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Analysis of fixed volume swaps for hedging financial risk at large-scale wind projects

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ABSTRACT

Large scale wind power projects are increasingly selling power directly into wholesale electricity markets without the benefits of stable (fixed price) off-take agreements. As a result, many wind power producers seek financial hedging contracts to mitigate exposure to price risk. One particular hedging contract - the "fixed volume price swap" - has gained widespread use, but it poses several liabilities for wind power producers that reduce its effectiveness. In this paper, we examine problems associated with fixed volume swaps and explore possibilities for improving their performance. Using a hypothetical wind power project in the Southwest Power Pool (SPP) market as a case study, we first look at how "shape risk" (an imbalance between actual wind power production and hourly production targets specified by contract terms) negatively impacts contract performance and whether this could be remedied through improved contract design. Using a multi-objective optimization algorithm, we find examples of alternative contract parameters (hourly wind power production targets) that are more effective at increasing revenues during low performing months and do so at a lower cost than conventional fixed volume swaps. Then we examine how "basis risk" (a discrepancy in market prices between the "node" where the wind project injects power into the grid, and the regional hub price) can negatively impact contract performance. Overall, our results suggest that wind power producers would be better served hedging substantially lower volumes of wind power production, and in certain months should not be hedging at all. Another key finding is that contract performance improves with modest reductions in basis risk. This indicates that eliminating transmission congestion issues across the grid may not be necessary to improve contract performance.

1. Introduction

Despite falling costs of renewable energy (Sukunta, 2020; U.S. Energy Information Administration, 2021), financial instability for renewable energy producers looms large as a factor that could slow decarbonization efforts (United Nations Framework Convention on Climate Change, 2015; Intergovernmental Panel on Climate Change, 2019). The International Energy Agency (IEA) estimates that $2.3 trillion in annual investment in clean energy technologies will be required to achieve emissions reduction goals set out in the Paris Climate Agreement (Reicher et al., 2017)' and a significant source of these funds is likely to be private sector investment. In general, lenders see revenue uncertainty as a credit risk that increases the required "cost of capital" (e.g. interest rate on borrowed sums) for renewable energy developers. This in turn increases total project costs, reduces profitability and – potentially – could slow the rate of investment in zero carbon energy (Bartlett, 2019).

In the United States, strong competition and a limited pool of customers have depressed prices for coveted power purchase agreement (PPA) contracts, in which developers are matched with large "off-take" customers (often utilities) who buy the electricity at a set price for a specific period of time (generally 10–25 years) (Bartlett, 2019; Schwabe et al., 2017). Instead, wind projects are increasingly selling directly into the wholesale market as "merchant generators", leaving them exposed not only to fluctuations in the amount of generation they produce, but also fluctuations in the market price of electricity ($/MWh) (Schwabe et al., 2017; Dahlke, 2018).

To mitigate this financial risk, wind power producers often seek some kind of hedge against price fluctuations. A widely used hedging model is the "fixed volume price swap," which was used to manage price risk at 48.4% of all merchant or part-merchant wind capacity in the U.S. in 2017 (Caplan, 2018) (Fig. 1). Fixed volume swaps involve wind developers trading actual wholesale electricity prices for a pre-determined fixed price (referred to as the "strike"), which is typically lower than the

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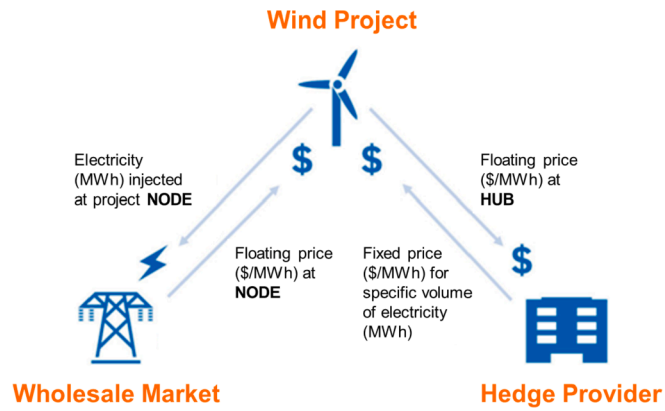

Fig. 1. Example of a fixed volume price swap between a wind power producer and hedge provider.

average market price, allowing the hedge-provider to profit. Wind projects have been willing to pay this premium in order to reduce their exposure to electricity price volatility and secure lower cost financing. However, in some instances, these financial hedging options may limit (or even reduce) the control that wind developers have over projected revenues from their projects.

In fixed volume price swaps, the wind developer sells electricity for a price determined locally at the "node", i.e., the location where the wind project is physically connected to the larger grid. Note, however, the payouts from the financial exchange with the hedge provider are based on the difference between the agreed-upon strike and the "hub" price (i.e. the weighted average price of electricity across the entire system) (Eqs. (1)–(2)) (Eberhardt and Brozynski, 2017).

$$R_t = NP_t * W_t + Contract_t \tag{1}$$

$$Contract_t = (S - HP_t) * T_t \tag{2}$$

where,

R_t = Net revenues for wind producer in hour t
NP_t = Price at the node in dollars per megawatt-hour in hour t
W_t = Total wind production in megawatt-hours hour t
T_t = Hedged wind production in megawatt-hours hour t
$Contract_t$ = Financial exchange (dollars) with hedge provider in hour t
S = Agreed-upon strike price in dollars per megawatt-hour
HP_t = Price at the hub in dollars per megawatt-hour in hour t

As long as $NP_t = HP_t$ and $W_t = T_t$, the contract effectively fixes the price realized by the wind producer at the agreed-upon strike. However, node and hub prices frequently diverge, often the result of transmission congestion that constrains prices from equalizing across the grid, including locational oversaturation of wind power that results in temporary low prices at certain nodes. This price mismatch results in "basis risk" that prevents the hedge contract from adequately stabilizing the wind developers' revenues (Eberhardt and Brozynski, 2017). Hourly wind production targets (T_t) are set for each hour of the day, in theory representing the "firm" (reliable) production capabilities of the project. If these targets are set improperly, it can result in the wind farm underproducing relative to its contracted obligations and incurring penalties, and/or a small percentage of actual project output benefiting from the hedge (Bartlett, 2019). This so-called "shape risk" is another way contract performance can be degraded.

