Informing early design decisions through functional analysis of maintenance drivers: Application in marine renewables

N. Algarra and A. Dong

***Abstract*—Operational expenditures dominate the cost of long field-life systems, with maintenance comprising a significant proportion for many systems. However, engineers lack the tools to assess maintenance during conceptual design. Familiar systems mitigate this problem by providing historical maintenance data from which empirical models can be derived. Emerging technologies, like marine renewables, lack operational maintenance data. As a result, engineers must make decisions with no historical data and minimal, if any, operational experience. The high operations cost incurred from basic maintenance tasks, and the loss of energy production during maintenance, further highlight maintenance as a critical cost driver. This paper develops a data-driven model to estimate maintenance intervals of long field-life systems during conceptual design. The model links the elementary functions of a component to maintenance requirements. Relative maintenance considerations were determined by mining function and maintenance data from manuals of long field-life systems. Machine learning was applied to generate a function-maintenance model from the maintenance data. The model consisted of functions grouped into buckets of increasing maintenance demand. The machine learning model was applied to an exemplary long field-life system, a wave energy converter, to explore possible redesigns to reduce maintenance costs. This paper shows that maintenance costs, actions and intervals can be confidently accounted. The function-maintenance model offers two beneficial impacts: it reduces life cycle cost uncertainty, and allows engineers to make informed decisions during conceptual design when redesign costs are at their lowest.**

***Index Terms*—Functional analysis, Design for maintenance, Early design, Concept evaluation . . .**

I. Introduction

OVER the anticipated lifespan of a marine renewable energy device, operations and maintenance (O&M) are expected to account for up to one-third of the project's total cost [1]–[3]. For example, Neary [4] uses 6 inputs to predict O&M costs, 5 of which explicitly call out maintenance:

- Marine ops → Performing onsite *maintenance*
- Shore-side ops → Towing the device shore-side to perform *maintenance*
- Replacement parts → Recoverable parts used during *maintenance*
- Consumables → Parts consumed during *maintenance*
- Downtime → What a *maintenance* program looks to minimize

Though O&M accounts for a significant portion of project costs, it is nearly impossible to estimate until the latter design stages when the detailed design, environmental factors, and location are determined. At this stage of the project, O&M is treated as a cost to be mitigated as opposed to a design variable that can be optimized. Whether the relevant evaluation criteria of a particular marine renewable is the levelized cost of energy or the total cost of ownership, O&M remains a significant cost driver and a key factor influencing commercial viability. Yet, existing research for the prediction of maintenance requires an extant, completed design with materials and component choices detailed. These approaches are more about predicting maintenance costs after a design is completed rather than designing with potential maintenance costs in mind. This research aims to develop an approach to maintenance cost assessment during the early stages of system design, typically called conceptual design.

Work in the design for maintainability field has shown that maintenance is not a set of actions that occur to a device once designed and manufactured. Instead, maintenance is an aspect of the device that is inherent to the culmination of design decisions made throughout the development of the device [5], [6]. From the idea that O&M is primarily maintenance and that maintenance is a result of the design of a system, we conclude that O&M cost reduction should start during conceptual design.

If O&M should be considered during conceptual design, can it be meaningfully reduced? Do design tools exist to understand the drivers of O&M to make design changes effectively? This research aims to determine if the myriad of functions embodied in a long field-life system have an identifiable relationship with their maintenance demands – that is, do certain functions have more maintenance requirements than other functions? Furthermore, can heuristics be developed – to be used in early design – to guide and inform designers of the relative maintenance implications of the functions within a system? By providing this information during

N. Algarra is a graduate student at Oregon State University in the Design Engineering Lab of the School of Mechanical, Industrial and Manufacturing Engineering. Dearborn Hall 1891 SW Campus Way Corvallis, OR, 97330, U.S.A. (e-mail: algarran@oregonstate.edu).

A. Dong is the School Head of Mechanical, Industrial and Manufacturing Engineering at Oregon State University and a professor in the Design Engineering Lab. 208 Rogers Hall 2000 NW Monroe Ave Corvallis, OR, 97330, U.S.A. (e-mail: andy.dong@oregonstate.edu).

Digital Object Identifier:
https://doi.org/10.36688/ewtec-2023-262

conceptual design, design engineers could alter the functional approach to reduce the usage of functions determined to have a "significant" impact on O&M or make changes to the physical architecture to facilitate maintenance.

The approach developed in this research relies on machine learning applied over maintenance data. Function-maintenance relationships were determined by mining data from the maintenance manuals of two long field-life systems: the Learjet 25 series twin-engine business jet and the CJ610 turbojet engine. The function implemented by the component and the flow of energy (e.g., mechanical energy, electrical energy) and material (e.g., solid, liquid, or mixture) through the function were determined to create a data point. Each data point relates a component or assembly to its function, flow, and maintenance requirements. The function-maintenance data was then processed using machine learning to build a model to associate functions into categories of maintenance requirements. Heuristics were developed to inform designers on the maintenance implications of chosen functionality and to guide informed decision-making from the earliest stages of development.

The Background section first discusses the relevant research on conceptual design and the extent to which operations and maintenance are key drivers of the cost of systems. Functional modeling and Machine learning are then discussed. In the Methods section, the Data mining and Functional modeling processes utilized are described. Developing the model and Application to the Laboratory Upgrade Point Absorber explain the development of the machine learning model from the data and the application of the function-maintenance model to the Laboratory Upgrade Point Absorber (LUPA), an operational research prototype wave energy converter [7]. In the Results, the findings from the model's development, the model's implications and the LUPA application are expanded on. The Conclusion and Future work is then presented.

