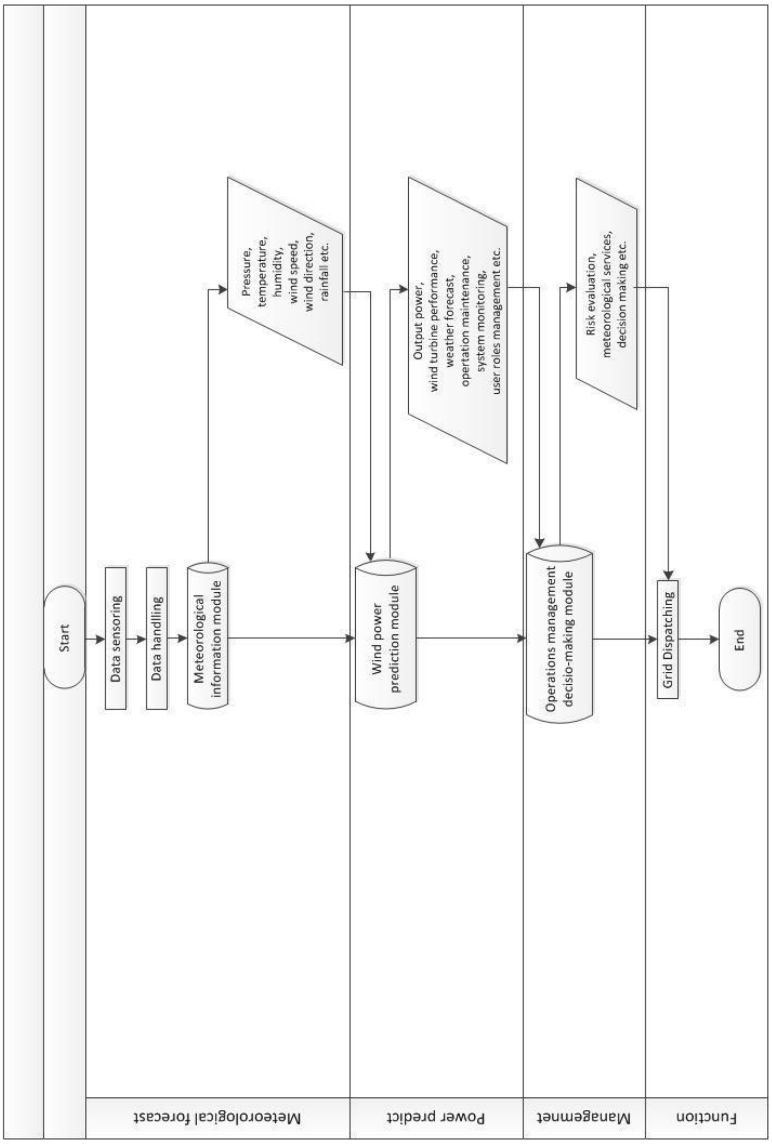

Figure 14. System structure and process. adopted from Liu & Yang, 2015 (Paper 3)

Table 2. Typical failures related to weather conditions.

Source: Meteorological information service support system in wind park application, 2015 (paper 3)

Failure parts	Possible reasons	Weather conditions	Actions
Blade	Blade drive not ready	EWEs	Emergency stop
Rotor	Result of imbalance, blades and hub corrosion etc., brake sensor failure	Rain, snow and other hash meteorological condition	Normal stop

Gearbox	Over temperature, gearbox oil pressure too low	High temperature	Normal stop
Generator	Over speed, over temperature, bearing faults, current too high/low, frequency sensor failure	High temperature and/or humidity	Emergency stop Normal stop
Yaw system	Yaw brake set unintentionally	Extreme changes in wind speed / direction	Normal stop
Tower	Weather or other failure may cause excessive vibration	EWEs	Emergency stop

Maintenances include regular, active, and passive maintenance. Passive maintenance, which is sudden maintenance, accounts for a portion of operating maintenance expenses and revenue. Sudden maintenance includes all unplanned failures that require man-made repair, from manually resetting the wind turbine to replacing damaged gearbox. Accidental failure of critical components (including gearbox, generator, shaft, blade, hydraulic system, transformer, and converter) can significantly increase maintenance costs. Failure to replace these components in a timely manner can lead to significant wind turbine downtime and loss of revenue. Maintenance should be scheduled to carry out in time of low wind power.

Mean absolute error of the forecasting results

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Y_i - Y_i' |$$

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Y_i - Y_i')^2}$$

Standard deviation of error

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (Y_i - Y_i')^2}$$

Coefficient of determination

$$R^2 = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} \quad (Y_i - Y_i')^2}$$

Wind speed (m/s)

$$V = \sqrt{u^2 + v^2}$$

Wind power density (W/m^2) ρ: kg/m^3

$$D_{wp} = \frac{1}{2n}\sum_{i=1}^{n} \quad \left(\rho \cdot V_i^{\,3}\right)$$

3.3.4 Data collection

The important quantitative process is to predict wind speed in 2019 through ML and DL algorithms by training reanalysis data during 2015-2018, which retrieved from Climate Data Store.

This research analyzes reanalysis data, which named Uncertainties in Ensembles of Regional Reanalysis (UERRA), obtained from Public Datasets in European Centre for Medium-Range Weather Forecasts (ECMWF). ECMWF aims at advancing global numerical weather forecasting (NWP) through international collaboration. UERRA is a research project among 5 pre-operational Copernicus Projects in ECMWF during 2014-2018. The objective of UERRA is to produce ensembles of European regional meteorological reanalysis of Essential Climate Variables (ECVs) for several decades and to estimate the associated uncertainties in the data sets. It also includes recovery of historical (last century) data and creation of user-friendly data services. Data format is .netcdf and .grib and this research retrieved the former format. Python is used for creating mathematical models and analyzing data in this research. The reanalysis data of wind speed obtained four times in each day for 00-, 06-, 12-, and 24-h.

4 Result and Findings

This chapter depicts results and findings of this research about three algorithms. The training performance and testing performance are also showed here.

4.1 Results of Algorithm

This research uses AI technologies, such as, fully-connected neural network (FCNN), long short time memory (LSTM) and extreme gradient boosting (XGBoost). Figure 15 shows the hierarchy diagram about them.

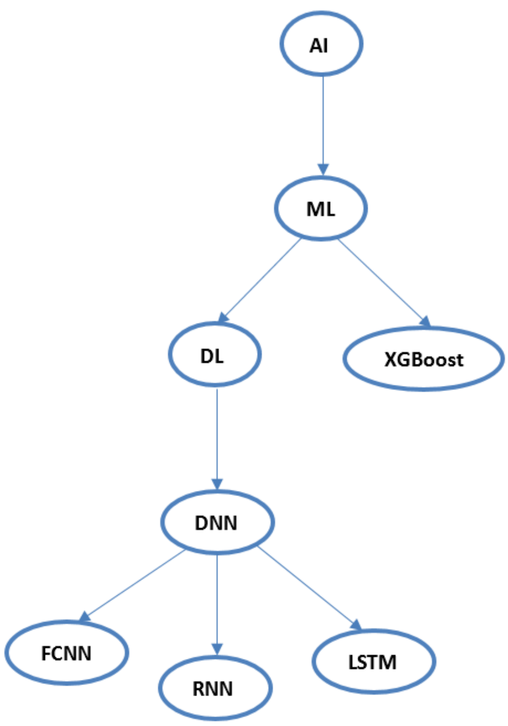

Figure 15. Tree structure of technologies related to Artificial Intelligence.

- Fully-connected neural network

The line chart of predicted wind speed by using a FCNN is shown in figure 16 and figure 17 depicts its prediction performance.

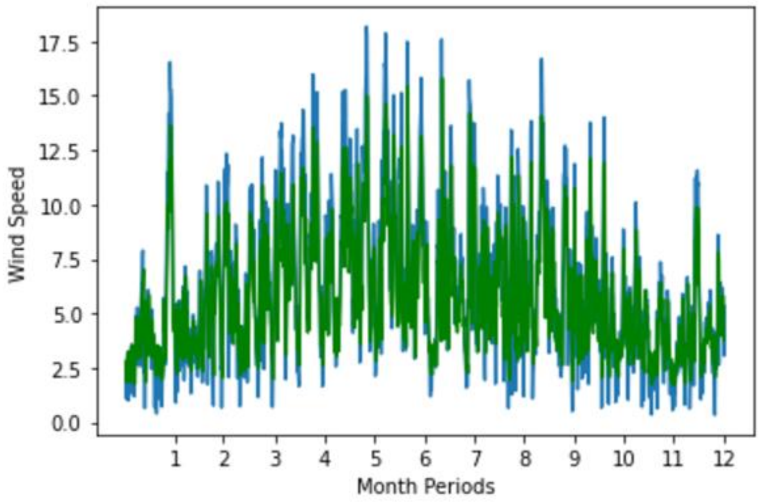

Figure 16. Wind speed prediction using fully-connected neural network.

```
10 times inference last 1.8487 seconds
Train Performacne RMSE :  1.892591
Test Performacne RMSE :  2.006670
Train Performacne MAE :  1.428197
Test Performacne MAE :  1.526733
Train Performacne R2 :  0.667309
Test Performacne R2 :  0.685465
```

Figure 17. Prediction performance of fully-connected network.

- Long Short-Term Memory network

The line chart of predicted wind speed by using a fully-connected neural network is shown in figure 18 and figure 19 depicts its prediction performance.

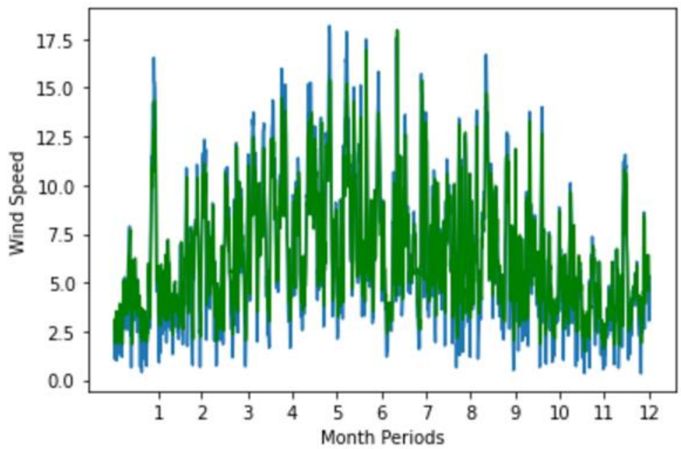

Figure 18. Wind speed prediction using LSTMs.

```
10 times inference last 0.5338 seconds
Train Performance: 1.81 RMSE
Test Performance: 1.90 RMSE
Train Score: 1.37 MAE
Test Score: 1.46 MAE
Train Performacne R2 :  0.694626
Test Performacne R2 :  0.717418
```

Figure 19. Prediction performance of LSTMs.

- XGBoost Regression

The line chart of predicted wind speed by using a fully-connected neural network is shown in figure 20 and figure 21 depicts its prediction performance.

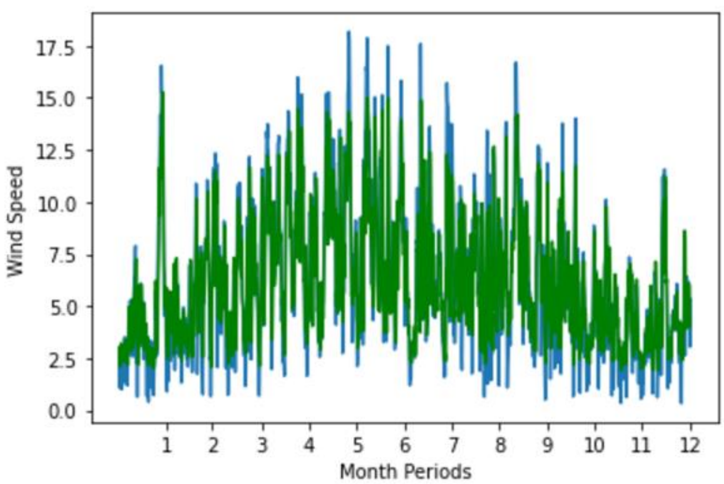

Figure 20. Wind speed prediction using XGBoost Regression.

```
10 times inference last 42.0237 seconds
Train Performacne RMSE :  1.394653
Test Performacne RMSE :  1.938518
Train Performacne MAE :  1.084520
Test Performacne MAE :  1.472376
Train Performacne R2 :  0.819341
Test Performacne R2 :  0.706468
```

Figure 21. Prediction performance of XGBoost Regression.

Training performance and testing performance, which include the value of RMSE, MAE, R2, for each algorithm are displayed in table 3.

Table 3. Performance for each algorithm.

Algorithm	**Value**	**Training Performance**	**Testing Performance**
Fully-connected neural network	RMSE	1.892591	2.006670
	MAE	1.428197	1.526733
	R^2	0.667309	0.685465
LSTMs	RMSE	1.81	1.90
	MAE	1.37	1.46
	R^2	0.694925	0.717418
XGBoost Regression	RMSE	1.394653	1.938518
	MAE	1.084520	1.472376
	R^2	0.819341	0.706468

Training time and testing time for each algorithm are displayed in table 4.

Table 4. Training time and inference time for each model.

(second : s)

	Training Time	**Inference Time**
Fully-connected neural network	151.4038s for 1 time epochs=60 batch size=2 verbose=2	1.8487s for 10 times
LSTMs	182.8195s for 1 time epochs=20 batch size=1 verbose=2	0.5338s for 10 times
	0s	42.037s for 10 times

XGBoost is applied to quickly achieve comparable accuracy with LSTM but a lot less time to improve the prediction. As it can be seen from table 3, XGBoost performs better than FCNNs and can also reach nearly the same effect as LSTMs. From the aspect of statistics, the results of XGBoost and LSTMs are equivalent. XGBoost only has a little bit overfitting when using the model to train the data set and predict as it can be neglected that the differences in a few digits after the decimal point. With the help of this situation, the uncertainty in this decision-making process can be handled more effectively. Besides this, it is also employed to reduce computational time. XGBoost is not DL but a ML technique used for regression and classification problems, so its significant advantage is running many times faster than DL algorithm. It is a ML algorithm rather than a neural network or DL, so it has no training time but learning time, which is the same as running time of model, so-called inference time which is shown in table 4.

As it can be seen in table 3 and table 4, the results clearly demonstrate that the XGBoost algorithm shows an overall better performance as compared to the traditional FCNN and LSTMs method as it saves much model running time and has equivalent MAE, RMSE and R2 with DL algorithm. It is a regression based on a decision tree. Wind speed forecasts can be deep ML or not deep. It is commonly believed that DL has better performance. The algorithm used in this research compares both, XGBoost is one of the best algorithms for which is not DL since it is validated that it can reach the same level of accuracy but save much computational time.

