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WIND ENERGY SCIENCE DISCUSSIONS

A Decision Support System for the Continuous Economic Evaluation of Wind Farms

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Abstract

This paper presents a decision support system that integrates digital twin technology with advanced economic evaluation tools to enable continuous and holistic assessment of wind farm investments. The framework combines real-time turbine health data, including remaining useful life estimates derived from SCADA and condition monitoring systems, with financial models employing discounted cash flow, scenario testing, Monte Carlo simulations, and real-options valuation. Implemented through the open-source DigiWind platform, the system adheres to FAIR data principles and provides a flexible, interoperable environment for asset management. A case study on an 8 MW wind turbine in Germany demonstrates the framework's ability to guide decisions such as life extension, repowering, decommissioning, or sale under volatile market conditions. Results highlight the importance of coupling technical reliability forecasts with market-based financial outlooks to capture both risks and upside potential, offering a scalable and transparent tool for investors, operators, and policymakers navigating the evolving wind energy sector.

Keywords: *Wind Farm Valuation, Real-Options Valuation, System Integration, Data Management, Feed-in Tariff, Decision Support System, Digital Twin*

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Nomenclature

AEP	Annual Energy Production
BPMN	Business Process Modelling Notation
CAPEX	Capital Expenditures
CF	Capacity Factor
CMS	Condition Monitoring System
DCF	Discounted Cash Flow
FAIR	Findable, Accessible, Interoperable, and Reusable
IEA	International Energy Agency
L	Lifespan of Turbine
MC	Monte Carlo
MDP	Markov Decision Process
MQTT	Message Queuing Telemetry Transport
OPEX	Operating Expenditures
PSP	Power Sale Price
P(x)	Probability of a Future Event Occurring
RECs	Renewable Energy Credits
RUL	Remaining Useful Life
ROV	Real-Options Value
SCADA	Supervisory Control and Data Acquisition
S	Standard Deviation
σ	Variance

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

1. Introduction

After its first 20 plus years, the megawatt class of commercial wind moves into a next generation that is contending with two emerging issues: (1) wind farms are shifting from purely energy-generating assets to tradable financial commodities, while the methods used to evaluate them have not progressed (Boyd, Karimirad, Sivakumar, Jalilvand, & Desmond, 2022) (Morthorst, 1999), and (2) wind portfolios are growing to gigawatt-scale sizes, yet fleet- and data-management have not kept pace (Clifton, et al., 2023). This paper addresses these challenges by linking two proven frameworks: a digital twin model that integrates day-to-day operational data with remaining useful life (RUL) estimates, and a decision support model that connects this data to long-term economic outlooks.

The transition to larger wind fleets introduces new challenges in performance monitoring, predictive maintenance, and resource allocation, as operators now must address varying needs of each turbine in an expansive, yet dynamic environment (Leahy, Gallagher, O'Donovan, & O'Sullivan, 2019) (Pandit, Astolfi, J., D., & M., 2022). These complexities are amplified by external factors, such as changing grid codes and new evolving technologies, all of which demand integrated data management systems (Hameed, Vatn, & Heggset, 2011). As the industry continues to scale, flexible but scalable integration platforms are essential to manage these complexities.

As fleets grow, it also becomes essential to understand the health of each turbine. Advances in reliability engineering have improved predictions of RUL for turbine components (Hung Do & Söffker, 2021). Techniques combining SCADA (Supervisory Control and Data Acquisition) and condition monitoring system (CMS) data with data-driven models are becoming more common; deep learning models are especially promising due to their ability to process complex, nonlinear time-series data (Shah, Daoliang, & Kumar, 2024). Traditionally, physics-based and data-driven approaches have been independent but recent research has begun to combine them into physics-informed models (Saathoff, Rosemeier, & Rathmann, 2021), with a key implementation being physics-informed neural networks (Yucesan & Viana, 2020).

Better RUL predictions have enabled more strategic maintenance planning, helping to reduce operational costs. However, this does not fully reflect the current economic context. Wind farms are now being traded as financial commodities, with revenues linked to dynamic market conditions – including electricity prices, Renewable Energy Credits (RECs), carbon pricing, and capacity markets (Schwabe, Feldman, Settle, & Fields, 2017). Their long-term value also depends on broader economic trends, as institutional investors increasingly view wind assets like traditional civil infrastructure investments (i.e. toll highways) (Khurshid, Irfan, & Labi, 2021) (Lacal-Arántegui, Uihlein, & Yusta, 2020) (Waheed, Hudson, & Haas, 2013).

