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EQUIPMENT HEALTH SCORES (EHSS) FOR RELIABILITY ASSESSMENT: A FRAMEWORK FOR REFINERY EQUIPMENT HEALTH SCORING

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ABSTRACT

This paper presents a comprehensive framework for assessing and quantifying the health of critical refinery equipment through the development and implementation of Equipment Health Scores (EHSs). The framework integrates both data-driven and event-driven approaches to create a dynamic health scoring system that effectively captures equipment condition and performance trends over time. By analyzing critical parameters across static, rotating, and electrical equipment, the study establishes a standardized methodology for health assessment that aligns with international standards including ISO 14224 and ISO 17359. The framework incorporates three fundamental components: historical health scores, real-time condition monitoring modifiers, and reliability metrics. The methodology was validated using operational data from refinery facilities, demonstrating its effectiveness in predicting equipment degradation and optimizing maintenance strategies. The study also establishes clear correlations between health scores and asset readiness indices, providing valuable insights for maintenance planning and resource allocation. This framework represents a significant advancement in refinery equipment health monitoring, offering a practical tool for reliability engineers and maintenance professionals to enhance asset management decisions and operational excellence.

KEYWORDS: Reliability Assessment, Health Scoring, Equipment Health Scores, Refinery Equipment, Condition Monitoring, Asset Management, Predictive Maintenance, Equipment Reliability, Asset Readiness, Maintenance Optimization.

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1. INTRODUCTION

The reliability and operational efficiency of refinery equipment are crucial factors in maintaining safe, productive, and profitable operations in the petroleum industry. As refineries face increasing pressure to optimize performance while managing aging infrastructure, the need for sophisticated health monitoring systems has become paramount. Traditional approaches to equipment maintenance and reliability assessment often rely on reactive measures or simplified preventive schedules, which may not adequately address the complex degradation patterns of modern refinery equipment.

To address degradation patterns over time and make decision respectively, two aspects are necessary such as asset types and real-time data acquisition. However, previous studies on health monitoring often focus on specific equipment and lack real-time data integration. For example, models by Jahromi et al. (2009) and Selva et al. (2021) are limited to electrical assets and single-condition metrics. While, Duffuaa & Raouf (2015) and Selvik & Aven (2011) focus on Reliability Centered Maintenance which offers snapshots of overall reliability but lacks of real-time integration. And, the latest study by Al-Anzi et al. (2022) investigates a structured system architecture of refinery for anomaly detection using plant health index. Despite of anomaly detection benefits, it lacks scoring standardization for each metrics. To overcome all shortcomings, this paper proposes novel equipment health scores (EHSs) framework combining mathematical aggregation, real-time vision, risk logic, and practical information system for refinery domain.

Moreover, the proposed framework addresses the limitations of conventional methods by incorporating both quantitative and qualitative factors that influence equipment reliability and performance. To do so, a novelty model of health scoring is formulated around three-component decomposition, namely initial health score, health score modifier, and reliability score. Inspired by neural perceptron formulation, weighted aggregation is put to the formulation adding model flexibility to various asset types. The detailed formulation will be discussed rigorously later in the section 3.

The development of this framework was driven by several key objectives: (1) to establish a standardized methodology for assessing equipment health across different asset classes, (2) to create a dynamic scoring system that reflects both gradual degradation and sudden changes in equipment condition, and (3) to provide actionable insights for maintenance planning and resource allocation.

The framework builds upon established international standards, particularly ISO 14224 and ISO 17359, while introducing innovative approaches to data integration and analysis. By considering multiple parameters including operational data, condition monitoring results, and maintenance history, the system provides a more nuanced and accurate assessment of equipment health than traditional single-parameter approaches.

The methodology encompasses three primary equipment categories: static equipment (such as vessels and heat exchangers), rotating equipment (including pumps and compressors), and electrical/instrumentation equipment. For each category, specific EHSs were identified and weighted according to their impact on overall equipment reliability and performance.

The significance of this research lies in its practical application to real-world refinery operations. The framework provides reliability engineers and maintenance professionals with a structured approach to equipment health assessment, enabling more informed decision-making in maintenance planning and asset management.