Managing financial uncertainty for wind power producers has been the focus of several previous research studies, with most seeking to identify optimal strategies for "bidding" (selling) into competitive markets and managing day-ahead forecast errors in wind availability (Bitar et al., 2010; Xiao et al., 2015; Dai and Qiao, 2015; Botterud et al., 2010; Daraeepour et al., 2019). A smaller group of studies have examined how to mitigate wind farm's financial risk through the use of financial instruments (Fernandes et al., 2016; D'Amico et al., 2020). Sin and Baldick explored how wind power producers can use financial instruments to manage the uncertainties of the real-time market (Shin and Baldick, 2018). Pircalabu and Jung considered optimal designs for hedging volumetric and price risk for wind power producers in European markets (Pircalabu and Jung, 2017). There has been no peer-reviewed research exploring fixed volume price swaps, although they are widely used in the wind industry, and there is evidence that these contracts perform poorly for wind projects. In this paper, we examine the structure of fixed volume swaps negotiated between wind developers and hedge providers, and their sensitivity to basis and shape risk. We then explore how improvements could be made to these contracts, specifically by changing hourly wind production targets that the asset owner is required to meet. The results from this study should prove valuable to wind developers seeking to make informed decisions about how to minimize revenue uncertainty, thus helping them to get new projects off the ground.

2. Methods

2.1. Study area and data

We focus our analysis on the Southwest Power Pool (SPP) market in the U.S., which has members in 14 states and a service territory of 546,000 mile^2 (Fig. 2). The SPP market had approximately 22.5 GW of wind energy capacity as of the end of 2019, making up 24.9% of its total generating capacity (Southwest Power Pool, 2020a). To incorporate this large amount of wind and maintain reliability across the grid, SPP has approved an extensive transmission plan for 2021, and is integrating electric storage resources in compliance with FERC Order 2222, which requires grid operators to allow distributed energy resources to participate in wholesale markets (Southwest Power Pool, 2020b). This area was chosen because of its persistent high wind speeds and a history of transmission issues, which are representative of the difficulties wind developers face in finding a suitable site with high enough potential revenues to justify project development (Nimmagadda et al., 2014). In addition, fixed volume price swaps are particularly common in SPP (Bartlett, 2019).

Despite high average wind speeds over much of the SPP footprint, wind power faces challenges there due to limited transmission capabilities and so-called "covariance risk". Wind power production increases cubically with wind speeds, so wind power projects tend to

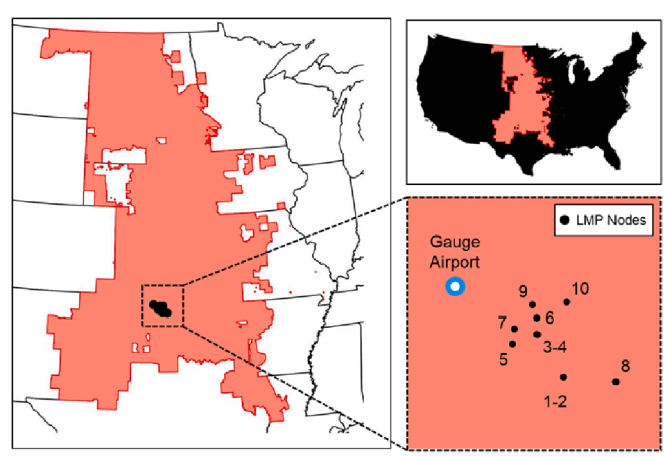

Fig. 2. Map of Southwest Power Pool (SPP) system. Numbers shown in inset correspond to nodes listed in Table 1, and also denote ranked proximity to the hypothetical wind farm being modeled.

cluster around the locations with the greatest wind resources. As a result, when one wind farm is experiencing a period of high wind production, it is more likely that other nearby wind farms are also delivering large amounts of electricity onto the grid simultaneously (Taylor, 2019). This can overload existing transmission capacity, resulting in local saturation of wind power and forced curtailment of excess wind power. Furthermore, because wind power plants' marginal costs are zero, congestion can cause prices at the node drop to zero (or even become negative, since some wind farms receiving PTCs can bid below zero and still experience positive revenues). To alleviate some of these issues, SPP currently is planning $545 million worth of transmission upgrades for the 20-year planning horizon that includes 78 projects in 8 states (Southwest Power Pool, 2020c).

Our data consists of hourly wind power production data at a hypothetical 198.6 MW wind project location within SPP for two years (2015–2016) provided by a developer. In order to extend our wind power production data to match the same five years of price data, we first obtained daily wind speed data for 2015–2019 from Gage Airport, OK, located 32 miles from the wind farm site. Daily wind speeds over the period 2018–2020 are then used to conditionally bootstrap (re-sample) hourly wind power production from 2015 and 2016, yielding hourly wind power production records for 2018–2020.

We also obtained five years of hourly nodal and hub price data (2015–2019) for the 'real-time' SPP market, from 10 nodes in close proximity to the wind farm site (Fig. 2), as well as the 'hub'. In the SPP market, locational marginal prices are determined in dollars per megawatt-hour ($/MWh) at thousands of nodes across the system. Prices at the trading hub are determined as the weighted average of all system nodes (Schwabe et al., 2017). Typically, financial derivatives related to wholesale electricity markets (including fixed volume swaps for wind farms) are settled based on hub prices, because hub pricing is less volatile, less subject to market power, and easier to project based on historical data (Bartlett, 2019). Wind generators tend to sell into real-time markets because their production is difficult to predict 24 h in advance, and failing to meet day-ahead obligations can result in costly penalties (Shin and Baldick, 2018; McElroy et al., 2018). Thus, in our analysis, we use real-time price information at both the node and hub.

Fig. 3 shows time series of monthly SPP hub prices alongside prices at selected nodes. Basis risk, as described above, is a difference between hub and nodal prices that can reduce the effectiveness of hedging contracts. Fig. 3 shows significant variation in nodal prices across the nodes in our fairly small study area, as well as through time. The wide disparity seen in nodal and hub prices during certain time intervals within our study region suggests that there is transmission congestion affecting the grid during these times. With no congestion, nodal prices should be uniform across space (and equal to hub prices) (Goggin et al., 2018). For example, April 2017 has average monthly prices ranging from -$32.40/MWh in the OKGEWDWRD1LD2 node, to $90.30/MWh in the WFEC_MOORELAND_2 node. This month had the highest average wind speeds in this 5-year time span at 15.4 m per second. Without adequate transmission, extremely high wind speeds created "pockets" of extremely high wind power penetration at certain nodes, causing prices to crash, while prices at other nodes (and the hub) remained high (Goggin et al., 2018).

Wind power production, like nodal pricing, shows strong seasonal patterns (Fig. 4) (Raja et al., 2020). Average monthly wind speeds at Gauge Airport (20 miles from our hypothetical wind farm site) show peaks in the Spring and early Fall and troughs in late Summer and Winter.

