Optimization of Wind Farm Design for Objectives Beyond LCOE

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Abstract. For wind farms that participate actively in electricity markets versus receiving a fixed kiloWatt-hour payment, design and operational objectives must go beyond the levelized cost of energy (LCOE) to account for system value and profitability of the farm over its lifetime. This work introduces "beyond LCOE" objectives for farm design and illustrates their impact in a multi-objective optimization case study for LCOE and value-based objectives. The case study shows that the best designs from an LCOE perspective are not those that have the highest value and vice versa. Thus, designing wind farms in the future will require new optimization approaches to address the broader system and market context to ensure overall profitability of the project.

1. Introduction

Wind farm design practice has evolved significantly over the last few decades. One key trend has been the adoption and proliferation in the use of formal optimization techniques at various stages of project development. Through the 2000s, most wind farms were designed using manual workflows that relied heavily on heuristics and the knowledge of experienced designers. Even as late as 2010, industry wind farm designers expressed distrust of formal optimization approaches for a number of reasons, for example: 1) most optimization capabilities focused only on annual energy production (AEP) as an objective and neglected key cost elements that drive the levelized cost of energy (LCOE)\(^1\), 2) accuracy of models for predicting farm AEP or costs were limited due to spareness of data and model uncertainties, and 3) practical design limitations due to permitting, exclusion zones, setbacks, and other requirements made the farm design problem so constrained that optimization was unnecessary [2].

However, a growing body of academic research at the time suggested potential benefits of applying formal optimization technique to be large. By 2010, already some 75 publications on the topic demonstrated potential gains in AEP and/or reductions in LCOE [3]. Coupled to this, the development of commercial capabilities for LCOE-driven wind farm design catalyzed

\[ LCOE = \frac{FCR \times CAPEX + OPEX}{AEP} \]  

(1)

where FCR is the fixed-charge rate that accounts for financing terms of the project. Other terms are described in the text.

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\(^1\) LCOE can be calculated using multiple methodologies. See Appendices B and C of [1] for a detailed breakdown of LCOE calculations with the basic equation.
broader adoption of optimization from 2010 through 2020.\textsuperscript{2} In particular, the community has developed capability for LCOE-based wind farm design optimization that includes key cost drivers and addresses key design constraints including:

- **AEP**: AEP is still a key driver of LCOE and a focus of ongoing research, e.g., to improve flow and wake model accuracy while increasing computational efficiency (see \cite{2} for discussion).

- **Capital Expenditures (CAPEX) for the Balance of System (BOS)**: The design of the electrical system (a key cost component) by itself is a challenging optimization problem \cite{5}. Other BOS costs such as roads (especially in complex terrain) have also been considered.

- **CAPEX for turbines and foundations**: Increasingly, sites with turbines of multiple hub heights or multiple turbine types show potential for reducing LCOE \cite{6, 7, 8} or in offshore sites with varied sea-depths and soil conditions \cite{9}.

- **Operational Expenditures (OPEX)**: While more difficult to assess, there is increasing interest in operational strategies to increase reliability and reduce OPEX \cite{10} or to address site suitability \cite{6, 11}.

For more detail on recent developments in wind farm design optimization see \cite{2}.

1.1. From LCOE to Beyond LCOE

While efforts continue in research and commercial software development to support LCOE-based wind farm design optimization, there are broader market trends and dynamics that are requiring the community to look "Beyond LCOE." LCOE has been a successful overarching metric in the past where, in many markets, wind farms received a constant unit of revenue for every kiloWatt-hour (kW-hr) produced. This was true in large part in the United States with power purchase agreements (PPAs) and in Europe with feed-in-tariffs (FITs); both of which provided secure revenue streams over the lifetime of the farm operation. The security of these price support instruments were valuable for accelerating large-scale development of wind energy in many countries \cite{12}. The resulting exponential growth in deployment also drove down LCOE to position wind energy to be competitive with other electricity generation technologies.

However, with shares of wind energy in many systems reaching tens of percent or more, not just the cost, but the value of wind energy to the electricity system becomes important. Large levels of variable renewable energy (VRE) resources in an electricity market and grid system will affect the dynamics of that market and system \cite{13, 14, 15}. This creates feedback effects on the value of wind energy in a given system and market context in multiple ways:

- **Energy markets (wholesale prices)**: In wholesale, or merchant, energy markets, increasing amounts of wind energy in a system leads to a negative-correlation of wind speed and price \cite{16, 17}. This can potentially be mitigated by combining VREs together \cite{18, 19}.

- **Energy markets (curtailment)**: Even with a PPA, curtailment may increase with more wind energy in the system (again which may be mitigated through storage) \cite{20}.