Despite these changing operational and economic conditions, existing decision support tools mostly focus on short-term operations or layout optimization; they fail to integrate RUL predictions with long-term economic outcomes. (Arbaoui &

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

Asbik, 2010) (Bourhim, Berrhazi, Ouammi, & Benchrifa, 2021) (Stefanakou, Nikitakos, Lilas, & Pavlogeorgatos, 2019) (Hietanen, Snedker, Dykes, & Bayati, 2024) . This creates a gap in end-of-life planning, leaving asset owners unsure whether to extend, repower, decommission, or sell – especially in a changing market.

The digital transformation in wind energy, through digital twins and decision support tools, presents an opportunity to bridge this gap – offering both operational connectivity and long-term planning capabilities (Stadtmann, et al., 2023). However, this adoption is restricted by challenges like data inconsistency, lack of standardized platforms, and regulatory issues around data privacy and cybersecurity. As Clifton et al. (2023) note, many of these challenges stem from the lack of FAIR (findable, accessible, interoperable, reusable) data frameworks. Without clean and consistent data, it's difficult to apply predictive models or gain trust in digital tools (Clifton, et al., 2023). A lack of a clearly demonstrated use-case also limits early adopters.

One initiative addressing these challenges is the DigiWind platform developed by Fraunhofer IWES (Wiens, et al., 2024). DigiWind provides the building blocks to integrate SCADA and CMS data into a unified system, breaking down data silos that make turbine health difficult to assess. The foundation supports the use of digital twins and economic models, enabling a shift from reactive to proactive long-term asset planning.

While RUL models provide more accurate predictions at the component level, their value is limited if not connected to market-based decision making. A flexible tool is needed to combine RULs with economic forecasts for informed long-term planning. A model previously developed by Kerr & Carriveau does this by integrating RUL estimates and historical annual energy production (AEP) data into a financial framework. It uses traditional project finance tools, ie. discounted cash flow (DCF), alongside advanced methods like scenario testing, real-options analysis, and Monte Carlo (MC) simulations to support informed investment decisions.

This paper builds on those efforts by combining two proven processes:

1. A publicly available digital twin platform that integrates SCADA and RUL models (Wiens, et al., 2024), and
2. An economic decision support tool that translates operational data into long-term financial outcomes.

Together, these tools create a holistic framework for investment decision-making. This project builds on the work of the IEA Wind Task 43 Wind Digitalization working group, which highlighted digital twins as a core component of future decision support systems.

2. Methodology

The digital twin platform and the economic decision support platform were integrated, and the functionality will be highlighted through a case study in Section 3. The steps and components for integration are outlined below:

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

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2.1 Digital Twin Framework

The digital twin framework "DigiWind" (Wiens, et al., 2024) creates a platform to build digital twins and decision support systems for the wind energy industry. The framework provides a foundation for a wide range of microservices, or processes, which perform specific tasks like retrospective evaluations, performance monitoring, and scenario-modelling. The framework relies on an input, a desired task (or process), and an output which is common practice in systems integration. Each process (or, service) in the framework is independent. Communication between processes is enabled by Message Queuing Telemetry Transport (MQTT), which is embedded in a Docker[1] environment. The processes were arranged in a workflow model in the Business Process Modelling Notation (BPMN), providing clearer documentation and seamless integration. The system includes an integrated knowledge base and simulation model versioning to enable automation, documentation, and reproducibility of results.

2.2 Remaining Useful Life Calculation

The DigiWind platform was expanded to incorporate the economic evaluation model as a new process. First, an existing process was used to calculate the RUL of a single turbine. A surrogate model is used to calculate the RUL of each component, which was completed using the methodology described in (Requate, Meyer, & Hofmann, 2023). Environmental conditions (wind speed, turbulence intensity, and wind direction) are mapped to damage increments for 10 min interval to adhere to SCADA standards. The damage increments are computed from the rain flow counting method, an established methodology in reliability engineering. In the case of partial operation, the damage increments of the 10-min interval are scaled accordingly. A simple workflow of the RUL service is depicted in Figure 1.

