Indian Wind Power

Volume: 7 Issue: 5 December 2021-January 2022 ₹ 10/-
Bimonthly, Chennai

Expertise and Research & Development for Wind and Solar Energy Stakeholders

Resource Assessment

Wind Energy

- Carry out Nationwide Wind Resource Assessment
- Estimation of Wind Potential in the country through Wind Atlas preparation
- Design and implement the comprehensive Resource Assessment Programme
- Analysis of wind data to identify Wind Farmable locations
- Verification and vetting of wind data generated by private entrepreneurs
- Consultancy services for Feasibility Studies, Technical Due Diligence, Micro-siting and preparing DPR for Wind Farming and Repowering assessment

Offshore Wind Energy

- Nodal Agency for Offshore Wind Energy development in India
- Met-Ocean Measurement
- Demarcation of Offshore Wind Energy Blocks
- Geophysical and Geotechnical Studies

Solar Energy

- Solar Radiation Resource Assessment
- Investor & bankable grade Solar / Meteorological data
- GIS enabled Indian Solar Atlas
- Calibration of solar sensors as per International Standards
- Consultancy on Solar Energy Projects

Forecasting

- Wind Power Forecasting Services
- Solar Power Forecasting Services

Testing (Large & Small)

- Power Performance measurements
- Load measurements
- Power Quality measurements
- Safety and function tests
- Yaw efficiency test
- User defined measurements
- Duration Test

The services are as per internationally accepted procedures & stipulations and certified as per the requirements of ISO 9001 & NABL accredited as per the requirements of ISO/ IEC 17025 : 2005

Standards & Certification

- Preparation of Indian standards on wind turbines
- Accord Type Certification to Wind Turbines. Type Certification Services are certified as per ISO 9001
- Issue the recommendation for grid synchronization to facilitate installation of prototype wind turbines
- Technical Due Diligence for Wind Farm Projects

Training

National, International and Customized Training on:

- Wind and Solar Resource Measurement & Analysis
- Wind and Solar Energy Technology
- Testing and Certification of Wind Turbines
- Installation, Commissioning and Operation & Maintenance of Wind Turbines
- Grid Integration of Renewable Energy System
- Forecasting of Wind and Solar Energy Production
- Seminar / Workshops on Wind and Solar Energy

नीवे NIWE

NATIONAL INSTITUTE OF WIND ENERGY

An Autonomous Research & Development Institution under the Ministry of New and Renewable Energy, Government of India

Velachery - Tambaram Main Road, Pallikaranai, Chennai - 600 100

Phone : +91-44-2246 3982 / 83 / 84 Fax : +91-44-2246 3980 E-mail : info.niwe@nic.in Website : http://niwe.res.in

IWTMA
INDIAN WIND TURBINE MANUFACTURERS ASSOCIATION

Indian Wind Power

A Bi-monthly Magazine of Indian Wind Turbine Manufacturers Association

Volume: 7 Issue: 5 December 2021 - January 2022

Contents

Indian Wind Turbine Manufacturers Association

4 h Floor, Samson Tower, 403 L, Pantheon Road, Egmore
Chennai 600 008.
Email : secretarygeneral@indianwindpower.com
associatedirector@indianwindpower.com
Website : www.indianwindpower.com

(For Internal Circulation only)

From the Desk of the Chairman – IWTMA

Dear Readers,

Greetings from IWTMA!

We are living in times with unprecedented opportunities. While there will be challenges along the way, it is heartening to have the new and bold pledge of India to achieve 500 GW renewable energy capacity by 2030 and to become net carbon neutral by 2070. It is my firm belief that wind energy and green hydrogen will play a great role in meeting our county's climate and RE targets.

Recent Highlights

- The recent Union Budget presented by the Hon'ble Finance Minister for FY 2022-23 had no significant positive announcements for the wind energy sector. As expected, Government of India withdrew the Concessional Customs Duty (CCDC) on wind components which were available to the sector for over two decades. The industry has responded well and continues its push towards 'Make in India' or 'Atmanirbhar Bharat'. However, the industry will make a representation to the Government on the continuity of CCDC for items that are currently not manufactured in the country or items that cannot be manufactured in the country such as Balsa Wood, Pultruded Carbon Fibre Rods and Permanent Magnets.
- The recent conflict between Russia and Ukraine has pushed the price of crude oil to USD 110 per barrel which will have a ripple effect on petroleum products and result in increase of commodity prices. While this may impact our own profitability and supply chains in the short term, it also goes to show that Renewable Energy is a fitting answer to all such challenges in the long run.

Need for conducive policy framework

- To stop reverse bidding with immediate effect – Last five years have clearly shown that reverse bidding is detrimental to the interests of the wind energy sector. We should have transparent and closed bidding process where each bidder has to submit tariff only one time. Further, the bidding process must facilitate optimum utilization of all seven windy states with different PLFs so that 15 GW of installed capacity can come up per annum.
- PLI scheme across the entire manufacturing value chain for wind energy - Aggressive bidding and lowering of tariff has forced OEMs to introduce new models in quick succession with target of achieving lower LCoE. This results in high costs of R&D, tooling and technology for OEMs. Each new model introduced also has a cascading effect on the corresponding components manufacturing which is mostly carried out by the MSME sector. It has become imperative to support domestic manufacturing and for that purpose PLI across the entire manufacturing chain is required especially for new and larger turbines.
- The domestic market for Wind Energy continues to suffer with procurement restricted to SECI auctions. Open Access with ISTS waiver for captive, sale to exchanges and sale to C&I customers has not yet become operational. Mandatory enforcement of RPO with penalty mechanism is needed. Uniform wheeling and banking charges to be decided by Central Government for all the seven windy states. Renewable Energy generated electricity sales to be brought into GST regime with uniform GST rate to close the loop and enable pass through.

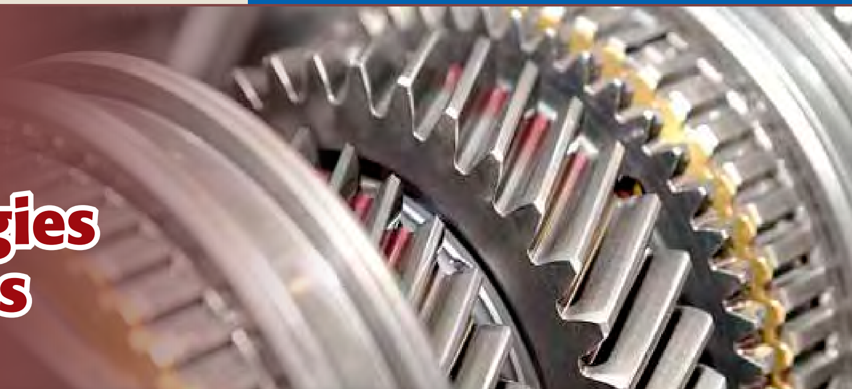
We welcome the announcement of the Hon'ble Minister Shri R. K. Singh at the 'Azadi Ka Amrit Mahotsav' organized by MNRE on Green Hydrogen Policy. Green hydrogen will further drive the need for wind energy. Green hydrogen will play a large role in India's energy transition and thus open up great avenues of new opportunity and provide a long runway for growth for our wind energy sector.

To achieve our potential and to make the most of the new emerging and exciting landscape, we have to work together, relentlessly engage with policy makers to have the right policy framework and ensure that all stakeholders' interests are aligned towards common goals.

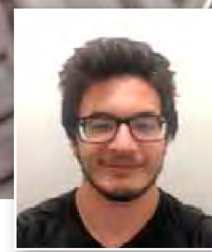
As you are all aware, IWTMA along with M/s. PDA Trade Fairs Private Limited, is organizing its flagship event titled "Windergy India 2022" at Pragati Maidan, New Delhi, from the 27th to the 29th April 2022. We look forward to your presence as an exhibitor/delegate/visitor to join hands in making a "Cleaner, Greener India" to fight climate change and global warming.

Wishing our readers a Happy Holi and see you at Windergy!

With regards,
Tulsi Tanti
Chairman



Latest Advances in Lubrication Technologies used in Wind Turbines



Dr. Raj Shah
Director, Koehler Instrument Company
New York &
Adjunct Full Professor, Dept. of Material Science and Chemical Engineering, State University of New York, Stony Brook, New York

Sharon Lin
Intern

Blerim Gashi
Intern

Koehler Instrument Company
Holtsville, New York

Introduction

Wind turbines are a renewable energy source, growing at a rate as high as 16% in 2021. Although a positive contribution to our environment, wind turbines may be damaged by unsteady wind gusts. These wind gusts can cause micro pitting, scuffing, and corrosion. Micro pitting is caused by rolling-sliding contact which affects the gears of the wind turbines. Scuffing is caused by friction which damages the surface of the wind turbines. Corrosion can be caused by structural vibration which increases wear[1]. The damages to the gears of the wind turbines are costly to repair. Therefore, to prevent damages to the gears of the wind turbines, lubricants are used to increase wear resistance and reduce friction[2].

Figure 1: *Lubrication on the gearbox*

The temperature of the lubricant usually heats up when working because of the contact between the bearing and the gear. A lubrication oil heating system is needed to heat the lubricant to the perfect temperature for being most effective on the wind turbine.

For wind turbines to work effectively with minimum wear and friction, the gearbox, generator, main shaft, and blades need to be lubricated by synthetic lubricants[3]. The gearbox uses a combination of forced and splash lubrication. Forced lubrication is applied on the device while splash lubrication is applied on the pieces of movement. The temperature of the lubricant usually heats up when working because of the contact between the bearing and the gear. A lubrication oil heating system is needed to heat the lubricant to the perfect temperature for being most effective on the wind turbine[4]. The speed of the wind is usually between 3 and 13.5 m/s, so the lubrication on the wind turbine must also withstand the speed[5].

Lubes and Greases Used in Wind Turbines

Differences in Lubes and Greases Used in Wind Turbines and Other Machineries

There are many types of lubricants that are used in machinery. Mineral oil-based lubricants are widely used throughout the world. However, these oils have poor biodegradability and are highly toxic, therefore polluting the environment which makes them a bad choice to use in wind turbines[6]. Vegetable oils can be derived from tree-borne oils, seeds, or any other non-edible oil. These oils are usually produced through transesterification which reacts these oils with alcohols which produces fatty acids that can be used as vegetable oil lubricants. Chemically modified vegetable oils can form bio-based grease which allows them to be used as lubricants[7]. Vegetable oils are more environment friendly than mineral oil-based lubricants. However, it has poor

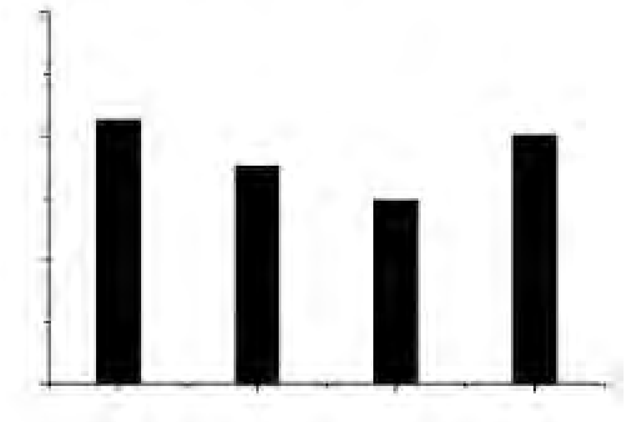


Figure 2*: Mineral oil vs Synthetic Oil*[8]

thermal properties, low viscosity and low oxidative properties making vegetable oil lubricants have poor performance[6]. Unlike other machinery, wind turbines require the use of a synthetic lubricant which means vegetable oil and mineral oil are not used as lubricants.

In research performed by Mia and colleagues[8], mineral oil and certain synthetic oils like polyalphaolefin were applied to the gearbox of the wind turbines. The high-pressure viscosity of the mineral oil was not able to be measured while the high-pressure viscosity of the polyalphaolefin was able to be measured. It was also discovered that polyalphaolefin had a better low-temperature fluidity which falls in the range of -30 to 100°C. Additionally, polyalphaolefin was found to have a lower friction coefficient and a lower wear scar when compared to mineral oil[8]. Therefore, a synthetic lubricant is used for wind turbines.

Along with the use of a synthetic lubricant, ionic liquid additives are used because of their effectiveness in wind turbines. Ionic compounds are organic salts that are held together by the Coulomb force[9]. Ionic liquids are liquids at room temperature and can be used as the base when temperatures exceed 250°C. Ionic liquid additives can be added to nonpolar base oils like mineral oil or coconut oil[10]. They are also added to synthetic oils like polyalphaolefin, polyethylene glycol and palm oil-based tri-methylolpropane ester[11]. These lubricant additives also have low vapor pressure properties, high thermal and chemical properties, and high viscosity allowing the lubricant to have a high reduction in wear and friction[6]. The properties of lubricant additives and the formation of a tribofilm are what allow lubricants with ionic liquid additives to be used in wind turbines.

A synthetic lubricant additive that can also be used on wind turbines is the boron nitride lubricant additive. The nano-colloidal boron nitride lubricant additive is derived from milled boron nitride using a ball milling set up to reduce the size of boron nitride which allows for the boron nitride to improve thermal properties, reaction rate and tribological properties. The boron nitride lubricant additive can be added to many base oils like synthetic gear oil[12].

Ways to Advance Standard Lubrication

Tests on Ionic Liquid Lubricant Additives

Ionic liquids are ionic compounds that are made of organic cations and weak organic anions. Ionic liquids can form ordered layers and tribofilms[2]. Many tests were conducted on lubricants with ionic liquid additives. These tests include hydrolysis stability analysis, corrosion tests and other tribological tests. The hydrolysis stability analysis test was conducted at 80°C for 6 hours and the lubricant with halogen ionic liquid additives containing [THTDP] and [NTf2] was found to have lower hydrolysis stability[6]. The hydrogen stability analysis test is conducted under the ASTM D2619 method. The lubricant, water and copper strip are sealed into a container. The lubricant is rotated with water at 93.3°C for 2 days. The change in acid number and the corrosion to the copper strip are measured. If the copper strip is not severely impacted, then the lubricant is hydrolytically stable[13].

Researchers found that ionic liquids containing hydrogen are sensitive to moisture which will cause corrosion and form toxic species[2]. Since halogen ionic compounds are sensitive to moisture, with the adsorption of water, products like HF are produced which causes tribocorrosion leading to increased friction and wear, hence diminishing its effectiveness as a lubricant[14]. This is supported by the corrosion tests performed which indicated that the lubricants with halogen ionic liquid additives increase corrosion[6]. The corrosion test is done under ASTM D130 conditions. The copper strip is submerged into the ionic liquid for 3 hours at 150°C. The corrosion on the copper strip is compared to the original copper and under ASTM copper strip corrosion standards, wear and friction properties were determined[15].

A tribological test performed on ionic liquids is the four-ball test which is performed under ASTM D4172 guidelines. Three steel balls are held together tightly with the fourth steel ball rotating on top of the three balls at 1200 revolutions per minute for an hour[16]. It was discovered that the ionic liquids produce tribofilm which decreases the friction coefficient and reduces wear[9].

Therefore, over time this lubricant additive may not be as efficient and may cause damage to the wind turbines. To prevent this, halogen-free ionic liquids like phosphonium-based ionic liquid are used because it is less sensitive to moisture[2].

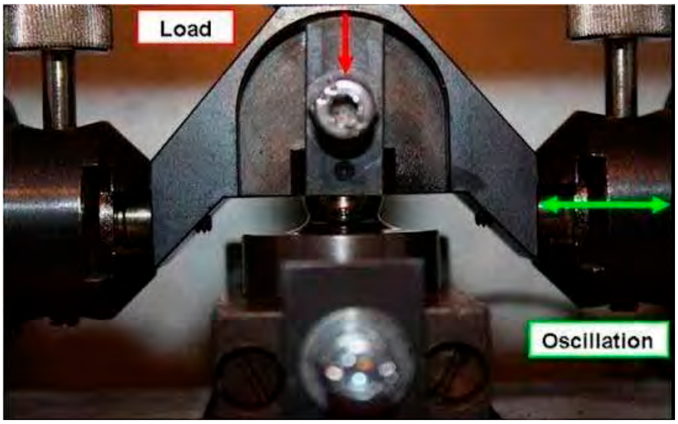


Figure 3*: Ball on Disk Test*[14]

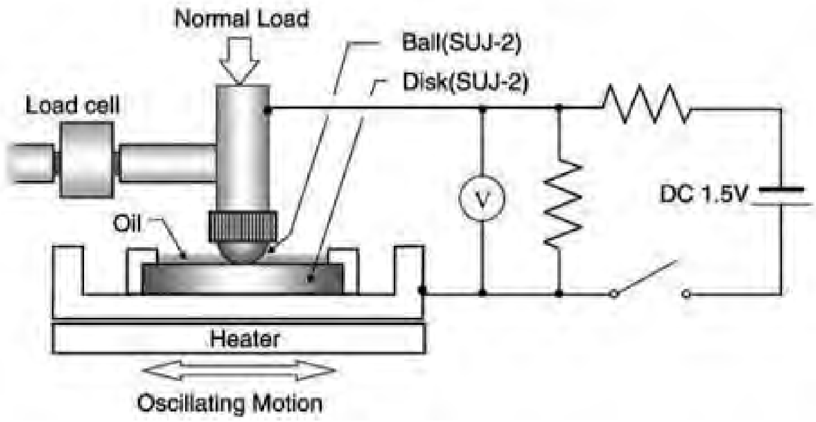


Figure 4*: Ball on Disk Diagram*[9]

Tests on Boron Nitride Additives

Boron nitride has a crystalline structure that is like the structure of MoS_2, a widely used solid lubricant and additive that is effective in reducing wear and friction[17]. Boron nitride consists of covalent bonds and van der Waal forces which is like the bonds of MoS_2[17]. To measure the tribological properties of the boron nitride lubricant, the sliding friction test was performed on a bench-top linear reciprocation sliding contact test rig at 100°C for 1 hour with a 1 GPa stress. It was determined that with the boron nitride lubricant, the friction coefficient decreased by 0.02. X-ray photoelectron spectroscopy was used to determine the formation of tribofilm which contains elements like carbon, oxygen, nitrogen, sulfur, iron, phosphorous and boron. The iron, boron, and nitrogen elements were already present before the test. The formation of carbon and oxygen is expected because of the presence of the contact surface. However, phosphorous and sulfur were formed due to a reaction between the lubricant and the contact surface[12].

To measure the wear properties of boron nitride, the surface treatment durability test was performed. This test was performed for 4 hours at 100°C with 2.5 GPa stress. This test indicates that the boron nitride lubricant improves wear resistance[12].