- **Energy markets (imbalance costs)**: There are often imbalance costs associated predictability of VREs. Such costs can be mitigated again through storage or aggregating together geographically dispersed assets with low-to-negative production correlation \cite{21}.

- **Capacity markets**: Wind energy can participate in some capacity markets throughout the world. However, the capacity value has historically been low \cite{22}. As more wind energy is deployed in a given market, there is also evidence that this depresses the capacity value for new entrants \cite{22, 23}.

\textsuperscript{2} This transformation is illustrated in the evolution of presentations in the biennial Wind Energy Systems Engineering Workshop \cite{4}.
Service markets: Ancillary service markets involve standby reductions or increases to supply to support basic grid reliability. There are very few regions where VREs can participate in these markets but, looking ahead, this is expected to change [13; 24].

In all of these markets, the timing of the generation, its predictability, and its dispatchability matter for how much revenue a wind farm can expect. Compounding this may be significant changes in market structure as VREs grow to 30-50% or more of a given system’s energy supply. Figure 1 from [15] and based on [13] illustrates how the share of revenue may shift from energy markets to capacity and service markets in future high-VRE systems.

![Figure 1](image.png)

**Figure 1.** Illustration of how the make-up of electricity markets may change from the 20th century, energy dominated model to a 21st century model where capacity and service markets provide the largest sources of revenue [15].

Looking ahead, there is a growing recognition that project developers need to look beyond LCOE to objectives that take into account the changing dynamics of high-VRE electricity grid systems and their impacts on the revenues the farm will achieve throughout its operational lifetime [14; 15; 25].

However, as revenue depends on a system context that is uncertain and evolving, assessment of wind farm profitability within a design optimization context presents a significant challenge. As a result, efforts to develop metrics that capture these more sophisticated market dynamics while being simple enough to support physical design of wind (and other VRE) technologies and projects are needed.

In this study, multi-objective optimization is performed to assess the trade-off between LCOE (the traditional objective for wind farm design) against a value-related objective of capacity factor. The impact on the wind farm design is explored as well as the extent to which objectives of LCOE and value-driven objectives push the farm design in different directions.

In section 2, an overview of the metrics is provided along with considerations of the problem formulation for wind farm design optimization based on the different metrics. In section 3, the impact of the metrics on wind farm design in a simplified optimization case study is presented. The work concludes in section 4 that value-related objectives will result in different wind farm designs than those minimize the LCOE. Looking ahead, this may indicate a shift in how wind farms are designed - from minimizing cost of energy to maximizing system value and profit.

2. Shifting from LCOE to Value-based Objectives in Wind Farm Design Optimization

One of the most attractive features of LCOE as a design objective is that it does not require addressing the market context for a wind farm. Any metric going beyond LCOE will need to address not only the resource but also the market context. Simpson et. al. laid out an approach
to better capture the time-varying value of wind energy in merchant markets [25]. Beginning from larger system-wide assessment metrics used by economists and system planners, two new metrics were defined for the Cost of Valued Energy (COVE) and LACEs (simplified Levelized Avoided Cost of Energy)).

As shown in Fig. 2, the elements that make up system LCOE (sLCOE) and revised system LCOE (rsLCOE) are depicted along with subsets that make up LCOE as well as Levelized Avoided Cost of Energy (LACE). Note that for sLCOE and rsLCOE, simulation not just of the VRE power plant, but the full system is required with endogenous relationships between them. In Fig. 3, the new metrics proposed in [25] for COVE and LACE-simplified (LACEs) are depicted that depend mainly on the VRE characteristics and the energy demand in a region.

**Figure 2.** Illustration of different metrics for assessment of wind farms from an electric system market perspective as shown in [25] (sLCOE, rsLCOE and LACE).

**Figure 3.** Illustration of different metrics for assessment of wind farms from an electric system market perspective as shown in [25] (COVE and LACEs).

These new metrics, COVE and LACEs, provide a simplified way of accounting for the time-varying nature of energy prices to more accurately assess profitability of wind farms operating in wholesale/merchant markets that is also tractable for design optimization of individual wind turbines and/or full wind farms. Details for calculation of COVE can be found in [25] but
the key contribution of the metric is establishing a relationship between the level of wind in a system, residual demand, electricity prices and therefore revenue.

2.1. The Wind Farm Design Optimization Problem Beyond LCOE

Wind farm design can be optimized for AEP, LCOE, value-based objectives such as COVE, LACEs, or any other user-defined objective. In 2018, a team of 75+ wind energy researchers from across the globe explored wind turbine and farm design innovations that could either reduce LCOE or increase the system value of wind energy [15]. In many cases, the innovations suggested for increasing system value would also increase LCOE - illustrating a potential trade-off between LCOE and value-objectives. An extract of these innovations relevant for wind farm design are presented in Table 1 along with their expected impacts to LCOE and value.

