Grid Vātēs - A Dynamic Line Rating Educational Sandbox

Matt Carney
mcarney@gatech.edu
Georgia Institute of Technology

Abstract

Transmission line load limits are largely determined by environmental conditions, with factors such as minimum clearance distance and maximum thermal thresholds being influenced by ambient temperature, wind speed, wind direction, and solar irradiance. Dynamic line ratings (DLR) present an beneficial approach to grid operation, optimizing load capacity while maintaining safety through the use of weather forecasts and real-time monitoring. Improving the accuracy of DLR forecasts has been the subject of extensive research, employing various techniques like time series modeling, deep learning, and specialty software. However, a gap remains in understanding and building intuition on the relationship between weather forecasts, their uncertainty, and their impact on dynamic line ratings. To address this gap, Grid Vātēs - A Dynamic Line Rating Experimental Sandbox was developed, leveraging three main learning components: 1.) The benefits of DLR, 2.) The impact of uncertainty in probabilistic weather forecasts on DLR forecasts, and 3.) A scenario analysis knowledge check. Grid Vātēs offers a novel and interactive approach to understand the relationship between weather forecasts and their impact on dynamic line ratings and can be accessed here: https://grid-vates.streamlit.app/.

1. Introduction

Transmission line conveyance load limits are largely dependent on environmental conditions. This includes a minimum clearance distance to nearby objects and a maximum thermal threshold, both of which are heavily influenced by the ambient temperature, wind speed, wind direction, and solar irradiance. Historically, these load limits have been conservatively calculated by the worst-case-scenario conditions annually or seasonally. This ensures the safe operation of the grid but also underutilizes current infrastructure.

1.1 Background - DLR

Dynamic line ratings (DLR) is an approach to electric grid operation that maximizes the load permissible by environmental conditions while maintaining safety. This can either include numerical weather models and/or real time monitoring. In either case, forecasting the dynamic line rating is dependent on weather forecasts which possess different degrees of uncertainty.

1.2 Experimental Tooling Gap

There has been extensive research on improving the accuracy of dynamic line rating forecasts, which include time series modeling (Zhan, Chung, Demeter, 2017), deep learning (Safari et al., 2021) and specialty software (Theodosoglou et al, 2017). However, there appears to be a gap in both academic research and practical tooling to help explain, understand and educate about the relationship between the various weather forecasts, their uncertainty, and the impact they have on the resulting dynamic line rating. Accordingly, as described further in Section 4, I developed Grid Vātēs - A Dynamic Line Rating Experimental Sandbox.(Vātēs is a Latin term used to refer to a prophet, seer, or poet; someone believed to possess the ability to predict the future (Harper, 2023)). It includes three main learning components: 1.) The benefits of DLR, 2.) The impact of uncertainty in probabilistic weather forecasts on DLR forecasts, and 3.) A scenario analysis knowledge check.

2. Related Work

As previously mentioned, there doesn't appear to be any current tooling that has the same functionality as Grid Vātēs. However, related work either relevant to teaching similar STEM concepts or a STEM web application are provided.

2.1 STEM Concepts

In the pursuit of teaching music processing (audio decompression, segmentation, onset detection- all of which have an underlying time series components) Müller and Zalkow (2019) found that utilizing Jupyter notebooks to embed textbook like explanations of subject matter, and algorithms with Python code examples to demonstrate how to implement the theory, to be successful. This embodies the "Grok it and Use it" philosophy of presenting focused, technical information and then allowing the student to experiment.

Furthermore, Galen et al. (2022) found success in the use of Jupyter notebooks in teaching a weather forecasting class in the 2020s. The authors identified that numerical weather prediction models have changed over the past decades and thus not only do the technical skills taught to students need to be current, but the methods of which the teaching occurs can also utilize new technology. The Python notebooks allowed for analyzing, plotting, and interpreting datasets, and model outputs, while also containing contextual information. This facilitates an active approach, where the contents are presented as a practical activity (Galen et al., 2022).