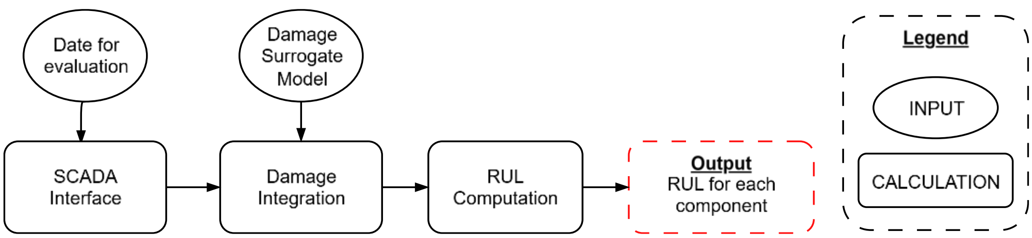

Figure 1: Process for RUL estimation

The current date is the starting date for the RUL estimate. All required environmental conditions are pulled from the SCADA database into the interface. The RUL estimate is then calculated by integrating the damage estimates (scaled to the full lifetime). The outcome of the RUL service can be a single value for the RUL or the complete trajectory, as shown in Figure 2.

[1] Docker is a software to build, ship, and run applications in a lightweight environment.

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

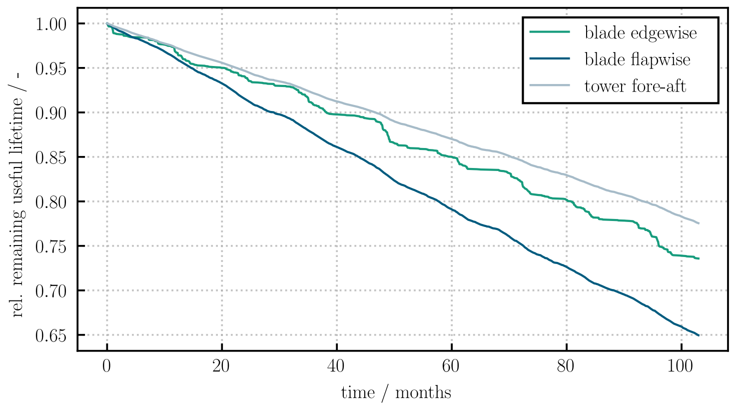

Figure 2: RUL curves for various components of a wind turbine

An RUL trend is provided for each component. The shape of the progression can be non-linear, as shown by the edgewise blade RUL trend. In this example, the degradation of the blade is the fastest, which could trigger a replacement of the blade mount. The economic decision model, incorporated as a service, extrapolates the RUL trends to determine the replacement year for the component. By combining the unique trends for each component, a holistic view of the asset can be created.

2.2 Economic Decision Support Framework

This section describes an economic decision support framework designed to provide realistic and flexible outlooks for wind assets. Historically, major investment decisions (whether to repower, maintain, decommission, or sell), have often been made without a full understanding of the long-term risks. Informed decision making requires bridging the gap between an assets current state of health and future market conditions.

An economic evaluation model was developed by the authors (Kerr & Carriveau). The purpose of the economic model is to link potential market futures into the asset valuation and decision-making process, concepts that are typically not combined. The model uses inputs from the digital twin, such as SCADA data and RULs, along with market conditions to build an economic forecast. While rooted in traditional project finance tools like DCF analysis, the framework builds upon them with advanced methods like scenario testing, Real-Options valuation (ROV), and MC simulations to capture market uncertainty. The model outputs key financial metrics (e.g. NPV), probabilistic curves, and scenario-based recommendations. The framework is also ripe for future expansion, with the potential to incorporate tools like Markov Decision Processes (MDPs) to adapt to changing conditions over time. The economic evaluation model integrates with the DigiWind platform, creating an automated data pipeline. The structure of the underlying economic evaluation model is shown in Figure 3.

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

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Figure 4 outlines the framework's logic, detailing data inputs (circular nodes), user interventions (diamond nodes), and calculations (rectangular nodes). The key integration with the DigiWind platform occurs at the "RUL Data" and "Turbine
135 Data" nodes. These nodes create an automated pipeline, feeding turbine health and operation data into the economic model.