2.2. Alternative contract designs

A goal of this study is to identify modifications to the design of fixed volume price swaps to reduce shape risk for wind power producers, while also maintaining targets that are satisfying to hedge providers. Typically, a fixed volume swap only applies to a portion of the electricity produced by a wind farm (values of T_t in Eq. (2)). From a wind farm's distribution of annual power production estimated from historical wind speed data, a hedge provider estimates the median (P50) year, and multiplies this number by 80% as an approximation of the 1st percentile (P99) year – in other words, an amount of generation that will be exceeded roughly 99 out of 100 years (Eberhardt and Brozynski, 2017). This annual amount is allocated over 8760 h based on historical averages for each month. Hourly targets for each month are calculated by taking the average value for off-peak and peak hours, resulting in blocks of energy that are eligible for a fixed volume swap (Fig. 5).

An important feature of the fixed volume swaps is that if actual wind power production falls below the hedge target in any given hour, the wind power producer is obligated to buy "make-up" power on the real-time market (typically at a higher than average price). In addition, any electricity production that exceeds the hourly target is not subject to the hedge, and is simply sold as usual in the real-time market, potentially at much lower prices. Previous analyses have shown that this mismatch between actual wind power production and hourly targets (also known as "shape" risk) can significantly degrade the efficacy of fixed volume swap contracts for wind developers (Bartlett, 2019). An initial research question here is whether "compromise" hedge targets can be identified that improve financial performance for the wind producer, while also satisfying financial performance requirements for the hedge provider.

To simulate (and optimize) the financial performance of a hypothetical wind farm, we embed a simple simulation model of the wind

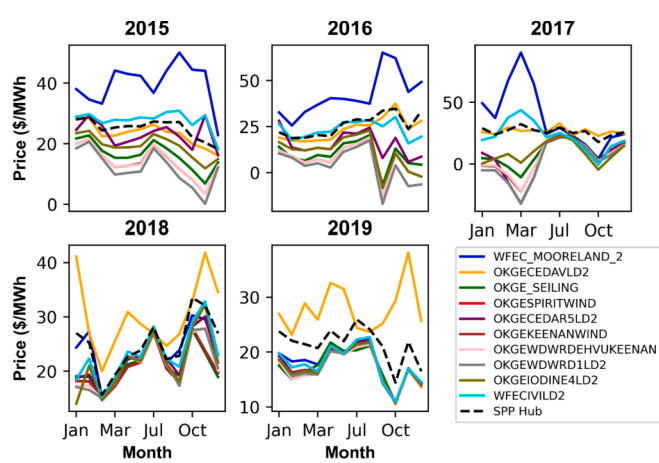

Fig. 3. Average monthly hub and nodal prices by year.

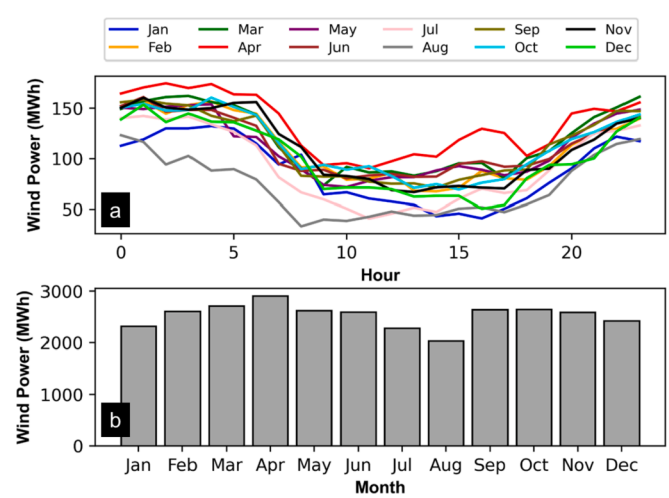

Fig. 4. a) wind speeds for each month averaged over 5 years; b) within day wind power production patterns and the hypothetical wind farm.

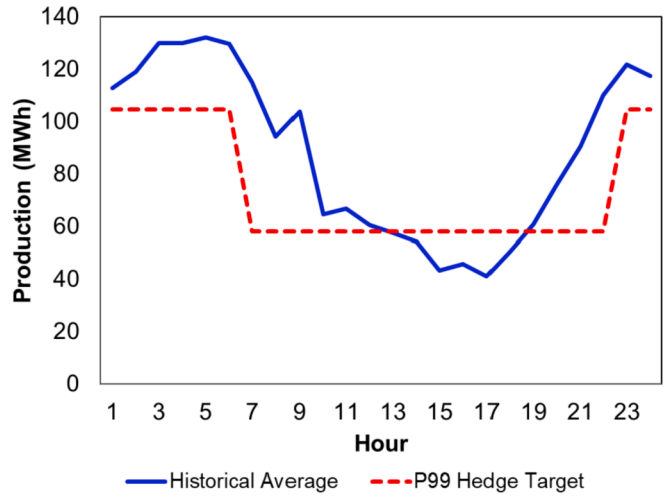

Fig. 5. Average hourly wind power production vs. "P99" hedge targets for January for the hypothetical wind farm.

farm's operations (including use of fixed volume swaps) (Eq. (3)) within a many-objective evolutionary algorithm (MOEA) to identify optimal peak and off-peak hedge targets for each calendar month. We make use of a widely used MOEA known as the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (Platypus NSGA-II Model, 2021). NSGA-II has been used widely in the past to help solve problems dealing with conflicting dual objectives (when one objective increases, the other decreases), which is likely the case in our problem. MOEAs, such as the NSGA-II, can be used to help developers of renewable energy projects and grid operators optimize the construction and operations of new plants by taking into consideration cost and reliability (Igbinovia and Křupka, 2019). Previous research used an MOEA to optimize scheduling in power system markets with a high penetration of renewables (Zhang et al., 2020). NSGA-II has previously been used to optimize an energy management system for a grid-connected micro-grid with renewable energy and energy storage resources (Teo et al., 2020). In our use of the NSGA-II algorithm, we used default parameters for population size and mutation rate.

The function evaluated by NSGA-II is a simulation model of wind power revenues for the hypothetical project, which employs an hourly time step and calculates revenues as follows:

$$R(t) = W(t)*max(0, NP(t)) - max(T(t) - W(t), 0)*NP(t) + (S - HP(t))*T(t) \tag{3}$$

where,

$R(t)$ = wind developer revenues in hour t
$W(t)$ = wind power produced in hour t
$NP(t)$ = electricity price at node in hour t
$T(t)$ = hedge target for given hour type and calendar month
S = contract strike price
$HP(t)$ = electricity price at hub in hour t

The first part of the equation $W(t) * max\ (0, NP(t))$ calculates revenues from selling all wind farm output directly into the wholesale market at the nodal price, with the *max* function preventing these revenues from going negative during periods of local oversupply (i.e. wind power production is curtailed rather than sold at a negative price). The second part of the equation, $max(T(t) - W(t), 0) * NP(t)$, accounts for any "makeup" power the wind power producer must purchase at the node if it underproduces relative to a pre-specified wind production volume $T(t)$. The final part of the equation $(S - HP(t)) * T(t)$ represents the financial exchange between the wind power producer and the contract counterparty, the hedge provider. Note that when $S < HP(t)$, the financial exchange is negative, with the wind power producer paying the hedge provider.

