INL/JOU-23-75714-Revision-0

Integration of New Technology Considering the Trade-Offs Between Operational Benefits and Risks: A Case Study of Dynamic Line Rating

December 2024

Changing the World's Energy Future

Timothy R McJunkin, Katya L Le Blanc, Ruixuan Li, Alexander Abboud, Tyler Bennett Phillips

Idaho National Laboratory

INL/JOU-23-75714-Revision-0

Integration of New Technology Considering the Trade-Offs Between Operational Benefits and Risks: A Case Study of Dynamic Line Rating

Timothy R McJunkin, Katya L Le Blanc, Ruixuan Li, Alexander Abboud, Tyler Bennett Phillips

December 2024

Idaho National Laboratory
Idaho Falls, Idaho 83415

http://www.inl.gov

Prepared for the
U.S. Department of Energy
Under DOE Idaho Operations Office
Contract DE-AC07-05ID14517

Integration of new technology considering the trade-offs between operational benefits and risks: A case study of dynamic line rating

Timothy R. McJunkin*, *Senior Member, IEEE,* Katya L. Le Blanc*, *Senior Member, IEEE,* Ruixuan Li*, Alexander W. Abboud†, Tyler Phillips* *Member, IEEE,*
*Idaho National Laboratory, Idaho Falls, Idaho, {timothy.mcjunkin,katya.leblanc,ruixuan.li,tyler.phillips}@inl.gov
† Honeywell International Inc., Broomfield, Colorado, awabboud@yahoo.com

***Abstract*—Electric grid operators are adept at handling complexity and uncertainty. However, with increasing introduction of renewable generation, distributed energy resources, and more frequent severe weather events, operators will experience new workload and challenging decision scenarios. This paper quantifies risks and benefits from an operator's perspective of introducing weather based forecast Dynamic Line Ratings (DLR) using variable wind conditions in addition to ambient temperature to relieve transmission congestion and facilitating more offshore wind (OSW). A concept of operations (CONOPS) applied to a forecast DLR implementation and its integration with OSW is defined. A method for evaluating tradeoffs of derating to make the rating more conservative but decreasing the benefit was developed and applied to a case study for two existing overhead transmission lines on Long Island, New York. The CONOPS uses historical day-ahead and hour-ahead High Resolution Rapid Refresh weather forecasts and weather station data to support planning and real-time operations. The analysis determines the risk of downgrades in real-time operational rating compared to the forecast and quantifies the frequency and severity of last-minute downgrades. The risk is compared against the benefits in increased capacity to provide insights on the additional amount of uncertainty DLR and OSW will add to the operator's workload.**

***Index Terms*—grid technology integration, human factors, concept of operations, weather forecast based dynamic line rating, transmission systems, benefits, risks**

I. Introduction

Electric grid operators successfully handle a large amount of complexity and uncertainty in everyday operations. However, variability and uncertainty are increasing due to the growth of renewables and distributed energy combined with retirements of dispatchable generation and more frequent extreme weather events. Operational challenges induced by resource adequacy in the Midwest and western United States [1], as well as planned deployment of offshore wind power in the eastern United States increase motivation to considering novel technology to overcome transmission limitations. The increased challenges of preventing large scale outages [2] while driving aggressively towards the global need to decarbonize and balancing the need to operate the system in a financially optimal manner will fall to the operator.

Authored by Battelle Energy Alliance, LLC under Contract No. DE-AC07-05ID14517 with the U.S. Department of Energy (DOE). Work supported through the DOE Office of Electricity Transmission Reliability and Renewable Integration Program.

Increases in system complexity, variability, and uncertainty pose challenges to control room operators and engineers in electric grid operation. Before new technologies are introduced, there needs to be a clear understanding of how reliable they are, what conditions they are unreliable in, and what impact that will have on operator decision making. Unfortunately, the concept of operations for new technology to harmonize it with existing processes and technology is consistently overlooked.

One key task that transmission operators perform is preventing lines from overheating or the possibility of faults due to sagging lines when transmission lines are overloaded. Utilities use thermal ratings that are typically seasonally adjusted static line ratings (SLR). Some utilities have been using using ambient adjusted ratings (AAR), which take into account near-real time temperatures, for over a decade, and more utilities are adopting AAR to comply with FERC Order 881. Utilities develop these ratings with conservative wind speed assumptions using standard calculations like those in IEEE 738 [3] or applicable standards. The top level steady state heat transfer equations for calculating thermal rating that include mechanisms of coulombic and solar irradiance heating as well as the effects of convection and radiative cooling, given in

$$I^2R(T_c) + q_s = q_c + q_r \tag{1}$$

where q_s is the solar radiation heating, q_c is the convection cooling, and q_r cooling through radiation; T_c is the core temperature of the conductor, I is the current, and R is the resistance of the line. $I^2R(T_c)$ resistive heating of the conductor. To use this for a line rating, conservative weather assumptions for air temperature, solar radiance, wind speed and direction are used to calculate the heating an cooling factors with a maximum conductor temperature T_max that is chosen by the utility based on recommendations of the manufacturers, and the equation is solved for I_{max} as

$$I_{max} = \sqrt{\frac{q_c + q_r - q_s}{R(T_{max})}}. \tag{2}$$

The details of the heating and cooling factors can be found in many articles for the curious reader [3]–[5]. Of importance is the fact the convection cooling is very sensitive to the wind speed and direction with a directional shift of wind from being perpendicular to a line segment to being parallel with the line will reduce the cooling effect by over sixty percent.

Dynamic line rating (DLR) using both ambient temperature and wind conditions and the same fundamental steady state heat transfer equations, as proposed as early as 1977 [6], [7] could provide additional system flexibility by using real-time weather conditions instead of conservative assumption used in SLR or AAR; however, the use of DLR technologies that use forecast or real time wind conditions continue to be rare, with some notable exceptions in North America of pilot projects like ones in PJM, CAISO, and Idaho Power Company. Use of DLR based on forecast wind conditions may be limited due to operational uncertainty and the localization of weather conditions associated with wind. As weather measurements and forecasting continue to advance, localized weather conditions can be captured by sensors or approximated, and may allow utilities more flexibility to use additional transmission capacity. The cost including more distributed reserve resources due to the uncertainty causing forecast errors was examined in [5].

In this paper, we are specifically interested in investigating how frequently and by how much a forecast DLR will miss and require a "last-minute" downgrade. A miss could require the operator to act in real-time to protect the system based on the displayed DLR information. If the last-minute downgrades are too frequent or too large, it may degrade the operator's trust in DLR [8] or may increase the operator's workload [9] to an unacceptable level. In addition, we want to understand the tradeoffs between having more transmission capacity when it is needed (benefits) and adding additional burden to the operator and potential harm to the system if operator is unable to manage last minute downgrades (risk).

DLR can benefit the operator by relaxing the thermal limits when the wind speeds are above average or temperatures are cold. As an example, a higher rating could reduce the severity of contingency violation from one that would require shedding of customer electric load to a long-term emergency rating condition where an operator has more time to plan a response. Though many papers discuss the potential benefits [5], [10]–[13], none have adequately addressed that operators will need to manage a system that is exposed to additional risk of forecast misses where the wind speed dropping unexpectedly causing normal operation to become an overloaded condition requiring the operator to act.