II. Background

A. Conceptual Design

The design of systems typically proceeds along 6 phases: 1. Specification development/planning, 2. Conceptual design, 3. Product design, 4. Production, 5. Service and 6. Product retirement [8]. This research concerns the second phase, conceptual design (interchangeably called early design). Conceptual design can best be understood by the inputs and outputs of the phase. Device requirements in terms of performance, development timeline, budget, and measures of success are vital inputs into the conceptual design phase; without defining the *what* and *why* of a device, engineers can not effectively make decisions that lead toward the accomplishment of the design goals. Upon leaving the conceptual design phase, the design team will have a rough idea of how the device will operate, the components and system architecture, and the functional structure of the device. Ullman [8] describes the conceptual design phase as "the least managed, the least documented and the least understood." Design research echoes the sentiment that the conceptual design phase is underutilized, overlooked, and sped through as quickly as possible [9]–[11]. In the specific field of marine renewables, with few exceptions [12], [13], the conceptual design phase has been largely neglected [11]. This is particularly concerning considering the lack of design convergence; how are different archetypes assessed before investing significant capital into a concept?

During the early design phase, most of the lifetime costs of a device are determined. Exact values vary, but most scholarship agrees that 70-80% of a product's lifetime cost is committed during the conceptual design phase [8], [14]. Once concrete decisions are made, the costs incurred to make changes significantly increase throughout the development phase. "Very roughly, if the cost to make a change at the product concept stage is $1, the cost is $10 at the detail design stage and $100 at the production stage" [9]. The importance of a focused conceptual design phase is best described by, "...the decisions made during the design process have the greatest effect on the cost of a product for the least investment" [8].

B. Operations and maintenance as a key driver of operational expenditure

The authors broadly define long field-life systems as any product where the operational expenditure (OPEX) will account for a significant portion of the life cycle cost. The primary aspect of concern within OPEX is O&M, with extreme cases putting O&M costs at 60-80% of life cycle costs [9]. The most developed marine renewable systems, offshore wind farms, have estimated O&M costs of 30% of the lifetime costs [1], [2] or of the cost per kWh [15]. Upon entering the detailed design phase, using the best-case scenario of committed cost (70%) and O&M costs as a percentage of lifetime costs (30%), O&M alone has locked in 21% of the system's total lifetime cost. The remaining 9% of lifetime costs attributed to O&M are the costs that engineers influence.

Thus far in the marine renewable field, O&M has been treated as a given for a system and is addressed late in the project when the system's detailed design is complete and the project's location and related environmental factors are determined. Recent literature has explored cost reduction through simulating various O&M strategies, exploring differences in transportation methods, predicting weather windows and their impact on downtime, as well as location and the relative value of more energetic environments on power production versus maintenance impacts. Simulated strategies ranging from no maintenance to conducting maintenance as soon as possible to reduce downtime have been explored. The results of these studies showed that no maintenance strategy is not a viable option [16], [17], indicating to developers that maintenance must be addressed in the design of the device. While there has been significant O&M cost reductions through these means over the last decade, further reduction is still needed to make marine renewables an economically attractive investments.

The design for maintainability field concerns itself with the portion of lifetime costs attributed to O&M that are not locked in upon concept selection. Design for maintainability can be summarized by five axioms: simplicity in design, standardized parts, control of the maintenance environment, simple assembly/disassembly procedures, and clearly identified parts/connections [5], [6]. These axioms are effective when leveraged during the detailed design phase. However, they are ineffective at assessing various alternative designs prior to a significant investment towards a chosen design.

Returning to the marine renewable field, a significant contributing factor to high O&M costs is the lack of historical maintenance data and the tendency of developers to keep lessons learned internal [7], [12], [18]. The reasons behind this lack of transparency and sharing are not unknown; innovative cost-cutting strategies and designs could represent a significant commercial asset to those with the experience and knowledge. The development and open sharing of assessment tools for use during early design can help to bridge the knowledge gap.

C. Functional modeling

Functional modeling is a design method that facilitates the decomposition of a system into an abstract model comprised of elementary electro-mechanical actions performed or embodied to make a component-agnostic model of the system. This abstract model captures the functional approach taken by the designer to achieve the intended outcome. These elementary actions, called functions, describe what is happening to the flow of material, energy, or signal as it passes through the system. Functions operate on these flows to transform them into useful work. For example, a "convert" function operates on the flow of, say, electrical energy to convert it into mechanical energy for the purpose of spinning a shaft. By abstracting away from specific electro-mechanical components, designers can step back and develop a deeper understanding of the potential design space (i.e., the main ways outcomes can be achieved). Functional modeling has proven to be an effective tool for a wide range of tasks including failure analysis [19], reliability prediction [20] and centering design work on customer requirements [21], among others. The strengths of functional modeling that this research relies on are functional modeling's abstraction of physical architecture that allows for new insights to be gained and its utility during early/conceptual design.

Multiple functional languages have been developed to meet the specific needs of fields as well as general languages intended to encompass all mechanical design. Hirtz [22] developed one such language by reconciling multiple previous efforts into a list of 52 functions and 82 flows that are combined to make a verb-object pair, called a function-flow pair henceforth. Functions are organized into 3 levels. Flows

Component	Function			Flow		
	Level 1	Level 2	Level 3	Level 1	Level 2	Level 3
Hydraulic Line	Channel	Transfer	Transmit	Energy	Hydraulic Energy	Pressure
Filter	Change Magnitude	Stop	Prevent	Material	Solid	Particulate

TABLE I: Functions and Flows of example components at 3 levels

are organized into a hierarchy of 4 levels, though the 4th level will not be used in this research since the 4th level of description contains more detail than is needed for this research. The lowest level (level 1) is the most abstract and levels gradually increase in descriptive specificity. Table I displays two example components and the components' functions and flows at all 3 levels. Function-flow pairs can be extracted from Table I. The level 1 function-flow pair for the filter is *Change Magnitude Material*. Upon decomposing that verb-object pair, the filter's level 1 functionality is realized, to change the magnitude of a flow of material. The level 2 function-flow pair is *Stop Material*, and level 3 yields the most descriptive function-flow pair the filter, to *Prevent Particulate*.

Since functional modeling is abstract and can suffer from problems with inter-modeler reliability, it is worth expanding on the lens through which functionality can be assessed. Deng [23] groups functionality into purpose functions and action functions. Purpose functions are descriptions of the designer's intention and are generally more abstract, whereas action functions describe physical interactions. As purpose and action functions are described at two different levels of abstraction, they are not necessarily mutually exclusive. An example of the difference can be found in the hydraulic line in Table I. The purpose – or designer intent – is to transfer pressure to some location. The action – or physical description of the system in question – is to transfer a liquid to some location. The function-flow pairs could be: *Transmit Pressure* and *Transport Liquid* for the purpose and action functions, respectively. Both are accurate functional descriptions of a hydraulic line, but *Transmit Pressure* is abstracted further. It is possible to imagine multiple means to *Transmit Pressure* other than a liquid; both a solid and a gas could be leveraged to apply pressure at some location.

