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WIND SPEED FORECASTING IN BIG DATA AND MACHINE LEARNING: FROM PRESENTS, OPPORTUNITIES AND FUTURE TRENDS

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Abstract: Wind speed forecasting is an exciting study because it covers the fields of climate and energy disciplines, where the most widely used research focus is forecasting. During the last decade, the use of wind speed forecasting analysis techniques has seen a significant change from the traditional statistical method to machine learning. in this article discusses publication trends from 1945 to the end of 2020 using co-occurences.

Keywords: wind speed forecasting; bibliometric; co-occurrence; corpus.

2010 AMS Subject Classification: 93A30, 62-07.

1. INTRODUCTION

The application of big data and machine learning is massive that it has been used in the last decade including cases of climatology[1][2], energy modeling[3][4], engineering big data solutions[5], and other disciplines including of its opportunities and future trends[6][7]. The application of this

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technique can also be used for forecasting case studies including regression[8], neural network[9][10][11][12]. Meanwhile, Classification following Decision tree[13], Support Vector Machine[14][15], Naive Bayes[16]. Then, Clustering includes Hierarchical[17][18], partitioning[19], co-occurences[20], scalable[21], and high dimensional[22]. Association analysis also includes Apriori[23], rapid association rule mining[24], and also estimates using metaheursitic techniques such as local search versus global search[25], Single-solution versus population-based[26], Hybridization and memetic algorithms[27], Parallel metaheuristics[28], Nature-inspired and metaphor-based metaheuristics[29], and Ancient- inspired metaheuristic[30].Then, this paper will conduct a study on meta-analysis of papers that have been published in the Scopus database using the keyword "wind speed forecasting" .

2. MATERIALS AND METHODS

Data collection

In this study, publication data was taken from Scopus sources using the keyword "wind speed forecasting" starting 1945 to 2020, in short for 75 years.

Data analysis

Information in text form is important information and can be obtained from various sources such as books, newspapers, websites, or e-mail messages. Text is an expanse of language, both in speech or in writing, which has meaning, is practical and useful for the public and relates to the real world [31]. To analyze frequently occurring keywords, the step most crucial is to measure how often words appear together relative either how often they appear separately [32] [33] [34]. Besides, the correlation between words. Regarding text, correlation between words is measured in binary form - words appear together or not. The common measure for such binary correlation is the coefficient α in Table 1 and Eq(1).

Table 1: Co-Appearing Words [32] [33]

	Has Word A	**No Word A**	**Total**
Has Word A	a_{11}	a_{10}	$a_{1.}$
No Word A	a_{01}	a_{00}	$a_{0.}$
Total	$a_{.1}$	$a_{.0}$	a_{Total}

$$\alpha = \frac{a_{11}a_{00} - a_{10}a_{01}}{\sqrt{a_{1.}a_{0.}a_{.0}a_{.1}}}$$
(1)

In the selection of Chi Square features based on statistical theory, Eq(2) represents of two events of which are, the emergence of features and the emergence of categories, where each term value is ordered from the highest based on the following calculation

$$X^2(D,t,c) = \sum_{e_t \in \{0,1\}} \sum_{e_c \in \{0,1\}} \left(\frac{N_{e_t e_c} - E_{e_t e_c}}{E_{e_t e_c}} \right)^2$$
(2)

The chi Square feature selection is done by sorting each feature based on the Chi Square feature selection results from the largest value to the smallest value[8][35]. Meanwhile, the chi-square feature selection value that is greater than the significant value indicates the rejection of the independence hypothesis. Whereas if two events show dependent, then the feature resembles or is the same as the corresponding category label in the category.

3. RESULTS AND DISCUSSION

Wind Speed in Climate to Energy

Research studies on wind speed are very important to use because they involve the needs in terms of climate, including assessing the monsoon[36]. The monsoon in Indonesia is part of the East and Southeast Asian Monsoons and this extension of the monsoon system is called the North Australian monsoon[37]. The characteristic of the East Asian monsoon is the strong winter component. The flow of air from the North to the Northeast affects China and the South China Sea, then crosses the equator to the southern hemisphere and becomes the northwestern Monsoon of the North Australian Sea[38][39].