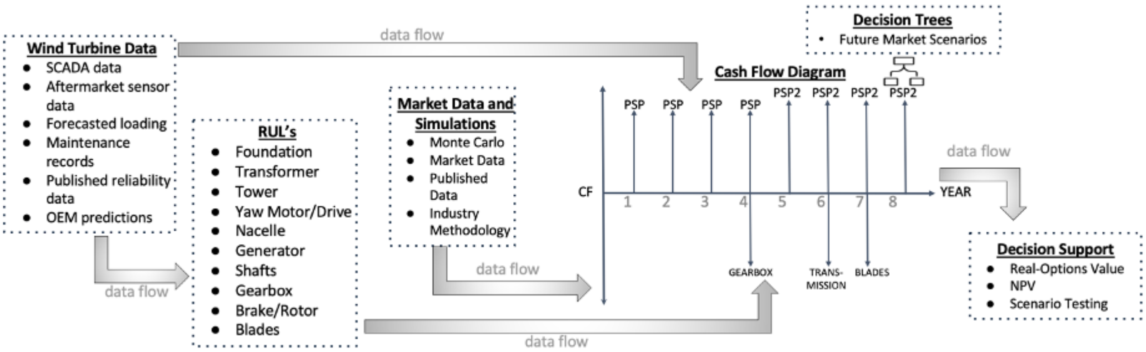
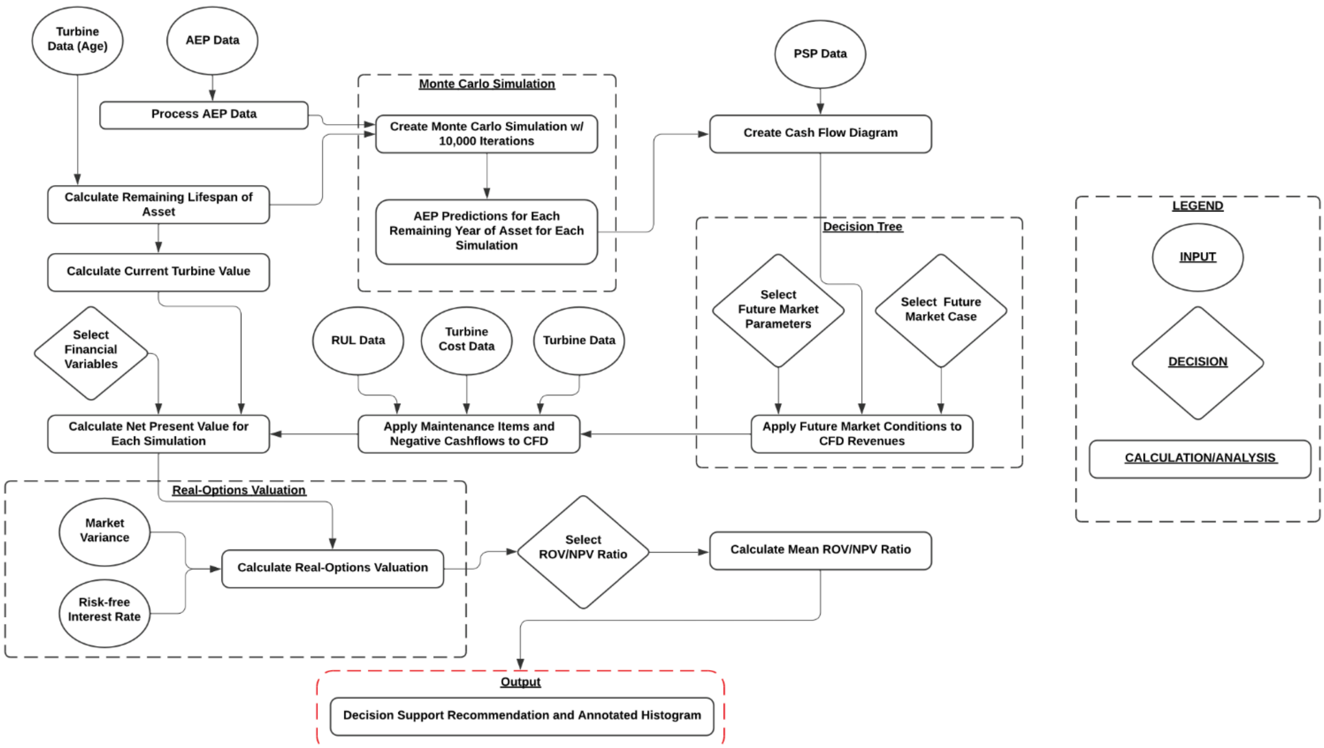


Figure 3: Proposed Decision Support Framework



140 **Figure 4:** Economic Model Methodology

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

2.3 Integration of the Models into the Framework

First, the economic decision framework (described in Section 2.2) is integrated as a new service in the DigiWind framework according to Section 2.1. When the MQTT interface receives a message, the respective evaluation program is run (i.e. RUL calculation, economic model, etc.). All necessary data points must be included for the economic calculations. An ontology was used to describe and document how the application services interact, including their required inputs and outputs. The process was contextualized in the digital twin framework through a WESgraph (Quaeghebeur, Sanchez Perez-Moreno, & Zaaijer, 2020) in Figure 5. This ontology can be utilized for describing physical or computational aspects explicitly in a machine-readable manner.

