Active tip speed ratio control can significantly increase annual energy production

Amir Hosseini^{*}, Trevor Cannon[†], and Ahmad Vasel-Be-Hagh[†]

*Independent Researcher

[†] Mechanical Engineering Department, Tennessee Tech University, Cookeville, TN 38501, USA

corresponding email: avaselbehagh@tntech.edu

Track 4: Wind turbines and wind plants

Introductory Summary

Operating a wind turbine at the optimal tip speed ratio (TSR) yields maximum power coefficient, a measure of efficiency. Manufacturers measure optimal TSR for a single isolated unit, and wind farm operators ensure every wind turbine within the farm runs at that TSR. This practice is wrong since it does not account for the aerodynamic interactions of wind turbines. These interactions affect the optimal TSR. In other words, every turbine's optimal TSR depends on the site, wind direction, and farm's layout and is not the same as what the manufacturers measure for single isolated units. Applying a TSR optimization to the Lillgrund wind farm with 48 2.3-MW turbines using the Jensen wake model and particle swarm optimization method increased the annual energy production by approximately 4%.

Keywords: wake control, tip speed ratio, wake loss

Introduction

The wind goes into a wind turbine. The turbine's rotating blades extract the wind's kinetic energy and cause much chaos in it. Hence, the wind leaving the turbine forms a turbulent, low-speed region behind the turbine. This region, which slightly expands as it flows further downstream, is called a "wake." It takes a long $% \mathcal{A}$ distance for a wake to recover to the undisturbed, high-energy status it used to have upstream of the turbine that causes the wake. Also, the wind direction changes; therefore, this wake region forms in every direction. Hence, it is impossible to find a wake-free spot for any turbine within a utility-scale wind farm. Every turbine gets some exposure to upstream wake, leading to a significant reduction in its energy production [1-2]. Wind farm layout optimization means finding the spots with minimum exposure to upstream wakes as a whole. Wind farm layout optimization is necessary but not enough. What needs to take place beyond that is active wake control. Active wake control aims to actively alter the wake direction or strength as wind direction and speed change in real-time [3]. Researchers have offered several active wake control strategies. One of the most researched ones is yaw control [4-8]. The yaw control strategy proposed deviating a turbine from its optimal yaw (zero degrees) in order to steer the wake away from downstream turbines. While this decreases the power production of the yawed turbine, it increases the power production of the downstream turbines. The gain appears to be more than the loss. This research proposes adjusting turbines' TSR in real-time. The deviation from the TSR value proposed by the manufacturer will decrease the production of the adjusted turbine; however, it increases the power production of its downstream counterparts. This research shows that similar to the yaw control strategy, the TSR control leads to an overall increase in the annual energy production. We tested the idea by applying it to the Lillgrund wind farm. The layout, the C_p -TSR and C_t -TSR curves, the power curve, and also the wind information used for this study are presented in Figure 1.

Methods The authors employed particle swarm optimization (PSO) technique to identify the optimal value of TSR for every turbine in every wind direction. They employed the C_t -TSR curve provided by the turbine manufacturer (Figure 1) to achieve this goal. PSO had an input vector of 48 TSRs. Every time that the PSO updated the said input vector throughout its convergence journey to the optimal TSR values, the algorithm used the data presented in Figure 1 to calculate the C_t and C_p associated with every TSR. The new C_t was then inserted into the Jensen model as,

$$\delta_{ij} = (1 - \sqrt{1 - C_t}) (\frac{D}{D + 2k_w x_{ij}})^2 \tag{1}$$

to calculate the wind speed deficit caused by each turbine. In Equation 1, $k_w = 0.04$ is the expansion coefficient. The algorithm then corrected the wind speed deficit as [9],

$$\delta' = \left(\frac{A_{overlap}}{A}\right)\delta\tag{2}$$

with A and $A_{overlap}$ being the rotor area and the fraction of the downstream rotor area covered by the wake from the upstream turbine. The algorithm corrected the deficit for all upstream turbines that affected the turbine of interest. The inlet wind speed into the turbine of interest was then calculated as,

$$U_{in} = U_{\infty} \left[1 - \left(\sum_{j=1}^{N} \delta_{ij}^{\prime 2} \right)^{\frac{1}{2}} \right]$$
(3)

with N being the number of turbines upstream of turbine *i*. Knowing U_{in} allowed for calculating the turbine's power production using the power curve provided by the manufacturer (Figure ??). See [10] for detailed explanation on PSO.