2. LITERATURE REVIEW

A comprehensive understanding of asset Health Scores is essential for developing a robust equipment reliability framework. Health Scores have long been used in asset management to assess condition and inform maintenance decisions, particularly within critical infrastructure sectors. Jahromi et al. (2009) introduced a health index methodology for power transformers that aggregates condition parameters into a single index, facilitating risk-based asset prioritization. Similarly, Montanari et al. (2021) emphasized self-assessment strategies for electrical assets within smart grid contexts, integrating real-time monitoring to guide operational decisions. These studies underscore the value of composite health scoring systems in predictive maintenance.

Reliability-Centered Maintenance (RCM), as explored by Duffuaa & Raouf (2015), and Selvik & Aven (2011), provides the conceptual foundation for prioritizing maintenance activities based on failure modes and operational consequences. Tang et al. (2017) further contribute by identifying Maintenance Significant Items (MSIs), enhancing the focus of RCM on critical components. However, such methodologies often fall short in dynamically adjusting to condition changes, highlighting a gap addressed by integrated health scoring.

International standards such as ISO 14224 (Ciliberti et al., 2019) and ISO 17359 (Hitchcock, 2006) provide structured guidance for failure data collection and condition monitoring. Yet, their practical application often lacks contextual adaptation in refinery operations. Al-Anzi et al. (2022) propose a plant-wide health index as an anomaly detection tool in oil refineries, pointing toward the need for standardized, real-time, and scalable solutions.

Additionally, ISO 14224:2016 introduces a taxonomic structure that supports structured reliability and maintenance (RM) data collection across industries. Eleven asset types discussed in this study fall under Level 6, categorized as equipment units (see Figure 2.1). Each equipment unit consists of subunits at Level 7, which are further composed of components or maintainable items at Level 8. To enable consistent data aggregation and analysis, ISO 14224 recommends that each equipment unit clearly define its system boundary, encompassing all relevant subunits. This hierarchical classification supports consistent health assessment, benchmarking, and reliability modeling across diverse equipment types.

Figure 2.1 illustrates the taxonomy structure referenced in ISO 14224, highlighting how equipment, subunits, and components are organized for reliability analysis.

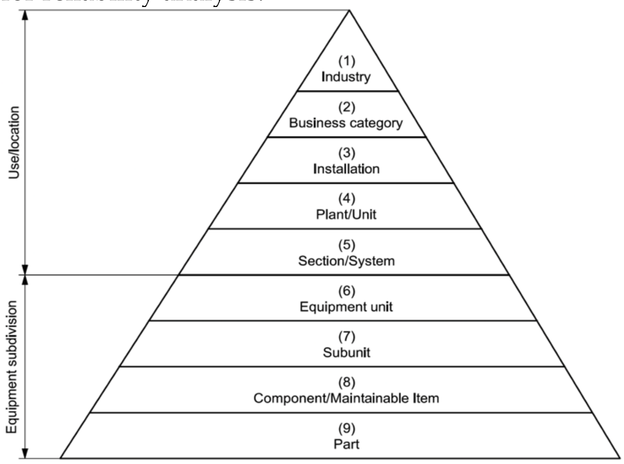

Figure 2.1. Taxonomic Classification with Hierarchical Levels.

Figure 2.2 illustrates the mapping of literature contributions to the core components of the proposed framework: asset health scoring, RCM principles, ISO standards, and refinery-specific applications. Table 2.1 summarizes each reference, highlighting its contribution, scope, and identified gaps, which collectively inform the framework development.

Table 2.1. Key Contributions of Reviewed Literature to EHS-Based Reliability Assessment.