In addition, while these design choices are focused on the farm design (pre-construction), they may include features related to underlying turbine design as well as the operational/control strategy of the farm (post-construction). Other choices that a farm developer can make that are broader than the single farm level (e.g. geographically dispersed assets) or go beyond electricity markets (e.g. power-to-x, desalination) are excluded.

| Design choice | Description | Value Impact | LCOE Impact |
|---------------|-------------|--------------|-------------|
| High capacity factor turbines | Low specific power machines approaching and below 200 W/m² | Increased COVE | Increased CAPEX per MW rated capacity |
| Low-wind-speed turbines | Low specific power machines that also cut out at lower wind speeds | Increased COVE | Decreased AEP per MW rated capacity |
| Overplanting: number of turbines | Farm rated capacity less than sum of turbine rated capacity | Increased COVE and capacity value | Increased CAPEX and OPEX per MW rated capacity |
| Overplanting: operational strategy | Derate turbines in regular operation for increased dispatchability and predictability | Increased COVE, capacity value and service value | Decreased AEP per MW rated capacity |
| Added sensing | Additional sensing (remote sensors, meteorological towers, etc) deployment | Reduce imbalance costs, increase energy value through more accurate bids | Increased CAPEX and OPEX of sensing equipment |
| Hybridization | Incorporate solar, storage or other technologies for a hybrid VRE power plant | Increase COVE, capacity value and service value | Increased CAPEX and OPEX for additional technology |

Table 1. Innovations in wind farm design to improve system value.

Looking at Table 1, it is obvious that all of these design choices could be combined into a single farm design. Recent work has illustrated the opportunity of including multiple turbines with varied hub heights and rated powers in a single wind farm even from an LCOE perspective [6; 7; 8]. Here, we are considering mixing turbines to increase the overall farm value and profitability. Low specific power and even low-wind turbines [26] can produce more power (compared to a high specific power machine of the same power rating) at lower wind speeds which are often correlated with higher electricity prices in systems with high shares of wind energy. However, this comes at a cost to LCOE since, in the case of low specific power, the
machines will likely either have higher CAPEX per unit rated power (since CAPEX tends to scale with the rotor swept area), or in the case of low-wind, the machines will have a lower AEP per unit rated power since their cut-out wind speeds are lower to reduce CAPEX [26].

Overplanting through either increased turbine number or operating with a lower plant capacity than the sum of the rated power of the individual machines are similar strategies for improving the predictability and dispatchability of wind energy for increased system value. Traditional thermal power plants (especially natural gas plants) expect to regularly operate below rated conditions. While this certainly increases LCOE for a wind farm (either increasing CAPEX through additional turbines or reducing the AEP per turbine from derating), the potential system value can be increased.

Investment into sensing technologies, commercial data sets, forecasting modeling capabilities is part of the overall wind farm design problem since often, decisions related to sensing deployment are part of the pre-construction development process. This investment comes at an increase in LCOE in terms of CAPEX and OPEX but may increase AEP and/or reduce LCOE through improved feedforward-control capabilities. Improved forecasting will reduce imbalance costs associated with production forecast errors.

Finally, hybridization is similar to overplanting in terms of improving the dispatchability and predictability of energy generation from the assets, but instead uses the anti- or inverse-correlation of production from multiple generation technologies together (with or without storage). See [19] for a detailed review of potential for hybrid power plant design optimization.

3. Case Study in Wind Farm Design for Value-Based Objectives

Having explored the pathways and metrics for designing a wind farm to perform well in a "Beyond LCOE" world, a simple case study in farm design is introduced to look at a Pareto front of LCOE versus capacity factor (CF) as a proxy for capacity value – with an outlook towards additional objectives such as COVE and others.

3.1. Case Study Description: IEA Wind Task 37 Optimization Case Study 1

The case study here uses the IEA Wind Task 37 optimization case study 1 wind farm as described in [27]. The wind farm for the baseline analysis consists of 16 IEA Wind 3.4 MW reference turbines [28] in a circular wind farm of radius 1300 m. The wind rose is bi-modal wind rose as shown in Fig 4. As described in [27], the design landscape is highly multi-modal and optimization for energy production can converge to many AEP-optimized local optima.

![Figure 4. IEA Wind Task 37 wind plant optimization Case Study 1 wind rose as shown in [27] along with the initial layout for the 16 turbine case.](image-url)
3.2. Case Study Results: Capacity Factor versus LCOE

For the case study, value-enhancing design strategies from Table 1 are chosen, including the use of overplanting (via number of turbines), low specific power turbines, and varied hub heights, and used to explore a multi-objective optimization of capacity factor versus LCOE.

