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Integrating complex asset health modelling techniques with continuous time simulation modelling: A practical tool for maintenance and capital investments analysis

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ABSTRACT

An Asset Health Index (AHI) is a tool that processes data about asset's condition. That index is intended to explore if alterations can be generated in the health of the asset along its life cycle. These data can be obtained during the asset's operation, but they can also come from other information sources such as geographical information systems, supplier's reliability records, relevant external agent's records, etc. The tool (AHI) provides an objective point of view to justify, for instance, the extension of an asset useful life, or to identify which assets from a fleet are candidates for an early replacement, or renovation, as a consequence of a premature aging.

This paper describes how to build the AHI model as a continuous time simulation model, which is then implemented using Vensim simulation environment. This is done in order to: 1) improve model formulating robustness, 2) benefit of the outstanding software optimization features for AHI model parameters calibration; and 2) easy the provision of predictions for asset degradation, operational and capital investments risk under different possible exogenous scenarios and endogenous managerial options.

The process of model building, and parameterization is applied to an industrial case of a regasification terminal. Several strategies involving major maintenance scheduling are compared in terms of total expenditure in assets over their life cycle.

1. Introduction

An Asset Health Index (AHI) is an asset score, which is designed, in some way, to reflect or characterize the asset's condition and thus, its performance in terms of fulfilling the role established by the organization (De la Fuente et al., 2021a). AHI represent a practical method to quantify the general health of a complex asset. For simple assessments, CBM technologies can precisely estimate the status of and specific asset with defined and specifics failure modes. However, most of these assets are composed of multiple subsystems, and each subsystem can be characterized by multiple modes of degradation and failure. From a pure theoretical perspective, every failure mode of every item that composes a system can be modelled and estimated. In some cases, it may be considered that an asset has reached the end of its useful life, when several subsystems have reached a state of deterioration that prevents the continuity of service required by the business (Hjartarson and Otal, 2006a). This calculation can be complex and a significative investment in time and resources. It is in the case of complex systems where the health index, based on the results of operational observations, field inspections and laboratory tests, produces a single objective and quantitative indicator. It may be used as a tool to manage assets, to identify capital investment needs and maintenance programs, allowing (Naderian et al., 2008; Naderian et al., 2009; Azmi et al., 2017): 1) Compare the health of equipment located in similar technical locations, to study possible premature deterioration and optimize operation plans and/or asset maintenance if necessary; 2) Communicate more accurately with manufacturers/builders, to understand the behaviour of assets of different manufacturers/builders in specific technical locations; and 3) Support decision-making processes in future investments in assets, or in extension of the life of these (Silvestri et al., 2020).

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Asset Health Indicators are widely used in supporting maintenance and replacement strategies based on asset condition and performance in some countries, to justify asset replacement schemes to the regulators (GB DNO groups, 2017; Australian Local Government Association, 2015; Federation of Canadian Municipalities (FCM) & other seven partner organizations, 2021).

A proper design of a health index should meet the following requirements (Hjartarson and Otal, 2006b):

- The index must be indicative of the suitability of the asset to provide continuity to the service and representative of the general health of the asset.
- The index should contain objective and verifiable measures of the condition of the asset, instead of subjective observations.
- The index must be understandable and easily interpreted.

Several methods and models fulfilling these requirements have been reviewed, for instance, the ones by Kinetrics (Naderian et al., 2008; Naderian et al., 2009), DNV GL (Vermeer et al., 2015), Terna (Scatiggio and Pompili, 2021) and GB DNO (GB DNO groups, 2017).

Although most of these models build a streamlined approach to introduce different influent factors to estimate the lifetime expectation/remaining useful life of an asset, several drawbacks are still present in their model formulation:

i) The AHI procedure seems not to be properly robust from the scientific perspective, original models are built mostly by practitioners in specific sectors with very specific assets.
ii) Many influent factors are evaluated based on assumptions that are never discussed (e.g. ranges of numerical values are given as scales for different factors while it is almost unclear what is the basis to define such ranges);
iii) The procedure proposed is mainly presented in its development and never demonstrated completely with, at least, some case-based reasoning or at least a complete industrial case which would enable a proper validation of the AHI model proposed.

There are approaches in the literature to identify asset health (López de Calle et al., 2019) used mainly in CBM applications based on dynamic health assessment, but the concept is different from the one used in this paper, now the health assessment allows comparison and decision-making among different assets.

To overcome these weakness points, in this paper the methodology adopted to model the AHI is only loosely based on the OFGEM Network Asset Indices Methodology (GB DNO groups, 2017) (similar approach as in the example previously presented in (Crespo Márquez et al., 2020)). This method is selected because it is considered simple for simulation model building purposes and very practical in its implementation, if a more robust scientific design of the model format is reached.

More precisely, the method (GB DNO groups, 2017) requires: 1) The identification of the asset, which includes the category of the equipment under study, the current age, the expected life, the name of the manufacturer/builder, the model of the equipment and the location of the installation; 2) The operation and maintenance data recorded during a certain period of time; and 3) The condition of the equipment, that is, the results of the analyses performed on the equipment in site, results of readings of physical variables, results of visual inspections, etc.

The health index model adopted in this paper contains values between 0.5 and 10, thus being able to compare health between different types of assets. There are other indices that go from 0 to 1 and others that go from 1 to 100. In any case, they all have the same functionality, normalize the health of different assets to be able to compare them with each other.

In order to provide the modeling process with a more scientific approach and robustness, continuous time simulation modelling is used in this paper. This method offers high rigour for writing mathematicall equations, and to help to trace and to understand the importance of model existing feedback loops. Finally, the models developed using this methodlogy support multiparametric optimisation, that will result essential for parameters calibration and model validation activities in this work (García, 2018).

Regarding the continuous time dynamic simulation adopted, in this paper difference equations in the simulation models are used, and as suggested by (García, 2018). We will assume, however, that that change in our system occurs at discrete points in time (when the information is retrieved) and that each variable at time t + 1 will be a function of the current values:

$$x_{t+1} = f(x_t)$$

where $f(x_t)$ may be either a linear or nonlinear. Notice that for the equation to be solved the initial value of the variable x0 should be known and it is assumed that the time of the simulation will be advanced in fixed time increments and that all system variables will be recalculated at each time increment. The time increment of the simulation matches the time step for which the data is retrieved from the systems. The modelling methodology followed has been System Dynamics (see a complete list of approaches in (Powell, 2021)), and some of the system dynamic tools such as the stock and flow diagrams (SFDs) will provide a graphical representation of the model and variables typology at a glance (Powell, 1968) (some other innovative uses of system dynamics models, integrated with other modelling methodologies, can be found in (Institute of Assets Management (IAM), 2016; Vermeer et al., 2015; Teixeira et al., 2012)). The software package use for the implementation of the model equation is Vensim, a registered trademark of Ventana Systems Inc. (the reader can find other Vensim models' materials in (Scatiggio and Pompili, 2021)).

Finally, and to overcome above mentioned drawback number iii), the process of model building, and parameterization is applied to an industrial case of a regasification terminal. Several strategies involving major maintenance scheduling are compared in terms of total expenditure in assets over their life cycle. This can provide a precise understanding of the benefits of the methodology for businesses and industry.

2. A simulation model to advance in robustness and practical implementation

As mentioned in the abstract and Introduction Section of this paper, despite the fact that Asset Health Indexing (AHI) is becoming a very popular tool, there is a clear need for research to make their implementation more practical in real life applications and within existing engineering assets and management systems (Crespo Márquez et al., 2020). In particular, we find interesting to improve in the following aspects:

- Easy the implementation of the mathematical model of the AHI.
- Use the simple model format in (GB DNO groups, 2017), but now taking the advantages of dynamic simulation model optimization features for model parameters calibration, according to an specific asset dataset.
- Improve results precission and optimization of the future asset management policies, specially those related to major overhauls, life extension or equipment renovation. This will be possible thanks to new capabilities to project FHI under diffeerent scenarios as well as the possible management strategies, optimizing parameters defining those policies.

- Easy simulations and what-if scenario analysis for AHI and LCC projections.
- Fast modification and uptade of the model parameters and projections results according to new data registered and/or expected operational changes.
- Etc.

To that end, in the sequel the process that will be followed is explained in Fig. 1. The formal AHI mathematical model with GB DNO groups methodology is explained in Section 3. Then, this mathematical model is translated into a continuous time formal simulation model in Section 4, where some system dynamics methodology and process elements are used to describe variables typologies and relationships among the different simulation model elements. In Section 4, the loss functions used is described and its equations presented. In Section 5 the implementation of the formal simulation model in Vensim language is presented. In the same Section it is shown how this model can use optimization algorithms to minimize the loss function, for different AHI model configurations. Section 6 contains the final version of the AHI simulation model before it is put into operation. Section 6 is reserved to Results of some case studies and their discussion. The paper finished with the conclusions obtained, future research lines and the list of references that were consulted.

3. AHI modelling methodology

The application procedure for calculating the health index (Crespo Márquez et al., 2020), is based on 5 consecutive steps, in which, starting from a design life associated with an equipment's category, a current health index is reached. For this, a series of factors related to the location, operation and condition of the asset are considered. It is presented in the following Fig. 2, the model, with the 5 steps for calculating the health index of an asset. For a precise description of the methodology and formulation of the AHI the reader is addressed to (Serra et al., 2019).

A synthesis of formulation is as follows: The provider defines a design theoretical life for every asset depending on the equipment category. Once identified manufacturing/built data, model and technical design specifications of an asset, its design life can be adapted by the owner according to accumulated experience and the information provided by different manufacturers and builders. This estimated owner life will be considered for accounting purposes and to measure asset depreciation and asset book value over time. The estimated owner life can then be adjusted according to the characteristics of the asset location and loading.

$$Estimated\ life = \frac{Design\ life\,(books)}{F_{FL} \cdot F_{EL}} \tag{1}$$

Where:

F_{FL}: Combined functional location factor.

F_{EL}: Expected Load factor.

The load factor (F_C), as well as the location factor (F_E), is inherent in the functional location of the asset.

The Combined functional location factor (F_{FL}) is based on the impact of the asset functional location on its operation and maintenance. The specific location factors considered are proposed by GB DNO groups methodology (GB DNO groups, 2017) and must be adapted depending on the specific industry and on the specific asset (De la Fuente et al., 2021b).

With:

$$F_{FL} = \max(F_{DC}, F_A, F_T, F_{AT}, F_{PS}) \tag{2}$$

And

F_{DC}: Distance to the coast factor.

F_A: Altitude above sea level factor.

F_T: Annual average of outside temperature factor.

F_{AT}: Exposure to corrosive atmosphere factor.

F_{PS}: Exposure to dust in suspension factor.

The load factor (F_{EL}) measures the load request that is made on the asset in that location, in front of the maximum admissible load. Normally, this data is provided when the asset is commissioned, and it is part of the technical specifications of the asset. In general, the following equation is used:

$$F_{EL} = \frac{Load\ under\ normal\ operating\ conditions}{Maximum\ permissible\ load} \tag{3}$$

A fundamental hypothesis of the methodology is that the irreversible degradation of an asset follows an exponential behaviour with respect to its age, and in step number 3, the aging rate (β) of the asset is determined by the natural logarithm of the quotient between the asset health index when new (H_{new}) and the asset health index when reaching its expected life ($H_{estimated\ life}$). The equation for its calculation is the following:

$$\beta = \frac{\ln \frac{H_{new}}{H_{estimated\ life}}}{Estimated\ life} \tag{4}$$

With:

Estimated life: Time calculated in (1).

HI_{new}: Health index for a new asset;

$HI_{estimated\ life}$: Health index for the asset expected life time;

The health index (HI) is considered as a dimensionless number between 0.5 and 10, with an exponential behaviour with respect to the age "t" of the asset, which is characterized by the aging rate as follows:

$$HI_t = HI_{new} \cdot e^{\beta \cdot t} \tag{5}$$

Where HI_t is defined in step 4 of the methodology as the initial health index of the asset. The methodology (in (GB DNO groups, 2017)) ends in step 5, estimating the actual health index of the asset - AHI_t -, using health and reliability modifiers, as follows:

$$AHI_t = HI_t \cdot HM_t \cdot RM_t \tag{6}$$

Where,

HI: Initial health index.

HM: Health modifier.

RM: Reliability modifier.

In the GB DNO model, the equations to obtain the value of the health modifier (MS) and the reliability modifier (MF) are the following:

$$HM_t = \prod_{j=1}^{j=n} HM_{j_t} \tag{7}$$

Where,

*j = 1...n*index used for different health modifiers,

MS_{j_t}: health modifier j at a given age.

$$RM_t = \prod_{k=1}^{k=m} RM_{kt} \tag{8}$$

Where,

*k = 1...m*index used for different reliability modifiers,

MF_{kt}: reliability modifier k at a given age.