Reference	Key Contribution	Domain	Relevance to EHS Framework	Identified Gaps
Jahromi et al. (2009)	Developed health index for transformer assets	Health Indicator Models	Aggregation of condition parameters into a composite score	Limited to electrical assets
Montanari et al. (2021)	Real-time self-assessment in smart grids	Health Indicator Models	Integration of dynamic data in health scoring	Focused on electrical grids only
Vermeer et al. (2015)	Decision support using health and risk models	Health & Risk Models	Risk-based decision-making using Health Scores	General framework, lacks refinery focus
Selva et al. (2021)	Statistical modeling for transformer health index	Condition-based Management	Quantitative method for asset health prediction	Focus on single asset type
Duffuaa & Raouf (2015)	RCM conceptual foundation	RCM Principles	Systematic identification of failure-driven maintenance	Static approach, lacks real-time integration
Selvik & Aven (2011)	Reliability and risk-centered framework	RCM Principles	Integration of reliability and risk in maintenance	Limited implementation guidelines
Tang et al. (2017)	Framework for identifying MSIs in RCM	RCM Enhancement	Prioritization of critical components	No health scoring integration
Ciliberti et al. (2019)	Big data with ISO 14224 for asset optimization	ISO Standards	Structured failure data and analytics	Complex implementation
Hitchcock (2006)	Overview of ISO 17359 for condition monitoring	ISO Standards	Standardized CM process	Requires customization for refinery use
Al-Anzi et al. (2022)	Plant Health Index for refinery anomaly detection	Refinery Application	Early warning for process anomalies	Lacks scoring standardization

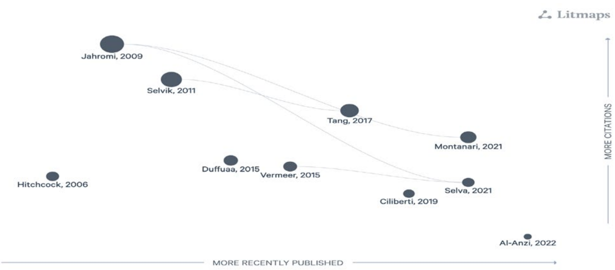

Figure 2.2. Literature Mapping for Health Indicator-Based Reliability Framework.

3. METHODOLOGY

3.1. *Conceptual Framework for EHS-based Health Scoring*

The health scoring framework begins with the identification of the system's goals, namely, improving equipment reliability and minimizing unplanned downtime. It employs both data-driven and event-driven approaches. Real-time data is collected through sensors and monitoring systems, while event-based inputs include maintenance activities and inspection results. The Equipment Health Scores (EHSs), such as operating temperature, vibration, pressure, running hours, MTTR, MTBF, and direct inspection, are evaluated, and the higher the level and criticality of the indicator, the more influence it has on the final score. As shown in Figure 3.1, the overall scoring system integrates both real-time and historical parameters to reflect equipment condition over time.

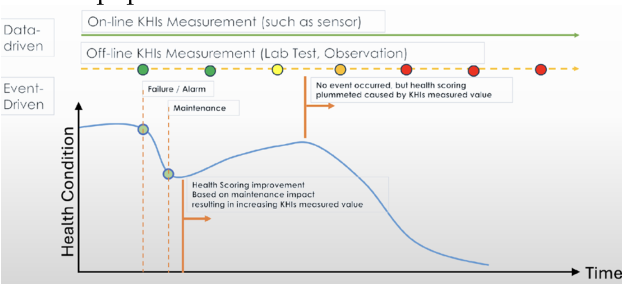

Figure 3.1. Data-driven and Event-driven Framework for Health Score Calculation.

Building on this foundation, the health scoring methodology defines EHSs as structured, measurable indicators that provide a comprehensive view of an equipment's operational integrity, historical wear, and current performance state. These EHSs are extracted from two main input streams. The first, data-driven inputs, rely on continuous or periodic data acquisition systems such as Distributed Control Systems (DCS), SCADA, and historian platforms, capturing parameters like temperature, vibration, or fluid pressure in near real-time. The second stream, event-driven inputs, comes from discrete activities such as visual inspections, maintenance logs, or component failures typically recorded in the CMMS. These two data sources are not mutually exclusive but are instead synthesized to provide a time-sensitive and operationally relevant health snapshot.

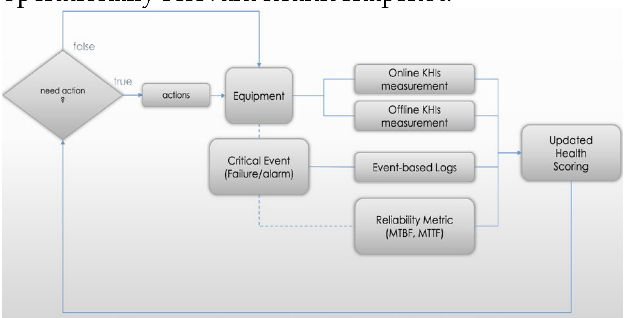

Figure 3.2. Block Diagram of The Relationship between Data, Events, Equipment, and Health Score.

