Accessibility for maintenance in engine room: a prediction tool for operational costs estimation during the design process

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ABSTRACT

When dealing with maintenance in ships engine room, the space available around machinery and systems (clearance) plays an important role and may significantly affect the cost of the maintenance intervention. In a first part of a current research study (Gualeni et al., 2021), a quantitative relation between the maintenance costs increment due to the clearance reduction is determined, using a Bayesian approach to General Linear Model (GLM), with reference to a single item/component of a larger system (Sánchez-Herguedas, 2021). This paper represents the second part of the activity and it enforces a systemic view over the whole machinery or system (Sanders et al., 2012). The aim is to identify not only the relation between maintenance costs and clearance reduction, but how the clearance reductions of the single components/items interact and affect the whole system/machinery accessibility and maintainability, meant as relevant emerging properties.

The system emerging properties are investigated through the design and application of a Hidden Markov Model (Salvatier et al., 2016); i.e., the system is modelled by a Markov process with unobservable states. The sequence of states is the maintainability of the system (which incorporates each one of the single components) while the evidence is the increase in cost of maintenance related to the space reduction.

By predicting a sequence of states, it is therefore possible to predict the interactions between the system components clearances and determine how the emerging maintainability property is affected by the engine room design.

Keywords: Maintenance; OpEx estimation; systems thinking; Hidden Markov Model; probabilistic inference.

1. INTRODUCTION

The present study aims to develop a tool able to estimate the increment in terms of maintenance hours (and therefore costs) for a component/system when the clearances around it suggested by the supplier are not respected. This is common especially in engine rooms of naval ships, research vessels and mega-yachts, since generally they are not large size ships, and they are characterized by a significant technology amount installed onboard (Celik, 2009). To develop this approach and the related tool, the space available to operate around/on the component must be defined and quantified.

While considering the best approach in developing the tool, two interconnected points of view can be defined:

1. Designing the tool focusing on the components/items

2. Designing the tool focusing on the whole system made by the several components/items

The first aspect was analyzed in Gualeni et al. (2021). The authors defined a GLM (General Linear Model) which considers the cost increase and the clearance reduction as continuous parameters, and it is applied to one component at a time. A general linear relationship is thought to exist between the reduction of clearance and cost increase. The huge advantage of the general linear approach is that it allows defining a continuously generative model, trained with all the necessary evidence provided, that returns the cost increase. The observations are randomly sampled from the most suitable distribution, characterized by a shape that can be varied acting on its input parameters, then disturbed with a random gaussian noise.

However, the present paper focuses on the second aspect.

2. PROBABILISTIC INFERENTIAL APPROACH

As it is well-known, the two main branches in statistics are called Descriptive and Inferential.

Descriptive statistics is the term given to the data analysis that helps to describe, show or summarize data in such a meaningful way that patterns might emerge from it. However, this branch of statistics does not allow making conclusions beyond the analyzed data or reach conclusions regarding any hypotheses that might have been made. With descriptive statistics there is no uncertainty, because only the items that have been measured can be described, without trying to infer properties about a larger population.

This type of statistics usually describes data with two main tools:

- Central tendency, which is a way of describing the central position of a probability density distribution for a data set.
- Spread or dispersion, which represents the deviation from the most probable values.

Often, it is not possible to have access to the whole investigated population, but only a limited number of data is instead available and therefore a smaller sample must be considered. This is thought however to be representative of the larger population (Trochim, 2006).

Inferential statistics takes data from a sample and makes inferences about the larger population from which the sample was drawn. This sample needs to accurately reflect the population, without requiring any further specific property. To be more arbitrary as possible, it is recommended to use a random sampling method. When using the inferential statistics, there will always be an error between the properties of the global population and the sample’s ones. This error is always included in the results and an interval of confidence is outlined.

It is worth reminding that within the inferential statistics there are two main approaches: frequentist and Bayesian inference.

- Frequentist inference calibrates the plausibility of propositions by considering repeated sampling of a population distribution to produce datasets. By considering the dataset’s characteristics under repeated sampling, the frequentist properties of a statistical proposition can be quantified as fixed values.
- Bayesian inference preserves uncertainty. It is based on Bayes’ theorem and updates an initial guess on the probability based on evidence.

The approach used in the present work relies on Bayesian inference, which is the core of the implemented model. Bayesian statistics uses probability to quantify uncertainty or degree of belief, and probability distributions are used to represent the states of belief and is widely used in predictive models [Vairo et al., 2019].