The values shown in Table 1 represent values of $T(t)$ for a conventional P99 contract. In our experiment, however, these 24 hourly hedge targets are the primary decision variables (unknowns to be optimized using the NSGA-II algorithm). Peak hours are defined as any hour of the day between 0600 and 2100, with the remaining hours defined as off-peak (Table 2).

The MOEA evaluates the function shown in Eq. (3) over a predefined number of iterations known as 'generations', along the way identifying combinations of decision variables (here, the hedge targets $T(t)$), that yield 'non-dominated' solutions in terms of two objectives: 1) maximize profits of the wind power producer; and 2) maximize "floor improvement," or the increase in revenues over the worst performing 10 months during a 5-year period (2015–2019), relative to a scenario in which no hedging occurs (Eq. (4)). In this experiment, the function in Eq. (3) was evaluated over 75,000 generations for each scenario tested.

$$Maximize \quad Objective \quad 1: \sum_{t}^{T} R(t) \tag{4}$$

$$Maximize \quad Objective \quad 2: \sum_{k}^{K} \widehat{X}(k) - \sum_{m}^{M} X(m) \tag{5}$$

where,

T = set of all hours
$\widehat{X}(k)$ = total revenues in month k with hedging in place
K = set of 10 worst performing months with hedging in place
X(m)=total revenues in month m without hedging in place
M=set of 10 worst performing months without hedging in place

In theory, effective hedging via a fixed volume swap should have two main effects for the wind power producer: 1) reduce total profits (the net exchange with the hedge provider will be negative, representing a "premium" paid by the wind developer to incentivize the hedge provider to participate); and 2) increased revenues during the worst performing months, with the latter benefiting the wind power producer by stabilizing its financial flows. The "strike price" (S in Eq. (3)) is kept constant across every scenario tested; we assume S to be the $-per-megawatt ($/MWh) price that results in the contract counterparty making a profit of 10% in its exchange with the wind power producer ($22.64/MWh). We also include as a constraint within NSGA-II that profits for the hedge provider must be between 9% and 11%, meaning any solution considered must result in acceptable profits for the hedge provider.

Given these two objectives and a constraint guaranteeing profitability for the hedge provider, the MOEA then allows us to analyze a frontier of solutions over which profits for the wind power producer (expressed as % of maximum theoretical profits with no contract in place), as well as "floor improvement" (increase in revenues over the 10 worst performing months) are balanced to varying degrees. Accompanying each solution are corresponding values of decision variables (peak

Table 1
Nearest SPP System Nodes to the hypothetical wind project.

Node	Proximity to Wind Farm (km)
1. OKGEIODINE4LD2	4.94
2. WFECVICILD2	4.97
3. OKGEWDWRD1LD2	18.99
4. OKGEWDWRDEHVUKEENAN_WIND	19.15
5. OKGEKEENANWIND	22.29
6. OKGECEDAR5LD2	25.83
7. OKGESPIRITWIND	26.23
8. OKGE_SEILING	27.65
9. OKGECEDAVLD2	31.82
10. WFEC_MOORELAND_2	32.49

Table 2
Peak and off-peak hourly wind production volumes (in MWh) for each calendar month.

Month	Peak	Off-peak
Jan	58.03	104.74
Feb	76.47	123.88
Mar	82.69	130.79
Apr	98.55	139.63
May	77	123.22
Jun	79.78	122.94
Jul	57.75	114.36
Aug	44.35	88.43
Sep	78.12	125.61
Oct	79.26	124.89
Nov	76.34	124.21
Dec	67.59	114.02

and off-peak hedge targets) for each month of the year.

2.3. Basis risk sensitivity analysis

We also explore the potential for reductions in the frequency and magnitude of divergences between nodal and hub prices (i.e. lower "basis risk") to improve the performance of fixed volume swaps. In the context of our modeling analysis, reducing basis risk can be thought of as a rough proxy for a real-world decision to add or improve transmission infrastructure, which could have the effect of reducing differences in locational marginal prices among nodes and the hub. In reality, improved transmission capacity could also lower market prices overall, which we do not account for in our sensitivity analysis. Note as well that wind power developers likely have limited control over whether or not new transmission capacity is added at specific locations. However, a better understanding of the relationship between basis risk and contract performance may aid significantly in the future selection of wind project sites. In order to explore the sensitivity of fixed volume swaps to basis risk, we experimentally control basis risk by gradually altering the bias and standard deviation of errors between nodal and hub prices across several testable scenarios. The rest of this section of the paper details the construction of basis risk scenarios representing a wide range of potential future conditions.

We measure basis risk as the hourly difference between hub prices and the prices at a given node, as follows:

$$B = HP - NP \tag{6}$$

where,

B = vector of observed hub and nodal price differences
HP = vector of observed hub prices
NP = vector of observed nodal prices

Keeping hub prices constant, we can then systematically alter basis risk several ways, including reducing mean bias and standard deviation (Eq. (7)).

$$\widehat{B} = \frac{(B-\mu)}{(1-a)^{*}\delta} \tag{7}$$

where

a = fraction ranging from 0.9 to 0
δ = standard deviation of observed hub and nodal price differences
$\widehat{B}$ = vector of altered hub and nodal price differences
μ = mean of observed hub and nodal price differences

By gradually decreasing the value of a from 0.9 to 0, we can suppress the magnitude of positive and negative differences between nodal and hub prices until they approximate a standard normal distribution. Nodal prices are then altered by back-calculating with the new values of $\widehat{B}$:

$$\widehat{NP} = HP - \widehat{B} \tag{8}$$

where,

$\widehat{NP}$ = vector of altered nodal prices

Table 3 lists the 13 basis risk scenarios tested. For scenarios in which the standard deviation of price differences is altered, the corresponding values of a are shown. For example, under the "standard normal" scenario, the mean difference between nodal and hub prices is equal to zero and the standard deviation is 1 ($a = 0$). In the "Mean Zero 10" scenario ($a = 0.10$), the mean of the differences between nodal and hub prices is zero and the standard deviation is only 10% of observed basis risk. In the "Mean Zero 90" scenario ($a = 0.90$), the mean is again zero and the standard deviation is 90% of observed basis risk (i.e. close to historical conditions).