MS and MF will take values within ranges to be calibrated according to the impact of each single modifier for the health of a given class of asset. This point will be discussed later in the dynamic simulation model Section. Finally, the actual health index of a system can be obtained and represented as in Fig. 3, where each asset conforming the system may have a different degradation speed.

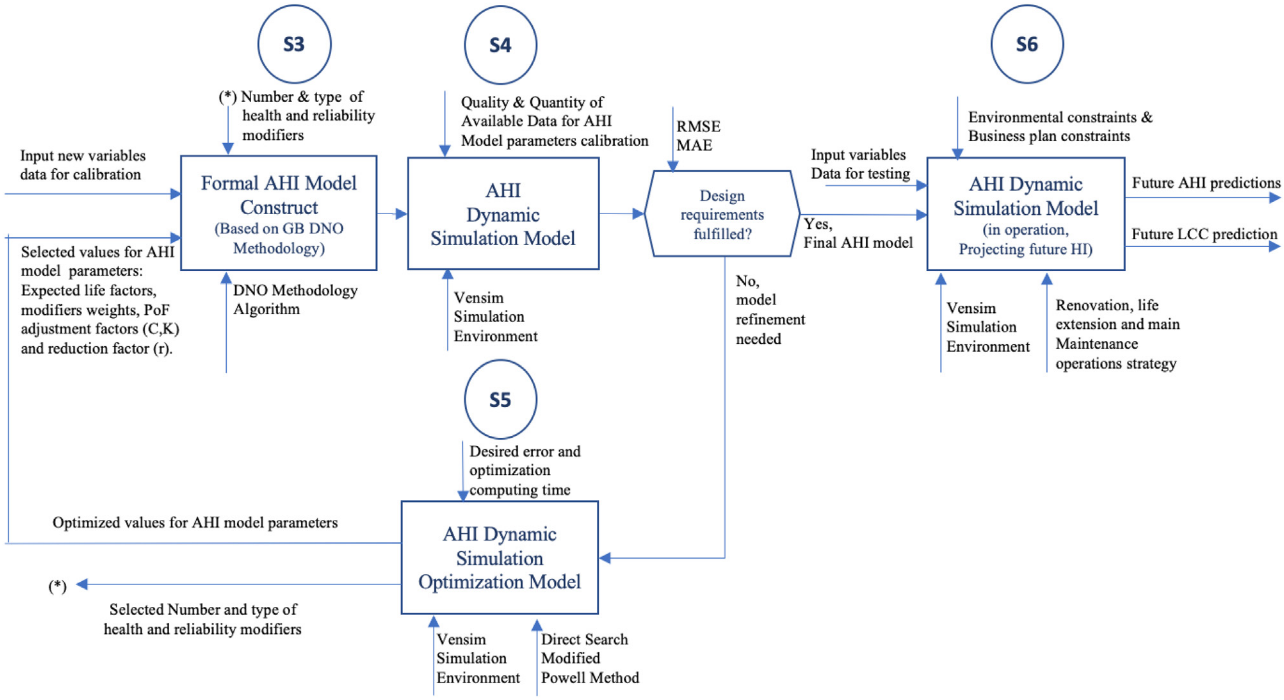

Fig. 1. IDEF Diagram of the process followed, indicating the Sections of the paper in circles.

Asset initial condition can be restored after major maintenance intervention or assets renovations or replacement.

Table 1 provides a simple interpretation for an AHI, in this example and for an asset with a normal life expected of 50 years, recommendations for action are adjusted.

A more elaborated interpretation of the AHI can be given linking the AHI value to a probability of failure (PoF) of the asset. The methodology formulates this relationship using the first three terms of the Taylor series for the exponential function as follows (GB DNO groups, 2017):

$$PoF_t = K \cdot \left[1 + (C \cdot H_t) + \frac{(C \cdot H_t)^2}{2!} + \frac{(C \cdot H_t)^3}{3!}\right] \tag{9}$$

Where:

C: Constant value, equal for all assets, (in (GB DNO groups, 2017) C value is selected such that the PoF for AHI = 10 is ten times higher than the PoF of a new element;

K: Constant value to be calibrated, considering asset observed failure frequency per annum, the AHI distribution of asset population and the volume of assets within the population.

H_t : Equals AHI_t when $AHI_t \geq 4$, H_t = 4 otherwise.

The methodology states that the reason for this formulation is that "...this implementation is able to describe a situation where the probability of failure rises more rapidly as asset health degrades (common in literature), but at a more controlled rate than a full exponential function would describe". C defines the shape of the curve, K scales the PoF to a failure rate, and H_t limits the transition from constant PoF to an exponential relationship. Finally, the method suggests that the health index can be projected into the future (Future Health Index – FHI_t), departing from a given age ($t0$). The methodology proposes to do this evaluating a corrected aging rate (βc) of the asset in the following way:

$$\beta c = \frac{\ln \frac{AHI_{t0}}{HI_{new}}}{t0} \tag{10}$$

$$FHI_t = HI_{new} \cdot e^{\beta c \cdot t} \tag{11}$$

With t $\geq$ $t0$, when projection is made, and $\beta_C \leq 2 \cdot \beta$ (according to (GB DNO groups, 2017)). At this point the method presents some limitation when maintaining that for high values of FHI_t, the recommendation is to introduce a reduction factor in this formulation, and Eq. (11) would be transformed into Eq. (12)

$$FHI_t = AHI_t \cdot e^{\frac{\beta c}{r} \cdot t} \tag{12}$$

With r: reduction factor, that in the DNO methodology is defined as

$$r = \begin{cases} 1 & \text{for } \mathrm{AHI}_t < 2 \\ 1 + (\mathrm{AHI}_t - 2) \cdot \left(0.5/3.5\right), & \text{for } 2 \leq \mathrm{AHI}_t \leq 5.5 \\ 1.5 & \text{for } \mathrm{AHI}_t > 5.5 \end{cases} \tag{13}$$

4. Dynamic simulation modelling methodology

4.1. The AHI continuous time simulation model

In this Section a continuous simulation model of the previous AHI loosely based on the OFGEM Network Asset Indices Methodology is presented. This model translates equations in Section 3 to the language of simulation, adding interesting dynamic features that can now be considered, improving flexibility in future model utilization. The dynamic simulation model that will now be presented can be characterized as follows:

- It is a non linear model because of the nature of the AHI.
- The model will be formalized in difference equations
- The simulation time will advance at constant time intervals and the final time will depend on the purpose of the analysis to carry out.
- The model formulation can be used regardless the software package selected for its computer implementation, i.e. Although diagrams use in Fig. 4 are Vensim diagrams, maths can be implemented in any dynamic simulation package in the market.

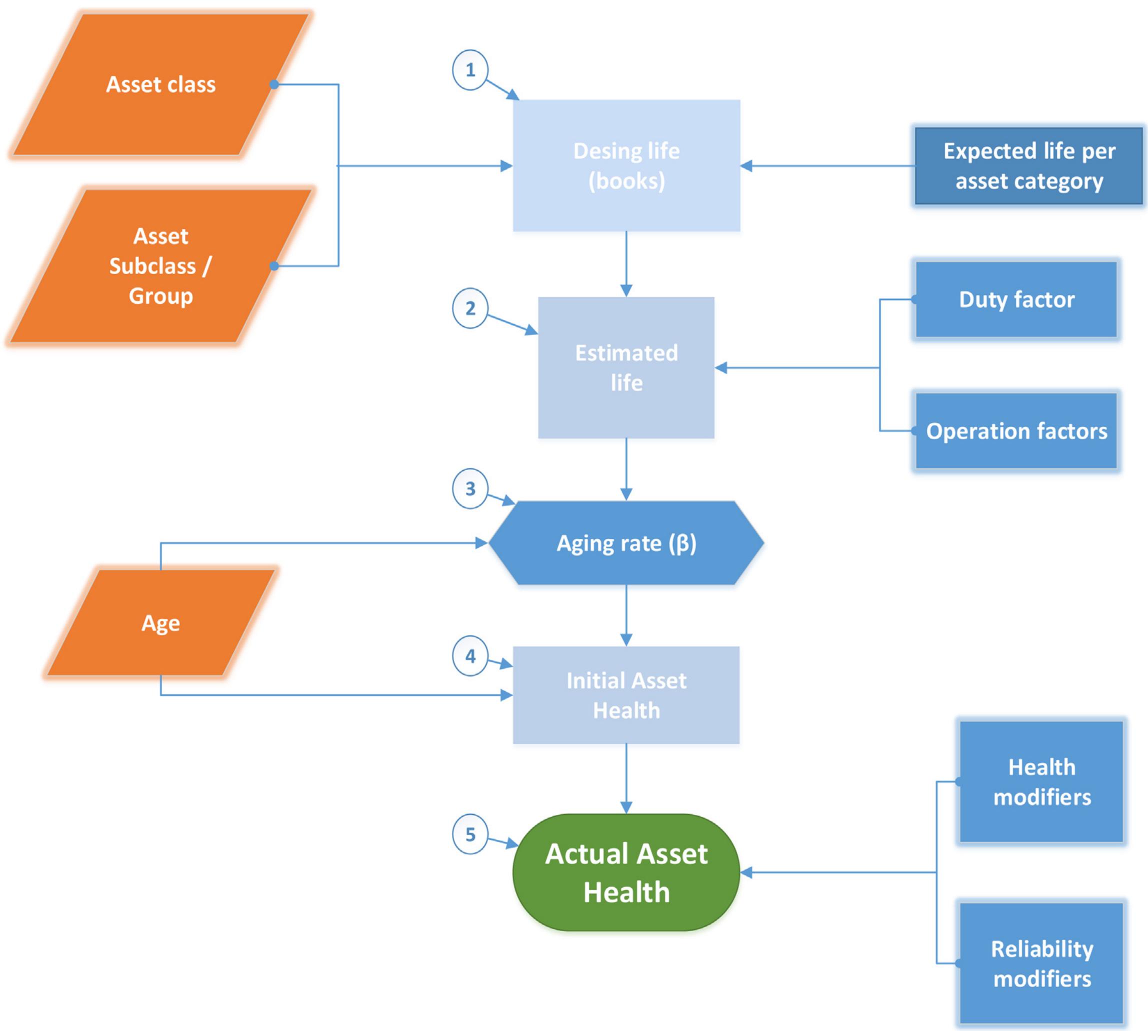

Fig. 2. Procedure to calculate the AHI.

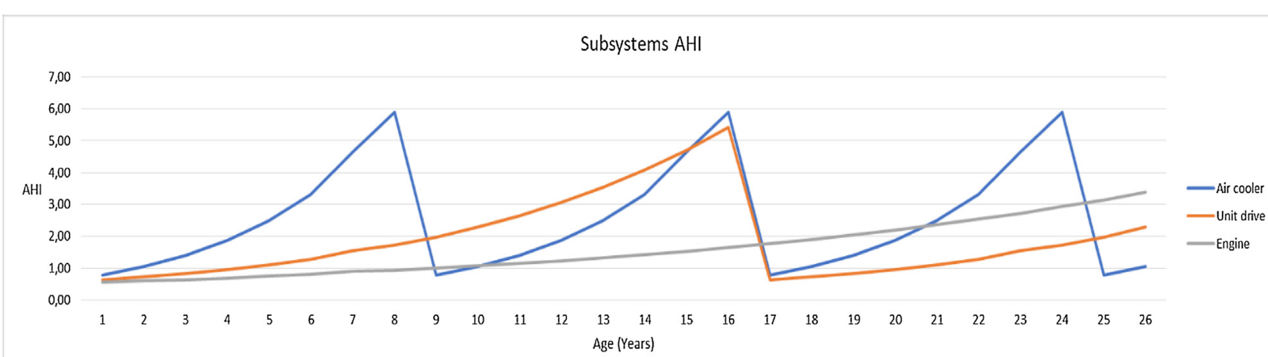

Fig. 3. Health index for different assets of a system (one colour per asset).

In the following sub sections, first the Stock and Flow Diagram (SFD) will be shown, and then the notation of the variables included in the model will be presented. Finally, the simulation model formal equations will be listed.