Accounting for uncertainty is critical whenever data limitations exist that lead to imprecise inference about preferences, sensitivities, and any aspects of behaviour, while Bayesian analysis is itself conceptually simple. This limitation has been overcome applying Markov Chain Monte Carlo (MCMC) algorithm (Neal R.M., 1993).

3. HIDDEN MARKOV MODEL (HMM)

A Hidden Markov Model (HMM) is a combination of two processes: a Markov Chain, which determines the state at time t, and a state-dependent process which generates an observation. This observation is called emission and it is indicated with E, while S stands for state. For each state S, more than one type of emission E can be obtained (Satish, 2003).

Only the state-dependent process, i.e., the emission, can be observed, while the Markov Chain (the states) remains unknown and hidden. The goal is to learn about the hidden states by observing the emissions.

A model can be composed by n possible states and m possible emissions. Figure 1 shows the transitions between the different states. Each transition has a probability, and each state has an emission probability as well (Van den Bosh, 2010).

These probabilities can be grouped into two matrices:

- Transition matrix, representing the states' transitions probabilities.
- Emission matrix, representing the probabilities to get an emission given a certain state.

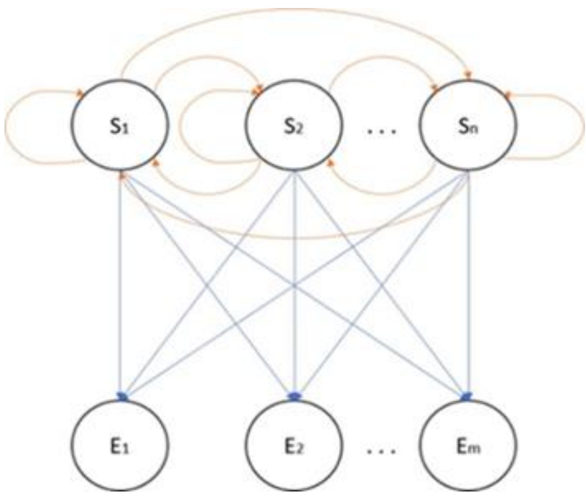

Figure 1. States and emissions of a Hidden Markov Model.

A MCMC simulation can be performed by generating several samples according to the transition matrix. Subsequently, the emission matrix constitutes the basis on which the emission associated to the state is determined. Inferential statistics can be applied to this type of model, by simulating and deducing the transition and emission matrices through a forward-backward algorithm, given observations on either the states or the emissions.

4. DESIGNING THE MODEL

Different approaches in solving the proposed problem are always possible. Two of them have been identified. As already mentioned, the first model considers one item per time, while the second one considers all the system's components simultaneously, including the inter-relations between the components as well, in accordance with the Systemic approach.

For considering n elements, a Hidden Markov Model is structured. The maintenance cost/time increase scenario is now translated into a hidden state (hidden states are unobservable entities). Therefore, three states have been defined, while the space reduction ranges are considered as the possible emissions (the observable entities) for each state.

A real combination of element's states is randomly generated. According to this combination, a sequence of emissions is then generated as test data set (Rabiner, 2013). At this point, the true hypothetical state of each component is defined and a series of emissions, which constitutes the observations, is available. Afterwards, three possible cases (sub-models) arise, in relation with the knowledge about the transition matrix and the emission matrix. In fact, the cases that can be considered are:

- Both matrices, emission, and transition ones, are known.
- Only the emission matrix is known.
- No matrix is available.

In the first sub-model, assuming that both transition and emission matrices are known, maybe from experience, inference is performed only to obtain the probability density function of being in one specific state. As prior distribution for each state, a Categorical distribution (a generalisation of the Bernoulli distribution when the possible outcomes are more than two, with the same probability for each component) can be chosen. In order not to introduce an excessive amount of prior knowledge, which can block the inferential process into local solutions, the elements of evidence can be implemented using a Categorical distribution as well.

Subsequently, the MCMC sampling can be performed using the Metropolis-Hastings sampling within Gibbs algorithm, because it is more suitable to a multi-parameter case, treating each component as independent from the others. The state that is more likely to occur in the Markov Chain is defined as the "forecast state".

The second sub-model can be used when less information on the system is available. It has been assumed that only the emission matrix is available, while the transition one is unknown. However, this second matrix can be inferred, using a Dirichlet distribution with equal initial likelihoods as prior, while the remaining variables can be defined as in the previous case. While performing the MCMC sampling, not only the states but also the transition matrix components can be sampled and inferred.

