Data-Driven Asset Health Index – An application to evaluate Quay Cranes in container ports

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Abstract

Ports worldwide seek for more efficient and sustainable operations, relying on critical and valuable assets as their cranes. Internet of Things (IoT) technologies enable a better understanding of critical assets' behaviour and lifecycle based on data, and development of asset management decision support tools. The Asset Health Index (AHI) is an asset condition score, designed to characterise the state of complex assets. This paper describes the process of developing a data-driven AHI. IoT sensors and Programmable Logic Controllers (PLC) in real operation time, together with information systems, and other more traditional sources of data are some of the data sources for the AHI. The index captures and quantifies dimensions affecting the asset lifecycle, allowing the comparison of the condition of assets and prioritise maintenance investments. The case study is conducted in Quay Cranes of the Port of Felixstowe (UK) as the object of this study and proof of concept.

Keywords: Asset health index, port asset management, digital asset management, maritime ports resilience, quay cranes, container ports

1. Introduction

Ports play an important role in the worldwide economy as essential nodes in the global trading network. Given that approximately 80% of global trade relies on maritime transportation (UNCTAD, 2020; Zhang et al., 2018), the efficiency of ports is crucial and keeps attracting attention from academia (Hidalgo-Gallego et al., 2022; Nayak et al., 2022; Yap & Ho, 2021). Moreover, Ports' location along the coasts, rivers or lakes directly expose the critical infrastructures to a harsh environment, resulting in accelerated deterioration and unforeseen disruptions that may impact the port itself, the regional economy, and the operation of the whole supply chain (Bai et al., 2022; Ke et al., 2022; Smythe, 2013). One of the main challenges that port face today is the necessity to become more efficient, competitive, and sustainable (de la Peña Zarzuelo et al., 2020). The efficiency of the port operation is often influenced by the availability and condition of quay cranes (i.e. ship to shore cranes) (Bartošek & Marek, 2013; Chao & Lin, 2011). Quay Cranes (QC) are critical port assets whose availability and condition influence deeply port operations. The unavailability of QCs due to breakdowns could paralyse not only the essential port operation but also impact the wider shipping industry (Crespo del Castillo et al., 2023; Hsieh et al., 2014; Lin et al., 2020) in the form of vessel delays, rerates, cargo delays, etc. For instance, container vessels are forced to stay at anchorage and the handling operations are stopped once the port operation is disrupted (Tabernacle, 1995). Early detection of faults in quay cranes components, and deterioration monitoring allows for timely maintenance interventions, thereby, reducing unplanned disruptions to the container handling operations (Acciaro & Sys, 2020; Bierwirth & Meisel, 2010;

Crespo del Castillo et al., 2023; Y. Gao & Ge, 2022). Adopting predictive asset management practices also play a significant role in ensuring the resilience of the supply chain (de la Peña Zarzuelo et al., 2020; J. Gao et al., 2022). Recent academic works on improving port infrastructure asset management practices have focussed on minimising structural risks (Luo et al.,2021; Seng et al.,2019; Zhang et al., 2017; Zhou et al., 2022), optimising maintenance investments (Simkins & Stewart, 2015) and scheduling of vessels and workload allocation of QCs (Bierwirth & Meisel, 2010; He et al., 2021; Tang et al., 2022). These works not only provide crucial insights on managing container ports but also emphasise the need for monitoring and predicting the condition of QCs considering their criticality to port operations.

Asset Health Index (AHI) is often used as a metric to evaluate the condition of physical assets such as machinery, equipment, and infrastructure. It is designed to provide a quantitative measure of the overall health of the asset, based on a set of indicators such as performance, maintenance, and reliability. AHI is often expressed as a dimensionless quantity as it is usually calculated as a weighted combination of several indicators, each of which may have different units of measurement. By expressing the AHI as a dimensionless quantity, it allows for easy comparison and ranking of different assets regardless of the units of measurement of different indicators (Serra et al., 2019). AHIs have been widely used to support maintenance decisions by providing thresholds for repair (Crespo del Castillo et al., 2021; De la Fuente et al., 2018; Herrera et al., 2022) or probability of failure of the assets (Crespo del Castillo et al., 2021; Janatabadi et al., 2021). AHIs have been used to manage bridges (Hadjidemetriou et al., 2020), railways (Janatabadi et al., 2021), highways (Majidifard et al., 2020; Shah et al., 2013), power transformers (Alqudsi & El-Hag, 2019), power transmission lines (Hashim et al., 2019), pipelines (Angkasuwansiri et al. 2015), and buildings (Salado Castillo et al., 2022). While these efforts provide a significant understanding of assets' condition and aid in maintenance planning, they often rely on sparse inspection data. Internet of Things (IoT) technologies produce near-real-time data and have proven to be effective in improving fault diagnosis and predictive analytics (Acciaro & Sys, 2020), particularly for port asset management (Herrera et al., 2022; Jakovlev et al., 2022; Li et al., 2022; Merino et al., 2022; Molavi et al., 2020; Zhou & Hu, 2022). Literature (see section 2) suggests that data-driven AHI have the potential of providing more accurate and timely information of the condition of target assets when incorporating IoT monitoring.

This paper develops a methodology to develop data-driven AHIs, including modifiers that captures reliability, operation, and health of assets based on real-time data gathered from sensors (Section 3). The methodology is applied to a case study of quay cranes at the Port of Felixstowe and the results are presented in Section 4. The conclusions are drawn and recommendations for future research are discussed in Section 5.

2. Literature Review

This section reviews the concept of Asset Health Index (AHI) as well as the role of sensing technologies in the context of assets' health.

2.1. Asset Health Index (AHI)

The concept of asset health is defined in *EN 13306:2010* as *'measure of the condition of an asset and the proximity to the end of its useful life'* (European Committee for Standardization, 2010). AHIs represent assets' state or condition at a given time (F. Yang et al., 2016). From a theoretical perspective, every failure mode associated with each component of an asset can be modelled. However, often due to the unavailability of data, most of the AHI or condition indices aggregate historical values to parametrise metrics to define threshold levels that trigger interventions (Crespo del Castillo et al., 2021; Crespo Márquez et al., 2021a).

AHI research has its origin in the British telecommunication Distribution Network Operators (DNO) which are companies that own and operate the network of towers, transformers, cables, and meters that carry electricity and distribute it throughout Great Britain (Walker, 2017). This research by Walker (2017) set out a common methodology for assessing condition-based risk for electricity distribution assets based on normal expected life and health modifiers such as location, duty, and historical observed condition. Walker (2017) modelled the exponential trend of AHI based on input data from sensors monitoring the condition of the asset and operational characteristics that influence the deterioration of the asset health to estimate the probability of condition-based failure (PoF) of the asset. Crespo Marquez et al., (2021) extended this methodology by normalising the AHI to provide a close-to-reality representation of the asset's health by including reliability modifiers (operations, preventive and corrective maintenance, quality of maintenance, etc.) The AHI obtained was employed to compare the health of a fleet of assets to prioritise candidates for replacement or renovation. However, a key challenge observed in these methodologies is the presence of a skew in AHI calculation when dealing with extreme values of the modifiers.