4.2. Simulation time versus age of the asset

In Section 3 the health index is calculated for a given age of the asset in Eqs. (5) and (6). For most of static assets (containers, tanks, exchangers, poles, structures, etc.), the age of the asset simply changes according to the course of time, which can be matched with the simulation time (t). However, for many dynamic assets (pumps, compressors, blowers, etc.), the course of time is replaced by the accumulation of operating time (AOT) as a more suitable indicator of age. The rational for that is that operation ages these assets much more than the passage of time and therefore offers a better reference to measure and compare the health of the asset. In fact, most of major maintenance activities in dynamic assets are

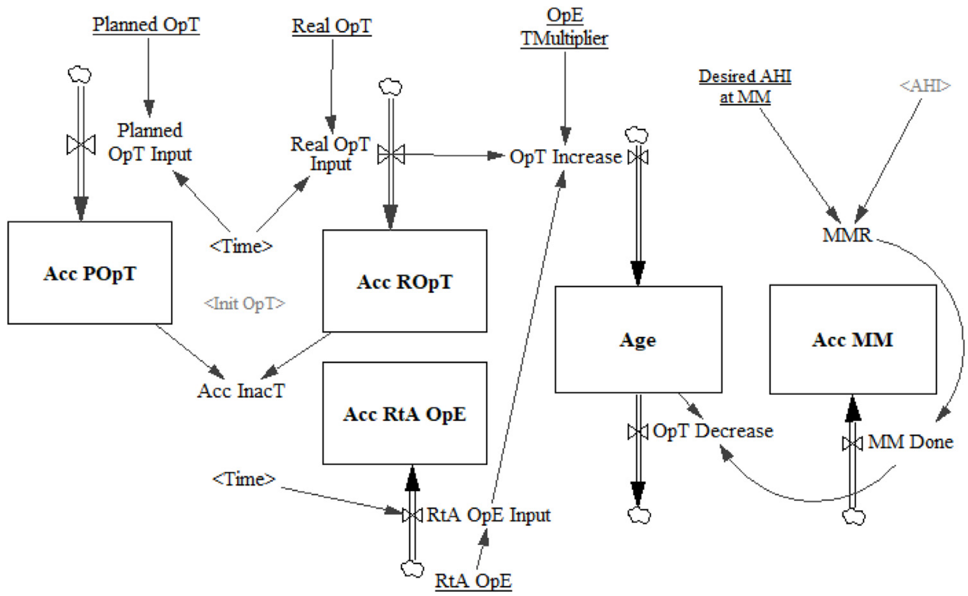

Fig. 4. SFD of an asset's age dynamic model.

associated, beside other factors, to operating time, not to calendar times. Therefore, age and simulation time will be, in general, decoupled. In fact, age will be another variable to model, according to each specific scenario. This offers the possibility of:

- Advancing the age of the asset according to specific events that may take place in its operation and/or maintenance:
  - Thus, for example, many manufacturers make an equivalence between "to start/to stop an equipment" with the consumption of a certain number of operating hours.
  - It is also possible to model consumption of certain hours of operation after each major maintenance (assuming that after the repair the equipment is not as good as new, i.e. is older).
- Measuring the real operating time of an asset compared to its expected operating time. Long times of inactivity can become an indicator of potential increase in the probability of failure.
- Replacing a desired age with a desired health when controlling the schedule of maintenance major interventions along the asset's life cycle.

Therefore, the challenge here is combining appropriately the modelling of age with the modelling of health, especially when the GB DNO groups methodology is, at least, loosely adopted. To that end, in Fig. 4 a stock and flow diagram (SFD) of the modeling of age is presented. The reader may notice that the model accumulates in stock variables:

- The number of operating hours since the last major maintenance;
- The total number of real and expected operating hours;
- The number of relevant-to-age operational events;
- The number of major maintenances (that could be relevant to age).

This offers the analyst different opportunities to control age according to most relevant assets operational and maintenance age-related events. This will easy to model *how old the equipment is* (age) since its last renovation or overhaul, which is required to determine later *how is it irreversibly deteriorated* (health).

4.3. Static versus dynamic aging factor

In the GB DNO groups methodology, the load factor (Fc) in Eq. (3) conditions the expected life of the asset in Eq. (1), and because of that, the expected pattern of the Health Index (HI_t) over the asset life cycle, driven by the aging factor in Eq. (4). However, in general, the load factor of an asset may change over time, and in the same way, it can change its life expectancy and aging rate. A dynamic model of the asset health index should take this into account and allow life expectancy to be modified dynamically when changes in the load factor are noticed. The dynamic model in this paper considers now β as a model variable β_t.

For different purposes, capturing the differences in aging factor (expected versus real) over time, can be very interesting. For instances, changes in asset load can alter significantly the business plan, by introducing new capex schedules. Fig. 5 presents the SFD of these calculations (notice that all variables in this Figure are modeled as auxiliary variables in the dynamic simulation model).

4.4. Modeling AHI. An irreversible dynamic index of degradation

The health of an asset measures its irreversible deterioration or degradation; therefore, the index must be monotonically increasing. A decrease in the index must be only due to a renovation or major maintenance of the asset. In order to model that, Fig. 5 SFD presents AHI as a stock or level variable, that can only increase in value when the calculated Dynamic AHI (considering all possible effects: modifiers and factors) exceeds the value of the AHI stored. AHI will decrease in value when the major overhaul is accomplished (*MMR*).

In Fig. 5 SFD, it is also modeled the Age of the system when the last major maintenance is accomplished ($Age\ at\ MM_t$). Notice that to hold this information over time, dynamically, a stock variable is used.

In the equations of the dynamic simulation model, the formulations of the health index, health and reliability modifiers will differ substantially from the one used in (GB DNO groups, 2017) (Eqs. (6)–(8)) and an exponential proportional model is now proposed (as in (Márquez et al., 2013)). This requires *HM Input Table* and *RM Input Tables* to me normalized, playing the role of covariates, and the utilization of covariates coefficients *HM Coef* and *RM Coef*.

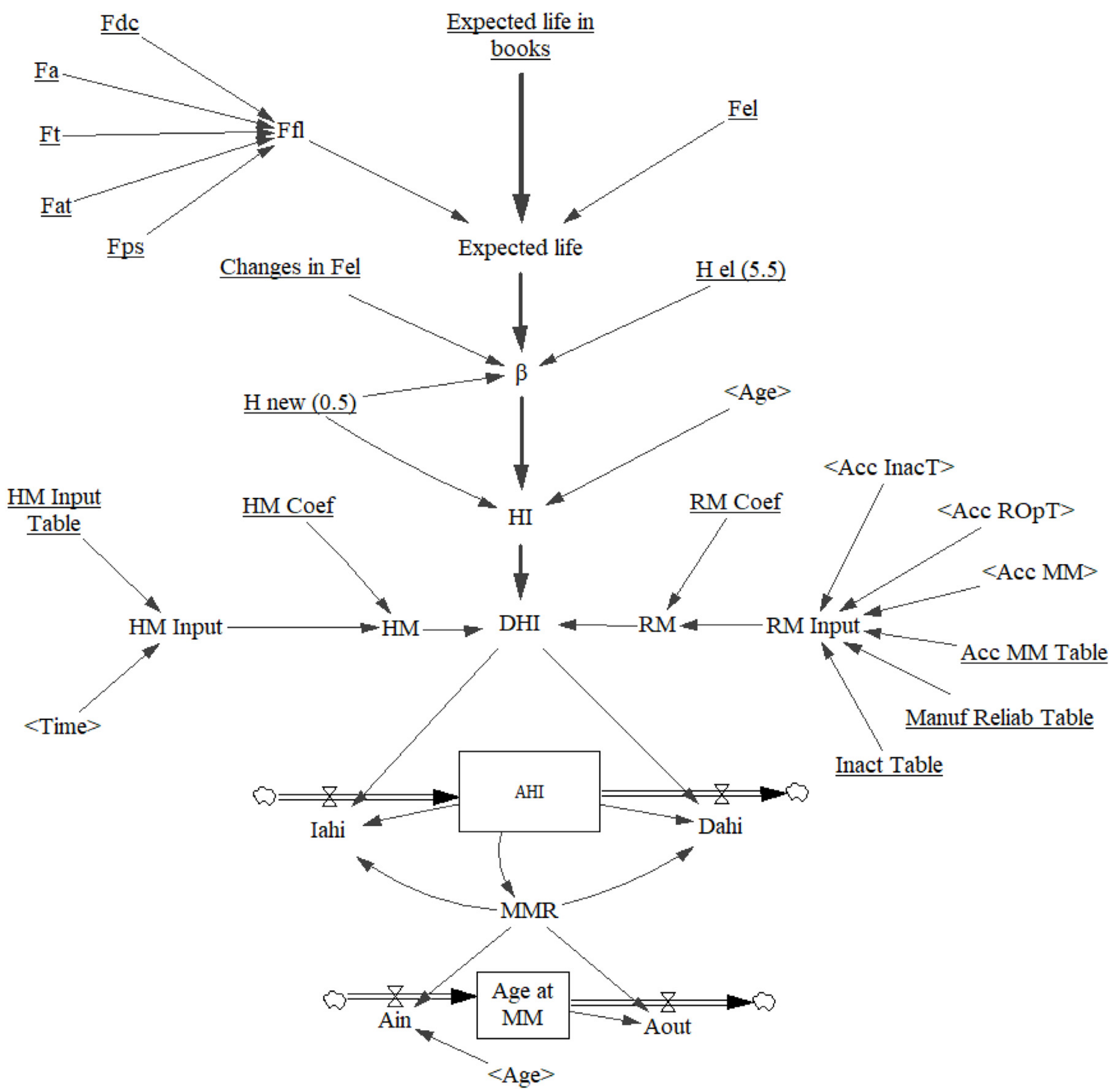

Fig. 5. SFD of an asset's Health Index dynamic model.

Table 1
Asset Health index and expected lifetime.

AHI	Condition	Expected Lifetime	Requirements
0.5–4	Very good	More than 15 years	Normal maintenance
4–5.5	Good	More than 10 years	Normal maintenance
5.5–7	Fair	From 3 to 10 years	Increase diagnostic testing, possible replacement depending on criticality
7–8	Poor	Less than 3 years	Start planning process to replace
8–10	Very poor	Near to the end of life	Immediately assess risk; replace or rebuild based on assessment

4.5. Linking AHI to probability of failure. Assessing OPEX and CAPEX

Once modeled AHI as a stock variable, operational expenditure (OpEx) and capital expenditure (CapEx) per periods can be modeled. To that end, it is needed:

- To obtain the failure rate as a function of C, K and r values, as in Eq. (5), parameters that will be calibrated by the software, as described later. This is needed to estimate the OpEx, by multiplying failure rate by the average corrective maintenance cost of a failure, and then adding an estimated PM cost.
- To determine whether there is a need of a major maintenance intervention according to the maximum asset health allowance policy.

Notice that the OpEx and CapEx variables are considered as financial flow variables in the dynamic model (See Fig. 6), these flows are accumulated in stock financial variables: Accumulated OpEx and Accumulated CapEx, respectively. Adding these two accumulations we obtain the total expenditure in the asset (TotEx), over the entire simulation period. Error variables for the OpEx and CapEx time series estimations are generated for the purpose of subsequent parameter calibration before putting the model into operation. In order to do so, financial records over a long time are necessary,

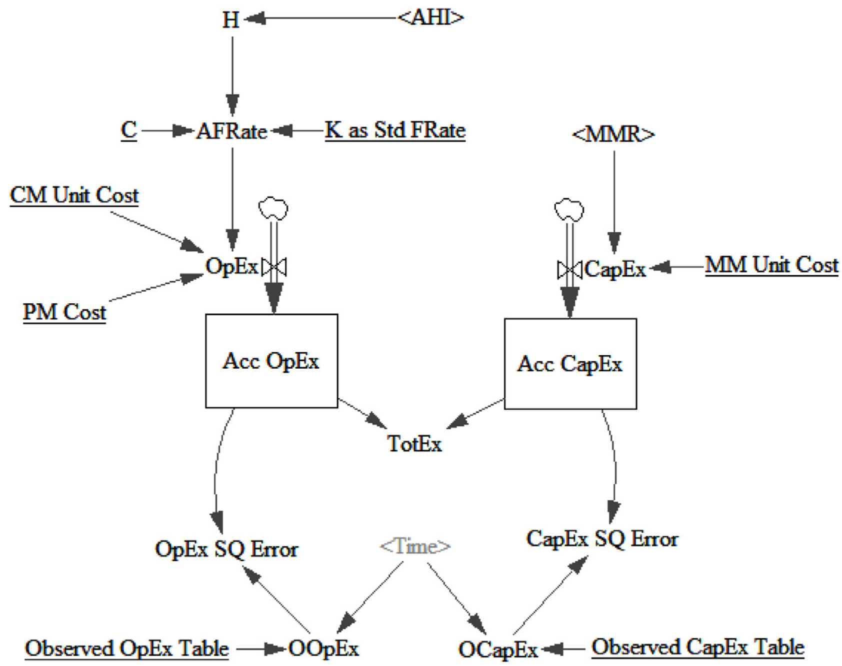

Fig. 6. SFD of an asset's TotEx and financial predictions errors in the model.

which is many times a bottleneck of this process, as a consequence of an incomplete asset's expenses registration in many companies and organizations.