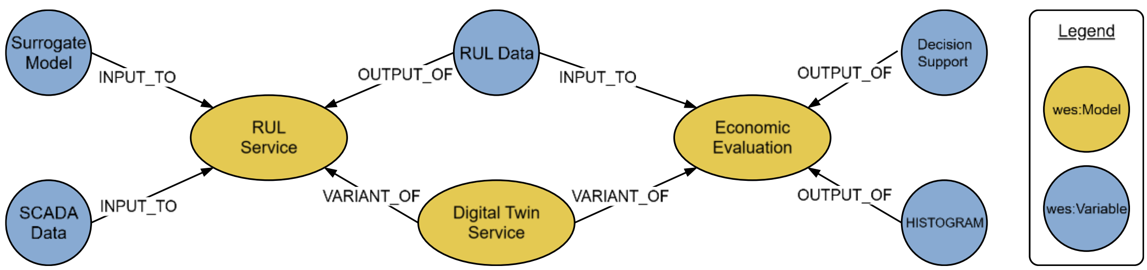


Figure 5: Application of the WESgraph to Annotate the Microservices and Their Interfaces

Blue nodes refer to the *variable* concept of the WESgraph, which practically refers to an input or output. The yellow nodes refer to the *model* concept from WESgraph, which relates to a model (i.e. RUL, economic, digital twin). As seen above, each model requires at least one input. Even as requirements get more complex, this allows the services to remain consistent. This ensures that the digital twin integration meets the FAIR data principles. SPARQL queries, like the one in Listing 1, can be used to apply the ontology above.

Listing 1: Example of SPARQL query to infer compatible services from the ontology

```
PREFIX wes: <http://www.semanticweb.org/batman/ontologies/WESgraph#>
PREFIX : <http://www.iwes.fraunhofer.de/digiwind#>
SELECT ?start ?end ?variable WHERE {{
        ?variable wes:inputToModel ?end .
        ?end wes:variantOfModel :DigitalTwinService .
    } OPTIONAL {
        ?variable wes:outputVariableOfModel ?start .
        ?start wes:variantOfModel :DigitalTwinService .
    }
   ?variable wes:outputVariableOfModel ?start .}
```

The query identifies services that are connected by the same variable, which links outputs from one service that may be an input for another. This process helps formalize the structure of the system, while documenting any required interactions. The integration of the RUL and economic evaluation model can be described through a BPMN diagram, seen in Figure 6.

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

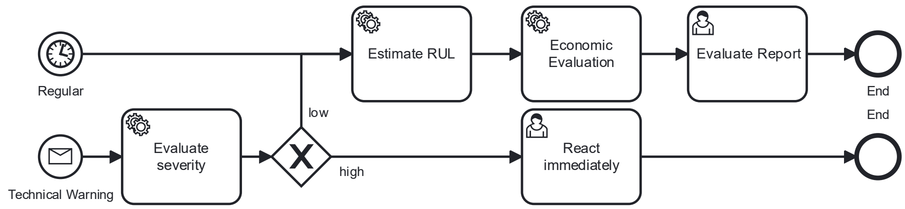


Figure 6: Workflow of the system (generic integration: data streams from the database are excluded)

The sequential steps of the decision support system are presented across the top level. Two triggers for the process are given in the left side of the diagram. A "regular event" means that the evaluation is run on a set schedule, whereas the "technical warning" run is triggered when a technical trigger is reached. The diagram then contains automated and manual tasks, indicated by a gear and a human, respectively. This process is integrated through the transfer of messages. The process is started when a message arrives, and results are added to an outgoing message. This allows for the DigiWind platform to calculate the RULs, and send them to the economic evaluation model, which requires a RULs input.

3. Case Study

The DigiWind framework and the economic evaluation framework were combined to create an investment decision support system. A case study was created to highlight the value of the integrated system.

Germany was selected as the location for the case study. Germany has struggled in recent years with volatile energy prices; one consistent source of energy, while intermittent, have been renewable sources. The German market employs a minimum cap price, or feed-in tariff, to incentivise the development of renewable assets. While this is beneficial for the short-term outlook of an investment, it creates a risky scenario where the cap price could change over time and lower future revenue. This creates caution among investors, and often confusion regarding the decision-making process for an asset (Blickwedel, Harzendorf, Schelenz, & Jacobs, 2021) .

When relying on a decision support tool to provide the current value to an asset, it is essential to create sensitives around the different future market conditions. As seen through the economic evaluation framework, many future market conditions can be accounted for through changes in the power sale price (PSP) and the AEP. In the case of the renewable energy market in Germany, we assume there is a possibility that the feed-in tariff will end, and the PSP will revert to the spot market price. This would create a stark financial outlook for potential investors but is essential to fully understand the risk associated with an

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

asset, or to conduct any sort of asset management planning (Summerfield-Ryan & Park, 2023) . For this case, the future PSP can be modelled as an incremental decrease from the current PSP with different probabilities.