AHIs can be used as key input parameters in a Life Cycle Cost Analysis (LCCA) (Crespo Márquez et al., 2021b; Serra et al., 2019). LCCA is a methodology used to determine the most cost-effective solution among different competing options over the entire life of an asset, considering all direct and indirect costs and benefits associated with owning, operating, maintaining, and disposing of the asset (European Committee for Standardization, 2010; International Organization for Standardization, 2014), including the operational and safety impacts of its failure or disruption (Sasidharan et al., 2020; Sasidharan & Eskandari Torbaghan, 2020). The latter is key to setting predictive maintenance strategies (Durán et al., 2020; International Organization for Standardization, 2014; Mondello et al., 2021). For instance, Serra et al., (2019) employed LCCA to identify the optimal replacement window while reducing the total expenditure. Similarly, De la Fuente et al., (2018) proposed an AHI methodology to allow cost estimations to be made more realistic and life cycle costing models to be operated more accurately. On the other hand, Crespo Marquez, (2022) proposed a cost-model-based AHI employing Cox's proportional-hazards model to better represent the health of asset when the values of the modifiers employed are extreme. The authors employed weights to different modifiers based on their importance and demonstrated their applicability through a case study on cryogenic pumps. The implementation of LCCA from the design stage allows for a better performing asset that requires less maintenance and repair costs, resulting in lower operating costs over the asset's life cycle (Durán et al., 2020).

2.2. Sensing technologies for asset health monitoring

Infrastructure health monitoring using sensing technologies has motivated researchers and asset owners to explore condition indexes. In most of the cases of application, they are not data driven but just expert criteria, and do not often capture the multiple factors that contribute to asset's health. This health or condition indexes are practical for prioritising investments in large portfolios or asset networks (Hadjidemetriou et al., 2020). Hong et al., (2013) presented approach based on Markov chains for bridges that considered expert opinion for setting the weights for calculating the AHI. On the other hand, Hashim et al., (2019) presented a condition based method, that employed aggregated historical values for setting the weights. The weighted aggregation of indexes based on historical values or different aspects of the infrastructure evaluation can be found in literature (Inkoom & Sobanjo, 2018; Sanchez-Gonzalez et al., 2019; Scholz et al., 2015; Velasquez & Lara, 2018; Verhoeven & Flintsch, 2011) with the same lack of data driven focus, and evaluation of the reliability and health dimensions complexity.

On the other hand, Crespo del Castillo et al., (2021) applied Walker (2007) methodology defining the states of the asset based on data collected but did not integrate information from other sources. The AHI was calculated based on real-time PLC data (0.4 seconds of sample time) being fed into the model. While this work demonstrates the role of AHI in real-time decision-making, it was largely based on the operational data from PLC which alone does not give a clear insight into the physical condition of the asset. This evidences that neither the expert criteria, nor data driven approach isolated can reflect the actual asset's health. Finally, data driven indexes tend to be applied to components or simple systems, but not to complex assets that are composed by multiple systems and have multiple dimensions affecting degradation. These data driven approaches tend to be conceptually used like the remaining useful life prognosis (F. Yang et al., 2016), diverging from the lifecycle perspective, as Liu et al., (2019) that relate a RUL prediction model based on health index (HI) similarity. In most of the aforementioned data driven approaches, the concept of health index is not applied to lifecycle and does not use any knowledge from engineering or reliability, but a prognosed deduction from multiple data points with an interpretation (Alqudsi & El-Hag, 2019; Heywood & Mcgrail, 2015).

The review of existing AHI methodologies highlights the following challenges:

- Integrating different dimensions, of reliability and maintenance management, data from sensors (e.g., vibration, temperature, acoustics etc.), and operational data (e.g., loading, maintenance schedules etc.) that impact the asset's condition or deterioration.
- There is a gap in the most advanced AHI, that is the integration of real-time data from IoT sensors into the picture. This makes the process data-driven and means a great novelty not only for generating more valuable modifiers but also to learn from the collected data and define ranges of operation for certain physical dimensions.

3. Methodology

The development process of the proposed AHI consists of six steps (see Figure 1). The methodology is extending the proposed approaches in literature (Crespo del Castillo et al., 2021; Crespo Márquez, 2022; Serra et al., 2019), but adding new stages 5 and 6. The main contribution of the presented methodology are the steps 5 and 6. The fifth step calculates the Operational AHI that integrates the information from the actual operation type, characterized here as load. In previous works it has been called a modifier (which can be argued as it impacts the health more than modifiers), and it has been integrated in the formulas differently. In the sixth step, the core novelty is using data captured from IoT from the field to integrate that information in the health score, something that has not been achieved in the previous approaches reviewed in this paper. The modifiers employed within the proposed methodology are associated with indicators that impact the health and the reliability of the asset. They are gathered from the data pertaining to the engineering parameters (e.g., vibration, temperature) collected from the sensors installed on the assets combined with the crane's operational data and maintenance logs (e.g., oil samplings, motor current etc.). The last step also presents a novel and conceptual approach to integrate data from multiple sources (that represents a major challenge for ports (J. Gao et al., 2022; Jakovlev et al., 2022)), and a way of translating the signals from sensors into information that helps to quantify the condition of critical assets for the business. The following subsections explain each step of the methodology in detail.

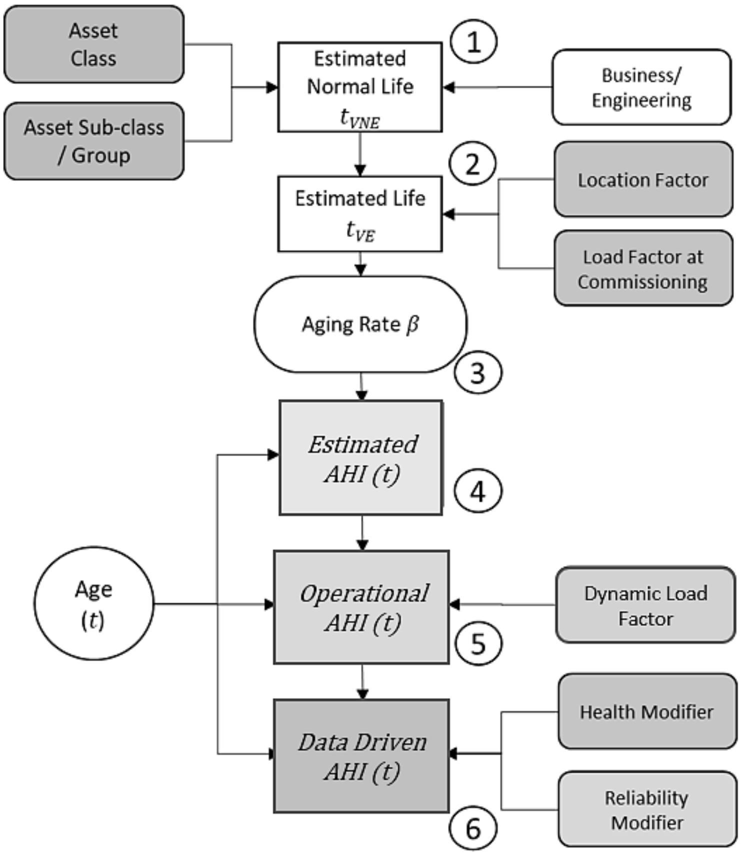

Figure 1: Data-Driven Asset Health Index (AHI) Procedure adapted from (Crespo del Castillo et al., 2021; Crespo Márquez, 2022)

3.1. Defining the asset and obtaining its design life

The asset of interest is identified by following the asset-hierarchy process. This enables the gathering information pertaining to location and operational aspects for the asset of interest. The design life (t_{DL}) of the asset is obtained from the manufacturer or the engineering experts with relevant know-how.