3. Results and discussion

Our discussion of results is organized as follows. First, we compare the performance of a traditional P99 fixed volume swap to alternative contract designs identified, and discuss how wind power production targets could be adjusted to improve outcomes for the wind power producer. Then we examine the approximate Pareto frontiers identified by NSGA-II and explore how tradeoffs between the wind developer's dual competing objectives (maximizing average profits and "floor" improvement) changes across the 10 nodes considered in the SPP system, and as a function of basis risk.

3.1. Alternative contract designs

Fig. 6a shows the performance of non-dominated solutions identified for each of the 10 SPP nodes under observed (historical) levels of basis risk. Each point represents a single alternative hedge design (i.e. a distinct set of 24 hourly wind power production targets, 2 (1 peak and 1 off peak) for each calendar month). The ideal point for a wind power producer would be the upper right corner (i.e., x = 1), indicating total revenues equal to the theoretical maximum (revenues with no hedge in place); and maximized improvement in the 10 worst-performing months (y-axis). The fact that no solution is able to achieve this means that, in examining their preferred hedge contract design, wind developers will need to balance their desire for increased revenues during the worst-performing months against total revenues. Note that there is considerable variation in the position and range of the tradeoff curves identified across nodes. For example, results for the node 'WFEC_MOORELAND_2' show that a maximum improvement of nearly $700,000 is possible for the 10 worst performing months, though the contract design that achieves this would cause a roughly 1.75% loss in total profits over the 5-year period, relative to the theoretical maximum (no hedge) (see black star in Fig. 6a). Comparing contract performance frontiers shown in

Table 3
Basis risk scenarios explored.

Scenario Name	Altered Basis Risk
No Basis Risk	0
Mean Zero 10	(B - μ)/(δ*(1–0.10))
Mean Zero 20	(B - μ)/(δ*(1–0.20))
Mean Zero 30	(B - μ)/(δ*(1–0.30))
Mean Zero 40	(B - μ)/(δ*(1–0.40))
Mean Zero 50	(B - μ)/(δ*(1–0.50))
Mean Zero 60	(B - μ)/(δ*(1–0.60))
Mean Zero 70	(B - μ)/(δ*(1–0.70))
Mean Zero 80	(B - μ)/(δ*(1–0.80))
Mean Zero 90	(B - μ)/(δ*(1–0.90))
Mean Zero	B - μ
Standard Normal	(B - μ)/δ
Observed	Observed Basis Risk

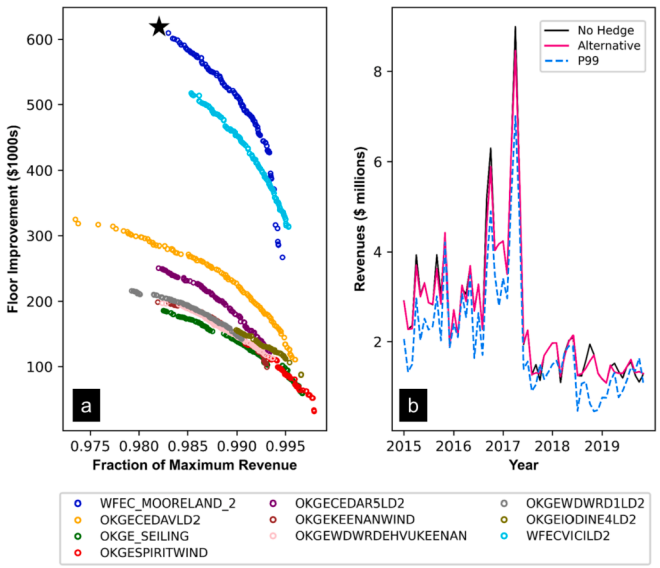

Fig. 6. a) Comparison of tradeoffs between profits (measured as a fraction of theoretical maximum) (x-axis) and "floor improvement" ($) (y-axis) for each SPP node considered; b) Monthly revenues for the wind power producer at the WFEC_MOORELAND_2 node with hedging (orange), without hedging (blue), and with the P99 hedge (green) under the maximum floor improvement solution, resulting in a roughly $600,000 increase over the 10 worst-performing months. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 6a, we find that nodal sites with the poorest floor improvement (e.g. 'OKGEIODINE4LD2,' 'OKGESPIRITWIND,' 'OKGEWDWRD1LD2') are generally the locations that have the lowest prices relative to the hub in our study time frame. The nodes 'OKGEWDWRD1LD2' and 'OKGEWDWRDEHVUKEENAN_WIND' also exhibit relatively low correlations with hub prices (see Fig. 4). These nodal price conditions disrupt the ability of the hedging contracts to improve performances during low revenue months due to basis risk.

Fig. 6b shows the performance of this same contract design over the 5-year simulation period (60 months), with revenue improvement occurring during a handful of low performing months. With no hedge in place, wind developer revenues calculated for the 'WFEC_MOORELAND_2' node show elevated monthly revenues until a major spike in April 2017; after that revenues fall low and remain persistently so throughout the rest of the simulation period. These revenue fluctuations for the wind power producer are directly correlated with spikes in nodal prices during this time frame (see Fig. 3). Average monthly prices at 'WFEC_MOORELAND_2' average around $33/MWh over the 5-year period, with average monthly prices above hub prices for much of 2016–2018, spiking to roughly $90/MWh in April 2017 (Fig. 3). Throughout the remainder of the study period, the average price at the 'WFEC_MOORELAND_2' node hovers around $20/MWh, which explains the depressed monthly revenues seen in the second half of Fig. 6b.

Note that with the hedge in place, the overall structure of these revenue dynamics remains mostly unchanged compared to conditions with no hedge in place, with small increases during low performing months (contract payouts from the hedge provider to the wind developer), which are offset by slightly larger decreases during high performing months (payments from the wind developer to the hedge provider). Although improvements are modest compared to conditions with no hedge in place, the alternative hedge design compares very favorably to a traditional P99 contract, which negatively impacts financial performance across nearly every month in the 5-year period. The use of a P99 contract over the period 2015–2019 in the SPP market would have resulted in a considerable financial loss for a wind power producer (yielding total revenues 25–30% lower than if they had not hedged at all). At the same time, there is no evidence that the use of a P99 fixed volume swap would protect the wind power producer from low revenue months; in fact, it reduces the revenue floor by nearly $1 million in the worst performing month. The comparatively poor performance of the P99 contract is a phenomenon we find to be consistent across every node considered. Fig. A2 in the Appendix shows similar information to Fig. 6b for the remaining nine nodes, with hedged revenues reflecting performance under an alternative contract that maximizes floor improvement.