DLR and other grid enhancing technologies are anticipated to be a part of the solution towards the United States near-term goal of 30 GW of offshore wind energy by 2030 [14]. Dynamic rating for direct current subsea cables for offshore wind (OSW) to the point of connection with the land-based transmission system are considered in [15]. However, many of the challenges to connecting OSW to load centers are on the overhead transmission lines. OSW may benefit from a concurrent cooling effect where the wind that turns the turbines also cools nearby lines [16].

One gap in the DLR literature is a clear concept or theory of operation that describes how forecast wind-informed DLR would be implemented operationally including what constraints to put on dynamic ratings to be appropriately conservative. DLR researchers and vendors have intentionally avoided describing how utilities should implement to avoid being overly prescriptive and limit the flexibility for utilities to implement DLR in a way that suits their system. However, without a clear theory of operations, it is difficult to predict what conditions the operator will encounter when using wind informed DLR, and how it will effect their decision making. A purpose of this paper is to document a plausible theory of operations and use that concept as a framework for analyzing the conditions that operators will encounter. Though utilities may choose to implement wind-informed DLR differently than described here, this analytical method serves as baseline for understanding how a particular implementation will affect operator decision making, and can be repeated with a different theory of operations.

This paper begins with Section II including a description of the operational background information including standard thermal line rating application, background on weather based DLR, and a plausible theory of operations integrating DLR into the existing day-ahead planning and real-time operations of transmission operations. Section III presents a use case of the general application of forecast and real-time operations implementing DLR followed by a specific consideration of using DLR in facilitating near-term OSW installation. The analysis methodology is described and applied in this section. The analysis in the use case uses historical forecast and real-time observations from Long Island, New York to compare the expected benefits of increased transmission capacity and OSW with the expected magnitude and frequency forecast misses that impact operators. A discussion of the potential benefits and risks this technology may present to transmission operators is given in Section IV, which is followed by conclusions in Section V including future use this study to in inform research on the capability of system operators to effectively respond when conditions deviate significantly form the forecast.

II. Background

A. Standard application of thermal ratings

In today's control room thermal ratings are set based on conservative assumptions for the weather conditions and allowed conductor temperature. Several ranges of operation are defined based on the amount of time a transmission line can operate safely at a given load, l, specified as current (amperes) or power flow (voltamperes) limits. The ratings that divide these ranges include: normal (n), emergency (e), and load dump (d) with relay setting (r) set to trip above these limits [17]. Operators are required take necessary actions to resolve real-time overloads and contingency analysis violations in time limits commiserate with the severity of the issue, Table I. The importance of this information in this context is the time frame an operator has to respond would be dependent on the magnitude of a forecast miss (e.g., DLR moving from value that would be normal operation to one where increasingly fast actions need be taken.

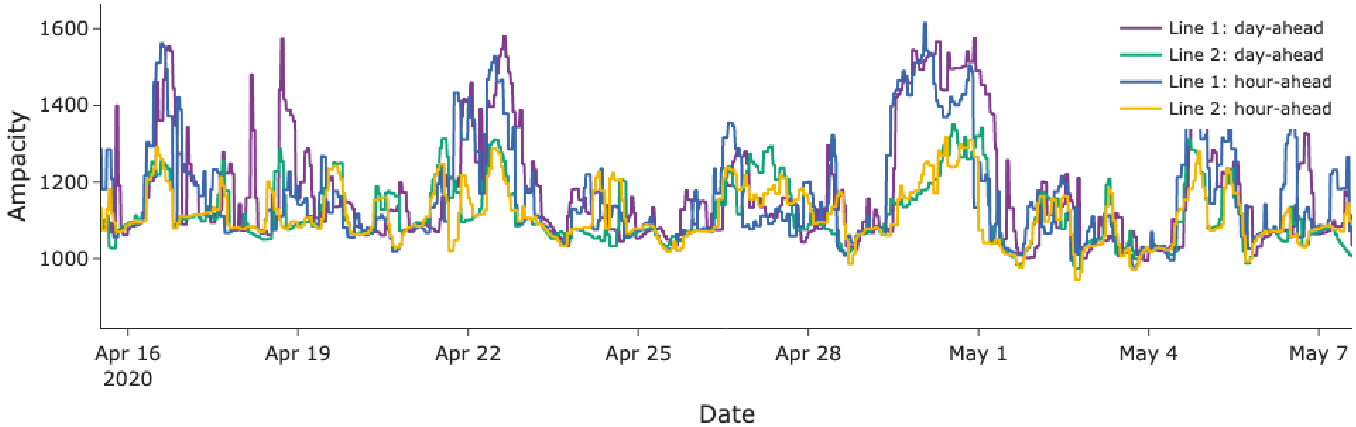


Fig. 1. Example time series of day-ahead forecast ratings and hour-ahead forecast rating.

TABLE I
SUMMARY OF OPERATING RANGES BASED ON THERMAL CONSTRAINTS OF TRANSMISSION LINES.

Name	Range	Description
Continuous/Normal	$l \leq n$	System is safely operated continuously
Emergency (Long)	$n < l \leq e$	System can be operated for a limited time (e.g., 1 hour)
Emergency (Short)	$e < l \leq d$	System can be operated for a shorter limited time (e.g., 15 minutes)
Load dump	$d < l \leq r$	System cannot be operated safely in this range operators or automation must shed customer load immediately to protect from larger scale failures
Relay trip	$l > r$	Relays will automatically command breakers to open to protect the line

B. Weather based dynamic thermal ratings

These ratings are determined using four relevant weather variables: ambient temperature, solar heat input, wind speed and wind direction [18]. SLRs have been commonly extended to use measured ambient temperatures. However, adopting rating methods that include wind [4] have lagged in part due to the volatility in wind adjusted ratings, see Figure 1. Furthermore, ratings needed for optimal economic dispatch decisions in the day ahead planning and markets require accurate high spatial resolution forecasts. Viafora [19] discusses the use of dynamic rating of overhead transmission lines and transformers for dynamic DC optimal power flow day ahead dispatch of generation applying historical weather conditions in Denmark; however, the paper does not actually use forecasted weather in the day ahead dispatch. In [20], Abboud provides a basis for mapping National Oceanic and Atmospheric Administration's High-Resolution Rapid Refresh (HRRR) model [21] for meteorological predictions to the limiting line segment of a transmission line's day ahead and hour ahead DLR. For this paper, forecasts from the HRRR models for the Long Island, New York area are used to calculate the hour-ahead real-time operational DLR baseline and for the day-ahead forecast dispatch decisions. HRRR was chosen as the forecast resource because it provides updated forecasts hourly for 15 minute intervals over the next 18 hours and provides 36 hour ahead forecast with hourly intervals four times a day that can serve to produce day-ahead DLR forecasts for dispatch of generation planning when combined with load and generation forecasts for the system.

Weather based DLR, which provides the greatest potential increase in ratings by accounting for the heightened cooling provided by wind, can create risks to the system. DLR has the potential to provide relief in situations where the "fuse length" is increased by the current weather conditions. However, DLR can also create a situation where a change in weather can shorten the fuse length. Care in implementing the technology can control how large and how frequently misses put an operator into a bad position, e.g., go from a continuous operating range to a load dump range with an unforecasted decrease in wind speed or shift in direction. Limiting the normal DLR to the lower limit of the load dump range is practical guidance for utilities to maximize the benefits while always providing a minimum of the short-term emergency rating response time limits to the operator should there be a last-minute downgrade. Though each line in a system may have unique characteristics that influence choice of static ratings, e.g., vegetation, susceptibility to wildfire, etc., a maximum of 130% of the static continuous rating was chosen for our case study analysis in the next section based on a survey of typical continuous and load dump ratings [22].

