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Relationship Between Wind Turbine Availability and Maintenance Cost Structures: A Field-Based Study

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Abstract:

Understanding the relationship between wind turbine availability and maintenance cost structures is essential for optimizing asset performance and lifecycle expenditures. This study investigates the statistical relationship between availability metrics and maintenance cost components using empirical field data. Operational and financial records from 15 wind farms were analyzed over a five-year period, including annual availability, corrective maintenance labor hours, spare parts expenditure, and total normalized OPEX. Pearson and Spearman correlation analyses were conducted to assess linear and monotonic relationships between availability and cost indicators. The results reveal a statistically significant negative correlation (R ranging from −0.71 to −0.76) between availability and corrective maintenance cost intensity, indicating that declining availability is strongly associated with increasing unplanned maintenance expenditure. Additional regression analysis confirms the robustness of this relationship after controlling for turbine age and site conditions. These findings support integrated health and cost evaluation approaches for data-driven decision-making in wind farm asset management.

1. INTRODUCTION

Wind energy deployment has expanded steadily worldwide over the past decade, and wind farms have become an important part of low-carbon power systems. As installed capacity continues to grow, the economic performance of wind power projects is increasingly determined by long-term operational performance rather than construction-stage investment alone. In particular, operations and maintenance costs account for a substantial share of lifecycle expenditure, especially for aging turbines, offshore projects, and wind farms located in areas with difficult access conditions. Unplanned downtime, corrective maintenance, and component replacement can reduce energy yield and increase the levelized cost of electricity, making operational reliability a key factor in asset profitability [1,2]. Recent work has also emphasized that wind farm asset health should be assessed through multi-dimensional indicators, including equipment condition, operational performance, maintenance status, and reliability-related variables, and that these indicators are closely associated with actual operating outcomes [3]. In this context, turbine availability is not only a technical indicator of production continuity, but also a practical signal reflecting maintenance effectiveness, asset health, and the stability of wind farm operation [4,5].

Recent studies have made clear progress in wind farm operations and maintenance research. Maintenance modeling has gradually shifted from simplified cost assumptions to more detailed frameworks that consider logistics, spare parts planning, resource allocation, weather windows, and site accessibility [6,7]. At the same time, condition monitoring and predictive maintenance methods based on SCADA data, vibration signals, and machine learning models have been widely used to detect abnormal turbine behavior and support earlier fault identification [8,9]. The increasing availability of open operational datasets has further improved the comparability of fault diagnosis methods and enabled validation across different turbine types and operating conditions [10]. In addition, optimization-based maintenance strategies, including preventive maintenance, condition-based maintenance, and risk-based scheduling, have been proposed to balance reliability improvement and cost control under operational uncertainty [11,12]. These studies have provided useful technical tools for improving wind farm maintenance decisions. However, the empirical relationship between turbine availability and maintenance cost structure remains insufficiently quantified [13]. Many existing studies rely on simulated wind farms, assumed failure distributions, or generalized cost parameters, which limits their ability to reflect real cost behavior under field operating conditions [14,15]. In data-driven maintenance research,

model performance is often evaluated through diagnostic accuracy, fault classification, or remaining useful life prediction, while maintenance cost is treated as an external variable or aggregated outcome [16,17]. As a result, the relationship between declining availability and specific cost components, such as corrective labor hours, spare parts consumption, and normalized operational expenditure, is often discussed indirectly rather than measured through empirical operating records [18]. This limitation is important because wind farm maintenance cost is not driven by a single factor. Turbine age, failure frequency, component type, site accessibility, crew availability, weather conditions, and maintenance strategy can all influence both downtime and expenditure. For example, two turbines with similar annual availability may have different cost structures if one suffers from repeated minor failures while the other experiences fewer but more expensive component replacements [19,20]. Similarly, a wind farm with moderate availability loss may still face high operational expenditure if corrective maintenance requires specialized labor, long travel time, or costly spare parts [21,22]. Therefore, availability should be examined together with disaggregated maintenance cost indicators rather than treated as an isolated performance metric. Field-based studies that connect availability, reliability, and cost are still limited by sample size, short observation periods, or insufficient control of confounding factors. Turbine age, site characteristics, and operational practices are not always considered systematically, even though they directly affect downtime patterns and maintenance expenditure [23]. These limitations reduce the comparability of existing findings and restrict their usefulness for asset-level decision-making. For wind farm owners and operators, a clearer empirical understanding of how availability is linked to different maintenance cost components is needed to support budget planning, maintenance prioritization, and long-term asset management.