East Asian monsoons are formed during winter in the Northern Hemisphere, namely in December, January and February[40]. High pressure is on the Asian continent and low pressure in the southern hemisphere due to the summer on the Australian continent, so that the wind blows from Asia to Australia. During this period, from the tip of southern Sumatra, Java, Bali, Nusa Tenggara to Irian, the monsoon winds blew from west to east.

In fact, during the summer in the Northern Hemisphere, namely June, July and August. Low pressure is on the Asian continent and high pressure is on the Australian continent, so that the wind blows from Australia to Asia[41]. From the tip of southern Sumatra, Java, Bali, Nusa Tenggara to Irian, the monsoon wind blows from east to west. This period brings dry air masses, so it can be said that this period coincides with the dry season in most parts of Indonesia. Then, wind speed is also useful for oceanographic studies, one of which is for analyzing the level of fertility of a waters that always fluctuates because it is influenced by oceanographic phenomena that occur. Meanwhile, [42] conducted by the North Pacific region with 2-year data series, in 1999 and 2000 concluded that chlorophyll-a concentrations were higher during periods of relatively strong winds, whereas chlorophyll-a concentrations decreased during periods of relatively weak winds. This pattern shows that most areas with increasing wind speed can deepen the mixed layer vertically in the ocean so as to cool the ocean surface and increase the concentration of chlorophyll-a.

The wind speed study can be useful as renewable energy[43]. Air that moves has mass, density and velocity. So that with these factors, the wind has kinetic energy and potential energy[44][45]. However, the velocity factor dominates the position of the mass towards the earth's surface. Thus the kinetic energy is more dominant than potential energy. The movement of air molecules has kinetic energy, so that locally the number of air molecules moving through an area during a certain period of time determines the amount of power. This area is not the surface area of the earth, but the area upright.

Different topography or altitude causes different wind potential, and because wind power is proportional to wind speed cube, even a small difference in wind speed will result in a large difference in power. Wind conditions and speed determine the rotor type and size. Average wind speeds ranging from 3 m/s are adequate for small size propeller wind turbines, above 5 m/s for medium 5 wind turbines and above 6 m/s for large wind turbines[46]. Thus the wind power system makes use of wind through windmills to generate electricity[47]. Wind energy is an alternative energy that has good prospects because it is always available in nature, and is a clean and renewable energy source[48]. The process of utilizing wind energy goes through two conversion stages, namely: The wind flow will move the rotor which causes the rotor to rotate in accordance with the wind blowing. Also, the rotation of the rotor is connected to the generator so that electricity can be generated. Thus, wind energy is kinetic energy or energy caused by wind speed to be used to rotate windmill blades [49] [50].

Scopus Database

In this paper, we are performing corpus analysis and the dataset was generated on Scopus using the keyword “Wind Speed Forecasting”, it was found that 8430 total publications during 1945 to last 2020, including 2745 open access, 891 Gold access, 206 hybrid gold, 1043 bronze access, and 1473 green access. Figure 1 represents that in the Scopus database the first published paper was in 1945 and up to 2020 there was a quite drastic increase, more specifically the increase was seen in early 2000 to 2016. Then, Table 2 explains that the Chinese academy of sciences has published the most with 213 papers, and followed by Ministry of Education China 198 papers, and National Oceanic and Atmospheric Administration 197 papers. Overall, universities and institutions in the Republic of China (ROC) were the leading contributors to the paper for this study.