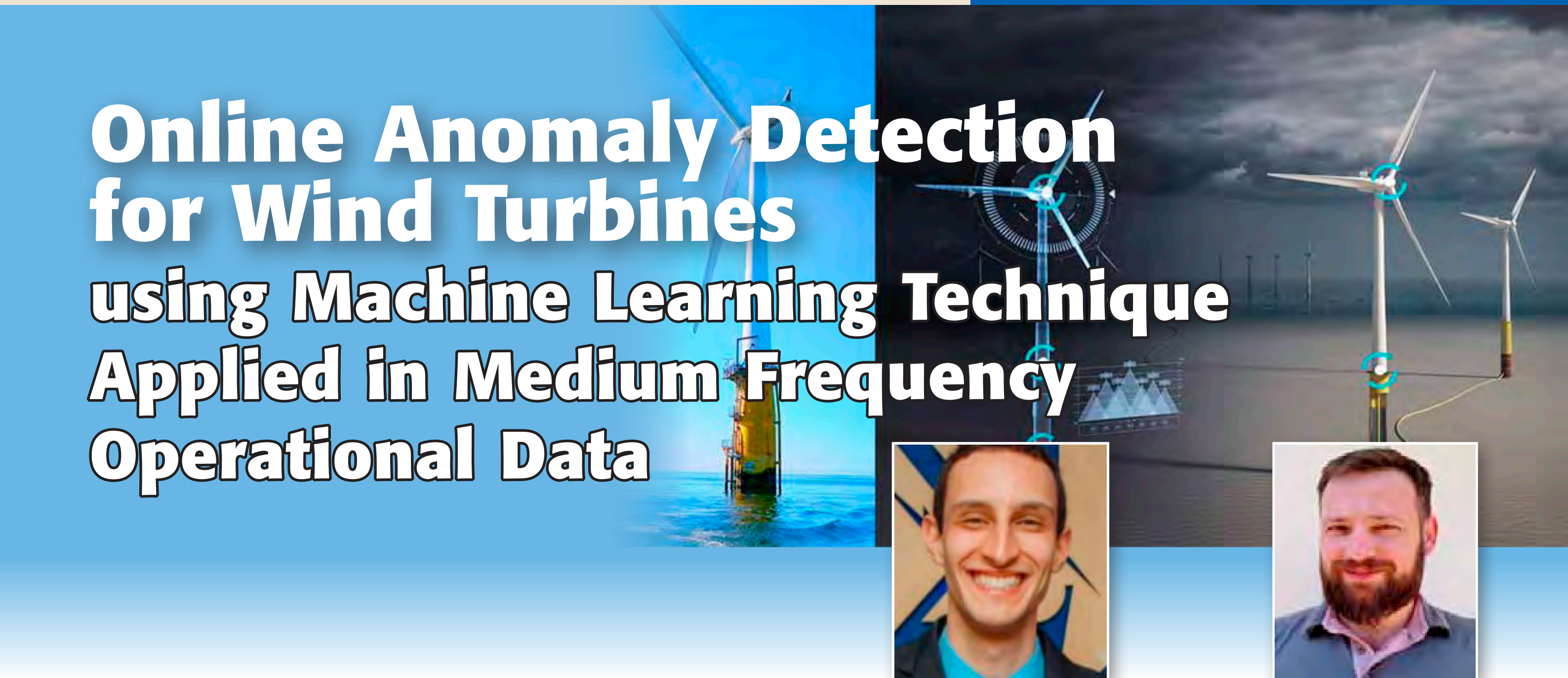
Conclusion

Wind turbines are extremely useful in reducing the need for fossil fuels to produce energy. Not only is it a sustainable resource, but it is also a renewable resource, hence helping the prevention of global warming. However, wind turbines may be damaged due to external factors. To prevent this, lubricants are used.

There are many types of lubricants used like solid lubricants liquid lubricants. The best solid lubricant is found to be MoS_2 and while current research has not found a way for MoS_2 to be applied to wind turbines, perhaps MoS_2 nanoparticle additives can be applied to wind turbine lubricants. Liquid lubricants like halogen-free ionic liquid additives seem to have the most potential in the wind turbine industry.

References

1. Greco, A., Sheng, S., Keller, J., & Erdemir, A. (2013). Material wear and fatigue in wind turbine systems. Wear, 302(1-2), 1583–1591. https://doi.org/10.1016/j.wear.2013.01.060
2. Gutierrez, M., Haselkorn, M., & Iglesias, P. (2016). The lubrication ability of ionic liquids as additives for wind turbine gearboxes oils. Lubricants, 4(2), 14. https://doi.org/10.3390/lubricants4020014
3. Cuffari, B. (2019, August 28). Using lubricants for wind turbines. AZoCleantech.com. Retrieved January 9, 2022, from https://www.azocleantech.com/article.aspx?ArticleID=944
4. Cen, H., Zhang, T., Tian, W., & Zheng, Y. (2019). Fault analysis and adaptive design of wind turbine lubrication system. International Journal of Performability Engineering. https://doi.org/10.23940/ijpe.19.02.p8.431440
5. Yan, Y., Li, J., & Gao, D. (2014). Condition parameter modeling for anomaly detection in wind turbines. Energies, 7(5), 3104–3120. https://doi.org/10.3390/en7053104
6. Cigno, E., Magagnoli, C., Pierce, M. S., & Iglesias, P. (2017). Lubricating ability of two phosphonium-based ionic liquids as additives of a bio-oil for use in wind turbines gearboxes. Wear, 376-377, 756–765. https://doi.org/10.1016/j.wear.2017.01.010
7. Panchal, T. M., Patel, A., Chauhan, D. D., Thomas, M., & Patel, J. V. (2017). A methodological review on bio-lubricants from vegetable oil based resources. Renewable and Sustainable Energy Reviews, 70, 65–70. https://doi.org/10.1016/j.rser.2016.11.105
8. Mia, S., Mizukami, S., Fukuda, R., Morita, S., & Ohno, N. (2010). High-pressure behavior and tribological properties of wind turbine gear oil. Journal of Mechanical Science and Technology, 24(1), 111–114. https://doi.org/10.1007/s12206-009-1179-5
9. Kamimura, H., Kubo, T., Minami, I., & Mori, S. (2007). Effect and mechanism of additives for ionic liquids as new lubricants. Tribology International, 40(4), 620–625. https://doi.org/10.1016/j.triboint.2005.11.009
10. Qu, J., Bansal, D. G., Yu, B., Howe, J. Y., Luo, H., Dai, S., Li, H., Blau, P. J., Bunting, B. G., Mordukhovich, G., & Smolenski, D. J. (2012). Antiwear performance and mechanism of an oil miscible Ionic Liquid as a lubricant additive. ACS Applied Materials & Interfaces, 4(2), 997– 1002. https://doi.org/10.1021/am201646k
11. Naveed, T., Zahid, R., Mufti, R. A., Waqas, M., & Hanif, M. T. (2020). A review on tribological performance of ionic liquids as additives to Bio Lubricants. Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology, 135065012097380. https://doi.org/10.1177/1350650120973805
12. Greco, A., Mistry, K., Sista, V., Eryilmaz, O., & Erdemir, A. (2011). Friction and wear behaviour of boron based surface treatment and nano-particle lubricant additives for wind turbine gearbox applications. Wear, 271(9-10), 1754–1760. https://doi.org/10.1016/j.wear.2010.11.060
13. Lal, K., & Carrick, V. (1994). Performance testing of lubricants based on high oleic vegetable oils. Journal of Synthetic Lubrication, 11(3), 189–206. https://doi.org/10.1002/jsl.3000110304
14. Totolin, V., Minami, I., Gabler, C., & Dörr, N. (2013). Halogen-free borate ionic liquids as novel lubricants for Tribological Applications. Tribology International, 67, 191–198. https://doi.org/10.1016/j.triboint.2013.08.002
15. Jayadas, N. H., & Nair, K. P. (2006). Elucidation of the corrosion mechanism of vegetable oil-based lubricants. Journal of Tribology, 129(2), 419–423. https://doi.org/10.1115/1.
16. ASTM D4172 "Wear Characteristics of Lubricating Fluid (Four Ball Method)" (ASTM International)
17. Kimura, Y., Wakabayashi, T., Okada, K., Wada, T., & Nishikawa, H. (1999). Boron nitride as a lubricant additive. Wear, 232(2), 199–206. https://doi.org/10.1016/s0043-1648(99)00146-5



Online Anomaly Detection for Wind Turbines

using Machine Learning Technique Applied in Medium Frequency Operational Data

Grégory Calegari Marchesan
Wind Turbines Operation Engineer

Haral Jonas Serafini
Wind Turbines Product Engineer

WEG Electric Equipment, Jaraguá do Sul, SC, Brazil

Abstract

Wind turbines are equipped with hundreds of sensors, connected to control units, which provide operational data used for both real-time autonomous operation and post-processing analysis. Further, excellence in energy production is required from the wind turbines, to guarantee the return on investment for the wind farm owner. The usage of 10-min data (slow frequency) statistics of several operational channels is predominant in the industry for key performance indicators, including anomaly detection and predictive maintenance. Several solutions have used data analytics and artificial intelligence. High or medium frequency data, however, is not often available but could provide faster feedback in several cases. This paper discusses the implementation of machine learning for wind turbines' online anomaly detection using medium-frequency operational data. The focus is on performance anomaly but the methodology can be applied to any other metric. All steps of the implementation are discussed. It starts from the original method of performance anomaly detection, based on a very time-consuming visual post-operation analysis of performance charts. It explains the several trials to define the best cost-benefit machine learning algorithm, which resulted in a decision tree with five inputs for anomaly detection solution. It details the choice for cloud versus edge computing, in which edge solution was chosen but anomalies are saved in the cloud. Also introduces the scoping and development of a user-friendly, web-based reporting application. Results after 18 months of operation show a robust solution with an accuracy of about 94.69%, reducing the time spent in analysis by 87.65% compared to the traditional method and having a possibility to improve energy production up to 25.7 MWh per turbine per month, in 2.1 MW wind turbines. However, the model is flexible enough to be applied to other wind turbines models.

...excellence in energy production is required from the wind turbines, to guarantee the return on investment for the wind farm owner. The usage of 10-min data (slow frequency) statistics of several operational channels is predominant in the industry for key performance indicators, including anomaly detection and predictive maintenance.

1. Introduction

The wind energy industry is continuously growing and the wind turbines are getting larger. Once the turbines get larger, the operational costs involved in lost power production and operation and maintenance increase as well (Sieros *et al.,* 2012). Additionally, these turbines have a lot of sensors and collect a large number of variables that can be used to analyze and predict anomalies.

On the other hand, data science and machine learning area are growing as never before and provides powerful and already validated techniques to process data and generates intelligence from a huge amount of data.

This way, wind turbines data, and data science and machine learning is a perfect solution to improve wind farms power production and reduce operational costs.

This paper proposes an online supervised machine learning solution that detects anomalies in wind turbines (WT) performance based on engineering chosen variables, runs in edge computing, providing extremely low cost in the processing, and generates reliable anomaly reports, showing them in the company Internet of Things (IoT) platform.

1.1. State-of-Art

Data science and machine learning techniques are not new in the wind energy industry. One of the main reasons is the huge amount of data available due to the many sensors installed in the turbine to monitor its condition. Stetco (Stetco *et al.,* 2019) presents an interesting review about the machine learning techniques applied to wind turbines. The paper shows the steps from data science applied to the wind turbines context and concludes that most of the models rely on simulated data or SCADA data, and most cases use supervised learning.

In the general, there are several fields where machine learning can be applied to wind turbines data to condition monitoring. Jimenez (Jiménez *et al.,* 2020) uses machine learning to classification delamination problems in wind turbines blades and uses supervised learning. Another paper (CUI; Bangalore; Tjernberg, 2018) uses machine learning to estimate the temperatures of a gearbox and analyzes the deviation between the predicted and the real values. Its result shows that deviations can detect possible anomalies that can evolve to failures.

...data science and machine learning area are growing as never before and provides powerful and already validated techniques to process data and generates intelligence... This way, wind turbines data, and data science and machine learning is a perfect solution to improve wind farms power production and reduce operational costs.

In the power performance monitoring scenario, Clifton (Clifton *et al.,* 2013) uses aero structural simulations and wind speed, turbulence, hub-height and wind shear to create regression trees to predict the power output according to each situation. According to the paper, the power predicted by the model using the highlighted features is three times more efficient than using the traditional power curve methodology. Additionally, Marvuglia (Marvuglia; Messineo, 2012) presents a data-driven approach using GMR (Generalized Mapping Regressor), Multi-Layer Perceptron (MLP), and a General Regression Neural Network (GRNN) to estimate the relationship between wind speed and power output, to create a quality control and understand the site power performance. Ti, Deng, and Yang (TI; Deng; Yang, 2020) use machine learning ANN (Artificial Neural Network) and CFD simulations to improve turbine wake predictions. As result, the model showed good agreement between the numerical simulations and measurement data, showing the neural network could understand well the behavior. Moreno *et al* (Moreno *et al.,* 2020) use machine learning approaches and ensemble method to detect anomalies in performance with high accuracy of 98.64% applying the method in 10 minutes power samples, and considering the features of wind speed and power production.

However, to the best of our knowledge, none of the aforementioned papers or others available in the literature dealt with an anomaly detector using online monitoring, running the detector every 10 seconds, and had a validated methodology with high accuracy with 18 months of the application running with field data.

So far, the use of simulations and 10-min average data values available from the SCADA system can lead to errors due to the instant changes in the wind speed or power, which can only be detected using high or medium-frequency data.

Another advantage of the proposed methodology is the data required. The present paper uses only turbine data which is simpler than other approaches.

1.2. Original Method for Anomaly Detection

The original anomaly detection relies on visual analysis of patterns in two operational plots of the wind turbine.

The first step is to identify an anomalous-specific period to be closely evaluated. It uses a wind turbine power curve (Pv), which is a plot of electric power generation over wind speed (IEC, 2005). Any wind turbine has a characteristic power

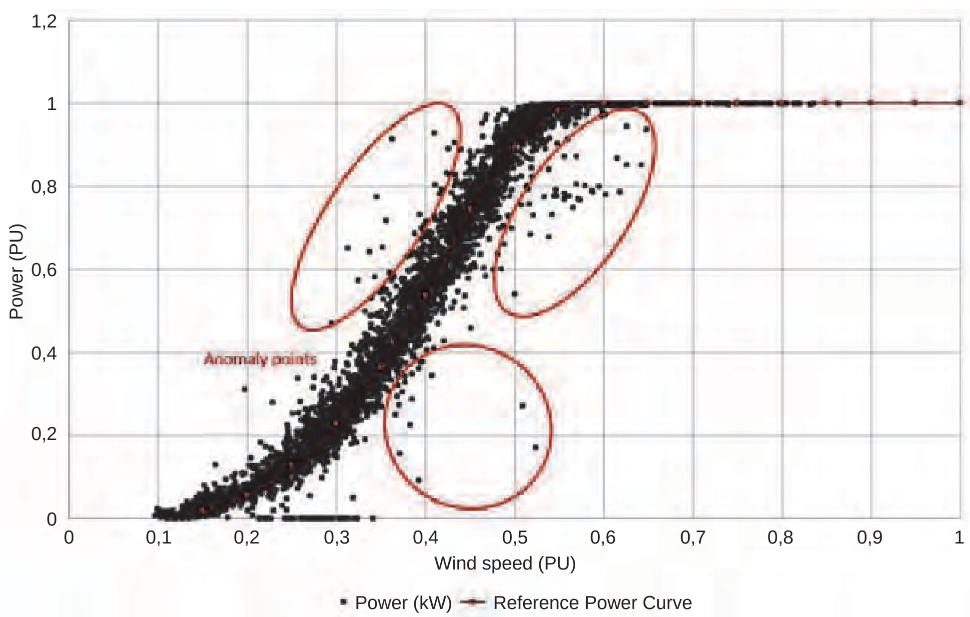


Figure 1: *Anomalies Example*

curve, defined by design parameters (Predescu *et al.,* 2009). Environmental parameters, like wind speed turbulence or air density and site parameters, like terrain roughness, can affect the performance of the turbine, shifting the real power generated in a specific wind speed from its characteristic power. In addition, performance can be compromised by wind turbine degradation, like blade coating erosion.

Performance evaluation of wind turbines includes periodic analysis of Pv scatter plot of 10-min data. Evaluating the plot, an analyst can identify anomalous samples from the characteristic power curve, and evaluate details of that specific 10-min sample. Figure 1 shows a Pv plot with a wind turbine characteristic power curve and 10-min samples obtained in one month, with some anomalous points.

Once the anomalous 10-min samples are detected, the time-series of that specific sample can be evaluated. The original technique used by the authors is to plot, within the same 10-min period, some variables that are known to affect the power performance of the turbine. In this case, power is given by Equation 1, where P is the dependent variable electric power and x1, x2, , xn are the independent variables.

$$P = f(x1,x2,...,xn) \ldots (1)$$

For the original analysis, variables were chosen, from the available channels, defined by experts based on the physics behind the power production. After this, a time-series plot is generated like presented in Figure 2, where about 2 hours of data is shown, using 1-sec resolution data. For the original case, three independent variables x1, x2, and x3 were chosen and shown.

The analysis of the plot shows periods of anomaly, in which time window a set of trends in independent variables. An expert analysis finds patterns in the independent variables according to Table 1.

Table 1: Patterns of Independent Variables

Performance	Normal	Anomaly
X1	Higher than zero	Close to zero
X2	High	High
X3	Varies more	Varies less

This briefly described method for detection of a given anomaly is very time-consuming once demands a two-step process of selecting the 10-min sample in the Pv plot and then evaluating the time-series plot. In addition, it is subjected to errors once relies on the expert subjective capacity to identify the phenomenon.

2. Implementation

2.1. Processing Architecture Definition

Initially, the architecture for the solution was thought, from the anomaly detection until the detailed reports in an IoT platform, to help the expert to work on its cause and decide on eventual correction in the wind turbine. The architecture according to Figure 3 was defined.

In a wind farm, there are several wind turbines connected via an industrial network to a server, including an industrial computer and a gateway device used to transfer data from and to the operation headquarter.

The anomaly detector runs over medium-frequency data (about 10-sec data) for each wind turbine, in the local wind farm server, used as edge computing.

Within the wind farm, a data sample is acquired through polling from each wind turbine within a period that is dependent on the internal network speed and number of turbines. Once the data is collected, the implemented algorithm runs and, if an anomaly is detected, it's generated a report that is sent to the cloud, for posterior analysis of the expert.

A very important choice was to decide where to run the detection algorithm. Two options (Carr, 2020) were traded, edge computing and cloud computing. Edge computing was preferred because it hasn't any cost involved and it isn't necessary to load and store all 10-sec data from local to the cloud. The initial idea was to run the algorithm in 1-sec data, but the existing local gateway was not able to gather data faster than 10-sec. However, the data rate used had no impact on algorithm performance.

In the first wind farm, the sampling period has been found varying from 11 to 17sec. In the data set used for training, the sampling period was 1-sec. The original dataset was then resampled from 1s to 10s of the sampling period to train the algorithms.

The trained model is manually loaded into the wind farm server, which acquires the chosen channels data of each wind turbine and runs the anomaly detection algorithm in each sample. In case an anomaly is detected, a report, with alarms and data, is generated and locally stored in the wind farm server and then sent to a cloud service. The reports are evaluated by the expert for confirming or not the anomaly. If an anomaly is not confirmed, eventually the trained model is tuned. Implementation details follow below.

2.2. Machine Learning Algorithm Choice

The process includes the decision of an expert, so, a proper technique would be supervised machine learning. Two approaches were evaluated - classification and regression. The regression approach presented an additional challenge which was to identify a reasonable threshold for the detection. So classification approach was used, classifying the samples as "normal"and "anomalous".

To train the model, 1-sec data were categorized in 1 for anomalous performance detected, 0 for normal performance detected or empty for the non-clear situation, based on the knowledge of an expert. In total, it used 79770 samples with non-empty values. During classification, one important detail observed by the expert was the spike seen in both power and X3. Samples immediately before clear spikes were more prone to be classified as 1. Finally, it is also important to mention the inherent inaccuracy of the classification of the database provided by the expert once the analysis is subjective. To provide a more accurate database, a second expert opinion was requested for proper critical revision of the database.