The reader can notice how the diagrams in previous three figures focus on model structure, and will remain the same regardless de complexity of the model due to the number of assets, health and reliability modifiers. Since variables are subscripted vectors this complexity is transparent in the diagram.

4.6. Notation of the variables

The notation that we will use together with the indication of the typology of the variable used in previous four figures, are as follows:

4.6.1. Constants, parameters and input tables

$Fdc\,(i) = Distance\ to\ the\ coast\ factor$.
$Fa\,(i) = Altitude\ above\ sea\ level\ factor$.
$Ft\,(i) = Annual\ average\ of\ outside\ temperature\ factor$.
$Fat\,(i) = Exposure\ to\ corrosive\ atmosphere\ factor$.
$Fps\,(i) = Exposure\ to\ dust\ in\ suspension\ factor$.
$Ffl\,(i) = Compined\ functional\ location\ factor$.
$Fel\,(i) = Expected\ load\ factor\ in\ selected\ functional\ location$.
$Expected\ Life\ in\ books\,(i) = Expected\ Life\ of\ asset\ i\ in\ books$.
$Expected\ Life\,(i) = Expected\ Life\ of\ asset\ i$.
$OpE\ TMultiplier\,(i) = Operational\ event\ time\ multiplier$.
$Changes\ in\ Fel\,(i)_t = Changes\ in\ load\ factor\ of\ the\ asset\ at\ interval\ t$.
$Hel = Health\ index\ at\ the\ expected\ life\ of\ an\ asset\,(5.5)$.
$Hnew = Health\ index\ when\ an\ asset\ is\ new\,(0.5)$.
$HM\ Coef\ \ (j) = Coefficient\ of\ contrinution\ of\ Health\ Modifier\ j$.
$RM\ Coef\ \ (k) = Coefficient\ of\ contrinution\ of\ Reliability\ Modifier\ k$.
$HM\ Input\ Table\,(i,j)(x)$= Table with changes in the H modifier value j over tine
$RM\ Input\ Table\,(i,k)(y)$)= Table with changes in the K modifier value k
$Real\ OpT\,(i)_t = Table\ with\ real\ operational\ time\ of\ the\ asset\ i\ at\ interval\ t$.
$Planned\ OpT\,(i)_t = Table\ with\ planned\ operational\ time\ of\ the\ asset\ i\ at\ interval\ t$.
$RtA\ OpE\,(i)_t = Table\ with\ relevant\ to\ age\ oper\ events\ of\ the\ asset\ i\ at\ interval\ t$.
$Desired\ AHI\ at\ MM\,(i) = Desired\ health\ of\ the\ asset\ i\ to\ do\ the\ major\ maintenance$
$Desired\ Age\ at\ MM\,(i) = Desired\ age\ of\ the\ asset\ i\ to\ do\ the\ major\ maintenance$
$Oberved\ OpEx\ Table\,(i)_t = Table\ with\ observed\ OpEx\ of\ asset\ i\ over\ time$
$Oberved\ CapEx\ Table\,(i)_t = Table\ with\ observed\ CapEx\ of\ asset\ i\ over\ time$
$CM\ Unit\ Cost\,(i) = Average\ unit\ cost\ per\ corrective\ maintenance\ for\ asset\ i$.
$PM\ Cost\,(i) = Average\ preventive\ maintenance\ cost\ per\ time\ of\ asset\ i$.
$MM\ Unit\ Cost\,(i) = Average\ unit\ cost\ per\ major\ maintenance\ for\ asset\ i$.
With: $i = 1\ldots n\ assets$; j=1...m health modifiers; k=1...r reliability modifiers

4.6.2. Auxiliary variables

$\beta\,(i)_t = Aging\ rate\ of\ asset\ i\ at\ interval\ t$.
$HI\,(i)_t = Initial\ Health\ Index\ of\ asset\ i\ at\ interval\ t$.
$HIe\,(i)_t = Initial\ Health\ Index\ of\ asset\ i\ with\ constant\ initial\ load\ factor\ at\ interval\ t$.
$DAHI\,(i)_t = Dynamic\ Health\ Index\ of\ asset\ i\ at\ interval\ t$.
$MMR\,(i)_t = Request\ of\ Major\ Maintenance\ in\ asset\ i\ at\ interval\ t$.
$HM\ Input\,(i,j)_t = Input\ of\ health\ modifier\ j\ for\ asset\ i\ at\ interval\ t$.
$RM\ Input\,(i,k)_t = Input\ of\ reliability\ modifier\ k\ for\ asset\ i\ at\ interval\ t$.
$Acc\ InacT\,(i)_t = Accumulated\ Inactivity\ Time\ of\ asset\ i\ at\ time\ t$.
$OpEx\,(i)_t = Operational\ Expenditure\ on\ asset\ i\ at\ interval\ t$
$CapEx\,(i)_t = Capital\ Expenditure\ on\ asset\ i\ at\ interval\ t$
$OOpEx\,(i)_t = Observed\ Operational\ Expenditure\ on\ asset\ i\ at\ interval\ t$
$OCapEx\,(i)_t = Observed\ Capital\ Expenditure\ on\ asset\ i\ at\ interval\ t$
$TotEx\,(i)_t = Total\ Expenditure\ on\ asset\ i\ at\ interval\ t$
$H\,(i)_t = H\ value\ for\ asset\ i\ at\ time\ interval\ t$
$OpEx\ SQ\ Error\,(i)_t = Quadratic\ error\ of\ OpEx\ values\ for\ asset\ i\ at\ time\ interval\ t$

CapEx SQ Error $(i)_t$ = *Quadratic error of CapEx values for asset i at time interval t*

AFRate $(i)_t$ = *Actual Failure Rate of asset i at interval t*

4.6.3. Stock variables

Age $(i)_t$ = *Age of asset i at time t.*

AHI $(i)_t$ = *Actual Asset i Health Index at time t.*

Acc POpT $(i)_t$ = *Accumulated Planned Operational Time of asset i at time t.*

Acc ROpT $(i)_t$ = *Accumulated Real Operational Time of asset i at time t.*

Acc MM $(i)_t$ = *Accumulated number of Major MAintenances in asset i at time t.*

Acc RtA OpE $(i)_t$ = *Accumulated number of RtA Op Events in asset i at time t.*

Age at MM $(i)_t$ = *Age of the asset i at the time of its last major maintenance at time t.*

4.6.4. Flow variables

Iahi $(i)_t$ = *Increase in Actual Asset i Health Index at interval t.*

Dahi $(i)_t$ = *Decrease in Actual Asset i Health Index at interval t.*

Planned OpT Input $(i)_t$ = *Increase in planned operational time for asset i at interval t.*

Real OpT Input $(i)_t$ = *Increase in real operational time for asset i at interval t.*

RtA OpE Input $(i)_t$ = *Relevant to age operational event for asset i at interval t.*

OpT Increase $(i)_t$ = *Increase of operational time of asset i at interval t.*

OpT Decrease $(i)_t$ = *Decrease of operational time of asset i at interval t.*

MM Done $(i)_t$ = *Major Maintenance Done in asset i at interval t.*

Ain $(i)_t$ = *Age at MM increase in asset i at time interval t.*

Aout $(i)_t$ = *Age at MM decrease in asset i at time interval t.*

4.7. Equations

The equation for each one of the above declared variables are now presented:

47.1. Constants & Parameters

$$Fdc\,(i) = Fdc_i,\ \text{Data} \tag{14}$$

$$Fa\,(i) = Fa_i,\ \text{Data} \tag{15}$$

$$Ft\,(i) = Ft_i,\ \text{Data} \tag{16}$$

$$Fat\,(i) = Fat_i,\ \text{Data} \tag{17}$$

$$Fps\,(i) = Fps_i,\ \text{Data} \tag{18}$$

$$Fel\,(i) = Fel_i,\ \text{Data} \tag{19}$$

$$F_{FL} = max(Fdc_i,\ Fa_i, Ft_i, Fat_i, Fps_i) \tag{20}$$

$$Expected\ Life\ in\ books\,(i) = Expected\ Life\ in\ books_i.\ Data \tag{21}$$

$$OpE\ TMultiplier\,(i) = OpETM_i,\ Data \tag{20}$$

$$Hel = 5.5 \tag{22}$$

$$Hnew = 0.5 \tag{23}$$

$$HM\ Coef\ (j) = HMCoef_j,\ Data \tag{24}$$

$$RM\ Coef\ (k) = RMCoef_k,\ Data \tag{25}$$

$$Desired\ AHI\ at\ MM\,(i) = DAMM\ (i),\ Data \tag{26}$$

$$Desired\ Age\ at\ MM\,(i) = DAgMM\ (i),\ Data \tag{27}$$

$$Expected\ life(i) = Expected\ Life\ in\ books_i/(F_{FL}\cdot Fel_i) \tag{28}$$

4.7.2. Tables

$$Changes\ in\ Fel\,(i)_t = fel\_input\,(t)_i,\ Data\ table \tag{29}$$

$$Real\ OpT\,(i)_t = RealOpT(t)_i,\ Data\ table \tag{30}$$

$$Planned\ OpT\,(i)_t = PlaOpT\,(t)_i,\ Data\ table \tag{31}$$

$$RtA\ OpE\,(i)_t = RtAOpE\,(t)_i,\ Data\ table \tag{32}$$

$$HM\ Input\ Table\,(i,j)(x) = Table\ HMIT(i,j)(x) \tag{33}$$

$$RM\ Input\ Table\ (i,k)(y) = Table\ RMIT(i,k)(y) \tag{34}$$

$$Oberved\ OpEx\,(i)_t = ObsOpEx(t)_i,\ Data\ table \tag{35}$$

$$Oberved\ CapEx\,(i)_t = ObsCapEx(t)_i,\ Data\ table \tag{36}$$

With: $i = 1\ldots n$ *assets*; j = 1...m health modifiers; k = 1...r reliability modifiers

4.7.3. Auxiliary variables

$$\beta\,(i)_t = \ln(\frac{H_{new}}{H_{el}})/(\frac{Expected\ life\,(i)}{Changes\ in\ Fel\,(i)_t}) \tag{37}$$

$$HI(i)_t = H_{new}\cdot e^{\beta(i)_t\ \cdot\ Age(i)_t} \tag{38}$$

$$DHI(i)_t = HI(i)_t{}^{e^{(HM(i)_t+RM(i)_t)}} \tag{39}$$

$$HM(i)_t = \sum\nolimits_{j=1}^{j=m}(HM\ Coef\ \ (j)\cdot HM\ Input(i,j)_t) \tag{40}$$

$$RM(i)_t = \sum\nolimits_{k=1}^{k=r}(RM\ Coef\ \ (k)\cdot RM\ Input(i,k)_t) \tag{41}$$

$$HM\ Input(i,j)_t = HM\ Input\ Table\,(i,j)(t) \tag{42}$$

The equation for the *RM Input* could be formulated as the one for the *HM Input*, as

$$HM\ Input(i,k)_t = RM\ Input\ Table\,(i,k)(t) \tag{43}$$

However, in the case of this paper's model, some of the reliability modifiers are dynamically calculated in other auxiliary and stock variables of the model in the following way:

$$RM\ Input(i, Inactivity)_t$$
$$= RM\ Input\ Table\,(i, Inactivity)(Acc\ InacT\ (i)_t) \tag{44}$$

$$RM\ Input(i,MM)_t = RM\ Input\ Table\,(i,MM)(Acc\ MM\ (i)_t) \tag{45}$$

$$RM\ Input(i,MR)_t = RM\ Input\ Table\,(i,MR)(t) \tag{46}$$

Where in this case three reliability modifiers are considered, named: Inactivity, MM and RM. Representing: the total number of hours of inactivity of the asset, the accumulated number of major maintenances and the expected reliability of the manufacturer over time.