Now that we have discussed levels of abstraction, function-flow pairs, and purpose versus action functions, we have come to the second strength of functional modeling: its use during conceptual design. During conceptual design, the functional approach must be selected before specific components are sized and selected. Herein lies the strength of functional modeling. Long before an engineer implements, say, a level 3 function-flow pair of *Transmit Pressure* and the component with which to accomplish this task, such as the hydraulic line from Table I, the engineer chose an elementary action, to *Channel Energy* from one location to another. Though this step was described in a single sentence, the actual design process could take months or years before designers get from *Channel Energy* to the choice of the specific component selection of a hydraulic line to implement this function. Nonetheless, the choice of functional approach determined the potential maintenance costs because there are a finite number of ways that energy can be transferred from one location to another.

D. Machine learning

Machine learning has proven effective at extracting valuable insights from data sets that are too large for a human, regardless of their expertise in the area, to comprehend, let alone derive useful information from [24]. Machine learning models are categorized into 2 types: supervised and unsupervised learning. Unsupervised learning is performed when the model has no prior information on the features or variables and makes predictions primarily by associating data points based on similarities. Supervised machine learning requires that information on what the features in the data set mean is given to the model. A type of supervised machine learning model called a Decision Tree is utilized in this work. This background section will focus on the relevant information for Decision Trees.

Decision Trees are a popular machine learning model whose primary attribute is their simplicity. Decision trees are often represented as a tree that starts at a single node and branches out into additional nodes that can each branch out further. Each node represents a characteristic of the system (such as its color); depending upon the attribute of that characteristic (e.g., the color is red), the tree is traversed in the "red" direction rather than, say the "green" direction. Once a node fails to reduce information entropy by a certain preset parameter or is manually pruned, that branch ceases to split and becomes a "leaf" node. Each leaf node has a final determination on any data points following the branches down to that node. That determination could be a category or a numeric value.

A decision tree can be used to learn a function-maintenance model because each piece of information on the functions, flows and function-flow pairs embodied in a part can serve as a possible node in the decision tree. Fig. 1 shows a truncated decision tree created from this research; the topmost node could be phrased colloquially as "does the level 3 flow *Object* occur more than 0 times in this part?". If yes, proceed down the left branch to reach "Does the Level 2 function-flow pair *Guide Gas* occur 0 times in this part?". Upon reaching a node cell – leaf or not – the predicted category (in this case, relative maintenance bucket) is given, followed by the probability of the other categories in increasing numeric order from top left to bottom right. The predicted category is based on all occurrences of parts in the training data set that match the series of binary choices presented through the decision tree and the category of those data points.

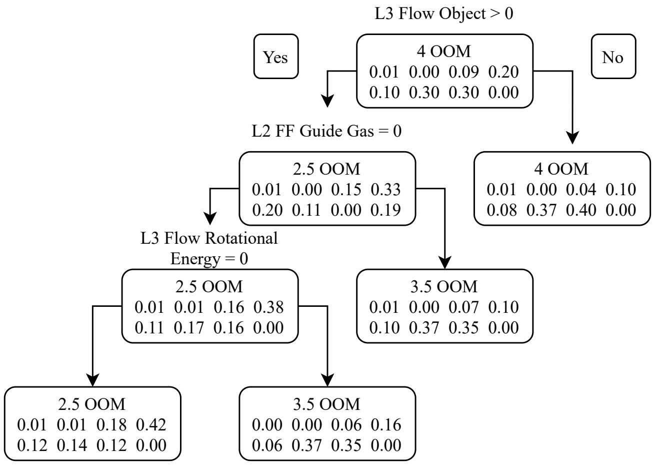

Fig. 1: Truncated decision tree shows the series of binary that the decision tree follows that results in a predicted category

III. Methods

A. Data mining

The Learjet 25 series represents a typical long field-life system. The 25 series were produced from 1966 until 1982, with 500 number still in service worldwide as of 2006 [25]. With even the newest Learjets over 40 years old, the wealth of knowledge on maintenance requirements, procedures and timelines is well documented. It represents an exemplary data set from which to harvest maintenance information.

The Learjet 25 series and CJ610 turbojet engine maintenance manuals were first reviewed to identify all maintenance actions throughout the manuals. For this research, "maintenance" is defined as any time an operator or maintenance personnel must inspect, repair, replace or service a component or assembly. "Maintenance" includes all types of preventative maintenance – time-based, failure-finding, risk-based, condition-based and predictive. This broad definition allowed the authors to capture all interactions with the system; examples include checking filters for particulate build-up, applying lubricant, a scheduled overhaul of an assembly, etc.

Maintenance actions were then limited to those with a unit of time associated with the action. Maintenance actions associated with a specific incident were not included; inspections following an overweight landing are one example. The Learjet manual provides an equivalency chart that relates aircraft age, total flight time, average monthly use, average flight length and total landings back to flight hours. Flight hours were used as the standard time measurement as it was the most frequently used and had a direct relationship to all other frequency measures. The CJ610 manual provided information on converting engine power cycles to average flight length, allowing its maintenance actions to be translated into flight hours.