Several classification machine learning algorithms were tried, including Decision Tree, Artificial Neural Networks (ANN), Logistic Regression, Random Forest, K-nearest Neighbors (KNN),

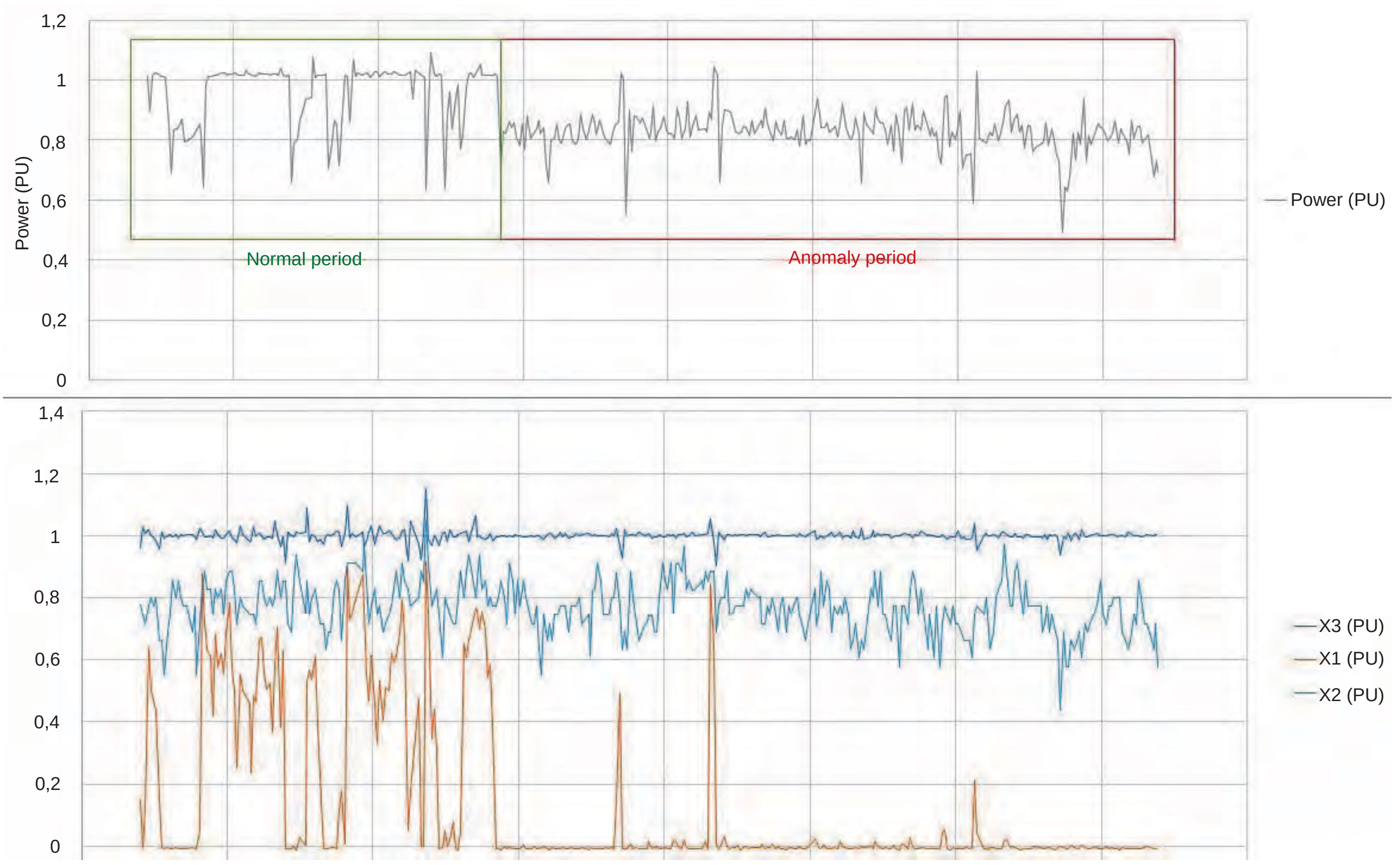


Figure 2: *Time-Series of a Given Period. Time-Windows Show Two Different Conditions: Normal and Anomalous Performance*

and LSTM (for classification), evaluating them for accuracy, precision, recall, and F1Score (Brownlee, 2020).

Dataset was imbalanced, being 17% anomalous samples and 83% with normal operation samples. Techniques were applied to balance the dataset and tested against the previously chosen algorithms. However, the data augmentation techniques didn't present good results.

From the engineering and physics perspective, six independent variables captured by wind turbines have the potential to affect the performance anomaly. To evaluate reducing the model complexity, a dimension reduction technique, feature selection, was applied. After this, just five variables were kept.

Initially, WEKA (Frank; Witten, 2016) was used to implement the basis for the algorithms described above, and after an initial evaluation of the results, Python was chosen, Scikit-learn (Pedregosa *et al.*, 2011), Grid-Search, and Keras (Chollet *et al.,* 2015) to implement a fined tuned version. Cross-validation defined in (Brownlee, 2020) was applied. The summary of the best results can be found in Table 2. The ANN and KNN were discarded in the initial analysis.

Once the performance metrics are calculated, the next step performed was to trade performance and implementation feasibility. To do this, a pugh matrix technique was adopted and the resulting trade can be seen in Table 3. In the pugh matrix, the recall was defined as the most important Key Performance Indicator (KPI) to minimize the number of undetected anomalous cases. Additionally, precision was in the second place, to minimize the false alarms. Further, accuracy was not so important because we were working with an imbalanced database.

As one can see in Table 3, the best performing in the pugh matrix was Decision Tree and Logistic Regression.

For the field test, Decision Tree, Logistic Regression, and LSTM were implemented in the edge computing, running the three models for each 10-sec sample in the field with real-time data. Even though LSTM does have not high results in the Pugh Matrix, with high processing time and lower precision, it was tested in the field, because it is a powerful neural network to deal with time-series.

Once the alarms and reports were generated, the quality of the predictors was evaluated with experts support. The data was collected from different turbines in different wind farms.

After two weeks of test, the metrics were calculated and shown in Table 4. Therefore, the Decision Tree was the best fit to solve this problem, with higher metrics in all categories.

Additionally, the Decision Tree was an interesting choice, once it can handle imbalanced datasets better than regression algorithms.

2.3. Machine Learning Algorithm Implementation

Once the model was chosen and fine-tuned, the next step was to implement it in the field as presented in the architecture in Figure 3.

Table 2: Summary of Tried Techniques Performance

Algorithm	Decision Tree	Random Forest	LSTM	Logistic Regression
Train database size		59360		
Test database size		20410		
Accuracy	97.55%	97.75%	99.60%	97.18%
Precision	39.35%	47.57%	17.91%	48.33%
Recall	84.14%	74.14%	97.59%	89.66%
F1-Score	53.63%	57.95%	30.27%	62.80%

With the trained model, PMML file (Grossman *et al.,* 2002) was generated to export the trained model in Python to be processed by the edge agent, which runs a Java Program.

If the model output identifies an anomalous sample, it is not immediately reported to prevent a relevant number of false positives requiring man-hours effort to be evaluated. Methods to prevent false positives were evaluated and a voting technique was decided. After several trials, voting of three positives in the last six samples was adopted. If this criterion is met, the predicted anomaly channel assumes 1 and a report is then created.

2.4. Report the Anomaly in the Company IoT Platform

Due to the intrinsic nature of the anomaly and the machine learning approach, false positives and negatives are always possible. Therefore, it was decided to submit any detected anomaly for the scrutiny of an expert in wind turbine operation, who will be in charge to confirm or reject the positive detection as well as take the appropriate actions (which are not relevant for this paper). This is done using an online anomaly report.

The report was conceived to replicate, at least, the same level of information that a specialist originally had access to (see item 1.2).

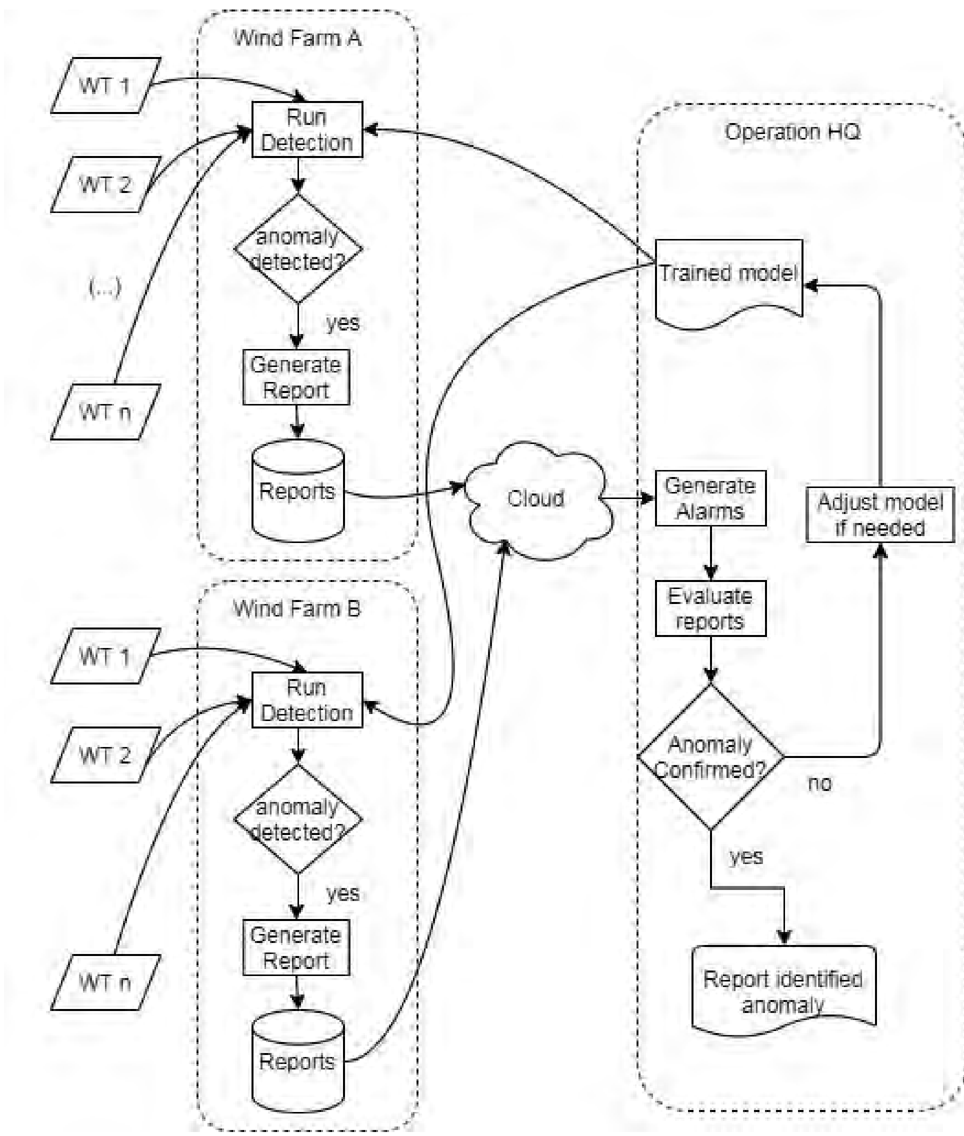


Figure 3: *Architecture of Wind Turbines (WT) Anomaly Detection Process. Just Two Wind Farms (WF) are shown, but number is virtually unlimited. Operation Head Quarter (HQ) is a virtual place where remote operation is located.*

Table 3: Pugh Matrix of the Techniques Tried

	Weight	Reason	Decision Tree	Random Forest	LSTM	Logistic Regression
Accuracy	1	Imbalanced dataset	5	5	5	5
Precision	4	Minimize false positives	2	3	1	3
Recall	5	Minimize undetected cases	5	4	5	5
F1-Score	4	Harmonic Mean	3	3	2	4
Processing Time	3	Important, but hit is more	5	3	1	4
		Total	65	58	45	70

Table 4 : Result About the Field Data for the three Implemented Algorithms

Algorithm	Decision Tree	Logistic Regression	LSTM
Field Test samples	1800	1800	1800
Accuracy	81.2%	80.4%	77.4%
Precision	89.8%	89.1%	84.6%
Recall	72.2%	71.4%	69.6%
F1-Score	80.0%	79.3%	76.4%

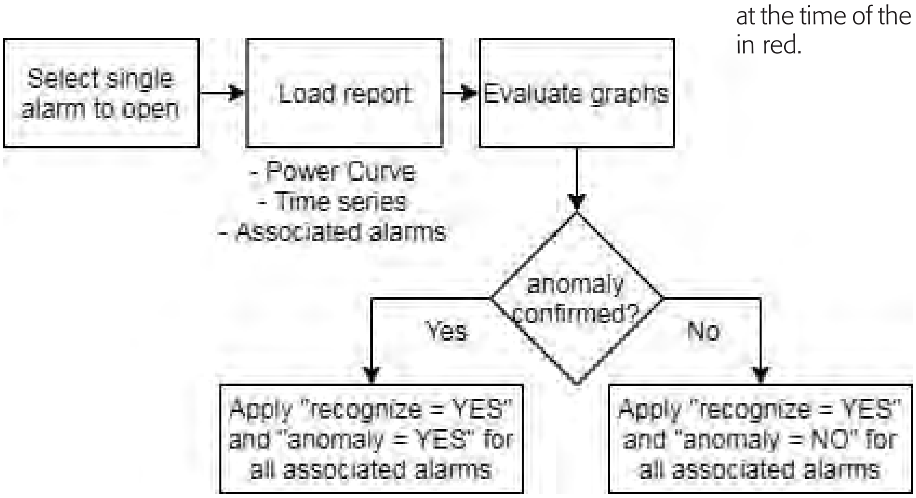


Figure 4*: Process of Anomaly Alarms Analysis*

The first data set of the report is the Pv curve. With the same samples recorded, three channels are used: power, wind, and predicted anomaly. Power and wind are plot in a scatter plot as explained in item 1.2 and predicted performance changes the symbol of each sample. The second data set of the report is the time-series. To allow a proper analysis of the sequence of events, it was decided to get 60 samples before the predicted positive. The algorithm then counts the following sequence of 60 samples: if none of those has any recurrence of predictive positive, the report is then finished with the previous 60 samples, the predictive positive, and the following 60 samples, totalizing 121 samples. However, if, within the following 60 samples any recurrence of predictive positive happens, the counter is zeroed and the report sample size is extended. To prevent a big report size in an eventual long period of sequential anomalous samples, the maximum quantity of a report is set in 360 samples. It is important to remark that both power curve and time-series graphs include samples predicted as normal and predicted as anomalous.

To implement this process, a web-based application was specifically designed for plotting the graphs, automatize the association of alarms to reports and change statuses at a minimum operator action.

In the present case, each sample in which an anomaly is predicted generates an alarm. For evaluating every single alarm, the report that contains it is opened and evaluated. A single report is associated with more than one alarm. Once the operator loads and evaluates the report, the recognition status of all alarms associated with that specific report assumes Recognized = YES. The operator has also to choose between anomaly confirmed = YES or anomaly confirmed = NO. In Figure 4, the process is summarized.

Figure 5 presents the power curve graph and two buttons, one for anomaly confirmed and the other for anomaly not confirmed. It shows the power curve with all samples generated at the time of the report, with the anomalous samples highlighted in red.

Figure 6 shows the time-series generated from the anomaly report. Includes the web address bar, the quick-access left panel, the time-series graph, and two buttons for confirming or not confirming the anomaly for the given alarms. The plot time duration is the same as the report. Back-coloured in light red is the period predicted as an anomaly. Back-coloured in White is the period predicted as normal.

So, with the use of these two plots, the operator can evaluate if there's an anomaly.

3. Value of the Application after 18 Months of Use

To evaluate better the online anomaly detector after the field implementation, we got results from 18 months. Three analyses were done:

- a direct comparison between the time consuming for both original and implemented methods to detect an anomaly;
- an estimate for the difference between the accuracy of the detection;
- and an estimation about the overall energy production improvement brought by the online anomaly detector running;

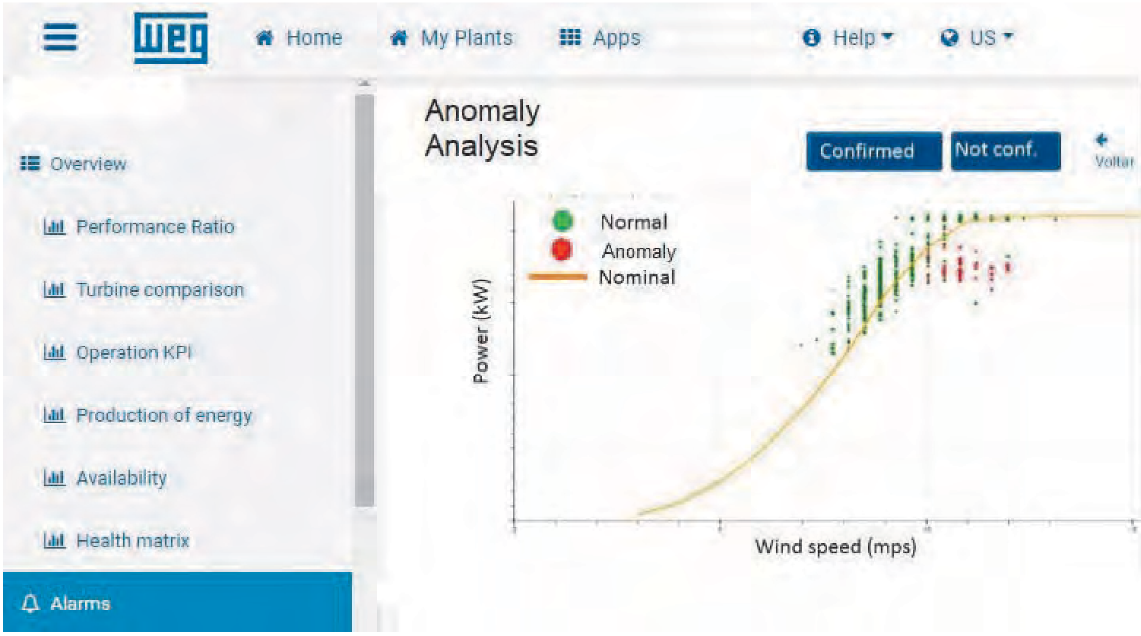


Figure 5: *Screen of Web-based Anomaly Alarm Evaluation with Pv Plot*

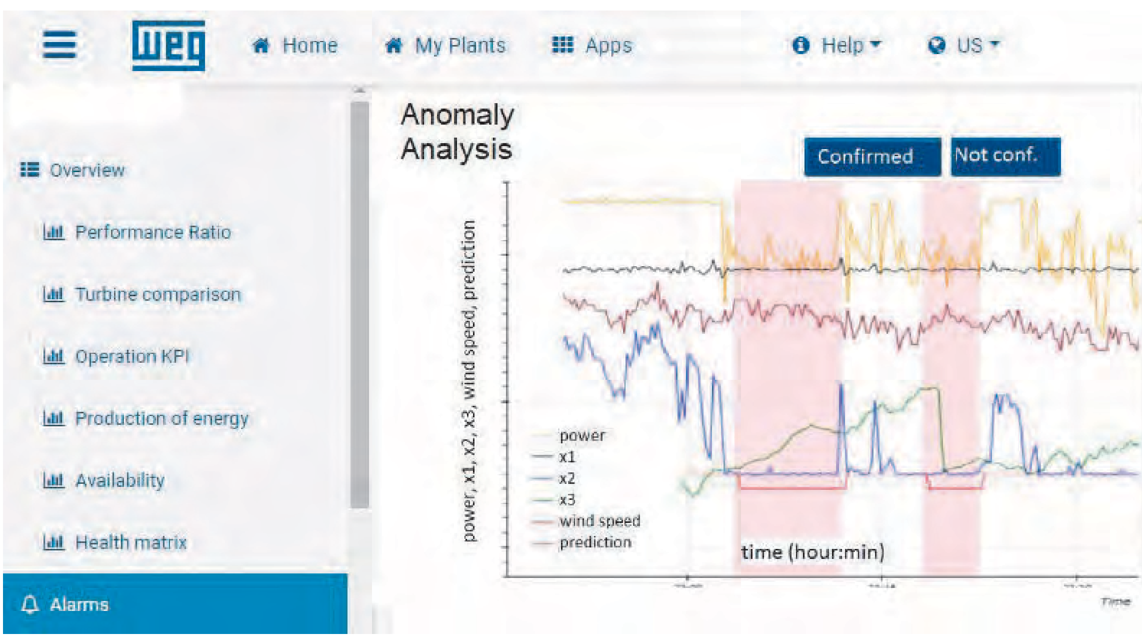


Figure 6: *Screen of Web-Based Anomaly Alarm Evaluation with Time-Series Plot*

The analysis is depicted below.