The strategies for major maintenance release can be formulated as in Eq. (47) or in Eq. (48):

$$MMR\,(i)_t = \begin{cases} 1,\ if\ AHI(i)_t \geq Desired\ AHI\ at\ MM(i) \\ 0,\ Otherwise \end{cases} \tag{47}$$

$$MMR\,(i)_t = \begin{cases} 1,\ if\ Age(i)_t \geq Desired\ Age\ at\ MM(i) \\ 0,\ Otherwise \end{cases} \tag{48}$$

$$TotEx\,(i)_t = Acc\ OpEx\,(i)_t + Acc\ CapEx\,(i)_t \tag{49}$$

$$H\,(i)_t = \begin{cases} AHI(i)_t,\ if\ AHI(i)_t \geq 4 \\ 4,\ Otherwise \end{cases} \tag{50}$$

$$Acc\ InacT\,(i)_t = Acc\ POpT\,(i)_t - Acc\ ROpT\,(i)_t \tag{51}$$

$$OPeEx\,(i)_t = AFRate(i)_t \cdot CM\ Unit\ Cost + PM\ Cost \tag{52}$$

$$CapEx\,(i)_t = MMR(i)_t \cdot MM\ Unit\ Cost \tag{53}$$

$$OOPeEx(i)_t = Observed\ OpEx\ Table(i)_t \tag{54}$$

$$CapEx(i)_t = Observed\ CapEx\ Table(i)_t \tag{55}$$

$$OpEx\ SQ\ Error\,(i)_t = (OOPeEx(i)_t - Acc\ OPeEx\,(i)_t)^2 \tag{56}$$

$$CapEx\ SQ\ Error(i)_t = (OCapEx(i)_t - Acc\ CapEx\,(i)_t)^2 \tag{57}$$

4.7.4. Stock variables

$$Age(i)_t = Age(i)_{t-1} + OpT\ Increase\,(i)_t - OpT\ Decrease\,(i)_t \tag{58}$$

$$Age(i)_{to} = Ageo\,(i)\,,\ Initial\ condition \tag{59}$$

$$Age\ at\ MM(i)_t = Age\ at\ MM(i)_{t-1} + Ain\,(i)_t - Aout\,(i)_t \tag{60}$$

$$Age\ at\ MM(i)_{to} = Age\ at\ MMo\,(i)\,,\ Initial\ condition \tag{61}$$

$$AHI(i)_t = AHI(i)_{t-1} + Iahi\,(i)_t - Dahi\,(i)_t \tag{62}$$

$$AHI(i)_{to} = AHIo\,(i)\,,\ Initial\ condition \tag{63}$$

$$AccPOpT(i)_t = AccPOpT(i)_{t-1} + Planned\ OpT\ Input\,(i)_t \tag{64}$$

$$AccPOpT(i)_{to} = AccPOpTo\,(i)\,,\ Initial\ condition \tag{65}$$

$$AccROpT(i)_t = AccROpT(i)_{t-1} + Real\ OpT\ Input\,(i)_t \tag{66}$$

$$AccROpT(i)_{to} = AccROpTo\,(i)\,,\ Initial\ condition \tag{67}$$

$$AccMM(i)_t = AccMM(i)_{t-1} + MM\ Done\,(i)_t \tag{68}$$

$$AccMM(i)_{to} = AccMMo\,(i)\,,\ Initial\ condition \tag{69}$$

$$AccRtAOpE(i)_t = AccRtAOpE(i)_{t-1} + RtA\ OpE\ Input\,(i)_t \tag{70}$$

$$AccRtAOpE(i)_{to} = AccRtAOpE\,(i)\,,\ Initial\ condition \tag{71}$$

$$Acc\ OpEx(i)_t = Acc\ OpEx(i)_{t-1} + OpEx\,(i)_t \tag{72}$$

$$Acc\ OpEx(i)_{to} = Acc\ OpExo\,(i)\,,\ Initial\ condition \tag{73}$$

$$Acc\ CapEx(i)_t = Acc\ CapEx(i)_{t-1} + CapEx\,(i)_t \tag{74}$$

$$Acc\ CapEx(i)_{to} = Acc\ CapExo\,(i)\,,\ Initial\ condition \tag{75}$$

4.7.5. Flow variables

$$Iahi\,(i)_t = \begin{cases} DHI(i)_t,\ if\ AHI(i)_{t-1} < DHI(i)_t\ and\ MMR\,(i)_t = 0 \\ 0,\ Otherwise \end{cases} \tag{76}$$

$$Dahi\,(i)_t = \begin{cases} AHI(i)_t,\ if\ AHI(i)_{t-1} < DHI(i)_t\ and\ MMR\,(i)_t = 0 \\ AHI(i)_t - Hnew,\ if\ AHI(i)_{t-1} < DHI(i)_t\ and\ MMR\,(i)_t = 1 \\ AHI(i)_t,\ if\ AHI(i)_{t-1} < DHI(i)_t\ and\ MMR\,(i)_t = 0 \end{cases} \tag{77}$$

$$Planned\ OpT\ Input\,(i)_t = Planned\ OpT\,(i)_t \tag{78}$$

$$Real\ OpT\ Input\,(i)_t = Real\ OpT\,(i)_t \tag{79}$$

$$RtA\ OpE\ Input\,(i)_t = RtA\ OpE\,(i)_t \tag{80}$$

$$OpT\ Increase\,(i)_t = RtA\ OpE\,(i)_t \cdot OpE\ TMultiplier\,(i) + Real\ OpT\ Input\,(i)_t \tag{81}$$

$$OpT\ Decrease\,(i)_t = \begin{cases} Age(i)_{t-1},\ if\ MM\ Done\,(i)_t = 1 \\ 0,\ Otherwise \end{cases} \tag{82}$$

$$MM\ Done\,(i)_t = \begin{cases} 1,\ if\ MMR\,(i)_t = 1 \\ 0,\ Otherwise \end{cases} \tag{83}$$

$$Ain\,(i)_t = \begin{cases} Age(i)_{t-1},\ if\ MMR\,(i)_t = 1 \\ 0,\ Otherwise \end{cases} \tag{84}$$

$$Aout\,(i)_t = \begin{cases} Age\ at\ MM(i)_{t-1},\ if\ MMR\,(i)_t = 1 \\ 0,\ Otherwise \end{cases} \tag{85}$$

5. Implementation in Vensim and optimization model

Vensim provides high rigour for writing model equations, helps to trace and to understand the importance of model existing feedback loops and supports multiparametric optimisation that will result essential for this work (García, 2018). The reader can find all our Vensim language equations of the model in previous Figures in Appendix A to this paper. In those equations the reader can verify that:

- Several variables are subscripted and that allows to introduce new subscript elements (for instance new assets, new modifiers, etc).
- Most of Data inputs (values of factors, table for operating hrs, modifiers, etc.) and observed data (values of OpEx and CapEx series) are imported from Excel (the reader should review Vensim Manuals to understand de input data set up in Excel, to be uploaded automatically to Vensim.
- The model will need separate runs to: calibrate parameters and to project future result of desired scenarios.

When calibrating parameters, the following considerations are made:

- The value for the factors to adjust the expected life of the asset are constant along the simulation period (Ffl & Fel). The range of variation to measure the impact of functional location and load is directly taken from the GB DNO document, where these values are general for a vast number of asset classes. In this work it is considered that relative ranges used for of each one of the factors are robust, can be now utilized and they will not be considered in the calibration.
- The range of variation and the possible impact of each health and reliability modifier, despite the fact that can be guessed by the experts in the asset (technologists), will be then calibrated. This relative impact of each one of the modifiers is defined in the values *HM Coef* (j) and *RM Coef* (k) in the model.
- Regarding the link between AHI and the asset failure rate. K is considered a standard failure rate for the asset in good health, therefore it is known and does not need calibration, and C is a constant that can be computed to fulfill that, in the worst possible asset condition ($AHI = 10$), the failure rate is 10 times higher than the failure rate for the asset as new. So, k & C are not considered for calibration.

The process relies on tools provided by Vensim for optimization and calibration of model parameters. Vensim uses the direct-search method that does not evaluate the gradient (Powell Modified Method), to calibrate model parameters (Powell, 2021; Powell, 1968). The optimization model implemented in the Vensim Powell Optimizer is as follows:

Objective Function:

$$Min \sum_t \sum_i OpEx\ SQ\ Error(i)_t + CapEx\ SQ\ Error(i)_t$$

with t = 1. . .Final Simulation Time and with i = 1. . .n assets.

Subject to:

$0 \le HM\ Coef\ (j) \le 1$ with j = 1. . .m health modifiers

$0 \leq RM \quad Coef\,(k) \leq 1$ with$k = 1 \ldots r$ reliability modifiers

Notice that the impact of the modifiers can never improve the existing equipment irreversible degradation, at a certain time. This is why the lower limit for the two calibrated parameters is 0. Also, the higher limit of these parameters could be selected according to the failure rates observed in the plant, but under reasonable condition will never exceed 2. Finally, the analyst can select to stop the algorithm according to a maximum number of iterations or according to a certain tolerance criterion for the solution (in Vensim).

6. Model version to put into operation for TotEx projection

In order to build the final version of the model to project assets expenses and investments the analyst must proceed as follows:

- To identify the values for the parameters: $HM\,Coef\;(j)\,and\;RM\,Coef\;(k)$, providing a better fit, as a result of the calibration.
- To compute the final value of the asset AHI_t at the end of the model calibration period (t_0).
- To estimate the value of the constant aging rate for the projection βc, as in Eq. (10), where t_0 is the final time of the calibration period.

$$\beta c = \frac{\ln \frac{AHI_{t0}}{HI_{new}}}{t0} \tag{10}$$

- To gather information about expected operating hours and load: These are input tables $Planed\,OpT(t)$ and $Changes\,in\,Fel(t)$.
- Run the model with the corrected aging rate (βc) assuming no *RM nor HM* impact. This means assuming a similar average impact of modifiers over the projected period.

When this is done, the final model version to put into operations can be written, and simulations with it can be made, testing available data, to project AHI and TotEx for the asset over the expected life cycle. In Fig. 7, structure modifications to be made using this model, compared to the calibration phase one, is presented.

7. Model results and sample industrial application

In order to show versatility of the tools, different sample results will be provided. Sample results have to do with the selection of model structure, and with the utilization of the model in real life cases for projection of maintenance cost and capital investments in assets. To illustrate this potential application, in the next paragraph two possible major maintenance release control policies will be modelled and analysed (sometimes these control policies are names MMR strategies): MMR age-based control policy and MMR AHI-based control policy.

7.1. Comparing age based vs. AHI based equipment MM control

Understanding the relationship between assets age, degradation and renovation is very important. At present, most capitalized industrial and infrastructure assets follow a process of restoration and renovation which is based on age. There is a desired age established for major maintenance or replacement activities and these activities are carried our when reaching this set point and financial resources are available (see feedback loop "-1"). For these cases (strategy 1: MMR age-based strategy) the asset's health is not included in the scheduling decision-making process (see Fig. 8).

A different approach (strategy 2: AHI -based strategy) tries to avoid situations of too early or too late equipment MM/renovation when scheduling these activities based on age only (see Fig. 9).

The idea is the consideration of factors related to the functional location of the equipment and to their operational and maintenance history. Gaining this information and considering it in decision making scheduling MM/renovation intervention based on a certain desirable AHI limit adds a new feedback loop to assets life cycle control (loop -2). This new loop adds the impact of a changes in load through the aging factor β, and the impact of operational and maintenance records through the health and reliability modifiers (HM and RM). Some of the reliability modifiers may add new dynamics to the problem, see for instance the effect of MM accumulation in a certain asset (loop +1 in Fig. 9). The greater number of major maintenances accumulated the more accelerated degradation. This accelerates the degradation process and shortens the time to the next overhaul since desired AHI limit will be reached earlier.

7.2. Testing different model structures with a simple initial example

Strategies in 7.1 are now modelled. The idea is to simulate behaviour of the asset (asset name GA 101 A in this example) under both MM Released control strategies, named now "Age base (15.000 h)" and "AHI Based (5.5)" in Figs. 10 and 11. These Figures show AHI_t and $Age\;at\;MM_t$. The idea is the reader to appreciate the difference in these fundamental variables under both strategies, In Fig. 10 AHI curve is always under 6 units while in Fig. 11, AHI reaches its maximum possible value (= 10) because MM is not released despite the fact that $AHI_t \geq 5.5$.

Both graphs have a different scale for each variable. In Fig. 12, however, same scale is maintained to show AHI_t under both strategies, compared with the original Health Index without the effect of the Modifiers. Fig. 13 shows the corresponding failure rate.

Fig. 14 shows the difference in accumulated overhauls over time, resulting under both circumstances, leading to different Capex, Opex and Totex.

In the next Section these different MMR control policies or strategies are applied to a complete plant analysis including a set of 54 assets of different types. Overall results are presented and analyzed.