To address these gaps, this study examines the relationship between turbine availability and maintenance cost structure using empirical data from 15 wind farms over a five-year period. Annual availability is analyzed together with corrective maintenance labor hours, spare parts expenditure, and normalized operational expenditure. Correlation analysis is used to evaluate both linear and monotonic associations, while regression models are applied to account for turbine age and site-related factors. By using observed field data and disaggregated cost components, this study aims to clarify how changes in turbine availability are associated with maintenance labor intensity, spare parts demand, and overall operational expenditure. The results are expected to provide practical evidence for identifying cost-sensitive availability patterns,

improving maintenance planning, and supporting more informed wind farm asset management strategies.

2.Materials and Methods

2.1 Sample and study area description

The analysis uses operational records from 15 utility-scale onshore wind farms operating under commercial conditions. The dataset covers 312 horizontal-axis wind turbines with rated capacities between 2.0 and 3.6 MW. All units were continuously grid-connected during the study period. Data were collected for five consecutive calendar years, including annual availability, maintenance activities, and cost information. The wind farms are distributed across sites with different terrain and access characteristics, such as flat inland locations, hilly regions, and coastal areas with moderate logistical constraints. At the beginning of the observation period, turbine age ranged from 2 to 11 years, allowing representation of multiple stages of the operational lifecycle.

2.2 Experimental design and comparison framework

This study follows an observational field design, as controlled intervention is not feasible in operating wind farms. The primary analysis compares observations with relatively high annual availability to those with lower availability within the same time frame. To limit structural bias, comparisons were conducted among turbines with similar rated capacity and generation type whenever possible. A comparison framework was further established by grouping data into turbine age classes and site categories. This approach enables assessment of availability-related cost differences under comparable operating conditions, rather than across fundamentally different turbine designs or locations.

2.3 Measurement methods and quality control

Annual availability was derived from SCADA operational logs and defined as the proportion of time a turbine was technically available for power production relative to total calendar time. Periods of grid curtailment were excluded from the calculation. Maintenance cost data were extracted from operator accounting systems and included corrective maintenance labor hours, spare parts costs, and total operational expenditure normalized by installed capacity. All

monetary values were converted to constant prices using annual inflation adjustments. Quality control procedures included cross-validation of downtime records with maintenance work orders, screening for incomplete annual entries, and consistency checks for abnormal values. Records associated with exceptional events, such as severe weather damage, were removed to maintain focus on routine maintenance behavior.

2.4 Data processing and analytical models

All variables were aggregated at the annual wind-farm level prior to analysis. Linear relationships between availability and cost indicators were examined using Pearson correlation, while rank-based associations were evaluated using Spearman correlation. To quantify the availability–cost relationship while accounting for confounding effects, a multiple linear regression model was applied:

$$C_i=\alpha+\beta A_i+\gamma T_i+\delta S_i+\varepsilon_i,$$

where C_i represents normalized maintenance cost intensity, A_i denotes annual availability,T_i is turbine age, and S_i corresponds to site-related categorical variables. Corrective maintenance cost intensity was additionally calculated as

$$CMI=\frac{H_c}{A\cdot P_r},$$

where H_c is corrective maintenance labor hours andP_r is rated power. This formulation enables comparison across turbines of different capacities.

2.5 Statistical evaluation and robustness analysis

All statistical tests were conducted using a significance threshold of 0.05. Regression assumptions were examined through residual analysis and variance inflation factor diagnostics to assess multicollinearity. Robustness checks were performed by repeating the analysis on data subsets defined by turbine age group and site category. These procedures confirm that the observed relationships are not dominated by individual projects or extreme operating conditions. All computations were carried out using standard statistical software, and key results were independently reproduced to reduce the risk of implementation error.