The third sub-model is the most generic one and at the same time it is the most common. In fact, no information is available, and all the inter-relations between the components are inferred from the observations. As in the previous case, also the emission matrix needs to be estimated by inference, using a Dirichlet distribution as prior as well. This approach relies on the Baum-Welch algorithm and is the most interesting when dealing with the problem proposed in this work, because most of the times these probabilities which compose these matrices are difficult to obtain. If an adequate (high) number of samples is generated and the starting point of the chain is chosen to avoid local minimums of the error function, this approach leads to good results. In particular, the M-H within Gibbs algorithm seeks the absolute minimum of the error following the evolution of the Markov chain. In this way the Markov chain converges to what is thought to be the posterior most likely value.

Figure 2 represents the flow chart of the described approach, showing the generation of evidence on the left side and the predictive model on the right side, then compared to check the accuracy of the prediction.

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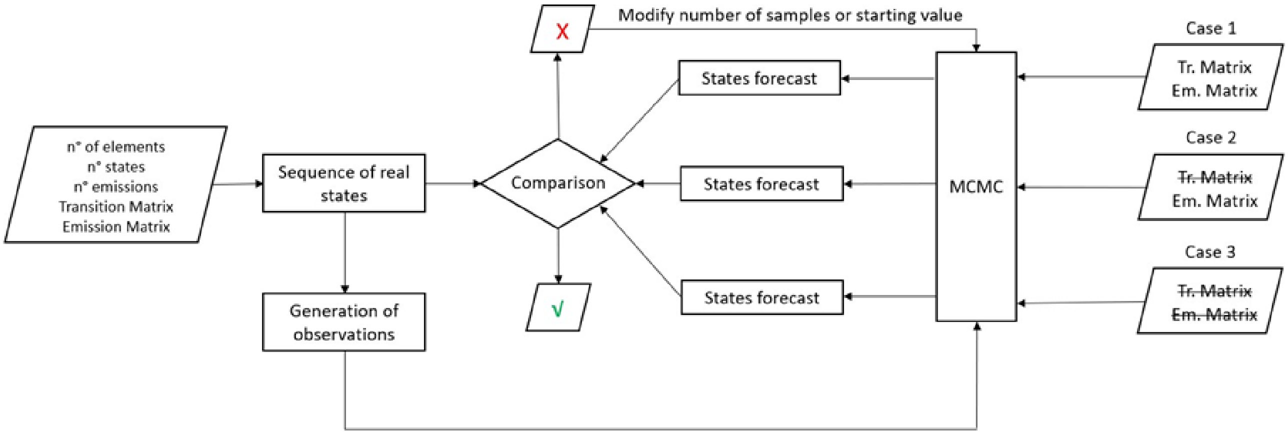

Figure 2. HMM flow-chart.

5. GENERATION OF DATA

The training / test data are generated following the methodology described in Gualeni et al. (2021). A Beta distribution is used to represent the probability density function for the clearance reduction, and, for the purposes of the present paper, the maintenance cost/time is described by a uniform distribution, considering no available prior information, to successively generate the observations (Bernardo, 2006). The Beta distribution's parameters (a and b) can be modified on need, varying the expected value and the variance of the probability density function. In this case the Beta distribution is used for the space probability density function for clearance reduction; on the other side, costs are sampled from a uniform probability density function.

With reference to the three layouts identified for the research activity and shown in figures 3, 4, 5, the clearances reduction, representing the expected values of proper generative (Beta) distributions about systems emissions, are reported in table 1.

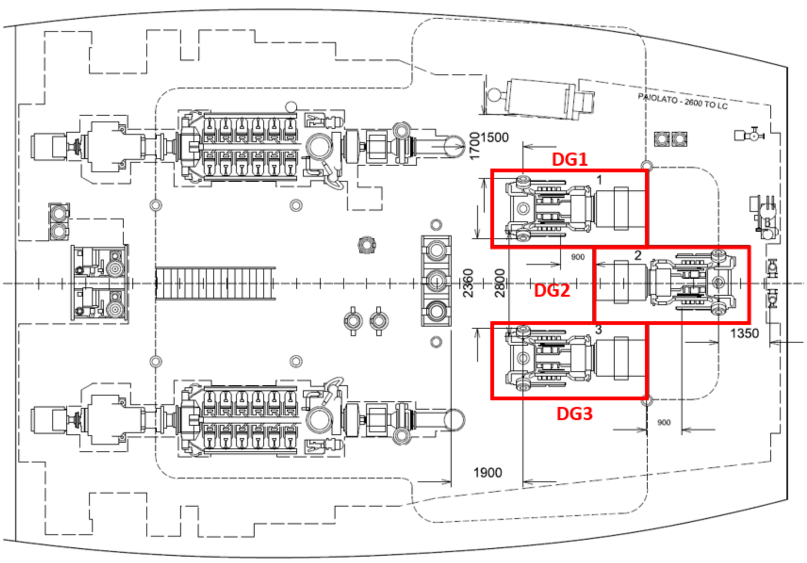

Figure 3: engine room first layout.

