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Evaluation of Predictive Maintenance by Marginal Utility: A Case Study on Offshore Wind

Rasmus Dovnborg Frederiksen [1,*], Grzegorz Radzki [2], Grzegorz Bocewicz [2], Peter Nielsen [1] and Zbigniew Banaszak [2]

[1] Department of Materials and Production, Aalborg University, 9220 Aalborg, Denmark
[2] Faculty of Electronics and Computer Science, Koszalin University of Technology, 75-453 Koszalin, Poland
* Correspondence: rasmusdf@mp.aau.dk

Abstract

This paper investigates the relationship between the benefits achieved by predictive maintenance implementation and the related costs incurred intentionally or not. Specifically, we seek to establish an evaluation method for predictive maintenance that includes prediction model performance, which will better indicate that a predictive maintenance strategy built on the model will succeed in providing benefits compared to a pre-existing maintenance strategy. This will help justifying the costs and complexities of implementing new maintenance procedures and ensure positive financial outcomes. We demonstrate this method with a case study based on scheduled maintenance of an offshore wind farm where a declarative modeling approach is used to simulate service costs and operations, while a deep learning model provides insights on imminent downtime events. The results of this case study show that predictive maintenance is only profitable under specific conditions, such as limited service resources and high prediction model performance, and a profitable performance threshold for the underlying model is obtained.

Keywords: predictive maintenance; failure prediction; machine learning; offshore wind farm; marginal utility; maintenance evaluation

1. Introduction

Predictive analytics, driven by artificial intelligence (AI) and machine learning (ML) algorithms, is widely applied across diverse sectors and domains. These AI/ML-enabled methodologies facilitate more precise decision-making and support operational management in production and service contexts, including material and data flow logistics and predictions of future outcomes based on these decisions [1,2]. Prominent applications of AI/ML-driven techniques lies in the analysis and prediction of various supply-chain distribution strategies [3] or improvements in maintenance operations [4], naturally leading to the application of predictive maintenance.

In pursuit of improving the levelized cost of energy (LCOE) for wind energy, great attention is paid to improving the maintenance of wind turbines (WTs) [5], and this is especially true for offshore wind farms (OWFs) [6,7] given the high servicing costs. Part of this effort is the development of predictive maintenance, where improvements to LCOE are derived from improved availability facilitated by the prediction and subsequent prevention of downtime events of WTs. A fundamental component of such predictive maintenance is the underlying AI/ML model, and such models are inherently uncertain, leading to unclear benefits of predictive maintenance and, in the worst case, incurring unexpected costs.

Check for updates

Academic Editor: Marco Zucca

Received: 2 July 2026
Revised: 11 August 2026
Accepted: 24 August 2026
Published: 1 September 2026

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The research presented in this paper aims to develop an evaluation method that enables decision-makers to effectively oversee the development and implementation of predictive maintenance strategies. This will involve quantifying a more exact cost–benefit matrix of the maintenance operations, both with and without AI/ML model support. From this, it will be evident that the performance of the underlying AI/ML model will have significant impact on the effectiveness of the predictive maintenance strategy built upon the model. Such analyses will also lead to a better understanding of how best to implement predictive maintenance, such as being used as feedback in the AI/ML training process, thus ensuring cost-effective predictive model development and identifying which maintenance operations have the best potential for predictive maintenance improvement.

The base evaluation elements underlying such cost–benefit analysis was developed in prior work [8–10], where maintenance costs and efficiency were evaluated by declarative modeling. Whereas these former papers focused on presenting the basics of maintenance efficiency calculations, this paper utilizes the approach to create a more generalized evaluation method with which the implementation of predictive maintenance can be better analyzed and give more context to the business impacts of AI/ML modeling. Thus, the contribution of this article is the integration of some specific elements of prior work into a complete and standalone marginal utility framework for evaluating predictive maintenance strategies at a strategical scale, an approach not previously attempted.

In practical implementations of predictive maintenance, it is expected that a pre-existing maintenance strategy, such as reactive or preventive maintenance, is in place. Implementing predictive maintenance will require replacement or modifications of this pre-existing maintenance strategy, wherein lies the ambition for improvement but also the risk of negative disruptions. This baseline maintenance and the modification of maintenance must be carefully considered in the cost–benefit analysis of predictive maintenance; therefore, the concept of marginal utility is introduced to help in this endeavor. In this context, the marginal utility of the implementation of predictive maintenance is the additional value (or detrimental cost) created by the implementation compared to the value of existing maintenance.

The fundamental elements required for this method of maintenance evaluation and comparison, as well as the underlying requirements, are discussed in Section 3. Before this, Section 2 explores the background related to predictive maintenance, specifically how prediction models are used in the maintenance of the wind energy industry, and alternative sources for similar efforts in reducing the cost of predictive maintenance. Section 4 gives a numerical example of how this method works in a simple reactive maintenance scenario, while Section 5 consists of a more in-depth and realistic implementation case study for the scheduled maintenance of an OWF. In the end, Section 6 discusses our method and results and further implications of our method, and it provides an overview of certain components that should be more intensely scrutinized for actual implementation. Section 7 contains the conclusions of this paper.

2. Background

AI/ML models are highly valued in the energy sector for a variety of tasks, especially for renewable energy assets because intermittent availability requires higher levels of control. Review articles provide a general overview of how predictive modeling is applied in the renewable energy sector, with several systematic reviews offering in-depth insights for photovoltaic (PV) power generation [11–13] and the generation of wind power [14–16]. For the specific application of using ML models in predictive maintenance, there are also review articles available [6,17].

The analysis and development of effective ML solutions for OWFs have become increasingly important [7,18,19]. One main direction of these solutions relies on forecasting opera-

tionally relevant variables such as wind speed and other meteorological aspects [15,20–22]; motions and mooring loads [23]; wake losses [24]; and power generation [25–27]. The other main direction of ML solutions is focused on the predictions and classification of WT operational status and failure modes, such as converter fault detection [28], blade icing events [29], equipment failure prediction [30], etc. It is the latter direction that is best suited for predictive maintenance.

Using AI/ML methods, predictive maintenance enables accurate just-in-time maintenance of equipment, facilitating proactive maintenance scheduling and strategic service resource allocation, such as technical expertise, transport vessels, spare parts, and aligning activities with the near-future conditions of assets [31]. This is the ambition of predictive maintenance, but this comes at the cost of injecting some aspects of uncertainty into an otherwise relatively stable process. By creating predictive maintenance strategies on the basis of AI/ML modeling, the efficiency of such maintenance is then highly dependent on the performance of inherently uncertain prediction models.

Central to the motivation of developing predictive maintenance is the objective of achieving optimal utility of the assets at minimal costs; striking a balance between minimizing unnecessary resource expenditures (e.g., operational curtailment, service involvement, spare parts usage) caused by premature interventions; and mitigating severe failures and negative operational impacts resulting from delayed interventions. In relation to AI/ML and the conventional confusion matrix of prediction outcomes, the list below states the potential impacts of prediction maintenance:

1. Benefit of True Positives (TPs): Avoiding costs of failure events, which include reactive maintenance operations and operational downtime.
2. Benefit of True Negatives (TNs): Avoiding costs related to unnecessary preventive maintenance.
3. Cost of False Positives (FPs): Additional costs associated with unnecessary mobilization of maintenance resources.
4. Cost of False Negatives (FNs): All costs related to regular failure events and reactive maintenance, plus an additional sense of false security.