Furthermore, Figure 3.2 illustrates the dynamic interaction between data, operational events, and equipment health scores. In this model, scores naturally decline with usage and degradation but can also recover significantly through corrective actions such as component replacement or targeted maintenance. This adaptive scoring approach ensures that health assessments remain accurate and actionable, aligning with ongoing operational realities. As such, EHSs not only reflect past performance but also support predictive diagnostics, enabling maintenance teams to identify which assets are trending toward failure and require intervention. This hybrid model, combining both real-time responsiveness and historical grounding, ensures that the health scoring methodology remains aligned with the evolving condition and performance demands of refinery equipment.

To support this scoring framework, a classification of key indicators that influence the health score has been established, as illustrated in Figure 3.3. These indicators are organized into three primary layers. The first is the Initial or Past Health Score, calculated based on equipment age, expected life, design load, and duty cycle. This baseline represents the theoretical condition of the asset prior to incorporating real-time data. The second layer is the Health Score Modifier, which adjusts the score upward or downward based on actual condition monitoring inputs. These include offline inspection results, real-time diagnostic measurements, and periodic test findings. The third and final layer is Reliability, which reflects the asset's performance history through metrics such as Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR). Collectively, these layers provide a multi-dimensional, evidence-based evaluation of asset health.

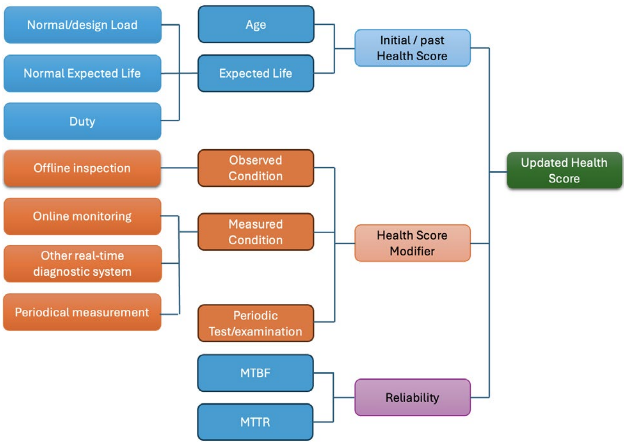

Figure 3.3. Classification of Equipment Health Scores Influencing Equipment Health Scoring.

The classification helps ensure transparency and consistency in how scores are calculated across various equipment types. It also provides a mechanism for scaling the model according to available data and the asset's operational criticality. By defining clear categories of influence, the system promotes both diagnostic precision and predictive reliability, forming a foundational element of data-informed asset management.

3.2. *Integration of Historical, Real-time, and Reliability-based Components*

The health scoring framework integrates three key components to assess the condition of refinery equipment: historical health score modeling, real-time condition monitoring modifiers, and reliability-based metrics. This integration ensures that both long-term degradation patterns and immediate anomalies are accounted for in the health evaluation, making the score not only reflective of equipment aging but also responsive to operational changes. Historical health score modeling is derived from aggregated performance records, past inspection reports, design specifications, and prior failure data. These scores represent a baseline for equipment health and are progressively updated over time to reflect operating history, workload, and maintenance interventions. Parameters such as asset age, expected life span, duty cycle, and design load are compared to determine the initial score, which reflects theoretical health under assumed normal conditions.

Building upon this baseline, real-time condition monitoring modifiers are applied to adjust the health score dynamically. These modifiers rely on continuous input from online sensors that measure parameters such as vibration levels, pressure, temperature, and lubricant condition. When these values deviate from predefined operating thresholds, the health score is adjusted accordingly. For instance, a sustained increase in vibration or temperature may indicate bearing degradation or mechanical imbalance, thus reducing the score. These inputs are normalized and mapped onto a health impact scale to allow consistent interpretation across different asset types. This real-time adjustment capability ensures that the scoring system remains sensitive to developing issues, even in between scheduled inspections or maintenance windows. The operational mechanism of this live score adjustment is illustrated in Figure 3.4, which depicts how health scoring curves respond to real-time operational changes.