3.1. Time Consumption Comparison for 18 Months

As described in item 1.2, the first step in the original method is to evaluate the Pv curve, which was created and evaluated at the end of each month. The total population of the comparison is the number of turbines-month monitored with a total of 5544 turbines-months to monitor in the period.

It takes 147 seconds for an expert to perform a graphic evaluation of the Pv curve using 10-min samples to identify anomalous points. So, we have Equation 2:

$$\text{Time for 10 - min plot evaluation} = 147(s) \times 5544 \text{ (analysis)} = 226.38 \text{ hours} \quad \dots (2)$$

Once a point is identified as an anomaly, it is necessary to generate the high-frequency plot. Detail steps are not within the scope of this paper, but included high frequency (1-sec) snaplogs copy, data conversion from control unit proprietary format to an open format, import in data analysis tool, filter by desired time window (the same of 10-min sample), select the channels needed and then perform the analysis. The total time for each analysis is around 1140 seconds. It is challengeable to estimate the number of time-series analyses that would have been done. So, a sample of 50 Pv curves randomly selected were chosen and the total number of analyses needed was counted to 26 analyses, so, applying this ratio of 26/50 in total 5544 turbine months, a total of 2883 analysis would have been necessary.

Calculating in Equation 3:

$$\begin{gathered} \textit{Time for 1 - sec Analysis} = \\ 1140(s) \times 2883\ (analysis) = \ 912.95\ hours \quad \ldots(3) \end{gathered}$$

Summing up with 226.38 hours, the total estimated time in the original method is Equation 4:

$$\begin{gathered} \textit{Time for original method} = \\ 226.38\ (h) + 912.95\ (h) = \ 1139.33\ hours \ldots(4) \end{gathered}$$

With the current application, the time demanding to evaluate each report is about 50 seconds, which multiply by the total number of reports generated in the period, 10140, gives Equation 5:

$$\begin{gathered} \textit{Total time with anomaly detection} = \\ 50(s) \times 10140\ (reports) = \ 140.8\ hours \quad \ldots(5) \end{gathered}$$

Therefore, the time needed to perform the same number of analyses in the current application is Equation 6:

$$\text{Improvement with anomaly detector} = \frac{140.80\ (h)}{1139.33\ (h)} = 12.35\% \quad \ldots(6)$$

So, the anomaly detector reduced the original time spent in analysis by 87.65% (100% - 12.35%) compared to the original time needed. Thus, the implementation of the algorithm minimized a lot of hours of analysis due to the online monitoring, and it is a great advantage of the chosen approach.

3.2. Detection Precision Comparison

In the original method, there is no review of the resulting analysis, therefore the accuracy is unknown.

A total number of 10140 reports were evaluated and recognized. About the alarms, during the period of 18 months, 188656 alarms were classified as TRUE POSITIVES (it means, the anomaly was confirmed) and 10575 were classified as FALSE POSITIVES. To make it clear, every report can have up to 360 alarms, where each alarm represents an analysis executed for each 10-sec sample. So, the overall accuracy is 94.69% during the period, which is a very high accuracy, once the turbines changed a lot during the period of 18 months. So, this shows the robustness of the machine learning trained algorithm implemented in the fleet.

Further, although it's not possible to evaluate the number of false negatives through the reports generated, a second performance tool was used to verify turbines performance in the period. In conclusion, no significant false negatives were detected in the online anomaly detector. This is a good result and a consequence of focusing on 'recall' when training the model.

3.3. Energy Improvement Estimation

To estimate the overall energy improvement, some assumptions were done:

- From the anomalies, just under-performance were considered;
- If the turbine is under-performing without the machine learning algorithm, the specialist takes about one month to analyze and apply the correction;
- If the turbine is under-performing and the algorithm is running in real-time, the operator can apply the correction after about one day;
- According to (Kim; Kim; Kim, 2021), the AEP (annual energy production) can decrease up to 4.0% due to the atmospheric stability, turbulence intensity, and wind shear;
- The average capacity factor for Brazil, according to ONS (ONS) is 42.5%, which means a 21.42 MWh produced by day for a wind turbine of 2.1 MW;
- The probability of anomaly depends on the site and turbine conditions, and cannot be estimated;
- To compose the analysis, the estimated cost R$ (Brazilian Real)/MWh is R$ (Brazilian Real) 190.31, which is the average cost provided by CCEE (CCEE) in the last 2 years. (1 R$ (Brazilian Real) is equal to Rs. 14.10)

So, using the premises explained above, Table 5 was built, which shows the energy and money saved by running the online anomaly detector, in one wind turbine for one month. So, the biggest advantages of the online anomaly detector are the automatic analysis and the online detection, once the expert can act much faster than the traditional method.

Table 5: Energy Generation Improvement Lead by the Online Anomaly Detector, Estimated for 1 Wind Turbine During One-Month

Method	Capacity Factor	Expected Production Monthly (MWh)	Estimate Maximum Energy lost (%)	Maximum Energy Lost (MWh)	Overall monthly production (MWh)	Maximum money lost due to under-performance (R$) (Brazilian Real)
Traditional Method	42.5%	664.02	4.0%	26.56	637.46	5054.63
Online Anomaly Detector			0.13%	0.86	663.16	163.66

As Table 5 shows, using the anomaly detector, we can save up to R$ (Brazilian Real) 4890.97 per turbine per month, increasing the energy production of the wind turbines. Additionally, based on the reports generated, it is possible to save up to 462.6 MWh in energy production per wind turbine in the 18 months of operation.

4. Conclusions

This paper presented a novelty solution to detect anomalies in wind turbines using medium frequency operational data and supervised machine learning. In the paper, some results were focused on the power curve, however, the method can be generalized to other issues.

The implemented solution runs on edge computing, with a pre-trained anomaly detector embedded in local servers of the wind farms and makes reports available on the WEG IoT Platform. When an anomaly is detected, a report is automatically generated and sent to the IoT platform, for recognition from the expert.

After 18 months of application validation, it could reduce the overall time for analysis by 87.65% when compared to the original time and still keeps 94.69% of accuracy in detecting anomalies. This shows that an anomaly detection machine learning solution is completely applicable to medium frequency data in wind turbines and can bring a lot of time reduction as well as keep high accuracy in detecting anomalies.

Further, regarding the energy improvement, it's estimated that the implementation of this app can contribute up to 25.7 MWh in turbine monthly power production, which means a saving of R$ (Brazilian Real) 4890.97 per turbine per month.

5. Future Developments

The method developed for creating this detection application can be generalized for other specific analyses behind the performance. Virtually any detection currently done by high or medium frequency time-series analysis can be subjected to the same process described here, starting from the understanding of the original method of detection and the machine learning algorithm choice.

Implementation and reporting are even easier if the communication chain is already implemented, once would demand just configuring of new data channels in the network architecture and creating new customized reports.

References

- Brownlee, J. Imbalanced classification with Python: better metrics, balance skewed classes, cost-sensitive learning. [S.l.]: Machine Learning Mastery, 2020. 35–103 p. Cited 2 times in pages 7 and 8.
- Carr, D. F. Edge computing vs. cloud computing: What's the difference? 2020. Available on: https://enterprisersproject.com/article/2020/4/edge-computing-vs-cloud-what-is-difference. Access on 01/07/2021. Cited in page 6.
- CCEE: Câmara de comercialização de energia elétrica: Média mensal. Available on:..https://www.ccee.org.br/portal/faces/pages_publico/oquefazemos/como_ccee_atua/precos/preco_media_mensal. Access on 01/07/2021. Cited in page 14.
- Chollet, F. *et al.* Keras. [S.l.]: GitHub, 2015. Available on: https://github.com/fchollet/keras. Access on 22/07/2021. Cited in page 8.
- Clifton, A. *et al.* Using machine learning to predict wind turbine power output. Environmental research letters, IOP Publishing, v. 8, n. 2, p. 024009, 2013. Cited in page 3.
- Cui, Y.; Bangalore, P.; Tjernberg, L. B. An anomaly detection approach based on machine learning and scada data for condition monitoring of wind turbines. In: IEEE. 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS). [S.l.], 2018. p. 1–6. Cited in page 2.
- Frank, M. A. H. E.; Witten, I. H. The weka workbench: Online appendix for "data mining: Practical machine learning tools and techniques". Fourth Edition, 2016. Cited in page 8.
- Grossman, R. *et al.* The management and mining of multiple predictive models using the predictive modeling markup language. Information and Software Technology, v. 41, p. 589–595, 04 2002. Cited in page 9.
- International Electrotechnical Commission. IEC61400-12-1: Wind Turbines- Part 12-1: Power performance measurements of electricity producing wind turbine. Geneva, Switzerland, 2005. Cited in page 3.
- Jiménez, A. A. *et al.* Maintenance management based on machine learning and nonlinear features in wind turbines. Renewable Energy, Elsevier, v. 146, p. 316–328, 2020. Cited in page 2.
- Marvuglia, A.; Messineo, A. Monitoring of wind farms power curves using machine learning techniques. Applied Energy, Elsevier, v. 98, p. 574–583, 2012. Cited in page 3.
- Moreno, S. R. *et al.* Wind turbines anomaly detection based on power curves and ensemble learning. IET Renewable Power Generation, IET, v. 14, n. 19, p. 4086–4093, 2020. Cited in page 3.
- ONS: Operador Nacional do Sistema Elétrico: Resultados da operação. Available on: http://www.ons.org.br/Paginas/resultados-da-operacao/boletim-geracao-eolica.aspx. Access on 01/07/2021. Cited in page 14.
- Pedregosa, F. *et al.* Scikit-learn: Machine learning in python. Journal of machine learning research, v. 12, n. Oct, p. 2825–2830, 2011. Cited in page 8.
- Predescu, M. *et al.* Influence of the number of blades on the mechanical power curve of wind turbines. In: International Conference on Renewable Energies and Power Quality (ICREPQ09), Valencia (Spain), 15th to 17th April. [S.l.: s.n.], 2009. Cited in page 3.
- Sieros, G. *et al.* Upscaling wind turbines: theoretical and practical aspects and their impact on the cost of energy. Wind energy, Wiley Online Library, v. 15, n. 1, p. 3–17, 2012. Cited in page 2.
- Stetco, A. *et al.* Machine learning methods for wind turbine condition monitoring: A review. Renewable Energy, v. 133, p. 620–635, 2019. ISSN 0960-1481. Cited in page 2.
- TI, Z.; Deng, X. W.; Yang, H. Wake modeling of wind turbines using machine learning. Applied Energy, Elsevier, v. 257, p. 114025, 2020. Cited in page 3.

RE Generation Capacity Addition to Touch 16 GW in 2022-23: ICRA

The country's renewable energy capacity addition is estimated to touch 16 GW in the next financial year in view of the strong pipeline of 55 GW clean energy projects, according to ICRA. "The outlook for the capacity addition in the Renewable Energy sector remains strong with a large project pipeline of over 55 GW and the highly competitive tariffs offered by these projects," rating agency ICRA said.

It expects RE capacity addition to increase from 7.4 GW reported in FY 2021 to 12.5 GW in FY 2022 and further to 16 GW in FY 2023.

Source: PTI, January 10, 2022

Bangladesh Bets Big on Wind Energy to Curb Climate Change

Bangladesh aims to significantly expand renewable energy sources in its total energy mix in its relentless pursuit of a net-zero carbon footprints. As one of the key steps in this regard, the Sustainable and Renewable Energy Development Authority (SREDA) has set a target of generating 5,000 MW of onshore and offshore wind power by 2030. The country currently generates only 2.9 MW of wind power. According to SREDA officials, the huge target is being considered as an immediate option for the next few years in compliance with the government's commitment to promoting renewable energy – given the fact that an American agency recently pegged the country's wind power generation potential at 30,000 MW.

Source: Dhaka Tribune, 8 January 2022

Adani Transmission bags two green energy transmission projects worth Rs 1,400 crore

Adani Transmission has bagged two projects totalling Rs 1,400 crore, which includes a transmission line that will evacuate 3 GW of renewable energy from Gujarat. The two projects will help it move closer to its target of setting up 20,000 circuit kilometer (ckt km) of transmission lines by 2022. This project entailing capex of Rs 1,200 crore will evacuate 3 GW of renewable energy from solar and wind farms in Gujarat.

Source: Moneycontrol.com, December 2021

NTPC Could Build New Coal-Fired Power Plants if Needed, Says Chairman

NTPC Ltd could build new coal-fired power plants if needed, the state-run company Chairman Mr. Gurdeep Singh has said. "We should not be shying away. If there is a requirement, we may have to go for new coal-based power plants," Singh also said that the company was considering building nuclear power plants, but discussions were preliminary.

Source: Reuters February 04, 2022

Siemens Gamesa to Supply Turbines for 302 MW Wind Project in India

Siemens Gamesa Renewable Energy S.A. has secured a new order from Ayana Renewable Power Six Private Limited to supply 84 units of SG 3.6-145 turbines for a 302 MW wind energy project in Karnataka's Gadag district in India. Ayana was awarded this wind energy project in the recently announced SECI ISTS Tranche X tender and will develop the infrastructure for the farm.

Source: Wind Insider, 7th January 2022

BPCL plans Rs 25,000 crore green power push to be net zero on emissions by 2040

Bharat Petroleum Corporation Ltd (BPCL) is setting aside Rs 25,000 crore to build a robust renewable energy portfolio by 2040 and is putting in place a team to push the diversification, which will be strategic to the company's ambition to be "net zero" on emissions by the year.

Even as the public sector oil marketing company is in the process of privatisation, BPCL aims to build 10 GW of renewable energy capacity by 2040 through organic and inorganic routes. The company currently has a capacity of 45 megawatts (MW).

Oil companies across the world have been investing heavily in renewable energy, like wind and solar power, as they chart a transition towards cleaner energy sources.

Source: Moneycontrol.com, January 03, 2022

Wind Turbine O & M Market is likely to reach US$ 39.8 Bn by 2031

According to the report, the global wind turbine operations and maintenance market stood at US$ 15.4 Bn in 2020 and is likely to reach US$ 39.8 Bn by 2031, expanding at a CAGR of around 9% between 2021 and 2031. Wind turbine operations and maintenance services include operations, maintenance, asset administration, remote monitoring and repair of wind turbines installed at wind farms.

Source: Wind Insider, 11th January 2022

ADB as Lead Arranger for Financing of "Monsoon Wind Project"

Asian Development Bank (ADB) was appointed as Lead Arranger for financing of the "Monsoon Wind Project", the first cross-border wind power project between Laos and Vietnam and the largest wind farm in ASEAN, with the total loan amount of US$ 650 million. The 600 MW Monsoon Wind Project is located in the Sekong and Attapeu provinces in Southern Laos. Green energy produced from the project could save over 35 million tonnes of greenhouse gas over its lifetime, complying with COP26's goal on Net Zero Greenhouse Gas Emissions.

Source: Wind Insider, 8th January 2022

Minimizing Error vs Minimizing Penalty in RE Forecasting under Indian Regulation

Since the system operators in India have to do curtailment on variable renewable energy due to intermittency and variability of the wind and solar power generation, the forecasting takes an important role in creating a sustainable solution for maximum utilization of renewable energy.

Abhik Kumar Das
Technical Director
Del2infinity Energy Consulting
contact@del2infinity.xyz

1. Introduction

Forecasting can be viewed as a scientific technique to predict or estimate the future trend of variables like wind or solar power generation, estimation of load, etc. to maintain the demand-supply equilibrium in complex power grid. The wind and solar power generated is intermittent in nature and highly variable depending on the different parameters of nature. Due to the intermittency and variability, wind and solar energy shows ramping patterns in renewable energy generation and hence large penetration of renewable energy creates instability in existing grid unless proper forecasting and scheduling is performed. The concept of forecasting and scheduling of renewable energy generators and the commercial settlement was introduced in Indian context by CERC through Indian Electricity Grid Code (IEGC), 2010[1] and the Renewable Regulatory Fund mechanism[2] was envisaged to be implemented from January 1, 2011. Due to several implementation issues, the mechanism was never made operational. To formulate an implementable framework, CERC on 31.03.2015 issued draft, a Amendment. Based on comments and suggestions received from various stakeholders, CERC published the third amendment to IEGC which was issued on 07.08.2015. On the same date CERC also issued 2nd amendment to regulation for Deviation Settlement Mechanism and other related matters[3]. Since the system operators in India have to do curtailment on variable renewable energy due to intermittency and variability of the wind and solar power generation, the forecasting takes an important role in creating a sustainable solution for maximum utilization of renewable energy. After CERC regulation, Forum of Regulators (FOR)[4] and other state regulators issued or drafted regulations related to the forecasting and scheduling of wind and solar power. Apart from regulatory framework, this paper concentrates on the forecasting methodology and penalty due to regulations related to forecasting and scheduling of wind and solar energy.

2. A Brief of DSM Penalty under Indian Regulation

(Refer Table 1 on next page)

3. Mathematical Model of Error function

In a simple mathematical framework, the forecasting and scheduling under Indian regulation can be viewed as follows.