From the Learjet manual, extracted maintenance actions were primarily found in the following chapters: Airworthiness Limitations, Time Limits/Maintenance Checks, and Servicing. From the CJ610 manual, all maintenance actions were found in "Engine General" chapter. The authors manually extracted the maintenance information by transcribing the maintenance task as described in the manual and the associated

Manual	Maintenance task from manual	Component	Identified Level 1/2/3 function	Identified Level 1/2/3 flow
Learjet 25 series	Aileron for security, operation and general condition	Aileron	Control Magnitude Change Condition	Energy Mechanical energy Rotational energy
Learjet 25 series	Lubricate ball joint connector	Ball joint	Channel Guide Allow degree of freedom	Energy Mechanical energy Translational energy

TABLE II: Example maintenance task and derived components, functions and flows

time interval into a spreadsheet. The maintenance task was then examined to determine the critical part(s) of concern that said maintenance task is seeking to maintain the functionality of. Based on the author's maintenance-centered definitions, the part of concern was assessed, whether it was a component or an assembly. A component is a part that is replaced wholesale without further disassembly. An assembly is anything outside that definition. For example, a hydraulic actuator, though it contains a variety of parts such as the piston, cylinder and seal, would generally not have those parts replaced individually during routine maintenance. The entire hydraulic actuator would be removed and replaced, making a hydraulic actuator a component. Table II contains a few sample data points with all mined data; notice the maintenance task "Lubricate ball joint connector" was refined down to "Ball joint" as that is the part of concern that the maintenance task is meant to maintain the functionality of.

B. Functional modeling

Functional decomposition began once the maintenance action, maintenance frequency, and component versus assembly information were extracted, as well as crucial part(s) of concern identified from the maintenance actions. As previously described, the functional basis presented by Hirtz [22] was used as the functional language for this work. The decision to utilize this functional language was due to its popularity and glossary of all functions and flows with a definition and example of each. The glossary allowed the authors to maintain a high level of consistency when evaluating functionality.

Each part of concern was then assessed using the respective maintenance manual or [26] to determine functionality. All parts were prescribed at least 1, and at most 5, function(s) and their respective flow(s) at all 3 levels of abstraction. When evaluating functionality, the authors maintained designer's intent as the primary evaluating factor to ensure all functionality was assessed based on purpose as opposed to action. Table II shows sample parts, the mined data from their respective maintenance manual and all information derived by the authors.

C. Developing the model

Once the data was collected from the maintenance manuals, processing began to prepare the data to train and test the model. The model was trained on the features: Functions, Flows, Function-Flow pairs, Function Count, and Component versus Assembly. Functions, Flows, and Function-Flow pairs were each recorded separately for all 3 levels, with a value of 0 to 4, based on the instances of that Function/Flow/Function-Flow pair being performed by the part in question. Function count was recorded with a value of 1 to 4, based on the total number of functions a single part performed. Component versus Assembly was determined based on the author's maintenance-centered definition of a component and an assembly, as described in the Data Mining section. Component versus Assembly was the only categorical feature, with the remaining features being continuous values.

To ensure the results could be generalized to other long field-life systems regardless of the maintenance timescale of the device, the authors decided to conduct a categorical regression. By sorting the mean time between maintenance (MTBM) values into relative buckets of increasing maintenance demands, the results would better scale to systems with various average maintenance intervals. The training data contained MTBM values ranging from 1.5 to 30,000 flight hours, with 99% of data points below the midpoint of 15,000 flight hours. It was decided to utilize buckets based on order of magnitude increases. The "0 Bucket" was centered on a 1 flight hour maintenance interval, with each whole bucket increase being centered on the next higher order of magnitude. Half orders of magnitude were utilized to further break down buckets. As an order of magnitude is defined as a factor of 10 increase, a half order of magnitude is defined as an increase of the square root of 10, approximately 3.16. This categorization was chosen because the differences between buckets are easily understood and can still be utilized regardless of the starting point of the "0 Bucket". Since all buckets are defined relative to each other, the difference in MTBM between a part in the "2.5 Bucket" and the "3.5 Bucket" maintains a consistent 1 order of magnitude increase, regardless of the specific MTBM values on which the buckets are centered. This will allow designers to use this model even if the MTBM range of their specific system is not consistent with the data used to train this model.

Once all data points were assigned to their maintenance bucket, the data was split into a training set and a testing set, containing 70% and 30% of all data points, respectively. The training set was used to develop a decision tree using the *rpart* and *rpart.plot* packages in *R*. The complexity parameter value is the minimum decrease in the coefficient of determination (R^2) required for the model to expand on a particular branch of the decision tree. By adjusting the complexity parameter, the authors could balance model accuracy and overfitting the decision tree to match the training data.

D. Laboratory Upgrade Point Absorber application

To investigate the external validity of the model, the authors applied the model to the Laboratory Upgrade Point Absorber (LUPA) developed at Oregon State University. LUPA is a tank-scale, open-source wave energy converter meant for researchers and developers to help offset the high costs of tank-scale testing and to encourage the open sharing of data and lessons learned. The reasoning for selecting LUPA to apply our model to was similar to that of the reasoning in selecting maintenance manuals for the model that being accessibility. LUPA, specifically designed as an open-source platform, was the only fully designed and manufactured wave energy converter with publicly available documentation. The authors reviewed 3D models, the bill of materials and other device documentation to determine the functionality of the 162 unique electro-mechanical parts in LUPA. All features used to train the model were documented then formatted and input into the model. The model was executed and output a predicted bucket of maintenance frequency for each part.

The authors collaborated with an expert design engineer (unaffiliated with this project or LUPA) to provide an external assessment of the maintenance frequency of selected LUPA parts to compare to the model's results. Dr. Robert Paasch, Professor Emeritus of Mechanical Engineering at Oregon State University, was the expert design engineer. Dr Paasch's research background is in design theory, applied design processes, reliability and survivability in the marine renewable energy and automotive engineering fields. Of the 162 unique electro-mechanical parts in LUPA, 30 unique parts were selected at random from maintenance buckets in the same ratio of buckets as the model predicted. The number of parts selected from each predicted maintenance bucket are as follows: 7 parts from both the 2 and 3.5 OOM buckets, 12 parts from the 2.5 OOM bucket and 4 parts from the 4 OOM bucket. The list of parts was provided to Dr. Paasch with the following prompt:

> A list of 30 unique electro-mechanical parts is included along with all 3D model parts and assemblies, the bill of materials and all available design documents. Please review these parts and assess the relative maintenance demand of the parts. For the purposes of this work, "maintenance" is defined as any time an operator or maintenance personnel must inspect, repair, replace or service a component or assembly. "Maintenance" includes all types of preventative maintenance – time-based, failure finding, risk-based, condition-based and predictive. Please assign all parts to the 4 relative maintenance buckets; the buckets are based on order of magnitude (OOM) relative differences. The 4 buckets are listed below with a brief description.
>
> - 2 OOM bucket - parts in this bucket require the most frequent maintenance
> - 2.5 OOM bucket - parts in this bucket require maintenance approximately 3.16 times, a half OOM, less frequently than parts in the 2 OOM bucket
> - 3.5 OOM bucket - parts in this bucket require maintenance approximately 10 times, 1 OOM, less frequently than parts in the 2.5 OOM bucket and 13.16 times, 1.5 OOMs, less frequently than parts in the 2 OOM bucket
> - 4 OOM bucket - parts in this bucket require the least frequent maintenance; 2 OOMs, 1.5 OOMs and a half OOM less frequent maintenance than the 2 OOM bucket, 2.5 OOM bucket and 3.5 OOM bucket, respectively

IV. Results and Discussion

This section presents the results, first discussing the function-maintenance model created and its role as an early design tool. Then, the section describes the predictive capability of the model and compares the outcome with the opinion of an expert design engineer with years of experience in marine renewable energy and design for maintainability. The results section concludes with redesign recommendations for a current wave energy converter based on the model's prediction of maintenance requirements.

A. Function-maintenance model

The resultant function-maintenance decision tree created is 11 layers deep with 25 possible leaf nodes, shown in Fig. 2. Of the 8 possible relative maintenance buckets (0, 1, 2, 2.5, 3, 3.5, 4, 4.5), only 6 of them are predicted by the model. This is to be expected as the two buckets that are never predicted, 0 OOM and 4.5 OOM, contain a combined total of 17 data points out of the 1995 total data points. Of the 6 predicted maintenance buckets, 3.5 OOM and 2.5 OOM were the most frequently predicted. Based on the data used to train the model and its spread, the 0 OOM bucket was centered at a frequency of 1 flight hour maintenance interval. This centers the 3.5 OOM bucket on a 3,162 flight hour maintenance interval and the 2.5 OOM bucket on a 316 flight hour maintenance interval. Please note that calculating the exact value that the maintenance buckets are centered around is only possible because all of the training data is on the same time scale. Regardless of the exact values, the model provides valuable information on the relative frequency of two predictions. A component predicted to be in the 2.5 OOM bucket must be maintained 10 times as frequently as a component predicted to be in the 3.5 OOM bucket. Depending on the particular system and how maintenance intervals are measured, this could mean 100,000 cycles versus 1,000,000 cycles or monthly versus annual maintenance.

The authors explored a random forest model to ascertain whether a more accurate model could be generated since random forests are generally more accurate than decision trees. A random forest model could be described as the average of a large number of decision trees, each trained on a different subset of the training data and on different features. Though random forests are less prone to overfitting the particulars of the training data, we decided to utilize a decision tree for 2 reasons. The decision tree consistently predicted more conservatively (more frequent maintenance) than

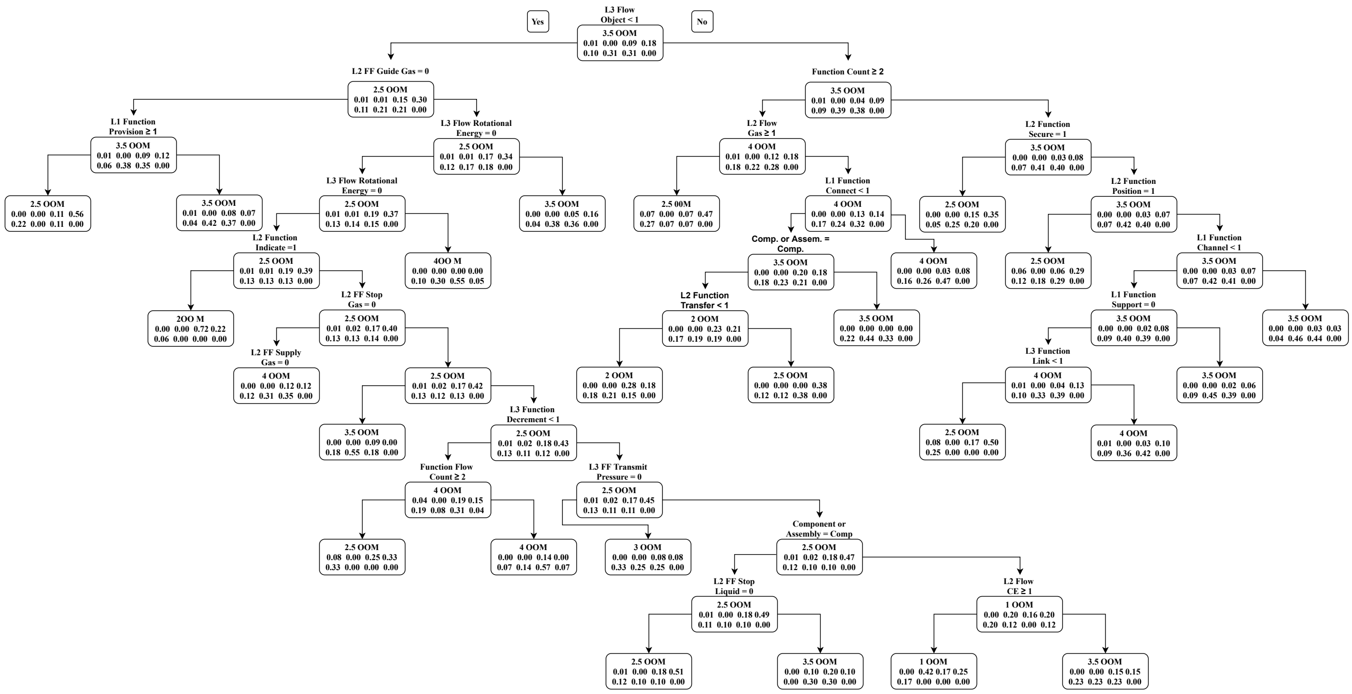

Fig. 2: Function-maintenance decision tree

the random forest. In the scenario of the early design phase of a marine renewable energy system, a more conservative estimate is preferred. Once the detailed design phase is reached, information on specific components can be used to refine maintenance frequency. The second reason was that a decision tree could be represented by a single image (Fig. 2), whereas a random forest contains the results of hundreds of different decision trees.