Only a few sources critically assess the consequences of errors made by prediction and forecasting models in the context of wind energy, such as wind power forecast errors [19,32]. Some optimal cost decision analysis is performed in some fundamental areas of research [33] or in the case of very specific applications [34–36] where failure costs are integrated into the ML training process but are not explicitly evaluated in the context of incorrect predictions. There appears to be a gap in wind industry research regarding this type of analysis, specifically where the potential costs of false predictions are considered in the evaluations of the impacts of implementing ML models for predictive maintenance. Certain studies that would benefit from such a cost evaluation model include [29,30,37,38] among others.

We surmise that work on improving predictive maintenance evaluation methods is required to ensure the effective and intentional implementation of such maintenance strategies involving risk. Without such evaluations, there is a risk of costly or even counterproductive applications of predictive maintenance, as the impacts of false predictions are not understood or included in the benefit analysis. This paper develops a method of evaluation based on cost–benefit analyses of predictive maintenance implemented in single short-term maintenance scenarios. These scenarios are based on OWF maintenance campaigns and will vary in the available service resources and the performance of the ML models applied. The maintenance cost–benefit results of the scenarios are compared to a baseline preventive maintenance scenario without any ML models applied such that the marginal utility of predictive maintenance can be evaluated per scenario.

Ultimately, the goal is to formulate a model-agnostic method that can determine when an AI/ML-driven maintenance strategy will outperform pre-existing maintenance approaches, and in doing so, we also establish a "balancing point" along the most relevant scenario variables that separates which specific circumstances lead to value-adding or detrimental predictive maintenance. As will be shown with numerical examples, the formulation of such a marginal utility methodology will require the introduction of several relevant concepts borrowed from other studies, such as cost-sensitive classifications [33], expected value theory [39], and decision-theoretic optimization [35,40].

Although this paper is limited to the specific OWF scenarios presented, the general method used can, with careful considerations, be modified according to much more diverse settings. Regardless of the domain of application, such a method can help decision makers take the right actions in regard to the implementation of predictive maintenance and decide when AI/ML models are precise enough for certain applications.

Furthermore, it is evidently even more difficult to find studies that facilitate the estimation and accounting of the AI/ML training process itself. These costs include expenditure on the installation of asset operation monitoring sensors and their maintenance, data management, computing costs of training accurate models, computing costs of inference, cloud costs of server hosting, and costs of maintaining digital infrastructure and models. The best examples of AI/ML pricing [41,42] are focused on the perspective of selling and trading data and models on marketplaces, which does not translate well to internally trained AI/ML services for industrial applications. These sources do indeed still support the general expectation of increasing AI/ML costs, as more accurate models are desired. This dynamic leads to another cost–benefit tradeoff between how well predictive maintenance will perform and the costs required to implement such predictive maintenance. While the method in this paper allows for the inclusion of these AI/ML costs, sadly, they have not been evaluated in the case study presented, as such an endeavor would entail a complete study on a scale far beyond what this paper presents.

3. Methods

The purpose of this section is to formulate the complete process of the maintenance evaluation method. In previous works, we have presented methods for evaluating the expected value of singular predictive maintenance actions given imperfect information [8], and we have used declarative modeling to estimate the relationship between the benefits of predictive maintenance and the additional costs of complexity [9,10]. The previous research and approaches will act as the foundation for the method developed in this paper. What the previous methods were lacking was a comparative framework that allows for broader evaluations of decisions concerning changing overall maintenance strategies, which is method presented below.

Marginal Utility of Maintenance

To estimate the marginal utility of a change in maintenance strategy, it is necessary to define some cost–benefit structures of maintenance operations. This research will conveniently isolate these cost–benefits to just a few parameters relevant for this purpose. For a maintenance service mission of an OWF, the costs parameters are the costs of maintenance performed and the costs of downtime events (lost production). These costs must be subtracted from the total potential revenue of WTs to obtain profits over the maintenance period. We therefore simplify the OWF profits, P, for any maintenance period of time, T, as follows:

$$P_T = Rev_T - CD_T - CS_T \quad (1)$$

where Rev_T is the total potential revenue from energy production, CD_T is the value of lost production from downtime, and CS_T is the cost of service/maintenance. CS_T is highly dependent on how maintenance operations are performed and contains costs related to mobilization, salary, spare parts, etc. In practical cases, CS_T can itself be quite challenging to estimate, but this can be facilitated with simulations, as in the case study of this paper.

Rev_T and CD_T are calculated in similar ways, as both relate to power generation. Power generation from wind energy can be simplified to rely on only a few variables, namely the nominal power output of the WT, the price of energy, and wind conditions. This simplified calculation of Rev_T can be seen in Equation (2), where MW is the nominal power output of the WT, p_t is the price of power at time t, and PC_t is the power curve at time t, a relative measure of how much of the nominal power output the WT can produce at certain wind speeds. Multiplication of the scalar 0.96 is a commonly used discount rate in the wind sector to discount power calculations due to highly dynamic and noisy systems.

$$Rev_T = \sum_{t \in T} MW \cdot PC_t \cdot p_t \cdot 0.96 \tag{2}$$

CD_T denotes the costs related to the events of WT downtime, which require a complete stop with respect to WT production, thus reducing the actual power produced. It is calculated using Equation (2), with the difference of limiting the power generation calculation to the time of downtime only. Using the notation of single downtime events, $D \in \mathcal{D}_T$, and an average duration of h as the mean duration, the costs of downtime is calculated as follows:

$$CD_T = \sum_{D \in \mathcal{D}_T} h \cdot MW \cdot PC_t \cdot p_t \cdot 0.96 \tag{3}$$

Reflecting different maintenance missions, Equation (1) is further modified with notation indicating service missions, denoted as S_i per mission $i \in I$, where I is the set of all possible mission configurations. In actuality, there is an indeterminately large number of service mission configurations, as any change in service resources, their use, scheduling, and planning strategies will constitute a different service mission configuration. Thus, we have the following extension of the OWF profit equation as a function of the service mission:

$$P_T(S_i) = Rev_T - CD_T(S_i) - CS_T(S_i) \tag{4}$$

Cost of downtime and cost of service both depend on the service mission, the service costs is a direct result of the service mission's configuration, and cost of downtime changes as a more efficient service mission will result in fewer downtime events, thus incurring fewer downtime losses. Furthermore, when comparing service mission configurations where only the performance of AI/ML prediction models changes, Equation (1) can also been used as a business impact score, a performance metric indicating the business value of better or worse model performance.

On the basis of Equation (4), we can now formulate the marginal utility between two service mission configurations, $\Delta P_{T,S_i,S_j}$, as the difference in profits between them:

$$\Delta P_{T,S_i,S_j} = P_T(S_i) - P_T(S_j), \tag{5}$$

where S_i and S_j are the two different mission configurations compared. In the context of this paper, S_j denotes the preexisting maintenance configuration compared to a predictive maintenance mission S_i. This consequently leads to the below three outcomes of the marginal utility analysis of predictive maintenance:

1. $\Delta P_{T,S_i,S_j} > 0 \longrightarrow$ Indicating positive business value of the implementation of predictive maintenance.
2. $\Delta P_{T,S_i,S_j} < 0 \longrightarrow$ Indicating negative business value of the implementation of predictive maintenance.