Let A1, A2,…, An be the variables and P1, P2, …, Pn be the parameters required to forecast the next estimated variable $\hat{A}_{n+1}$ the forecast process ϕ can be viewed as:

$$\hat{A}_{n+1} = \phi\ (A_i, P_i \mid i = 1, 2, \ldots n)$$

And the error can be viewed as difference between the actual and estimated value as:

$$e = \frac{\hat{A}_{n+1} - A_{n+1}}{AvC}$$

Where, AvC represent the available capacity of the plant. As per Indian regulation (shown in Table 1), we can state that

$$-m \quad e \quad +m$$

Though there are many different methodologies to forecast depending on the historical data like -

(a) Persistence method: "What you see is what you get"

(b) Using Numerical Weather Prediction to predict meteorological variables

(c) Physical approach

(d) Statistical approach and

(e) Using AI/ML

Forecasting methodology can be viewed as the error minimization problem under some specific constraints. For daily forecast in 96 data points (as per Indian regulation 15 minute = 1 Time-block, hence in 24 hours we have 96 data points), let the actual generation vector be

$$\hat{x} = \{x_i + \in R^+ \mid i \in Z/_{96}Z\}$$

Table 1: DSM Penalty for Intra-State and Inter-State Regulation and Mathematical Framework

Case		Payment on Actual Generation	Payment on Schedule Generation	Payment on Schedule Generation
	Abs Error	Deviation Charge (Payment to DSM account by Generators)	For Under-Injection (Actual < Schedule) Deviation Charge payable by RE generators	For Over-Injection (Actual > Schedule) Deviation Charge payable to RE generators
A	0 – 15%	0	At the Fixed Rate for the shortfall energy upto for absolute error upto 15%	At the Fixed Rate for the excess energy upto for absolute error upto 15%
B	15% – 25%	INR 0.50 per kWh for quantum of short fall or excess energy beyond 15% and upto 25% of deviation from the schedule	At the Fixed Rate for the shortfall energy for absolute error upto 15% + 110% of the Fixed Rate for balance energy beyond 15% and upto 25%	At the Fixed Rate for the excess energy for absolute error upto 15% + 90% of the Fixed Rate for balance energy beyond 15% and upto 25%
C	25% – 35%	INR 0.50 per kWh upto 25% + INR 1.00 per kWh for quantum of short fall or excess energy beyond 25% and upto 35% of deviation from the schedule	At the Fixed Rate for the shortfall energy for absolute error upto 15% + 110% of the Fixed Rate for balance energy beyond 15% and upto 25% + 120% of the Fixed Rate for balance energy beyond 25% and upto 35%	At the Fixed Rate for the excess energy for absolute error upto 15% + 90% of the Fixed Rate for balance energy beyond 15% and upto 25% + 80% of the Fixed Rate for balance energy beyond 25% and upto 35%
D	>35%	INR 0.50 per kWh upto 25% + INR 1.00 per kWh for 25% upto 35% + INR 1.50 per kWh for quantum of shortfall or excess energy beyond 35%	At the Fixed Rate for the shortfall energy for absolute error upto 15% + 110% of the Fixed Rate for balance energy beyond 15% and upto 25% + 120% of the Fixed Rate for balance energy beyond 25% and upto 35% + 130% of the Fixed Rate for balance energy beyond 35%	At the Fixed Rate for the excess energy for absolute error upto 15% + 90% of the Fixed Rate for balance energy beyond 15% and upto 25% + 80% of the Fixed Rate for balance energy beyond 25% and upto 35% + 70% of the Fixed Rate for balance energy beyond 35%

And the forecast or estimated vector be,

$$\hat{x} = \{\hat{x}_i + \in R^+ \mid \hat{x}_l = E(x_i), i \in Z/_{96}Z\}$$

Where $E(x_i)$ represents the expectation of x_i such that $d(x_i, \hat{x}_i)$ is minimum. Here the distance/ error measure follows three simple rules:

1. $d(x,y) \quad 0$ such that $d(x,x) = 0$
2. $d(x,y) = d(y,x)$
3. $d(x,y) \quad d(x,z) + d(x,z)$ for any z

In standard error minimization problem we can consider -

$$d(x,y) = \|x - y\| \text{ and } d(\mathbf{x},\mathbf{y}) = \frac{1}{96}\sum_{i=1}^{96}(x_i - y_i)^2$$

But for penalty minimization problem under Indian regulation, we can represent the distance function as follows:

$$d_P(x,y) = \begin{matrix} 0 & if\ |x-y| \le \alpha Avc \\ c & if\ \alpha Avc < |x-y| \le \beta Avc \\ c+k & if\ \beta Avc < |x-y| \le \gamma Avc \\ c+2k & if\ |x-y| > \gamma Avc \end{matrix}$$

Where Indian regulation fixes the value of c, k, α, β, γ such that $0 < \alpha < \beta < \gamma < 1$.

Hence, the standard minimization problem can be viewed as,

$$\hat{x} = E(x) \text{ such that } d(x,y) \text{ is minimum.}$$

Whereas, the penalty minimization problem is viewed as -

$$\hat{x} = E(x) \text{ such that } d_p(x,y) \text{ is minimum.}$$

4. Ball/Urn Model of Forecasting

To simplify the penalty minimization problem, for $\alpha = 10\%$, we can consider,

$$B = \{b_i \in R^+ \mid i \in Z/_{10}Z\}$$
$$\min(b_i) = \alpha(i-1)\ AvC$$
$$\max(b_i) = \alpha(i)\ AvC$$

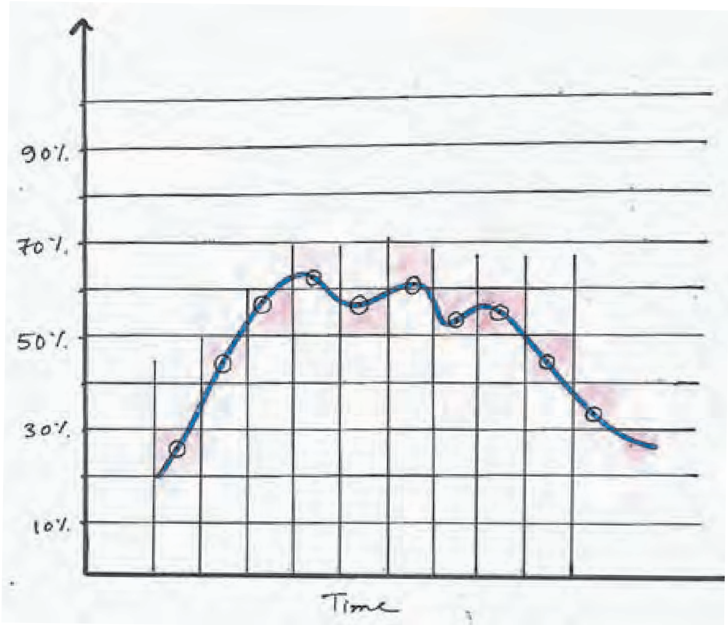


Figure 1: Time vs Blocks of Actual and Forecast Block

Such that the continuous curve shown in figure 1, can be discretised in 10 blocks in such a way that the forecast lies in around the +/- 10% of the actual value at each time block.

Hence the forecasting by probabilistic model using ball/urn can be represented as-

$$\widehat{x_i} = \mathbb{E}(x_i) \leftrightarrow \Pr\{\widehat{x_i} \in b_k | \, x_i \in b_k\} = \frac{\Pr\{x_i, \widehat{x_i} \in b_k\}}{\Pr\{x_i \in b_k\}}$$

Here the probability Pr $\{x_i, \hat{x}_i \in b_k\}$ can be viewed as the forecasting parameter and the probability Pr $\{x_i \in b_k\}$ can be viewed as the weather parameter. The condition probability Pr $\{\hat{x}_i \in b_k \,|\, x_i \in b_k\}$ can be represented using Bayes' Theorem of probability considering the priori and posterior probability on the forecasting model. Here the ball/Urn model represent the forecasting strategy in to Forecasting = Playing with 10 balls / 10 Urns.

For an instant (15 min Time block) we have to choose one ball/ one urn independent of AvC of the solar/wind plant. It is easy to see that the ball/Urn model in forecasting is independent to the available capacity (AvC) of the solar/wind plant and hence it is computationally easy to play with. Hence, using Stochastic

$$T = \begin{bmatrix} p(1\to1) & p(1\to2) & & p(1\to9) & p(1\to10) \\ p(2\to1) & p(2\to2) & & p(2\to9) & p(2\to10) \\ & & & & \\ p(9\to1) & p(9\to2) & & p(9\to9) & p(9\to10) \\ p(10\to1) & p(10\to2) & & p(10\to9) & p(10\to10) \end{bmatrix}$$

Markov Model, we can represent the ball/Urn model using the transition matrix T defined as,

Hence, forecasting strategy can be represented as follows:

Let Ini ial state = b = [0,0,0,0,1,0,0,0,0,0]

Then the Next state = bT

And Next of next state = (bT)T = bT^2

And for any instant, T(Priori) -> T(Posteriori) using the Bayes' Theorem.

Conclusion

To predict the estimated variable error minimization is a simple method for forecasting process. But if the penalty due to the deviation error is not linear with error as in the present Indian regulation for DSM calculation, penalty minimization process can be used effectively in the forecasting process. The penalty minimization process can transform the forecasting process into ball/Urn model independent of available capacity and hence simple Markov type of models can be used in predicting the actual generation to facilitate the forecasting and scheduling of wind and solar power generation.

References

1. Indian Electricity Grid Code, Central Electricity Regulatory Commission, 2010 (http://cercind.gov.in/2010/ORDER/February2010/IEGC_Review_Proposal.pdf)
2. Procedure for implementation of the mechanism of Renewable Regulatory Fund, Central Electricity Regulatory Commission, 2011. (http://www.cercind.gov.in/Regulations/Detailed_Procedure_IEGC.pdf)
3 Framework on Forecasting, Scheduling and Imbalance Handling for Variable Renewable Energy Sources (Wind and Solar), Central Electricity Regulatory Commission. (http://www.cercind.gov.in/2015/regulation/SOR7.pdf)
4. Model Regulations on Forecasting, Scheduling and Deviation Settlement of Wind and Solar Generating Stations at the State level. (http://www.forumofregulators.gov.in/Data/study/MR.pdf)

Snippets

GE Renewable Energy Opens Hybrid Factory in Vallam, Tamil Nadu

GE Renewable Energy has announced the opening of a new renewable hybrid factory in Vallam, near Chennai. The site employs 250 employees including 20 women. This facility that has been set up following the lean principles of reducing waste and improving productivity and is well suited to strengthen GE's place in the hybrids space. The Chennai factory will make the flexinverter and flexreservoir products from GE's newly-launched flex portfolio.

Source: TNN, February 08, 2022

Japanese Consortium Teams Up to Reduce Cost of Floating Offshore Wind

MODEC together with JERA, Toyo Construction and Furukawa Electric has received, notice of acceptance of their joint grant application, under the Green Innovation Fund program of the New Energy and Industrial Technology Development Organization (NEDO), to conduct a project to develop cost-reducing technology for tension leg platform (TLP) floating offshore wind turbines project. To achieve carbon neutrality by 2050, the Japanese government has set a goal of increasing offshore wind power generation capacity, including floating offshore wind, to 30–45 GW by 2040.

Source: Wind Insider, 14th February 2022

annual generation than its predecessor, in Indian low-wind conditions. Backed by smart monitoring system and optimized for all-weather conditions, the SG 3.4-145 is the right fit for the Indian market, delivering high profitability and reduced LCoE. The perfect turbine made for India, made in India. The SG 3.4-145 is indeed geared up to deliver India's positive energy.

SIEMENS Gamesa
RENEWABLE ENERGY

Artificial Intelligence Based Forecasting Developed for Variable Wind and Solar Energy Resources



Dr. Albert John Varghese
Head of Department
(Electrical Engineering)
Rungta College of Engineering & Technology, Bhilai (Chattisgarh)

Dr. Rejo Roy
Assistant Professor
(Electrical Engineering)
Rungta College of Engineering & Technology, Bhilai (Chattisgarh)

Dr. Shambhu Ratan Awasthi
Former General Manager, BHEL
Former Director (Research)
Rabindranath Tagore University, Bhopal, M.P.

Replacing fossil fuels with renewable sources of energy has emerged as an effective means to fight against climate change. There are various sources of renewable energy. However, wind and solar resources have major share in grid connected power systems in several countries including India. Incidentally, both these sources i.e. wind and solar are of variable nature which makes their generation scheduling a challenging task. Here comes the role of forecasting which is highly complicated due to variable nature of these resources. Even for short-term forecasting, huge database is needed which is analyzed using special algorithms and large computational capability. The current surge in variable power generation and related grid management challenges make wind and solar power forecasting an unavoidable task for generation scheduling by the Load Dispatch Centers.

The current surge in variable power generation and related grid management challenges make wind and solar power forecasting an unavoidable task for generation scheduling by the Load Dispatch Centers

This paper deals with the development of a common algorithm capable of forecasting wind and solar power. The research was conducted by the authors (Dr. Albert and Dr. Rejo under the supervision of Dr. S.R. Awasthi) while pursuing their Ph.D. degree.

1. Forecasting

Forecasting is the process where future data are predicted on the basis of present and past data. This is generally achieved by analysing the trends of data. The forecasting process comprises of:

- Consideration of the past and present events, seasonal trends and daily variations which are reflected in the final results.
- Optimization of the forecasting technique to improve the accuracy of the forecasted values.
- Use of forecasted information for generation scheduling.

The forecasting may be classified on the basis of time duration ahead as given in the Table 1.

The accuracy of the forecasted results depends on the accuracy of the past data considered.

2. Development of Hybrid Approach for Variable Renewable Energy Resources

Solar and wind energy are the most widely used resources of renewable energy. Their availability varies from season to season, day to day and even within a day. Due to this variability, forecasting of large solar PV power plants and wind farms becomes very complicated and challenging. A reasonably reliable forecast provides the basis to the operator to workout the generation schedule and communicate to the state load dispatch centre who is responsible for scheduling the generation. Forecasting of variable wind and solar resource helps in generation scheduling which is necessary to improve the reliability. The focus of the research continues to be on improving the accuracy of forecasting to facilitate effective management of power generation.

Forecasting model depends on:

- Environment of the forecast
- Availability of historical data
- Forecast Horizon (or time period ahead)
- Cost/benefit analysis
- Computational facility and execution time for forecasting.

The artificial intelligence methods mimic the reasoning and optimization capability of brain and this has become possible

Table 1: Forecasting Types Based on Time Duration Ahead

Type	Time Duration ahead	Uses
Very Short-Term Forecasting	Minutes to Few Hours	Energy trading, Real time dispatch
Short-Term Forecasting	Few hours to few days	Scheduling, Day to Day Operations
Medium-Term Forecasting	Few Days, Weeks to months	Spinning reserves, Risk Management and raw materials procurement Energy Price Distribution
Long-Term Forecasting	Few Months, Quarters or Years	Determining future projects and availability of fuel resources, maintenance and operation management

only because of computer based analysis. A new generation of artificial intelligence techniques have emerged which help in improving the forecasting process. Two widely accepted approaches are classified below:

- Artificial Neural Networks
- Bio-Inspired Algorithms

3. Objectives of the Research Work

The objectives of the research work were set as below:

The ANN is combined with Bio Inspired Algorithms to develop a short-term forecasting model, which has the following objectives:

- To develop a common algorithm applicable for short-term forecasting of both solar PV and wind power.
- To increase the reliability of solar PV and wind power by minimizing error.
- To minimize the execution time for short-term forecasting where huge amount of data is used to train ANN.

4. Methodology

The various steps involved in the implementation of the proposed idea have been summarised below.

Steps: Neural networks implementation using MATLAB

a. Data collection: Hourly values of Solar irradiance, Temperature, and Wind speed.[1]

b. Creating the Neural Network: Inputs and targets for the supervised learning needs to be defined.

c. Configuration of the Network: Number of neurons in each layer, number of iterations and error is defined.

d. Initializing the weights and biases for the network for optimization: First initialization is done and values of weight and bias are computed automatically by the Neural Network toolbox of MATLAB after that.

e. Training the Network: There are 8760 hourly values in a year. Bayesian Regularization is applied for training of neural network. Values to be used for training, testing and validation are defined.

f. Optimization of the network: The network is optimized using an algorithm or combination of algorithms for selecting the weight and bias of the network.

g. Validating the results: Analysis of the errors, regression plots and comparison of forecasted and actual values are done.

Steps: ANN Tuned with Hybrid Evolutionary Algorithm (PSO + GA)

PSO and GA are called evolutionary algorithms as they share a lot of common features like:

(i) They have a group of population that are randomly generated to calculate fitness of population.

(ii) The optimum search using random methods are updated in the memory for the population.

(iii) They do not give assurance of achieving success.

Nevertheless, PSO does not have mechanisms like crossover and mutation similar to GA. It updates its memory with the value of an internal velocity. In PSO, the particles look for a best solution. The method of sharing information in PSO is different. Only the best particle provides information to the whole population i.e. a

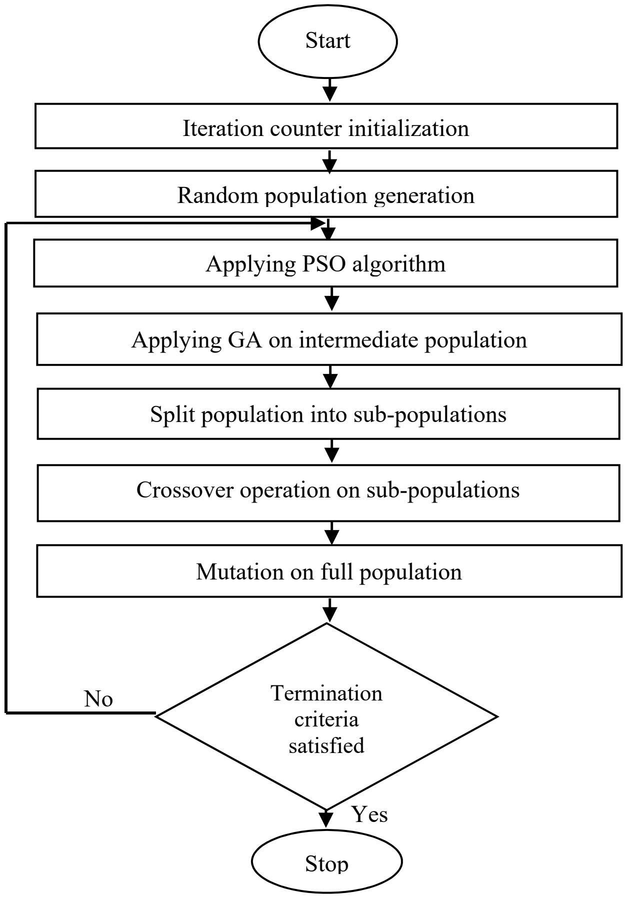


Figure 1: Flowchart of GA+PSO Model

unidirectional sharing of information, while in GA, information is shared by chromosomes. The entire population moves in a group in the direction of achieving optimization. The particles in GA quickly converge to a best solution in local minima[2]. Flowchart of GA+PSO Model is shown in Figure 1.

Forecasting Accuracy

Forecast error is the difference between actual value and the forecasted value. It can be mathematically obtained as:

Forecast Error = Actual value – Forecasted Value

Forecast accuracy shows as to how accurate the forecast is.

Forecast Accuracy = {1 – (Forecast Error/Actual Value)}*100

If the forecast value is lower than the actual value, it is called under-forecasting. If the forecast value is greater than the actual value, it is called as over-forecasting. It helps in adjusting the forecast by an amount corresponding to which this expected value differs from zero. If the forecasting accuracy or forecasting error is not adjusted the actual outcome will be affected by the forecast and the reliability of the forecasts will be significantly lower[3, 4].

Limitations of Forecasting

The forecasted values depend on the number of historical data considered i.e., it is for 1 or 2 or 3 years and whether the data considered is at 10 min or half-an hour, hour or one hour intervals and so on. With the increase in data, the accuracy of forecasting increases but at the same time the execution time increases and more powerful large memory computer capable of handling massive data would be required. It is prerequisite that data has to be authentic.

5. Application of Developed Methodology

The developed methodology is applied to match the pattern of the solar and wind resource power of the solar PV system and wind power system at Bhilai in Chhattisgarh at latitude 21.220 degree North and longitude 81.380 degree East. Hourly solar radiation, wind speed and temperature data for a year were sourced from PVGIS4. The relevant specifications are given below:

Solar PV System

- Solar Panel : 3 kW mono-crystalline silicon
- Elevation : 15m agl, Rooftop
- Inclined : 26° facing south (angle of latitude)

Table 2: Inputs for Forecasting and Output

Parameters	Solar Power Forecasting	Wind Power Forecasting
Input	Solar Irradiance (Watt/m²) Temperature (°C)	Wind Speed (m/s) Temperature (°C)
Iterations limit	20,000	8,000
Total Hourly Data used	8760 hourly data (For a period of one year)	8760 hourly data (For a period of one year)
Training	70% of the data	70% of the data
Validation	15% of the data	15% of the data
Testing	15% of the data	15% of the data
Output	Solar PV Power (Watt)	Wind Power (Watt)

Wind Power System

- Make & model : Enair make, Model 30 Pro
- Wind Turbine output : 3 kW
- Rated wind speed : 11m/s
- Rotor diameter : 3.8 m
- Swept area : 11.34 m²
- Wind power : Computed from Manufacturer's Power Curve

Execution in MATLAB Using Neural Network Training Toolbox

The weights of neurons of artificial neural network are optimized using a hybrid evolutionary algorithm which is a combination of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The weights of neurons can be optimized for improved performance in terms of reduced error and lower execution time.

Solar and Wind Power Forecasting (6 Hour Ahead)

For forecasting the next interval values, irradiance and wind speed input values for 6 hours are fed and the next 6 intervals of forecasted solar PV power and wind power values using the designed ANN are achieved. The values are entered after the ANN is trained completely.