Figure 22 shows reanalysis data, training data and testing data of wind speed from 2015 to 2019. As it can be seen from the graph, the blue curve displays the trend of reanalysis data during 2015-2019, the orange curve represents the variation of training data on wind speed and green curve shows the predicted wind speed.

Besides these, it presents the variation of wind speed for each year during 2015-2019. The highest wind speed occurred in March, February, April, March, and April separately in the years of 2015, 2016, 2017, 2018 and 2019. Vice versa, the lowest wind speed occurred in August, February, July, August, and December separately in the years of 2015, 2016, 2017, 2018 and 2019.

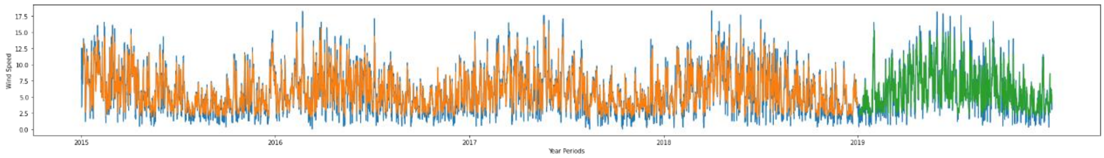

Figure 22. Average daily wind speed during 2015-2019.

As it can be seen in figure 23, the average wind speed for every 6 hours in each month in the year of 2019 are drawn individually. The variation features of wind speed are: Judging the variation of wind speed in 2019, the highest wind speed occurred in April and the lowest wind speed occurred in December in the year 2019.

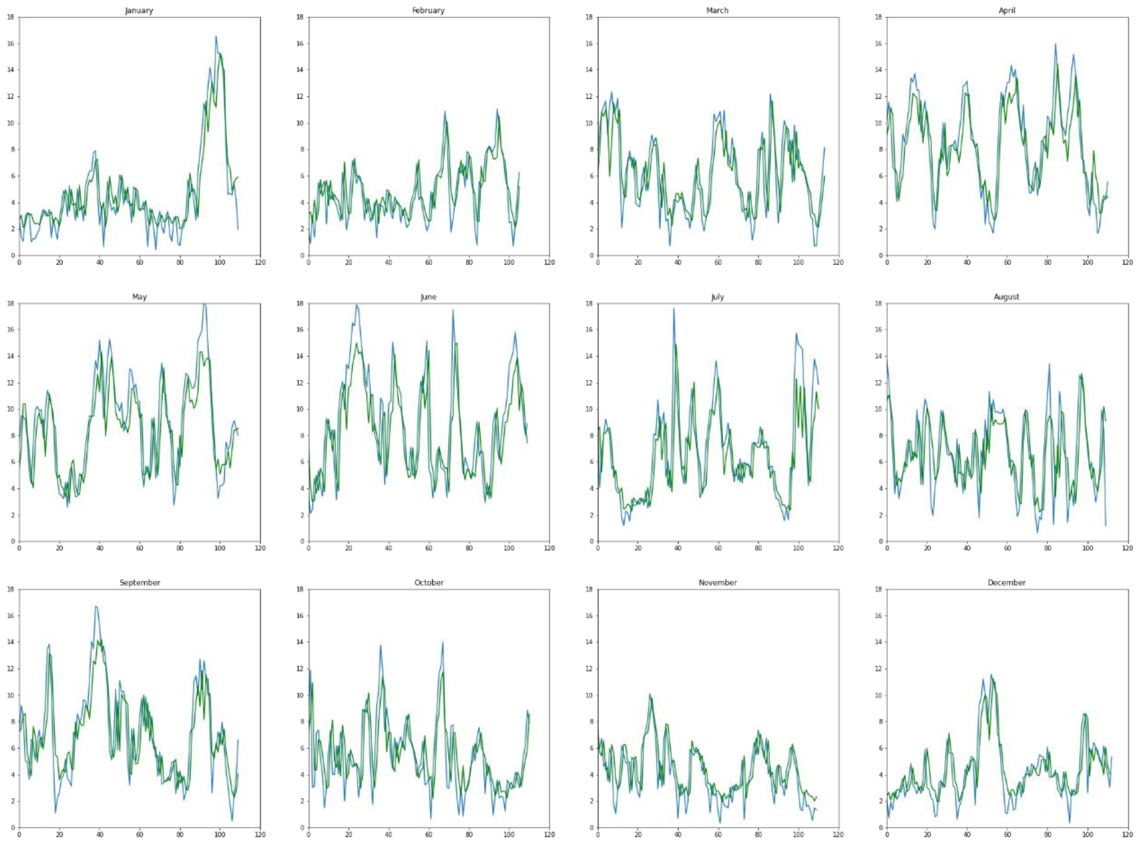

Figure 23. Monthly wind speed in each month in 2019.

According to Finnish Meteorological Institute, Finland located in the zone of westerly air disturbances, there are great variations in air pressure and winds, especially in winter. In the whole country, the wind blows most commonly from the southwest and least commonly from the northeast. The average wind speed is between 2.5 and 4 m/s inland, slightly higher on the coast and 5 to 7 m/s in maritime regions. Wind speeds are typically highest in winter and lowest in summer. Moderate winds are typical of Finland; high winds are rare, particularly inland. Vaasa located in the southwest coast of Finland. The research results are consistent with features above.

4.2 Findings

4.2.1 Findings of algorithm

ML and DL algorithms include an exciting prospect for many industries and businesses to drive self-service, increase agent productivity and make workflows more reliable. Based on the overview of ML and DL with illustrations and differences, each of them is focusing on respective characteristics and future trends. DL algorithms need to clean up big data and they do not suit every case. In some practical cases, it makes nonsense when making decisions in the management layer as the dataset training time for DL algorithms is too long. In the Research Design part of Chapter 3, it has been found that an ML approach has been applied to predict wind speed. Wind power prediction models are achieved in an adaptive and effective way by effectively reducing training time of FCNN and LSTM respectively. The hybrid algorithm introduced in this research, which is based on FCNN, LSTM and XGBoost is completely novel in this disciplinary area, which uses hybrid DL algorithm to execute energy management, basically only two related exist in the existing literature. Moreover, from the data analysis and results, the optimized algorithm which is based on LSTMs algorithm and XGBoost technique has better performance in the Vaasa meteorological observation site.

The WPF method is an effective way to reduce the impact of wind power intermittently to the power grid. Forecast results can be published and sent to the power grid dispatch terminal and wind farm monitoring center in real time. Meanwhile, the grid scheduling center and wind farm monitoring center can make prediction requests to the forecast server at any time.

4.2.2 Findings of managerial aspect

This research uses meteorological methods to provide a decision support tool for decision-makers. This meteorological information service decision support system in wind park application is beneficial both to wind farms and power systems. One hand, it provides support for reasonable maintenance plans, participates in market competition, and reduces the operating cost of wind farms. On the other hand, it provides support for power grid scheduling and proper scheduling, effectively reducing the adverse effects of intermittent wind power on power systems. Its successful implementation will produce enormous economic and social benefits.

The main contribution of this research is to achieve decision optimization on a decision support system by using AI technology. It was concluded that the proposed system is very promising for potential applications in wind (power) energy management. The findings of this research will provide strategic management for more enterprises in the field of wind power, which plan to implement systems with awareness of risk factors to avoid equipment failure, supply with regular, active, and passive maintenance, optimize energy management, give businesses an advantage over competitors and always be aware of the changing market.

For further work, it is necessary to use many methods to reach the optimum results in wind speed prediction, EWEs risk management and optional service decisions, the comparison between many methods ensure best performance of the system and realize the objective aims of the research.

5 Summary of Publications

5.1 Overview of Papers

Titles of published articles with keywords are listed in Table 5. An overview of the aims, methods and the main results/contribution are shown in Table 6.
The original articles (paper 1-4) are attached in Appendix.

Table 5. List of articles´ titles with key words.

Paper	Title	Key words
Paper 1	A review of Innovation in Wind Power Forecast	Wind energy resource, WPF, weather forecast, literature research, descriptive research.
Paper 2	The Impact of Climate Change on Wind Power Enterprises	WPF, WPEs, climate change, global wind energy resource distribution, climate data record.
Paper 3	Meteorological information service support system in wind park application	Operations management, Decision support systems, Information management,
Paper 4	A Study on Renewable Energy Potential based on the Global Atmospheric Data	Renewable energy, climate change, reanalysis, ERA-20C data, resources potential.

Table 6. Overview of the articles' aims, methods and the main results/contribution.

	Aims	Methods	Main results/contribution
Paper 1	To review the most recent articles in the topic of WER and WPF	Systematic review, cluster analysis, association analysis, litera-	Explore the research gaps in this area and highlight the possible future

	methods. To review the innovations.	ture review, descriptive research.	research points.
Paper 2	To survey the impact of climate change on WPF and the influences on WPEs.	Literature review, descriptive research, contingency approach.	WPD, which represents wind resources, plays a critical role. Air temperature, humidity, wind direction, wind speed, air pressure and rainfall directly influence the wind power output.
Paper 3	To propose a conceptual framework and make it can be used for decision-making.	Literature review, descriptive research, exploratory research, mathematical modeling, interdisciplinary approach.	This structured framework, which involves three major modules and certain processes, provides new insight for decision making in WPEs.
Paper 4	To find a correlation between the meteorological factors and the renewable energy potential and make the conceptual framework empirical.	Literature review, case study, quantitative analysis, mathematical modeling, time series analysis, regression analysis, interdisciplinary approach.	Use the global atmospheric reanalysis data to analyze the potential of renewable energy sources In Vaasa region in Finland.

5.2 Logical Connection of Papers

This study is founded on a thorough literature review. Hence paper 1 is the foundation for the following research since it reviews the innovations in the domain of WPF. Paper

2 makes a survey on the specific branch. In fact, paper 4 tests the framework which was proposed from paper 3.

Figure 24 shows the logical connections among four papers.

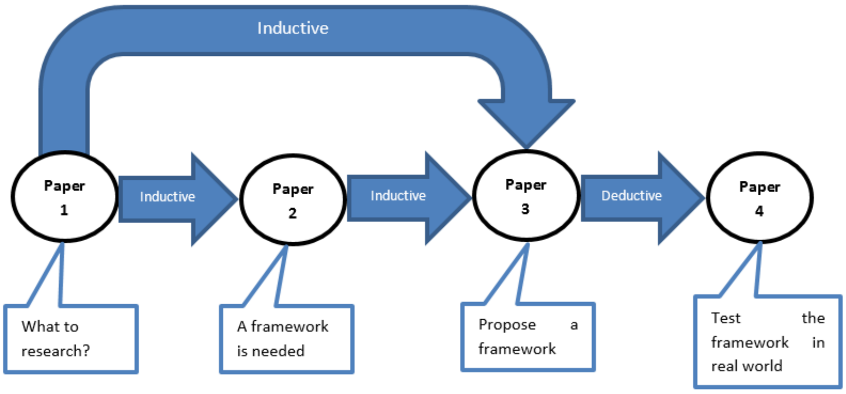

Figure 24. Logical connections among the papers.

5.3 Summary of Individual Papers

5.3.1 A review of innovation in wind power forecast

Sub-question 1. What is the innovation in the development process of WPF among so much relevant research?

This paper is the theoretical foundation of the whole research. It roughly researches main topics in the field of WERs and WFP.

In answering sub-question 1, Paper 1 uses different methods to review relevant articles to find the possible research prospect.

In this paper, several methodologies, including systematic review, cluster analysis and association analysis, are used to depict and generalize different popular WPF methods. Paper 1 reviewed several different WPF methods, which were used in wind energy systems, to summarize their own theory and characteristics. The corresponding innovations are also reviewed in detail. This paper aims to find out the research gap and open a new view to provide a research path for researchers in this same field.

Paper 1 describes some single algorithms, such as Kalman Filters (KF), Artificial Neural Network (ANN), Support Vector Machine (SVM), fuzzy logic and time series model. Time series model includes auto regression (AR), moving average (MA), autoregressive moving-average (ARMA) and autoregressive integrated moving average (ARIMA). Some hybrid algorithms, such as KF+SVM, ARIM+ANN, ARIMA+KF, ARIMA+SVM, also are compared in determined case studies.

As it can be seen, there is no single best forecasting algorithm that can be applied to any wind farm. As a result of this study, it can be said that each algorithm or combined algorithm both has its advantages and disadvantages. Meanwhile, the characteristics of terrain in a variety of districts in different countries are different. Therefore, paper 1 shows there is still space to increase the prediction accuracies respectively in scales of long-term, medium-term, short-term, and very short-term WPF.

Paper 1 suggests that the future study can be topics about increasing the prediction accuracy and system reliability.

5.3.2 The impact of climate change on wind power enterprises

Sub-question 2. How climate change influences WPEs and what factors affect wind power output?

This paper is a preliminary basis of connecting wind power with meteorology. It aims to study the impact of climate changes on WPEs and draw a framework to determine the relationship between wind power density and wind power.
In answering sub-question 2, Paper 2 was developed based on paper 1. It reviewed some most recent relevant research which combines climate change with wind power predicting and summarized the art-of-state. Paper 2 draws a framework which assesses

wind resources and finds correlations between wind power and some meteorological elements.

Six major meteorological elements, including air temperature, humidity, wind direction, wind speed, air pressure and rainfall, may have a relationship with wind power. Besides these, other meteorological elements may also be connected to wind power, such as relative humidity, rainfall, and snowfall. In some practical cases, wind farms can be located in places with complex terrain. However, different terrain, surface roughness, obstacles, and ground conditions such as undulating terrain, land-to-sea junctions, or uneven distribution of precipitation or cloud volumes also influence wind speed.

The outcome of Paper 2 is proposing a rough framework which aims to help decision-makers of WPEs to make strategic decisions including site selection, management and maintenance of wind power station, and long-term wind power generation forecast etc. Paper 2 suggested that future research should explore deeply in climate data record (CDR) to help develop more effective wind speed and WPF methods by finding specific algorithms.

5.3.3 Meteorological information service decision support system in wind park application

Sub-question 3. Can there be a general framework to help forecasting wind speed and wind power more effectively in decision-making?

This paper is the hub of this interdisciplinary research as it is involved in domains of operation management, weather forecast and wind power generation. It mixes these subjects together and practices them in a conceptual framework.

In answering sub-question 3, this paper designs and provides a meteorological information service system. The proposed system, which involves meteorological information module, wind power prediction module and operations management decision-making module, can be seen in the picture of system structure and process in Figure 10. It provides benchmarking to support decision making directly and indirectly based on processing meteorological information and evaluating its impact on service operations. Additionally, it provides meteorological forecasting and decision support in case of EWEs.

The Meteorological Information module includes meteorological data collection and NWP. This module also sends early warning messages in case of EWEs, so managers can take countermeasures in advance to avoid economic losses. Wind Power Prediction module utilizes meteorological data to predict wind power output based on real-time measuring, NWP, and WPF. Operations Management module uses predicted results from the previous module to evaluate failure probabilities in different parts of the wind turbines. It can help a lot in decision making to optimize maintenance schedules and maximize wind power output. Table 1 shows the corresponding actions to specific machine failures.