7.3. Developing an industrial case for application

7.3.1. Introduction

The model has been used to develop a plan for capital investment (CapEx), operations and maintenance (OpEx) Expenditure to support the associated strategic decision-making processes in a Company (Regasification Terminal) for the period 2019–2035. The goal was using the model to develop a profile of expected expenses associated with a total of 54 assets of a Regasification Terminal (the C̈ompanÿ). The company decided to follow the approach established in the guides prepared for this purpose by the Institute of Assets Management (IAM) (2016). Consisting in the following steps:

1 Evaluation of the criticality of the Assets.
2 Assessment of the assets' health, both current and projected. Obtaining the health index to the condition of the assets, in order to obtain the probability of failure of each asset until the year 2035, based on the current failure probabilities and the evolution of the health of said assets throughout the period under study.
3 Forecast of the evolution of costs or economic risks throughout the life cycle of the Assets under study, considering the results of the previous point and the major revisions and major maintenance planned.
4 Study of the different strategies for major maintenance release, again applying the methodology used in points 2 and 3 above, in order to facilitate technical-economic decision making in relation to major revisions or the Equipment renewal, with a horizon of 2019–2035.

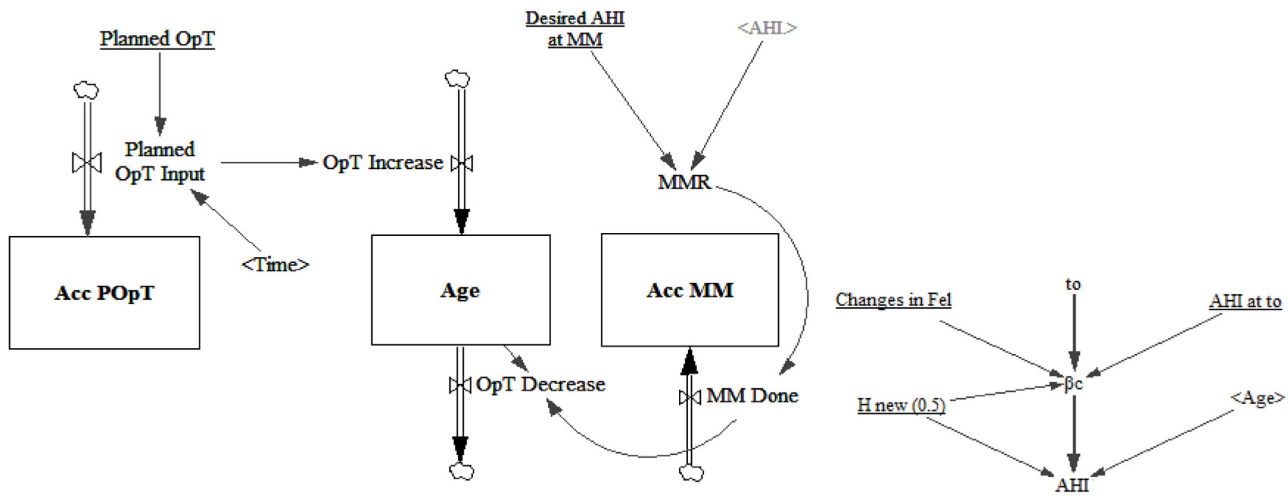

Fig. 7. Changes in the Stock and flow diagram of the model to put into operation.

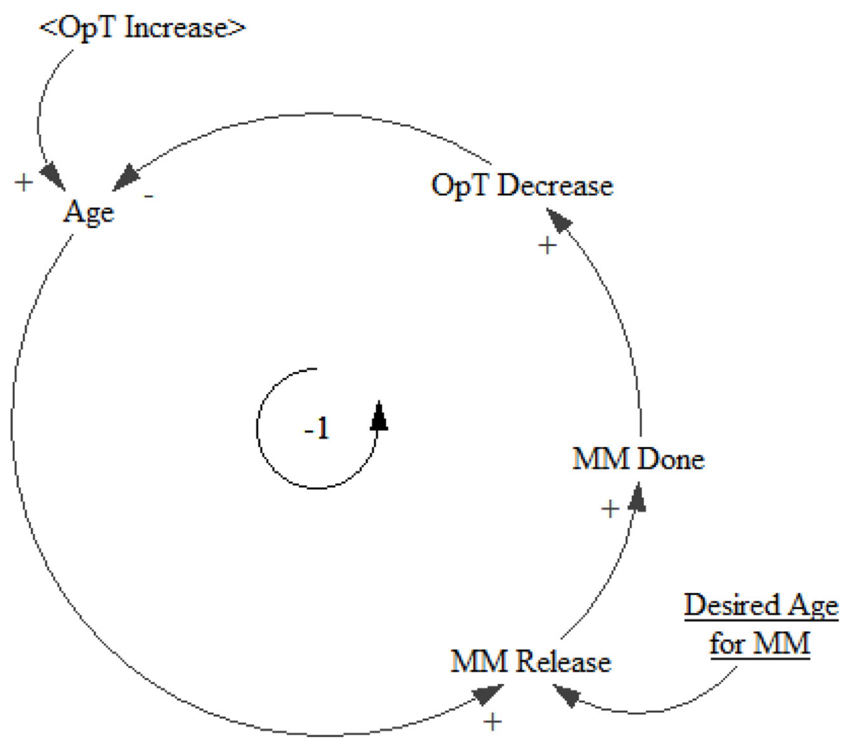

Fig. 8. Negative feedback loops in an age base MM/renovation strategy.

5 Making a better estimate, as of March 2019, of the expected expense profile for the assets, during the 2019–2035 period

For the purpose of this study, historical data recorded by the company, regarding O&M of these equipment since its commissioning (2009) has been available to the project review team.

7.3.2. Asset's expense profile based on the evolution of its health index

Keeping the asset's probability of failure within an acceptable range, requires preventive maintenance and major maintenance (also called överhaulsöf the equipment). After the overhaul the asset is practically in a situation of äs neẅ. Therefore, it is understood that by carrying out the overhaul when the $AHI = 5.5$, the failure rates will remain under control, as expected for the established maintenance plans. If this major maintenance is postponed, the frequency of failures will grow, and so will increase the needs for corrections and their costs, or the needs for preventive activities to retain reliability within a desired range, and their cost, decreasing efficiency in assets management.

Major maintenance activities schedules were originally recommended by the manufacturers and builders of each piece of equipment, according to functional location and operating conditions (and are often taken as generic or standard). However, after ten years of plant operation, the actual use of the asset or even its location, environmental conditions, etc., may differ from those that the manufacturer/builder had assumed in their recommendations. Of course, this may affect original failure rates considered and subsequently financial statements.

In this context, the analysis attempted to determine the multiplying factors that apply to the failure rate of each asset, due to the effect of aging (AHI), and the associated cost of maintenance,

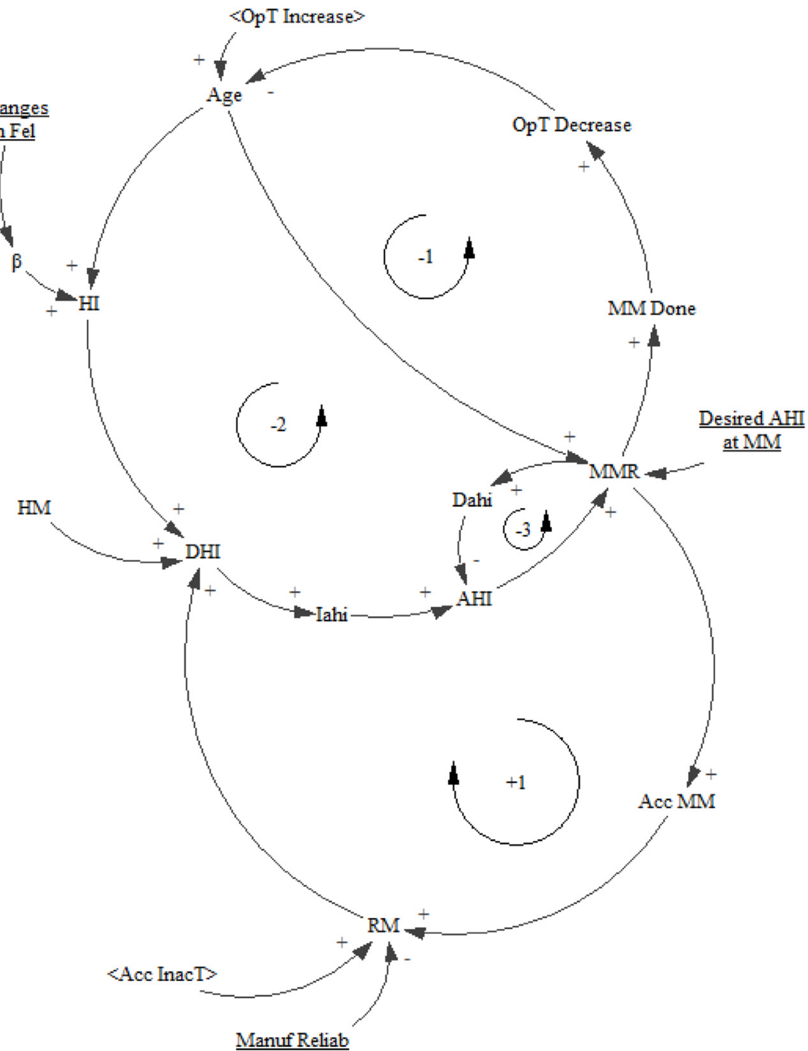

Fig. 9. Feedback loops in AHI based MM/renovation strategy.

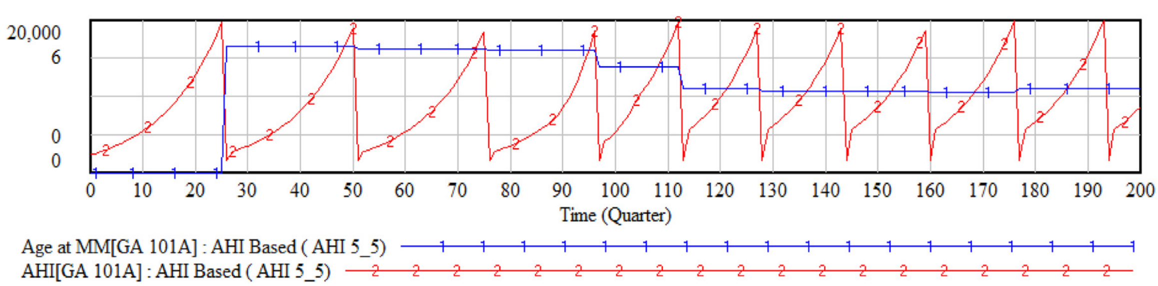

Fig. 10. AHI based MMR strategy. AHI and Age at MM variables.

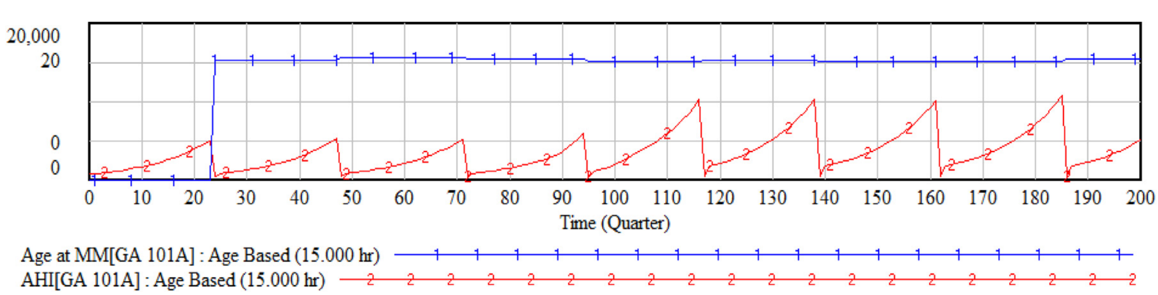

Fig. 11. Age based MMR strategy. AHI and Age at MM variables.

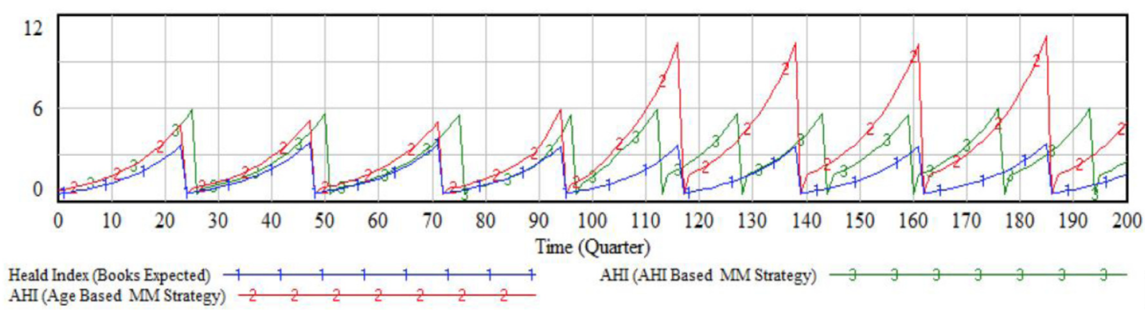

Fig. 12. Age based MMR strategy. AHI and Age at MM variables.

