Prediction of the Speed and Wind Direction Using Machine Learning

Balachandra Pattanaik1*, S Manikandan2, S Peniel Pauldoss3, and S Gobinath4
1Department of Electrical and Computer Engineering, Bule Hora University, Bule Hora, Ethiopia, Africa.
2Department of Electrical and Electronics Engineering, Meenakshi Sundararajan Engineering College, Chennai, Tamil Nadu, India
3Department of Mechanical Engineering, Brilliant Group of Technical Institutions, Hyderabad, Telangana, India
4Department of Mechanical Engineering, Kongunadu College of Engineering and Technology, Tholurpatti, Tamil Nadu, India
Email: *balapk1971@gmail.com

Abstract. The wind is a free energy source; however, its high unpredictability is a significant integration problem of large wind power plant into an energy system. In a wind conversion system, the wind speeds are a vital power-generated tracking, regulation, schedules and dispatch and satisfy consumer requirements. This paper proposes using the machine learning (ML) based ant colony optimization (ACO) method for the wind speed prediction. A correlation among predicted and real data from climate models showed strong consensus. The significance of the current research depends on its ability to forecast wind speeds, a crucial precursor to performing successful incorporation of wind power.

Keywords: ML system, wind direction, wind speed and ACO

1. Introduction
For the smart grid potential generation, wind power is a viable source of electricity. The key explanation for the fact that wind power is renewable and easily available. Another big factor for promising wind power penetration into the future smart grid is the new and fast growth of power electronic converter technologies. For planning a wind farm and organizing a power grid with large production units installed in the wind industry, wind speed and direction are important [1-5]. Since wind is an unpredictable energy source that can dramatically influence the electrical grid's reliability and efficiency, its prediction is important to incorporate a wind farm into the electrical system properly [6-8].

That is because a null-carbon generation system needs smaller installation spaces, is accessible anywhere. Moreover, it has further facilitated the rapid implementation of wind power systems with the development of electronics and related control technology [9-12]. For a scalable and sophisticated power grid, the estimation of wind parameters is very critical. The estimation of wind power generation is made possible by forecasting wind variables, which benefits a wind farm in its development, more from its upkeep and preparation. Wind energy is one of the most expensive renewable energy sources and the greatest available option [13-15]. Therefore, a variety of nations are becoming conscious that wind power offers an important chance to develop power in the future. Even if the wind generation has major environmental benefits and aims to produce electricity in its lifetime, it is worth less than traditional
generation sources because of the intermittent weather variables. That is why power instability leads to significant reliability and regulation of the power grid issues [16-18].

Two models are reported in this section (direction and speed prediction). Various time ranges for training data have been taken into account: one day, a week and a month to achieve the least quantity of data possible to the best performance. For the final study, an ML algorithm was used, which showed the best results for some data: ACO.

2. Methods
ACO is a probabilistic algorithm to solve the cost optimization functions in which better paths can be identified through graphs. For informatics and operational analysis, ACO is commonly applicable. The actions of the ants in pursuit of the best direction of a food location inspired its production. In general, the actual ant's pheromone-based system of knowledge sharing is the primary ACO modeling process [19-21]. Artificial ants reflect techniques of heuristic optimization inspired by biological ants. For some optimization works and several maps, such as cars, the hybridization of artificial ants and quest techniques has become an alternative strategy.

ACO is an AI-driven metaheuristic optimization algorithm, as shown in fig. 1 focused on biological ants colonies' actions. Artificial ants are the simulating agents who map the best available choices for the discovery of the area. Their world is transmitted through biological ants excrete pheromones for milk. The ACO artificial ants save their positions and solutions; thus, additional ants can find better solutions in subsequent quest phases.

![Figure 1. Flowchart of the ACO algorithm.](image-url)

The ACO checks the world's strongest parameter collection of the models to improve wind power prediction software's forecast efficiency. The ACO methodology is especially used to determine the optimal parameters for the wind power prediction model (neuron relation weights).

The ACO algorithm generates a graph in full by n parameters of the model. In the beginning, m ants are located at n nodes (sites) randomly. The data list stores the nodes to which the ants have passed and...
the data for each ant $k$ is placed. The concentration of Pheromone — $\xi_{ij}(0)$ is first set at 0 on either leg. Based upon the pheromone level on each leg, the ants select the following node.

The probability $\rho_{kij}(t)$ that the ant travels from parameter $i$ to parameter $j$ at the $t$ step can be expressed as follows:

$$
\rho_{kij}(t) = \begin{cases} 
\frac{\xi_{ij}^\alpha(t) \cdot \eta_{ij}^\beta(t)}{\sum_{\forall d \in \text{record}_k} \xi_{id}^\alpha(t) \cdot \eta_{id}^\beta(t)}, & j \neq \text{record}_k \\
0, & \text{otherwise}
\end{cases}
$$

(1)

$\alpha$ and $\beta$ are the heuristic coefficient of the message and heuristic expectation coefficient used in the distribution of weights for heuristic operations. Here $\xi_{ij}$ is a heuristic message and is generally measured as $1/d_{ij}$.

3. Results

The wind speed prediction is illustrated in figure 2. The model training for power and the number of data are shown in fig. 3. The wind power forecasting using the ML-based ant colony optimization algorithm is shown in figure 4.