A functional 8 MW wind turbine located in Germany was selected as the basis of the study. An open-source wind database was selected, and the data was upscaled to the 8 MW turbine so that order-of-magnitude RULs could be calculated. It was assumed that the existing turbine was 20 years old. This represents a practical scenario where an aging turbine is approaching the end of its initial power purchase agreement, and the owner (or a potential investor) is unsure whether to extend the life of, sell, or decommission the asset. It is assumed that the turbine has a 15-year remaining lifespan, making the total lifespan of the turbine 35 years.

The RULs for major components like the blades, hub, and tower were calculated using damage models as outlined previous publications (Wiens, et al., 2024). The resulting RULs that were used for the model were 2 years for the blades; 5 years for the hub; and 10 years for the tower. In this paper, the SCADA data was taken from the Hill of Towie wind farm open dataset (Clerc & Lingkan, 2025). All inputs and their reference sources can be seen below in **Table 1**.

The calculated RULs were then fed into the economic evaluation framework. Replacement costs for the components were calculated using the NREL WISDEM model. This allows the replacement components to be represented as a cash flow on the cash flow diagram. The cost of replacement that was used for the major components was €1.2M for the blades, €0.6M for the hub system, and €0.5M for the tower.

As noted, the initial PSP in this case would be the current market cap price of €73/MWh, whereas the future PSP would be €50/MWh. The future PSP was determined by collecting ten years of average German market reference prices, i.e. the price without a feed-in tariff. While the variance in the system can be quite complex and include policy, regulatory, technological, and economic factors, only the variance in the market reference price was taken for the case study. 10 years of average market reference prices were collected, and the variance in the sample dataset was determined to be 10%. This was selected as the variance.

Several other variables were required for the model. For example, the capital expenditures (CAPEX) and operating expenditures (OPEX) were selected to be €1,600/kW and €35/kW/year, respectively. The capacity factor (CF) was calculated from the actual turbine data and was 27%. While this is lower than the market average, the turbine data is from a prototype turbine that does not have full uptime capability. The standard deviation in the AEP was determined to be 16%, which is useful for sampling different AEPs per year in the model. Finally, the discount rate and risk-free rate were assumed to be 6%, and 4%, respectively. A summary of all inputs can be seen in **Table 1** below.

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

Ultimately, the model uses the magnitude of the NPV and the ratio between the NPV/ROV to guide the decision making. For the purpose of the case study, only two scenarios were implemented. Namely, to "keep the asset" or to "sell the asset". If the NPV is negative, the recommendation is to sell the asset, and vice versa for a positive NPV. The exception is when there is large upside potential through a large, positive ROV, but a slightly negative NPV (NPV/ROV >= -0.10). In this case, the model still recommends that the owner "keep the asset" despite there being a negative NPV.

Table 1: Input Variables for the Case Study

Variable	Value	Source
$\text{Blades}_{\text{RUL}}$	2.2 years (2 year used)	(Wiens, et al., 2024)
Hub_{RUL}	6.9 years (5 years used)	(Wiens, et al., 2024)
$\text{Tower}_{\text{RUL}}$	13.7 years (10 years used)	(Wiens, et al., 2024)
$\text{Blades}_{\text{Cost}}$	\$1,395,276 EUR (\$1,200,000 used)	(Dykes, et al., 2015)
$\text{Hub System}_{\text{Cost}}$	\$698,650 EUR (\$600,000 used)	(Dykes, et al., 2015)
$\text{Tower}_{\text{Cost}}$	\$552,880 EUR (\$500,000 used)	(Dykes, et al., 2015)
$\text{PSP}_{\text{Original}}$	\$73/MWh	(Market value overview, 2025)
$\text{PSP}_{\text{Proposed}}$	\$50/MWh	(Market value overview, 2025)
σ_{Market}	10%	(Market value overview, 2025)
P(x)_{PSP}	Variable	N/A
Year_{PSP}	Variable	N/A
CF	27%	N/A
$\text{L}_{\text{Original}}$	35 years	N/A
$\text{Age}_{\text{Turbine}}$	20 years	N/A
CAPEX	\$1600 EUR/kW	(Stehly, Duffy, & Mulas Hernando, 2024)
OPEX	\$35 EUR/kw/year	(Stehly, Duffy, & Mulas Hernando, 2024)
$\text{Capacity}_{\text{Nameplat}}$	8 MW	N/A
S_{AEP}	16%	N/A
$\text{Rate}_{\text{Discount}}$	6%	N/A
$\text{Rate}_{\text{Risk-Free}}$	4%	N/A

Three different scenarios were used to stress and detail the capabilities of the model. Scenario 1 represents the scenario described above, but where there is 75% certainty that the market cap will end at the end of year 5. Scenario 2 and Scenario 3 have the same base assumptions but assume that the market cap will end in year 1 with 90% and 99% certainty, respectively. Scenario 1, 2, and 3 can be seen below in Figures 7, 8, and 9, respectively.