The data in the plot shown in Figure 3 are as given below:

- The first 6 hours from (0-6 hours) show the actual values of solar irradiance which are used to train ANN and
- The next 6 hours from (6-12 hours) gives the forecasted values of solar irradiance.

The plot in Figure 4 shows values for wind power based on wind speed values up to 6 hours and forecasted wind power for next 6 hours obtained for the Model.

A comparison of the short-term solar and wind power forecasting in terms of number of iterations, performance indicator, termination criterion, and execution time are given in Table 3.

6. Future Scope

Some of the other approaches gaining acceptance due to higher accuracy in forecasting are mainly:

- **Machine Learning:** These algorithms have the capacity to learn by itself. These algorithms can improve automatically by experience and using data. These make forecasts on the basis of sample data and they are explicitly programmed to do so. These are used for difficult problems which conventional algorithms find it difficult to solve.
- **Deep Learning:** Deep learning is a subset of machine learning which is modelled after the human brain. This offers lot of promise for time series forecasting and automatic learning of trends and seasonality. This has the capability to make intelligent decisions of its own.

Conclusion

The work focused mainly on short-term forecasting of solar PV power and wind power. Hourly forecasting of 6 hour ahead is done for solar PV power and wind power. The forecasting model used artificial intelligence based Artificial Neural Networks tuned using Genetic Algorithm and Particle Swarm Optimization. For solar PV and wind Power forecasting, the neural networks were run with the limits of 20000 and 8000 iterations, respectively. The training goal was set either to get mean square error i.e. performance to 1 or to get regression (i.e. R) value of 1. Finally, the mean square errors of 1.99 and 1.43 were achieved in 32:24 minutes and 13:29 minutes respectively for Solar PV and Wind Power forecasting.

The authors are keen to apply their developed methodology to forecast the wind and solar resource power at various wind farms and solar power plant sites. It is aimed to seek the

Figure 2.1: Training of Neural Network for Solar Power Forecasting

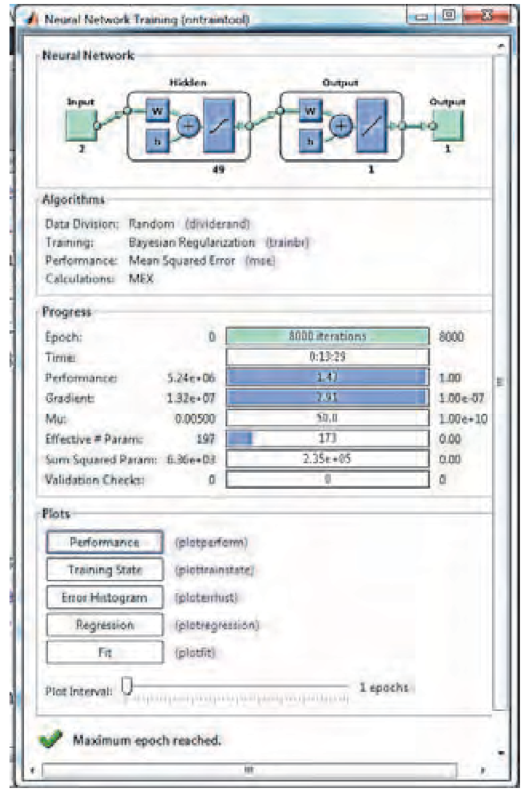


Figure 2.2: Training of Neural Network for Wind Power Forecasting

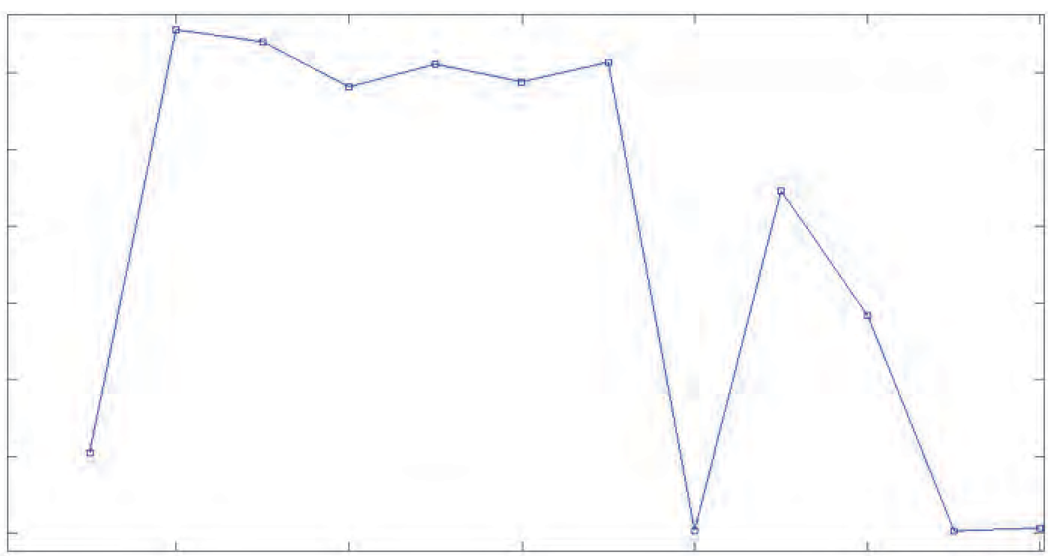


Figure 3: Forecasted Solar PV Power 6 Hour Ahead

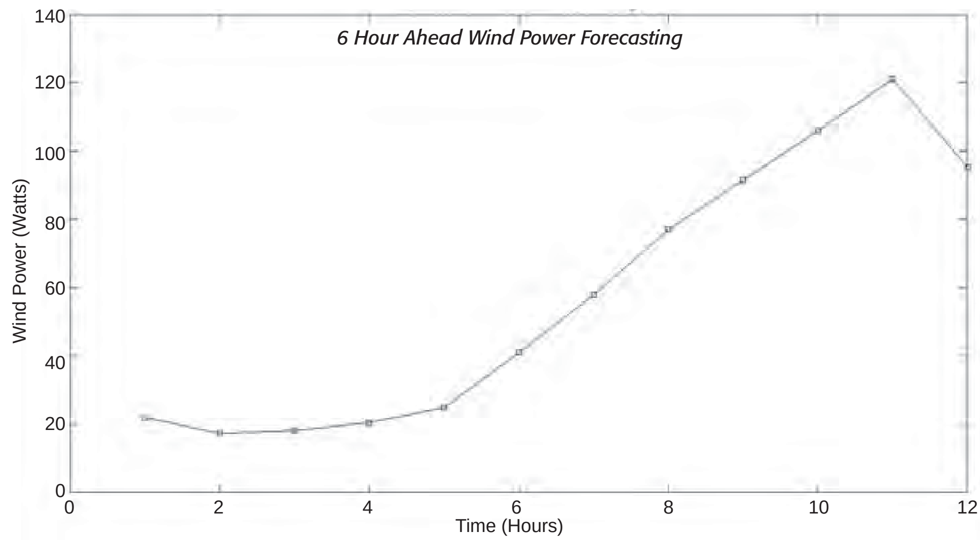


Figure 4: Forecasted Wind Power 6 Hour Ahead

Table 3: Forecasting Results

Parameters	Solar Power Forecasting	Wind Power Forecasting
Maximum number of iterations	20,000	8,000
Terminated due to	Maximum Iterations Reached	Maximum Iterations Reached
Performance indicator*(MSE)	1.99 (Refer Fig. 2.1)	1.43 (Refer Fig. 2.2)
Deviation from actual values	up to 3.164%	-2.5% to 0.14%
Execution Time (minutes)	32:24	13:29

* Ideal value of performance indicator is 1 i.e. zero error which means 100% of matching of forecasted values with actual values.

Table 4: Machine Learning v/s Deep Learning[5]

Parameter	Machine Learning	Deep Learning
Data Needed for Training	Less	Large
Training time	Shorter	Longer
Computational Requirement	Processor	Processor + Graphics Processor
Accuracy	Lower	Higher
Tuning	Limited Capability	Can be done in various ways
Interpretation	Easy/ Difficult – Algorithm Specific	Difficult

feedback of the power plant operators that would be used to improvise the developed methodology. It is also intended to apply the emerging techniques such as machine learning and deep learning in order to enhance the accuracy in forecasting and minimise the execution time.

References

1. Rejo Roy, Albert John Varghese, S.R. Awasthi, "ANN Optimization for Short Term Forecasting of Solar PV Power", Anusandhan – RNTU Journal, Vol. X, 2020.
2. Rejo Roy, Albert John Varghese, S.R. Awasthi, "Short-Term Power Forecasting for Renewable Energy Sources Using Genetics-Based Harmony Search Algorithm", Smart and Intelligent Systems - Algorithms for Intelligent Systems, Springer, Singapore, 2022.
3. Rejo Roy, Albert John Varghese, S.R. Awasthi, "Comparative Study of Genetic Algorithm V/S Genetics Based Harmony Search Algorithm For One Hour Ahead Wind Power Forecasting", Power and Renewable Energy Conference (IPRECON), IEEE International, 2021.
4. Rejo Roy, Albert John Varghese, S.R. Awasthi, "Evolution of wind power forecasting techniques", Anusandhan – RNTU Journal, Vol. X, Issue XXI, 2021.
5. Rejo Roy, Albert John Varghese, S.R. Awasthi, "Recent Developments in Solar Forecasting- A Review", BITCON 2020-National conference on New Horizons in Electrical Engineering to Combat current challenges, 2020.

Snippets

Japan Pushes for Undersea Cables to Solve Wind Power Puzzle

Hokkaido carries the potential to supply Tokyo and other parts of Japan with offshore wind energy, but the lack of adequate transmission capacity has kept the northernmost prefecture from becoming a hub for the renewable resource. Japan looks to allocate 5 billion yen ($43.4 million) in this fiscal year's supplementary budget toward a feasibility study for undersea cables that could help Hokkaido become a destination for offshore wind operators. Ishikari contains roughly 70 km of coastline, most of it facing ideal locations for installing offshore windmills. The city's coast could house over 100 offshore wind turbines depending on demand.

Source: Nikkei Asia, January 2, 2022

Green Energy Corridor II Phase

The Cabinet Committee on Economic Affairs has approved Rs. 12,031 Crore to set up the second phase of transmission projects last week to supply electricity from renewable energy projects to the national grid. The green energy corridor (GEC) will provide 20 GW of renewable energy from Gujarat, Himachal Pradesh, Karnataka, Kerala, Rajasthan, Tamil Nadu and Uttar Pradesh to the national grid. GEC is critical because it will ensure that the massive injection of electricity from renewable sources doesn't destabilise the national grid and that the frequency remains within the 49.90-50.05 Hz band. The government plans to complete the intra-state GEC with a target capacity of 9,700 km of transmission lines and sub-stations with a capacity to handle 22,600 MVA by June.

Source: The Hindustan Times, 10 January 2022

India's Clean Energy Push Propels Renewable Companies' Stocks

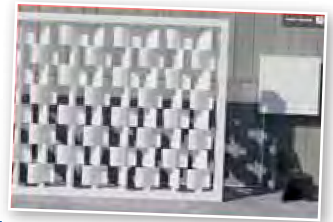
The Centre's push to increase renewables-based sources in India's overall energy mix have pushed up the prices of clean energy players' stocks over the past several months. Accordingly, shares of Suzlon Energy, Orient Green Power, Inox Wind, JSW Energy, Adani Green Energy, Websol Energy System, Borosil Renewables have seen a substantial rise. Earlier, Prime Minister Mr. Narendra Modi at the COP26 meet in Glasgow said India aims to increase its non-fossil energy capacity to 500 GW by 2030, besides the country wishes to fulfil 50 per cent of its energy requirements from renewable energy sources by 2030.

Source: IANS January 08, 2022

India to Add 10 GW Renewable Energy Capacity in 2022

India is estimated to add about 10 GW of total renewable energy capacity in 2022, down 10 per cent year-on-year, according to clean energy consultancy firm Bridge to India. Capacity addition prospects would depend greatly on the timeline for clarity on transmission lines in Rajasthan and Gujarat.

Source: ET Energy World, January 10, 2022



'Wind Turbine Wall' Turns Power Generation into an Aesthetic Feature

NYC-based designer Joe Doucet doesn't see why renewable energy generation shouldn't actively make a home more beautiful, so he's putting together a series of "kinetic walls" using rotary wind turbines to achieve some hypnotic visual effects. Each wall would feature some 25 vertical turbines, each connected to a 400-watt generator for a total peak power output of 10 kW.

Source: Newatlas.com, December 29, 2021

Thyssenkrupp Bets Big on Green Hydrogen Business

Thyssenkrupp is betting big on producing green hydrogen through its proprietary electrolyser technology in India at a time when plans are afoot at the headquarters to spin off its hydrogen business and take it to the bourses soon. The company said that there was a growing demand for electrolyser technology globally as well as in India as industries look for greener fuels to reduce their carbon footprint and meet their sustainability goals.

Source: ET Energy World, January 10, 2022

India to Attract Large Investments Due to COP26 Commitments: ICRA

The commitments on emission control made by India at the recent Glasgow COP26 summit are expected to benefit the country in the long-term with new technologies in energy efficiency, carbon reduction and green fuels. ICRA, in its recent research report, has analysed India's commitment in two phases – up to 2030, and the net-zero target for 2070. Incremental addition of 5 times in non-fossil fuels power generation capacity by 2030 is required for which India would need about $450-500 bn investments including investment towards transmission infrastructure and storage capabilities. In post-2030 projections, a steady pace of sequestration (1-3% range) would be needed to reach the net-zero levels in 2070. This calls out for a huge investment, which is estimated at annually Rs. 115-135 bn (per Niti Aayog report for carbon sequestration).

Source: ET Bureau, January 05, 2022,

Decarbonisation to see $395 bn Capex By 2030: Report

As the country moves more aggressively towards its decarbonisation goals with the overall energy economy shifting towards greener fuels, a Wall Street brokerage has said this space will see a capex of $395 billion by 2030.

Source: PTI January 11, 2022

Snippets

India's Renewable Energy Generation to Rise by 30% by 2024: IEA

India's renewable generation is expected to increase by 30 per cent by 2024 relative to 2021, according to a recent report by the International Energy Agency (IEA). It added that it was driven by state and central auctions, and India's target of 450 GW of installed renewable capacity. As India's demand for electricity continues to grow, the expansion of generation capacity accelerates from 2022 onwards. "While we expect 48% of new demand to be met by coal-fired generation, low-carbon sources provide about half of the additional supply," said the report titled 'Electricity Market Report'.

Source: ET Energy World, January 14, 2022

India and IRENA Strengthen Ties as Country Plans Major Renewables and Hydrogen Push

India's Ministry of New and Renewable Energy has signed a strategic partnership agreement with IRENA, signalling its intent to further strengthen its collaboration in the field of Renewable Energy. With massive renewable energy potential, India has an aim to become a major producer of green hydrogen to support the decarbonisation of its industrial economy. According to IRENA, hydrogen will account for around 12 per cent of total energy supply in a 1.5°C world by 2050. India is privileged to be among one of the few countries IRENA has signed Strategic Partnership Agreement with. IRENA will facilitate to host an innovation day in India and long-term national energy planned towards the achievement of ambitious long-term developmental targets in the sectors of housing, rural electrification, renewable energy, assured electricity supply and reduction in oil import dependence, among others.

Source: Evwind, REVE, January 17, 2022

World's Largest Offshore Wind Project Powers Ahead

KEPCO KPS has signed a MoU with TÜV SÜD Korea and Shinan-gun, to cooperate in the establishment of an industrial Operation & Maintenance ecosystem for the 8.2 GW Shinan offshore wind farm, which will be the world's largest offshore wind farm. The wind farm is planned to be built in phases and be fully commissioned by 2030. KRW 48 trillion (USD 43 billion) will be invested by 2030 and more than 1,600 O&M experts will be required for its construction.

Source: https://www.offshorewind.biz, January 14, 2022

GE Renewable Energy to Supply Turbines for 100-MW Wind Farm in Gujarat

GE Renewable Energy has said that it will supply, install, and commission 37 wind turbines to a 99.90-megawatt (MW) wind power project in Gujarat, managed by Continuum Green Energy. The wind farm project will provide local businesses and consumers with clean energy.

Source: ET Energy World, January 13, 2022

JSW to Invest Rs 2,200 Crores in Wind Power Project in Tamil Nadu

JSW Renew Energy Two (JRETL), a subsidiary of JSW Future Energy plans to raise Rs. 2,200 Crore through bank loans to fund a 450 MW wind power project scheduled to be finished by 31 March 2023 at Tuticorin and Dharapuram in Tamil Nadu. The offered term loan can be payable in over 70 quarterly instalments, starting after 12 months from the completion or commissioning date, whichever is earlier.

Source: Wind Insider, 17th January 2022

NTPC Could Build New Coal-Fired Power Plants if Needed, Says Chairman

NTPC Ltd. could build new coal-fired power plants if needed, the state-run company Chairman Mr. Gurdeep Singh has said. "We should not be shying away. If there is a requirement, we may have to go for new coal-based power plants," Singh also said that the company was considering building nuclear power plants, but discussions were preliminary.

Source: Reuters, February 04, 2022

Filling Investment Gap for Long-Term RE Targets A 'Gargantuan Task': Standing Committee on Energy

Filling the huge investment gap in the renewable energy sector to achieve the 500 GW capacity target by 2030 will be a gargantuan task, according to the 21st report by the Standing Committee on Energy presented in Parliament on 3 February 2021. "There is a huge gap between the required and actual investment and it will be a gargantuan task to fill this gap which requires an enabling framework to be created by the government," the Committee report noted. The Committee was informed by the renewable energy ministry that for the country's long term commitments, an additional investment of about Rs. 17 lakh Crore has been envisaged. "This would include associated transmission costs and the country would need an annual investment of Rs. 1.5-2 lakh Crore in the renewable energy sector against which our estimated investment for the last few years have been in the range of Rs. 75,000 Crore only," said the report titled 'Financial constraints in renewable energy sector'.

Source: ET Energy World, February 04, 2022

Green Hydrogen Policy

Hon'ble Prime Minister Shri Narendra Modi had launched the National Hydrogen Mission on India's 75th Independence Day (i.e. 15th August, 2021). The Mission aims to aid the government in meeting its climate targets and making India a green hydrogen hub. This will help in meeting the target of production of 5 million tonnes of Green hydrogen by 2030 and the related development of renewable energy capacity.

In line with the above announcement, a Green Hydrogen policy was framed by the Government of India, Ministry of Power and it was notified wide its notification no. 23/02/2022 R & R on 17th February 2022. The details of the policy is given below.

Hydrogen and Ammonia are envisaged to be the future fuels to replace fossil fuels. Production of these fuels by using power from renewable energy, termed as green hydrogen and green ammonia, is one of the major requirements towards environmentally sustainable energy security of the nation. Government of India is taking various measures to facilitate the transition from fossil fuel/fossil fuel based feed stocks to green hydrogen/green ammonia. The notification of this policy is one of the major steps in this endeavour.