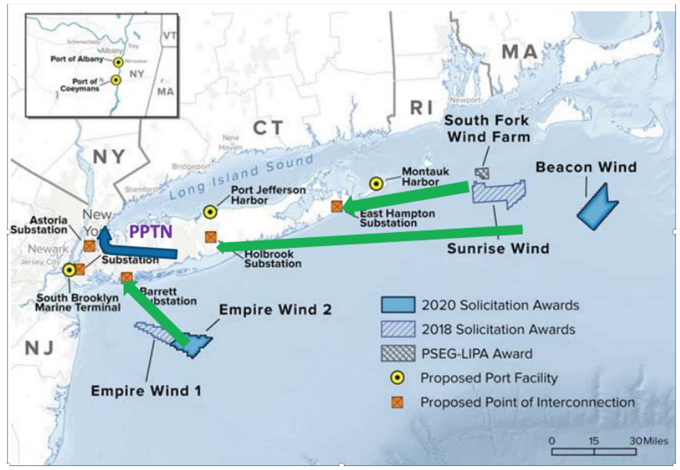
C. Concept of operations

A general treatment of using day-ahead DLR forecasts with optimal power flow (OPF) economic dispatch is beyond the scope of this paper. However, application of historical forecast to select an amount of OSW to be installed and day-ahead dispatch based on available transmission capacity considering the concurrent cooling of the transmission lines is considered

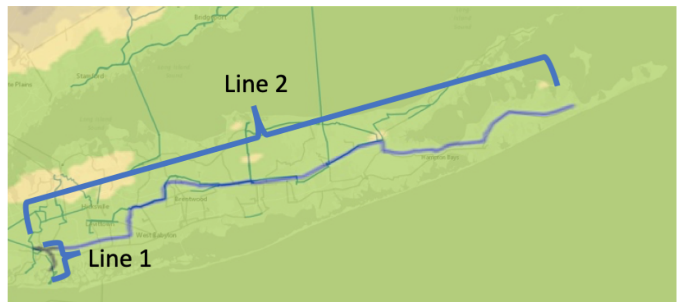
[16]. Day-ahead planning of the wind power needs to be constrained by both the wind production and the forecast transmission capacity. Similarly, to the general case for DLR, the deviations in the forecast will be realize by the operator as variations in the planned dispatch of generation that will need to be compensated for through standard practices of automatic generation control or redispatch by the operator. In this study, the analysis of operational risk and benefits is based on the following concept of operations.

- In the day-ahead planning, the operational approach for DLR and OSW dispatch include:
  - Use a day-ahead forecast as the thermal limits in day ahead planning, dispatch and/or markets,
  - Derate the DLR based on historical analysis of forecast ratings versus observed weather based ratings to limit magnitude and frequency of misses to a level that a utility determines to be manageable,
  - For OSW supported by lines using DLR to limit dispatch planning of wind resources to the minimum of forecast wind or line transfer capacity.
- In the hour-ahead task, the operational approach for DLR and OSW dispatch include:
  - Use an hour-ahead forecasted DLR for the operational limit hour by hour using the minimum forecasted rating of the hour that is ending and the next hour forecast. This rating will be applied to real-time loading and in determining contingency analysis violations,
  - If the hour-ahead forecast DLR drops below the day-ahead forecasted hourly limit, use the hour-ahead forecasted DLR calculated from the most recent observed weather conditions,
  - For OSW supported by lines using DLR to limit dispatch planning of wind resources to the minimum of forecasted wind and line transfer capacity.
- In real-time, the automatic control scheme for DLR and OSW dispatch include:
  - Limit DLR to the existing load dump limit,
  - If the real-time limit drops below the hour-ahead limit (last minute downgrade), use real-time DLR calculated from observed weather conditions,
  - For OSW supported by lines using DLR to limit real-time dispatch of wind resources to the minimum of forecasted wind or line transfer capacity.
- In real-time, the operational approach for DLR and OSW dispatch:
  - Notify operators of the automatic control actions and set point changes.

This summary is general practical guidance for a possible implementation of weather based DLR which can include OPF. This paper does not intend this as specific a recommendation to utilities but a possible implementation that makes use of available forecasted weather. Specifics provided in the case study are needed to present the potential for rewards benefits and risks for a hypothetical use of DLR. Each transmission system is recommended to perform their own risk analysis when implementing weather-based DLR.



(a)



(b)

Fig. 2. Map of the points of connection to overhead transmission lines for proposed OSW(a) and the general route of transmission lines connecting OSW connection points to NYISO transmission system from HIFLD (b).

III. DLR/OSW NY Case Analysis and Methods

A. Long Island OSW background

The proposed siting, current as of 2020, of large OSW off the coasts of Long Island, New York that would initially use existing overhead transmission lines to connect power to the heart of New York Independent System Operator (NYISO) transmission operations, provides an interesting example to study the benefits and risk associated with the general use of DLR for relieving congestion and the specific case of use of DLR for "on-shoring" wind. By surveying proposed offshore wind projects on the eastern coast, the projects to be constructed off the coast of New York's Long Island appear to be a good case study for considering as a DLR application. This is because of the large size of these projects, as well as New York state's goal of continuing to expand its offshore wind power. Due to a legislative mandate, by 2035 the state will increase its offshore wind capacity to at least 9,000 MW, the largest of any state. Since most of the power needs are within the New York City itself, and the offshore wind plants are off the coast of Long Island, the corridor of overhead transmission lines across the island into the city itself can be studied.

Figure 2 shows the location of four largest solicitation awards by The New York State Energy Research and Development Authority (NYSERDA). These are the Empire

Wind 1 and Empire Wind 2 project that provides 816 MW and 1260 MW capacity off the southern coast of the island to the Gowanus substation in Brooklyn, as the well as the Sunrise Wind project that provides 880 MW capacity off the island's eastern coast and connects to the central Holbrook substation, and the Beacon Wind project that will supply 1230 MW of capacity connected to the Astoria substation in Queens.

The Homeland Infrastructure Foundation Level Data (HIFLD) were used to determine the primary transmission lines of interest that can be modeled with DLR. The Empire Wind connections can be modeled by running an overhead line along existing corridors from the Barret substation to the Jamaica substation, referred to as Line 1. For the Beacon Wind project, line connecting the eastern point back to Jamaica substation is referred to as Line 2. The Sunrise wind is connected to the Holbrook substation and is not studied here although a portion of the line is the same route as Line 2. The map for the transmission line layout for Long Island is shown in Figure 2. The lines are a combination of 68 kV and 138 kV lines in HIFLD. The limiting sections would likely be the 68 kV lines. For the purposes of this example only, this case study will assume the 68 kV lines will follow the same path but be upgraded to 138 kV lines and assume all lines have an with SLR of 925 A.