3. $\Delta P_{T,S_i,S_j} = 0 \longrightarrow$ Reflects a situation with no change in the outcome of the maintenance mission. This case is significant because it can be used to quantify the minimum threshold for single parameters leading to positive business value of predictive maintenance.

In the following sections, this marginal utility measure will be used for analyses of OWF maintenance, where cost-efficient predictive maintenance is sought over preventive maintenance.

4. Numerical Example

The below example is constructed to illustrate how the method functions and to provide an an easy understanding of the outcomes and decision support created. All numbers used in this example, both costs and AI/ML model performance indicators, are fictitious so as to create the clearest scenario for showcasing the method while still relying on somewhat realistic cost numbers. This also means that all calculations are simplified, while the case study on the following section will more explicitly calculate all values.

4.1. Numerical Example—Reactive Maintenance

The example is based on reactive maintenance, where WT downtime events trigger maintenance actions as they occur. Predictive maintenance improvements will allow for this maintenance to occur before downtime events, thus preventing operational outage. The often-ignored additional risk in a scenario such as this is that triggering unnecessary maintenance based on wrongful predictions can become more costly than the value of preventing downtime events.

This maintenance scenario is based on one week of operations and reactive maintenance of 100 onshore WTs with a risk of severe downtime events at 2% per WT per day. It is assumed that there are good weather conditions throughout the whole week, bringing the production value per WT per day to €4000. The cost of maintenance is €25,000 per downtime event, and the lost production value is €4000 per downtime event, equivalent to a whole day of operations.

The calculation of costs for reactive maintenance, S_r, is easily carried out. With an average of two downtime events per day, the baseline maintenance costs and profits are as follows:

$$Rev_T = 7 \cdot 100 \cdot €4000 = €2{,}800{,}000 \quad (6)$$

$$CD_T(S_r) = 7 \cdot 100 \cdot 0.02 \cdot €4000 = €56{,}000 \quad (7)$$

$$CS_T(S_r) = 7 \cdot 100 \cdot 0.02 \cdot €25{,}000 = €350{,}000 \quad (8)$$

$$P_T(S_r) = Rev_T - CD_T(S_r) - CS_T(S_r) = €2{,}394{,}000 \quad (9)$$

These are the baseline profits that will be compared to predictive maintenance.

4.2. Numerical Example—Predictive Maintenance

The predictive maintenance strategy applied in this example is simple. The prediction models will, on each day, predict whether or not each WT has imminent downtime events, and the positive predictions will trigger maintenance actions immediately, preventing downtime events from occurring. This results in a total of 700 predictions made in total.

A cost–benefit matrix is presented in Table 1, and it is intended to mimic a confusion matrix such that the monetary outcomes of each quadrant are displayed instead of prediction distributions. The case of a TP prediction also counter-intuitively creates costs in the effect of the maintenance performed; however, it has the benefit of avoiding otherwise lost production with respect to downtime events. A TN prediction leads to no downtime event, no maintenance performed, and no costs incurred. An FP prediction incurs the costs

of unnecessary maintenance, and an FN prediction will incur the full costs of both the downtime event and the subsequent maintenance.

Table 1. Cost matrix for all four prediction outcomes of the numerical example.

Cost Matrix	Actual Positive	Actual Negative
Predicted Positive	€25,000	€25,000
Predicted Negative	€29,000	€0

From Table 1, it can be seen that there are options for incurring costs that would not be possible within the reactive maintenance strategy. The question becomes whether the benefit of predictive maintenance outweighs the additional costs, which depends on prediction model performance. In this example, let us introduce three differently performing models. Their performance metrics can be seen in Table 2, which are designed specifically to showcase the impact that not only improved accuracy can have on the results but also that accuracy alone can be misleading.

Table 2. Predictive models and summarized model performance for the numerical example.

	Model 1	Model 2	Model 3
TP	7	13	10
FP	7	2	0
FN	7	1	4
TN	679	684	686
Accuracy	0.98	0.996	0.994
Precision	0.5	0.867	1
Recall	0.5	0.929	0.714
F1 Score	0.5	0.897	0.833

The resulting costs associated with predictive maintenance are found by simply multiplying the prediction outcomes with the cost matrix, resulting in the costs displayed in Table 3. From this table, the monetary outcomes of differences in model performance is demonstrated. Although Model 3 is not the best-performing model in terms of accuracy and F1 score, it is nevertheless the model achieving the lowest costs. Precision is, in the example, the best metric for considering the minimization of costs, as this will result in avoiding very costly false positives. However, such an observation is heavily reliant on the case and the cost dynamics of the case.

Table 3. Maintenance costs of predictive maintenance.

	Model 1 Cost	Model 2 Cost	Model 3 Cost
TP	€175,000	€325,000	€250,000
FP	€175,000	€50,000	€0
FN	€203,000	€29,000	€116,000
TN	€0	€0	€0
Total	€553,000	€404,000	€366,000

The profits under predictive maintenance strategies based on each model can now be found.

$$P_T(S_{M1}) = Rev_T - €553{,}000 = €2{,}247{,}000 \quad (10)$$

$$P_T(S_{M2}) = Rev_T - €404{,}000 = €2{,}396{,}000 \quad (11)$$

$$P_T(S_{M3}) = Rev_T - €366{,}000 = €2{,}434{,}000 \quad (12)$$

And the following marginal utility values for predictive maintenance are found as well.

$$\Delta P_{T,S_{M1},S_r} = €2{,}247{,}000 - €2{,}394{,}000 = -€147{,}000 \quad (13)$$

$$\Delta P_{T,S_{M2},S_r} = €2{,}396{,}000 - €2{,}394{,}000 = €2000 \quad (14)$$

$$\Delta P_{T,S_{M3},S_r} = €2{,}434{,}000 - €2{,}394{,}000 = €40{,}000 \quad (15)$$

The key takeaway from this example is that the marginal utility of predictive maintenance is not guaranteed, even with a seemingly well-performing model, as is the case with Model 1, which actually has large negative marginal utility due to the substantial costs incurred by too many false positives. Even in the case of Model 2, there is barely any upside in the implementation of predictive maintenance with this model. Only a few mistakes are enough to negate all positive impacts created from the otherwise best-performing model. A second takeaway is that relying on an arbitrarily chosen performance metric in the model's training process is suboptimal, and careful consideration should be given in the model's training process to find the correct metrics for the case at hand.

The above example showcases how easily the marginal utility method for predictive maintenance business value estimation can be applied. However, this is only the case with such a fairly simple reactive maintenance setup, which allows the costs of service actions and downtime to be easily determined. In the following case study, much more detail will be added, as well as a comparison of predictive maintenance with a preventive maintenance baseline. This requires more intricate and complex approaches to find the impact that predictive information has on all cost measures.