2.2 STEM Web Applications

Web based applications have also been successful for the implementation of STEM topics such as ENDURE, an interactive web based app to guide protein design choice by per-reside breakdown analysis (Engelberger et al, 2023), the monitoring of lake quality through a Strealit web app (Jaelani, Pangestu, 2023), and the development of an interactive web app (R/Shiny) for visualizing and analyzing biological datasets (Jia, et al., 2022).

3. Educational Principles Employed

There are an abundance of educational technologies and pedagogical styles available for teaching for Science, Technology, Engineering, and Mathematics (STEM) material including problem centered learning, inquiry based learning, experiential learning, design based learning, cooperative learning, constructivism and behaviorism. Implementing one of these techniques may be successful, though it's likely a combination, or an integrated approach that includes several methodologies will yield the greatest success (Thibut et al., 2021).

3.1 "Grock it and Use It" (Microlearning and Experiential Learning)

One main philosophy that appears to thread through the majority of the impactful learning styles is to "Grok it and Use It" (Riepen et al, 2021). This philosophy emphasizes the idea of understanding a topic thoroughly and intuitively by trying it in practice (Riepen et al, 2021), essentially matching theoretical knowledge with practical applications. In order to implement this "Grok it and Use It" approach, Grid Vātēs uses a combination of content based micro learning and experiential learning. Microlearning focuses on delivering bite-sized bits of information to students that can be easily consumed. Microlearning for STEM education was found to be successful with independent learning by stimulating a learner's motivation, appropriate for an online learning framework, and capable of building up comprehensive learning objectives through single topics (Garshasbi, Yecies, Shen, 2021). The experiential learning focuses on hands-on practical applications, engaging students in real-world scenarios and experiments. This allows the students to directly experience the theoretical concepts and reflect on the subject matter. Essentially, from a practical perspective, Grid Vātēs an experimental sandbox that is embedded with context.

3.2 Emphasis on Sensitivity and Scenario Analysis

For teaching probability, the diversification of the learning environment can lead to increased the interest of students and if the course objectives can be merged with games or simulation, more permanent learning can be achieved (Koparan, 2020). Furthermore, Galen et al. (2022) found success in the use of Jupyter notebooks in teaching a weather forecasting class in the 2020s. The authors identified that numerical weather prediction models have changed over the past decades and thus not only do the technical skills taught to students need to be current, but the methods of which the teaching occurs can also utilize new technology. The Python notebooks allowed for analyzing, plotting, and interpreting datasets, and model outputs, while also containing contextual information. (Note- Grid Vātēs is a web app, not a Jupypter notebook. This example was to demonstrate the educational utility of having content and interactiveness in one space).

To illustrate the impact of various probabilistic weather forecasts on dynamic line ratings, Grid Vātēs includes an interactive sensitivity analysis page, which is described further in Section 4.4. This interactive analysis will help users understand to the extent which weather forecast uncertainty affects the reliability of a dynamic line rating. Furthermore, there will also be real-world scenarios knowledge check with our rating provides from which the user has to match to the correct set of environmental conditions (ie. sunny and consistent low wind, rainy and high wind variability, etc.).

3.3 Tooling, HCI and UI Best Practices

As with any technology, the success of an educational tool can largely depend on the medium which it is delivered. A Jupyter notebook was considered as it provides a one-shop-shop for the efficient delivery of both content and real world examples. However, there are drawbacks with this approach. Most notably, it requires that the user knows (at least basic) Python in order to run and/or modify the notebooks, which could result in a significant barrier to entry. An alternative approach is a web based application. The accessibility and user friendliness that web apps provide is often more advantageous for education than a stand alone computational tool (Engelberger et al., 2023). This will significantly lower the barrier to entry to the tool as it won't require knowledge of Python and, in general, will provide ease of access. Furthermore, a web app facilitates a high degree of interactivity and has the ability to guide users through various analyses and visualizations.