The process of extracting needed weather data for calculating DLR ratings was done with MesoWest data set that has been used in previously modeled regions [20]. This contains 72 weather stations with publicly available data near the transmission lines to be modeled. Weather data and forecasts were processed with the general line ampacity state solver (GLASS) developed at Idaho National Laboratory [23]. GLASS parses all of the weather and forecast data to calculate the ampacity at every single span along the transmission line, then provides the limit for the line as the minimum rating for all the individual spans between structures limits. The span with the lowest rating experiences the least cooling and would therefore create the "hot spot" with the greatest temperature and greatest sag. Without considering terrain and other potential faulting hazards the span with the lowest rating would be the critical point of the circuit with respect to the thermal rating. Note, the span that is critical will change based on local temperatures, wind speed or direction. The method of rating is based on IEEE 738 [3] using computational fluid dynamics analysis to map weather station or forecast weather conditions to every line span on the lines. This is repeated for the set weather data and two sets forecast time periods to arrive at day-ahead, hour-ahead, and 15-minute observed ratings as well as expected wind generation. Complete data sets for observed, hour-ahead forecast, day ahead forecast and Beacon were recorded for only the calendar year 2020. Since the other wind farms data in that year is incomplete, this case study will use Beacon for both a wind farm supported by Line 1 and 2. Although the method is limited in the sense of not being able to directly measure the temperature or sag, using this method allows for a comparison of forecasts with real-time weather conditions to assess the benefit, that is the time and magnitude of the increase in rating, and the risk, the unexpected magnitude and frequency of decreases from the DLR rating used for day-ahead planning and hour-ahead used as the operational rating.

B. Risks and benefits of using hour-ahead forecasts for real-time operation

This case study applies archived 2020 hour-ahead forecast weather forecast from the HRRR to calculate DLR for the next hour interval. As a first step to mitigate potential for misses, the minimum of the previous hour ahead forecast and the current hour ahead forecast is used as the baseline operating thermal limit (BOTL),

$$I_{BOTL}(T) = \min[I_{HAF}(T), I_{HAF}(T-1)], \tag{3}$$

that will be valid for time t in the range $(t_{T-1}, t_T]$, where $I_{HAF}(T)$ and $I_{HAF}(T-1)$ are the new hour-ahead forecast (HAF) rating and previous HAF rating respectively. To evaluate the benefits and risks tradeoffs, proposed operational thermal limit (OTL) be found by reducing $I_{BOTL}(t)$ by various derating levels for I_d between 0 and 140 A as

$$I_r(T, I_d) = I_{BOTL}(t) - I_d. \tag{4}$$

The OTL, $I_{OTL}(T, I_d)$, using the deratings is limited to a maximum of 130% of I_{SLR} and to a minimum of I_m,

$$I_{OTL}(T, I_d) = \max\left\{\min\left[\left(I_r(T, I_d)\right), 1.3 I_{SLR}\right], I_m\right\}. \tag{5}$$

I_m is a rating calculated using zero wind speed, full sun, and an ambient temperature of 40 C. I_m is very conservative except on the hottest days. An ambient adjusted rating could be safely substituted for I_m.

The derated forecasts are compared to real-time DLR, $I_{DLR}(t)$, which is calculated using observed weather conditions that are recorded four times each hour to find the largest miss for an OTL (MOTL) for an hour interval is

$$I_{MOTL}(t, I_d) = \min_{t \in T}(I_{DLR}(t) - I_{OTL}(T, I_d), 0) \tag{6}$$

limiting the maximum to 0 since negative values indicate a miss forecast that gives more operational margin. A summary of operational benefit (OB), i.e., increase in rating, and operational risk (OR), i.e., frequency and magnitude of misses for back tests of the forecast for various deratings is found as the mean of $I_{OTL}(t, T, I_d)$ and $I_{MOTL}(T, I_d)$

$$I_{OB}(I_d) = \sum_{i=1}^{N} \frac{I_{OTL}(T_i, I_d)}{N} \tag{7}$$

and

$$I_{OR}(I_d) = \sum_{i=1}^{N} \frac{I_{MOTL}(T_i, I_d)}{N} \tag{8}$$

where N is the number of hour-ahead forecasts in the back testing set of data. The summary risk and benefit of back testing the two lines in the study area with 2020 hour-ahead forecast from the HRRR and real-time weather stations acquiring data at 15-minute intervals are shown in Figure 3. As expected, the risk decreases with the decrease in benefit.

Although the summary is a useful graphic to consider choices of derating for given lines, the details of the expectation of frequency and size of misses are important since the

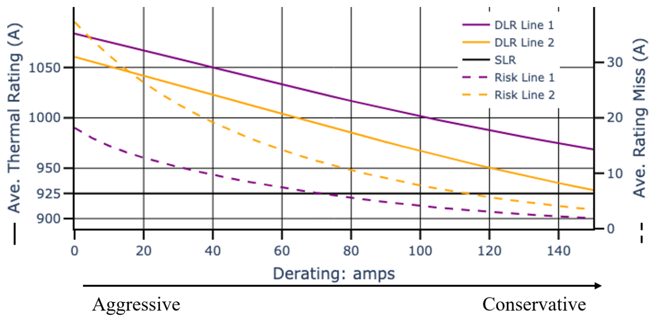
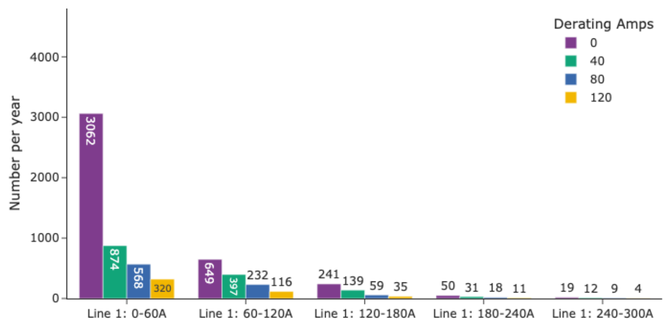
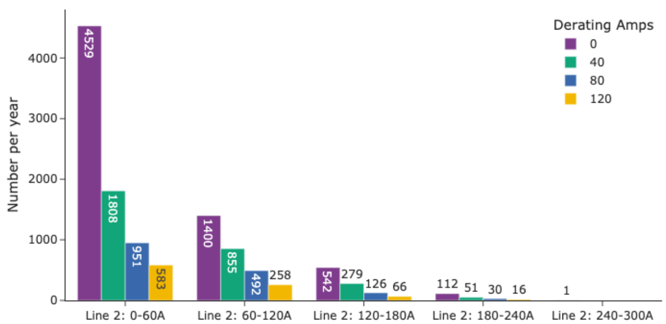


Fig. 3. The solid lines and the left vertical axis representing average ampacity for the hour-ahead forecast rating (average OTL DLR) and the SLR for reference to the gain in line rating. The dotted lines show the risk (average magnitude of OTL DLR misses in amperes) versus derating of the OTL DLR for each line. OTL DLR was capped at 130% of SLR or 1200 amps.



(a)



(b)

Fig. 4. The operational risk of using the rating is conveyed as histograms recording the number of misses between the operational thermal limit and real-time DLR for increasing magnitude bins for Line 1 (a) and Line 2 (b). The x-axis is the magnitude of misses (last minute downgrade amount) in amps

summary magnitude is diluted by the hours where real-time DLR was greater than the operational limit. Figure 4 presents the collection of $I_{MOTL}(T, I_d)$ as a histogram for selected deratings to allow further analysis of the expected frequency of misses of various magnitudes. The histogram shows diverse characteristics of the two lines where Line 2 shows many more misses less than 180 A but less in the highest range across the deratings. The number is also representative of the amount of location-based reserve generation or storage that the system will need to have available to compensate for the misses. Note that the power that needs to be applied for a 100 A miss could be as high as 40 MW for a 138 kV line.