5. Case Study—Preventive Maintenance

The case study is based on a contractually obliged yearly check-up of an OWF consisting of 23 WTs with 6 MW nominal power output. This is a case of preventive maintenance where the strategy consists of scheduling visits for all WTs in an optimal manner with regard to service costs only, reducing the problem down to a shortest-route scheduling problem. The objective of predictive maintenance in this context is to optimize operations during the maintenance period by providing predictions on imminent downtime events and prioritizing maintenance routes with respect to this information, thus minimizing operational downtime. The goal of the case study is then to find under which conditions this inclusion of predictive information will provide a positive business value or whether it increases the complexity and cost of service to a degree that is not profitable.

A notable distinction between this case study and the reactive maintenance example is that preventive maintenance performed will prevent some downtime events entirely by chance, as this is one of the purposes of such maintenance strategies. Predictive maintenance will, in this context, only improve the chances of prevention by targeting high-priority WTs for maintenance.

This preventive maintenance case displays the usefulness of marginal utility analysis well, as the cost dynamics are highly intertwined and complex, as is the case in many similar industrial applications where the positive impacts of predictive maintenance will be more uncertain and unclear. While the case study is based on a real OWF, the name of the OWF is omitted and the locations of WTs are scrambled. All costs and variables have been

simplified slightly for ease of simulation and study, but all results obtained from the analysis are still adequate for comparing maintenance solutions and obtaining general insights into the potential of improvements. However, in real-world implementations, incorporating enhancements into the declarative model and configurations (such as accounting for temporally variable wind speeds and power prices) will significantly improve the results and ensure the accuracy of final profit numbers, making them more applicable for financially sensitive business operations.

5.1. Case Study Setup

A map of the OWF can be seen in Figure 1, and the WT specifications are found in Table 4. The case is based on an OWF with subsidized energy prices, and the power curve factor is assumed to be constant at a high mean. This is intended to showcase the most relevant scenario of effective maintenance intervention, as maintenance during low- to no-wind conditions would incur less additional downtime event costs because the WTs would not operate, thus giving predictive maintenance no real option to create positive business impacts. Based on historical data from the OWF, the average risk of downtime events and the average duration of such events are calculated and used. The risk of downtime events is much higher than the reactive maintenance example, as that example was based on severe downtime events lasting approximately 24 h, whereas this preventive maintenance case study concerns all minor downtime events such that the average downtime period is 4 h.

Following Equation (2) and these site-specific characteristics, the total potential revenue is as follows:

$$Rev_T = €1{,}335{,}398 \tag{16}$$

The service mission purpose concerns one or more service teams visiting all WTs within the OWF for as many days as required, with three days being the maximum in this case study. The service costs consists of the daily salary of the service teams, the rent of accompanying vessels, and the fuel costs for transportation. The scheduling of such maintenance operations and simulation of associated costs are undertaken with a declarative modeling approach, which is presented in the following section. For each service mission configuration, this simulation model will provide a cost-optimal service mission schedule along with all related service costs. This allows for an evaluation of the impact of changing certain parameters of maintenance missions, such as service resources, the inclusion of predictions, and the performance of the prediction model. Compared to the example of reactive maintenance, the maintenance operations and the potential impacts are significantly increased in complexity, requiring a more complex setup for the estimation of costs and benefits.

Table 4. Configuration of WTs.

Nominal Power	6 MW	MW
Power Prices	€168/MWh	$p_t, \forall t \in T$
Mean Downtime Duration	4 h	h
Mean Downtime Risk (Daily)	20%	
Power Curve Factor	0.80	$PC_t, \forall t \in T$
Max Maintenance Period	3 days	T

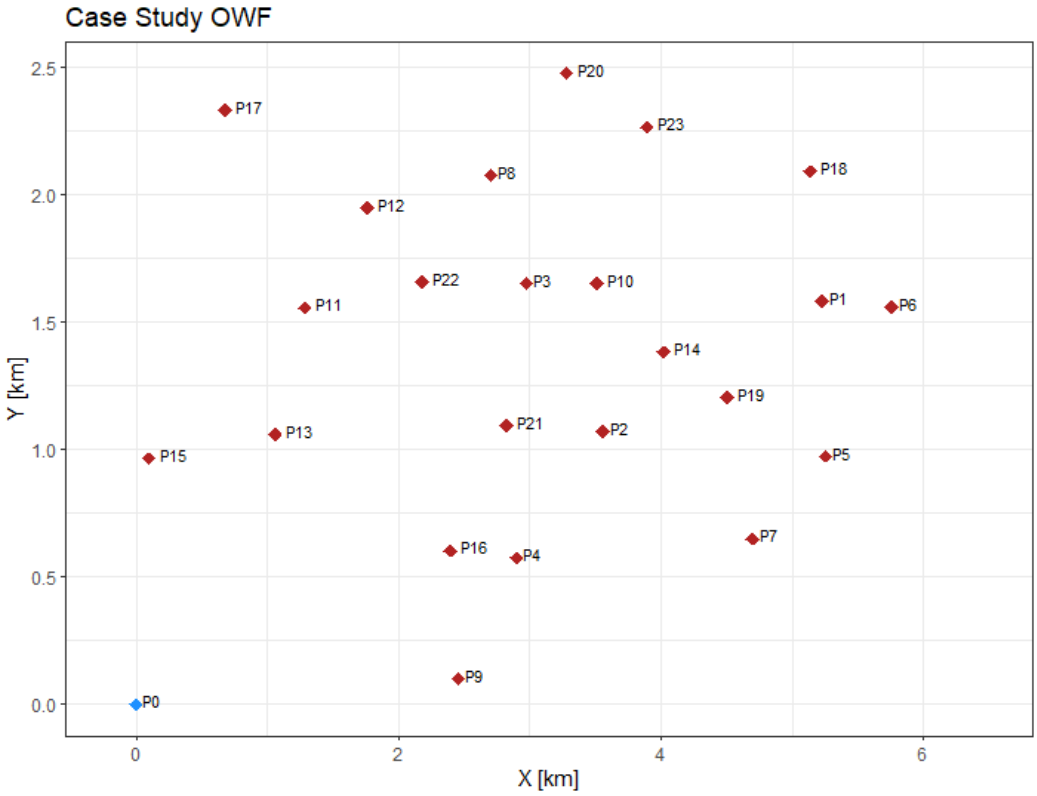

Figure 1. A map of the OWF used for the case study. The map is based on a real OWF, but the latitude and longitude coordinates have been scrambled and converted to Cartesian coordinates for confidentiality reasons.

The prediction models to be tested are deep learning models trained on historical data of similar WTs that are present at the OWF. Three models with increasing performance are tested, each trained with an increasing amount of training data, thus leading to improved metrics. The models' performance can be seen in Table 5, and further information about these specific model architecture and their training process can be found in [43,44]. As the marginal utility evaluation method presented is model-agnostic, the above models can be replaced and compared with any other equivalent prediction models, and further inspiration for similar modeling approaches can be found in [29,30,45].

Table 5. Predictive models and summarized model performance.

	Model 1	**Model 2**	**Model 3**
Precision	0.82	0.88	0.94
Recall	0.89	0.96	0.98
Accuracy	0.86	0.92	0.96
F1 Score	0.85	0.91	0.96

5.2. Declarative Modeling of Service Operations

The cost matrix used in the example of reactive maintenance cannot be constructed with respect to this case study, as the cost–benefits of predictive maintenance in this context are far too complex for evaluation using our method. The impact of predictive maintenance on service costs is dependent on the degree of increased complexity in the specific schedule change, a schedule that itself requires a complex model to achieve. For this dual purpose, we employ a declarative model. The declarative modeling approach in the context of

the preventive maintenance of OWFs was the subject of previous work, and a detailed presentation and analysis can be found in [40,46]. The necessary details for the purpose of this paper are presented in the section below.