We also explore the underlying structures of alternative hedging contracts identified and compare these alongside a traditional P99 contract. Fig. 7 shows the monthly peak and off-peak wind production targets for the alternative fixed volume swap contract designs that maximized the floor improvement at each node under observed basis risk. Uniformly, the alternative contract designs all involve hedging significantly lower volumes of wind power production than conventional P99 contracts. The heuristic manner in which hourly production volumes ($T(t)$ in Eq. (3)) are calculated in P99 contracts often does a poor job of tracking intra-day wind patterns, instead assigning peak- and off-peak targets as "blocks" that wind power producers must meet (see Fig. 5). This regularly create conditions where the quantity $max(T(t) - W(t), 0)$ in Eq. (3) is non-zero, triggering a need for the wind developer to purchase "make-up" power on the spot market to deliver to the hedge provider. Lower wind hours tend to be hours with higher nodal prices, and these purchases of make-up power can be expensive. Although less of the wind power production is hedged with the production volumes set lower, the alternative contract designs help mitigate some negative consequences of the widely known "shape risk" problem in P99 contracts (Lee et al., 2018).

Moreover, we find that in several months it would be beneficial to the developer to not to hedge at all. In general, our results suggest that in summer (when nodal prices tend to be high and wind production tends to be low), it is not advantageous for developers to cover large volumes of wind power production (if any) using fixed volume swaps. The strike price in the contract (S in Eq. (3)) is $22.64/MWh; this is lower than the hub price more often than not during summer months, meaning the contract disproportionately pays out to the hedge provider (the quantity $(S - HP(t)) * T(t)$ in Eq. (3) becomes negative). Thus, the alternative contract designs tend to minimize $T(t)$ during these months. An added advantage of hedging much lower amounts of wind generation during summer (or not hedging at all), is that the wind developer can avoid buying particularly expensive "make-up" power as a result of missing its hourly production targets. Instead, we find that the developer should concentrate on hedging wind production against low prices during the 2 or 3 months out of the year when wind production is high and hub prices

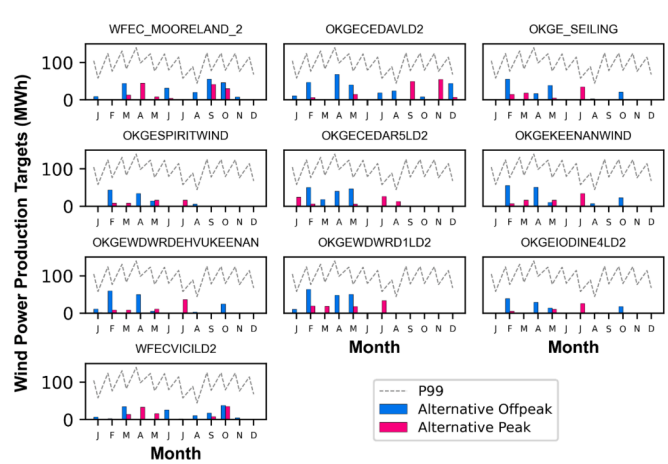

Fig. 7. Monthly wind power production targets ($T(t)$) identified for the maximum floor improvement contract design at each node, compared alongside targets specified by a conventional P99.

are low, i.e. Spring and Fall. Concentrating on hedging during these months allows the wind developer to more effectively protect against low prices, while avoiding paying exorbitant sums to the hedge provider.

We do notice important differences in the monthly hedge targets identified for each node; these differences are entirely due to differences in nodal prices, and they likely explain observed differences in the shape and position of the tradeoff frontiers shown in Fig. 6. For example, as noted above, the "WFEC_MOORELAND_2" node experienced a significant spike in its nodal price in April 2017 (see Fig. 3). If a hypothetical wind power producer engaged in a P99 fixed volume swap at this node simultaneously experienced lower than normal wind speeds (causing it to under-produce relative to the hourly targets specified in the contract), the wind producer would be required to purchase make-up power on the spot market at a very high price (Lee et al., 2018). Fig. 6b shows that the net effect on the wind producer's monthly revenues would be a loss of roughly $600,000, compared to conditions in which no hedge is in place. Figs. A3–A4 in the appendix also shows similar information to Fig. 7, but for every level of basis risk considered. In general, the wind power production volumes identified for the alternative contracts appear robust to changes in basis risk. When basis risk is altered in our experiment, the results show that the decision of whether or not to hedge may change, but the amount hedged changes very little across basis risk scenarios. If the wind producer does decide to hedge, the contract design with observed basis risk will likely resemble the contract design with no basis risk. No matter the level of basis risk, we observe that production volumes tend to be much lower than those suggested by the P99 contract, and typically concentrated in months that exhibit higher wind speeds and lower prices.

3.2. Sensitivity of performance frontiers to altered basis risk

Fig. 8 shows similar tradeoff frontiers as Fig. 6a, but for several selected basis risk scenarios. Note that contracts are re-optimized for each scenario (e.g. for any given node, new Pareto optimal wind power production volumes are identified for each level of basis risk considered). This assumption would approximate real-world conditions if the parameters of fixed volume swaps could be re-calibrated each year, for

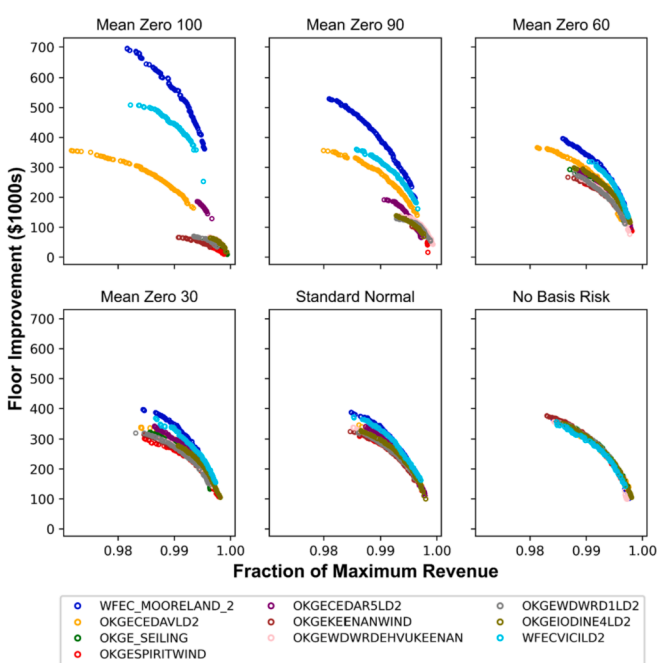

Fig. 8. Contract performance frontiers for each node across six selected basis risk scenarios.

example, to address gradual changes in basis risk (e.g. resulting from transmission upgrades). As basis risk is gradually decreased, ranging from "Mean Zero 100", "Mean Zero 90", to "Standard Normal" and "No Basis Risk" (hub prices = nodal prices), we see the nodal differences in contract performance frontiers collapse. In theory, a "No Basis Risk" scenario would occur if transmission constraints were eliminated across the system, allowing locational marginal prices to equalize across the grid (Goggin et al., 2018). These conditions would ensure that when the wind power producer experiences nodal prices below the contract strike price (S in Eq. (3)), the hub price also reflects these conditions and triggers a payout. Note however, that even if basis risk is eliminated, the maximum revenue improvement identified is on the order of $375,000 over the 10 worst performing months. As basis risk is diminished, some nodes (e.g. 'OKGEKEENANWIND') show higher upper bounds in revenue improvement. At the same time, other nodes (most notably 'WFEC_MOORELAND_2', which often exhibited higher average prices than the node) show reduced potential to improve revenue performance under lower basis risk, likely because this would entail lower nodal prices.