The policy provides as follows:

- Green Hydrogen/Ammonia manufacturers may purchase renewable power from the power exchange or set up renewable energy capacity themselves or through any other, developer, anywhere.
- Open access will be granted within 15 days of receipt of application.
- The Green Hydrogen/Ammonia manufacturer can bank his unconsumed renewable power, up to 30 days, with distribution company and take it back when required.
- Distribution licensees can also procure and supply Renewable Energy to the manufacturers of Green Hydrogen/Green Ammonia in their States at concessional prices which will only include the cost of procurement, wheeling charges and a small margin as determined by the State Commission.
- Waiver of inter-state transmission charges for a period of 25 years will be allowed to the manufacturers of Green Hydrogen and Green Ammonia for the projects commissioned before 30th June 2025.
- The manufacturers of Green Hydrogen/Ammonia and the renewable energy plant shall be given connectivity to the grid on priority basis to avoid any procedural delays.
- The benefit of Renewable Purchase Obligation (RPO) will be granted incentive to the hydrogen/Ammonia manufacturer and the Distribution licensee for consumption of renewable power.
- To ensure ease of doing business a single portal for carrying out all the activities including statutory clearances in a time bound manner will be set up by MNRE.
- Connectivity, at the generation end and the Green Hydrogen/Green Ammonia manufacturing end, to the ISTS for Renewable Energy capacity set up for the purpose of manufacturing Green Hydrogen/Green Ammonia shall be granted on priority.
- Manufacturers of Green Hydrogen/Green Ammonia shall be allowed to set up bunkers near Ports for storage of Green Ammonia for export/use by shipping. The land for the storage for this purpose shall be provided by the respective Port Authorities at applicable charges.

The implementation of this Policy will provide clean fuel to the common people of the country. This will reduce dependence on fossil fuel and also reduce crude oil imports. The objective also is for our country to emerge as an export Hub for Green Hydrogen and Green Ammonia.

The policy promotes Renewable Energy (RE) generation as RE will be the basic ingredient in making green hydrogen. This in turn will help in meeting the international commitments for clean energy.

Source: **Press Information Bureau,** *New Delhi, 17 Feb 2022*

Snippets

Climate Action: India to Set Up Two Carbon Capture and Utilisation Centres

India will set up two national Centres of Excellence (CoEs) in 'Carbon Capture and Utilization' (CCU) which will help the county reach its emission mitigation goal under the Paris Agreement on climate change. These two centres will come up at IIT Bombay, Mumbai and Jawaharlal Nehru Centre for Advanced Scientific Research (JNCASR), Bengaluru. The CCU along with India's forest carbon sequestration plan will accelerate achieving the country's long-term climate goal of reaching zero' emission by 2070.

Source: PIB Delhi, 10th Feb 2022

Voluntary Carbon Markets: Here to Stay?

(Part one of a new series on the role of carbon offsets in the net-zero journeys of energy-intensive companies)

Elena Belletti
Head of Carbon, Energy Transition Practice
Rachel Schelble
Research Director, Corporate Research, Wood Mackenzie

How can the world accelerate down a net zero pathway when some emissions cannot be abated by current technology? For some companies in hard-to-abate industries, carbon offsets can provide a practical pathway to carbon neutrality, at least while necessary abatement solutions are developed.

What is carbon offsetting?

The concept of carbon offsetting was introduced as part of the Kyoto Protocol in 1997. In broad terms, carbon markets connect entities that generate carbon emissions with entities that have a surplus of carbon reduction. An emitting company can offset a tonne of carbon emissions by acquiring an equivalent credit created by a low-carbon project.

Why is this necessary? Energy-intensive industries (such as oil and gas, aviation, metals and mining, and cement) can be tough, or even impossible, to fully decarbonise with current technologies. Metals and mining, in particular, poses something of a paradox as the industry is tasked with meeting booming demand for raw materials that are vital to the energy transition, while simultaneously cutting emissions. These industries need practical instruments to compensate for residual emissions while long-term solutions evolve.

The system is not without its critics. Some see offsets as a green washing tactic that can be used in place of real carbon mitigation solutions. In our view, offsets can work effectively as a tool in the decarbonisation toolbox, but it is true that high emitters cannot simply trade their way to a lower carbon future. Oil and gas companies, for example, have important roles to play both as buyers of carbon offset in the voluntary carbon market, and as developers of carbon avoidance and sequestration projects.

What is the voluntary carbon market?

There are two types of markets where carbon is traded as a commodity:

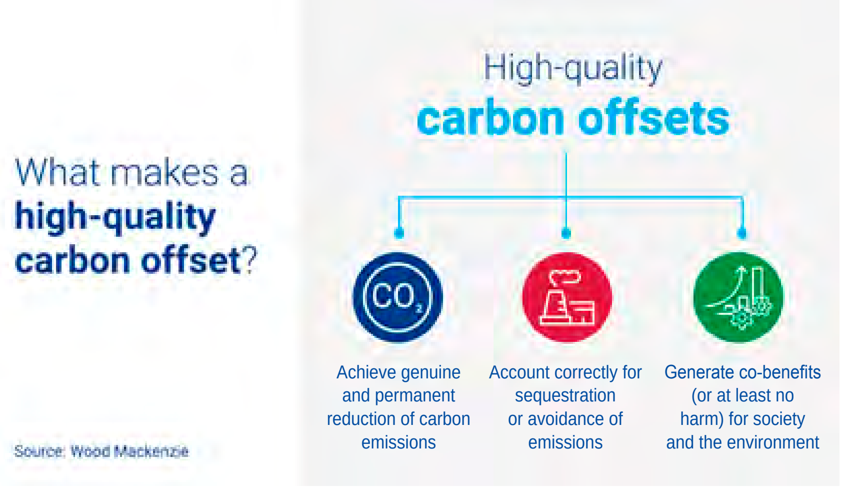
1. In compliance-based carbon markets, companies are obligated to buy allowances for emissions above a certain mandated threshold. (This is primarily 'cap-and-trade'; carbon taxes are another type of mandatory instrument, but they don't establish a carbon market).
2. The voluntary carbon market trades carbon offsets on an optional basis. It connects suppliers with buyers through market intermediaries and allows companies to meet self-imposed net zero targets. While compliance markets tend to cover Scope 1 emissions, voluntary markets can meet demand for emissions compensation along the value chain.

Carbon offset projects fall into two broad categories: removal and avoidance. They range in size from very small (for example, micro-grid solar panels) to large, industrial installations (such as carbon capture and storage associated with a coal-fired power plant).

Third-party auditors assess the amount of emissions reduction or avoidance a project can deliver and issue a corresponding number of tradeable offsets that can be sold on the voluntary carbon market.

What do carbon offsets cost?

Voluntary carbon markets traded around 300 million tonnes of emissions in 2021, for a value of US$1 billion. This represents around 0.8% of global GHG emissions. The average price for offsets traded is currently around US$5/tonne of carbon.



This price is unsustainably low. Why? Carbon markets are a great concept, but in practice have been beset by inconsistencies. Too many credits were created, often from poor quality projects. As confidence in the market ebbed, prices sank.

At COP26, nearly 200 countries came together to agree the terms of Article 6 of the Paris Rulebook. This paved the way for an enhanced transparency framework with consistent accounting and reporting targets. It's a gamechanger for the value of carbon offsets.

How will carbon markets evolve?

COP26 outcomes will continue to boost confidence in carbon offsets, but the Paris Rulebook didn't directly establish a global carbon market. Each country will decide if, and how, to integrate carbon markets into national legislation, or whether to enter partnerships with other countries.

Our view is that COP26 outcomes will push more countries to establish national compliance carbon markets or other forms of carbon pricing; as well as further integrate offsetting into their compliance mechanisms. Over the next decade, we expect to see an evolution of markets at national and regional level. A truly global, integrated and cooperative market with a minimum carbon price could lie ahead.

However, we don't expect compliance markets to replace their voluntary counterparts. Rather, the two will continue to exist in parallel for the foreseeable future and will both experience significant increases in prices and scope.

Fluence and ReNew to Set Up JV to Boost Energy Storage Sector in India

Fluence, a global market leader in energy storage products, services and digital applications for renewables and storage, and ReNew Power has announced an agreement to form a new company to meet the needs of local customers across India that will address the fast-developing energy storage market in India. ReNew and Fluence's 50:50 JV will cater to a market projected to reach 27 GW/108 GWh by 2030.

Source: Energy Storage Pro, 20th January 2022

Cabinet Approves Rs 1,500 Crore Infusion in IREDA to Boost RE Financing

This will enable Indian Renewable Energy Development Agency (IREDA) to lend Rs 12,000 crore to the renewable energy sector. This will enhance IREDA's net worth and will help IREDA to create renewable energy capacity of 3,500 to 4,000 MW.

Source: Indian Express, January 19, 2022

Indian Oil Forays into Wind Lubricants

Indian Oil offer unique, high-performance semi-synthetic product for windmill gearboxes. This product has been evaluated against the stringent requirements of wind turbine gearboxes including DIN 51517 part 3, Flender and Winergy Rev 3 specifications.

Source: Wind Insider, 10th February 2022

Tata Power in Advanced Talks to Raise $600-700 Million for its RE Biz

Tata Power is in advanced talks with investors, including Canadian Pension Plan Investment Board (CPPIB) as well as Singaporean sovereign fund Temasek Holdings and private equity firm General Atlantic to raise as much as $600-700 million (Rs 4478 crore - 5225 crore) for the renewable energy business at an equity valuation of around $6-7 billion. Sovereign money managers of the Middle East were also being tapped for a potential transaction. The asset monetization of renewable energy will help the company meet long-term targets. Tata Power has set targets to set up renewable capacity of 15 and 25 GW by FY 25 and FY 30, respectively.

Source: ET Bureau, February 08, 2022

IIT Madras and Saint-Gobain India Sign MoU to Develop a 100% RE Research Park

Saint-Gobain India will provide Rs. 1 crore to the Research Park of IIT Madras over the next three years in order to accelerate the development of a low carbon future and help India achieve 100 % renewable energy. The cooperation will concentrate on tackling energy concerns, promoting the greatest use of alternative energy sources, and developing sustainable models to assure energy efficiency. The partnership is an endeavour to support the institute's purpose of ensuring 100% use of renewable energy sources and the model will be developed within the span of three years by the institute.

Source: Solar Quarter, 14th February 2022

Hydrogen to Clean up Energy with $10 Trillion Spend – Study

The hydrogen market will result in one of the largest disruptions to the energy sector in history and will help decarbonise the landscape, thanks to an anticipated $10 trillion spend to be made through 2050, according to a new report released by Rethink Energy.

Source: Smart Energy International, 21 January 2022

ReNew Power Commissions Gujarat's First Wind-Solar Hybrid Project

ReNew Power has commissioned Gujarat's first wind-solar hybrid project at the Chlor-Alkali unit of Grasim Industries in Bharuch, Gujarat. The first phase of the hybrid project, with 17.6 MW commercial scale wind-solar commenced operations is expected to generate about 80 million units of renewable energy every year, mitigating about 75,000 tonnes of carbon emissions annually.

Source: ET Energy World, February 08, 2022

Regulatory Update on Wind Power

Compiled by
Dharmendra Gupta
DGM – Regulatory & Govt. Affairs,
O2 Power Private Limited

1. MNRE Considered REGS as Essential Service

Ministry of New and Renewable Energy has issued Office Memorandum F. No. 283/18/2020-GRID SOLAR dated 14.01.2022 and considered Renewable Energy Generating Stations (REGS) under essential service due to rise in cases of COVID-19. MNRE has requested the state authorities to facilitate/ensure uninterrupted movement of personnel; goods and services required for operation of REGS, as was requested vide MNRE's earlier letter dated 26.03.2020. Additionally, it has been requested that the functioning of corporate offices of REGS may also be allowed, with appropriate safeguards in place, as these offices carry out off-field crucial processes/operations like forecasting, scheduling, planning, remote monitoring, supervision and control which are critical for their smooth operation.

2. PFC and REC Reduced Lending Rates to Boost Renewable Energy

Power Finance Corporation and REC Limited have reduced lending rates by 40 basis points for all types of loans. The companies revised lending rates to 8.25% for loans of renewable energy projects to give the sector boost, where long-term funding is required. The reduction in rates has been possible due to lower cost of borrowings by these organizations, in the past year or so. Power and Renewable Energy Minister Mr. R K Singh has said that continued reduction of lending rates by REC and PFC will help power utilities to borrow at competitive rates and invest in improving the power sector infrastructure, thereby benefitting the consumer by way of reliable and cheap power.

3. Revised Guidelines For Charging Infrastructure For Electric Vehicles

The Ministry of Power has released the revised 'Charging Infrastructure for Electric Vehicles (EVs) Guidelines' to enable faster adoption by ensuring safe, reliable and affordable infrastructure. The guidelines also provide affordable tariffs for charging station operators/ owners and EV owners and proactively support for creation of EV charging infrastructure. The Guidelines allow that no license is required for an individual/entity to set up charging stations, provided that they have to meet the technical, safety and performance standards. Guideline allows EV owners to charge their vehicles at their residence or offices using their existing electricity connections. The public charging stations will be provided with connectivity within seven days in metro cities, 15 days in other municipal areas, and 30 days in rural areas.

4. MNRE Issued Revised List of Models and Manufacturers List

Ministry of New and Renewable Energy, Government of India, Wind Energy Division has issued the Wind Turbine Models included in the Revised List of Models and Manufacturers (RLMM) after declaration of new procedure (i.e 01 November 2018) as on 21st January 2022. The RLMM list for wind energy is a key document to support SNAs, investors, lenders and developers in the sector. According to the MNRE, around 70-80% indigenisation has been achieved with strong domestic manufacturing in the wind sector. The list comprises 15 approved firms in all, a good mix of international and domestic players.

5. Cabinet Approved Intra-State Transmission System–Green Energy Corridor Phase-II

The Cabinet Committee on Economic Affairs approved the scheme on Green Energy Corridor (GEC) Phase-II for Intra-State Transmission System (InSTS) for addition of approximately 10,750 circuit kilometres (ckm) of transmission lines and approx. 27,500 Mega Volt-Amperes (MVA) transformation capacity of substations. The scheme will facilitate grid integration and power evacuation of approximately 20 GW of Renewable Energy (RE) power projects in seven States namely, Gujarat, Himachal Pradesh, Karnataka, Kerala, Rajasthan, Tamil Nadu and Uttar Pradesh.

6. Madras High Court Order Regarding 20 to 25 Years Old Wind Projects in Tamil Nadu

Madras High Court has passed a favorable order for captive consumers/wind projects, regarding Banking facility of power by wind mills, which are 20 to 25 years old in the State of Tamil Nadu. The Tamil Nadu Generation and Distribution Corporation (TANGEDCO) had erroneously issued directions to the effect that the WEGs commissioned before 31.3.2016, which have exhausted its life period of 20 years and the WEGs commissioned after 1.4.2016, which will have a life span of 25 years shall not be permitted to continue wheeling and adjustment of wind energy since there is no subsisting contract or regulatory approval for such extension.

The High Court heard the matter & directed TANGEDCO to adhere terms of the existing Energy Wheeling Agreement by continuing to adopt the arrangement of captive adjustment of wind energy generated and to consequently account for all the generated units and to provide banking facility and adjustment of all such units till date as per the orders passed by APTEL in Appeal No.191/2018, etc. Batch dated 28.1.2021 and pass orders in consonance with the orders passed by APTEL. The Order also clarified that as and when CERC/ MNRE notifies the approved Indian Wind Turbine Certification Scheme and any other safety aspects, the wind developers shall strictly abide and comply with all the guidelines and safety standards.

Renewable Energy to Responsible Energy

The Responsible Energy Initiative is a futures-led collaborative inquiry into how the renewable energy sector in India and Asia can scale in an ecologically safe and socially just way.

The Renewable Energy to Responsible Energy Initiative aims to enable the renewable energy sector in the Asia Pacific region to adopt business models and value chains that are ecologically safe, rights respecting and socially just. The initiative aims to engage with investors, developers, manufacturers, large procurers, together with other pertinent actors in the renewable energy sector to identify, set and action new norms. In India, the core partners for the Renewable Energy Initiative are The Energy and Resources Institute (TERI), Forum for the Future and World Resources Institute (WRI India), with expert support from Landesa, WWF-India and the Business and Human Rights Resource Centre (BHRRC).

The Challenge

The rise of renewables has brought great hope for our ability to tackle climate change. Scaling renewable energy is critical to the rapid transition to a low carbon economy and has the potential to expand access to affordable, clean energy; create jobs and help economies to thrive; and reduce air pollution, a primary concern for urban citizens in Asia.

Unless the potential negative social and environmental impacts are adequately addressed, the growth of the sector in Asia-Pacific and across the World may be put in jeopardy, which would be unacceptable from a climate perspective.

This is a critical moment in the development of the sector. Renewable energy is scaling rapidly; financing models are shifting from public to private; and policy and regulatory mechanisms are changing. Economic stimulus packages are being developed to support recovery from COVID-19, with many focused on building the industries we need to ride the shocks of the future, including renewable energy.

At the same time, we are seeing significant risks emerge that the industry may scale in a way that does not account for environmental, social and human rights impacts across the industry value chain, particularly in the race to revive failing economies impacted by the pandemic. From land and labour rights and local livelihood challenges to impact on biodiversity, the potential negative impacts of the large-scale implementation are becoming increasingly clear.

Unless the potential negative social and environmental impacts are adequately addressed, the growth of the sector in Asia-Pacific and across the World may be put in jeopardy, which would be unacceptable from a climate perspective.

Key Objectives and Outcomes

The Responsible Energy Initiative brings together renewable energy companies, investors and procurers to:

- Establish a systemic understanding of the implications of inaction, barriers to integrating Environmental, Social and Governance (ESG) practices into business models and governance, and opportunities for shifting mindsets and behaviours such that the sector can accelerate and be a net positive force in achieving a sustainable future.
- Identify ways to transform business models, practices (including governance around investment) and the system participants operate within so that the sector is better placed to deliver long-term value for both society and shareholders.
- Pilot interventions that demonstrate a shift in business models, practices and the wider system. These shifts will be in both how the renewable energy industry responds to its environmental and social impacts, and the wider system, including investors, policy makers, financiers and those procuring renewable energy encouraging and incentivising just and regenerative approaches to ESG.
- Support the scaling of approaches that enable the acceleration of renewables across the Asia Pacific region in a fair and just way by curating multi-country learning and insights to share and engage a wider group of renewable energy stakeholders across the region.

By paying attention to all ESG impacts, the renewables sector in Asia will be better able to operate sustainably and ensure access to long-term finance, enhancing its ability to accelerate the clean energy transition and also secure its own resilience.

Report: Renewable Energy to Responsible Energy: A Call to Action

The report launched in March 2021 analyses the environmental and social risks and impacts associated with the production and deployment of renewable energy through select technologies in India.

Brief Executive Summary

The rapid rise of renewable energy (RE) is a keystone element of our transition to a low carbon economy in India and globally. RE has the potential to dramatically cut greenhouse gas emissions, expand access to affordable, clean energy for all, create jobs and help economies and societies thrive in the long-term. However, all new technologies bring both potential upsides and downsides, and RE is no exception. The rapid scaling of RE in many parts of the world, including India, is placing increasing pressure on natural resources, albeit on a relatively lower scale than conventional systems. These pressures include mineral use for equipment manufacture, land used for siting large-scale projects, water used for the operation and maintenance of certain technologies, and the challenge of sustainably managing technologies at their end-of-life. In some cases these pressures cause adverse environmental impacts and are also driving social inequities and human rights abuses.[1] Yet, the well-recognised positive impacts of RE mean that the deployment of the technology is often viewed as inherently good, and these environmental and social risks may not be adequately recognised.

Avoiding these adverse impacts will be critical in ensuring that the sector does operate in a sustainable fashion and avoids damaging investor and other stakeholders' confidence in ways that may ultimately hamper the uptake and growth of RE in India. At the same time, the RE sector is uniquely poised to accelerate the country's just and fair transition to low carbon energy, and to lead the way in addressing challenges that have plagued the broader infrastructure sector and others for decades. Awareness is growing amongst the different stakeholders of both the risks and the opportunities, and the Indian RE sector is beginning to respond to the emerging challenges. However, a number of critical gaps remain as Environmental, Social and Governance (ESG) practices take time to mature, and legal and corporate accountability mechanisms remain light. To facilitate the rapid scaling of the RE sector in India, there is support across government and the private sector to expand the domestic supply chain, diversify sources of finance and position India as a leader in deployment. It is a timely opportunity for collective action by key stakeholders to take a deeper look into the holistic ESG risks and impact of the RE sector in India - and globally - across the value chain to ensure that it develops in ways that will drive just and regenerative outcomes for society and environment.