C. Real-time Operation using day-ahead forecast Risks and Benefit

Although increasing operational ratings as described in the previous section may have benefits, most economic gains are provided by increases in ratings that are forecast in advance to include them in planning or used in day-ahead markets using optimal power flow with the forecast rating for unit commitment and economic dispatch. In operation, the day-ahead forecast (DAF) rating can be higher or lower than the hour-ahead rating. The risk of using DAF DLR increases when the number of times that the day-ahead forecast rating is higher than the hour-ahead forecast rating increases. This section will perform an analysis similar to the last section for the day-ahead DLR forecast starting with a construction of the equations beginning with the baseline of the day-ahead thermal limit (BDATL) using the 36-hour HRRR forecast, that is available in time to give the forecast for the day-ahead ratings,

$$I_{BDATL}(T) = \min\left(I_{DAF}(T), I_{DAF}(T-1)\right) \tag{9}$$

where I_{DAF} are the hour interval forecast for each of the 24 hour intervals of study period. Deratings are applied to find proposed day-ahead thermal limits (DATL)

$$I_{DATL}(T, I_d) = \max(I_r(T), I_{min}) \text{ where,} \tag{10}$$

$$I_r(T) = \min(I_{BDTL}(T) - I_d, 1.3 I_{SLR}). \tag{11}$$

The magnitude of forecast misses of the DATL (MDATL) are calculated as

$$I_{MDATL}(T, I_d) = \min\left[I_{OTL}\left(T, 0 - I_{DALT}(T, l_d)\right)\right] \tag{12}$$

where the $I_{OTL}(T, 0)$ is the operational rating without derating, i.e., $I_d = 0$. Of course, that does not consider any choices about derating that might be made in the operational rating, but for the sake of brevity we do not consider the cascading and likely iterative, process. The day-ahead beneift (DAB) and risk (DAR) are also considered as

$$I_{DAB}(I_d) = \sum_{i=1}^{N} \frac{I_{DATL}(T_i, I_d)}{N}, \tag{13}$$

and

$$I_{DAR}(I_d) = \sum_{i=1}^{N} \frac{I_{MDTL}(T_i, I_d)}{N}, \tag{14}$$

respectively, where N is the total number of day-ahead forecasts.

The potential reward versus risk with a range of deratings of the day-ahead forecast is shown in Figure 5. The reward is the average increase in rating that may allow optimization of planning in the day-ahead markets. The risk gives a measure of the potential for errors in the forecast rating that can impact the operational time frame with unwelcome surprises for the operators. As with the hour-ahead operational rating the summary of the risk may need to be more carefully considered with respect to the expected frequency and magnitude of misses as shown in the histograms of $I_{MDATL}(T, I_d)$ in Figure 6. An even more pronounced variation in the characteristics of the two lines exist compared to the operational rating. Line 2, again, has a much larger number of misses in the lowest

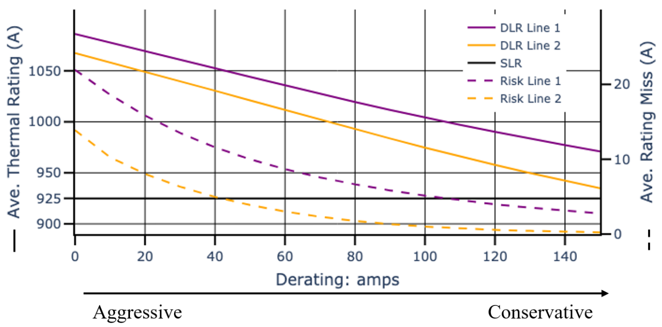
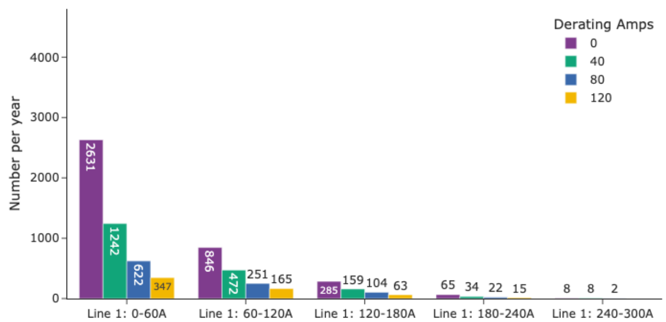
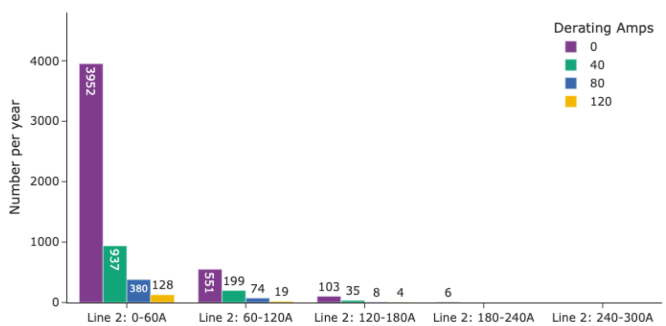


Fig. 5. The solid lines and the left vertical axis representing average ampacity are the day-ahead forecast benefit (average DAF DLR) and the SLR for reference to the gain in the line rating. The dotted lines and the right vertical axis show the risk (average magnitude of DAF DLR misses) versus derating of the DAF DLR for each line. DAF DLR was capped at 130 % of SLR or 1200 A.



(a)



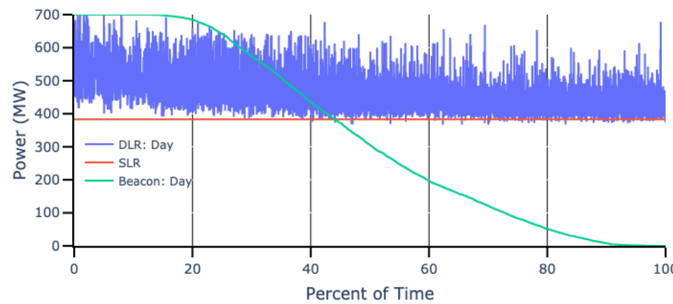
(b)

Fig. 6. The risk of using the DAF DLR conveyed as histograms of the number of misses between DAF DLR and OTL for increasing magnitude bins for Line 1 (a) and Line 2 (b). The x-axis is the miss amount in amps.

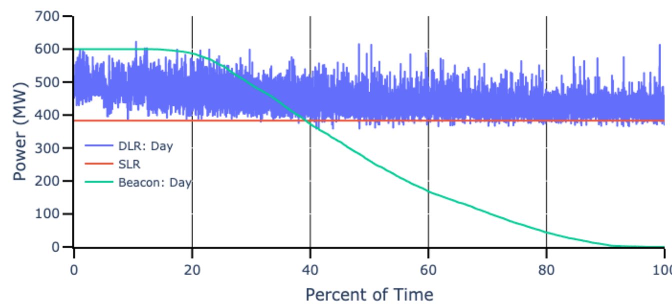
range of misses, i.e., below 60 A, with a quick progression towards lower frequency of misses above 60 A. The derating choice most likely should focuses on more the frequency of larger magnitude misses that would more greatly affect the operator's tasks.