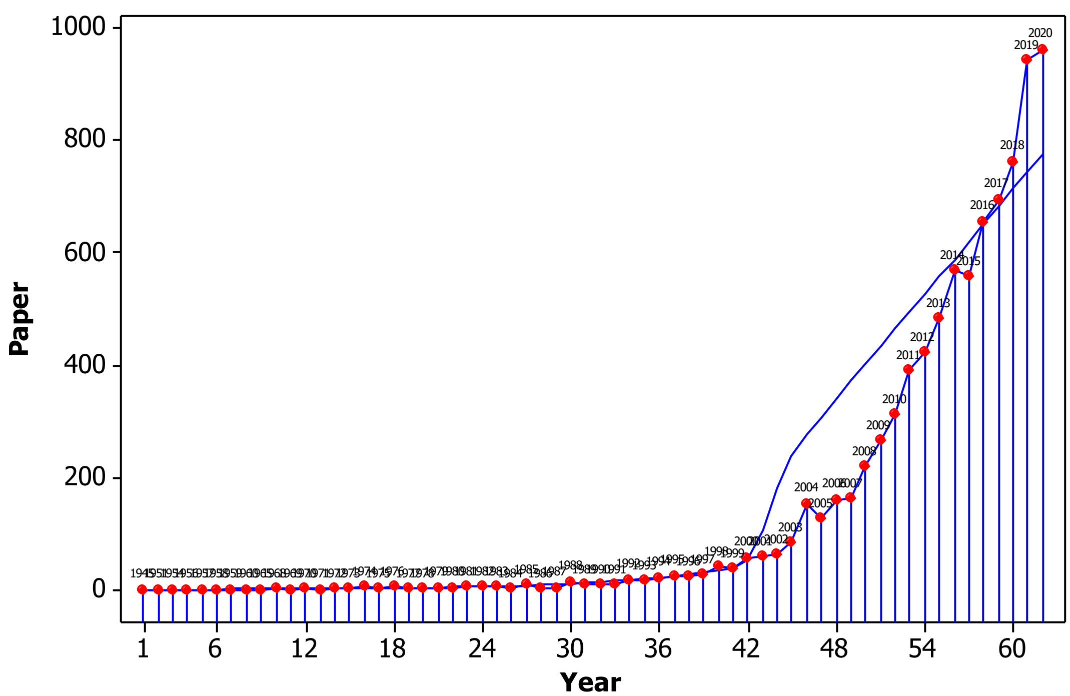

Figure 1. Paper Publication from 1945 to Last 2020

Table 2: Top 10 Affiliation

AFFILIATION	**Number Paper**
Chinese Academy of Sciences	213
Ministry of Education China	198
National Oceanic and Atmospheric Administration	197
National Center for Atmospheric Research	168
North China Electric Power University	136
Lanzhou University	110
Danmarks Tekniske Universitet	99
University of Colorado Boulder	93
Dongbei University of Finance and Economics	92
Nanjing University of Information Science & Technology	92

Table 3: Top 10 Journal Sources

SOURCE TITLE	**Number Paper**
Monthly Weather Review	235
Weather And Forecasting	183
Renewable Energy	164
Energies	124
Energy Conversion And Management	118
Journal Of Applied Meteorology And Climatology	114
Quarterly Journal Of The Royal Meteorological Society	102
Atmospheric Environment	94
Journal Of Geophysical Research Atmospheres	92
Applied Energy	88

In line with this, Table 3 highlight top 10 journal sources, top-3 source title tersebut adalah Monthly Weather Review, Weather And Forecasting, and Renewable Energy. It can be seen that although there are numerous specialist journals on Climate and Energy, the most cited papers have been published mainly in wind speed forecasting not necessarily on Climate and Energy Journal. This phenomenon demonstrates that there is a constant growing consideration for the subject, this is apparent as indicated by the growing number of quotations per year on each article.