Paper 3 suggests the future research will be implemented with the proposed conceptual model. To some extent, paper 3 is the theoretical foundation of paper 4 which demonstrates empirical research by analyzing CDR data.

5.3.4 A Study on renewable energy potential based on the global atmospheric data

Sub-question 4. How to use the global atmospheric reanalysis data to analyze the potential of WERs in Finland?

This paper analyzes ERA-20C global datasets from ECMWF and tries to identify the meteorological factors (wind speed, solar radiation, rainfall, evaporation etc.) with their effects on the overall utilization potential of these RERs. What is the correlation between the meteorological factors and the renewable energy potential?

Paper 4 is developed based on paper 3 and uses the proposed pilot conceptual meteorological information service decision support system from paper 3.

In answering sub-question 4, this paper starts by retrieving the dataset of ERA-20C to analyze how climate change reflects on WPF. This paper continues such analysis in meteorological information service decision support systems, with deeper insights into WPD during the past 50 years, and to verify how this system helps decision-making in WPEs especially when EWEs come. This paper covers an important topic with the clearly presented purpose in terms of RQ 4, WPD of past fifty years 1961-2010 were studied from a point of view by analyzing global atmospheric reanalysis data, to find out the correlation between the meteorological factors and wind energy potential.

This research analyzes the existing ERA-20C global datasets describing the state of the atmosphere as well as land-surface and ocean-wave conditions from 1900 to 2010 obtained from Public Datasets in European Centre for Medium-Range Weather Forecasts (ECMWF). ECMWF aims at advancing global NWP through international collaboration. The data format is .netcdf and .grib. MATLAB and Python are used for creating models and analyzing data in this research.

Paper 4 demonstrates how to analyze the potential of WERs by using reanalysis data in a real case study. The specified location is Vaasa region in Finland and retrieved format is NetCDF. The highest resolution grid 0.125 degree * 0.125 degrees was chosen and a total data of 18262 days in 50 years were analyzed. Paper 4 uses MATLAB R2014a as the programming language to calculate, analyze and plot figures. It also plotted the variations of maximum WPD from every five years and every ten years. Analyzed results present a trend of WPD and give alarm to decision-maker to take action to avoid machine failures and financial losses. This Meteorological Information Service Decision Support system which was proposed in paper 3 can effectively help decision-maker at macro level and paper 4 is exactly a case study to validate this framework. The contribution of this paper is analyzing the potentials of WERs in terms of mastering the trend of WPD in Vaasa region in Finland.

Paper 4 proposes that the future research could be focused on forecasting the global potentials of RERs in the next decades.

5.3.5 Research in this study

Sub-question 5. What is the sufficient ML algorithm to improve the accuracy of wind speed prediction?

The follow-up research after these four papers in this study answers sub-question 5. It is developed based on paper 4 and reanalysis data of Uncertainties in Ensembles of Regional Reanalysis (UERRA) while paper 4 uses ERA-20C global datasets also retrieved from European Centre for Medium-Range Weather Forecasts (ECMWF). The research design in this study is the core part of this entire research. It uses reanalysis data of 2015-2018 from Public Datasets in ECMWF to predict wind speed of 2019. The reanalysis data in this research uses short term forecasting and picks up wind speed at the selected site for every six hours.

In answering sub-question 5, the research design in this study compares traditional algorithm FCNN, ML algorithm LSTM and DL algorithm XGBoost, by calculating RMSE, MAE, R2 in terms of training performance and test performance, to find an optimal wind speed predicting method. Besides this, it observes training time and inference time for each algorithm. The results come out that the XGBoost algorithm shows better performance as compared to the traditional FCNN and LSTMs method as it saves quite much model running time but also reaches the equivalent effect of MAE, RMSE and R2 as DL algorithm LSTM.

Besides this, the research design included in this study aims at optimizing energy management decision-making by optimal operational planning via predicting wind speed. It

provides a plan about when to turn off wind turbine group in order to repair and carry out maintenance during the low power generation period for wind power forecast to the next year, provide better wind energy assessment results and to optimize energy storage for the whole electrical grid, and aims at reducing carbon emissions by utilizing renewable energy maximally instead of fossil fuel. Wind power needs to be predicted accurately to make up for problems derived from burning fossil fuels.
Central research question: How to improve the accuracy of wind power forecasting by using artificial intelligence methods?

In answering the central research question, the research design in this study compares traditional algorithm and DL algorithms and determines a ML algorithm namely XGBoost to predict wind speed. And it is the core part of the whole research. It is possible that Meteorological Information Service Decision Support System, which was proposed in paper 3, can support decision-making effectively and create timely actions within the WPEs. Findings from this research contribute to WPF in WPEs. The main contribution of this research is to achieve decision optimization on a decision support system by using AI. It was concluded that the proposed system is promising for potential applications in wind (power) energy management.

6 Discussion and Conclusions

6.1 Contribution

The motivation of this research comes from the “environmentally friendly society”, “sustainable development” and “clean energy”. As everyone knows, the natural resources which human beings depend on are not unexhausted. Therefore, how to develop and utilize RERs in an efficient way is a popular and forever topic. Among all the RERs, wind energy has advantages, such as, low cost of wind power generation, clean to environment resource renewable despite the characteristic of uncertainty.

A lot of WPF techniques and methods used in wind energy systems have been reviewed in Chapter 2 of this study to summarize their own theory and characteristics in a variety of methods. And their corresponding innovations are also reviewed in detail. However, the main contribution of Chapter 2 is to provide a path for researchers in this same field.

The important points of view for this research were described and summarized from Chapter 3 to Chapter 5. The proposed structure and process of this conceptual information service system for improving productivity can help decision makers in WPEs while the electricity grid balance must be maintained between electricity consumption and generation at any moment. In the module of Meteorological Forecast, real-time meteorological data and weather forecasts are collected through meteorological sensors and equipment. Managers can get warning signals and take countermeasures quickly in advance when EWEs happen by predicting 50-year maximum wind speed uninterrupted. In the module of Power Prediction, it can provide WPF prediction by utilizing real-time wind measuring data and historical data as input. Models which combine different algorithms usually have higher accuracy and reliability than comparing using just a single algorithm. In the module of Operation Management, failure probabilities are evaluated to help decision makers to reduce maintenance cost and time and to improve the operational efficiency and reliability. Correspondent actions can be taken regarding typical failures in different parts of wind turbines according to real case statistics. Condition-based maintenance needs to be taken while there is a direct connection between business performance and operational management based on condition-based maintenance in WPEs.

6.2 Managerial Implications

This research develops a decision support tool for decision-maker from the domain of grid dispatching companies. The important quantitative process of it is predicting wind speed in 2019 through ML algorithm by training reanalysis data during 2015-2018, which retrieved from Climate Data Store. Then validate through analyzing the values of MAE, RMSE, R2 in the categories of training performance and testing performance.

The practical impact of this research is that it examines a method which can help the whole wind power generation process in a systematic way, develop a practical evaluation tool for management level, improve wind power prediction accuracy and reduce economic losses by increasing wind speed prediction accuracy. In the long term, it can effectively alleviate air pollution, water pollution and global warming problems. Besides of these, this research supports the growing recognition that the timeliness of making decision is just as important to the effectiveness of weather warnings as information provided in risk management of EWEs and actions of machine failures, and this factor should be considered in future research in addition to the investments and attention given to improving detection and warning capabilities.

The major managerial implications of this research are described as follows.

a. Provides a plan about when to turn off the wind turbine group to repair and carry out maintenance during the low power generation period for wind power forecast to the next year. Therefore, it can serve as an effective tool for wind farm management and decision-making.

The proposed structure and process of this conceptual information service system for improving productivity can help decision makers in WPEs while the electricity grid balance must be maintained between electricity consumption and generation at any moment. It is a holistic wind energy decision support system based on condition-based maintenance (CBM), which includes meteorological information module, wind power prediction module and operations management decision-making module, for decision makers to cut down operation and maintenance costs and implement a successful CBM strategy to achieve higher level of cost effectiveness.

b. Provides better wind energy assessment results and to optimize energy storage for the whole electrical grid.

It can generate a lot of value, such as, making electricity price can falling faster than expected. The development of energy storage has a close relationship with transition to the smart grid. Energy storage plays a crucial role in offsetting the intermittency of renewable energy including wind energy predictable plan helps in dispatching effectively and helps users to save electricity cost. Energy storage can help balance the power generation and improve power quality. Optimal plan of energy management can reduce economic loss when making decision.

c. Reduces the carbon emissions by utilizing renewable energy maximally instead of fossil fuel.

Burning fossil fuel is the main cause of climate change. Among a variety of traditional and new energy, to find the best plan of energy allocation among them to minimize carbon emissions and to make balance between them is becoming a popular topic. In the long term, this information system can reasonably help balancing the fossil fuels and renewable energy in the purpose of protecting the environment for human beings.

6.3 Research Limitations

From this research itself, reanalysis data are retrieved at the height of 30 meter as the same as a meteorological observatory.

This research originally plans to use reanalysis data of 2015-2018 from ERA5 data to predict wind speed of 2019 then compare them with historical data from Finnish Meteorological Institute in 2019. In practice, it is not easy to compare the predicted wind speed with historical wind speed in the year 2019 since there exists distortion since many observation data are missing.

Wind energy is one of the most dynamic renewable sources of energy with commercial potential, clean and green, low-cost, widespread, inexhaustible. Wind power can effectively mitigate air pollution, water pollution and global warming while providing a stable power supply for economic growth. However, wind power is intermittent and fluctuating as intermittent is a nature characteristic of wind energy itself. Wind power interval prediction plays an increasingly important role in evaluations of the uncertainty of wind power and becomes necessary for managing and planning power systems. Besides of this, energy storage systems with new technology can also compensate for improving the reliability of the system pertaining to power availability (Abazari, Babaei, Muyeen, & Kamwa, 2020; Vijay M, Singh, & Bhuvaneswari, 2020; R. Wang, Li, Fu, & Tang, 2020). Hannele, Jari and Samuli in Ilmatieteen Laitos (Finnish Meteorological Institue) have done related research about WPF accuracy and uncertainty in Finland in the year of 2013. They pointed out that the aggregation of wind power production will not only decrease prediction errors, but also decrease the variation and uncertainty of prediction errors by analyzing density function and kernel densities in three sites (Holttinen, Miettinen, & Sillanpää, 2013).

The ecological problem of wind power generation is interference to birds. Some types of wind turbine projects cause bird death, and these deaths may contribute to declines in the population of species also affected by other human-related impacts. The wind energy industry and the U.S. government are researching ways to reduce the effect of wind turbines on birds and bats. Modern wind turbines can be very large machines, and they may visually affect the landscape. Some people do not like the sound that wind turbine blades make as they turn in the wind. Producing the metals and other materials used to make wind turbine components has impacts on the environment, and fossil fuels may have been used to produce the materials.

The main solution is offshore wind power generation with higher cost from power generation but also high efficiency. Onshore wind power generation influences fisheries trade and marine mammals. In some regions over the world where the population is denser, to find the location for installing wind turbines are more restricted sometimes, offshore wind farms will be vigorously developed. Meanwhile, wind power generation makes a lot of noise, building wind farms in some empty places can be a possible better choice.

For the algorithms, there is no single best forecasting algorithm that can be applied to all renewable energy systems. As a result of this research, it can be shown that each algorithm or combined algorithm has its advantages and disadvantages. There is still space to increase the prediction accuracies respectively in scale of very short-term, short-term, medium-term, and long-term wind power predictions.
In general, there is considerable room for WPF development as wind power generation technology is not fully mature as there existed objective constraints. The limitations of this study include the research being established based on the existing literature. Meanwhile, some aspects are potentially ignored as this research is initially based on the existing literature. Furthermore, portability needs to be improved when planting into other wind farms.

6.4 Future Research

As wind power generation develops rapidly and the installed capacity is increasing fast in recent years, the innovative application of "environmentally friendly power supply" is getting much closer to our daily life. The dependence on electricity is increasing while the rapid development of society is changing day by day. The improvement of social production and the continuous development of people's standard of living have a strong demand for power resources. Human society urgently needs to improve the efficiency of electricity consumption as the power resources are in shortage. (Rudenko, Ershov, & Evstafiev, 2017).

Currently, mostly WPEs consider the results of weather forecasts as a factor in helping managers to make decisions which rely on historical and prevailing meteorological data. However, nearly no research considers the impact of climate change while climate change over 10 years or even longer. Further research may mainly aim at figuring out how climate change over decades can influence wind power through comparing and analyzing climate data records in complex terrain. More specifically, the objective is to explore the impact of climate change on weather conditions, especially EWEs which influence the wind power output in wind power enterprises. Besides this, as wind power has a cubic dependency on wind speed, this error from wind speed forecast can increase when predicting wind power. Therefore, finding solutions for getting higher accuracy of wind speed observation sites and developing better prediction models are continuously research tasks. In the future, more research is needed in the field of wind power prediction for the purpose of optimizing real time data, increasing the prediction accuracy and system reliability.

ML is widely used in many domains. The concept of DL has been introduced by Geoffrey Hinton, Yoshua Bengio, Yann Lecun in 2006. Recently, DL techniques have started to be used in the WPF area. DL usually has better performance than traditional ML in certain conditions when the training set is big enough.

Electric energy is one kind of secondary energy, it cannot be stored since electricity must be generated as much as needed. It is waste if it generates more than needed while power cuts will happen if less than needed. Therefore, the power generation must follow the load of the power to adjust which is called peak regulation. Thermal power plants have strong peak-regulating capacity while wind farms have poor peak-regulating capacity. For this reason, wind power and thermal power plants must be packaged into the grid, to achieve wind power peak. Aims to be integrated into the power grid, the wind power grid connection has always been a problem. The future research could include increasing electricity generating stability in power companies based on better peak regulation in practice.

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Appendices

Appendix 1. Paper 1: A Review of Innovation in Wind Power Forecast

Yang, W., Liu, Y., and Yang, G. (2014): A review of innovation in wind power forecast. *Proceedings of the 11th International conference on Innovation & Management*.

It has been published in Proceedings of the 11th International conference on Innovation & Management.

Wenshan Yang: Defining of the research design, methodology and research methods, verification and analysis of findings, writing the body text of the original article, editing the article at different stages.

Yang Liu: Editing the article at different stages.

Gengsheng Yang: Acquisition of research resources.

A Review of Innovation in Wind Power Forecast

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Abstract

It can be noticed that most existing literature related to the topic of wind energy resource focus on specific areas, such as, specific forecasting model, local energy plan and policy, power engineering, etc. The purpose of this paper is to contribute to the topic of wind resource exploitation and wind power prediction for relevant researchers and professionals. A review of existing literature in the areas of wind energy resource (WER) and wind power forecast (WPF) methods are presented in this paper, and the innovations in these relevant areas are also reviewed. We try to explore the research gaps in these areas to highlight the possible future research topics for the society.