D. Risks and Benefit using day-ahead forecast DLR for OSW Dispatch

Large scale OSW provides a potential benefit of additional clean power to coastal power systems but also a risk to operations when it produces less power than forecast. Use of DLR to accelerate the adoption of OSW by enhancing the capacity of existing transmission lines may present additional



(a)



(b)

Fig. 7. Wind power from OSW farms sorted from highest to lowest with associated hour ahead DLR forecast for Line 1 (a) and Line 2 (b).

risk of decreases in OSW power that can be delivered to loads. For this case study, the amount of wind generation that can be delivered to the central NYISO transmission system based on the existing transmission line utilizing DLR is limited by the minimum line rating or wind generation. For this case study, we first consider a practical size of a wind farm that can be supported by each of the two lines. To do this, the approximate power transfer limit using the nominal line voltage and the thermal limit is compared to the wind farm generation to find the deliverable wind, $P_{DW}(t)$, as minimum of wind power, $P_W(t)$, and thermal limit, $P_{TLT}(t)$, for each time period, T, is calculated as

$$P_{DW}(t) = \min(P_{TLT}(t), P_W(t)) \text{ , where} \tag{15}$$

$$P_W(t) = P_{WNP} P_{NW}(t), \text{ and} \tag{16}$$

$$P_{TLT}(t) \approx S_{TLT}(t) = 3V_{LN} I_{TL}(t) \tag{17}$$

with P_{WNP} as the name plate capacity of the wind farm and $P_{NW}(t)$ as the normalized variable wind power. Here reactive power is neglected allowing the power transfer limit to be approximated by the apparent power limit with V_{LN} as the nominal line to neutral voltage of the three-phase circuit and I_{TL} is the thermal rating in amperes. As with the forecast DLR, the hour-ahead and day-ahead forecasts of wind generation are derived from the HRRR forecast.

To find a reasonable nameplate generation capacity for the wind farm connected to each line, DLR of the connecting over-head transmission line and the expected power generation capacity of the wind at a location of a proposed wind farm installed name plate wind can be chosen. In Figure 7, power estimates based on historical wind data are sorted in descending order keeping the temporal association with the DLR of the transmission line expected to carry the power.

TABLE II
SUMMARY OF DAY-AHEAD DISPATCHABLE WIND ENERGY USING OVER-HEAD TRANSMISSION LINES USING DLR.

	Line 1	**Line 2**
Nameplate in MW	700	600
Annual day-ahead forecast generation in GWh	3,772	3,233
Day-ahead dispatchable using SLR in GWh (% of generation)	2,666 (71%)	2,535 (78%)
Day-ahead dispatchable using DLR in GWh (% of generation)	3,151 (84%)	2,884 (89%)
Dispatch curtailed due to DLR forecast miss in GWh (% of forecasted dispatchable generation)	139 (4.4%)	106 (3.7%)
Wind generation forecast miss in GWh (% of forecast dispatchable generation)	325 (10.3%)	258 (8.9%)
Total decrease from forecast in GWh (% of forecasted dispatchable generation)	464 (14.7%)	364 (12.6%)

Any power produced over the available line capacity would need to be curtailed so name plate for the two wind farms are chosen to be approximately the maximum of the transmission capacity with DLR, or 700 MW for OSW attached to Line 1 and 600 MW for Line 2. Setting farm total name plate to near the maximum DLR for each line minimizes wind curtailment due to transmission deficiency without a dramatic change in energy delivered.

Table II shows the benefit and risk of using DLR over SLR for overhead transmission lines connecting wind farms to load centers. The result shows the benefit in the increase in wind energy that can be planned using the day-ahead forecasted OSW generation and DAF DLR for the connecting lines and the risk in the amount the planned wind generation that will be curtailed due to both misses in DAF DLR and day-ahead OSW forecast. A significant benefit of 13% for line 1 and 11% for line 2 can be realized with a relatively small risk of 4% additional forecast wind energy curtailment due to line ratings.

Figure 8 shows a histogram of the frequency and magnitude of misses of the day-ahead forecast compared to the hour-ahead operational forecast. This shows that DLR has a positive effect of increasing the amount of wind generation that can be planned with relatively small additional risk of misses due to the forecast of DLR as compared to the intrinsic expected uncertainty of wind generation. Derating the DLR could control the misses due to DLR. For example derating Line 2 DLR by 80 MVA, i.e., approximately 20 A for the 138 kV lines, would decrease total misses to 12.5% while decreasing day ahead dispatched wind energy to 2,853 GWh (-1%); however, this does not change the occurrences of larger misses due to wind generation forecast error.

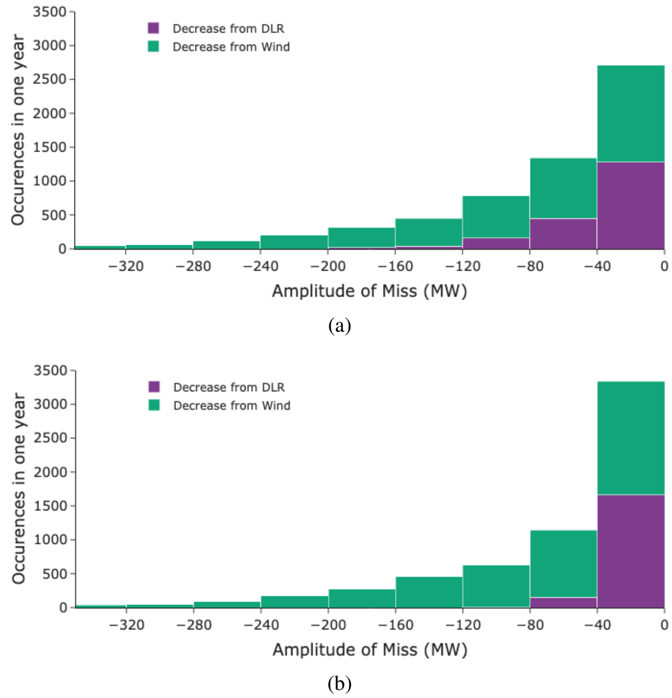


Fig. 8. Stacked histogram for the curtailment of wind generation caused by DLR (lower bar/purple) and wind generation (upper bar/green). Graph represents the misses in the day-ahead forecast with respect to hour-ahead operational forecast Line1 (a) Line 2 (b). DLR misses sum with the wind misses to give total number of curtailment occurrences.

IV. DISCUSSIONS

The analysis presented in this paper provides an overview of the relative tradeoffs with using forecast DLR to support installation of offshore wind. Based on this case study, it is possible to minimize the number of occurrences that the operator will need to manage a large last-minute downgrade due to a miss in the forecast to very few occurrences per year, while still allowing DLR to support some increase in the amount of wind generation. The analysis also provides insights for specific considerations for DLR forecast implementation related to the case study and highlights general considerations for any implementation using forecast DLR.

In this case study, using hour-ahead forecast DLR derated by 120 A reduced the magnitude of misses greater than 180 A to just 15 and 16 occurrences per year, while increasing the average line rating by approximately 65 A and 25 A on Line 1 and 2 respectively. Whether that number is manageable for operators will depend on what options are available to the operator to mitigate the miss coupled with the operator's existing workload. Utilities considering implementing forecast DLRs will need to consider system characteristics (e.g., prevailing wind, line span directions, terrain) along with an analysis like the one presented here as part of their implementation of DLR to manage the last minute downgrade occurrence frequency and magnitudes that the operators will experience. A utility can use an analysis like this to balance benefit and risk by deciding how much DLR will need to be derated to give an acceptable amount of operational risk to determine the value of introducing DLR to given lines.

Of note for the transmission lines of OSW study presented, the paths of the two lines have different characteristics that will influence the DLR even if the wind was exactly the same across both. Specifically, Line 1 is short and primarily north-south where Line 2 crosses the length of the island east-west and has spans that switch to north-south. Because DLR of a line is limited to the span with the lowest rating, Line 2 has a more diverse range of span directions compared to Line 1, suggesting that the effect of wind direction on DLR could be less pronounced on Line 2. Consequently, Line 2 will have a smaller benefit.