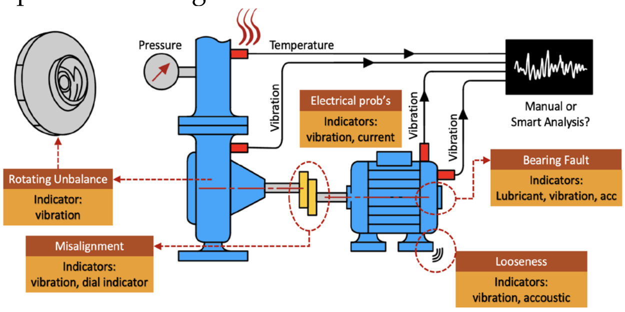

Figure 3.4. Example of Condition Monitoring on A Pump.

To complement both historical and real-time components, the model incorporates reliability-based metrics that provide a probabilistic understanding of equipment behavior over time. Metrics such as Mean Time Between Failures (MTBF), failure rate, and Mean Time To Repair (MTTR) are used to quantify asset dependability and the effectiveness of maintenance efforts. A higher MTBF score increases the overall health index, reflecting stable and reliable operation, while a lower MTTR reduces equipment downtime and contributes positively to the score. These reliability indicators are derived from failure reports, work order histories, and repair logs, typically managed within systems like CMMS. Table 3.1 summarizes these key reliability metrics and their role in projecting asset readiness and operational sustainability. In particular, the inclusion of reliability functions enables more accurate modeling of degradation trends, helping asset managers forecast failure windows and prioritize preventive actions accordingly.

Table 3.1. Key Reliability Metrics used in Health Score Modeling.

Metric	Symbol	Description
Mean Time Between Failures	MTBF	Average operational time between consecutive failures of equipment.
Mean Time To Repair	MTTR	Average time required to repair a failed component and return it to service.
Failure Rate	λ	Frequency at which an asset fails within a given operational period.
Availability	A	Ratio of time equipment is operational versus the total available time.
Reliability Function	R(t)	Probability that an asset performs its function without failure for time *t*.

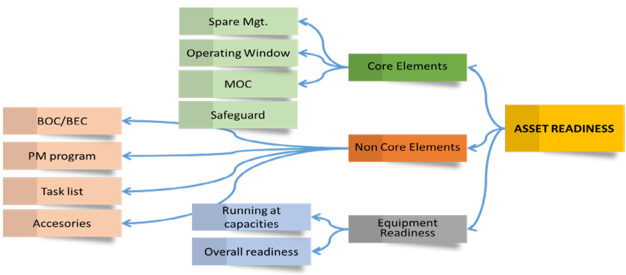

Figure 3.5. Data Classification for Asset Readiness Calculation.

Furthermore, equipment readiness is assessed through three dimensions: core elements, non-core elements, and operational readiness. Core elements include critical factors such as spare parts availability, Management of Change (MOC) protocols, operating windows, and safeguard systems. These are directly tied to operational risk and equipment resilience. Non-core elements include support functions such as Basic Operation Care (BOC), Preventive Maintenance (PM) programs, task list completion, and accessory condition. These elements help ensure the equipment's surrounding ecosystem is managed efficiently. The final category, readiness indicators, captures holistic operational metrics such as whether equipment is running at design capacity and its overall readiness to perform. These hierarchical readiness elements are visually represented in Figure 3.5, which outlines how each factor contributes to the broader understanding of health and availability.

By integrating historical records, live condition monitoring, and quantified reliability metrics, the scoring methodology delivers a robust, multi-layered assessment of asset condition. This integration not only strengthens predictive maintenance capabilities but also supports reliability-centered planning and continuous improvement in operational readiness. It ensures that scoring is not static or reactive but evolves in real-time alongside the equipment's performance, offering engineers and decision-makers an accurate, data-driven foundation for managing refinery assets.