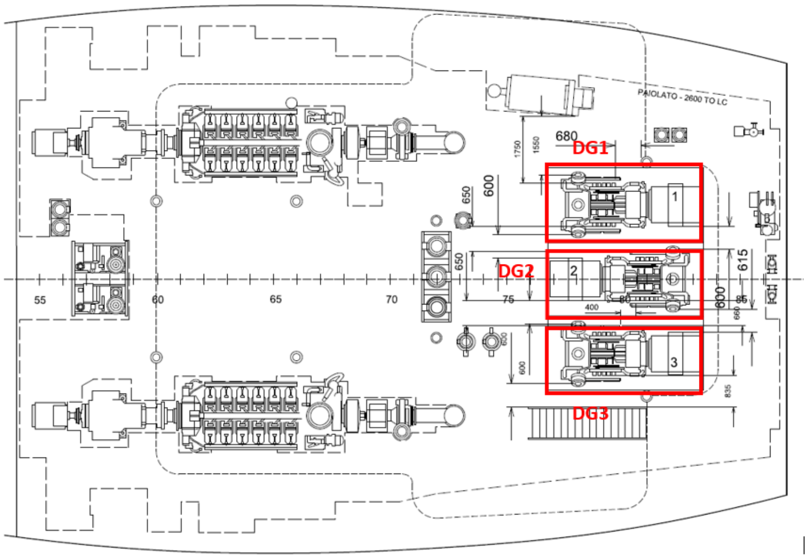

Figure 4: engine room second layout.

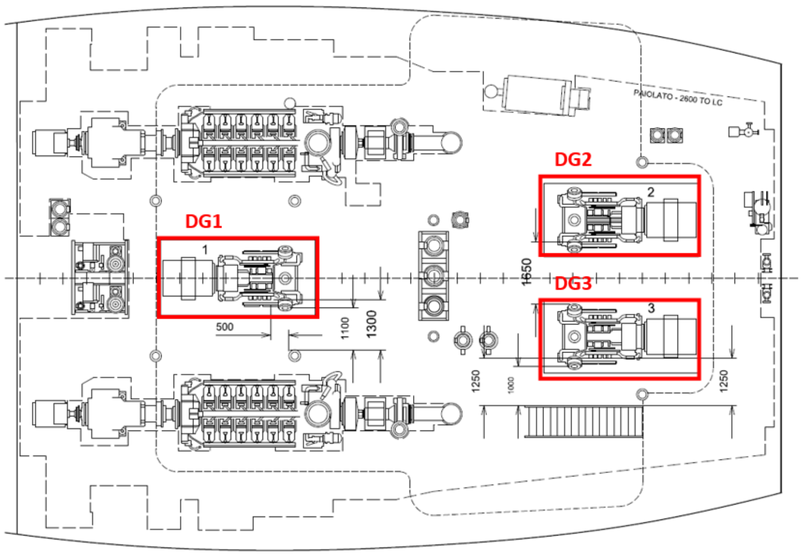

Figure 5: engine room third layout (original project).

Table 1: mean clearances reduction (%)-

first layout	
	Clearance reduction (%)
DG1	0,19
DG2	0,04
DG3	0,24
second layout	
	Clearance reduction (%)
DG1	0,57
DG2	0,57
DG3	0,57
third layout (original project)	
	Clearance reduction (%)
DG1	0

DG2	0
DG3	0

As mentioned above, starting from the expected clearances reductions related to each modified layout, it is possible to create the generative beta distributions, as shown in fig 6 and fig 7.