Keywords wind energy resource, wind power forecast, weather forecast, literature review

1 Introduction

In the last few decades, numerous researchers have put effort on exploiting, utilizing and optimizing energy. However, in recent years a large number of countries are moving to the exploitation of renewable and clean energy and this will be a long-term trend. Meanwhile, renewable energy education is becoming more and more popular and plays an important role in the improving of the quality of life (Kandpal & Broman, 2014).

In contrary to fossil fuel based and nuclear energy sources, renewable energy sources (RES) can effectively utilize natural resources, alleviate the pressure of energy crisis, and minimize the negative environmental impacts (Ozcan, 2014). A new research predicts that global energy demand in 2040 will be approximately 30% higher than it was in 2010. It is urgent that. Because the typical characteristics of wind energy are stochastic and intermittent, it is important to know and use appropriate renewable energy technologies in the whole process of producing wind power generation (Dashwood, 2012).

Changes in temperature, precipitation, sea level, and the frequency and severity of extreme events will likely affect how much wind power generation is produced, delivered, and consumed. One hand, weather forecast data as input of WPF system influence a lot. On the other hand, there exist various weather phenomena, such as, rainstorm, hail, thunderstorm and tornado, have high probability generate more or less damage to wind turbines.

The structure of the rest of the paper is as follows: Section 2 describes the methodology of writing a literature review upon which this paper is based and introduces some other methods. Section 3 reviews the major contribution and innovation of all the existing classic models in the wind power forecast and their links between in order to find research gaps. Section 4 discusses the research gaps and proposes for the future research. Section 5 concludes the paper and some final remarks.

2 Research methodology

The main methodology of this review paper is systematic review. The purpose of using this method is to find what kinds of advanced outcome did researchers have done before and specify the research gap, then determine what research content remain to study. Meanwhile, it can also provide a blueprint of state-of-art. The systematic review is a quite common way of collecting data, published in the literature, assessing methodological quality for high quality research questions. Systematic review are quite common in sciences where data are collected, published in the literature, and an assessment of methodological quality for a precisely defined subject would be helpful (Laberge, 2011). In this paper, contribution of each literature were associate and analyze together, it aims at finding out advanced things filling out the research gap.

Besides of this, cluster analysis helped to classify wind power forecast (WPF) methods. Furthermore, the methods of association analysis has also been used to do a synthesized analysis. Through a review of evidence from both qualitative and quantitative studies, disparate data are synthesized in order to better understand the topic of WER and WPF.

3 Descriptive analysis

3.1 Wind power forecasting by time scale

People usually use ultra-short term, short-term, medium-term and long-term time scales to predict wind power prediction in practice (Soman et al., 2010). There are different time scales when classifying wind power forecasting species according to time periods and one example is as follows (Peng et al., 2013; Soman et al., 2010).

a. Long term forecasting
   Long-term wind power predictions are utilized for maintenance and repair of the wind turbine and include the predictions from 1 day to 1 week.
b. Medium term forecasting
   Medium-term wind power predictions are utilized for power system management and energy trading and include the predictions for 6 h to 1 day ahead.
c. Short term forecasting
   Short-term wind power predictions are utilized for pre-load sharing and include the predictions from 30 min to 6 h.
d. Ultra-short term forecasting
   Very short-term wind power predictions are used for turbine control and load tracking and include the predictions for few seconds to 30 min ahead.

3.2 Wind power forecasting by predicting model

The methods of wind power prediction are usually divided into three groups (González-Mingueza & Muñoz-Gutiérrez, 2014).

- Statistic model

Statistical models are based on mathematical statistics analysis of the main variables associated with energy generation, such as wind speed and temperature at some points of measurement as well as the measures of wind generation at different point in the network.

- Physical model

Physical models are based on the use of numerical models. At first, get the results of meteorological data, such as, wind direction, wind speed, atmospheric pressure and air density. Then use some physical characteristics surrounding wind turbine to get the optimized predicting wind speed and direction in different hub height of wind turbine generator system. Finally, the wind power output can be predicted based on established physical model.

- Hybrid method

Hybrid method is a useful predicting way as it can improve the WPF accuracy by offsetting random error with one method from each other. However, this technique is not very mature even it is commonly used nowadays.

3.3 Commonly used wind power forecasting methods

In light of different input data which means whether use Numerical weather forecast (NWF), the wind power forecasting can be divided into numerical weather forecast forecasting method and historical meteorological data forecasting method.

- Kalman filters

Kalman filters (KF) is an optimal recursive data processing algorithm and it has been firstly achieved by Stanley Schmidt in 1958. The preliminary application of KF method for numerical weather forecasting has been reported in a few papers (Persson, 1991). In one case, a modified KF algorithms was applied to wind speed numerical predictions so as to improve the WPF accuracy. This literature indicates high performance in eliminating of any type of systematic errors and reducing the requirements in CPU time. In the end, this paper also mentions that this technique can not only be used in the traditional meteorological use but also engineering sector, such as, wind power integration (Louka et al., 2008).

- Time series model

Commonly used time series models include auto regressive (AR), moving average (MA), autoregressive moving-average model (ARMA) and auto regressive integrated moving average (ARIMA). Among these, one ARIMA model established by Box and Jenkins have been widely used for the purpose of time series forecasting (Box & Jenkins, 1976). Meanwhile, this book is extremely overall because it interpretes each kind of time models in detail and also gives samples of modelling.

- Artificial neural network (ANN)

Various artificial neural network (ANN) models are widely used, such as back propagation (BP) and radial basis function (RBF). An ANN is an information processing method which works like a human brain processes to find an algorithmic solution algorithmic solution in order to pick out the structure from the existing data (Carolin Mabel & Fernandez, 2008; Kariniotakis, Stavrakakis, & Nogaret, 1996). Based on normal BP network, one new wind power prediction model which optimized tabu search algorithm with memory function was developed (Han et al., 2011).

Existing methods for this purpose tend to yield results with poor accuracy because they cannot properly account for seasonal effects over the long term. However, one updated method improve the accuracy of daily average wind speed forecasting. This study aims to forecast the daily average wind speed over a long period of time, such as one year ahead. This method can forecast the daily average wind speed one year ahead with lower mean absolute errors compared to figures obtained without adjustment (Guo et al., 2011).

- Support vector machine (SVM)

This method was firstly developed by Corinna Cortes and Vapnik in 1995. It is similar to ANN but the most apparent difference is SVM focus on mathematic method and optimization mechanism. One typical research applied this SVM method to wind speed prediction has been done in 2004. The paper introduces SVM, the latest neural network algorithm, to wind speed prediction and compares their performance with the multilayer perceptron (MLP) neural networks. The result indicates that SVM comparing to MLP is closer to the actual wind speed (Mohandes et al., 2004).

The existing studies on using SVM for wind forecasting are very limited in that usually only one particular kernel function and a specific combination of parameters are picked and used in these studies. A systematic investigation focuses on kernel function encourage people to apply this method for wind energy applications. One research fill the research gap, it briefly introduce the principle of LS-SVM and analyze procedure for tuning LS-SVM parameters for optimal performance (J. Zhou et al., 2011). Least-squares support vector machines (LS-SVM) is a powerful technique which aims at getting higher accurate forecasting of wind speed. And it is widely used for forecasting short-term wind speed forecasting.

- Fuzzy logic

It is a useful and practical technique for modelling complex phenomena that may not yet be fully understood owing to its ability to deal with imprecise, uncertain data, or ambiguous relationships among data sets (Metternicht, 2001). This approach provides a simple method to draw definite conclusions from vague, ambiguous, or imprecise information, however it is not widely used because of the low accuracy as low ability of fuzzy logic prediction is low when studying (Klir & Folger, 1988). There are few up to date literature researching in this area, providing a possible research gap basing on its promising nature.

- Hybrid algorithm

There is no single best forecasting algorithm that can be applied to any wind farm due to the fact that wind speed patterns can be very different between wind farms and are usually influenced by many factors that are location-specific and difficult to control (Guo et al., 2011).

In a very recent literature, a novel hybrid modelling method which named SVR–UKF is proposed, integrating unscented Kalman filter (UKF) with support vector regression (SVR) in order to precisely update the short-term estimation of wind speed sequence (K. Chen & Yu, 2014). Using this method, the prediction errors are closer to zero with significantly smaller variations, whereas the prediction errors of the other methods are scattered more widely.

Each one of physical models, statistical models, spatial correlation models and artificial intelligence models has its advantages and disadvantages, for example, the time series model is one kind of statistical models and it is popular in use because its computation is simple, ANN and KF are popular due to their

good nonlinear performance. Thus, another research which introduces two hybrid algorithms and compare show both of them have good performance. In this literature, the authors establish two hybrid methods namely ARIMA-ANN model and ARIMA model based on single time series model, ANN model and KF model. The results show that: (1) Both of them have good forecasting accuracy; and (2) they are suitable for the jumping wind samplings, which can be applied to real-time wind power systems (H. of two new A.-A. and A.-K. hybrid methods for wind speed prediction Liu, Tian, & Li, 2012).
Other similar hybrid algorithms also exist, e.g. one research systematically and comprehensively investigated the applicability of this methodology based on two case studies on wind speed and wind power generation, respectively. Two hybrid models, namely, ARIMA–ANN and ARIMA–SVM, are selected to compare with the single ARIMA, ANN, and SVM forecasting models. The results show that the hybrid methodology does not always outperform the individual forecasting models based on ARIMA, ANN, or SVM. As such, the argument in some literature that the hybrid methodology is always superior to single models cannot hold for wind speed or power generation forecasting (Shi et al., 2012).

Table 1 Innovations in different forecasting methods

Methods	Literature	Innovation
Kalman filters	(Louka et al., 2008)	This literature has introduced two limited-area atmospheric models for wind speed forecasts, and particularly utilise Kalman filter to these data to eliminate any possible systematic errors, even in the lower resolution cases, contributing further to the significant reduction of the required CPU time. In particular, the paper contributes in the case of wind power prediction, which showed a remarkable improvement in the model forecasting skill. The major innovation is to counteract the drawback of Numerical Weather Prediction (NWP) models exhibiting systematic errors in the forecasts of certain meteorological parameters. Instead of increasing the model resolution that may provide considerable improvement of smaller scale flow characteristics, which remains as an open question to whether the use of higher resolution improves the forecast skill considerably, the methodology introduced in this paper showed high performance to the elimination of any type of systematic errors and most importantly it reduced the requirements in CPU time since its application to lower resolution data led to similar or even more accurate results compared to the costly high-resolution direct model outputs.

ANN	(Han et al., 2011)	It is urgent to improve the accuracy of short-term wind power forecast by NWF. BP network, as one of ANN, has been widely used in wind speed and wind power prediction. However, the BP algorithm has its apparent disadvantages, easily getting into local minima and the convergence rate is slow. The major innovation in this literature is that the authors use Tabu Search (TS), another algorithm which can achieve the global optimizations, to train BP network. It can be shown that the new method namely MTS-ANN model can solve the inherent shortcoming of BP network by improving the convergence probability and precision of BP network apparently.
	(Guo et al., 2011)	Another BP model also used to predict wind speed in the same year of 2011. In this literature, the authors integrate BP network with the idea of eliminating seasonal effects from actual wind speed datasets using seasonal exponential adjustment. This study aims to forecast the daily average wind speed over a long period of time, such as one year ahead. Existing methods for this purpose tend to yield results with poor accuracy because they cannot properly account for seasonal effects over the long term. To improve the accuracy of daily average wind speed forecasting,
SVM	(Mohandes et al., 2004)	This literature introduces support vector machine method for wind speed prediction, and compares it with multilayer perceptron (MLP). For these two algorithms, some results are shown after validating data from one case study which named Saudi Arabia which located in Madina city. One of the most important contributions is that parameters for both algorithms were optimized. Another finding is the lowest MSE of SVM is better that MLP in this case study.
LS-SVM	(J. Zhou et al., 2011)	This literature, for the first time, presents a systematic study on fine tuning of LS-SVM model parameters for one-step ahead wind speed forecasting. The authors impleted three SVM kernels which including linear, Gaussian, and polynomial kernels. The results show that the performance of linear kernel is worse than the other two kernels when the training sample size or SVM order is small. For Gaussian and polynomial kernels, both types of parameters should be considered jointly rather than independently for both kernels. LS-SVMs are compared against the persistence approach, and it is found that they can outperform the persistence model in the majority of cases.

Kalman filters+ SVM	(K. Chen & Yu, 2014)	Accuracy of wind speed forecasting is very important for improving and optimizing renewable wind power generation. However, one of the most apparent characteristics of the wind is strong stochastic nature and dynamic uncertainty. In this literature, a proposed approach named SVR–UKF, integrated unscented Kalman filter (UKF) with support vector regression (SVR), is developed to update the short-term estimation of wind speed sequence. The results indicate that the proposed method has much better performance in wind speed predictions than the other approaches across all the locations.
ARIMA+ANN, ARIMA+Kalman	(H. of two new A.-A. and A.-K. hybrid methods for wind speed prediction Liu et al., 2012)	This literature introduces two new hybrid models namely ARIMA-ANN model and an ARIMA-Kalman. After respectively comparing the multi-step ahead prediction results by an ARIMA-ANN model, an ARIMA-Kalman model and a pure ARIMA model, it can be proved that the performance of the two hybrid models is better than that of the pure ARIMA model, and the performance of the ARIMA-Kalman model is better than that of the ARIMAANN model. The major innovation is they improved the performance of the pure ARIMA model and utilize in bigger number of forecasting steps in order to lower the accuracy.
ARIMA+ANN, ARIMA+SVM	(Shi et al., 2012)	This literature compares two typical hybrid models, namely ARIMA–ANN and ARIMA–SVM, with three separately single models through two case studies about wind speed and wind power generation. The results show two hybrid models are viable when predicting wind speed and wind power generation. However, the most important contribution is that they found hybrid models are not superior to single methods in performance for all the forecasting time horizons investigated.

4 Discussions and future research

The present review provides a useful overview of the research on the use of identifying topic and key terms, identifying database and access software, conducting searches, identify sources as primary or secondary, summarizing and analyzing primary sources, organizing and writing reviews. The purpose of this paper is to contribute to the topic of WES exploitation and WPF for relevant researchers and amateurs. Furthermore, this paper also gives an overall roadmap of each knowledge and descriptive analysis.

Limitations of this review article are due to the scope and methods used. Only writing methods, classification of wind power forecast has been included. Surely, research derived from with other areas, for example, specific forecasting model, local energy plan and policy, power engineering. Meanwhile, the number of review papers is merely more than 20. Better statistic results are expected when there are more review samples.