To calculate LCOE, the CAPEX breakdown in [29] is used including the different contributions of tower, rotor, and drivetrain along with additional BOS and financing costs. The tower cost is modified as a function of hub-height based on [30] and non-electrical components are penalized in cost using a rotor loading penalty with increasing rotor size using the square-cubed law (assuming each size turbine incorporates the latest available innovations). The rest of the LCOE is based on [29] for land-based wind farms.

The case study included hub heights of 80, 100, and 120 m, rotor diameters of 120, 130 and 140 m, and turbine numbers ranging from 8 to 24 in steps of 4 with the assumption of turbine overplanting of 4 turbines for each case (the resulting LCOE for all cases is thus higher than a conventional wind farm). A Particle Swarm Optimization as in [9; 31] with minimum distance constraints of 2 rotor diameters between turbines was used. AEP for each configuration was optimized through placement of turbine positions. For simplicity, the impact of layout on BOS was neglected so that LCOE is independent of the resulting layout designs. The resulting Pareto front for the designs is shown below in Fig 5.

The LCOE for the cases ranged from 0.028 to 0.065 $/kWh and the capacity factor ranged from 0.30 to 0.85. In all cases the overplanting increased the LCOE relative to the baseline since CAPEX was increasing while AEP was limited by the rated capacity of the plant. Conversely, capacity factor for the overplanting cases increased since overall wake losses in the overplanting cases dropped considerably. The Pareto optimal designs from the full design sweep are provided in Table 2.

The Pareto optimal designs included plants of various sizes all with the maximum hub height of 120 m. For the study, it was assumed a large-diameter steel tower was used so that the mass profile of the tower is fairly linear as in [30]. Thus, the higher hub heights generally led to greater capacity factor and lower LCOE. Overall, the interplay of sensitivity around wind shear and the resource as well as scaling effects for turbine hub height and rotor size can potentially affect the results. This indicates that the details around technology options and resource conditions for a particular site will heavily influence the Pareto front results.

Notably, overall the Pareto design set did not include any 24 turbine plants and only one of the 20 turbine plants. Figure 6 shows Pareto optimal designs for the 12, 16, 20 turbine cases as well as one 24 turbine case to illustrate the relative density. Generally, for the layouts with

![Pareto front of capacity factor versus LCOE for the design optimization including overplanting, low specific power and varied hub height.](image-url)
| Turbine Number | Hub Height | Rotor Diameter | LCOE ($/kWh) | CF  |
|---------------|------------|----------------|--------------|-----|
| 8             | 120        | 120            | 0.036        | 0.77|
| 8             | 120        | 130            | 0.039        | 0.81|
| 8             | 120        | 140            | 0.043        | 0.85|
| 12            | 120        | 120            | 0.028        | 0.73|
| 12            | 120        | 130            | 0.032        | 0.75|
| 12            | 120        | 140            | 0.035        | 0.78|
| 16            | 120        | 120            | 0.035        | 0.78|
| 16            | 120        | 130            | 0.034        | 0.73|
| 20            | 120        | 130            | 0.031        | 0.64|

**Table 2.** Innovations in wind farm design to improve system value.

smaller turbine number, the turbines spread out further in the vertical direction to decrease wake losses in the highest frequency inflow direction from the west. For the 20 and 24 turbine cases, the high density of the turbines increased the overall wake losses and limited the performance of these designs in terms of both capacity factor and LCOE (via AEP). These wake losses were significant even with overplanting where not all turbines would be expected to operate at the same time. This could limit the viability of overplanting strategies for projects that are constrained on land availability.

![Figure 6. Best layouts out of 100 run for each of 12, 16, 20 and 24 turbines with 120 m rotor diameters at 120 m hub heights.](image)

**4. Conclusions**

This study explored the impact of ”beyond LCOE” metrics on wind farm design optimization. Value-based metrics including COVE (for energy markets) and capacity factor (for capacity markets) were compared to traditional design metrics of AEP and LCOE. In a simple case study, a Pareto-front of designs optimizing for capacity factor and LCOE was developed to compare how underlying design drivers of hub height, specific power and overplanting influenced each metric. Pareto-optimal designs were found that leveraged overplanting in particular to increase capacity factor at the expense of LCOE.

This work presents only a preliminary look at what is likely to become a significant area for research in wind farm design for objectives beyond LCOE. Many opportunities for future work exist, such as: 1) expansion of the problem scope and complexity for a more realistic wind farm design application (including BOS, loads and reliability, etc), 2) investigation of additional innovation pathways including wind farm control strategies, hybrid power plants, mixed-type turbines, etc, and 3) design optimization for a range of metrics including COVE and others in a variety of market and system contexts. Through such efforts, designers can increase value wind farms, ensure their profitability, and ultimately continue to make wind energy competitive in energy markets across the world.
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