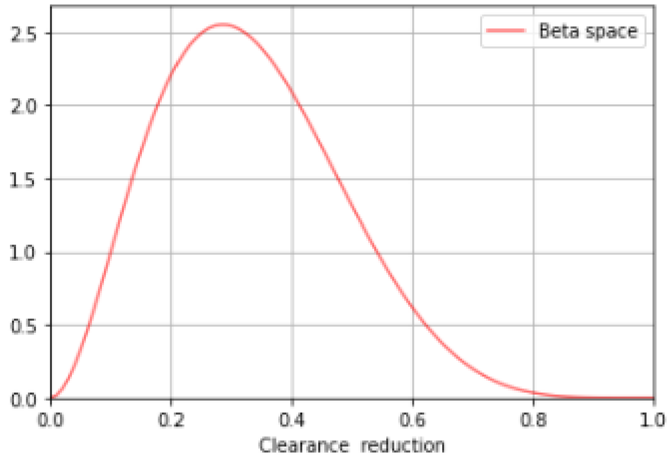

Figure 6: Generative distribution for the clearance reductions of the first layout (Beta distribution 1).

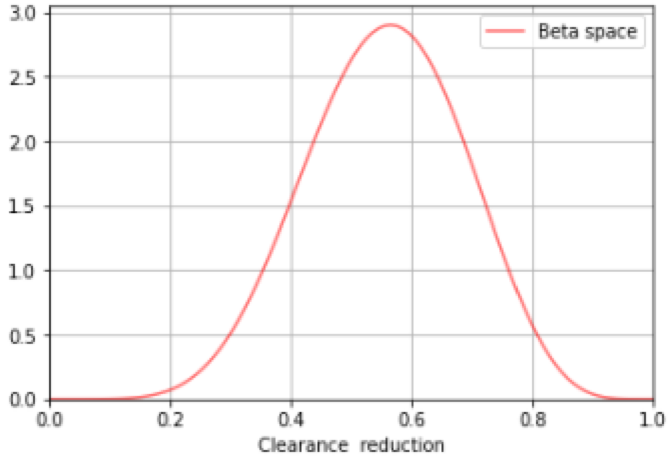

Figure 7: Generative distribution for the clearance reductions of the second layout (Beta distribution **2).**

The evidence on clearances reduction at each step are sampled from the beta distributions in figs 6 and 7.

6. DETERMINING THE STATE-EMISSION SEQUENCES

In the HMM, at each time step, an evidence of clearance reduction is generated, according to emission probability (beta distribution of figure 6 and 7) that is in relation with the state (which can be known or inferred from the observations).

The model (λ) depends on:

λ = (Q, O, A, B)

- Q: hidden sequence of states (maintenance cost/time)

- O: observed emission sequence
  = {σ1, …, σk}
- A: n x n transition probabilities (probability for the system to change the state)
  matrix A(i,j) = Pr[q t+1=j|q t =i]
- B: probability of generating an emission (the visible clearance reduction) in the actual state.
  B(i,j) = probability of generating σj in state qi = P[at =σj |qt = i]; where at is tth element of generated sequence

The problem we are going to solve with the HMM is a *Learning problem* (the third above mentioned sub-model):

- Given an observation sequence O and the set of states (clearance reductions) in the HMM, learn the HMM parameters A and B for generating the most probable sequence of maintenance time/cost increase.

7. RESULTS AND DISCUSSION

The input to such a learning algorithm would be an un-labelled sequence of observations O and a vocabulary of potential hidden states Q.

The standard algorithm for HMM training is the forward-backward, or Baum-Welch algorithm, a special case of the Expectation-Maximization (EM) algorithm (Bahl, 1983). The algorithm will let us train both the transition probabilities A and the emission probabilities B of the HMM. It is an iterative algorithm, computing an initial estimate for the probabilities, then using those estimates to compute a better estimate, and so on, iteratively improving the probabilities that it learns.

The HMM code is reported in Appendix A.

The prediction on the most probable sequence of maintenance time/cost increase is evaluated for both the first and second layout. In figures 8 (first layout) and 9 (second layout), a sequence of five possible predicted states are represented for each DG. The number of states in each sequence can be even higher but it implies a superior exponential computational effort. It is worthwhile mentioning that each bar represents the percentage of cost increase in relation with a sample of clearance reduction percentage derived from beta functions. For each DGi it has been considered sufficient and representative an evaluation of five states.

Considering the three DGs in a comprehensive view, it is possible to derive an assessment of the comprehensive Engine room solution.