Table 4: Top 20 Most Cited Paper

Authors	Title	Year	Cite
Powell M.D., Vickery P.J., Reinhold T.A. [51]	Reduced drag coefficient for high wind speeds in tropical cyclones	2003	956
Lei M., Shiyan L., Chuanwen J., Hongling L., Yan Z. [52]	A review on the forecasting of wind speed and generated power	2009	736
Kalogirou S.A. [53]	Artificial neural networks in renewable energy systems applications: A review	2000	707
Donlon C.J., Martin M., Stark J., Roberts-Jones J., Fiedler E., Wimmer W. [54]	The Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) system	2012	576
Janssen P.A.E.M. [55]	Quasi-linear theory of wind-wave generation applied to wave forecasting	1991	574
Atlas R., Hoffman R.N., Ardizzone J., Leidner S.M., Jusem J.C., Smith D.K., Gombos D. [56]	A cross-calibrated, multiplatform ocean surface wind velocity product for meteorological and oceanographic applications	2011	553
Chen S.X., Gooi H.B., Wang M.Q. [57]	Sizing of energy storage for microgrids	2012	552
Ummels B.C., Gibescu M., Pelgrum E., Kling W.L., Brand A.J. [58]	Impacts of wind power on thermal generation unit commitment and dispatch	2007	539
Mohandes M.A., Halawani T.O., Rehman S., Hussain A.A.[59]	Support vector machines for wind speed prediction	2004	522
Karki R., Hu P., Billinton R. [60]	A simplified wind power generation model for reliability evaluation	2006	502
Kavasseri R.G., Seetharaman K. [61]	Day-ahead wind speed forecasting using f-ARIMA models	2009	494
Zeng X., Zhao M., Dickinson R.E.[62]	Intercomparison of bulk aerodynamic algorithms for the computation of sea surface fluxes using TOGA COARE and TAO data	1998	493

Arge O.N., Pizzo V.J. [63]	Improvement in the prediction of solar wind conditions using near-real time solar magnetic field updates	2000	489
Howell R., Qin N., Edwards J., Durrani N.[47]	Wind tunnel and numerical study of a small vertical axis wind turbine	2010	478
Li G., Shi J.[64]	On comparing three artificial neural networks for wind speed forecasting	2010	455
Stoffelen A., Anderson D.[65]	Scatterometer data interpretation: Estimation and validation of the transfer function CMOD4	1997	451
Torres J.L., García A., De Blas M., De Francisco A.[66]	Forecast of hourly average wind speed with ARMA models in Navarre (Spain)	2005	446
Sideratos G., Hatziargyriou N.D.[67]	An advanced statistical method for wind power forecasting	2007	437
Soman S.S., Zareipour H., Malik O., Mandal P. [68]	A review of wind power and wind speed forecasting methods with different time horizons	2010	431
Erdem E., Shi J. [69]	ARMA based approaches for forecasting the tuple of wind speed and direction	2011	407

Table 4 describes as many as 20 papers that have the highest citation, we can see that the techniques commonly used are basic time series such as ARIMA / ARMA. However, there are also papers using machine learning such as support vector machines and neural networks. Both of these techniques promise high accuracy and precision when used for forecasting. To see the trend of method use, it can be seen in Figure 2 using co-occurences within 3 words distance. Information that can be retrieved is that popular techniques used are Artificial Neural Networks, Backpropagation, Regression Analysis, Time Series, Mathematical Models, Ensemble Forecasting, Artificial Intelligence, Decision Trees. What is interesting is that there are also many papers that use methods such as Wavelet Decomposition, Long Short-term Memory, and Fuzzy Inference. To evaluate the model, most papers still use Mean Square Error and Root Mean Square Error. In fact, to make predictions it is advisable to use The mean absolute percentage error (MAPE) and

Symmetric mean absolute percentage error (SMAPE or sMAPE) because there is a range that can be said whether the model is good or not.