3.3. Scoring Logic and Weighting Methodology

The health scoring framework utilizes a structured logic based on weighted aggregation to convert diverse Equipment Health Scores (EHSs) into a unified, interpretable health index. This methodology ensures that the health score reflects not only isolated measurements but also the broader operational, historical, and reliability context of each asset. The scoring system is designed to be dynamic, adapting in real time to changes in asset condition, inspection results, and failure patterns. By aggregating scores from multiple factors, each with assigned weights the health index (HI) serves as a comprehensive indicator of asset condition.

Generally, these multiple influencing factors are combined using a weight-based formulation, enabling a holistic representation of the asset's current condition by accounting for its age, operational behavior, historical performance, inspection outcomes, and reliability data. As each point of influence whether derived from inspection, conditional monitoring, or reliability metrics contributes differently to asset health, the composite score evolves over time in response to these inputs.

The health index (HI) is defined as a numerical value influenced by several key factors (denoted as F_i), each associated with a specific weight (B_i). The weighted sum of these factors is normalized relative to the maximum possible health score. The formula for calculating the health index can be written as:

$$HI = \frac{[\text{Factor's actual value}]}{[\text{Factor's maximum value}]} = \frac{F_1B_1 + F_2B_2 + F_3B_3 + \cdots + F_iB_i}{F_1^{max}B_1 + F_2^{max}B_2 + F_3^{max}B_3 + \cdots F_i^{max}B_i}$$

where i represents the total number of factors considered. These factors can include EHSs such as Age, Design and Obsolescence, Load Stress, Work Order History, Inspection Findings, and Conditional Measurements. Each of these elements contributes a unique perspective on equipment degradation and future failure risk.

In cases where the equipment consists of several grouped factors, such as units or subsystems each with its own indicator values, the score for each factor (F) can be further broken down into sub-factors (SF). Each sub-factor is assigned a corresponding weight (SB). The formula for calculating the factor score based on sub-factors is expressed as:

$$F = \frac{[\text{Subfactor's actual value}]}{[\text{Subfactor's maximum value}]} \times [\text{Normalizer}] = \frac{SF_1SB_1 + SF_2SB_2 + SF_3SB_3 + \cdots + SF_iSB_i}{SF_1^{max}SB_1 + SF_2^{max}SB_2 + SF_3^{max}SB_3 + \cdots + SF_i^{max}SB_i} \times K_k$$

Here, K_k is a normalization multiplier used to ensure that the calculated health index remains within a standardized scoring range. For example, if the total sub-factor weight is 10 and the full scoring range is 100, then the multiplier K_k is set as $10/100$. This normalization ensures consistency in score interpretation across different equipment types and scoring configurations.

Among all parameters, age is one of the most influential and widely adopted indicators for estimating equipment degradation. Age captures the impact of time-in-service relative to design life, and it is often grouped with design features such as the presence or absence of certain operational enhancements to form the Age and Design factor. To illustrate how this scoring system works in practice, Table 3.2 provides an example of how the "Age and Design" factor is scored and weighted in refinery health scoring models.

Table 3.2. Sample Scoring System for Age and Design in Refinery Equipment.

Current Age	Subfactor weight: 2 (SB1)	Weighting Factor
Based on initial in-service date	Normalized to baseline threshold	25%
	Condition	Score
	0 – 19 years	4 (SF_1^{max})
	20 – 29 years	3

	30 – 39 years	2 (SF_1)
	40 – 49 years	1
	50+ years	0
Load Tap Changer	subfactor weight : 2 (SB_2)	
	Condition	Score
	No LTC	4 (SF_1^{max})
	Yes – no LTC problems	3 (SF_2)
	Yes – minor LTC problems	2
	Yes – moderate LTC problems	1
	Yes – major LTC problems	0

This structured and transparent scoring logic allows stakeholders to track how each condition affects the final health score. More importantly, it supports consistency across asset types and facilitates prioritization in maintenance planning. With the ability to update scores as new data becomes available, the scoring system becomes a dynamic decision-support tool in reliability-centered asset management.