For several nodes, we observe some degree of threshold behavior in the position of the contract performance frontiers. For example, starting at the "No Basis Risk" scenario, and gradually adding more basis risk, the performance frontiers mostly retain their shape and position, though divergence across nodes increases. For some nodes, we find that allowing up to 70% or even 80% of mean adjusted basis risk still permits the position of the tradeoff frontiers to remain fairly stable across all nodes. The relatively robust performance of the fixed volume swap contracts at levels of basis risk below 70% for most nodes suggests that eliminating basis risk may not be necessary for the fixed volume price swap to perform at a near optimal level. Reducing the standard deviation of the difference between nodal and hub prices only 20–30% could substantially improve contract performance in many cases. In theory, this could come in the form of targeted transmission upgrades to reduce congestion in areas with large wind power penetration into the grid.

However, there is a tipping point beyond which basis risk appears to significantly worsen the tradeoff frontiers, at least in terms of maximum floor improvement (y-axis). For example, at 90% of actual basis risk, the floor improvement of the worst 10 performing months is cut in half for most nodes, relative to the No Basis Risk scenario, even as the cost (in terms of reduced revenues) remains the same. At "Mean Zero 100," floor improvement does not exceed $100,000 for most nodes, with the contracts appearing much less cost effective.

The results of our analysis also show that groupings of nodes react differently to changing basis risk. The two major groupings of nodes in the case of our study are those beginning with "OKGE" and "WFEC." The WFEC grouping of nodes actually increases floor improvement in higher basis risk scenarios. This grouping of nodes tends to experience significantly higher electricity prices compared to the OKGE grouping of nodes during the 5-year study period, even exceeding the hub price in March, April, and May, on average (see Fig. 4). The results of our model show that nodes with higher prices generally demonstrate higher maximum floor improvement through the use of fixed volume swaps – a somewhat unexpected result, given the designed purpose of the swaps to protect against periods of low prices. This phenomenon could be due to reduced levels of basis risk at higher priced nodes, which may allow the contract payments (which are triggered on hub prices) to more accurately reflect local price conditions.

Fig. A5 in the appendix shows similar information as Fig. 8, but with the contract performance frontiers grouped by node, instead of basis risk scenario. This provides an additional way to observe how gradual changes in basis risk may (or may not, in some cases) disrupt the performance of fixed volume swap contracts. For example, the shape and position of the performance frontiers at some nodes appears quite persistent (with contract recalibration), even as basis risk is dramatically altered. We also see the results differ by node family, with OKGE nodes generally showing increased maximum floor performance as basis risk

declines, while the WFEC nodes show the opposite.

The exception to this recommendation is in December during peak prices. In this month, the wind producer should hedge a significant amount of wind production with no basis risk, and gradually reduce the amount hedged as basis risk increases until the "mean zero 100" scenario, when they shouldn't be hedging at all. This experiment is a case in point that exposure to basis risk should not be the primary concern of wind power producer when designing hedging contracts.

4. Conclusions

Fixed volume price swap contracts pose financial difficulties for wind power projects due to both shape risk and basis risk (Lee et al., 2018). In this paper, we highlighted these deficiencies and proposed modest, achievable alterations that could improve the bottom line for wind developers, while maintaining expected revenues for hedge providers. Using hourly wind production, and hourly hub and nodal price data at a real, proposed wind farm, we identify alternative hedge targets that optimize revenue improvement in the 10 worst performing months as well as percentage of maximum profits to the developer. The takeaway from these experiments is that hedge contract designs can be restructured in way that allows the hedge provider to make an adequate return on investment, while preventing the wind developer from needlessly surrendering profits. This can mostly be done by being strategic about how, and when, wind power is hedged. In each month, our model generally recommends hedging far less than the P99 hedge targets, no matter the amount of basis risk.

Any analysis into the effects of basis risk, or shape risk, on hedge contract performance is highly location-based. This study analyzed 10 nodes in Northwestern Oklahoma in an area with a high prevalence of wind energy. A similar study done in another region of the SPP market with higher nodal prices may generate different results in terms of tradeoff frontiers of objective functions, as well as optimal hedge targets. Basis risk is pervasive across many regions of the grid, however, and the results of this study show that limited interventions in grid infrastructure can provide significant benefits to financial performance of wind projects. It is also important to note that other grid-enhancing technologies could be employed in lieu of expensive transmission upgrades that could free up interconnection of wind projects. Smart-grid technologies, such as routing electricity across the least-congested lines in the network, have been widely used in Europe and Australia, and have the potential to increase the interconnection capacity of wind projects in SPP given the right incentive structures (Tsuchida et al., 2021).

Follow-up studies exploring the implications of the joint planning and use of battery storage and hedging contracts with large scale wind power should be pursued. Design features such as battery sizing and depth of discharge could impact the choice of hedging strategies for large-scale wind projects. Short-term decisions about how the batteries are used, whether for frequency regulation or peak/off-peak arbitrage, may also affect the amount of wind production the project decides to hedge (Nasrolahpour et al., 2020). If the wind project is able to shift its production timing, this would likely have an effect on the optimal amount/timing of hedged production (He et al., 2016). Batteries may also help to alleviate the project's exposure to basis risk.

This study, and additional suggested areas of research exploring the intricacies of hedging financial risks for renewable energy producers, are needed by real-world practitioners to help mitigate investment risks in large scale renewable energy production. As energy markets evolve in the U.S., wind developers, and investors in wind energy, must continue adapt to these changes in order to realize a zero-carbon energy future. In the long run, issues of covariance risk and price suppression from low marginal cost renewable energy may force fundamental changes in wholesale markets in order to encourage investment in new renewable energy capacity.

Data availability

All data and code used in our analysis are publically available on Github at: https://github.com/romulus97/Zach_research/tree/master/repaperbatteries.

CRediT authorship contribution statement

Zachary Lucy: Formal analysis, Writing – original draft, Writing – review & editing. **Jordan Kern:** Conceptualization, Methodology, Writing – review & editing.