3.2. Evaluation of the impact of location and load factors to calculate the estimated life

The estimated life of the asset (Figure 2) is the ratio resulting from dividing the Design Life (t_{DL}) by the product of the location and load factors (Equation 1).

$$\mathrm{t_{EL}} = \frac{\mathrm{t_{DL}}}{\mathrm{F_l \ x \ F_{ld}}} \qquad (1)$$

Where, the location factor ($\mathrm{F_l}$) is calculated from the information gathered from the asset's functional location such as indoor/outdoor installation, distance to the coast, or exposure to extreme agents, etc (Walker, 2017). In the case of ports QC, depending on the situation of the port, the assets could be exposed to different salinity or weather conditions. The values go from 1 to 1.5, considering the effect on the design life as for example technical location. The load factor ($\mathrm{F_{ld}}$), measures the load request of the asset at a certain location that requires a typical condition of operation. It is calculated by comparing the normal condition of operation for a certain function and the maximum possible load that the asset can be subjected to (Equation 2).

$$\mathrm{F_{ld}} = \frac{\text{Load at normal conditions of operation}}{\text{Maximum permissible load}} \qquad (2)$$

3.3. Calculation of the ageing rate

The ageing rate represents how the different situations that the asset may undergo during its useful life will impact its health. The proposed methodology assumes the ageing rate of the asset to follow an exponential trend as reported in literature (Walker, 2017)). The ageing rate (β) is calculated using Equation 3:

$$\beta = \frac{\ln \frac{AHI_{EL}}{AHI_{new}}}{t_{EL}} = \frac{\ln \frac{5.5}{0.5}}{t_{EL}} \qquad (3)$$

Where AHI_{new} is the health index of a new asset, considered 0.5 instead of 0, to consider an initial (even minimum) degradation; AHI_{EL} is the health index of the asset at the end of its estimated service life (t_{EL}) defined as the value of 5.5.

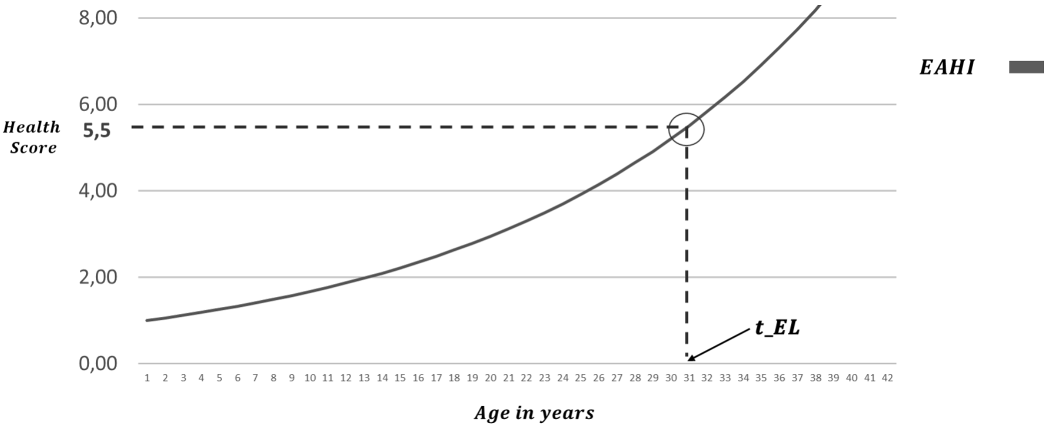

Figure 2: Estimated service life representation with Estimated AHI

3.4. Estimated Asset Health Index calculation

The Estimated AHI ($EAHI(t)$) of an asset is the projected estimation of the asset's health through its lifecycle based on the load and location factors estimated using Equation 4:

$$EAHI(\mathrm{t}) = \mathrm{AHI}_{\mathrm{new}} \cdot \mathrm{e}^{\beta \cdot \mathrm{t}} \qquad (4)$$

3.5. Operational AHI calculation

The effect of the dynamic load of operation is added to enrich the health index, by capturing the load at different points of time during asset operation. This modifies the $EAHI(\mathrm{t})$ by adding the effect of the Dynamic Load Factor (F_{ld} (t)) to calculate the operational AHI ($OAHI(t)$):

$$OAHI(\mathrm{t}) = \mathrm{AHI}_{\mathrm{new}} \cdot \mathrm{e}^{\mathrm{F}_{\mathrm{ld}}(\mathrm{t}) \cdot \beta \cdot \mathrm{t}} \qquad (5)$$

Where the dynamic load factor is the ratio between the existing load factor at a time t and the already existing F_{ld} at the normal operating conditions and estimated using Equation 6.

$$\mathrm{F}_{\mathrm{ld}}(\mathrm{t}) = \frac{\frac{\text{Load at instant (t)}}{\text{Maximum permissible load}}}{\mathrm{F}_{\mathrm{ld}}} = \frac{\text{Load at instant (t)}}{\text{Load at normal conditions of operation}} \qquad (6)$$

The introduction of the Operational AHI allows adjusting the current impairment to compare it with the impairment expected for the functional location. Then the load is a factor that describes the type of operation that has defined a certain moment of the life of the asset, but not a “load modifier” as it was previously called in other works. The Dynamic Load Factor multiplies the exponential function time as it will proportionally condition the impact on the exponential curve of life based on the type of operation. If it was a modifier, it would affect differently the curve, as it should be varying the slope but not the shape of the curve. The last difference between it and a modifier, is the fact that modifiers are normalized between 0 and 1, however the Dynamic Load Factor could have values over 1 if the conditions of operation are more stressful than by design.