This kind of mission should include the allocation of available service teams to the WTs, accounting for the availability, routing, and delivery/pick-up schedules of the transport vessels. Since service teams typically cannot complete maintenance for the entire OWF in a single day, the overall service mission S_i is divided into sequential daily submissions, S_q. These submissions, S_q, form a comprehensive service plan throughout the duration of the period $T : q = 1...ld$ (ld is the total number of service days). The declarative model presented in [46] enables the determination of optimal service missions for a given OWF based on the available service teams and the fleet of vessels, with the objective of minimizing OWF maintenance costs. Figure 2 illustrates the key elements of the planning of the mission schedule according to this model.

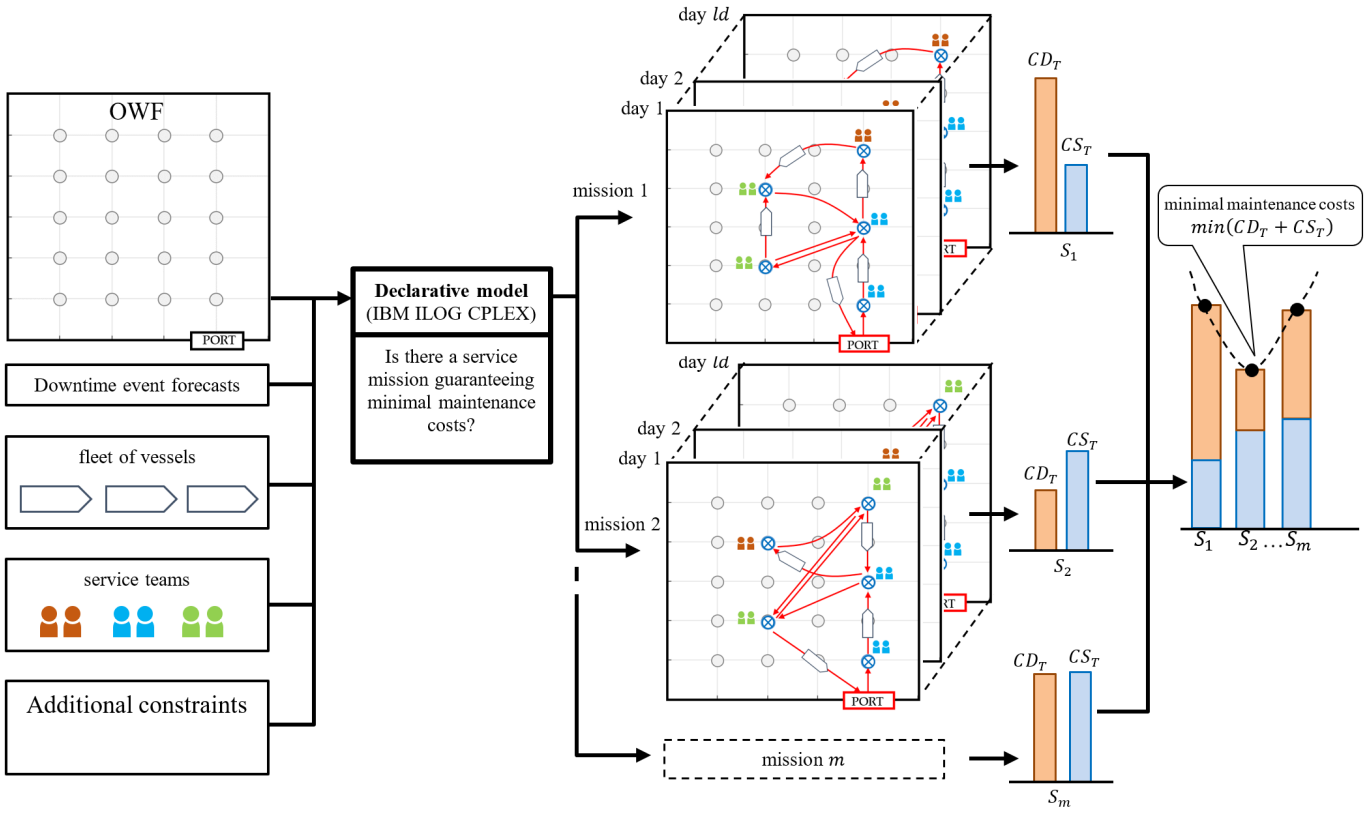

Figure 2. Declarative model driven evaluation of service missions.

The following assumptions are made when planning each sub-mission:

1. Each WT is serviced by a single dedicated service team.
2. Service teams are transported to WTs via a designated fleet of vessels.
3. Each WT requires two vessel visits: the first for team deployment and the second for team retrieval.
4. The service teams delivered to a WT by one vessel may be collected by another vessel if necessary.
5. Both the maintenance time required for each WT and the transport time between WT are known.

As alternative missions are evaluated based on overall maintenance costs, which are made up of CS_T and CD_T, these costs must be clearly defined in the context of this case study and in the declarative models. CS_T for this scenario is defined as follows:

$$CS_T(S_i) = \sum_{q=1}^{ld} \left(\sum_{v=1}^{NV} (vC_q^v + FC_q^v) + \sum_{\omega=1}^{NW} \omega C_q^\omega \right) \tag{17}$$

where the following variables are defined:

1. NV—number of vessels;
2. NW—number of service teams;
3. vC_q^v—fixed cost of renting/using the v-th vessel on the q-th day;
4. ωC_q^ω—fixed cost of the q-th working day of the ω-th service team;
5. FC_q^v—cost of fuel used during the sub-mission S_q, given by the following formula:

$$FC_q^v = pHC \cdot \left({}^q y_0^v - \sum_{k=0}^{ST} {}^q vw_n^v - {}^q st^v \right) / 60 \tag{18}$$

where the following variables are defined:

1. pHC—cost of fuel per hour;
2. ${}^q y_0^v$—the time of the vessel's return to the base of the q-th working day;
3. ${}^q vw_n^v$—waiting time of vehicle v when it arrives at WT_n of the q-th working day;
4. ${}^q st^v$—start time of the v-th vessel of the q-th working day.

From the above mission cost formulas, it is clear that fixed costs, which depend on the service resources used and the number of days required to complete the entire service mission, have a significant impact on the total cost. This results in overall maintenance costs that change in discrete, abrupt jumps as the service resources are deployed for different numbers of days, e.g., from 2 to 3 days, leading to optimal service solutions that reduce the number of days spent on maintenance.

Based on the CD_T formula in Section 3, this scenario introduces a slightly more detailed version. In this scenario and other realistic implementations of predictive maintenance, it is unknown whether actual downtime events are prevented after maintenance is performed. Instead of simply counting downtime events prevented, as in the reactive maintenance example, the expected cost of downtime is calculated on the basis of the probability of downtime events. More details on this process can be found in [8]. For preventive maintenance, the probability of downtime for all WTs is a representative average based on historical data of the whole site. For predictive maintenance, we will assume that the prediction model is well-calibrated such that the prediction output is equal to the probability of downtime. This assumption is important to the evaluation framework, as a probabilistic quantification of the costs of downtime is strictly required when dealing with such nondeterministic systems during predictive maintenance. This also positions this article as exemplary work demonstrating why calibration of AI/ML methods is highly valuable.