![Figure 2. wind speed forecast](image)

4. Conclusion

For a secure and sustainable balancing of the electricity grid, an accurate, short-term wind power estimation is critical. Based on the historical data of a wind farm, the application of a machine learning-based system is performed to predict the wind power, and which is carried out successfully. The model that has only been analyzed in this analysis and focused on only two factors (direction and speed) can help the regulation of wind turbines. It can be used to prepare wind turbine output and usage, which will greatly mitigate wind variability issues. We hope that the parameters for ACO versions should boost the findings further. Our study operations will be subject to this in the future. It has been found that wind power can be successfully predicted using the ant colony optimization algorithm (ACO), which provides good prediction accuracy and the interpretable model structure that performs forecast power output better.
Figure 3. Model training with data

Figure 4. Wind power prediction

References
[1] Demolli, H., Dokuz, A. S., Ecemis, A., & Gokcek, M. (2019). Wind power forecasting based on daily wind speed data using machine learning algorithms. *Energy Conversion and Management*, 198, 111823.

[2] Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in the forecasting of wind power generation. *Renewable Energy*, 37(1), 1-8.

[3] Wan, C., Xu, Z., Pinson, P., Dong, Z. Y., & Wong, K. P. (2013). Probabilistic forecasting of wind power generation using extreme learning machine. *IEEE Transactions on Power Systems*, 29(3), 033-1044.

[4] Lei, M., Shiyun, L., Chuwen, J., Hongling, L., & Yan, Z. (2009). A review on the forecasting of wind speed and generated power. *Renewable and Sustainable Energy Reviews*, 13(4), 915-920.
[5] Li, L. L., Zhao, X., Tseng, M. L., & Tan, R. R. (2020). Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. *Journal of Cleaner Production*, 242, 118447.

[6] Akilandeswari, A. (2014). A Multiplier-Less Lifting Scheme Based DWT Structure. *Computers and Software*, 203.

[7] Wardianto, D., Jama, J., & Syahril, S. (2020). The Effectiveness of Problem-Project Based Learning To Improve Students’ Understanding Toward Gasoline Motor. *International Journal of Scientific & Technology Research*, 9(3), 4900-4902.

[8] Balamurugan, M., Anand, M. S., Kumar, D. S., & Devi, A. S. (2018). Anonymous Location-Support and Self-Reliance Routing Protocol For Manet. *SCOPUS IJP HRD CITATION SCORE*, 9(2), 323.

[9] Sivagami, A. (2019). Multi-Sensor Approach in Structural Health Monitoring of Buildings. *Indian Journal of Public Health Research & Development*, 10(11).

[10] Balaji, V., Umapathy, N., Duraisamy, V., Umapathy, K., Venkatesan, P., & Saravanakumar, S. (2015). ENHANCING VARYING OVERHEAD AD HOC ON-DEMAND DISTANCE VECTOR WITH ARTIFICIAL ANTS. *Jurnal Teknologi*, 77(28).

[11] Balaji, N., Vijayalakshmi, S., Durgadevi, K., Mohanraj, K., & Mangayarkarasi, T. (2019). FPGA implementation of smart water quality monitoring system. *International Journal of Innovative Technology and Exploring Engineering*, 8(11), 3136-3139.

[12] Wang, S., Janabi, A., & Wang, B. (2020, October). Generalized Optimal SVPWM for the Switched-Capacitor Voltage Boost Converter, ECCE, (pp. 2708-2711). IEEE.

[13] Gibbons MS, Gilbert CL, Deshpande MS, inventors; Lear Corp, assignee. Methodology of maximizing charging power transfer for an electric vehicle when ac voltage sags. United States patent application US 15/801,772. 2019 May 2.

[14] Anitha, S., Keerthana, A., Kaviya, S. and JayaRajan, R., 2017. QUADRIPLEGIC AMBULATING ADDENDUM. *International Journal of MC Square Scientific Research*, 9(2), pp.15-23.

[15] Anjana, R. (2019, Feb). Fuzzy and PI Based Speed Control of BLDC Motor using Bidirectional Converter for Electric Vehicle Application. *Trends in Electrical Engineering*, 8(3), 35-45.

[16] Yadav, D., Parekh, U., Patel, K., Parmar, R., & Prakash, M. (2019). Application of Modified Three Phase Conduction Method to Minimize Torque Ripple in BLDC Motor. *IJRAR*, vol. 6(1), 155-156.

[17] Rajkumar, S., Sundaram, C. S., Sedhuraman, K., & Muruganandhan, D. (2019, March). Performance Analysis of Hub BLDC Motor Using Finite Element Analysis. In *2019 ICSCAN*, (pp. 1-5). IEEE.

[18] Gibbons, M. S., Gilbert, C. L., & Deshpande, M. S. (2019). *US Patent Application No. 15/801,772*.

[19] Nasiriani, K., & Pasandi, M. (2020). Dynamic Voltage Restorer (DVR) For Protecting Hybrid Grids. arXiv preprint arXiv:2006.16452.

[20] Gupta, G., & Kumar, D. (2020). Power Quality Mitigation using DSTATCOM and DVR.

[21] Macinnis, AG and Walls, F.G., Avago Technologies General IP Singapore Pte Ltd, 2018. Bounded rate near-lossless and lossless image compression. US Patent 9,883,180.