Regardless of the tooling, there are human computer interaction (HCI) and user experience (UI) best practices that should be upheld. First is the use of a clear and intuitive interface that guides users through the tools features and functionalities, using consistent navigation and logical organization of content. While it may sound trivial, Endgelberger et al. (2023) emphasized the importance of a well thought out welcome page that provides an overview of the tool and its functionality. Given that this is the first access point for the user, it's essential to set the stage and make it easier for the user to get started and use the tool effectively. Secondly, it's important to incorporate interactive elements such as sliders and drop down menus whenever possible to engage users while still maintaining satisfactory performance in terms of speed and responsiveness. This balance, designing with the front end in mind while making sure the back end can support, is important. One drawback that Jai et al. (2022) observed was that their R/Shiny application processes a whole dataset into RAM, which may not make it suitable for applications that need to process large datasets. Additionally, the following techniques can be embraced for impactful visualizations: 1.) Choose the right charts and graphs for the job, 2.) Use predictable patterns for layouts, 3.) Tell stories quickly with color cues, 3.) Incorporate contextual clues with shapes and designs, 5.) strategically use size to visualize values, and 6.) Apply text carefully and intentionally (Tableau). Although these are intended for dashboard design they are directly applicable to web based visual design as well. This was exemplified in the ENDURE web app which embedded a plethora of visualizations including heatmaps, conditionally colored dynamic tables, scatter plots and bar charts.

4. Solution - Grid Vātēs

The web app was built with Streamlit, a python based web development framework. In addition to a landing page, it includes three main learning components, each with their own respective page: 1.) The benefits of DLR, 2.) The impact of uncertainty in probabilistic weather forecasts on DLR forecasts, and 3.) A scenario analysis knowledge check.

4.1 Landing Page

The landing page serves two main purposes: 1.) To provide an overview of what DLR is, and 2.) To welcome the user and outline the functionality of the tool.

4.2 Benefits of DLR

This page provides the user background information of the importance of DLR.

4.3 Weather Forecasts- Sensitivity

This page is the crux of the web app and addresses the gap in current academic research and tooling.

4.3.1 Methodology

For each of the weather forecasts (Temperature, Solar Irradiance, Wind Velocity, Wind Direction) there are two groups of variables to experiment with - temporal decay and the initial distribution parameters. At t = 0, 1,000 random samples are generated from an initial distribution determined by the initial distribution parameters. Additionally, at t = 0 an end-state distribution of 1,000 is also generated. For every time step n an aggregate distribution is collated by selecting (n * temporal decay) samples of the end-state distribution and ((1000-n) * temporal decay) of the initial distribution. Thus, a temporal decay of 0.0 will persist the initial distribution through the time space and a temporal decay of 1.0 will linearly transition completely from the initial distribution at t=0 to the end-state distribution at the end of day 5 (t=120). A temporal decay of 0.5 will linearly transition from the initial at t=0 to 50% of the end state distribution at the end of day 5 (t=120).

The initial and end state distributions are as follows:

- Temperature : Normal(mean, std) -> Uniform(1%, 99% of Normal(mean, std))
- Solar Irradiance : Heat Flux is deterministic since it can b e calculated by the Earth's sphericity and orbital pattern. The maximum reduction of Solar Irradiance with 100% cloud cover is 0.75, thus the end-state distribution is Normal(ideal * cloud cover * 0.75)
- Wind Velocity : Normal(mean, std) -> Uniform(1%, 99% of Normal(mean, std))
- Wind Direction : vonMises(mean, Kappa) -> Uniform(1%, 99% of vonMises(mean, Kappa)) Note that a vonMises distribution is a circular normal distribution

Finally, for each time step t, the DLR is determined by randomly sampling a temperature, solar irradiance, wind velocity and wind direction value 1,000 times and calculated using the IEEE 738-2006 methodology.