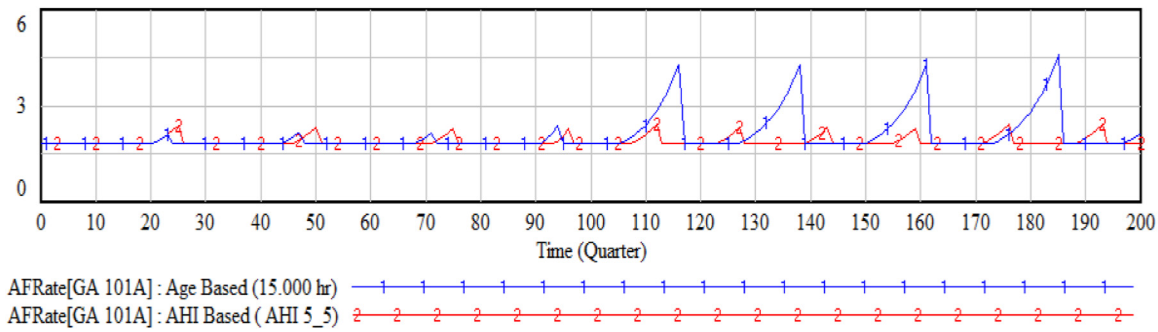

Fig. 13. Asset Failure Rate for both strategies (in failures/quarter).

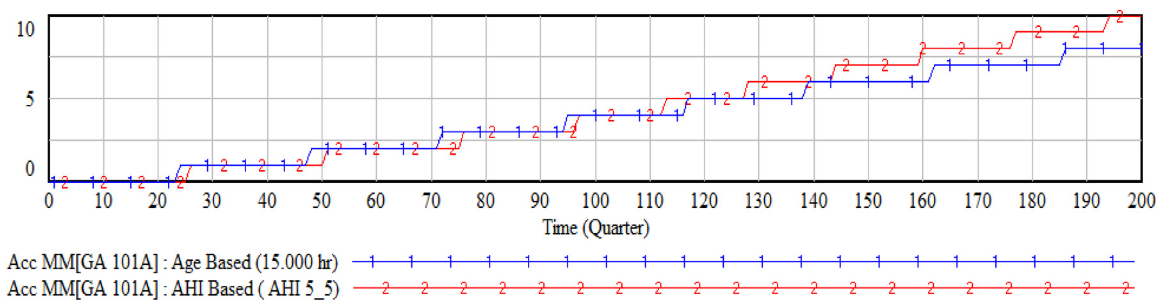

Fig. 14. Accumulated number for overhauls under both strategies.

affected by these new failure rates. On the other hand, a new strategy was proposed for major maintenance scheduling, in order to avoid out-of-control increase in the failure rates. More precisely, the strategies that were analyzed were the following:

- Strategy 1. Total expenditure on the asset (TotEx) is calculated executing its maintenance according to the manufacturer's recommendations (as in Fig. 15), without incorporating substantive changes to the original maintenance methodology (desired age-based overhauls).
- Strategy 2. TotEx is estimated assuming a standard OpEx but adjusting the overhauls schedule (CapEx) in order to maintain a controlled level of reliability (as in Fig. 16), avoiding the increase in the failure rate beyond the standard values considered (i.e. health index-based overhauls, with *AHI* $\leq$ 5.5).

In Figs. 17 & 18 , after the calibration period finished at the end of 2018 (graphs are the same until that point), projection of AHI values under both strategies are presented. Assets included within the named: KO Drum system of the plant are included. AHI projections and then translated to numbers in Table 2, for two Systems KO Drum and Fender (notice that some of the systems may consist of only one asset). Once the list of expenses and investments is projected, a financial calculation is done to compare both strategies. In this calculation inflation is considered but assets depreciation is not. So, CapEx only includes expected reinvestments until the year 2035.

7.3.3. *Industrial case results and findings*

The analysis identified Strategy 2 as the most appropriate for the fulfillment of dependability targets of the terminal. This was the only one strategy to ensure assets' reliability within standard limits in this type of industry. Besides that, and curiously, Strategy 2 scored the lowest updated TotEx value (77,966 M USD). The savings in higher reliability, are higher than the extra capital investment required in number of overhauls. Results obtained for the total 54 assets are included in Table 3.

8. Conclusions

In this paper we have used dynamic simulation models to evaluate assets health, and to project O&M expenses and capital investments over time accordingly. Especially when operating conditions and maintenance are variable and defined by multiple system parameters, it has been shown that continuous time dynamic simulation models can help to:

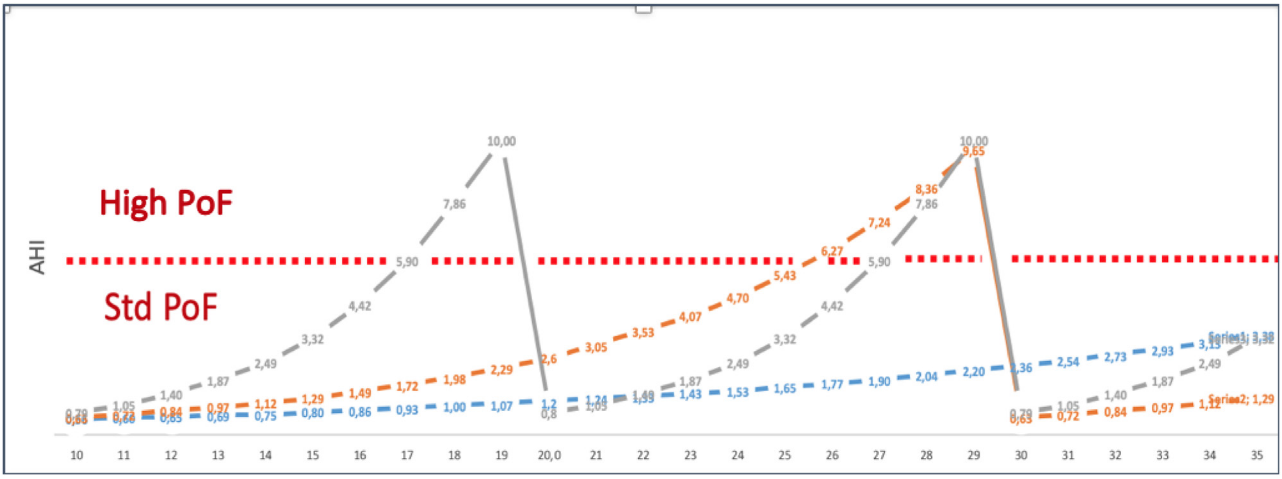

Fig. 15. Sample projection of AHÍ values for strategy 1.

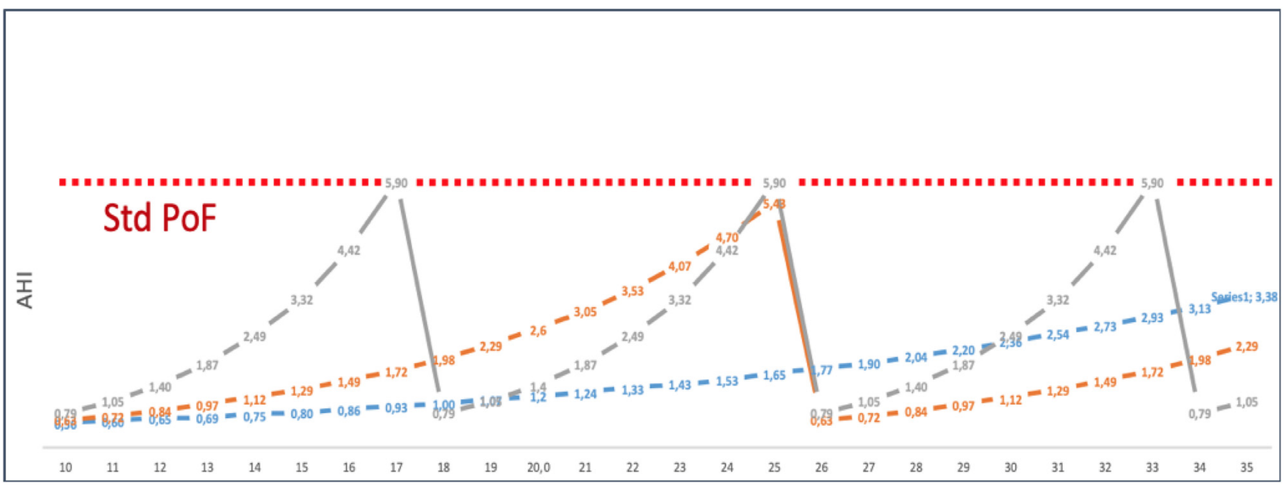

Fig. 16. Sample projection of AHÍ values for strategy 2.

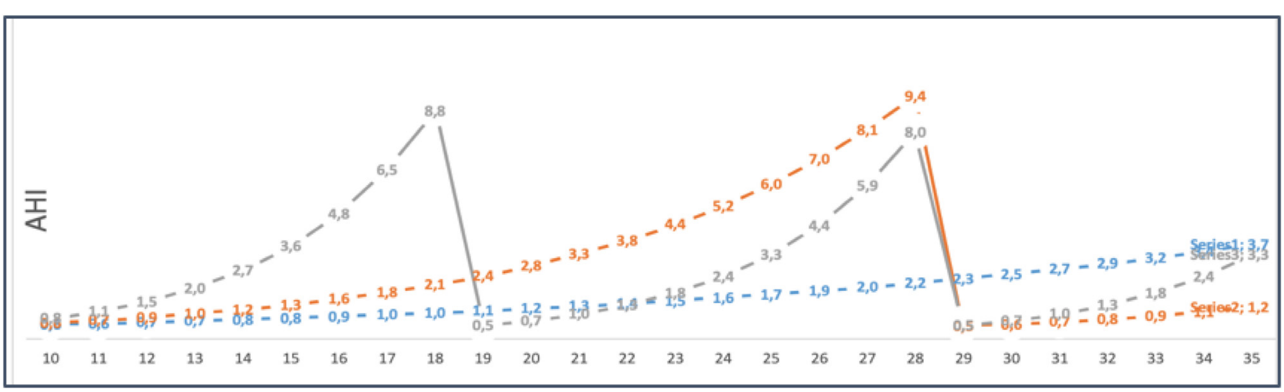

Fig. 17. Projection of AHÍ for Strategy 1 since 2019 and until 2035. KO Drum system.

- Adjust model structure for required accuracy;
- Understand dynamics of the possible strategies to implement in the model;
- Calibrate parameter values for optimal accuracy of the resulting prediction model;
- Visualize results of the different variable and investigate, properly, cause-effect relationships.
- Update the model features to adjust to variable operating conditions over time.

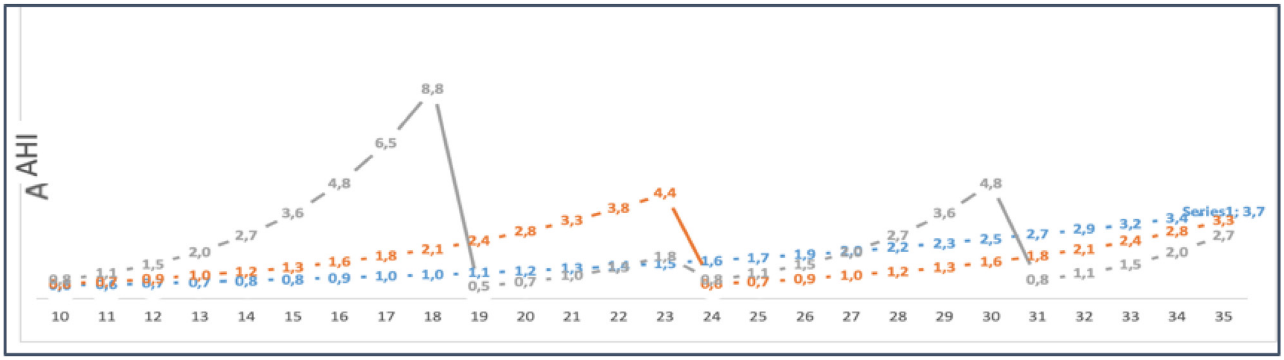

Fig. 18. Projection of AHÍ for Strategy 2 since 2019 and until 2035. KO Drum system.

Table 2
Annual CapEx (without depreciation) & Opex for both strategies, and two assets (Ko drum and "Punto de apoyo y amortiguación barco" ending 2035. Last two columns are for TotEx & VAN (Net Present Value) of Strategy 2 (the one that was selected).