Currently, mostly wind power enterprises consider the results of weather forecast as a factor in helping managers to make decisions which rely on historical and prevailing meteorological data. However, nearly no research considers the impact of climate change while climate change over 10 years or even longer. Further research may mainly aim at figuring out how climate change over decades can influence the wind power through comparing and analyzing climate data record in complex terrain. More specifically, the objective is to explore the impact of climate change on weather condition, especially extreme weather events which influence the wind power output in wind power enterprises.

5 Conclusions

In this paper, several methodologies, which including systematic review, cluster analysis and association analysis, are used to depict and generalize different popular WPF methods.

Many different wind power forecasting methods used in wind energy system have been reviewed in this paper to summarize their own theory and characteristics in different methods. And their corresponding innovations are also reviewed in detail. The important points were descripted in Section 3. So the main contribution is to provide a path for researchers in this same field.

There is no single best forecasting algorithm that can be applied to any wind farm and each algorithm. As a result of this study, it can be said that each algorithm or combined algorithm both has its advantages and disadvantages. There is still space to increase the prediction accuracies in very short-term, short-term, medium-term and long-term wind power predictions, respectively.

In the future, more research will still to be tried in wind power prediction for the purpose of increasing the prediction accuracy and system reliability.

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Appendix 2. Paper 2: The impact of climate change on wind power enterprises

Yang, W., Liu, Y., and Yang, G. (2014): The impact of climate change on wind power enterprises. *Proceedings of the 11th International conference on Innovation & Management*.

It has been published in Proceedings of the 11th International conference on Innovation & Management.

Wenshan Yang: Defining of the research design, methodology and research methods, verification and analysis of findings, writing the body text of the original article, editing the article at different stages.

Yang Liu: Editing the article at different stages.

Gengsheng Yang: Acquisition of research resources.

The impact of climate change on wind power enterprises

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Abstract

The aim of this study is to survey impact of climate change on wind power enterprises (WPEs). So the main work is to develop a new framework to determine the impacts climate change on WPEs. A huge database of climate data record (CDR) in used with meteorological and geographic variables for period 1979-present three times per day for 10 meter U wind component, 10 meter V wind component, total column water vapour, 2 meter temperature, medium cloud cover, mean sea level pressure, gravity wave dissipation, etc. Among these meteorological data, air density and wind speed can be used to predict the wind power density for wind farm site selecting. And wind speed, relative humidity, rainfall, snowfall over few decades can be chosen to draw graphs in order to analyze the significant correlation with wind power.

Keywords wind power forecast, WPEs, climate change, global wind energy resource distribution, CDR.

1 Introduction

Changes in temperature, precipitation, sea level, and the frequency and severity of extreme events will likely affect how much energy is produced, delivered, and consumed. It can be noticed that quite few researches regard climate change as a long-time measurement factor for renewable energy plant. Today, wind energy is widely used to produce electricity in many countries all over the world, such as China, United States, Germany, Spain, India, and Denmark. For wind energy, mostly wind power enterprises consider results of weather conditions as a factor for helping managers to make decisions which rely on historical and prevailing meteorological data. For example, they are more interested in the predicted and actual data of wind speed, wind direction and the rated power of the wind turbine. Long-term wind projects do not include the yet unknown impacts of climate changes on wind power (Pereira, Martins, Pes, da Cruz Segundo, & Lyra, 2013).

However, climate change is another concept which is not as same as weather condition. Climate change is a long-term accumulated effect of weather condition caused by many factors, and it directly results extreme weather events (EWEs) which has significant impacts on power generation. EWEs may generate rainstorm, typhoon, mudslide, extreme temperatures, hailstone across most parts of the world. With rising concerns about climate change, a recent similar climate change research report, man-made climate change contributed to some of 2012's most extreme weather, including the spring and summer heat waves that baked parts of the United States and Hurricane Sandy, which devastated coastal communities along the eastern coast of the country. Understanding the climate change phenomenon and its impact on wind power system is of increasing importance all over the world.

Wind power generations depend on the natural environment especially under extreme wind condition, which means the wind speed is near or over the cut-out speed (Lin et al., 2012). In addition to this, other disaster events including, lightning, strong wind, extreme temperatures, haze, fog acid rain and hail will result in sudden power drop under an extreme condition.

However, lack of good quality data, of sufficient record length and spatial coverage usually restricts model development and performance geared towards assessing the effects of climate change in these areas (Kenabatho, Parida, & Moalafhi, 2012).

This research mainly aims at figuring out how climate change over decades can influence the energy power through comparing and analyzing climate data record. More specifically, the objective is to explore the impact of climate change on weather condition especially extreme weather events which influence the power output in wind power enterprises from the sight of meteorology. Meanwhile, make summarize typical climatical characteristics over three selected meteorological stations. The specific goals are described here,

- Observe and analyze climate data record from approximately 1970 to recent days, and identify the main developing trend of climate change for three selected dissimilar typical meteorological stations.
- Explicit how climate data record can be used to eliminate economic loss in wind power enterprises.

Section 2 will give a literature review about the current research situation and also summarize the art-of-state. Section 3 will draw a framework which assessing wind resources and finding correlation between wind power and some meteorological elements. Section 4 presents discussions and finally summary, this part also gives future research prospects.

2 Literature review

Kenabatho et al. (2012) present an analysis of rainfall and climate data in order to determine the time of change in rainfall series and identify possible correlations between rainfall and temperature. They use historical rainfall, climate data from rainfall stations and large-scale CDR from 1965 to 2008. The results indicate that temperature is a significant rainfall predictor in Botswana. Meanwhile, they make predictions of future rainfall patterns in Botswana(Kenabatho et al., 2012).

According to Birgit Mannig et al. (2013), central Asia has already implemented the high-resolution regional climate REMO and they use REMO simulations to get higher accuracy results which are closer to observational data(Mannig et al., 2013).

From geographic aspect, Turkey is a country which located between Europe and Asia, bordering the Mediterranean, Aegean and Black Seas. One of the most apparent characteristics of this country is that its location between the colder European and warmer Asian and African systems also cause a wide variety of temperature and climate difference. Turkey has a rich potential of wind energy with 1002MW due to that this country surrounded by many mountains, and its unique geographical character creates a regular and moderate air inflow through its mountainous valley structures. A research investigated the renewable energy situation including hydropower, wind and geothermal potential in Turkey(Çapik, Yılmaz, & Çavuşoğlu, 2012).

A research review and explicit the trends of observed terrestrial near-surface wind speeds for many countries all over the world, and study the observed rates of atmospheric evaporative evaporation. In this study, they separately describe the trends of near-surface terrestrial wind speed and the trends in evaporative demand, then analyze the importance of wind speed to the evaporative process. It is not a review paper about wind resource but also a relevant reference to water resource assessment. The result show that near-surface terrestrial wind speeds are declining in both hemispheres for both the tropical and mid-latitudes. Four primary meteorological variables, which including wind speed, atmospheric humidity, radiation and air temperature, were also assessed. This paper also highlight the important role that wind speed trends play in governing evaporative demand trends (McVicar et al., 2012).

Another similar literature provides global and seasonal estimate of the “practical” wind power, which defined as delivered from wind turbines in high-wind locations over land and near-shore, obtained with a 3-D numerical model. They found that the global practical wind power potential varies significantly with season and hemisphere. Such as the highest wind power output are generated in the season of winter and oppositely the lowest are in summer (Archer & Jacobson, 2013).

One relevant research focuses on studying wind energy, solar energy, bio-energy resource separately in Mali by using modelling, satellite imagines and existing global datasets. The methods applied make extensive use of satellite remote sensing and meteorological mesoscale modeling. In this study, the preliminary wind resource map produced show that the North of Mali has more potential of wind energy (Nygaard et al., 2010).

3 Towards a conceptual framework

Some changes associated with climate evolution will likely benefit the wind energy industry while other changes may negatively impact wind energy developments, and expansion of wind energy installed capacity is poised to play a key role in climate change mitigation (Pryor & Barthelmie, 2010). Various wind power stations have different terrain feature which can be seen from global wind energy resource distribution.

This research mainly aims at figuring out how climate change over decades can influence the energy power through comparing and analyzing climate data record. More Specifically, classify all relative meteorological phenomenon which are closely related to power output of wind power enterprises after analyzing climate data record, and determine what factors influence them. Whether seasons effect? Whether time periods effect? Whether regional differences exist?

On one hand, there are different ways to estimate the wind resources at a site and wind resource varies significantly from one location to another. Wind power density (WPD) (W/m^2) can be predicted form wind speed and air density. WPD is a nonlinear function of the probability density function of wind speed [9]. Estimates of WPD are presented as wind class which ranging from 1 to 7 and the assessment of WPD play important role when site selecting. Accurate assessment of wind resource will not only reduce economic loss caused by EWEs but also increase the wind power output.

On the other hand, some few meteorological elements may have relationship with wind power. Six major meteorological elements including air temperature, humidity, wind speed, wind direction, air pressure and rainfall are analyzed. Besides of these, there are evaporation, snow depth, snowfall, total cloud cover, sunshine duration and so on. Among these, we propose the assumption that meteorological elements such as wind speed, relative humidity, rainfall, snowfall over few decades have correlations with wind power, which needs to be proved by analysis with longitudinal data over decades, and then try to determine the function expression by using variety of CDR variables and draw graphs to analyze the relationship between them.

4 Discussion and conclusion

Robert Vautard and his colleagues used a sophisticated regional climate model (this model describes the interactions between wind turbines and the atmosphere) to determine the climate impacts on all current (2012) and near-future (2020) wind energy production according to European Union energy and climate policies. The team found that wind farms form a weak but stable anticyclonic flow over Europe but only in winter there will be a significant impact on daily temperature and rainfall, and this effect is weaker than what natural interannual changes result for the climate change. They use a regional climate model describing the interactions between turbines and the atmosphere, and find limited impacts. However, the impacts remain much weaker than the natural climate interannual variability and changes expected from greenhouse gas emissions (Robert Vautard, Françoise Thais, Isabelle Tobin, François-Marie Bréon, Jean-Guy Devezeaux de Lavergne, Augustin Colette, 2014). This recent valuable research suggests a new and contrary direction to the impacts of climate change on WPEs.

The exploitation of off-shore wind power has more potential prospects comparing to that of on-shore as the coastal wind speed is higher than inland. Meteorological and hydrological factors definitely influence the wind power output, especially typhoon and seawater corrosion. Sea waves can scour foundation of wind turbine tower, corrode undersea cables affecting and affect its stability. Meanwhile, the historical meteorological data of wind and tide directly influence wind power site selection. Therefore, the further research may be related to coastal wind power forecast, and focus on the impact of climate change on offshore wind power plants due to its typical climatic characteristics. This suggests that further research into the links between large-scale climate variability and wind power generation is necessary and important.

In this paper, this work presents some of the most recent relevant research which combines climate change with wind power predicting. The outcome of this research is to help decision-makers of wind power enterprise on making strategic decisions which including site selection, management and maintenance of wind power station, and long-term wind power generation forecast etc. Furthermore, it also develops a proposal framework which to determine the relationship between and wind power density and wind power. And the further research should explore deeply in CDR so as to help the researchers in the field develop more effective wind speed and power forecasting methods by finding specific function expression.

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Appendix 3. Paper 3: Meteorological information service support system in wind park application

Liu, Y. and Yang, W. (2015): Meteorological information service support system in wind park application. *Benchmarking: An International Journal*, 22(2), pp. 222-237. https://doi.org/10.1108/BIJ-11-2012-0077.

Jufo-category of the publication 1, year 2015, and impact factor 2.60.

Article has been published in a peer-reviewed publication 2015.03.02.

Yang Liu: Defining of the research design, acquisition of research resources, programming, guidance in the research process, verification and analysis of findings, editing the article at different stages.

Wenshan Yang: Collecting and managing research material, data analysis, methodology and research methods, visualization of results, writing the body text of the original article.

Meteorological information service support system in wind park application

Abstract

Purpose – This paper introduces a holistic decision support system based on condition-based maintenance which utilizes meteorological forecasting information to support decision-making process in services of wind power enterprises.

Design/methodology/approach – A pilot conceptual system combining with meteorological information and operations management has been formulated in this study. The proposed system provides benchmarking to support decision-making directly and indirectly basing on processing meteorological information and evaluating its impact on service operations. It collects meteorological data to predict failure probabilities in different areas which need corresponding maintenance service and schedule the optimal maintenance periods. In addition, it provides meteorological forecasting and decision support in case of extreme weather events.

Findings – The conceptual study shows that there is a connection between the meteorological conditions and failures, and it is feasible to make service decisions based on the predictions of weather conditions and their impacts to failures.

Research limitations/implications – The research presented at the present phase is not much beyond a conceptual framework. The actual implementation and all possible related practical issues will be dealt with in future research.

Practical implications – It helps decision-makers to predict and identify possible categories of faults in wind turbine, make optimal service decisions to enhance the output performance of wind power generation, and take in advance emergency counteractions in case of extreme weather events.

Originality/value – It presents a novel concept and provides a roadmap to achieve optimal operations in wind park application through combining meteorological information system with service decision-making.

Keywords – information system, meteorological service, extreme weather events, decision-making, strategic management, condition-based maintenance.

Paper type – Research paper

1. Introduction

According to Global Wind Energy Council (2012), the number of wind turbines spinning around the world by the end of 2011 is 199,064. Among that, the amount of wind turbines up and running in China is 45,894 which count 23% of the total amount. That is to say, China's leadership in wind energy deployment is both an opportunity and a challenge for European and American companies to compete in this market and internationally. Europe remains a technology leader and is carving out the next frontier of wind energy with onshore and offshore deployments (Global Wind Energy Council, 2012). The wind energy potential of the Earth is huge and enough, in principle, to meet all the world's electricity needs. Virtually every country has sites with average wind speeds of more than 5 m/s measured at a height of 10 m, which are sufficient for using wind power to generate electricity (Sesto and Ancona, 1995).

Many of critical wind turbine faults are directly or indirectly related to weather conditions and extreme weather events (EWEs). This research intends to propose a pilot service support system which utilizes meteorological information to predict such situations which may lead to breakdowns and make it possible to take precautions in advance, and in addition to suggest other service related decisions based on condition-based maintenance (CBM), such as deciding the optimal time for maintenance during the predicted idle period. CBM is defined by a set of maintenance actions taken as a consequence of knowing the current operating status of equipment. Recent study considers it is a form of proactive equipment maintenance that forecasts incipient failures based on a real-time assessment of equipment condition obtained from embedded sensors and or external tests and measurements that are extracted directly from the equipment (Gulledge, Hiroshige and Iyer, 2010). Many recent studies show there is direct connection between service and business performance in wind power systems and demonstrate business potential analysis that optimal service decisions based on CBM in wind park application can significantly cut down operation and maintenance costs (El-Thalji and Jantunen, 2012; Tian et al., 2011; Nielsen and Sørensen, 2011), and by implementing a successful CBM strategy can also achieve higher level of cost effectiveness (El-Thalji and Jantunen, 2012), thus improve the operation and business performance.