Forecast DLR can be used for day ahead unit commitment, dispatch and market clearing. OPF for security constrained dispatch will not produce serious N-1 post contingency when derated forecast are less than the operational DLR. However, misses in the forecast DLR can yield situations where DLR itself is the cause of a contingency violations. As with operational ratings, forecast DLR derating can be chosen to mitigate the operational risk at the expense of decreased ratings. The utility may need to plan for additional reserves in locations that can mitigate any misses. Reserves could include storage, interruptible or flexible loads, as well as traditional generation assets.

As a summary of risk versus benefit, let's assume that the transmission operator wants to mitigate risk to limit hour-ahead forecast misses of 60 A to approximately once a day. The operator would need to derate the forecast rating by approximately 120 A on line 1 which would leave the average benefit of approximately 150 A (16%) increase in rating over SLR. To meet the same risk criteria on the day-ahead forecast, the rating would need to be decreased by nearly 80 A on line 1, yielding a benefit of approximately 90 A (10%) increase over the SLR. In this way, the utility can evaluate the trade-off and make operational and investment decisions.

When considering the day ahead forecast of wind energy production paired with day ahead forecast, the OSW case exhibits the expected benefit from concurrent cooling of transmission lines connecting to and in relatively close proximity to the wind generation, essentially highlighting the benefit of DLR where wind simultaneously increases wind generation and cools transmission lines. The investment in OSW farm should be informed by comparing the peak wind power with the peak DLR for the lines. Line 1 is shown to have better concurrence in DLR and production than Line 2 and thus allows a somewhat larger percentage of generated wind power to be dispatched as planned in the day ahead. The concurrence is likely due to shorter length and closer proximity with the extent of the line.

Uncertainty in DLR forecast lends about a 50 % smaller contribution to the risk of delivering the wind power scheduled in the day ahead forecast than the misses in forecast wind production itself. Concurrent cooling likely contributes significantly to the low frequency and magnitude of DLR misses that impact the delivery of power from the two OSW farms. If sections of the transmission system are not located where concurrent cooling is a factor the relative tradeoffs will be different. All the uncertainty and variability in wind generation will need to be offset by other generation resources and/or energy storage. Operators will be required to manage the variability and uncertainties involved in DLR, wind, and any new tools and resources that will be designed to help them.

V. Conclusion and Future Work

This paper has highlighted a method to analyze the tradeoffs between risk and benefits of applying dynamic line rating to operational and real-time ratings in a case study at a location where DLR is proposed to add capacity for installation of off-shore wind generation. The method of analysis using back testing of forecast DLR and weather station based DLR provides a mechanism for stakeholders to consider the benefits for increasing lines capacity balanced against the cost of incorporating a DLR system and the impacts on operations. The study of the case of using DLR to bolster the transfer of OSW shows anticipatable results that the concurrence of power production and line cooling holds such that DLR does not significantly increase the risk to scheduled wind power production over that of the wind itself.

This paper employs a simple method to derate the line rating by specific number amperes, capping it with the lines load dump rating. The current approach treats forecast uncertainty as equal across all environmental conditions. However, for instance, as the forecasted line rating increases due to changes in wind speed and angle, the volatility of these conditions can lead to an escalation of the uncertainty associated with the DLR. The inaccuracies in the forecasted line rating are related to forecasted weather factors. In the future, researchers could explore the relations of these factors and use data analytics to estimate the extent of uncertainty more accurately and derive other methods to conservatively derate the forecast rating.

This paper has focused on risk associated with the uncertainty when using forecast DLRs and characterizing the additional contingencies the use of DLR subject the operators to. It is also possible that there will be opportunistic availability of transmission or variable generation when forecasts miss would have a positive or beneficial effect on the system and operator needs. Providing situational awareness to the operators to these benefits could be a factor in their acceptance and utilization of DLR.

Future work will examine how operators would make decisions and respond under varying degrees of uncertainty. The analysis will be used as a base line for experiments with operators on how much uncertainty can be reasonably tolerated to further help utilities assess the impacts on operator workload and effective utilization and trust of DLR. Whereas the case study presented here only evaluated two lines, a more complete treatment of operational benefits and risk for the use of forecast DLR would include a topology consistent with a transmission utility with dispatch set with DLR informed OPF to produce realistic scenarios to consider effects of DLR misses on operations. In transmission operation, DLR and other sources of uncertainty will lead to scenarios requiring more complex decisions to be made. Accuracy and timeliness of operator responses impact the economic benefits of DLR. A future study of operators' responses will enhance the understanding of the effectiveness of DLR implementation.

Other future work will consider the operational perspective of including other technologies that have been developed and marketed towards relieving transmission congestion in the electricity system such as power flow controllers (PFC) and long duration battery storage [24]. OSW is one example where storage near the coastal connection could store energy that has no transmission path at time of production, i.e., waiting for a period of low wind generation and open transmission capacity to transfer the energy across the constrained line [25].

References

[1] "Western Assessment of Resource Adequacy." [Online]. Available: https://www.wecc.org/Reliability/2022Western\Assessmentof\Resource\Adequacy.pdf

[2] P. Fairley, "The unruly power grid," *IEEE Spectrum*, vol. 41, no. 8, pp. 22–27, 2004.

[3] "Standard for calculating current-temperature relationship of bare overhead line conductors," IEEE Standard 738, Tech. Rep., 2012.

[4] B. P. Bhattarai, J. P. Gentle, T. McJunkin, P. J. Hill, K. S. Myers, A. W. Abboud, R. Renwick, and D. Hengst, "Improvement of transmission line ampacity utilization by weather-based dynamic line rating," *IEEE Transactions on Power Delivery*, vol. 33, no. 4, pp. 1853–1863, 2018.

[5] F. Teng, R. Dupin, A. Michiorri, G. Kariniotakis, Y. Chen, and G. Strbac, "Understanding the benefits of dynamic line rating under multiple sources of uncertainty," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 3306–3314, 2017.

[6] M. Davis, "A new thermal rating approach: The real time thermal rating system for strategic overhead conductor transmission lines – part ii: Steady state thermal rating program," *IEEE Transactions on Power Apparatus and Systems*, vol. 96, no. 3, pp. 810–825, 1977.

[7] S. D. Foss, S. H. Lin, and R. A. Fernandes, "Dynamic thermal line ratings part i dynamic ampacity rating algorithm," *IEEE Transactions on Power Apparatus and Systems*, no. 6, pp. 1858–1864, 1983.

[8] A. J. Hillesheim and C. F. Rusnock, "Predicting the effects of automation reliability rates on human-automation team performance," in *2016 Winter Simulation Conference (WSC)*, 2016, pp. 1802–1813.

[9] M. R. Endsley and D. B. Kaber, "Level of automation effects on performance, situation awareness and workload in a dynamic control task," *Ergonomics*, vol. 42, no. 3, pp. 462–492, 1999, pMID: 10048306. [Online]. Available: https://doi.org/10.1080/001401399185595

[10] F. G. Erdinç, O. Erdinç, R. Yumurtacı, and J. P. Catalão, "A Comprehensive Overview of Dynamic Line Rating Combined with Other Flexibility Options from an Operational Point of View," *Energies 2020, Vol. 13, Page 6563*, vol. 13, no. 24, p. 6563, 12 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/24/6563/htm

[11] P. Castillo, I. Albizu, M. T. Bedialauneta, E. Fernandez, and R. Alberdi, "Benefits of dynamic line rating on system operation," in *2021 IEEE Electrical Power and Energy Conference (EPEC)*. IEEE, 2021, pp. 95–100.