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

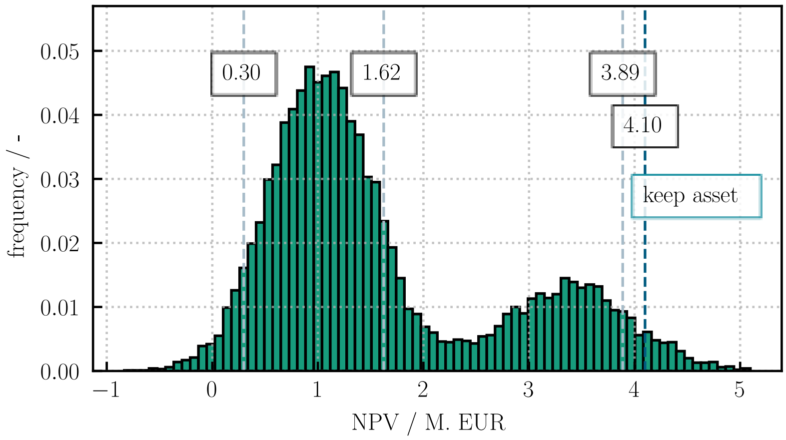


Figure 7: 75% Probability that the Feed-in Tariff Ends in Year 5 (Scenario 1)

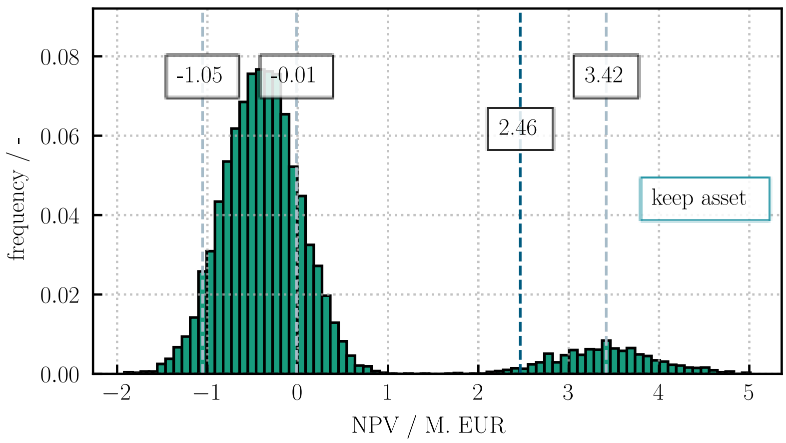


Figure 8: 90% Probability that the Feed-in Tariff Ends in Year 1 (Scenario 2)

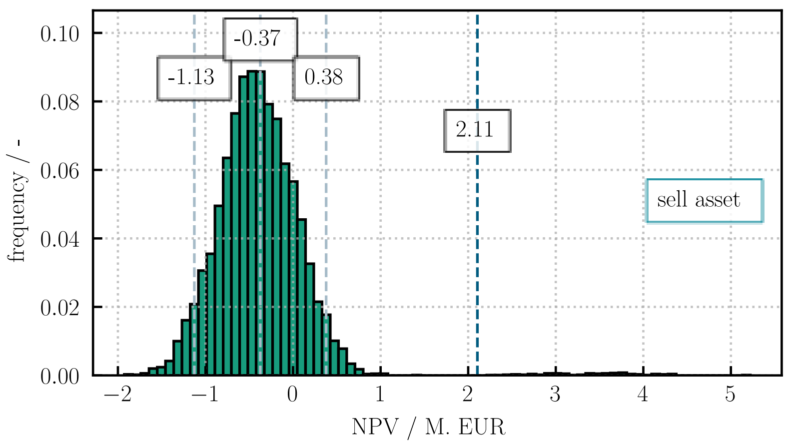


Figure 9: 99% Probability that the Feed-in Tariff Ends in Year 1 (Scenario 3)

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

4. Discussion

The case study was developed to demonstrate the influence that future market conditions can have on the decision making for an asset. Each vertical line on the plot represents a different percentile of the MC simulation. The centre grey line represents the mean-value; the left-most grey line represents the lower 5% confidence interval; the right-most grey line represents the upper 5% confidence interval; the dark blue line represents the real-options value. The real-options value can be seen as the upside potential, or the value of considering the asset in the current market and taking action when the market is more favourable. In other words, it is the value of the ability to decide when to act.