3.4. Classification of Equipment Types

To ensure accurate and tailored health assessment across a refinery's diverse asset base, equipment must be classified into distinct categories based on operational characteristics and maintenance demands. This methodology recognizes three primary groups: static equipment, rotating equipment, and electrical/instrumentation systems.

Static equipment, such as pressure vessels, heat exchangers, storage tanks, and piping systems, generally lacks moving parts but is critical for containment and thermal processes. These assets are assessed based on degradation mechanisms like corrosion, fouling, wall thinning, and insulation failure.

Rotating equipment includes pumps, compressors, turbines, and gearboxes, *i.e.*, components subject to dynamic mechanical stresses. Health monitoring for these assets focuses on vibration analysis, lubrication condition, alignment, and operational anomalies. A clear example is depicted in Figure 3.6, which presents a hierarchical classification structure of a compressor unit. The diagram illustrates how the compressor is broken down into its major subsystems: Power Transmission, Control & Monitoring, Compressor Core, Lubrication System, Shaft Seal System, and Miscellaneous Components. This breakdown supports modular condition evaluation and targeted diagnostics for each subsystem.

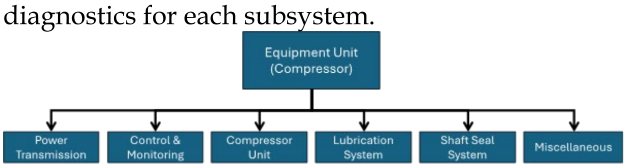

Figure 3.6. Equipment Unit Breakdown of Compressor System.

Electrical and instrumentation systems, encompassing transformers, switchgears, control panels, and sensors, require assessment based on insulation resistance, thermal performance, circuit continuity, and signal stability. These systems are vital for safe operation and automation of both static and rotating assets.

This classification framework not only streamlines health data interpretation but also enables the development of asset-specific equipment health scores (EHSs), scoring models, and reliability assessments tailored to each equipment type.

3.5. Selection and Justification of EHSs for Each Category

The selection of Equipment Health Scores (EHSs) is central to developing a comprehensive and credible health scoring framework. EHSs must be tailored to the operational characteristics, degradation patterns, and dominant failure modes of different equipment types, namely static, rotating, and electrical/instrumentation systems, so that the resulting scores reflect true risk and asset condition. Each category demands a specialized set of indicators that can reliably signal deterioration before failure occurs, thereby allowing for proactive intervention.

For static equipment such as pressure vessels, heat exchangers, columns, and storage tanks, the selected EHSs focus on long-term, gradual degradation. These include corrosion rate, wall thickness reduction, internal cleanliness, external coating integrity, and insulation condition. These parameters are typically assessed through periodic non-destructive testing (NDT), such as ultrasonic thickness gauging, visual inspections, and corrosion probes. The rationale behind selecting these EHSs lies in their direct impact on containment integrity, safety compliance, and process efficiency. Their degradation is usually slow but progressive, making periodic inspections critical in detecting early signs of failure such as wall thinning or cracking.

In contrast, rotating equipment such as pumps, compressors, turbines, and motors are subject to continuous mechanical motion, and thus require EHSs that can detect acute changes in operational dynamics. Relevant indicators include vibration levels, bearing and winding temperature, lubricant quality, alignment precision, and deviations in rotational speed. These parameters are often monitored in real time using online condition monitoring systems. Their selection is justified by the high criticality of rotating assets and the sudden, often catastrophic nature of their failures. Real-time data enables early detection of imbalance, misalignment, or component wear, conditions that can escalate rapidly if left unaddressed.

Electrical and instrumentation systems, including transformers, switchgear, motor control centers (MCCs), and control valves, exhibit unique degradation behaviors associated with insulation breakdown, overloads, and control inaccuracies. Accordingly, EHSs for this category focus on insulation resistance, thermal imaging for hotspot detection, breaker trip frequency, voltage and current stability, and signal drift. These indicators are essential for uncovering hidden faults that can compromise electrical safety and control reliability. Many of these EHSs are derived from periodic electrical testing and thermal scanning, and some can be obtained via smart relays or integrated asset management systems.