Figure 2. Co-occurrences within 3 words distance Nouns and Adjective

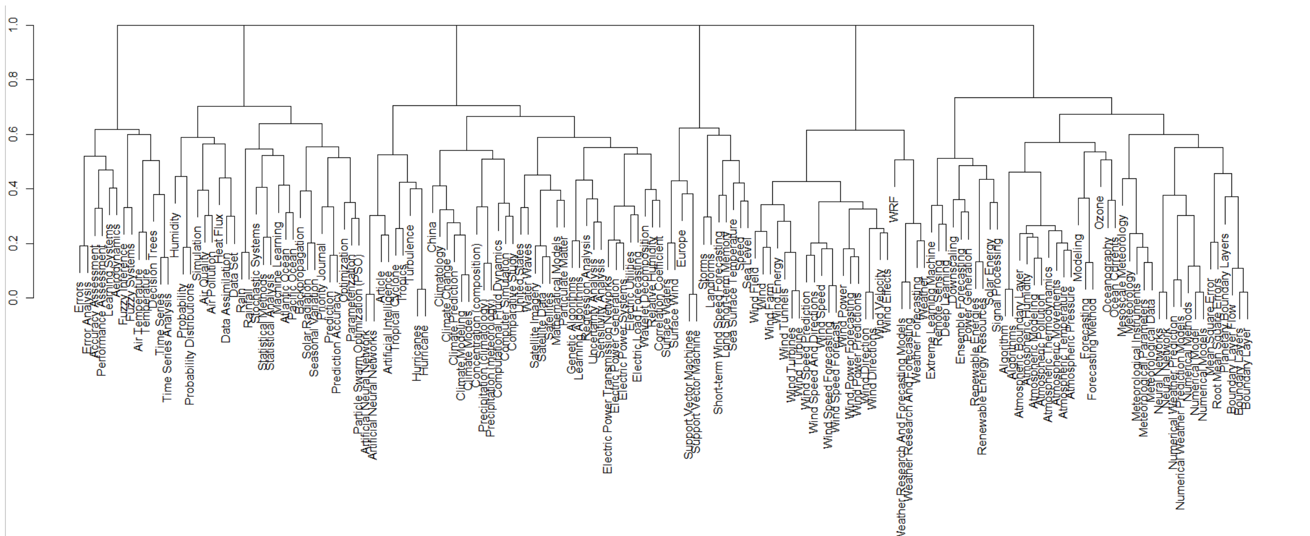

Figure 3. Cluster Dendogram

CONCLUDING REMARKS

Based on this analysis, the future trend will discuss a lot about the application of deep learning methods to forecast wind speed. However, the ensemble technique or also the hybird method which is very broad is still used because it combines information in both parametric and non-parametric methods so that the resulting information is richer,following ARIMA+FFNN [70], ARIMAX+FFNN [71]. SARIMA+SVR [72][73], Advanced techniques are also used, such as deep neural networks [74][75], long short term memory[76][77], facebook prophet model[78][79]. Meanwhile, the wind speed series are complex and exhibits several levels of seasonality[80]: the wind speed at a given hour is dependent not only on the load at the previous hour, but also on the wind speed at the same hour on the previous day, and on the wind speed at the same hour on the day with the same denomination in the previous week. At the same time, there are many important exogenous variables that must be considered, especially climate-related variables.

Besides, the technique used can also include combining optimization techniques with hybrids, such as ANFIS+Quantum-behaved PSO[81], ARIMA + FFNN + GA, VAR-NN-PSO[82], VAR-NN-GA[10], ARIMA+Deep Learning[83], VAR+GSTAR+SVM[84]. Also, multi kernel learning includes Fixed rules, Heuristic approaches, Bayesian approaches, Boosting approaches. For combinations also use the Linear combination, Nonlinear combination, Data-dependent combination. Another technique also uses the best feature selection using feature selection which aims to Reduce Overfitting, Less redundant data means less opportunity to make decisions based on noise. Improves Accuracy, Less misleading data means modeling accuracy improves. Reduces Training Time, fewer data points reduce algorithm complexity and algorithms train faster. Such as Random forest, Boruta, XgBoost, Random multinomial logit (RMNL), Auto-encoding networks with a bottleneck-layer, Submodular feature selection, local learning based feature selection, Recommender system based on feature selection. The feature selection methods are introduced into recommender system research.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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