3.6. *Data Driven AHI final calculation (adding data driven and information systems modifiers)*

The last step is enriching the operational AHI that considers the data driven effects of load in the asset with the physically measured condition, operating conditions, and the reliability at each point that constitutes a unit of the sample time of evaluation. The Data Driven Asset Health Index ($DDAHI(\mathrm{t})$) is then calculated as follows (Equations 8 and 9):

$$DDAHI(\mathrm{t}) = (DDAHI_{new} \cdot e^{F_{ld}\,(t) \cdot \beta \cdot t})^{\mathrm{e}^{(HM(\mathrm{t}) + RM(\mathrm{t}))}} \qquad (8)$$

$$DDAHI(\mathrm{t}) = (OAHI(\mathrm{t}))^{\mathrm{e}^{(HM(\mathrm{t}) + RM(\mathrm{t}))}} \qquad (9)$$

Where:

$HM(t)$: Health Modifier of the asset

$RM(t)$: Reliability Modifier of the asset

It can be seen in Figure 3, as an example of $DDAHI(\mathrm{t})$ curve versus $OAHI(t)$ and $EAHI$, is how the modifiers impact the previous functions, adding the effects of the data captured by the sensors, and the one from information systems (reliability) to the $OAHI(t)$. This paper adds the explained novelty in the concept of Dynamic Load Factor and its proportionality, but also combines modifiers that are elaborated from data from the sensors and used as a base for the formulas and conception (Crespo del Castillo et al., 2021; Crespo Márquez, 2022). The modifiers are normalised, with a range from 0 to 1 depending on the value for the certain timescale,8his range of values must be defined using data, previous work, and existing engineering and technical knowledge from technicians and manufacturers.

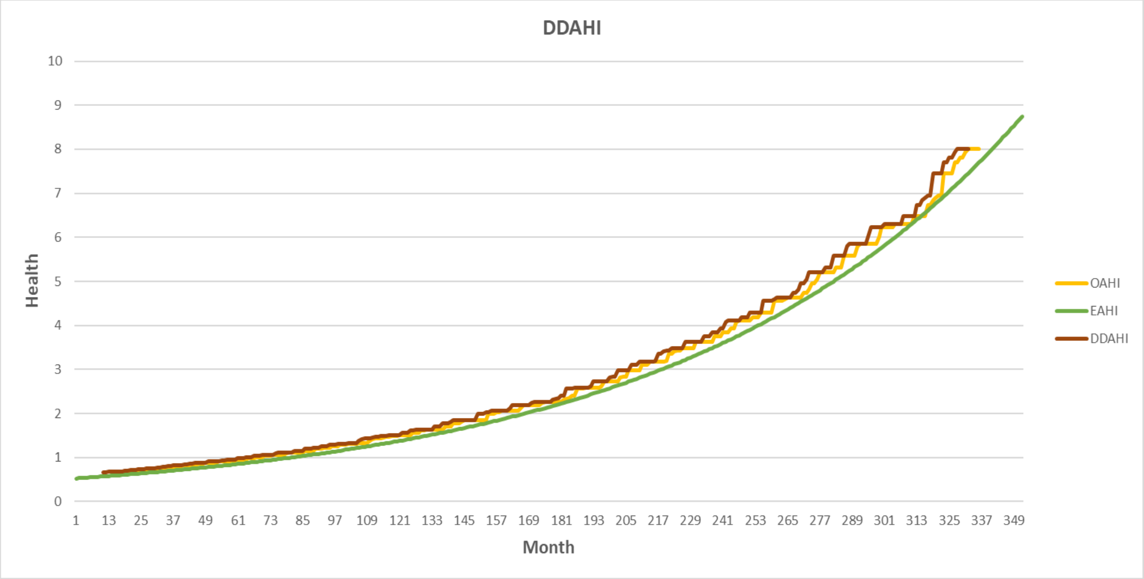

Figure 3: Example of a Data Driven Asset Health Index ($DDAHI(t)$) through the asset lifecycle

The modifiers themselves will be composed of a certain number of health and reliability modifiers that will compose the final HM(t) and RM(t) with some associated weights that will define the importance of each of the modifiers (Crespo Márquez, 2022). The sum of all the modifier weights will be equal to the maximum impact rate γ (for this rate all modifiers always take a value of 1):

$$\sum_{j=1}^{j=n} \gamma_j + \sum_{k=1}^{k=m} \gamma_k = \gamma \qquad (10)$$

γ_j: This is the weight assigned to health modifier *j*.

γ_k: This is the weight assigned to the reliability modifier *k*.

The maximum impact rate (γ) was introduced by (Crespo Márquez, 2022) as a measure to control the impact of the modifiers in the AHI. The effect of it is limiting the impact so if the values of the modifiers of the $DDAHI(\mathrm{t})$are maximum (value 1) since the beginning of the life, the earliest moment that the curve can real 10 (end of useful life) is the estimated life of the asset (Figure 4). The value of γ is obtained by forcing the estimated AHI to be equal to 10 (maximum limit of the AHI of the asset in the model) upon reaching the estimated normal life with defined a constant value of $\gamma = 0.301$.

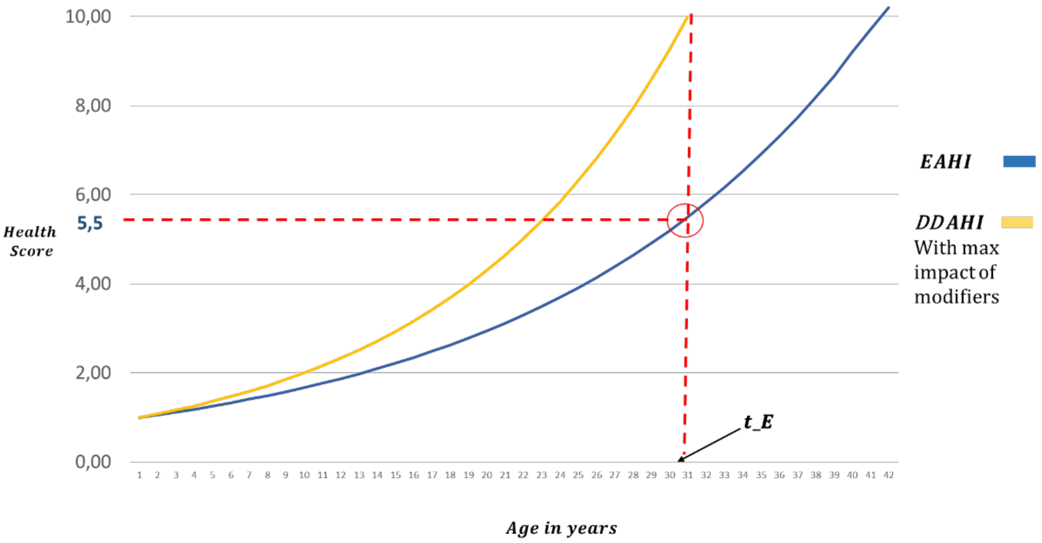

Figure 4: Graphical explanation of the maximum impact of modifiers in Data Driven Asset Health Index ($DDAHI(t)$)

3.1 Definition of the data driven modifiers and their ranges

The modifiers of the AHI are defined together by technicians and engineers that are experts on the operation of the asset. In the case of reliability modifiers, the ranges of values are defined according to experience and previous work as well as with some health modifiers whose ranges are well defined by the maintenance team or manufacturer. A challenge that the data driven approach brings, is the lack of definition of values for the ranges of admissible or “normal” operation conditions. Hence, data driven modifiers will have ranges of admissible operations defined from data analytics and machine learning applied to existing available data, and at the same time will provide novel information to the engineering and maintenance team by generating this ranges.