In the above context, the expected CD_T is formulated as follows:

$$CD_T(S_i) = \sum_{q=1}^{ld} \left(\sum_{WT_n \in US(q)} \Pr_q(WT_n) \cdot CD(WT_n) \right) \tag{19}$$

where the following variables are defined:

1. $\Pr_q(WT_n)$—probability of downtime for WT_n on day q.
2. $CD(WT_n)$—downtime cost associated with WT_n, which follows from Equation (3).
3. $US(q)$—set of WTs remaining for service at the end of day q.

Taking into account the above cost definitions, the declarative model allows the determination of service schedules for S_i according to the following statement:

$$\underset{S_i}{\text{argmin}}\{CS_T(S_i) + CD_T(S_i)\} \tag{20}$$

This ensures that, for each different service mission configuration, it is expected that the optimal schedule is found and that all changes in costs between service mission configurations are due to the parameter's change and not sub-optimal schedule solutions.

5.3. Baseline—Preventive Maintenance

With the cost of service and the cost of downtime provided by the declarative model, the profits of the baseline preventive maintenance are found and presented in Figure 3. This baseline is built on 10 different configurations with varying numbers of service teams and vessels. Note that only solutions with up to four service teams are available with both one and two vessels, as each vessel is restricted to four service teams.

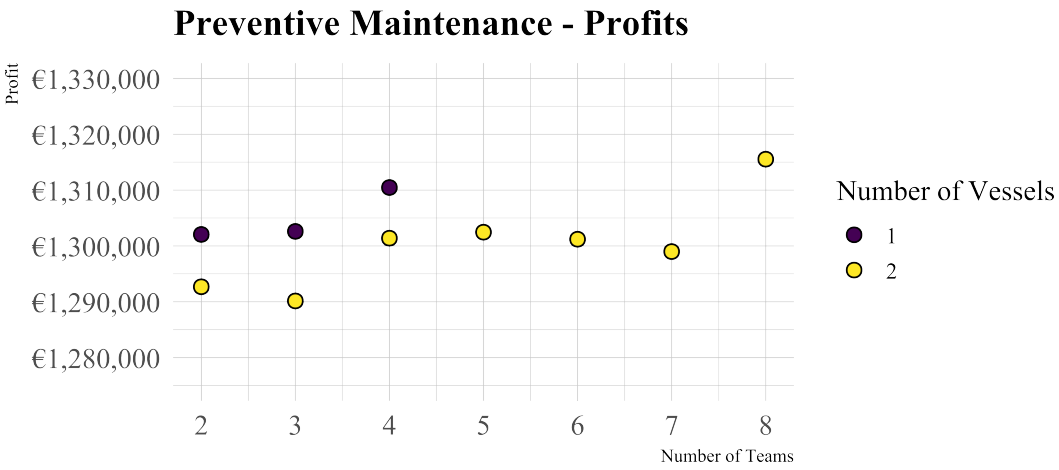

Figure 3. Baseline profits for preventive maintenance found for 10 configurations of varying service resources.

These results indicate that the increase in service resources results in a general, but not consistent, decrease in total costs, since improving overall service capabilities leads to fewer downtime events and maintenance completed in fewer days. The eight-team solution is by far the optimal, as it reduces the number of service days to a single day, minimizing the fixed daily costs of services and preventing all imminent downtime events; however, this is also quite unrealistic, as mobilizing this number of service resources requires that they be available in the first place, and there is an increased risk associated with bad weather and other conditional variables not included in our analysis.

The total number of downtime events for each scenario is presented in Figure 4. The figure displays the dynamics of preventive maintenance, which averts some downtime events by chance. Since the potential of predictive maintenance lies in the prevention of further downtime events, this potential is expected to diminish in scenarios that contain plenty of available service resources.

The preventive maintenance analysis is also a display of the nonlinearities that arise when trying to optimize maintenance operations. In this case study, the main tradeoff comes from increases in service costs in relation to minimizing downtime events. The intended benefit of predictive maintenance is to intelligently direct these service capabilities to properly reduce downtime events while minimizing the increase in service costs. The next section will present the extent to which this is possible and the conditions under which it is successful.

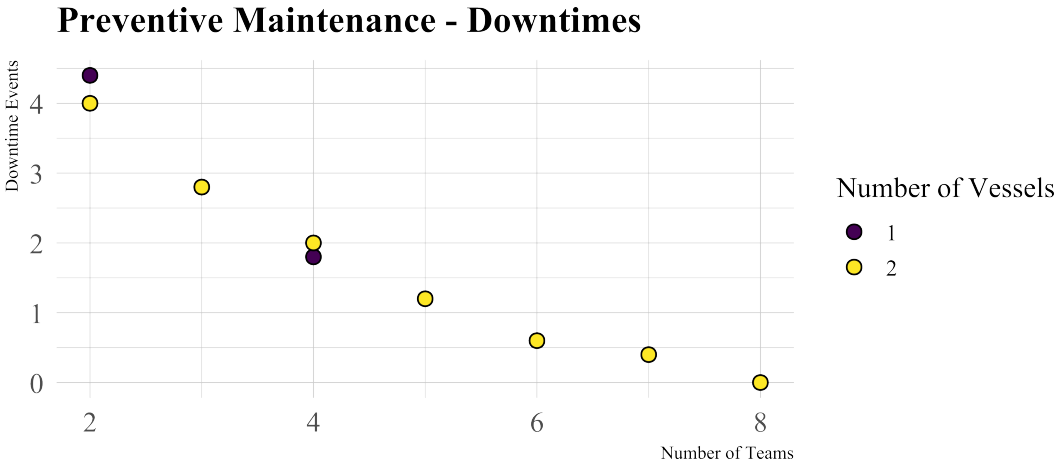

Figure 4. Downtime events with preventive maintenance for 10 configurations of varying service resources.

5.4. Results—Predictive Maintenance

With a focus on $\Delta P_{T,S_i,S_j}$ as defined in Equation (5), the following marginal utility of predictive maintenance missions, S_i, with respect to preventive maintenance, S_j, is found and analyzed. Each predictive mission configuration is compared to a preventive mission configuration with the same service resources available so that each of the three predictive models has 10 mission configurations compared to preventive maintenance. This will provide a significant basis for the marginal utility analysis of prediction model performance. The below presented figures are designed to display the key results and insights from this analysis, while all raw result numbers are available in Appendix A.

Figure 5 shows $\Delta P_{T,S_i,S_j}$ for all service mission configurations of all three prediction models under varying service resources. Each point indicates whether predictive maintenance will be cost-effective compared to an equivalent preventive maintenance solution, i.e., all points above the €0 line are positive-impact predictive maintenance scenarios.

When comparing the marginal utility of different models, it is obvious that the general trend for predictive maintenance is similar, with minor variations. Across the scenarios, the performance of models improves the outcomes in all regards, leading to the intuitive result that, as the prediction model improves, the prioritization of service resources becomes more efficient, which leads to higher marginal utility. But it is also evident that the model's performance is not the most significant factor for marginal utility.