3.Results and Discussion

3.1 Relationship between availability and maintenance cost at fleet scale

Analysis of the five-year dataset shows a consistent inverse relationship between annual availability and corrective maintenance cost intensity across the 15 wind farms. Both Pearson and Spearman tests indicate statistically significant negative correlations, with coefficients ranging from −0.71 to −0.76. This result indicates that years with lower availability tend to coincide with higher levels of unplanned maintenance effort. Similar associations between downtime and corrective cost have been reported in recent wind farm O&M studies, where frequent stoppages lead to repeated site access and repair activities [24,25]. The overall trend is illustrated in Fig.1, which shows an increase in cost intensity as availability decreases. These results confirm that availability reflects not only production performance but also maintenance burden under field conditions.

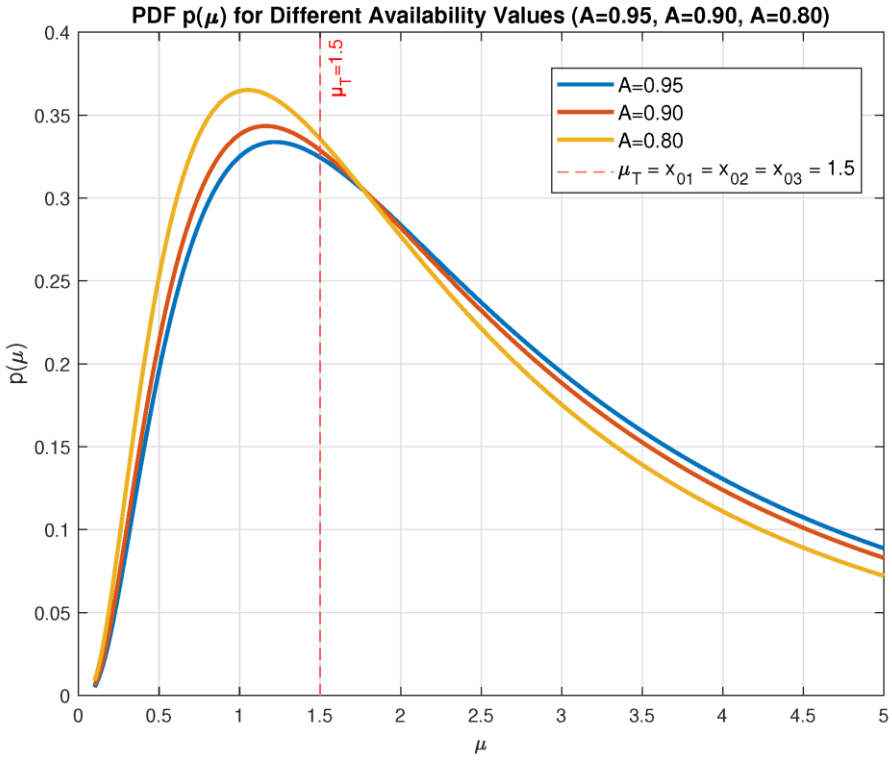


Figure 1 Relationship between annual turbine availability and corrective maintenance cost intensity across the analyzed wind farms.

3.2 Differences in response between labor and spare parts costs

When maintenance costs are examined by component, corrective labor hours show a stronger response to changes in availability than spare parts expenditure. Periods of reduced availability are mainly associated with increased labor demand, including inspection, troubleshooting, and repeated site visits. In contrast, spare parts costs rise more gradually, suggesting that availability losses are often driven by operational inefficiency rather than by immediate replacement of major components. This pattern is consistent with recent studies on maintenance logistics, which report that technician time and access constraints can dominate cost escalation once downtime events become frequent [26]. Comparable behavior has also been observed in maintenance modeling work, where service process characteristics influence availability and cost before major component failures become prevalent (Kontrec et al., 2024). The joint behavior of availability and cost components is illustrated in Fig.2.