To define the ranges and analyse the data for data driven modifiers this work takes the following approach:

(1) Time-domain features of the collected data are determined (mean standard deviation, root mean square)
(2) Based on the analysis and distribution, the thresholds are defined generating three ranges of values (normal, medium, high). The ranges will be continuously refined to better represent the operating conditions
(3) The number of measurements within a defined time window is calculated yielding feature values outside these thresholds for each feature
(4) Finally, once the count of data at each of the ranges is done, two manual thresholds are set based on the expertise of the maintenance team. If the average number of anomalies is below the lower threshold, the health modifier equals 0. If the average number of anomalies lies between these two thresholds, this number is linearized to a value between 0 and 1 according to Equation 11. If the number of anomalies exceeds the second threshold, the health modifier equals 1.

$$value = \frac{n_{anomalies,avg} - threshold_{min}}{threshold_{max} - threshold_{min}} \qquad (11)$$

Depending on the recommendations from experts, these critical thresholds will affect the deterioration rate of the asset in a certain way (e.g., beyond 'high' range of vibration, the asset deteriorates in a faster manner). This will then inform a standard path in which the asset accumulates operational time and degrades, and a way to detect when this deterioration is accelerated. These thresholds are initially defined by experts, but will be refined and data based, once there is enough failure and anomaly data collected to have trustworthy patterns based on the data.

3.7. AHI practical considerations

3.7.1. Placing the AHI in the asset's lifecycle

When the procedure of development of the AHI begins, it is critical to define not only the moment ("t") from the lifecycle, but also the historical data that the company has stored of the previous years. From the moment the sensors are installed, and data are being collected, $DDAHI(\mathrm{t})$ can be fully applied defining the ranges of the data driven modifiers and their value. Previously, the health index may only be the $EAHI(\mathrm{t})$, then depending on the data available from the load, and other reliability modifiers, an $OAHI$, and even a $DDAHI(\mathrm{t})$ based only on the reliability historical data could be projected until the data from the sensors is collected to enrich the indicator.

3.7.2. The non-returning values of AHI

As it is a measure of degradation, when the health index gets to a certain value it cannot return to earlier or smaller numerical values (if there is not a big maintenance or overhaul), as the degradation of an asset through its lifecycle is a one way path. So the model will include a condition that will keep the new value of the health index stable if it decreases (Equation 13):

$$OAHI(\mathrm{t}) = \max(\ OAHI(\mathrm{t})\ \ , OAHI(\mathrm{t}-1)\ ) \qquad (13)$$

$$DDAHI(\mathrm{t}) = \max(\ DDAHI(\mathrm{t})\ \ , DDAHI(\mathrm{t}-1)\ )$$

4. Case study

The AHI proposed was applied to a case study on two QCs at the Port of Felixstowe, the largest container port in the United Kingdom. The vibration from the QCs' hoist motors were monitored on a near-real time basis using IoT sensors transmitting data over 5G. Both the cranes were at different stages of their life cycle when vibration monitoring was initiated. QC1 is four years into operation while QC2 is approximately at the middle of its service life. QCs have a design life of 30 years, but the service life is often not more than 20 years (Y. Yang et al., 2018). Based on manufacturers and previous work (Gothandapani & Rahman, 2021; Sun et al., 2021) the design life is considered 30 years. Owing to the demanding coastal conditions and the exposition to hard corrosion and other factors, the location factor was defined to be 1,2. Then the load factor was defined considering the normal operation ranges of the crane where the average conditions of load compared to the maximum admissible at the normal operation mode equals 0.92 (Equation 2). The estimated life is calculated using Equation 1 as $\mathrm{t}_{\mathrm{EL}} = 25.083 \simeq 25\ years$ years. The ageing rate is estimated to be 0.096 based on Equation 3.

The ageing rate is the main input that defines the $EAHI(t)$ (Equation 14). This starting point defines the health of the asset just based on the factors impact, and it is close to the curve of estimated life that the expert engineers of the port will define based on their knowledge as projected life conditions calculations used to plan investments. It is calculated projected for the whole lifecycle with a monthly timescale (Figure 5). At the end of year 25, the value of the $EAHI(t)$ is 5.5 and from then the probabilities of failure will increase exponentially.

$$EAHI(\mathrm{t}) = EAHI_{new} \cdot \mathrm{e}^{\beta \cdot \mathrm{t}} \qquad (14)$$

With t as month and $\mathrm{EAHI}_{\mathrm{new}} = 0.5$

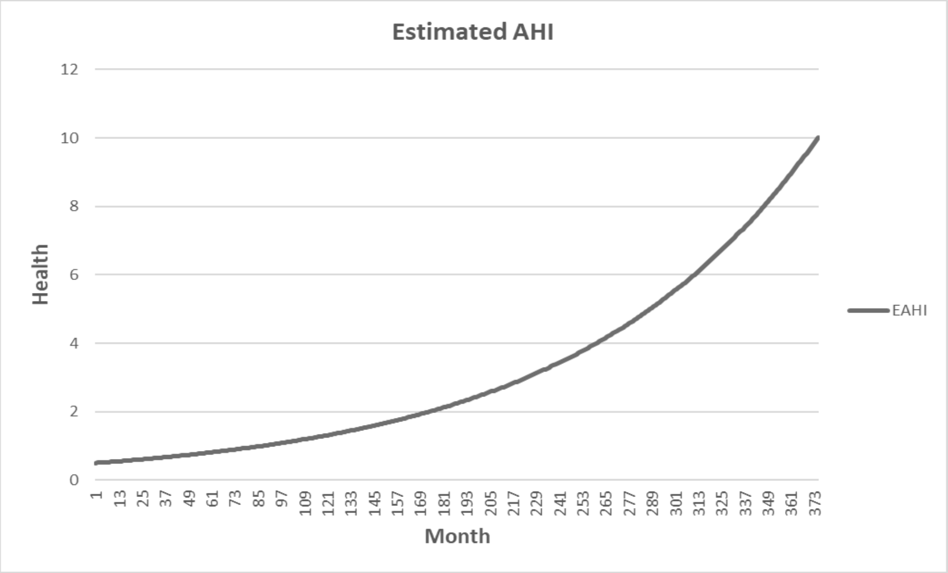

Figure 5: Projected Estimated Asset Health Index $EAHI(t)$ representation QC1

The $OAHI$ is calculated by adding the values of the dynamic load factor multiplying the exponent (Figure 6). The values of load to calculate the $OAHI$, are obtained from the PLCs at each moment of operation and correlated to speed.