In many recent studies, the relationship between wind speed modelling and electricity generation from wind turbines is also studied. In fact, wind park investors are interested in long-range forecasts and simulation of wind speed for two main reasons: to evaluate the profitability of building a wind farm in a given location, and to offset the risks associated with the variability of wind speed for an already operating wind farm (Caporin and Preś, 2012). The percentage of the world's electricity that could be produced from offshore devices is estimated to be around 7% by 2050, and this would employ a significant amount of people by this time, possibly around 1 million, mostly in the maintenance of existing installations (Esteban and Leary, 2012).

Optimal maintenance are affected by various factors, such as availability of resources, dependency on meteorological surrounding conditions, as well as a complex logistical process chain (Tracht, Westerholt and Schuh, 2013), and failure probability can be predicted based on condition monitoring data of wind energy systems (Tracht et al., 2013). Based on these theories, this paper develops a holistic system which combines with meteorological information and operations management. The proposed system provides benchmarking to support decision-making basing on processing meteorological information and evaluating its impact in service operations of wind power enterprises. The concept of such decision support system is built based on years of well-established previous studies utilizing sense and respond type of continuous adjustments in decision-making to achieve sustainable competitive advantage in operations strategy implementation (Liu, 2013).

The structure of this paper is as follows. Section 2 reviews the latest related studies. Section 3 introduces the research methodology. Section 4 describes the system structure and process in a conceptual framework. Section 5 discusses the managerial implications, research limitations and also recommendations for future research. Section 6 draws conclusions.

2. Review of related studies

2.1 Wind power as an energy source

Energy is the main intermediate strategic resource for economic development and growth in any country. This usually translates to better quality of life, and therefore it leads to higher primary energy consumption in all sectors, transportation, industry, services, household, etc. (Abulfotuh, 2007). Nowadays, the world faces a great challenge of saving our future in terms of developing renewable energy. Until now, a huge amount of the energy requirements all over the world is supplied originally from conventional energy sources like coal, crude oil, natural gas, etc. However, these patterns of energy are limited and often lead to pollution. Therefore, renewable energy resources will play an important role in our daily life in the world's future.

Renewable energy sources are those resources which can be used to produce energy again and again, e.g. solar energy, wind energy, biomass energy, geothermal energy, etc. and are also often called alternative sources of energy (Rathore and Panwar, 2007). Among the renewable energy sources wind energy is currently viewed as one of the most significant and attractive sources, which is a clean energy rather than coal, crude oil and natural gas. The outstanding characteristic of wind power is to save energy and protect environment although the intermittent character is a very critical problem.

The use of renewable energy sources is closely linked to sustainable development, because a sustainable supply of energy resources which must be used effectively and efficiently is required for it, as well as for progressing in environmental problems (Tolón-Becerra, Lastra-Bravo and Bienvenido-Bárcena, 2011). It is undoubtedly that sustainable development will definitely let managers handle with problems during the period of decision-making.

On one hand, wind power generation is becoming more and more popular in many countries, but it differs from conventional thermal generation due to the stochastic nature of wind. Thus wind power forecasting plays a key role in dealing with the challenges of balancing supply and demand in any electrical system, given the uncertainty associated with the wind park power output. Accurate wind power forecasting reduces the need for additional balancing energy and reserve power needed to utilize wind power (Foley et al., 2012).

On the other hand, the Nordic countries particularly experienced a number of extreme weather events (EWEs) during recent years and a significant number of wind power businesses were affected as a result. With the intensity and frequency of extreme weather predicted in the future, enhancing the resilience of businesses, especially wind power enterprises (WPEs) which are considered as highly vulnerable, has become necessary (Wedawatta et al., 2011). However, little research has been undertaken on how construction of WPEs is responding to the risk of EWEs.

2.2 Meteorological service and decision-making

Traditional maintenance techniques, such as preventive maintenance is scheduled in advance of failure and usually at regular intervals which are typically determined by the analysis of historical reliability data (Gulledge, Hiroshige and Iyer, 2010), and time-based maintenance (TBM) is labour intensive, ineffective in identifying problems that develop between scheduled inspections, and not cost-effective (Ahmad and Kamaruddin, 2012). Whereas CBM is scheduled by predicting the future status of the equipment based on operational or other characteristics. (Gulledge, Hiroshige and Iyer, 2010). Recent studies develop optimal CBM strategy and decision for wind power applications systems (Tian et al., 2011; Nielsen and Sørensen, 2011; El-Thalji and Jantunen, 2012). CBM is more efficient compared to preventive maintenance in many ways, e.g. condition monitoring and diagnostic practices have become significantly important part of offshore wind farms in order to cut down operation and maintenance costs (El-Thalji and Jantunen, 2012), and more realistic and worthwhile to apply than time-based maintenance (Ahmad and Kamaruddin, 2012). However, in wind park application it is typically hard to accurately predict with standalone meteorological data and may lead to a failure prediction. The other challenge is to enable CBM strategy to provide maintenance decisions and services at the right time i.e. maintenance is performed when it is needed and not too early and not too late i.e. causing breakdown and downtime (El-Thalji and Jantunen, 2012). Therefore a holistic system combining the complete meteorological service and decision-making is needed to increase the prediction accuracy and work together with the traditional preventive/corrective measures to provide optimal maintenance decisions.

Short-term prediction is mainly oriented to the spot (daily and intraday) market, system management and scheduling of some maintenance tasks, being of interest to system operators, electricity companies and wind park promoters (Costaa et al., 2008). Wind forecasting for energy generation and power system operations mainly focuses on the immediate short-term of seconds to minutes, the short-term of hours up to two days, and the medium term of two to seven days. This is because power system operations such as regulation, load following, balancing, unit commitment and scheduling, are carried out within these time frames. The science of wind power prediction is described as the application of the theories and practices of both meteorology and climatology specifically to wind power generation (Petersen et al., 1997).

- Numerical weather prediction

- In case of non-saturated power, because the wind power is equal to wind speed third cube and wind speed are much more regular than that of wind power, consequently a small wind speed error will amplify wind power errors much. It is wide and effective by using short-term wind power forecasting methods which combining numerical weather prediction (NWP) model with statistical models, so that we can develop operating mode for electric grid dispatching, provide support for arranging dispatch rationally, reduce the effects of intermittent power to wind power systems effectively. The wind data from now, yesterday, or last year in the same period cannot be used to predict wind in the next 24 hours, because wind is dependent on the weather, and the wind power output cannot be guaranteed at any particular time. Thus the integration of wind power into electrical grids can cause difficulties in the management of the power system (Marciukaitis, Katinas and Kavaliauskas, 2008).Meteorological service

Climate change is predicted to have a significant effect on the frequency of EWEs and the occurrence of natural disasters, such as hail, flood, tornado and thunderstorm. There is a need for facility managers to mitigate potential disruption and prepare for future events caused by natural phenomenon. Meteorological sector sends out early warnings to WPEs, using the results of real-time monitoring and weather forecasting from satellite, radar, observation stations.

The meteorological ensuring system is a derivative product which mainly involving EWE forecasting and warnings. This can prevent and mitigate climate change on crucial facilities and the impact of the project effectively. In current practice, however, that little risk assessment is undertaken by few organizations preparing integrated disaster management plans or business continuity plans to help them meet the challenge (Warren, 2010). As we learn more about possible climate change impacts, certain WPE protection strategies may become more desirable and feasible in management, and we can adopt strategies to minimize its negative impacts on wind power generation.

After studying how climate will change by predictions with wind power production and provide guidance in facing of EWEs, then facility managers can prepare for risk assessment and disaster plans after collecting scientific data related to the potential effects of climate change (Warren, 2010).

- Decision-making

There is relatively little research in the area of operations and service management in renewable energy sector such as wind power by utilizing meteorological information. Some notable studies connecting meteorological forecasting with renewable energy include e.g. Kaplan & Norton (2011) and Eckman & Stackhouse (2012). Changes in competitive environments have increased the importance of strategic management in corporations. Successful companies must be able to anticipate changes in operating environments and be able to react faster than their competitors (Kaplan and Norton, 2011). Earth observations are critical in enhancing the implementation of renewable energy technologies and improving energy efficiency (Eckman and Stackhouse, 2012). Other related research has been implemented by Liu, et al. (2012). According to the research from this group, they proposed a novel wind turbine fault diagnostic method based on the local mean decomposition technology, which is a new iterative approach to demodulate amplitude and frequency modulated signals, which is suitable for obtaining instantaneous frequencies in wind turbine condition monitoring and fault diagnosis. Finally, the experimental analysis of the wind turbine vibration signal proves the validity and availability of the new method (Liu et al., 2012).

Our research presented in this paper addresses this problem from a conceptual level to bridge the gap between meteorological information and decision-making in service operations management. Even though this whole concept is a huge research which is still in progress, nevertheless this paper can be a pilot which leads to new ideas and opens more research paths.

3. Research methodology

3.1 Overview

There are various types of strategies for conducting research in management and social sciences. Reisman (1988) defines research strategies such as ripple, embedding, bridging, transfer of technology, creative application, structuring, and empirical validation. This study uses mainly the following research strategies. Ripple is used to develop analytical models for assessing failure probabilities based on meteorological information and NWP. Embedding and bridging are used to associate the decision-making process in connection with the service needs which are based on the failure forecasts. Empirical validation is used to validate the developed theories by performing various case studies in different countries. Arbnor & Bjerke (1997) introduce three methodological approaches i.e. analytical, systems, and actors. The nature of this study is to create a holistic system which is a set of components and the relations among them. Holweg (2005) applies the systems approach and contingency theory to review existing contributions and synthesizes them into a conceptual model, which is very similar to the nature of this work. Therefore, systems and contingency based methodological approach is proposed to carry out this work. As the main contribution of this study is the integration of meteorological information with decision-making in service operations, it requires a new design in the research methodology to integrate the classic components. Kasanen, et al. (1993) describe the constructive approach as “problem-solving through the construction of organizational procedures or models”, and also propose a market-based validation for assessing this aspect of a construction. In this work the construct is the integrative holistic system and it is feasible to apply a weak market test to validate and implement the research objectives. In summary, the research methods include literature survey, descriptive conceptual analysis, analyzing qualitative data based on Silverman (2001) and also quantitative data, classification by simple statistics, and finally using Kasanen et al.’s (1993) the constructive research approach with weak market tests and pilots for implementation.

3.2 Case study

To achieve the entire objectives of this conceptual research, the empirical studies are important and numerous case studies should be carried out from different countries, and analyzing them with the proposed existing analytical models and creating new analytical models for further evaluation. Therefore, the selection of the case companies must be mostly representative wind park applications. The case studies will be carried out in future research.

3.3 Data collection and analysis

The data of cases in different countries are collected in the same manner: by asking senior managers or directors to answer the questionnaires. The interviewees are normally decision makers and middle management groups, who have good knowledge about the operations of their own wind parks. The interviewed high competence experts should be representative to know well the operations of the studied wind park. The data collected typically from limited and described application problems is mainly qualitative in nature and its validity and reliability can be ensured by improving the required careful documentation of the cases (Sykes, 1990; 1991). Firstly, the managers or directors are trained to understand every item of the questionnaires correctly by interview, email or telephone. Secondly, after they finish the questionnaires, the answers are analyzed with software. Thirdly, the discussion with the managers or directors reveals the results and verifies the validity and reliability of the data further.

4. System description

This section develops a conceptual framework for service support in wind park application. The proposed system involves 3 major modules: meteorological information module, wind power prediction module and operations management decision-making module. The complete system structure and process are illustrated in Figure 1.

4.1 Meteorological information module

This module includes meteorological data collection and NWP. First, meteorological data are collected by the wind speed sensor, wind direction sensor, temperature sensor, atmospheric pressure sensor, humidity sensor etc. installed on the wind-testing tower of the targeted wind park. Through wireless communicating module, original meteorological data from the wind-testing tower is converted into a digital signal and finally transmitted to the receiving terminal. Then NWP processes the meteorological data to parameters related to wind power output. NWP is a special version tailored to predicting wind power output and is different from the version used for commercial public weather forecasts. On the other hand, it also sends early warning messages in case of EWEs and managers in WPEs can get alarming signals in advance and take countermeasures quickly. With the new forecasting system it effectively links up the NWP model geared towards very short-range forecast of severe weather system. Currently, the suit is probably one of the few operational forecasting systems that effectively combine radar information, dense mesoscale NWP model prognoses for real-time EWEs risk assessment.

The following example illustrates how this is done in reality. A mountain area site located in central China has been chosen to test the proposed theory. The site is located nearby a wind park in operation, also including a meteorological station with anemometers between 30 and 70 m. This wind-testing tower has been brought into operation since November 2011. The mountain top has a height of 700 meters and has a direct distance of 34 kilometers to the local meteorological station, which has good correlation to predict the weather conditions for the wind park. The common meteorological disasters in this location are thunderstorm, flood, drought, low-temperature freeze and continuous rain.

- Measuring the maximum wind speeds in the meteorological station

The meteorological station is used to predict the 50-year wind base on annual average 10-minute maximum wind speeds. Through T-test to inspect the consistency for sequence of annual maximum wind speed from 1974 to 2011, it has been discovered that the values in 1982 experienced a mutation. It is necessary to correct references of maximum wind speeds from 1982 to 2011due to the diversion of the meteorological station. According to National Wind Energy Resource Evaluation Technology Provision and the type I extreme value distribution, the 50-year average 10-min maximum wind speed is 28.38 m/s.

- Predicting the 50-year maximum wind speed in the wind park

$$V_{50\_max} = u - \frac{1}{\alpha} ln\ ln\ (\frac{50}{50-1}\ )] \tag{1}$$

$$\mu = \frac{1}{n} \sum_{i=1}^{n} \quad V_i \tag{2}$$

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \quad (V_i - \mu)^2} \tag{3}$$

$$\alpha = \frac{C_1}{\sigma} \tag{4}$$

$$u = \mu - \frac{C_2}{\alpha} \tag{5}$$

Using Eqs. (1)-(5), it can be calculated that the 50-year maximum wind speed is 30.5 m/s.

- Predicting the 50-year extreme wind speed in the wind park

Gust factors are a ratio between a peak wind speed of some duration within a given data segment and the mean wind speed of the same segment. An optimum gust factor of about 1.4 is suggested for all types of fabric structures in general, which is an international standard value. Then it can be calculated that 50-year extreme wind speed is 42.7 m/s.

4.2 Wind power prediction module

This module utilizes the processed meteorological data to predict patterns of values related to wind power output. It is an intermediate process to obtain parameters to evaluate failure probabilities and calculate the optimal service decisions which are crucial information for the next process - operations management decision-making.