Report Scope and Purpose

This report is the outcome of the first stage of the Renewable Energy to Responsible Energy Initiative – a collaboration between World Resources Institute India (WRI India); The Energy and Resources Institute (TERI); Landesa; World Wildlife Fund for Nature, India (WWF India) and; Forum for the Future. The initiative has been established to support the RE sector in fulfilling its full potential in driving a just and regenerative future, providing the insights and the space for key stakeholders to collaborate and take forward practical collective action towards this end.

The purpose of this report is to set the stage and establish a compelling case for action by providing:

- an overview of the landscape for RE in India;
- a broad understanding of the environmental and social risks and impacts being generated by the Indian RE sector across the value chains;
- insights into the extent to which these impacts are currently being governed, managed and mitigated; and
- a call to stakeholders - RE developers, investors, financiers, procurers, policy makers and civil society actors - to collaborate on tangible and transformative solutions for scaling the production and deployment of RE in a just and regenerative manner.

The findings presented within this report are the result of a literature review; semi-structured interviews with industry, investors, civil society and government experts; as well as on-site visits. We are grateful to our expert panel of reviewers for their inputs.

Key Findings

Rapid scaling and Investment

The RE market landscape is developing at a fast pace in India. The government's 450 GW target[2] sets the scene for what has become the fourth most attractive RE market in the world.[3] With over 90 GW installed capacity at the end of 2020,[4] renewable energy accounts for approximately 24% of India's total installed capacity[5].

In addition to strong government support, increasing flows of investment are a key driver of this growth. The methods of financing have significantly shifted over the last decade. Initially primed by foreign sources such as concessional loans from multilateral agencies and development banks including the World Bank and Asian Development Bank, the landscape is now more commercially led with many local players at the helm. These flows of finance will need to continue to diversify[7] and accelerate in order to provide the estimated US$500 billion[8] required to meet the 450 GW target.

An Evolving Governance Structure

Multiple actors play a role in governing the RE sector. Public structures and regulatory mechanisms operating at both national and state levels are the primary means of governance. These mechanisms are also supported by the judiciary, some corporate governance initiatives and by civil society, with a long history of advocacy around infrastructure projects.

Governance at all levels is helping to ensure increased participation and consideration of environmental and social impacts in RE projects. However, emerging evidence regarding the environmental and social impacts associated with the production and deployment of RE suggests a need to understand how existing governance mechanisms can better support the sector in having just and regenerative impacts, securing its ability to thrive into the future.

Emerging Environmental and Social Impacts

Both the positive and adverse impacts across RE value chains are expected to amplify with the scaling of deployment. To date, the focus has been on accounting for the benefits of RE - namely, the significant contribution that it makes to reducing greenhouse gas emissions, as well as to reducing India's energy import bills. A rapid scaling of such RE-related benefits is critical to meeting Paris Agreement objectives. In India, the sector also delivers a wide range of benefits beyond emissions reductions, ranging from reductions in air, sound, soil and water pollution to greater opportunities for energy access in remote locations, the generation of green jobs and a significant contribution to the national economy and GDP.

Ensuring the sector fulfils its potential to deliver truly positive impact will require taking into account a number of critical concerns, including:

- Increased ecological and social vulnerabilities resulting from land-use changes;
- Labour and human rights abuses - particularly in locations where raw material extraction/mining, production and end-of life-stages of RE technologies take place, especially in the informal sector;
- Impacts on local and regional biodiversity during the construction and operation phases of the value chain in particular;
- Water-related competition and conflict arising from intensive water use associated with solar panel operation and maintenance;
- Energy justice concerns in instances where communities near project sites are not prioritised for improved access to electricity and other benefits. There are signs that some of the negative impacts disproportionately affect vulnerable segments of society - most notably women and marginalised communities - driving further inequity and hampering a broad range of socio-economic agendas.

A number of these impacts are observed in countries outside of India, through international supply chain relationships. Whilst the RE sector in India is neither the sole, nor at this point in time, the most significant contributor to these impacts, a more direct correlation might emerge for India and globally as the sector continues to grow rapidly. India is in a pole position to take the lead in forming an alliance of countries to reduce any negative impact from the supply chain and contribute to the sustainable growth of the sector. It is important to acknowledge that not all of the adverse impacts outlined in this report are unique to the RE sector. Some are common across the energy system, including in relation to fossil fuel sources. Others span multiple sectors. We have employed a 'Finitude, Fragility and Fairness' framework to provide an overview of the impacts and risks that need to be addressed in each of the key RE technology value chains in order for the sector to be regenerative and just.

Sector Responses

An important step in moving to a just and regenerative RE sector is establishing robust accountability frameworks for RE projects and organisations. A wide variety of approaches are currently being employed to varied standards across the different actors, from the RE companies that operate within legal and voluntary frameworks, to financiers who stipulate varying levels of standards and scrutiny, to industry associations raising awareness, to large buyers of RE who practice sustainable procurement. RE developers in India demonstrate a wide range of responses to their environmental and social responsibilities, from deeming their CSR programmes or philanthropic activities as a sufficient response, to those that are conducting Environmental and Social Impact Assessments (ESIAs) as a matter of policy, imposing ESG requirements on their contractors or suppliers, and directing R&D to critical challenges. India has a number of corporate governance mechanisms that can be applied in ways that will encourage the RE sector to address its environmental and social impacts. However, there is currently a nascent narrative on the specific applicability of these mechanisms to the RE sector and a general lack of evidence of their usage by different stakeholders. Financial actors have played a key role in influencing the uptake of ESG, but could be using their leverage to push for a greater level of environmental responsibility and respect for human rights across the life cycles and value chains of RE developers in India. One of the strongest drivers of change appears to be the World Bank and International Finance Corporation (IFC) Performance Standards and similar compliance provisions from other international financial institutions, such as the Asian Development Bank and the Asia Infrastructure and Investment Bank. Other financial actors investing in RE in India are beginning to apply ESG frameworks, but this is not yet the norm. There can be a misinformed perception that there is no need to manage environmental and social risks in the value chain, because the generation of RE is inherently sustainable.

At present, it is the large foreign private equity investors that are more likely to demand effective due diligence, especially at the pre-investment stage and early stages of deployment. The extent to which they continue to monitor ESG impacts throughout the project lifecycle is not always clear, and less attention is being paid to the ESG impacts of value chain activities outside of India, such as those relating to the sourcing of minerals or the production of the solar panels or wind turbines. ESG investing does present a clear opportunity to catalyse more concerted action on the part of RE developers. The increase in the number of ESG funds in India and growing numbers of signatories to the UN-supported Principles for Responsible Investment (PRI) bodes well in this regard. The challenge ahead though is in deepening investors' understanding of the potential that the RE sector holds to holistically contribute towards a just and regenerative future through its value chain. This extends beyond both the supply of green energy and foundational compliance with ESG standards. Generally, banks and non-banking financial companies lending to the RE sector are not recognising the full extent of ESG risks across the value chain. As an example, IREDA[11] notes in its Annual Report that it views "RE projects as the most environmentally benign and socially acceptable projects"[12] and even though it does apply its Environmental and Social Management System (ESMS) to these projects, it sees them as having relatively "minimal impacts."[13]

There is emerging evidence that some industry associations are playing an important role in proactively identifying current and future challenges for their parts of the sector and establishing task forces to shape a response. For instance, the National Solar Energy Federation of India is in the process of examining the issue of solar panel waste on behalf of its members. There are lessons to be learnt from associations in other countries in order to ensure the scope of attention is broadened.[14] Sustainable procurement of RE is not playing as substantial a role as it is in other sectors. Whereas sustainable procurement is now an established practice with companies accounting for the social and environmental impacts of their suppliers, its implementation with regard to suppliers of RE is still minimal.

Towards a just and regenerative RE sector the research conducted for this report reveals an RE sector that cannot be assumed to be inherently sustainable despite the key contributions it is making to a low carbon future. A complex mix of factors mean that there are still critical gaps when it comes to the implementation of ESG approaches by the RE sector. During the course of this research, several sector leaders, large procurers and investors shared their recognition that now is the time to move to a more proactive approach, one that systematically manages impacts whilst seeking a holistic just and regenerative effect throughout the lifecycle and value chain. They recognise that because some of the challenges are also shared with other sectors, they have the opportunity to lead and collaborate. Recognition and identification of environmental and social implications, and correspondingly implementing robust ESG approaches is a necessary first step on the journey towards ensuring a just and regenerative trajectory for the sector. From this first step, there is a real opportunity to move beyond doing less harm, to enabling social justice and economic resilience, as well as regenerating ecosystems. It demonstrates the possibility that efforts to achieve a 'just transition' towards a low carbon future can, and should, go far beyond traditional definitions to also look at the impacts of what is transitioned to, and how.

References

1. See for instance BHRRC, "Renewable Energy & Human Rights Benchmark Key Findings from the Wind & Solar Sectors", 2020, available at https:// media. business-humanrights.org/media/documents/files/Renewable_Energy_Benchmark_Key_Findings_Report.pdf (accessed January 2021).
2. Ministry of Renewable Energy, "Renewable Energy Sector Makes rapid Strides in 2019. Installed Re Capacity Crosses 84GW; Nearly 1o GW Re Capacity Added in 2019"; 9 January 2020 (posted by PIB Delhi), https://pib.gov. in/PressReleseDetail.aspx?PRID=1598948\
3. Koundal, A, "India's renewable power capacity is the fourth largest in the world, says PM Modi", ET Energy World, 26 November 2020, https:// energy.economictimes.indiatimes.com / news / renewable / indias-renewable-power-capacity-is-the-fourth-largest-in-the-world-says-pm-modi/79430910
4. Please note this excludes large hydro power. Source: CEA Dashboard Installed Capacity. Composition December 2020, accessed February 2021, https://cea.nic.in/dashboard/?lang=en.
5. This figure does not include large hydro power.
6. Alok Raj Gupta, "Financing India's renewable energy vision", ORF Issue Brief No. 336, January 2020, Observer Research Foundation, citing Ministry of Finance, Government of India, "Strategic Investment to Drive India's Renewable Energy Revolution", May 21, 2018
7. Bloomberg NEF, "India's 2030 RE Goals", 26 June 2020, https://data. bloomberglp.com/professional/sites/24/2020-06-26-Indias-Clean-Power-Revolution_Final.pdf
8. Tim Buckley and Saurabh Trivedi, IEEFA, "Capital Flows Underpinning India's Energy Transformation", 2021 http://ieefa.org/wp-content/ uploads/2021/02/Capital-Flows-Underpinning-Indias-Energy-Transformation_ February-2021.pdf (accessed February 2021)
9. Aaditya Ranjan Srivastava *et al.,* "Role of Renewable Energy in Indian Economy" IOP Conf. Ser.: Mater. Sci. Eng. 404 012046 (2018)
10. The 3-F Framework, shared in online course by Azim Premji University, 'Exploring Sustainability in the Indian Context', https://www.youtube. com/ watch?v=YsjMYrkW4DY (accessed January 2021)
11. The Indian Renewable Energy Development Agency Ltd ('IREDA') is a state-owned non-financial banking company currently under the mandate of the Ministry of New and Renewable Energy. During 2018/19 it dispersed loans amounting to 93.8 billion to RE projects including small hydro power; medium to large hydro projects above 25 MW, wind energy, bio-energy, solar energy, biofuel and alternative fuels.
12. IREDA, Environmental and Social Management System (Version 2.0). Available at: https://www.ireda.in/doc/csr/IREDAESMS.pdf
13. ibid
14. For an example, see the US Solar Energy Industries Association's (SEIA) pledge to eliminate forced labour in solar technology value chains

Courtesy: **The Energy and Resources Institute (TERI)**, *New Delhi*

Mukesh Ambani's $75 Billion Plan Aims to Make India a Hydrogen Hub

Billionaire Mukesh Ambani's ambitious effort to pivot his conglomerate Reliance Industries Ltd. toward green energy could transform India into a clean-hydrogen juggernaut. Ambani, announced plans to invest $75 billion in renewables infrastructure including generation plants, solar panels and electrolyzers. There is growing speculation that the strategy entails transforming all of that clean into hydrogen, one of the largest endorsements in the next-generation fuel. Analysts say Reliance is likely to opt for hydrogen in a bid to avoid India's wholesale electricity market, which is dominated by financially stressed utilities and plagued by delayed payments. "Reliance is preparing itself to capture the entire value chain of the green hydrogen economy.

Source: Bloomberg, January 31, 2022

Doosan Heavy Unveils Korea's Largest 8 MW Offshore Wind Turbine

Doosan Heavy Industries & Construction has announced implementation of the 8MW offshore wind turbine prototype at the Korea Wind Power Demonstration Center, Baeksu, This turbine, developed as an industry-academia-research sector cooperation project led by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) since 2018, is Korea's largest wind turbine to date with 100 meters long blade and 130 meters high tower and has a total height of 232.5 meters. The company also signed a supplier agreement last year to provide equipment for the 100MW Jeju Hallim Offshore Wind Farm, which is Korea's largest offshore wind farm to date.

Source: Wind Insider, 3rd February 2022

Know Our Member

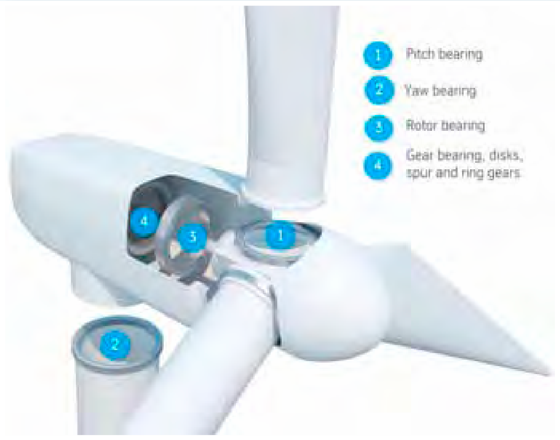
Rothe Erde India Private Limited

thyssenkrupp

About Rothe Erde India Private Limited

Rothe Erde India Private Limited is fully owned subsidiary of thyssenkrupp rothe erde Germany GmbH. Our journey started in 2007 by setting up 1st phase of our manufacturing plant at Nashik and to meet increasing demand from customers both in quantity and size of bearings. Today we are producing wide range of ball and roller slewing bearings and serving variety of applications which includes wind turbine, cranes, material handling equipment, excavators, defense etc.

We are major contributor to wind supply chain from India and fulfilling requirement of domestic as well as European wind OEMs to fulfill objective of green energy for the future.



About thyssenkrupp rothe erde Germany GmbH

thyssenkrupp rothe erde Germany GmbH is a business unit within the thyssenkrupp AG group.

thyssenkrupp rothe erde is the world's leading manufacturer of large slewing bearings and specializes in the production of slewing bearings and seamless rolled rings.

We have over 11 companies, with 15 plants in 10 countries. In this way, we work together so that we are always able to offer our customers innovative solutions worldwide. The head office of thyssenkrupp rothe erde is in Dortmund. Central functions for the business unit are provided from here. In order to ensure complete customer orientation, sales activities are decentralized and carried out locally by the respective country's organization.

thyssenkrupp rothe erde offers you fast and flexible decisions with the reliability and security of a global group. With production sites in different countries and related ring-rolling mills, thyssenkrupp rothe erde impresses customers as a global brand with a local presence.

As part of an international group, we are a strong and reliable partner who can offer stability and planning security for your projects. Our extensive knowledge from the wide range of diverse applications makes us a renowned supplier worldwide.

Products: Tailormade design of slewing bearings and geared rings.

Customized, instead of off the shelf- Special applications require customized solutions. This is why our products are developed and constructed in complete accordance with customers' requirements. Through close collaboration, we develop solutions which are unrivalled in terms of construction, material quality and performance.

Mr. Manish Aggarwal

The company is headed by Mr. Manish Aggarwal. He joined Rothe Erde in 2009 as General Manager-Sales & Purchase and was appointed as Chief Executive Officer and Managing Director in 2018.

You may like to visit us on https://www.thyssenkrupp-rotheerde.com

Or may write to info.rotheerdeindia@thyssenkrupp.com

Mr. Manish Aggarwal
Chief Executive Officer and Managing Director

Printed by R.R. Bharath and published by Dr. Rishi Muni Dwivedi on behalf of Indian Wind Turbine Manufacturers Association and printed at Ace Data Prinexcel Private Limited, 3/304 F, (SF No. 676/4B), Kulathur Road, Off NH 47 Bye Pass Road, Neelambur, Coimbatore 641062 and published at Indian Wind Turbine Manufacturers Association, Fourth Floor, Samson Towers, No. 403 L, Pantheon Road, Egmore, Chennai 600 008.
Editor: Dr. Rishi Muni Dwivedi

Windergy India 2022

27 – 29 April 2022, Hall 12 and 12A, Pragati Maidan, New Delhi

India's only comprehensive wind energy trade exhibition and conference, Windergy India will be hosted at Pragati Maidan in New Delhi from April 27 to 29, 2022, with support from the Ministry of New and Renewable Energy of the Government of India.

The Indian Renewable Energy Development Agency (IREDA), Indian Wind Power Association (IWPA), Independent Power Producers Association of India (IPPAI), Indian Energy Storage Alliance (IESA), National Institute of Wind Energy (NIWE), National Small Industries Corporation (NSIC), REAR Renewable Energy Association, Skill Council for Green Jobs (SCGJ), Solar Energy Corporation of India Limited (SECI), The Energy and Resources Institute (TERI), World Wind Energy Association (WWEA), and Indian Wind Energy Association (INWEA) are among the organisations that support Windergy India.

The event has been successful in delivering innovative technology, products, and services from around the world to a captive audience through a 3-day trade show and 2-day conference in its past editions. Similarly, apart from the trade exhibition, a two-day conference will be held on "Power of the Wind: India's Driver to Net-Zero" with BLoombergNEF as Knowledge Partner, Vasudha Foundation and Wind Independent Power Producers Association (WIPPA) as coorganisers. The conference includes high-level key note speeches, thought-provoking panel discussions, special addresses and technology presentations.

Shri R. K. Singh, Hon. Minister for Power and New & Renewable Energy, Government of India has kindly consented to inaugurate the conference and The Danish Ambassador, H .E. Freddy Svane, will inaugurate the exhibition. Shri Bhagawant Khuba Hon. Minister for State-New & Renewable Energy will deliver the valedictory address. Esteemed speakers such as Mr. Indu Shekhar Chaturvedi, Secretary, Ministry of New and Renewable Energy, Mr. V. K. Saraswat, Member, NITI Aayog, Mr. Tulsi Tanti, Chairman, Indian Wind Turbine Manufacturers Association (IWTMA), Ms. Gauri Singh, Deputy Director General, IRENA, Mr. Dinesh Jagdale, Joint Secretary, Ministry of New & Renewable Energy, Government of India are also part of the panel discussions.

Because the wind energy sector is heavily reliant on government policies and regulations, the conference will help the wind energy community better understand, analyse, and reflect on policy and regulatory challenges in India. Future electricity demands, efficient grid integration, and offshore would all be examined in depth, in addition to technology and green finance methods.

Windergy India expects to engage its exhibitors and visitors in meaningful discussions, resulting in the conversion of business potential into commerce by providing a vital common ground for various stakeholders to discuss policies, regulations, pricing, and cutting-edge technology, as well as assisting in the attraction of international investors to the region.

Registered with REGISTRAR OF NEWSPAPERS for India, New Delhi
Vide No. TNENG/2015/60605

December 2021 - January 2022
Date of Publishing: 26.02.2022

ACE DATA, Coimbatore