In Scenario 1, it is likely that the German market cap will ends after five years (modelled with p(x) = 75%). The ability to take advantage of the current (and strong) market for renewable power creates a favourable economic outlook. The mean NPV is $1,623,690 in this case, with the lower, upper, and ROV all being positive as well. The recommendation to "keep" the asset is in line with these statistics.

The timeline accelerates in Scenario 2. The market cap now ends after the first year of operation (modelled with 90% certainty). As a result, the power sale prices lower significantly, creating a poor economic outlook. The objective function suggests that since the average NPV is negative, the asset will lose money and should be sold. The value in the ROV is that it recognizes that there is natural volatility in the power market, and the trends that have occurred in the past can happen again. For example, what if the market cap is reinstated, or power prices naturally increase without the market cap in place. If the volatility is measured correctly, the ROV can capture the upside potential of this occurring and provide the value accordingly. Since the mean NPV was slightly negative, but the ROV was significantly positive, there is a case to be made for keeping the asset. There is significant upside potential modelled through the ROV, with little downside as modelled in the NPV. The upper limit of this logic was set at the NPV being negative, and larger than 10% of the ROV. The decision support model here suggests that the asset be kept.

Scenario 3 explores an accelerated timeline with very high certainty that the market cap will end after year one (modelled through 99% certainty). Once again, the power sale price lowers significantly, creating a poor economic outlook. In this case, the lower and mean NPV are negative, while the upper confidence NPV and ROV are positive. However, since the mean NPV is sufficiently negative, the upside potential represented through the ROV is not large enough to offset the risk. Therefore, the decision support model suggests sell the asset.

The case studies explore an important trade-off between future market conditions and decision making. The timing, magnitude, and context of a changing market condition can impact decision making in different ways; these risks need to be understood to make decisions on billion-dollar assets. The integration with the DigiWind platform is essential. It creates a single platform that can flexibly apply any RUL model to the real turbine data, then can make a suggestion for the asset in light of any future market conditions. This type of flexible, yet integrated, decision-making platform does not have familiar precedent in the industry.

5. Future Outlook

There are many ways to expand on this study in the future. A more detailed framework could be used to help make decisions such as whether to repower, sell, decommission, or keep the asset as-is. One option is to use a MDP, which helps decide the best way to act by using probabilities. This method integrates well with the current (MC) model used. The MC model can help define different asset "states", for example, high, medium, or low potential based on the current asset and market conditions. Each state can then be linked to different actions, like selling or repowering. The MC can also simulate future outcomes for each action taken within each state. From these simulations, the MDP determines "transition probabilities", the likelihood of moving from one state to another after taking a specific action. For example, if the asset is in a high potential state and the future outlook is strong, the model might show a high yield, suggesting that the asset should be kept. This approach would make decision-making more formalized.

The use of a probabilistic analysis allows any variable with uncertainty to be parameterized and varied. While RUL estimates have advanced rapidly, there is still significant uncertainty tied to these estimates. The integration of the RUL models and the economic evaluation framework allow for the error in the RUL models to directly be incorporated into the MC simulation. For example, if a convolutional neural network returns an RUL of 7 years for the existing blades, it may have a 10% uncertainty. The uncertainty can be modelled in the MC, so that over enough simulations the RUL of the blades will also have a range of 7 +/- 0.7 years. The ability to integrate uncertainty into each step of the process is a strong value proposition for applying this model.

The tool could also be reconfigured to optimize the operation of a farm. If the decision making were fixed, say if the owner were certain that they wanted to keep the farm, then, the operation could be optimized to create the most economically profitable scenario within this mindset. Ultimately, by having the economic framework integrated with the RUL models it creates the potential for new asset optimization methods.

6. Conclusion

The proposed tool allows for continuous and holistic investment decision support to be provided using real-time data. The digital twin platform allows for FAIR data principles to be used and uses an open-data platform that can easily be modified to include the latest wind energy advancements. It allows the most sophisticated RUL models (i.e. tower, blades, hub) to be

https://doi.org/10.5194/wes-2025-175
Preprint. Discussion started: 30 October 2025

incorporated. These RUL estimations can then feed the economic decision support model by serving as maintenance items on the DCF. Finally, project finance techniques can be used to suggest the most profitable option given the current health and anticipated market conditions for the wind farm.

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