[12] R. Dupin, A. Michiorri, and G. Kariniotakis, "Dynamic line rating day-ahead forecasts—cost benefit based selection of the optimal quantile," in *CIRED Workshop 2016*. IET, 2016, pp. 1–4.

[13] K. Morozovska and P. Hilber, "Risk analysis of wind farm connection to existing grids using dynamic line rating," in *2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*. IEEE, 2018, pp. 1–5.

[14] W. Musial, P. Spitsen, P. Duffy, P. Beiter, M. Marquis, R. Hammond, and M. Shields, "Offshore Wind Market Report: 2022 Edition," Tech. Rep., 2022.

[15] S. H. H. Kazmi, N. Viafora, T. S. Sorensen, T. H. Olesen, B. C. Pal, and J. Holboll, "Offshore Windfarm Design Optimization Using Dynamic Rating for Transmission Components," *IEEE Transactions on Power Systems*, vol. 37, no. 3, pp. 1820–1830, 5 2022.

[16] J. Gentle, K. S. Myers, T. Baldwin, I. West, K. Hart, B. Savage, M. Ellis, and P. Anderson, "Concurrent Wind Cooling in Power Transmission Lines 2012 Western Energy Policy Research Conference Concurrent Wind Cooling in Power Transmission Lines," 2012.

[17] "PJM Manual 03," 2022.

[18] "738-2012 IEEE Standard for Calculating the Current-Temperature Relationship of Bare Overhead Conductors."

[19] N. Viafora, K. Morozovska, S. H. H. Kazmi, T. Laneryd, P. Hilber, and J. Holboll, "Day-ahead dispatch optimization with dynamic thermal rating of transformers and overhead lines," *Electric Power Systems Research*, vol. 171, pp. 194–208, 6 2019.

[20] A. W. Abboud, J. P. Lehmer, and J. P. Gentle, "Forecasted dynamic line ratings for regional transmission lines," vol. 1, no. 1, 6 2022. [Online]. Available: https://www.osti.gov/biblio/1924479

[21] D. C. Dowell, C. R. Alexander, E. P. James, S. S. Weygandt, S. G. Benjamin, G. S. Manikin, B. T. Blake, J. M. Brown, J. B. Olson, M. Hu, T. G. Smirnova, T. Ladwig, J. S. Kenyon, R. Ahmadov, D. D. Turner, J. D. Duda, and T. I. Alcott, "The high-resolution rapid refresh (hrrr): An hourly updating convection-allowing forecast model. part i: Motivation and system description," *Weather and Forecasting*, vol. 37, no. 8, pp. 1371 – 1395, 2022. [Online]. Available: https://journals.ametsoc.org/view/journals/wefo/37/8/WAF-D-21-0151.1.xml

[22] "PJM - Ratings Information." [Online]. Available: https://pjm.com/markets-and-operations/etools/oasis/system-information/ratings-information.aspx?p=1

[23] A. W. Abboud, J. P. Gentle, T. R. McJunkin, and J. P. Lehmer, "Using Computational Fluid Dynamics of Wind Simulations Coupled with Weather Data to Calculate Dynamic Line Ratings," *IEEE Transactions on Power Delivery*, vol. 35, no. 2, pp. 745–753, 4 2020. [Online]. Available: https://doi.org/10.1109/TPWRD.2019.2925520

[24] "Grid-Enhancing Technologies: A Case Study on Ratepayer Impact," 2022. [Online]. Available: https://www.energy.gov/sites/default/files/2022-04/Grid%20Enhancing%20Technologies%20-%20A%20Case%20Study%20on%20Ratepayer%20Impact%20-%20February%202022%20CLEAN%20as%20of%20032322.pdf

[25] D. Katsaprakakis, "Energy storage for offshore wind farms," in *Offshore Wind Farms*. Woodhead Publishing, 2016.

Timothy R. McJunkin (SM'05) received the M.Sc. degree in electrical and computer engineering from Utah State University, Logan, UT, USA, and is currently working toward the Ph.D. degree at the Electrical Engineering Department, University of Idaho, Moscow, ID, USA. He has been with Idaho National Laboratory (INL) since 1999. He serves as the technical director for INL's Net-zero Micro-grid Progarm His current research and development interests interests are in resilient control of critical infrastructure, including human factors and cyber-security, smart grid for clean energy integration, robotics and automation, intelligent systems. Prior to joining INL, he was with Compaq Computer Corporation's Industry Standard Server Group (1994–1999), leading board level motherboard design of multiple server products. He has served an Adjunct Professor with the Electrical Engineering Department, Idaho State University.

Katya L. Le Blanc (SM'20) received the B.S. in Psychology from New Mexico Institute of Mining and Technology and M.S. and the Ph.D in cognitive psychology from New Mexico State. Dr. Le Blanc is a senior human factors scientist who has been conducting research in the energy sector at INL for 10 years. Her research in nuclear power plant modernization has led transformational change in the way field operators conduct procedures and has improved operator interfaces for control of nuclear power plant equipment in the field and in the control room. She has been working in design of human-system interfaces for transmission system technologies and cyber security of electric grid operation. She leads research in several complex, multidisciplinary subjects including nuclear power plant modernization, and cyber security risk characterization in nuclear power and critical infrastructure, and is the deputy National Technical director for Nuclear Energy Cyber program. Katya has over 100 technical publications in the subject of human factors in the energy sector.

Ruixuan Li recieved the B.S. in safety engineering from the Civil Aviation University in China, the M.S. in industrial engineering from the University of Buffalo and the Ph.D in human factors and ergonomics from the University of Minnesota. Dr. Ruixuan Li is a human factors research engineer in Idaho National Laboratory's Human Factors and Reliability Department. Her areas of expertise include research and development, human factors engineering, simulation, motion capture, and ergonomics. She first came to INL in August 2019 as a postdoctoral research associate. Prior to that, she was a graduate student researcher at University of Minnesota, where she helped develop user-studies for evaluating human factors on Motion Sickness in Virtual Reality. Her research interests include affordance perception, system design, visualization, human-machine interaction, human-automation interaction, and risk and resilience in cybersecurity.

Alexander W. Abboud received the B.S. degree in chemical engineering from the University of California, Davis, Davis, CA, USA, in 2009, and the Ph.D. degree in chemical engineering from the University of Utah, Salt Lake City, UT, USA, in 2015. He currently holds the position of Advanced Computational Fluid Dynamics Engineer at Honeywell. He was a Research Scientist with Idaho National Laboratory, Idaho Falls, ID, USA from 2017 to 2023. He specializes in computational fluid dynamics modeling with experience in a variety of systems including waste glass vitrification, coal combustion, fluidized beds, cryogenics and wind field flows.

Tyler Phillips (M'15) received the B.S. and M.S. degrees in mechanical engineering and the Ph.D. degree in computing, computational mathematics, science, and engineering from Boise State University, in 2009, 2014, and 2020, respectively. He is currently a Power and Energy Systems Researcher with Idaho National Laboratory, in the Energy and Environmental Science and Technology group. His research interests include power and energy system simulations, numerical computing, and data analysis in the areas of resilient control, resilience metrics, integration of renewable generation, microgrids, and dynamic line ratings. He is also involved with the interaction of human factors in power systems. Since 2015, he has been with the IEEE Power and Energy Society.