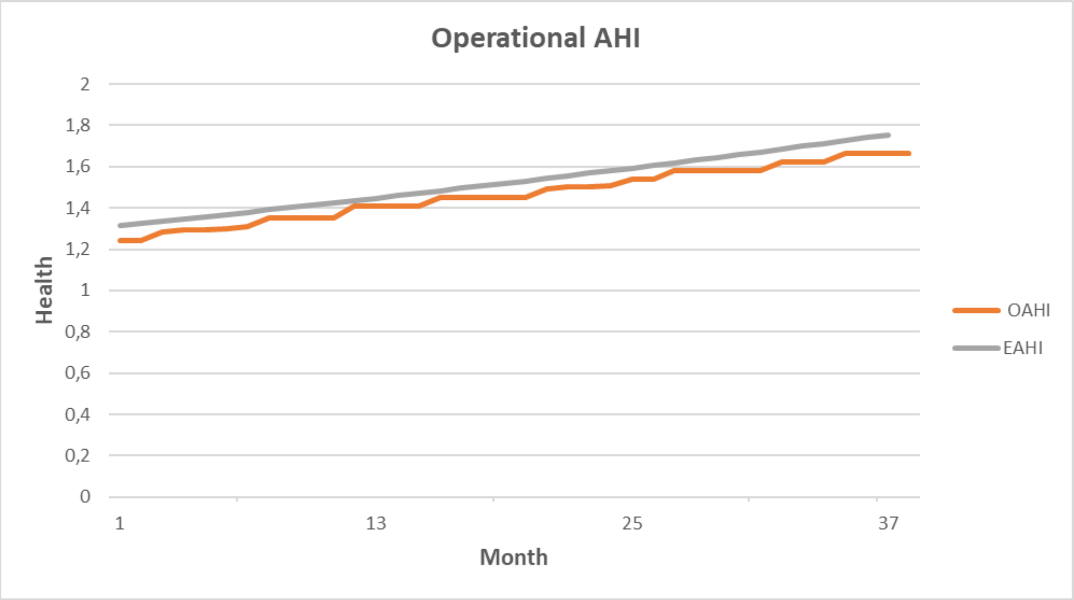

Figure 6: Operational Asset Health Index ($OAHI(t)$) representation QC1

The data driven AHI is calculated by considering the health and reliability modifiers that were identified from literature. Multiple workshops were conducted to capture the expert knowledge in terms of the weightage and ranges of each modifier (see Table 1).

Table 1: Ranges of values of modifiers

Modifiers		Weightage	Range		
			Low	Medium	High
He	alt	M1: Vibration*	0.33	From 0 to 2 sigma (of the	From 2 to 4 sigma (of the	Over 4 sigma (of the
		M2: Temperature*	0.17			

	M3: Motor Current	0.25	standard deviation)	standard deviation)	standard deviation)
	M4: Oil Samplings	0.25	Read=Normal Modifier value 0	Read=Caution Modifier value 0.5	Read=Serious Modifier value 0.5
Reliability	M5: Delay In preventive maintenance delivery	0.14	0 - 2 months Modifier value 0	2 - 4 months Modifier value 0 to 1 linear	Over 4 months Modifier Value 1
	M6: Number of Emergency Correctives (Mechanical/Electrical)	0.29	0 Ecorrectives Modifier value 0	1 Ecorrectives Modifier value 0.5	More than 1 Ecorrectives Modifier value 1
	M7: Number of Emergency Correctives (Operator Error)	0.28	0 Ecorrectives Modifier value 0	1 Ecorrectives Modifier value 0.5	More than 1 Ecorrectives Modifier value 1
	M8: Number of Emergency Correctives (Not Registered)	0.29	0 Ecorrectives Modifier value 0	1 Ecorrectives Modifier value 0.5	More than 1 Ecorrectives Modifier value 1

* The data for these modifiers are collected from IoT sensors

The input value of vibration and temperature are collected from installed IoT sensors, and motor current modifier is calculated by processing the data obtained from PLC logs. This is done by a time series analysis; the process is more complex than the one in the modifiers that just imply a count or a certain value at the end of the sampling period. To illustrate this complexity, the case of the first modifier (vibration) will be presented.

The process applied to vibration is the same in the other health modifiers (M1-3) that are calculated based on the data received from the sensors at the hoist motor. The purpose of the vibration data health modifier is to increase the information content of the AHI by enriching it with wear related information at a high frequency, e.g., on a daily basis. In parallel, the sensitivity of vibration data to environmental influences must be considered to avoid vibration data related false alarms leading to unnecessary inspections. To achieve this, the calculation of the vibration data health modifier is structured in the steps presented in methodology (Figure 7). It focuses on counting the number of data points that are out of the control chat ranges (possible anomalies), which means counting and associating the count of data discords to a value of the modifier.

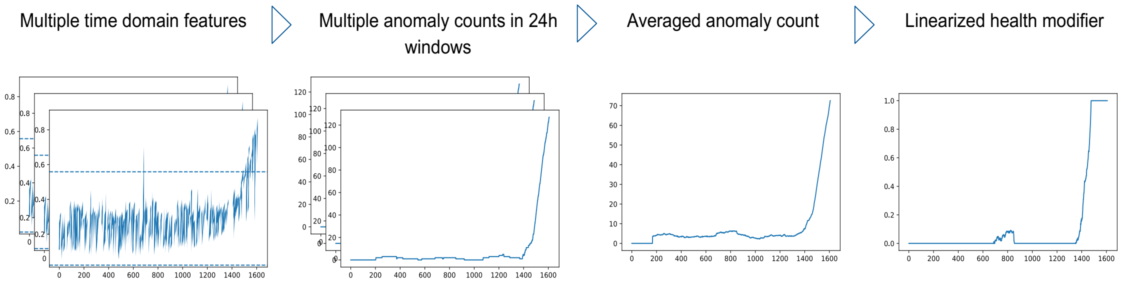

Figure 7: Stages to calculate the vibration modifier value

First, time-domain features of the vibration data are determined. These are the mean, standard deviation, root mean square, kurtosis, skewness, peak, peak to peak, the mean distance between peaks and the Kullbach Leiber divergence. Because of the low sampling frequency of the vibration data combined with the short lengths of the vibrations and their transient characteristics, no frequency-domain features were calculated. In this way, 10 time series are derived from the vibration data time series. Second, the standard deviations of these features were derived. Thresholds equal the feature's mean plus or minus two times these standard deviations were defined for each feature as in the example figure for energy of signal of vibration. An example is shown for a case with the values of the energy signal of vibration (Figure 8).

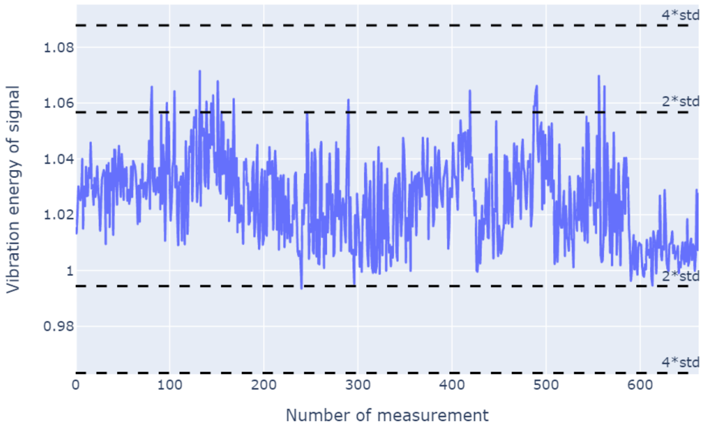

Figure 8: Example of energy signal for vibration with two and four sigma thresholds

Third, the number of measurements within 24-hour time window was calculated yielding feature values outside these thresholds for each feature. These measurements are defined as anomalies. This step creates another 10 time series based on the feature time series. Fourth, these 10 time series are averaged to determine the average number of anomalies within 24 hour time windows. Based on this single time series, the vibration health modifier is calculated. Finally, the formula presented in methodology (Equation 11) is applied to normalise the count (Figure 9). This way, the count of the data points out of the control charts considered as acceptable ranges (considered anomalies), will impact the value of the modifier, that as previously explained, is between 0 and 1. In Figure 10 a simulation of data points out of the range's anomalies, is presented to illustrate how the values of the modifier will react to the anomalies count. This simulation is necessary to illustrate the methodology as no anomalies (only data discords) occurred during the monitoring months, hence the values of the vibration and other data driven modifiers is zero.