Appendix A. Appendix

Fig. A1 (top left) shows the cumulative density of prices ordered from least to greatest across 5 years. A significant element of this plot is the high density of instances in which prices go negative as well as the number of instances in which prices are extremely high.

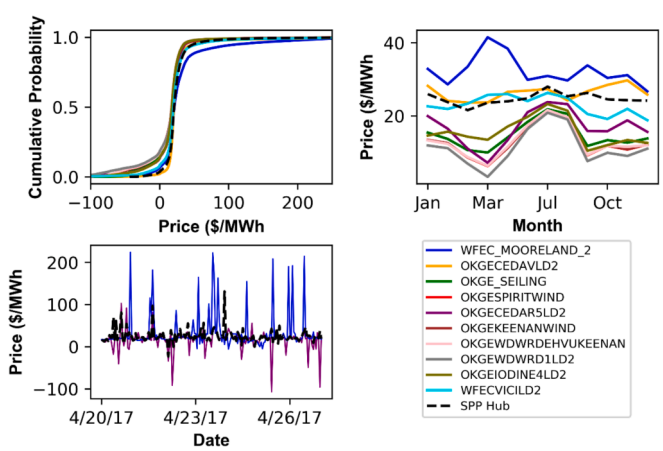

Fig. A1. a) Cumulative density plots of hub/nodal prices; b) monthly average prices over the 5-year period. c) disparity in prices between the hub and selected nodes for 10 days between 4/20/2017 and 4/30/2017.

Fig. A1 (top right) shows monthly prices for the hub and each node averaged across the 5-year period. This graph shows the typical seasonality in market prices, with certain months associated with lower nodal prices (April and September) and other months associated with elevated nodal prices (June, July, August); average hub prices remain remarkably stable across the year. Fig. A1 (bottom left) zooms-in to explore the dynamic nature of

basis risk for a few nodes, showing that the difference between nodal and hub prices can alternate between being negligible and very large.

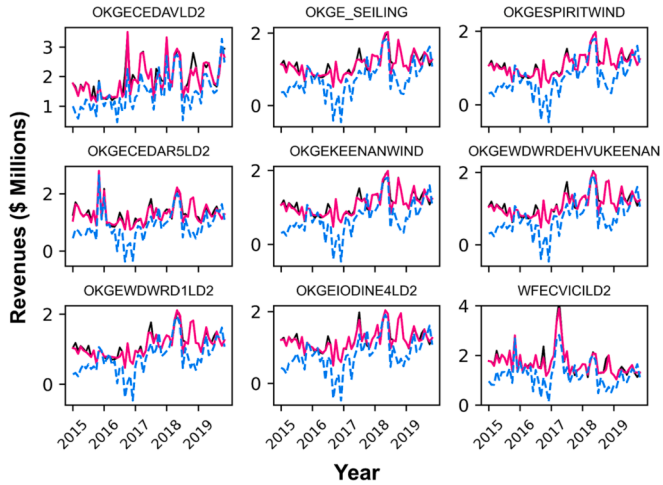

Fig. A2. Monthly revenues for the wind power producer at observed basis risk. A 'no-hedge' scenario is represented in black, with the blue dotted line showing the P99 contract and magenta showing alternative contract designs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

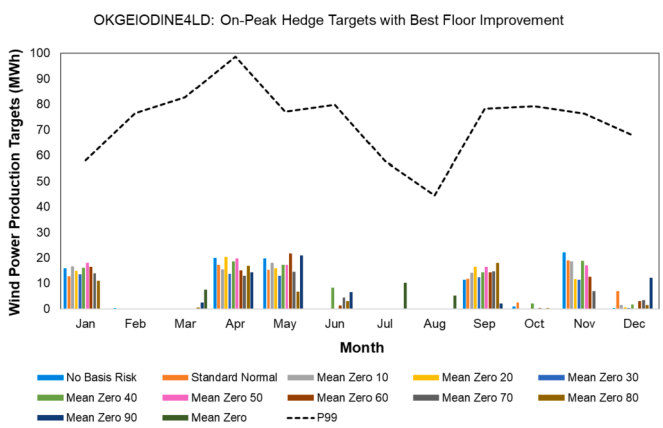

Fig. A3. Peak hour hedge targets under different levels of basis risk for OKGEIODINE4LD node.

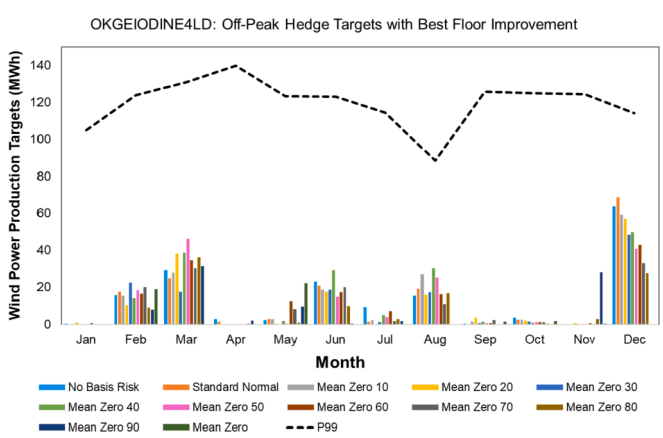

Fig. A4. Off-peak hour hedge targets under different levels of basis risk for OKGEIODINE4LD node.

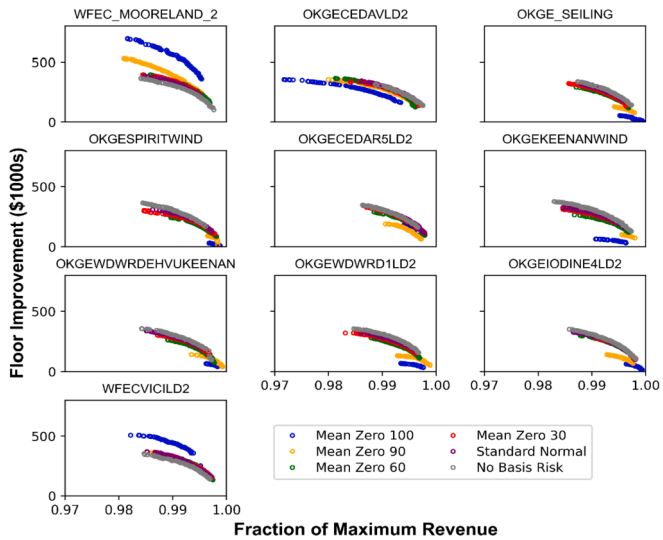

Fig. A5. Tradeoff frontiers at each node for several levels of basis risk.

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