The decision tree can be used to predict the results of data sets with thousands of parts or it can be used by a single engineer exploring a handful of different functional configurations through a series of binary response prompts on the functional attributes of the part. Predictions are straightforward and the relative impact of functional characteristics can be seen as the tree is traversed. Referring to Fig. 2, the node reached after responding in the affirmative twice, which could be expanded as "Does the level 3 flow of *Rotational Energy* occur 0 times in this part?" shows one such example. If the engineer responds in the affirmative, the part in question is more likely to be in the 2.5 OOM bucket than the 3.5 OOM bucket. Recall from earlier that this could be the difference between a monthly inspection of this part or an annual inspection of this part. If we explore each node beyond the predicted bucket, we can gain additional insights into the prediction probability and develop a confidence interval. Within each bucket is 2×4 matrix of probabilities corresponding to the 8 relative maintenance buckets the training data fell into. As in the previous example, the engineer is exploring functional configurations. By examining the node following the affirmative answer (a prediction of 2.5 OOM), the probability of the adjacent buckets, 2 OOM and 3 OOM, are 19% and 13%, respectively. The probability of that part falling within $\pm$ 0.5 OOMs is 69%. A similar calculation done after responding in the negative informs the engineer that the probability of that part falling into the 3.5 or 4 OOM bucket is 74%.

Another application of the model is backtracking up the tree to avoid high-maintenance functions. When defining the functional structure of the device or a subsystem, the designer can create a functional design and then explore back up the tree, considering which functional decisions are flexible, to determine if any changes can be made to eliminate high maintenance frequency functionality.

This model can be utilized during the earliest stages of design before significant resources are committed to developing a design that may be inherently more maintenance intensive than possible alternatives. In a field such as marine renewables, where there has been very little design convergence, this tool can help designers to make informed decisions across the diverse design space.

B. Building confidence in the model

As discussed in the methods, the model was trained on 70% of the extracted data and tested against the remaining 30%. The comparison of those results is shown in the confusion matrix in Fig. 3. The columns of the confusion matrix are the known maintenance buckets from the test data, while the rows are the predicted maintenance buckets for the same test data. Diagonally from the top left to bottom right are correctly predicted data points. Values above the grey diagonal were predicted to require more frequent maintenance than the actual maintenance frequency. Values below the diagonal were predicted to require less frequent maintenance than the actual maintenance frequency. The model has an overall accuracy of 40.1%, but a broader understanding of the prediction can be gained from Fig. 3. The intersection of the 3 OOM row and

Predicted Bucket \ Reference Bucket	0 OOM	1 OOM	2 OOM	2.5 OOM	3 OOM	3.5 OOM	4 OOM	4.5 OOM
0 OOM	0	0	0	0	0	0	0	0
1 OOM	0	0	1	2	0	0	0	0
2 OOM	0	0	7	4	0	3	5	0
2.5 OOM	5	0	24	102	27	16	19	0
3 OOM	0	0	0	3	2	1	2	0
3.5 OOM	0	1	7	29	23	100	122	0
4 OOM	2	0	7	10	8	37	29	0
4.5 OOM	0	0	0	0	0	0	0	0

Fig. 3: Confusion matrix of known versus model predicted maintenance values

Model predicted bucket \ Expert predicted bucket	0 OOM	1 OOM	2 OOM	2.5 OOM	3 OOM	3.5 OOM	4 OOM	4.5 OOM
0 OOM	0	0	0	0	0	0	0	0
1 OOM	0	0	0	0	0	0	0	0
2 OOM	0	0	1	1	0	2	3	0
2.5 OOM	0	0	3	3	0	1	5	0
3 OOM	0	0	0	0	0	0	0	0
3.5 OOM	0	0	0	1	0	1	5	0
4 OOM	0	0	2	0	0	1	1	0
4.5 OOM	0	0	0	0	0	0	0	0

Fig. 4: Confusion matrix of model predicted versus expert design engineer assessed maintenance values for 30 LUPA parts

column shows that the model predicted only 2 of 60 parts known to be in the 3 OOM bucket. One cell above and below represents the instances of the model predicting a maintenance interval ± 0.5 OOM greater or less than the known value. The model predicted 27 parts into the 2.5 OOM bucket and 23 parts into the 3.5 OOM bucket; this 1 OOM prediction spread captures 52 of 60 known 3 OOM parts.

It is relevant to acknowledge that this confusion matrix is built from the data trained on the Learjet and CJ610 maintenance manuals and used to test that same data. A limitation of the model is that it may not accurately predict the maintenance requirements of a generic long field-life system but may be too tuned to an aircraft's particular maintenance demands. For example, the level 2 function-flow pair *Guide Gas* describes all aerodynamic external parts of the plane and engine. This function-flow pair is likely significantly more common in airplanes than other long field-life systems. The abstract nature of functional modeling partly offsets these novelties of an airplane's functional structure. The level 2 function-flow pair *Guide Gas* can be viewed in its level 1 function-flow pair of *Channel Material*, which is more universally applicable and could apply to the hydrodynamics of the hull structure of a wave energy converter or of a subsea turbine yet still applying to the lift imparted on the airfoil of a wind turbine or of airplane wing.

As described in the *Laboratory upgrade point absorber application* methods section, this model was applied to a sample wave energy converter (the results of which are discussed in the following section). As opposed to examining the specific results of that application, in Fig. 4 the model's predictions are compared to the expert design engineer's assessment. The confusion matrix in Fig. 4 can be read the same as Fig. 3, with the grey diagonal indicating the model and expert assessing a part into the same maintenance bucket. Above the diagonal represents the model assessing a part requiring more frequent maintenance than the expert assessed and vice versa for below the diagonal.