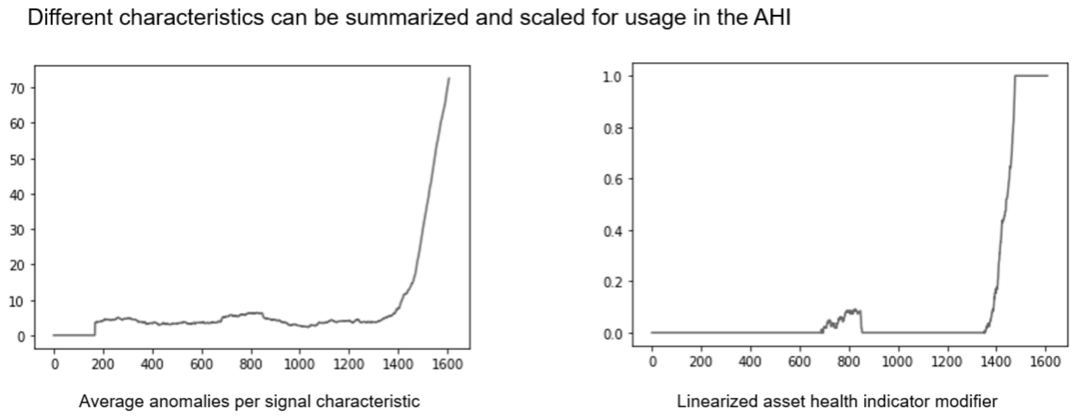

Figure 9: Example of linearised value of the modifier as a result of the process

On the other hand, the input values of other modifiers namely, oil samplings (M4), percentage of inactivity (M5), number of emergency correctives associated with operator error (M6) and non-registered (M7) are directly inputted from the PLC logs.

The values of the modifiers can be summarised as follows for QC1 (Table 2):

Table 2: QC1 modifiers values

QC1								
Month	Modifier 1 Vibration	Modifier 2 Temperature	Modifier 3 Motor Current	Modifier 4 Oil Samplings	Modifier 5 Delay meeting the Maintenance plan	Modifier 6 Number of Ecorrective - Mechanical/Electrical	Modifier 7 Number of Ecorrective - Operator Error	Modifier 8 Number of Ecorrective - Non Registered
1	0				0	0	0	0
. . .					. . .			
10					**0.5**			0
11					**0.5**			0
12					0			**0.6**
13					0			**0.6**
14					0			**0.6**
. . .					. . .			
45					0			0

Table 3: QC2 modifiers values

QC2								
Month	Modifier 1 Vibration	Modifier 2 Temperature	Modifier 3 Motor Current	Modifier 4 Oil Samplings	Modifier 5 Delay meeting the Maintenance plan	Modifier 6 Number of Ecorrective - Mechanical/Electrical	Modifier 7 Number of Ecorrective - Operator Error	Modifier 8 Number of Ecorrective - Non Registered
1	0				0	0	0	0
2					0	0	0	0
3					0	0	0	0
4					**0.5**	0	0	0
5					**0.5**	0	0	**1**
6					0	0	0	**1**
7					0	0	0	**0.5**
. . .					. . .			
31					0	**0.5**	0	
32					0	**1**		
. . .					. . .			
40	0	0	0	0	0	0	**0.5**	**1**
41	0	0	0	0	**0.5**	0	0	**1**
42	**0.03**	0	0	0	**0.5**	0	**0.5**	**1**

The definition and calculation of the modifiers and weights lead to the final calculation of the $DD\ AHI(\mathrm{t})$ in monthly bases so it can be compared to the $EAHI(\mathrm{t})$ and $OAHI(\mathrm{t})$ (Figure 10), considering for both calculations that the load factor (due to the different operational modes) is approximated to be randomly distributed between 0.92 and 0.98 for every data point. This approximation was developed as a way to represent the different operation types and recommended by the technicians.

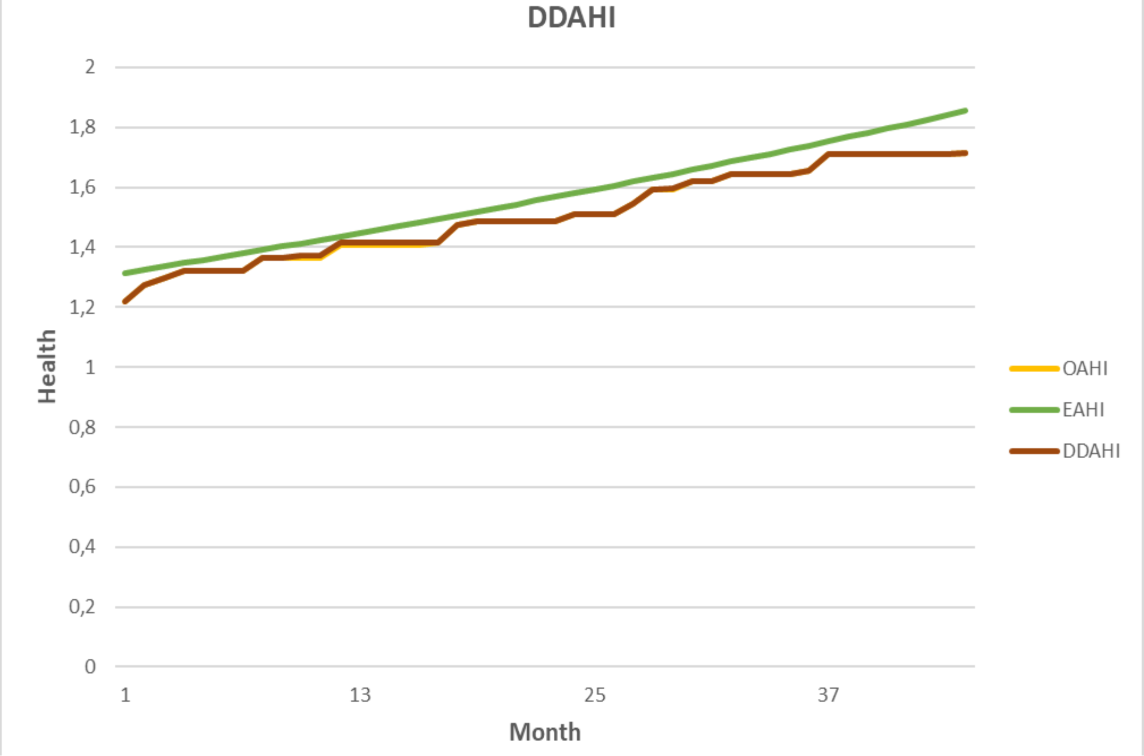

Figure 10: QC1 Data Driven Asset Health Index ($DDAHI(t)$) representation

In this case (Figure 10), there are only small deviations from the operation health index ($OAHI(\mathrm{t})$) when there where disruptions because of corrective outages as part of the reliability modifiers on some specific months.