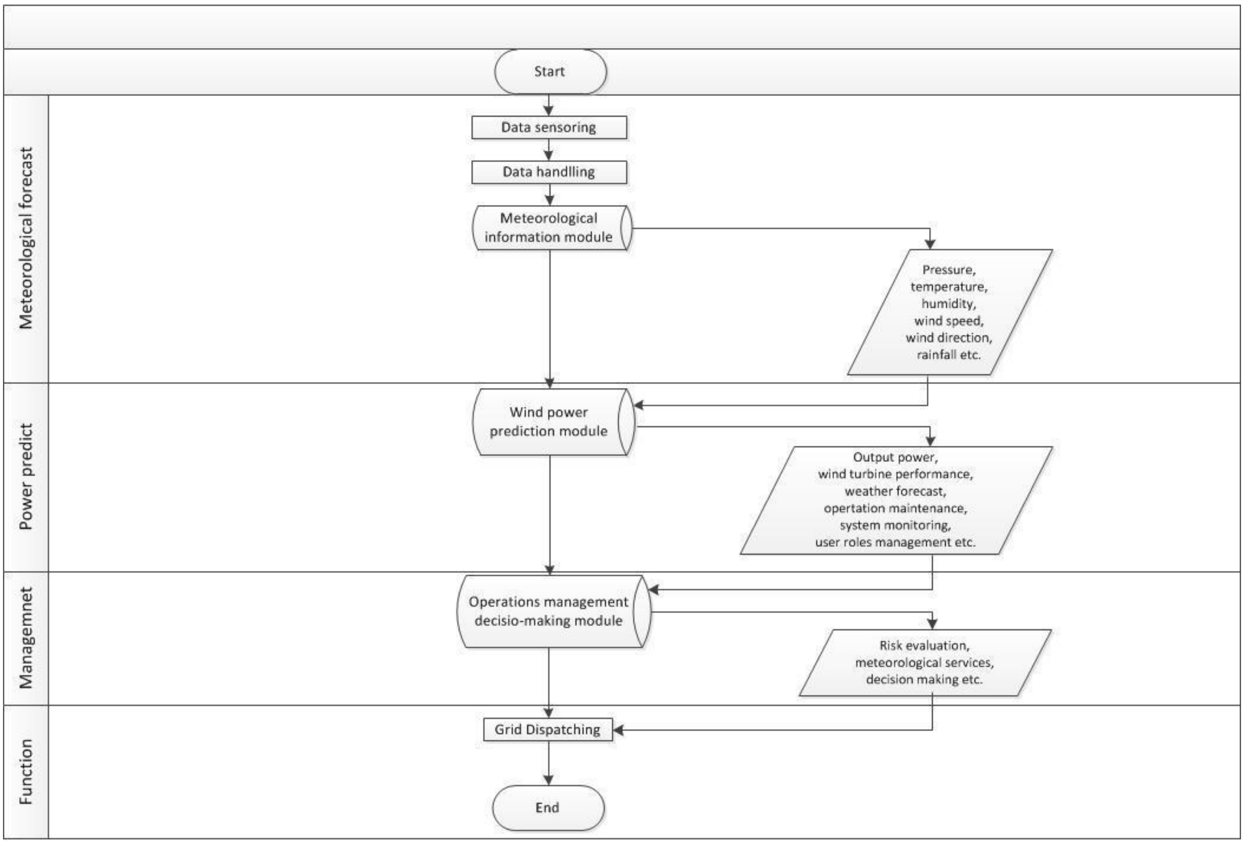

Figure 1. System structure and process

The wind power prediction module calculates the predicted amount of power output during particular hours and days based on the real-time meteorological data. In order to have an accurate prediction, short-term weather forecast is important for the dynamic control of wind turbine and for minimizing the scheduling errors which impact on grid reliability and market service costs (Lerner, Grundmeyer & Garvert 2009). Depending on their inputs, the forecast models are classified as physical or statistical or hybrid approaches. The best way is to use meteorological forecast data from NWP systems combining several prediction techniques (Giorgi, Ficarella & Tarantino 2011).

The module involves real-time wind measuring, NWP, and wind power forecasting. WPEs establish the forecasting model based on NWP and historical data related to wind, and they participate in prediction and report survey to dispatch center on time. Whether using ultra-short term wind power forecasting or long term wind power forecasting, they are all based on the foundation of real-time wind measuring data.

According to predicting and actual wind speed in wind parks, a mixed model of time series method and back-propagation neural networks arithmetic combining with meteorological data can be used in wind power prediction. The more accuracy of meteorological data is, the better forecasting results can be obtained. In addition, meteorological ensuring service can be provided to wind parks in the meantime.

This wind power predicting system mainly includes five parts: (i) data collection; (ii) NWP; (iii) wind power prediction; (iv) graphical user interface (GUI) software; (v) predicting database. The structure is shown in Figure 2.

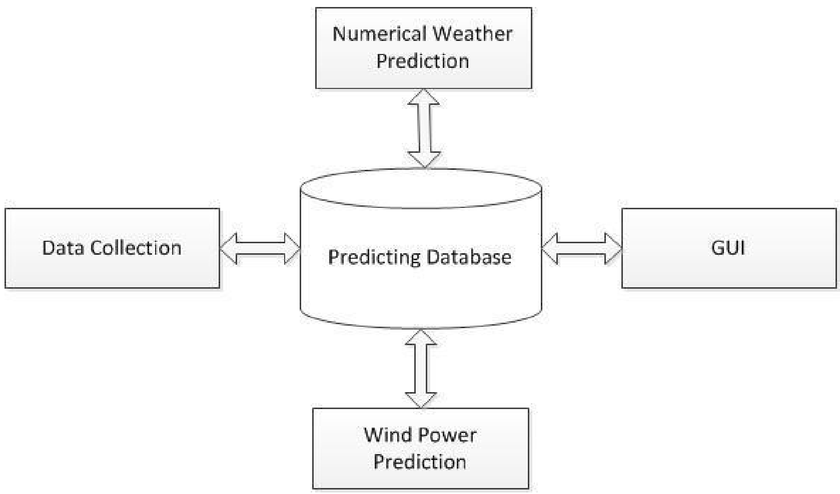

Figure 2. Structure of wind power prediction module

- Data collection aims to select a site to set up wind-testing tower and collect wind speed, wind direction, temperature, pressure etc. which are also the input variables of the wind power prediction module.
- NWP incorporates information representing the outer scale geophysical variability through evolving boundary conditions and by assimilating observations of the current state of the atmosphere to predict flow characteristics. In this research, NWP is responsible for dealing with all collected meteorological references, adapting rational mathematical models to calculate the results of future weather.

- Wind power prediction mainly focuses on predicting wind speed and wind power output which are crucial information for the next decision-making process. Wind speed and wind direction are the most important variables. Wind power is equal to wind speed third cube and wind speed are much more regular than that of wind power, and therefore it requires accurate wind measurement.
- GUI Software deals with data transforming and interactive interfaces.

4.3 Operations management decision-making module

This module mainly utilizes the prediction data from previous process to evaluate failure probabilities in different parts of the wind turbine and calculate the optimal service decisions for the wind park operations management.

The significance of failure analysis and fault diagnosis for wind turbine results lower breakdown rate, reduced maintenance cost and time, and improves the operational efficiency and reliability (Ma, He and Feng, 2012). The wind turbine is a complex system which transforms kinetic energy from wind power to electrical power. (Kostandyan and Sørensen, 2012). It consists of electrical, mechanical, hydraulic, structural, and software subsystems.

Many of critical wind turbine faults are directly or indirectly related to weather conditions and EWEs. Analysis to weather related faults can reveal the causes which can be even predicted, since the weather conditions resulting faults can be predicted with meteorological information system, making it possible to take precautions in advance to prevent such situations from happening. Other service decisions such as the optimal time for maintenance during idle period can be also predicted and scheduled in advance basing on meteorological information.

Statistics show that the determining time for the fault diagnosis takes up 70% to 90% of the total time, while the repair time takes up only about 10% to 30% (Wang and Fent, 2004). A wind turbine can be unavailable because of planned maintenance activities or because of unforeseen failures, incidents or accidents. Analysis of predictable sources of wind turbine failures such as weather conditions can help a lot in decision-making to optimize maintenance schedule and maximizes wind power output.

Each component has different physics of failure behavior depending on structure, shape, operational environment and many other parameters (Kostandyan and Sørensen, 2012). From the current structural characteristics of wind turbine shown in Figure 3 and its actual fault conditions, faults usually occur in parts such as gears, shafts, bearings, fastener and box.

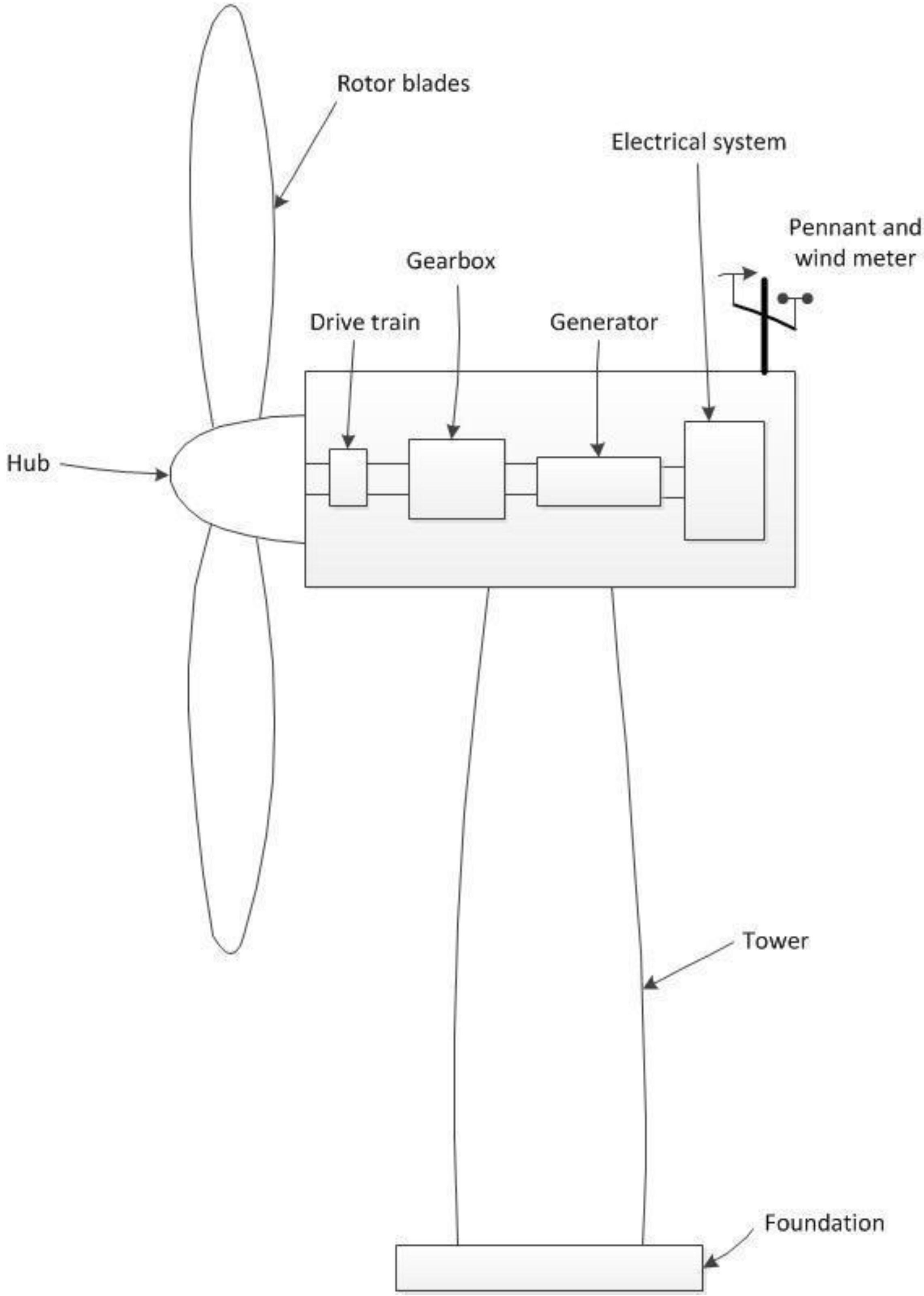

Figure 3. Main structure of wind turbine

According to real case statistics, Table 1 shows typical fault diagnosis related to weather conditions and the relevant actions need to be taken. The decision model can be built based on failure probabilities according to these conditions shown in Table 1.

Table 1. Typical failures related to weather conditions

Failure parts	Possible reasons	Weather conditions	Actions
Blade	Blade drive not ready	EWEs	Emergency stop
Rotor	Result of imbalance, blades and hub corrosion etc., brake sensor failure	Rain, snow and other hash meteorological condition	Normal stop
Gearbox	Over temperature, gearbox oil pressure too low	High temperature	Normal stop
Generator	Over speed, over temperature, bearing faults, current too high/low, frequency sensor failure	High temperature and / or humidity	Emergency stop Normal stop
Yaw system	Yaw brake set unintentionally	Extreme changes in wind speed / direction	Normal stop
Tower	Weather or other failure may cause excessive vibration	EWEs	Emergency stop

5. Discussion and future study

Based on collecting official documents, analytical results, lab experiments, and hypothesis test result, this investigation discuss the possible causes of wind power system failure from these four perspectives and presents practical suggestions for wind tower risk management and future action plans for the areas of structural design evaluation, construction and quality management, and engineering document review. By addressing study recommendations, project stakeholders can improve their risk management strategies. Construction firms can also utilize these findings to learn lessons for future reference. In terms of risk management, identifying the major causes of failure, one must understand the risk associated with these causes, and generate action plans that allow project managers to mitigate risk or employ control measures (Chou and Tu, 2011).

In addition to the conceptual design, this study has provided new insight for practical operations management in wind park application. It helps decision-makers to predict and identify possible categories of faults in wind turbine and make optimal service decisions to enhance the output performance of wind power generation.

Further research is needed related to sensitivity analysis of:

(1). Wind surveys and installations have so far concerned mostly onshore sites. However, a very interesting wind potential seems to exist also in offshore, shallow water locations, where there is the advantage of better wind conditions and less environmental restrictions, although the disadvantage of more difficult access and higher installation and maintenance costs must be taken into account (Sesto and Claudio, 1998). In that situation, the seawater salinity is one critical meteorological factor which will be studied in future research.

(2). Accumulated plastic strain depending on the temperature

Mean and temperature range factors. The proposed model is useful to predict damage values for solder joint in power electrical components. However, the real test data are required for the accurate model parameter estimation.

(3). In addition, operation and maintenance strategies might be developed based on the proposed approach. Especially strategies for renewable and replacement systems, where reliability updating might be implemented based on failure times.