From Fig. 4, the model predicted the same relative maintenance bucket as the expert design engineer 6 times, more conservatively 17 times, and less conservatively the remaining 7 times. The model's inaccuracy at higher OOM buckets is not surprising due to the nature of functional decomposition. The cell found in the 4 OOM column and 2 OOM row can be examined to understand this issue better. The damper plate is one of the 3 parts referred to by this cell. The damper plate is a solid circular piece of 6061 aluminium at the bottom of the spar that has lead ballast secured to it. When viewed functionally, the damper plate performs 2 function-flow pairs (listed at the 2nd level), *Change Mechanical Energy* and *Stabilize Solid*. These function-flow pairs describe the plate as stabilizing the weights secured to it and increasing the coefficient of drag of the spar. Both of these functions maximize the hull's relative motion to the spar and are essential to the correct functioning of the device. Despite its importance, the damper plate is just a solid piece of metal with no moving parts and should not warrant maintenance actions at the highest frequency level. Though this is a case of the model predicting more maintenance than is necessary, it shows that the model is capturing the functional importance of the damper plate. Like any tool or software used in engineering, this model still requires an engineer to review the results and assert their judgment, but the model can reduce the number of parts an engineer needs to assess.

C. *Laboratory upgrade point absorber application*

This section describes an application of the model to redesign LUPA, a wave energy converter, to reduce its maintenance costs. LUPA is a piece of laboratory equipment. It was not designed or intended for the activities and environmental conditions that a commercial wave energy converter will be expected to withstand. As such, design considerations that would be paramount to a commercial wave energy converter, like maintainability, took a lower priority than design considerations related to LUPA's role as an open-source platform for analyzing concepts, validating numerical models, and innovating control schemes.

The results from the LUPA application come from possible physical or functional redesigns. All redesigns are given from a maintenance-centric point of view and will not account for other possible design considerations. The redesigns presented are intended as examples of modifications to the physical or functional architecture of the device that could be stimulated by examining the functional drivers of maintenance more closely and from an earlier stage in development.

1) Carriage rail securement: The first redesign considered is in regard to the system that allows for vertical translation of the hull along the spar. Fig. 5 shows a simplified version of the system. The carriage rail is secured to the spar via 10 screws extending through the carriage rail into the spar, 3 of the holes for those screws are visible in Fig 5. The carriage at the top of Fig. 5 is the top carriage rail that the hull is secured to.

Upon analyzing the parts of this system, we find that the screws securing the carriage rail onto the spar are in the 2 OOM bucket, but the rail itself is in the 4 OOM bucket. From these results, we are clued into examining the screws and their function as a possible area for redesign.

Regarding the physical configuration and accessibility for maintenance, 2 things are concerning, visibility and accessibility. The screws are set into a hole, meaning they need to be viewed straight on where the carriage, and therefore the entire hull, is located and moving. To safely perform one possible maintenance task, say, verifying torque of the screws are within an acceptable range, the carriage and hull would need to be locked in place to allow maintenance personnel to access the screws. Suppose this is deemed unsafe to perform during *in situ* maintenance. In that case, the device may need to be removed from the water onto a maintenance vessel or towed to shore, increasing the operations cost to perform this relatively frequent maintenance task. If the engineers decide the maintenance task is to perform a visual inspection of the screws, possibly to verify a mark that indicates rotation of the screw, the hull would still need to be locked into place in multiple positions to allow for visual inspection of all screws.

Noting the potential maintenance difficulties, possible options to explore include: repositioning the screw to a more accessible location, securing the rail to the spar through other means and removing the need for screws by changing how the spar and hull move relative to each other. Expanding on the last two options, how could the functionality of the rail system – *Guide Mechanical Energy* – be performed without the need for screws? Securing the rail to the spar via stitch welding is an option; the need to inspect is still present, but the inspection is now offset from the motion of the hull and the failure of individual stitches can be seen more easily. Another option is removing the rail entirely and utilizing a linear sleeve bearing or rollers directly onto the spar itself.

2) Belt clamps: The second redesign prompted by the model results is for the clamping system that secures the top and bottom of the belt that drives the generator as the hull oscillates. The belt clamps consist of a toothed plate that matches the teeth on the belt, a flat plate that applies even pressure to keep the belt teeth engaged on the toothed plate and a mount that secures the 2 plates. The model predicted these 3 parts to be in the most frequent maintenance bucket, 2 OOM. Whether inspecting the physical parts or their functional decomposition, the essential role that the clamps provide for the device is immediately apparent. The clamps have 3 vital functions: *Position Object*, *Stop Mechanical Energy* and *Increment Mechanical Energy*; these function-flow pairs correlate to the clamps maintaining the alignment of the belt with the sprocket that drives the motor, stopping the movement of the belt and increasing friction against the belt.

A maintenance action may be to release the clamp to inspect for wear on the belt teeth, the toothed clamp, and the flat clamp. Unfortunately, the tension would have to be released on the belt to inspect for wear on any of these parts. Releasing tension will require re-tensioning post-inspection, which may require additional stabilization and equipment that needs to be accessible during routine maintenance. As a research prototype, this is of little concern, but for an ocean-deployed device, a vital aspect of the power take-off requiring frequent – and challenging – maintenance may lead to unacceptable downtime.

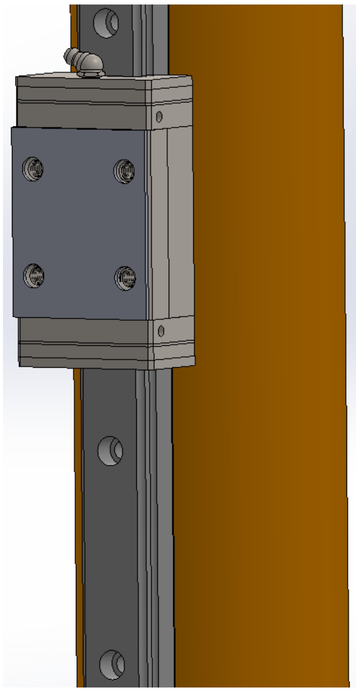

Fig. 5: 3D model of LUPA showing the carriage, carriage rail and spar. Model has been simplified to improve visibility. Note the 3 screw holes that secure the carriage rail to the spar.