Service mission configurations with high amounts of service resources leads to diminishing returns for predictive maintenance, as preventive maintenance is already efficient at preventing downtime events. There is simply a greater chance that predictive maintenance creates additional complexity in service schedules that does not return sufficient savings in downtime costs. This indicates that, in this specific case study, predictive maintenance is more efficient when service resources are limited, and these limited resources can be directed toward where they have more significant impacts.

From the perspective of a maintenance planner, these results are valuable in their own right. However, they also offer a practical implication: achieving the same level of maintenance efficiency with fewer service resources and freeing up resources to be reallocated to other areas.

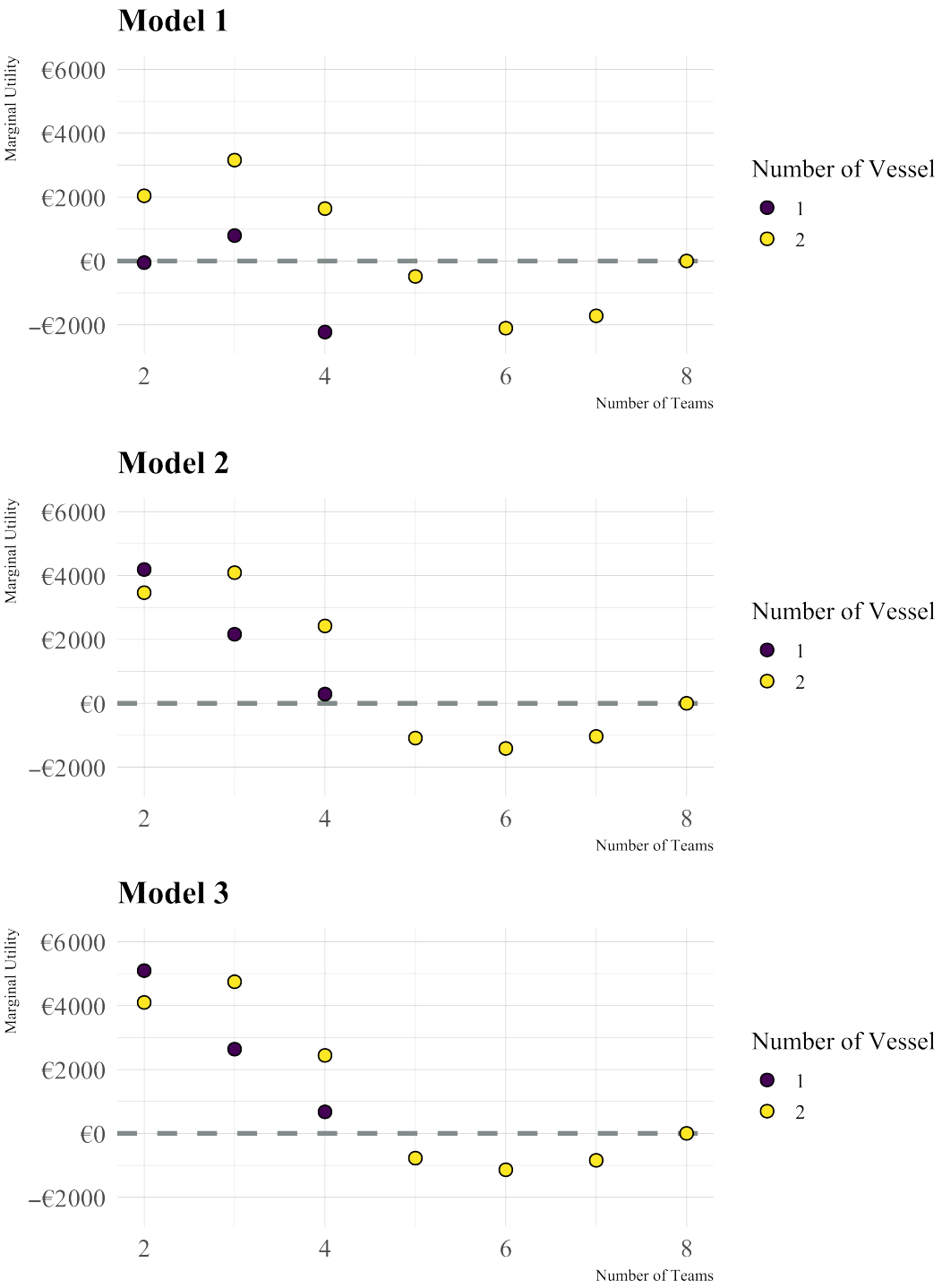

Figure 5. $\Delta P_{T,S_i,S_j}$ based on all three models for predictive maintenance. Values above the grey line indicate the positive marginal utility of predictive maintenance in that scenario.

To obtain a more relative sense of the improvements, Figure 6 shows the marginal utility in terms of cost savings. The figure presents the same results as before, but this time, the results are relative to the size of baseline maintenance operations. Under the best conditions, as much as 15% of savings can be achieved, and in the worst conditions, almost 10% in additional costs are incurred.

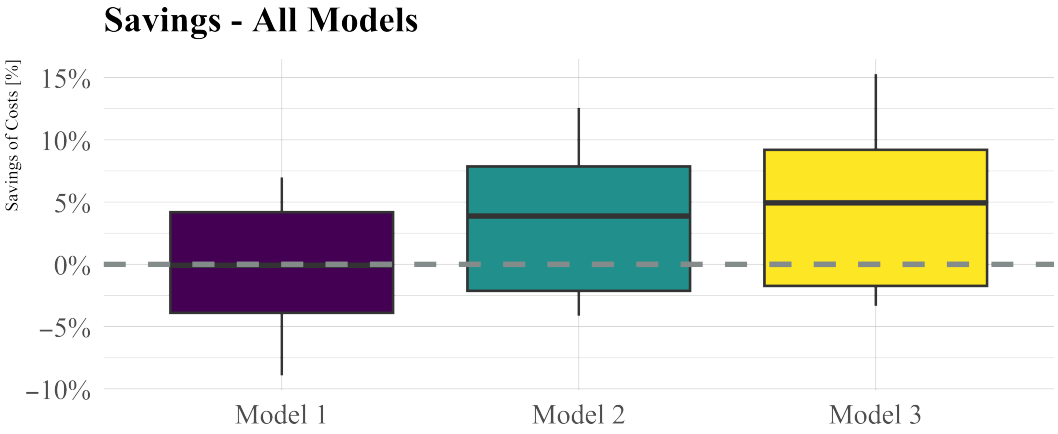

Figure 6. $\Delta P_{T,S_i,S_j}$ as a percentage of preventive maintenance costs.

Although the results above are quite specific to this case study, this provides a valuable demonstration of the knowledge generated and how the method can help us understand and map the maintenance dynamics of predictive maintenance. Similar efforts are integral to the successful business integration of predictive maintenance in areas where the profit potential is limited either by high costs of prediction failures or by highly efficient baseline maintenance.