6. Conclusions

This paper develops a conceptual system which utilizes the meteorological information for decision-making based on CBM in operations and service management for wind parks, which is a form of proactive equipment maintenance that forecasts incipient failures based on a real-time assessment of various external and internal conditions obtained from e.g. meteorological data and equipment monitoring system etc. The objective is to design an optimal service decision-making system based on CBM in wind park application to significantly cut down operation and maintenance costs and also implement a successful CBM strategy to achieve higher level of cost effectiveness, thus improve the operation and business performance. This paper bridges the gaps in current research of this area and opens up new research paths in the development of forecasting practices for service related decision-making, operations and risk management of EWEs in wind parks. It has shown that through the analysis of the meteorological information, it is possible to predict hash weather conditions which are harmful to cause faults in wind turbines. Modern NWP can provide reliable forecasts for wind parks as accurate as per quarter hour basis in the next couple of hours and also useful trend forecast up to days. By analyzing the approximate time-period of the 50-year maximum wind speed and extreme wind speed through EWEs forecasting, WPEs can effectively reduce and even avoid a huge number of losses in maintenance, and schedule service operations in more optimal periods. The basic idea has been already tested in a wind park in central China as depicted, but still lacks of systematic theory construction to be used as a decision support system. The implementation of this conceptual model will be dealt with in future research.

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Appendix 4. Paper 4: A study on renewable energy potential based on the global atmospheric data

Yang, W. and Liu, Y. (2015): A study on renewable energy potential based on the global atmospheric data. *Global Cleaner Production & Sustainable Consumption Conference.*

It has been published in Global Cleaner Production & Sustainable Consumption Conference 1 November 2015 - 4 November 2015.

Wenshan Yang: Defining of the research design, data analysis, methodology and research methods, verification and analysis of findings, writing the body text of the original article, editing the article at different stages.

Yang Liu: Acquisition of research resources, programming, guidance in the research process, visulazation of results, editing the article at different stages.

Title:

A study on renewable energy potential based on the global atmospheric data

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Full Paper: (Your paper must use **Normal style** and must fit in this box. Your paper should be no longer than 2500-9000 words. The box will 'expand' as you add text/diagrams into it.)

Abstract

According to U.S. EIA (Energy Information Administration) International Energy Statistics, nowadays fossil fuel is still the primary sources of energy, and the amount of fossil fuel power generation accounts around three-fifth in the world's total annual electricity net generation. However, fossil fuel power generation based on coal, oil and natural gas is now gradually being substituted due to the limited availability and environmental aspects such as global warming and pollution. In response to the concerns of climate change, many policy makers are becoming keen to re-examine the use of fossil fuels and promote renewable energy. Hydro, wind, tide, photovoltaic, geothermal are common renewable energy resources to generate electricity. In an effort to mitigate the pressure of burning fossil fuel on climate changes, it becomes more and more essential that renewable energy will eventually replace the conventional fuel. However, do we have sufficient renewable energy potential to replace conventional fuel and fulfil the world's energy consumption demands? Since many types of renewable energy such as the wind, solar, hydro are directly or indirectly related to meteorological factors and largely affected by them, this study analyzes the existing ERA-20C global datasets describing the state of the atmosphere as well as land-surface and ocean-wave conditions from 1900 to 2010 obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) and tries to identify the meteorological factors (wind speed, solar radiation, rainfall, evaporation etc.) with their effects on the overall utilization potential of these renewable energy resources. From this study, it can be found that a correlation between the meteorological factors and the renewable energy potential does exist, which implies forecasting models of renewable energy potential can be invented based on the global atmospheric data. The future study will focus on forecasting the global potential of these renewable energy resources in the next decades.

Keywords:
Renewable energy, climate change, reanalysis, ERA-20C data, resources potential.

1. Introduction

With an increasing energy demand, renewable energy is an appropriate way to satisfy energy consumption without environmental degradation (Hua, Oliphant, & Hu, 2016; A. Zahedi, 2010). Meanwhile, renewable energy technologies can play a crucial role in the transition towards a low-carbon economy (Albrecht, Laleman, & Vulsteke, 2015). Renewable energy development is a major response to address the issues of climate change and energy security. The utilization of renewable resources, however, highly depends on the climate conditions, which may be impacted in the future due to global climate change.

When discussing why climate changes occur and reduce its influence to human beings, it is essential to consider atmospheric dynamics rather than only focus on surface variables, in particular, temperature and precipitation (Trenberth Kevin E., 1990). Jacobsson and Karltorp (2012) pointed out that, in response to the threat of climate changes, the European Union electricity sector has to undergo a large-scale transformation process to reduce loss.

Many researchers have turned to use reanalysis data instead of historical data, for example, NARR, ERA-40, MERRA, and CFSR (Mesinger et al., 2010; Rienecker et al., 2011; Rose & Apt, 2015; Saha et al., 2010; Uppala et al., 2005).

The data resource is ERA-20C archive Version 2.0 by an independent intergovernmental organisation European Center for Medium range Weather Forecasting (ECMWF) which supported by 34 states. Long time period of measured meteorological data were revised by reanalysis of meteorological observations in ERA-20C project. ERA-20C is a global, high-resolution, coupled atmosphere–ocean–land surface–sea ice system to provide the best estimate of the state of these coupled domains over this period.

The aim of this research is to find out a correlation between the meteorological factors and the renewable energy potential, which implies that the forecasting models of renewable energy potential can be invented based on the global atmospheric data. In this paper, wind energy potential and solar energy potential in Vaasa region in Finland were roughly assessed by analysing ERA-20C reanalysis data.

2. Literature Review

Breslow and Sailor (2002) tried to find out the impacts of climate changes on wind speed and wind power output across the continent US. Two general circulation models provided similar trend until 2050 but various in the future 20 years.

After six years, Sailor et al. (2008) put further this idea by investigating in wind statistics from models about five-state region within the Northwest US. The results showed that summertime wind speeds may decrease by 5–10% while wintertime wind speeds may decrease or increase slightly.

In order to identify the changes in the future wind- and hydro-power resource potential in Norway, Seljom et al. (2011) evaluated the impact of climates changes with MARKAL Norway model. They found out that the reduction of heating demand will be significantly higher than the increase of cooling demand, and there may be lower cost of energy system and electricity production.

Wang et al. (2014) developed a general framework and applied grey cluster analysis method to compare analysis renewable energy vulnerability to climate change in China. The results depicted the distribution of areas rich in hydropower, wind power and solar energy potential, which helps to improve decision-making analysis.

In response to promote the transition towards a low carbon economy in Scotland, Sample et al. (2015) reviewed the potential impacts climate change and presented state of knowledge regarding the resilience of Scotland's hydropower resource to a changing climate.

Chang et al. (2015) proposed a new statistical downscaling framework using simulated weather research and forecasting (WRF) model to evaluate the climate change impact on wind resources in Taiwan Strait. It was found out that in the future wind energy density distributions are higher in the eastern half of Taiwan Strait but will reduce slightly comparing to the past time period.

Fant et al. (2015) presented a method that estimates the risk of climate-change on wind and solar resource potential. The assessment combines the risk-based climate projections from the Integrated Global Systems Model (IGSM), which considers emissions and global climate sensitivity uncertainty, with more regionally detailed climate information from 8 GCMs available from the Coupled Model Intercomparison Project phase 3 (CMIP-3).

3. Data analysis

3.1 Wind energy

Instead of pick out continent area, we identify the specific coordinate of longitude and latitude of the interested area (in this case the Vaasa region in Finland), then retrieve the dataset in the format of NetCDF. In order to retrieve specific geographic site in the particular observation area, we choose the highest resolution grid (0.125 degree * 0.125 degree) while the lowest resolution is 3 degree * 3 degree. We retrieve everyday meteorological record midnight 00:00 from 1st January 1961 to 31st December 2010, and a total data of 18262 days in 50 years were analyzed.

Wind speed V at the height of 100 meter can be calculated through 100 meter u wind component and 100 meter v wind component (Eq.1). Wind power directly depends on ambient natural resources and hence it is sensitive to climate variability. Wind power density is directly related with the electric power generation. It is proportional to the cube of speed and can be divided into different classes.

$$V = \sqrt{u^2 + v^2} \tag{1}$$

$$D_{wp} = \frac{1}{2n}\sum_{i=1}^{n} (\rho \cdot {V_i}^3) \tag{2}$$

In this research, we use MATLAB R2014a to calculate, analyze, and plot figures. Fig.1 shows the historical trend of wind power density in Vaasa region at the height of 100 meter from 1960 to 2010.

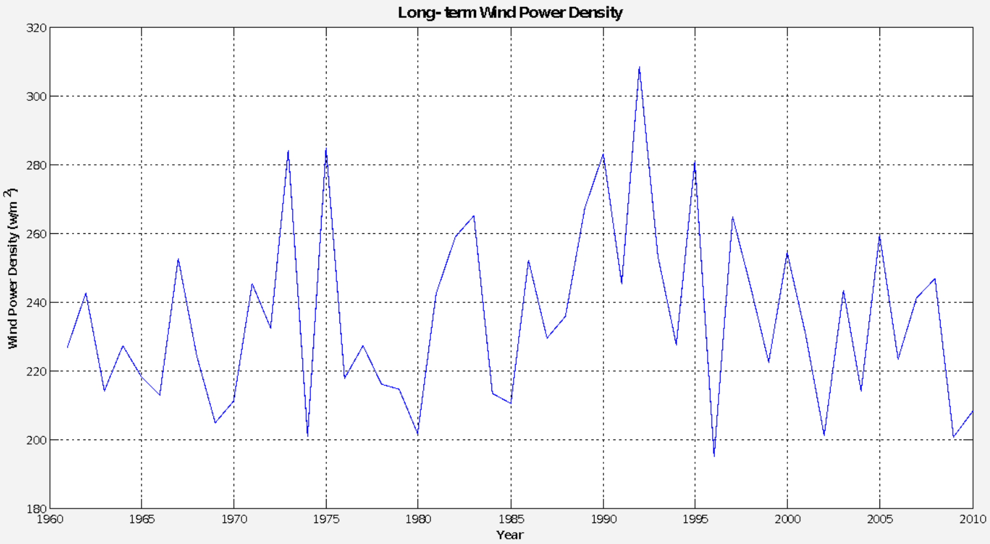

Fig. 1 Wind Power Density for all past 50 year (Year 1961-2010)

As can be seen from Fig. 1 that there are apparently fluctuations all through the past 50 years. We separately picked out maximum wind power density from every ten years and every five years, for example, time period 1971-1980 and 1971-1975. For each peak value in every ten years or every five years, the general variations are plotted in Fig. 2 and Fig. 3.

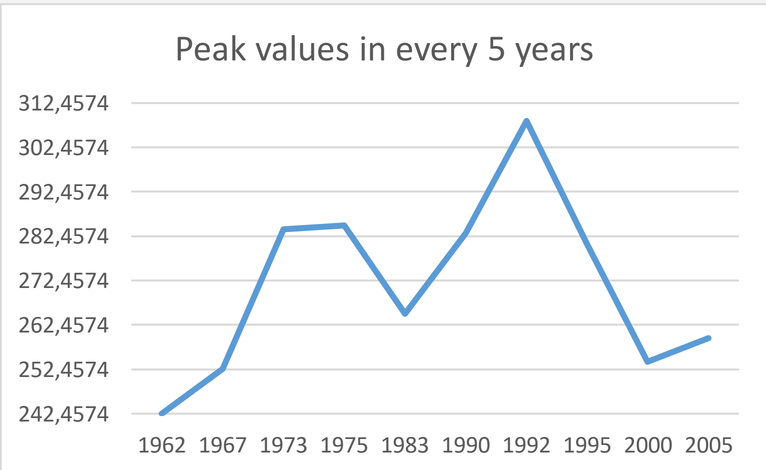

Fig 2. Peak of Wind Power Density for every 5 years

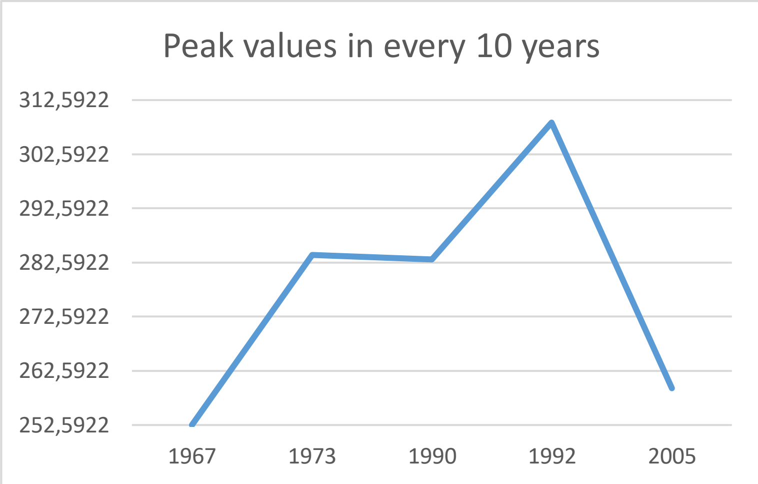

Fig 3. Peak of Wind Power Density for every 10 years

Therefore, it can be judged from the wind power density in above figures. Fig. 3 shows a more apparent trend when comparing with Fig. 2. It reveals a trend of fast increase from 1961 to 1973 and after that keeps stable during 1973-1990. And it presents a general trend of dramatic increase in the short period of 1990-1992 then a trend of sharp decrease in long-term 1992-2010.

3.2 Solar energy

Total radiation approximately equals to sum of direct radiation and diffuse radiation. Except of solar radiation, there are many other meteorological elements, which including cloud, sunny/rainy day, temperature and humidity, could influence solar power. These problems remain to be done in the future.

4. Conclusion

This study demonstrates the great potential of using global atmospheric reanalysis data to analyze the potential of renewable energy sources which are related with climate change. It can effectively help decision-maker in macro level through analyzing long-term atmospheric data. For the 20th century, we observed and analyzed the wind power density of past fifty years 1961-2010. In this study, the correlation between the meteorological factors and wind energy potential has been found out. The main outcomes of the present study are presented as follows:

(a) As illustrated in Fig. 1, wind power density for all the past 50 years from 1961 to 2010 was in fluctuation all the time.
(b) From Fig. 2 and Fig. 3, the characteristics of peak values about wind power density in every 5 and 10 years were separately depicted in the section of Data Analysis. And comparing peak values for each 10 years is easier than each 5 years.
(c) According to Climate Change 2014 Synthesis Report, 2005 and 1998 were the warmest two years in the instrumental global surface air temperature record since 1850, and twelve years (1995 to 2006) ranked among the 12 warmest years on record since 1850.
(d) The variation trend of wind power density is basically consistent with the changes in surface climate, in particular with the temperature.
(e) This study only focuses on peak values analysing as an exploratory study. More useful statistic information are expected in the future. For instance, investigating the trend about annual sum of wind power density.

Since ERA-20C global datasets includes the atmosphere, land-surface and ocean-wave reanalysis data from 1900 to 2010, we could also obtained the variation trend of natural resources (wind energy, solar energy, tidal energy, etc.) and forecast resources potential in the future. The future study may focus on forecasting the global potential of these renewable energy resources in the next decades.

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