First layout:

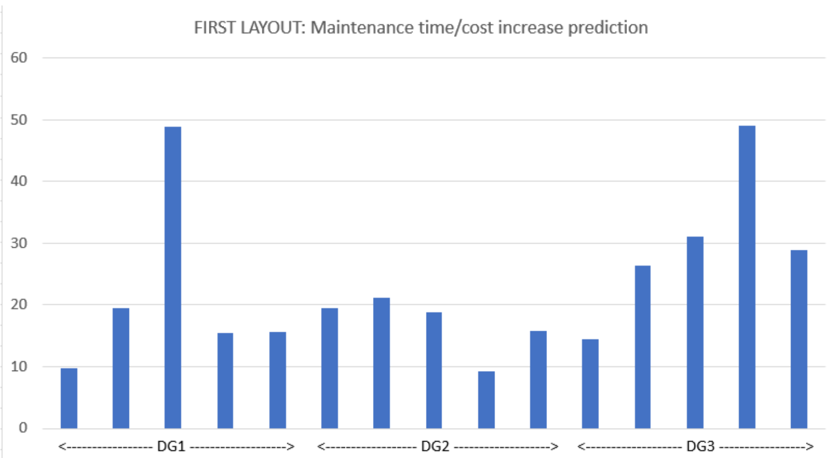

Figure 8: Predicted sequence of maintenance time/cost increase for the first layout.

Second layout:

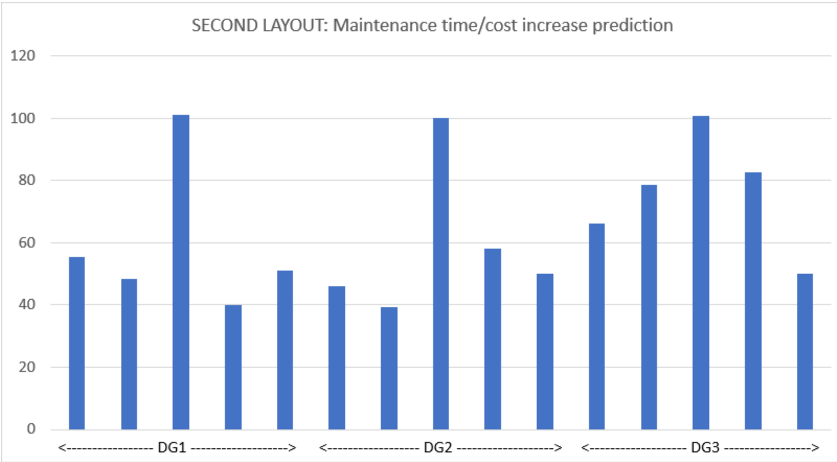

Figure 9: Predicted sequence of maintenance time/cost increase for the second layout.

Given the evidence on space reduction sampled from the beta distribution 1, for the first layout, and for the beta distribution 2 for the second layout, a remarkable comparability with the results obtained, with the evaluation methodology based on the focus about the item/element (summarized in table 2), can be observed.

Table 2: Cost increase prediction with the GLM in Gualeni et al. (2021).

	Group	Layout 1 cost increase [%]	Layout 2 cost increase [%]
DG1	Air suction and exhaust gas system	9.71	55.54
	Cylinder block	48.62	110.01
DG2	Air suction and exhaust gas system	0.00	55.54
	Cylinder block	15.57	110.01
DG3	Air suction and exhaust gas system	18.87	55.54
	Cylinder block	53.34	110.01

To favour this comparability, in table 3 the minimum, maximum and average values are reported for each configuration as derivable from figure 8 and 9.

Table 3: Cost increase (min, max, average) with HMM.

	Layout 1 cost increase [%]	Layout 2 cost increase [%]
Min	8,54	39,41
Max	48,62	101,01
Avg.	23,26	64,53

8. CONCLUSION

The HMM approach has proven to be a reliable method for predicting the state of the different systems and observing their relation with the total engine room layout, given the evidence on the space reduction for some components. The predictive capability of the method obviously depends on the representativeness of the observations, which, in this case, were generated by random samplings from appropriate distributions, deriving from field knowledge.

The method described in Gualeni et al. (2021) gave very close results, but the application of that method inevitably required to make assumptions also on the increases in maintenance costs, which in this second approach were not necessary, due to the characteristics of the Baum-Welch algorithm. In fact, it tests a multitude of samples (in this case, a uniform distribution was used for maintenance costs, so as not to need a priori knowledge), to select only those for which the model is likely to converge.

The proposed model, therefore, can represent a useful instrument to define, in the design phase, the most appropriate layout, adequately balancing the engine room space requirements with the containment of maintenance costs.

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