A possible redesign of this system is to separate the clamping action and the tensioning of the belt. A continuous belt "clamped" by a toothed idler at the top and bottom could be inspected more efficiently as a belt tensioner could adjust tension in the belt to allow for easier belt removal. Additionally, a continuous belt could be rotated during routine maintenance, distributing the wear on the belt across the entire length. This redesign would not address the root cause of the high maintenance frequency, but it would allow for a quicker and more thorough inspection of this vital system.

V. Conclusion

This research contributes to the design theory and design for maintainability fields in 2 manners. First, the research shows that functional decomposition can be related to maintenance intervals with a degree of confidence. In other words, a part's maintenance requirement is inherently related to the elementary functions that it performs. Second, the machine learning model of function-maintenance can be utilized in conceptual design to assess functional models and conceptual/high-level designs for their relative maintenance requirements. The current state of the design for maintainability field provides guidelines to improve maintainability but lacks assessment tools; this model works to close that gap. As shown through this paper's focus on marine renewables, this research has particular relevance to the subset of long field-life systems lacking historical maintenance data and a dominant design.

A. Future work

Future work includes expanding the data set used to train the model with maintenance information from diverse long field-life systems, codifying the functional decomposition of maintenance tasks to ensure consistent results, and applying the model towards the assessment of early design concepts.

Acknowledgement

N. Algarra thanks Dr. Robert Paasch for his time and enthusiasm in supporting graduate student work, and all those at Oregon State University who work with LUPA and freely lend its support to research in wave energy.

References

[1] J. Carroll, A. McDonald, and D. McMillan, "Failure rate, repair time and unscheduled o&m cost analysis of offshore wind turbines," *Wind energy*, vol. 19, pp. 996–1177, 2016.

[2] I. Dinwoodie, D. McMillan, M. Revie, I. Lazakis, and Y. Dalgie, "Development of a combined operational and strategic decision support model for offshore wind," *Energy Procedia*, vol. 35, pp. 157–166, 2013.

[3] R. Tiusanen, E. Heikkilä, M. Räikkönen, and T. Välisalo, "System approach to reliability engineering - case: wave energy converter," in *eProceedings of ESREL2020 PSAM15*, 2020. [Online]. Available: https://www.rpsonline.com.sg/proceedings/esrel2020/pdf/4968.pdf

[4] V. Neary, M. Lawson, M. Previsic, A. Copping, K. Hallett, A. LaBonte, J. Rieks, and D. Murray, "Methodology for design and economic analysis of marine energy conversion (mec) technologies," in *2nd Marine energy technology symposium*, 2014.

[5] Z. Tjiparur and G. Thompson, "Review of maintainability design principles and their application to conceptual design," *Journal of process mechanical engineering*, vol. 218, pp. 103–113, 2004.

[6] A. Desai and A. Mital, "Improving maintainability of products through the adoption of a comprehensive design for maintainability method," *International journal of industrial engineering*, vol. 17, pp. 103–114, 2010.

[7] B. Bosma, C. Beringer, M. Leary, and B. Robertson, "Design and modeling of a laboratory sclae wec point absorber," in *EWTEC 2021*, 2021.

[8] D. Ullman, *The Mechanical design process*. New York: McGraw-Hill, 1992.

[9] G. Dieter and L. Schmidt, *Engineering Design, fourth edition*. New York: McGraw-Hill, 2009.

[10] G. Hazelrigg, *Fundamentals of decision making for engineering design and systems engineering*. Hazelrigg, G. 2012, 2012.

[11] A. Trueworthy and B. DuPont, "The wave energy converter design process: methods applied in industry and shortcomings of current practices," *Journal of Marine Science and Engineering*, vol. 8, pp. 1–49, 2020.

[12] J. Falnes, "A review of wave-energy extraction," *Marine structures*, vol. 20, pp. 185–254, 2007.

[13] K. Bubbar, B. Buckham, and P. Wild, "A method for comparing wave energy converter conceptual designs based on potential power capture," *Renewable Energy*, vol. 115, pp. 797–807, 2018.

[14] J. Hartman, *Engineering economy and the decision-making process*. New Jersey: Pearson education, inc., 2007.

[15] G. van Bussel and C. Schöntag, "Operation and maintenance aspects of large offshore windfarms," in *Proceedings of EWEC*, 1997, pp. 272–275.

[16] S. Ambühl, L. Marquis, J. Kofoed, and J. Sørensen, "Operation and maintenance strategies for wave energy converter," *Journal of risk and reliability*, vol. 229, pp. 417–441, 2015.

[17] M. O'Connor, T. Lewis, and G. Dalton, "Weather window analysis of Irish west cost wave data with relevance to operations & maintenance of marine renewables," *Renewable Energy*, vol. 52, pp. 57–66, 2013.

[18] A. Falcao, "Wave energy utilization: a review of the technologies," *Renewable and sustainable energy reviews*, pp. 899–918, 2010.

[19] R. Stone, I. Tumer, and M. Van Wie, "The function-failure design method," *Journal of mechanical design*, vol. 127, pp. 397–407, 2005.

[20] B. O'Halloran, C. Hoyle, I. Tumer, and R. Stone, "The early design reliability prediction method," *Research in engineering design*, vol. 30, pp. 489–508, 2019.

[21] K. Otto and K. Wood, "Product evolution: a reverse engineering and redesign methodology," *Research in engineering design*, vol. 10, pp. 226–243, 1998.

[22] J. Hirtz, R. Stone, A. McAdams, S. Szykman, and K. Wood, "A functional basis for engineering desing: reconcilling and evolving previous efforts," *Research in engineering design*, vol. 13, pp. 65–82, 2002.

[23] Y. Deng, "Function and behavior representation in conceptual mechanical design," *Artificial intelligence for engineering design, analysis and manufacturing*, vol. 16, pp. 343–362, 2002.

[24] S. Burger, *Introduction to machine learning with R*. California: O'Reilly media, 2018.

[25] M. Thurber. A compelling alternative to buying a new jet. Business jet traveler. [Online]. Available: https://bjtonline.com/business-jet-news/a-compelling-alternative-to-buying-a-new-jet

[26] E. Avallone and T. Baumeister III, Eds., *Marks' standard handbook for mechanical engineers: tenth edition*. New York: McGraw-Hill, 1997.