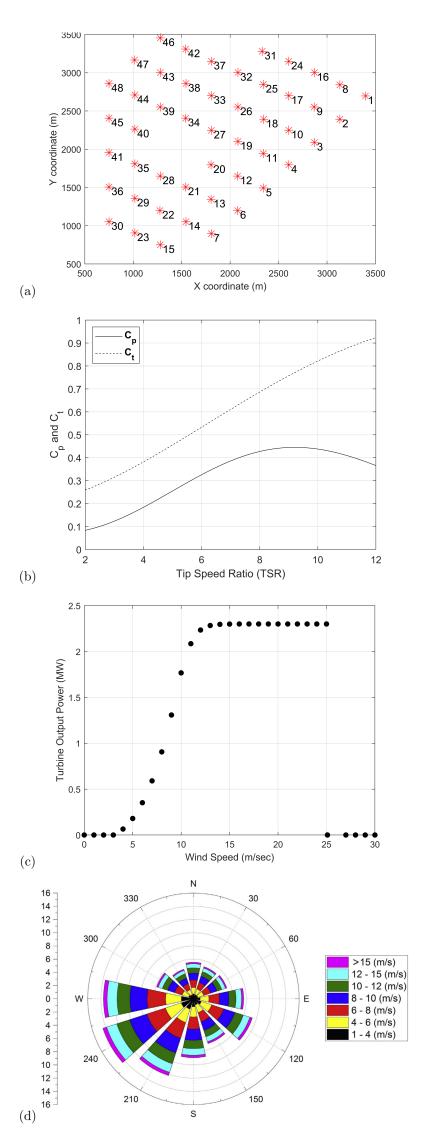


Figure 1: (a) Lillgrund's layout, (b) $C_p\mbox{-}{\rm TSR}$ and $C_t\mbox{-}{\rm TSR}$ curves, (c) power curves, (d) wind data.

Results and Conclusions

Figure 2 shows the annual energy production (AEP) of the farm in every wind direction with and without the implementation of an active TSR control. Total AEP increased by approximately 11 GWh. More detailed results will be presented in the oral presentation, including TSR distribution and the change in AEP of every wind turbine, at least in a couple of wind directions, including 150 degrees from the north.

Note that what makes the proposed active TSR control very unique is not just its significant impact on power and energy production. This strategy brings several other benefits, making it more exciting and promising. First, unlike yaw, pitch, and tilt control strategies, altering the TSR does not lead to any additional loading on the blades since the rotor still operates under normal conditions and is not misaligned in any direction. The proposed strategy appears to decrease the TSR overall. A reduced TSR is equivalent to a slower rotor, and a slower rotor generates less noise. The proposed strategy enhances the performance of wind farms by relaxing the leading-edge erosion phenomenon. It also decreases the chance of hurting bats and birds.

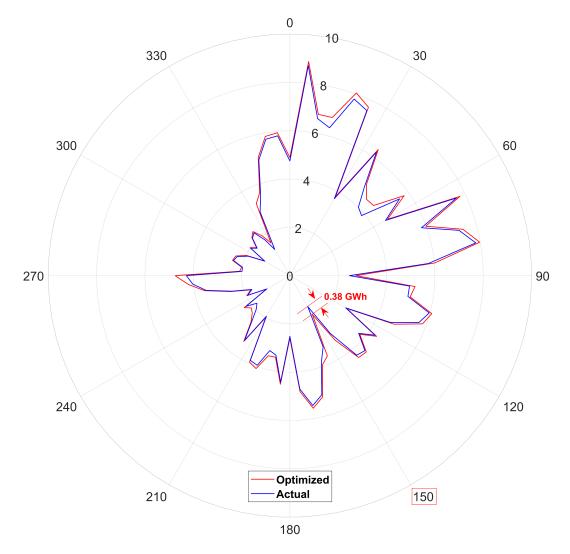


Figure 2: Wind farm's total AEP (GWh) vs. wind direction

References

- Barthelmie, R.J., Pryor S., Frandsen S.T., Hansen K.S., Schepers J., Rados K., Schlez W., Neubert W., Jensen L. and Neckelmann S., 2010: *Quantifying the impact of wind turbine wakes on power output* at offshore wind farms, Journal of Atmospheric and Oceanic Technology 27 (8). pp. 1302–1317.
- Vasel-Be-Hagh, A. and Archer C.L., 2017: Wind farm hub height optimization, Applied Energy 195. pp. 905–921.
- 3. Nash R., Nouri R. and A. Vasel-Be-Hagh, 2021: Wind turbine wake control strategies: A review and concept proposal, Energy Conversion and Management 245. no. 114581.
- Howland M., Lele S. and Dabiri J., 2019: Wind farm power optimization through wake steering, Proceedings of the National Academy of Sciences of the United States of America 116 (29). pp. 14495 14500.
- 5. Astolfi D., Castellani F. and Natili F., 2019: Wind turbine yaw control optimization and its impact on performance, Machines 7 (2). No. 41.
- 6. Ciri U., Rotea M. and Leonardi S., 2020: Increasing wind farm efficiency by yaw control: Beyond ideal studies towards a realistic assessment, Journal of Physics: Conference Series 1618 (2). No. 022029.
- van Dijk M.T., van Wingerden J.W., Ashuri T., Li Y., 2017: Wind farm multi-objective wake redirection for optimizing power production and loads, Energy 121. pp. 561–569.

- Archer, C.L. and Vasel-Be-Hagh, A., 2019: Wake steering via yaw control in multi-turbine wind farms: Recommendations based on large-eddy simulation, Sustainable Energy Technologies and Assessments 33. pp. 34-43.
- 9. Archer C., Vasel-Be-Hagh A., Yan C., Wu S., Pan Y., Brodie J. and Maguire A., 2018: *Review and evaluation of wake loss models for wind energy applications*, Applied Energy 226. pp. 1187 1207.
- 10. Kennedy, J., 2007: *Review of engelbrecht's fundamentals of computational swarm intelligence*, Genetic Programming and Evolvable Machines 8 (1). pp. 107–109.