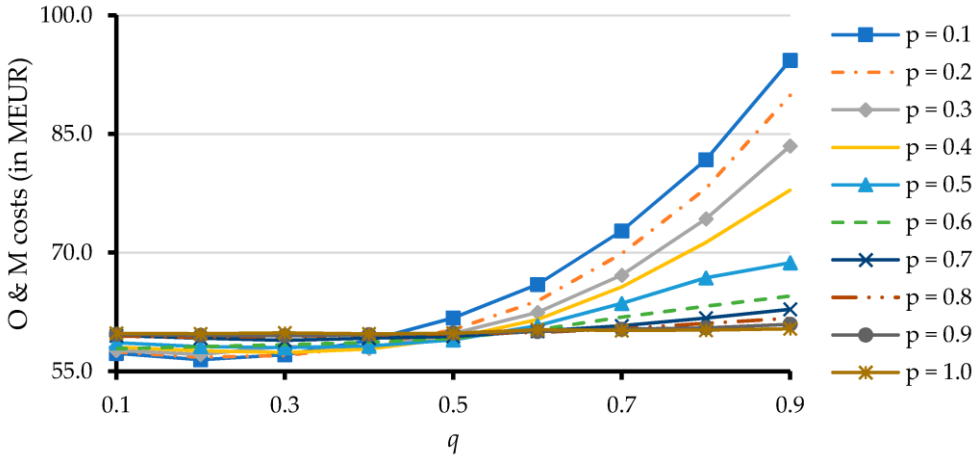


Figure 2 Variation in corrective labor hours and spare parts expenditure under different availability levels.

3.3 Regression analysis and robustness across operating conditions

Regression results show that availability remains a significant explanatory variable for normalized corrective maintenance cost after accounting for turbine age and site category. The estimated availability coefficient remains negative and statistically significant, indicating that the observed relationship is not solely explained by lifecycle stage or operating environment. This finding aligns with earlier reports showing that age and site conditions contribute to OpEx variation but do not fully account for differences in corrective maintenance demand [27]. Additional analyses conducted on age-stratified and site-specific subsets yield consistent

coefficient signs and comparable magnitudes. These results suggest that the availability–cost relationship is stable across heterogeneous field conditions and is not driven by a small number of projects.

3.4 Comparison with existing studies and implications for asset management

Compared with simulation-based maintenance optimization studies, the present analysis provides empirical evidence derived from multi-year operational data. Many recent studies emphasize condition monitoring accuracy or remaining useful life prediction, while maintenance cost is often treated indirectly or aggregated at system level [28]. By linking availability directly to disaggregated corrective cost components, this study offers a practical perspective for asset management. The results suggest that declining availability can serve as an early signal of rising corrective maintenance intensity and may support earlier intervention in maintenance planning, crew allocation, and spare parts preparation. The findings should be interpreted as statistical association rather than strict causality, as operator practices and accounting rules may influence cost allocation. Further work can improve inference by incorporating event-level failure classification and standardized cost reporting across operators.

4.Conclusion

This study analyzes the relationship between wind turbine availability and maintenance cost structure using operational and financial records from 15 onshore wind farms over five years. The results indicate a consistent negative association between annual availability and corrective maintenance cost intensity, with corrective labor hours showing the strongest response to availability changes. After accounting for turbine age and site conditions, availability remains a significant explanatory factor for corrective maintenance cost, suggesting that it reflects maintenance pressure in addition to production performance. By focusing on disaggregated cost components derived from field data, this work complements existing studies that rely mainly on simulated systems or aggregated O&M indicators. The findings indicate that sustained reductions in availability are associated with higher corrective workload and may be used to support maintenance planning, workforce allocation, and spare parts preparation in operating wind farms. The analysis is limited by the observational nature of the data and by differences in operator practices and cost accounting methods, and it does not resolve causality at the component level. Further research could improve resolution by incorporating event-level failure records,

component-specific cost data, and more consistent reporting standards across wind farm operators.

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