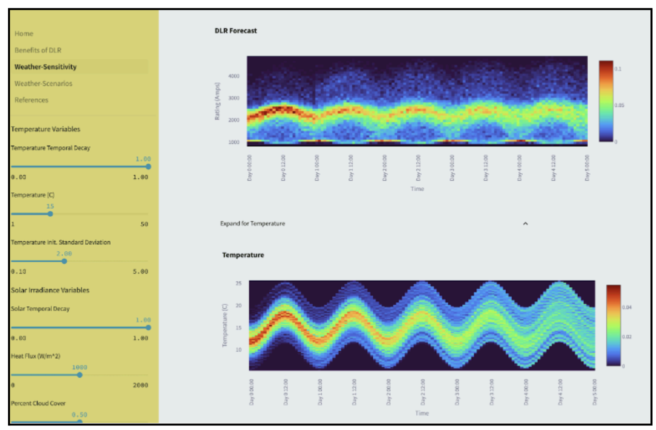

Figure 1 *- Weather - Sensitivity screenshot with parameter side panel, DLR forecast and Temperature forecast.*

4.4 Weather Forecasts- Scenarios

Here, the user is presented with several rating profiles (Figure 2) and they are asked to select the corresponding environmental conditions from a drop down which contains the correct answer and a brief explanation (Figure 3). This serves as a knowledge check to solidify educational concepts.

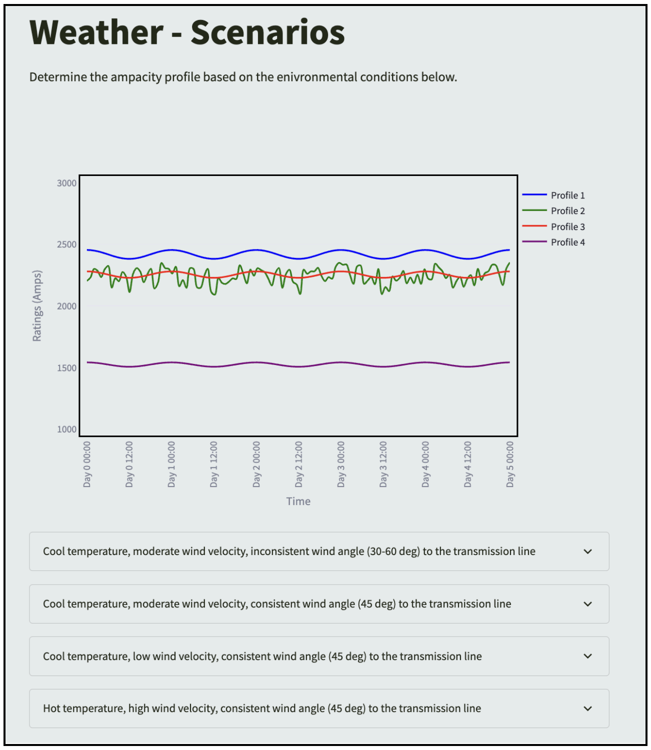

Figure 2 *- Weather - Scenario screenshot with rating profiles and environmental condition options*