6. Discussion

The marginal utility analysis presented in this paper is based on a case study carried out with plenty of assumptions and simplified factors. In an industrial setting, more effort should be placed into allowing for as many service operations complexities as possible in order to make possible the specification of the most relevant parameters for costs and revenue generation and to ensure marginal utility results that are as accurate as possible. Such additions could be weather windows and access constraints, spare-part supply chains, vessel and team availability constraints, electricity price variability, etc. While the declarative model allows for these additions, they were not required to showcase the validity of the methodology, but they will have significant impacts on the final marginal utility estimates and the resulting decisions on predictive maintenance implementation and predictive model training.

A significant neglected cost in the analysis of this paper is the cost of prediction models. For simple prediction models built with access to a well-functioning data infrastructure, the expenses associated can be almost negligible. However, for extensive training processes requiring data collection, model training compute, cloud deployment, and ongoing maintenance, the costs can be surprisingly substantial. In particular, as the use case requires better-performing models, the costs can be expected to increase as an upper limit on performance is approached, as this might demand exponentially greater effort and resources. The cost of predictive modeling should be reflected in the methodology of this paper if possible; however, finding such costs on a per-case basis is highly difficult, and as such, this step was omitted in our case study. We believe that such an analysis of the costs of predictive modeling and their relationship to the marginal utility of predictive maintenance should be a self-contained study.

A motivating factor for the creation of the method presented in this paper was an ambition to clarify an important aspect of AI/ML model training: deciding when a model is good enough for business implementation. Although this paper does not answer this question in full and only deals with the topic from the perspective of predictive maintenance, we provide a good foundation for further work in this regard. In the numerical example, the exact model performance leading to zero marginal utility can be found, as the cost

dynamics are easily calculated; thus, a model performance threshold is found. However, in many practical applications, the cost dynamics are much more complex and require much more intricate solutions to estimate, as shown in the case study. Further work on the estimation of cost dynamics in AI/ML applications would, from our perspective, grant the best opportunities for such applications to succeed in industrial and business environments.

7. Conclusions

This paper introduces a method for evaluating the implementation of predictive maintenance on the basis of preexisting maintenance by analyzing the marginal utility of changes to maintenance operations. The method is used to describe the relationship between prediction model performance and the impact it will have on maintenance costs, recognizing that inaccurate predictions can lead to counterproductive and detrimental business impacts. Furthermore, by repeating this exercise for several scenario configurations, it is demonstrated how the method can also identify other relevant parameters that influence the business value of predictive maintenance.

In the presented numerical example and the case study, this evaluation method was used to find the impacts of implementing predictive maintenance in the wind sector. The methodology was, in both cases, tested using three predictive models with varying performance levels to assess the impact on marginal utility, while the example and case study varied significantly in the complexity of maintenance operations and cost dynamics. As expected, it was demonstrated that a better-performing model yields higher marginal utility, but the value in these cases came from estimating how much more marginal utility resulted from improvements in the predictions. Consequently, justifying the costs associated with developing predictive models can become increasingly difficult, but the methods presented can also help clarify the risks and benefits of such spending.

Lastly, as a secondary result, our method made it clear that, under the specific conditions of this case study, the limitation of service resources was one of the factors leading to a higher marginal utility of predictive maintenance. This shows that the method can provide secondary utility by testing scenario parameters other than the intended predictive model performance.

Author Contributions: R.D.F.: Conceptualization, methodology, formal analysis, investigation, writing—original draft, writing—review and editing, and visualization; G.R.: software, validation, investigation, and data curation; G.B.: conceptualization, methodology, validation, formal analysis, writing—original draft, and visualization; P.N.: resources, writing—review and editing, supervision, and project administration; Z.B.: formal analysis, resources, writing—review and editing, and supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

This section presents all numerical results from the case study for the curious and detail-oriented reader. Each table presents as much data as necessary to recreate the results presented in Figures 3–6. The potential revenue is the same for all configurations below so as to avoid repeating that number, and it is stated here once: Rev_T = €1,335,398.40.

Table A1. Preventive maintenance baseline results. Total costs per service resource configuration. These values serve as the reference for calculating ΔP and % savings in Tables A2–A4.

Vessels	Teams	CS_T	CD_T	Total Cost (€)
1	2	€19,719	€13,624.93	€33,343.93
1	3	€24,130	€8670.41	€32,800.41
1	4	€19,366	€5573.84	€24,939.84
2	2	€30,326	€12,386.30	€42,712.30
2	3	€36,581	€8670.41	€45,251.41
2	4	€27,820	€6193.15	€34,013.15
2	5	€29,225	€3715.89	€32,940.89
2	6	€32,343	€1857.95	€34,200.95
2	7	€35,173	€1238.63	€36,411.63
2	8	€19,868	€0	€19,868.00

Table A2. Numerical results for predictive maintenance with Model 1.

Vessel	Team	CS_T	CD_T	Total Cost (€)	ΔP (€)	% Savings
1	2	€20,155	€13,239.49	€33,394.49	€−50.56	0%
1	3	€24,837	€7167.80	€32,004.80	€795.61	2%
1	4	€19,997	€7167.80	€27,164.80	€−2224.96	−9%
2	2	€30,374	€10,297	€40,671	€2041.30	5%
2	3	€34,925	€7167.80	€42,092.80	€3158.61	7%
2	4	€26,881	€5491.28	€32,372.28	€1640.87	5%
2	5	€29,533	€3890.99	€33,423.99	€−483.10	−1%
2	6	€32,413	€3890.99	€36,303.99	€−2103.04	−6%
2	7	€35,637	€2491.38	€38,128.38	€−1716.75	−5%
2	8	€19,868	€0	€19,868	€0	0%

Table A3. Numerical results for predictive maintenance with Model 2.

Vessel	Team	CS_T	CD_T	Total Cost (€)	ΔP (€)	% Savings
1	2	€20,338	€8816.82	€29,154.82	€4189.11	13%
1	3	€24,638	€5999.93	€30,637.93	€2162.49	7%
1	4	€19,625	€5024.88	€24,649.88	€289.96	1%
2	2	€30,432	€8816.82	€39,248.82	€3463.48	8%
2	3	€35,161	€5999.53	€41,160.93	€4090.49	9%
2	4	€26,566	€5024.88	€31,590.88	€2422.28	7%
2	5	€29,581	€4448.42	€34,029.42	€−1088.53	−3%
2	6	€32,284	€3329.32	€35,613.32	€−1412.37	−4%
2	7	€35,601	€1847.05	€37,448.05	€−1036.42	−3%
2	8	€19,868	€0	€19,868	€0	0%

Table A4. Numerical results for predictive maintenance with Model 3.

Vessel	Team	CS_T	CD_T	Total Cost (€)	ΔP (€)	% Savings
1	2	€20,214.97	€8034.50	€28,249.47	€5094.46	15%
1	3	€24,625.24	€5539.16	€30,164.40	€ 2636.02	8%
1	4	€19,574.32	€4692.43	€24,266.75	€673.09	3%
2	2	€30,579.34	€8034.50	€39,613.84	€4096.46	10%
2	3	€34,965.97	€5539.16	€40,505.13	€4746.29	10%
2	4	€26,880.42	€4692.43	€31,572.85	€2440.31	7%
2	5	€29,581	€4134.80	€33,715.80	€−774.90	−2%
2	6	€32,284	€3056.57	€35,340.57	€−1139.62	−3%
2	7	€35,601	€1654.32	€37,255.32	€−843.69	−2%
2	8	€19,868	€0	€19,868	€0	0%

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