There is a clear difference in the AHI for the age and moment of the lifecycle. Based on that, applied to QC2 (Figure 11) the values of all indexes begin from between 2 and 2,5 based on the age. The modifiers of health tend to affect more the $DDAHI(t)$ with more age and probability of an anomalous behaviour, due of the time in operation. It can be considered equivalent for the reliability modifiers, as the probability of outages occurring will increase the same way. In Figure 11, the outages counted for the reliability modifiers 7 and 8, make them raise to 1, that together with delays in preventive maintenance delivery, represents an increment that makes the $DDAHI(t)$ show the impact. This behaviour but with lower values of the modifiers can be captured at the last months of monitoring. Same as QC1, the monitoring period did not allow to capture any failure of the hoist motor so the health modifiers will have impacted the health in a more severe way.

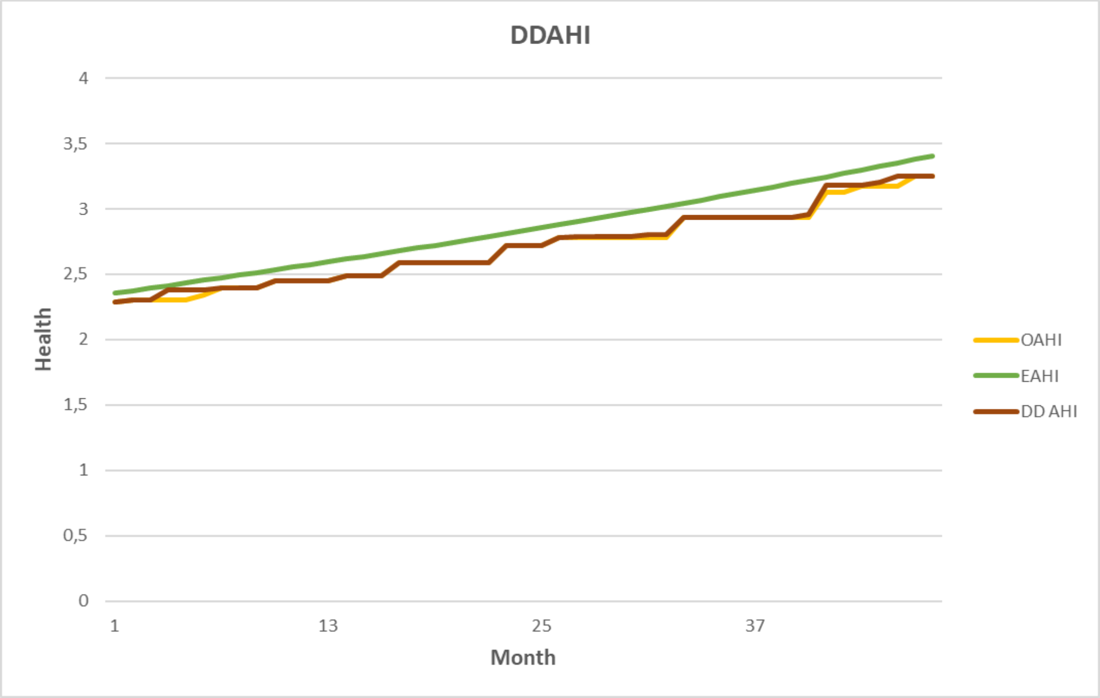

Figure 11: QC2 Data Driven Asset Health Index ($DDAHI(t)$) representation

5. Concluding discussion

This work presents a novel data driven approach for health indexes that can be applied to infrastructure and valuable industrial assets. AHI is introduced and placed in the state of the art through a deep literature review that arises the limitations on existing approaches as most of the health indexes applied to infrastructure are elaborated based on experts' qualitative judgement, or in the most advanced health indexes it is based on data from the historical in the information systems. It is made evident the impact that the Data Driven AHI can make for asset managers as a powerful decision-making supporting tool to prioritise investments and prepare for the overhaul based on multiple dimensions. The methodology to do so is presented as then applied to a case in Quay Cranes at the Port of Felixstowe.

The novelty that the paper proposes can be divided in three main points. The first and more important, is using data captured from IoT sensors near real time from the field, to make the AHI more representative of the actual behaviour of the asset. This way any physical dimension that could represent the symptom of a failure will be reflected as a modifier that will influence the values of the health. Furthermore, the AHI becomes more responsive and exact. The second is the redefinition of the concepts of the different AHI values through the methodology, that clarify the meaning, application, and data required. The estimated AHI as the initial projection of life based on the commissioning, the operational as the way of capturing the characteristics of operation, and the data driven AHI as the one that bring the information from the sensors. This provides a clear view of the process and definitions that was not existing in literature. Finally, the dynamic load factor was presented previously in literature as a "load modifier". In this paper it is presented as a factor, considering how it affects the Estimated AHI (wider impact than modifiers), and the definition of a modifier conceptually that which are normalised between 0 and 1. This paper proposed the operational load effect as a dynamic factor and adapted the formula of the Operational AHI by multiplying the dynamic load factor to the ageing rate in the exponential, as in previous works it was dividing and not impacting the condition accordingly to its conceptual meaning.

It must be highlighted that this research was developed during a certain period that does not allow to have values of the AHI for multiple years of the QC operation, and as a consequence, no failure happened during the data capturing time, reinforcing the fact that the lack of failure data is one of the main limitations for data driven approaches of asset management. It can be also discussed that methodology to define the control charts using sigma deviations (to count the point out of the ranges), is a conceptual first approach that needs to be further refined as the data base is wider, and the limits can adjust to better capture the effects of the measured dimensions. The modifiers used (apart from the data driven) have been defined with the engineers and experts at the port, and can be applicable to other assets, as this work uses modifiers from previous AHI works cited in the literature review.

The following step to this work will be refining the methodology itself and the exponential definition to make that more data based, and of course this has to be done for each type of asset, to monitoring for a longer time than in this paper, then look at the probability of failure related in a deeper way so it can be prognosed, and how different maintenance interventions have different effects on the asset health when looking and prognosing for the whole lifecycle. On parallel, once the Data Driven AHI is applied to multiple components of multiple assets composing a portfolio or fleet of assets, the next step is exploring how to manage dynamically the maintenance of the multiple assets, the possibility of aggregating different indexes at multiple levels and how to support asset managers decision making to prioritise capital investment.

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