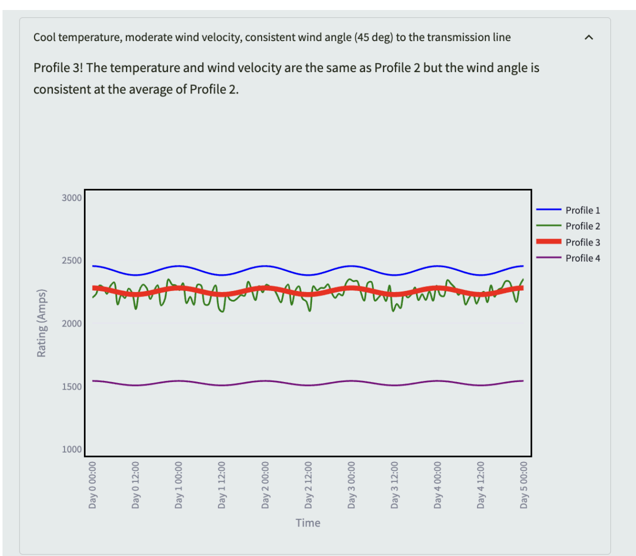

Figure 3 *- Weather - Scenario screenshot with correct answer*

5. Future Work

The Weather-Sensitivity tab runtime performance could be improved. This is due to the numerous monte carlo simulations that are being ran in the script and the fact that Streamlit re-runs the whole script even if just one parameter is changed. Potential options could be to investigate caching in Streamlit, a faster hosting service or an alternative Python framework. From a functionality perspective, supplementing the current linear temporal decay with a logarithmic temporal decay would be of value. Finally, adding quantitative values to the DLR forecast (median value, confidence interval heights) would further support the learning objective of analyzing the impact of the various weather conditions on the DLR forecast.

6. Conclusion

DLR is a paradigm that grid operators must adopt for the sustainable operation of the energy grid. A key aspect to a DLR implementation is the understanding of how various probabilistic weather forecasts impact the resulting DLR forecast. Grid Vātēs was developed to provide an introduction into the benefits of DLR, a weather sensitivity sandbox and a weather scenario knowledge check. In conclusion, Grid Vātēs offers a novel and interactive approach to understand the relationship between weather forecasts and their impact on dynamic line ratings. By combining microlearning and experiential learning, the platform equips learners with the knowledge and practical experience necessary for informed decision-making in electric grid operations, contributing to a more efficient and sustainable energy infrastructure.

7. References

Harper, D. (2023) Vates, Etymology. Available at: https://www.etymonline.com/word/vates (Accessed: 15 June 2023).

Zhan, J., Chung, C.Y., Demeter, E. (2017). Time Series Modeling for Dynamic Thermal Rating of Overhead Lines, IEE Transactions on Power Syste,s 32(3), 2172-2182. 10.1109/TPWRS.2016.2596285

Safari, et al. (2021). Secure probabilistic prediction of dynamic thermal line rating, Journal of Modern Power Systems and Clean Energy, 10(2), 378-387,. http://dx.doi.org/10.35833/MPCE.2020.000641

Theogosoglou, I., et al. (2017). Electrothermal analysis and temperature fluctuations' prediction of overhead power lines, Electrical and Power Systems, 87, 198-210. https://doi.org/10.1016/j.ijepes.2016.07.002

Thibaut., L., et al. (2018). Integrated STEM Education: A Systematic Review of Instructional Practices in Secondary Education. European Jourrnal of STEM Education, 3(1), 02. https://doi.org/10.20897/ejsteme/85525

Riepin, I., et al. (2021). Grok It and Use It: Teaching Energy Systems Modeling. http://dx.doi.org/10.2139/ssrn.4320978

Garshasbi, S., Yecies, B., Shen, J. (2021). Microlearning and Computer-Supported Collaborative Learning: An agenda towards a comprehensive online learning system, STEM Education (AIMS Sciences Journal), 3(4), 225-255. https://doi.org/10.3934/steme.2021016

Koparan, T. (2022). The impact of a game and simulation-based probability learning environment on the achievement and attitudes of prospective teachers, International Journal of Mathematical Education in Science and Technology, 53(9), 2319-2337. 10.1080/0020739X.2020.1868592

Galen, L.V., et al. (2022). Teaching a Weather Forecasting Class in the 2020s. Bulletin of the American Meteorological Society, 103(2), E248-E265. https://doi.org/10.1175/BAMS-D-20-0107.1

Engelberger, F., Zakary ,J.D., Künze, G. (2023). Guiding protein design choices by per-residue energy breakdown analysis with an interactive web application, Frontiers in Molecular Biosciences, 10. 10.3389/fmolb.2023.1178035

Jia, L., et al. (2022). Development of interactive biological web applications with R/Shiny, Briefings in Bioinformatics, 23(1), 1-15. https://doi.org/10.1093/bib/bbab415

Data visualization tips for more effective and engaging design (no date) Tableau. Available at: https://www.tableau.com/learn/articles/data-visualization-tips (Accessed: 08 June 2023).