Equipo	Descripción	Estrategia	Capex/Opex	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	Totex EST 2 USD (2018-2035)	VAN EST2 (MM USD en 2018)
100-V-101 KO Drum	KO drum del muelle	EST 1	Capex	0.0	58.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	138.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1,022,468	485,031
		EST 1	Opex	100.0	14.2	14.6	15.0	15.5	45.8	55.6	68.9	87.3	113.1	150.0	19.0	19.6	20.2	20.8	21.4	22.0	22.7		
		EST 2	Capex	0.0	58.3	0.0	0.0	0.0	119.4	0.0	0.0	0.0	0.0	0.0	0.0	80.8	0.0	0.0	0.0	0.0	0.0	738,573	382,706
		EST 2	Opex	100.0	14.2	14.6	15.0	15.5	45.8	16.4	16.9	17.4	17.9	18.5	19.0	61.8	20.2	20.8	21.4	22.0	22.7		
100-X-110C Fender	Punto de apoyos y amortiguación Barco	EST 1	Capex	0.0	24.7	0.0	0.0	0.0	0.0	1.2	0.0	0.0	0.0	0.0	33.2	0.0	0.0	0.0	0.0	1.7	0.0	331,483	151,058
		EST 1	Opex	24.6	9.0	9.2	9.5	9.8	10.1	10.4	14.8	18.0	23.9	33.6	12.0	12.4	12.8	13.1	13.5	14.0	19.9		
		EST 2	Capex	0.0	24.7	0.0	0.0	0.0	0.0	1.2	0.0	0.0	30.0	0.0	1.4	0.0	0.0	0.0	0.0	1.7	0.0	315,385	145,996
		EST 2	Opex	24.6	9.0	9.2	9.5	9.8	10.1	10.4	14.8	18.0	22.6	11.7	12.0	12.4	12.8	13.1	13.5	19.3	23.5		

Table 3
CapEx (no depreciation included) and OpEx, over the years, for both strategies until 2035. VAN represent Net Present Value of Strategy 2 (Selected Strategy). Values in Thousands USD$. All assets under analysis.

Est	Capex/Opex	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	VAN
EST 1	Capex	621	1,832	669	107	104	237	2,508	2,916	2,877	138	4,265	8,866	1,054	325	93	90	2,418	2,349	12,427 $
EST 1	Opex	6,911	7,161	7,036	7,126	7,372	7,766	8,108	8,304	8,565	8,927	9,445	9,659	9,426	9,618	9,830	10,166	10,520	10,808	66,667 $
EST 2	Capex	645	1,336	175	1,176	684	1,231	2,700	3,130	2,143	1,168	4,161	3,341	1,498	3,125	300	1,646	893	13	12,338 $
EST 2	Opex	6,757	7,132	6,893	7,103	7,362	7,723	7,942	8,025	8,271	8,557	8,863	9,129	9,403	9,657	9,867	10,173	10,456	10,786	65,491 $
EST 1	Totex	7,532	8,993	7,705	7,233	7,476	8,003	10,615	11,221	11,442	9,065	13,709	18,524	10,479	9,944	9,923	10,256	12,938	13,157	79,093 $
EST 2	Totex	7,402	8,469	7,068	8,279	8,046	8,954	10,643	11,155	10,414	9,725	13,025	12,470	10,901	12,782	10,167	11,819	11,349	10,799	77,829 $

Concerning the model built in Vensim for the regasification plant, we have:

- Provided the code of the Vensim models developed;
- Shown that it is possible, in a very practical manner at industrial level, increase robustness of the model format, initially developed by GB DNO, adopting a new formulation for AHI and using direct search techniques in the software, to properly calibrate parameters of the model the industrial case study.
- Provided appropriate inputs for the business plan under two scenarios.
- Demonstrated that, besides ensuring plant reliability according to an asset degradation under control (strategy 2), the strategy pays off to the company resulting in a lower TotEx, despite the fact of the computed increase in CapEx.

Therefore, it is demonstrated the adaptability for prediction accuracy of the simulation tool and how the simulation tool becomes a workbench to test different business strategies for a given scenario.

More future work could be accomplished, for instance extending the industrial case study in the paper, it is now easy to deal with prediction issues like:

- Changing preventive maintenance plans and/or operational plans and schedules, to check impact on asset health and in life cycle cost projections;
- To understand the impact of the PM plan fulfilment in asset health;
- To model the problem more precisely discriminating the failure modes of the assets linked to certain types of major maintenance interventions;
- Etc.

Finally, other options could result by using other asset health indexing algorithms and format.

Appendix A. Vensim Model Equations

.Subscript
$k:\ Inactivity,\ MM, RM \sim\sim|$
$j:\ Hm1, Hm2, Hm3 \sim\sim|$
$i:\ GA101A,\ GA\,231A \sim\sim|$
.Auxiliary variables
$RM\,[i] = \ SUM\,(RM\,Coef\ [K!]\,{}^{*}RM\,Input\,[i, K!])\ \sim\sim|$
$RM\,Input[i, Inactivity] = \ Inact\ Table(Acc\,InacT[i]) \sim\sim|$
$RM\,Input\,[i,\ MM] = \ Acc\,MM\,Table\,(Acc\,MM\,[i])\ \sim\sim|$
$RM\,Input[i, RM] = \ Manuf\ Reliab\,Table[i](Time) \sim\sim|$
$AFRate[i] = \ K\,as\,Std\,FRate[i]^{*}(1 + C[i]^{*}H[i] + ((C[i]^{*}H[i])^2/2) + ((C[i]^{*}H[i])^3/6)) \sim\sim|$
$H[i] = \ IF\ THEN\ ELSE(AHI[i] >= 4, AHI[i],\ 4) \sim\sim|$
$MMR\,[i] = \ IF\ THEN\ ELSE\,(\,AHI\,[i] >= Desired\,AHI\ at\ MM\,[i]\,,\ 1,\ 0)\ \sim\sim|$
$OpEx\ SQ\ Error[i] = \ (OOpEx[i] - Acc\ OpEx[i])^2 \sim\sim|$
$DHI[i] = \ HI[i]^{*}EXP(RM[i] + HM[i]) \sim\sim|$
$OCapEx[i] = \ Observed\ CapEx\ Table[i](Time) \sim\sim|$
$CapEx\ SQ\ Error[i] = \ (OCapEx[i] - Acc\ CapEx[i])^2 \sim\sim|$
$OOpEx\,[i] = Observed\ OpEx\ Table[i](Time) \sim\sim|$
$HI[i] = MIN("H\,new\,(0.5)"^{*}EXP(\beta[i]^{*}Age[i]), 10) \sim\sim|$

Acc InacT [i] = Acc POpT[i] − Acc ROpT[i] ~~|
HM Input[i, j] = HM Input Table[i, j](Time) ~~|
Expected life [i] = Expected life in books[i]/(Ffl[i]*Fel[i]) ~~|
TotEx [i] = Acc CapEx[i] + Acc OpEx[i] ~~|
HM [i] = SUM(HM Coef[J!]*HM Input[i, J!]) ~~|
β[i] = (LN("H el (5.5)"/"H new (0.5)"))/(Expected life[i] /Changes in Fel[i](Time)) ~~|
.Input Tables
Changes in Fel[GA 101A]([(0, 0) − (200, 1)], (0, 1), (200, 1)) ~~|
Changes in Fel[GA 231A]([(0, 0) − (200, 1)], (0, 1), (200, 1)) ~~|
HM Input Table[i, j]([(0, 0) − (200)], (0, 1), (200, 1)) ~~|
Observed OpEx Table[GA 101A]([(0, 0) − (200, 100)], (0, 1), (200, 100)) ~~|
Observed OpEx Table[GA 231A] ([(0, 0) − (200, 100)], (0, 1), (200, 100)) ~~|
RtA OpE([(0, 0) − (200, 20)], (0, 1), (200, 1)) ~~|
Observed CapEx Table[GA 101A]([(0, 0) − (200, 1000)], (0, 0), (200, 1000)) ~~|
Observed CapEx Table[GA 231A]((([(0, 0) − (200, 1000)], (0, 0), (200, 1000)) ~~|
Planned OpT[i]([(0, 0) − (200, 2000)], (0, 672), (200, 672)) ~~|
Real OpT[GA 231A]([(0, 0) − (200, 2000)], (0, 672), (200, 672)) ~~|
Real OpT[GA 101A]([(0, 0) − (200, 800)], (0, 672), (200, 672)) ~~|
Acc MM Table([(0, 0) − (20, 1)], (0, 0), (20, 0.5)) ~~|
Inact Table([(0, 0) − (1, 1)], (0, 0), (1, 0.5)) ~~|
.Flow variables variables
Dahi[i] = IF THEN ELSE(AHI[i] < DHI[i] : AND : MMR[i] = 0, AHI[i], IF THEN ELSE(MMR[i] = 1, AHI[i] − 0.5, 0)) ~~|
Iahi[i] = IFTHENELSE(AHI[i] < DHI[i] : AND : MMR[i] = 0, DHI [i], 0) ~~|
Ain[i] = IF THEN ELSE(MMR[i] = 1, Age[i], 0)~~|
MM Done[i] = IF THEN ELSE(MMR[i] = 1, 1, 0) ~~|
CapEx[i] = MMR[i]*MM Unit Cost[i] ~~|
Aout[i] = IF THEN ELSE(MMR[i] = 1, Age at MM[i], 0) ~~|
OpT Increase[i] = Real OpT Input[i] + RtA OpE Input*OpE TMultiplier ~~|
OpEx[i] = AFRate[i]*CM Unit Cost[i] + PM Cost[i] ~~|
RtA OpE Input = RtA OpE(Time) ~~|
Planned OpT Input[i] = Planned OpT[i](Time) ~~|
Real OpT Input[i] = Real OpT[i](Time) ~~|
OpT Decrease[i] = IF THEN ELSE(MM Done[i] = 1, Age[i], 0) ~~|
.Stock Variables
Age at MM[i] = INTEG (Ain[i] − Aout[i], 0) ~~|
Acc CapEx[i] = INTEG (CapEx[i], 0) ~~|
Acc OpEx[i] = INTEG (OpEx[i], 0) ~~|
Acc POpT[i] = INTEG (Planned OpT Input[i], Init OpT[i]) ~~|
Acc ROpT[i] = INTEG (Real OpT Input[i], Init OpT[i]) ~~|
Acc RtA OpE[i] = INTEG (RtA OpE Input, 0) ~~|
AHI[i] = INTEG (Iahi[i] − Dahi[i], DHI[i]) ~~|
Age[i] = INTEG (OpT Increase[i] − OpT Decrease[i], 0) ~~|
Acc MM[GA 101A] = INTEG (MM Done[GA 101A], 0) ~~|
Acc MM[GA 231A] = INTEG (MM Done[GA 231A], 1) ~~|
.Constants
RM Coef[k] = 0.01 ~~|
Manuf Reliab Table[GA 231A] = 0.1 ~~|
Manuf Reliab Table[GA 101A] = 0.3 ~~|
Fel[i] = 1, 1.1 ~~|
C[i] = 0.15 ~~|
Init OpT[i] = 8500, 15700 ~~|
Fdc[i] = 1, 1.5 ~~|
Ffl[i] = MAX(Fa[i], MAX(Fat[i], MAX(Fdc[i], MAX(Fps[i], Ft[i])))) ~~|
Fps[i] = 1 ~~|
CM Unit Cost[i] = 1000 ~~|
Ft[i] = 1 ~~|
PM Cost[i] = 3000 ~~|
Fa[i] = 1, 1.2 ~~|
Fat[i] = 1, 1.3 ~~|
MM Unit Cost[i] = 5000 ~~|
K as Std FRate[i] = 1, 2 ~~|
HM Coef[j] = 0.02 ~~|
"H el (5.5)" = 5.5 ~~|
"H new (0.5)" = 0.5 ~~|
Expected life in books[GA 101A] = 42500 ~~|
Expected life in books[GA 231A] = 25000 ~~|
OpE TMultiplier = 3 ~~|
.Parameters
Desired Age at MM[i] = 40 ~~|
Desired AHI at MM[i] = 5.5~~|
.Simulation Control
FINAL TIME = 200 ~Quarter ~The final time for the simulation. |
INITIAL TIME = 0 ~Quarter ~The initial time for the simulation. |
SAVEPER = TIME STEP ~Quarter [0,?]~The frequency with which output is stored. |
TIME STEP = 1 ~Quarter [0,?] ~The time step for the simulation. |

Declaration of Competing Interest

The authors of this paper declare no conflicts of interest that could be inherent in their submissions.

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