Ultimately, the justification for each EHS selection is rooted in failure mode analysis, operational impact, and data acquisition feasibility. Figure 3.5, previously described, reflects the layered classification of EHSs influencing the overall health score, demonstrating how initial design-related conditions, real-time performance data, and reliability metrics converge. This strategic selection process ensures that each equipment category is assessed based on its actual operational stressors and reliability risks. The EHSs are designed not only to be relevant but also measurable and actionable, enabling refinery operators to make informed, condition-based decisions. By aligning indicator selection with asset type and risk exposure, the health scoring system maintains both technical integrity and practical value in driving reliability-centered maintenance strategies.

4. FRAMEWORK IMPLEMENTATION

The implementation of the health scoring framework in refinery operations involves a structured flow of data acquisition, processing, scoring, and system integration. Data collection is performed through a combination of digital systems including the Distributed Control System (DCS), Computerized Maintenance Management System (CMMS), and specialized Predictive Maintenance (PdM) tools. The DCS and historian servers provide continuous process data—such as pressure, temperature, flow, and vibration readings—while CMMS supplies historical and event-based data, such as maintenance records, inspection results, and failure logs. PdM tools, including ultrasonic thickness gauges, thermographic cameras, and portable vibration analyzers, offer periodic diagnostics that supplement the real-time monitoring with condition-based information.

Once collected, this data is mapped into the EHS scoring model, as detailed in the framework. The scoring begins by assigning a numeric score to each parameter based on predefined condition ranges and degradation thresholds. For instance, vibration readings that exceed alert limits are scored lower (e.g., 1–2), while readings within optimal thresholds receive higher scores (e.g., 4–5). Each sub-factor score is then multiplied by its respective weight, and the results are aggregated into a factor score. These factor scores (e.g., for Age, Load Stress, Design Obsolescence, Inspection, Reliability, etc.) are combined using a weighted summation to produce the Health Index (HI). A normalization factor ensures comparability across asset types.

An example calculation might involve a rotating compressor with an operating age of 12 years (scored 2), high bearing temperature (scored 2.5), and moderate vibration (scored 3). After applying the weighting logic and adjustment modifiers (*e.g.*, based on availability and relevance of data), the final health score is generated, typically on a scale from 0 to 100.

The final Health Index is then integrated into the asset management system via digital dashboards or reliability monitoring platforms. This allows health scores to be visualized, trended over time, and used for automated prioritization of maintenance actions. Integration with the enterprise CMMS enables seamless linkage between condition scores and work order generation, supporting a risk-based maintenance strategy and improving operational reliability.

5. RESULTS AND VALIDATION

5.1. *General Equation for Equipment Health Score*

Health score consists of three parts: health initial score (H_{init}), health modifier score (H_{mod}), and health reliability score (H_R).

$$Health_{(i)} = H_{init(i)} + H_{mod(i)} + H_{R(i)} \quad \textbf{(1)}$$

where:

i is the identification number assigned to each each equipment.

$H_{init(i)}$ is health initial score of equipment i.

$H_{mod(i)}$ is health modifier score of equipment i.
$H_{R(i)}$ is health reliability score of equipment i.
To implement equation (1) across diverse equipment types with varying availability and data quality, each score component ($H_{init(i)}$, $H_{mod(i)}$, $H_{R(i)}$) is computed using the following normalization scheme:

$$H_{(i)} = \frac{\sum_{j=1}^{n} A_{(i,j)} \cdot W_{(i,j)} \cdot S_{(i,j)}}{\sum_{j=1}^{n} W_{(i,j)}} \quad \textbf{(2)}$$

where:
$H_{(i)}$ is either $H_{init(i)}$, $H_{mod(i)}$, or $H_{R(i)}$, each designates its corresponding $A_{(i,j)}$, $W_{(i,j)}$, and $S_{(i,j)}$.
i is the identification number assigned to each equipment type, e.g., $i = 1$ represents the jetties, $i = 2$ represents storage tanks, and so on.
j is the identification number assigned to each Key Health Indicator (EHS) on each equipment type.
n is the total number of EHSs on each equipment type ($j \leq n$).
$A_{i,j}$ is a binary flag (0 and 1), or fractional flag (0 to 1), indicating the availability and confidence level of data for the j-th EHS of the i-th equipment type.
$W_{i,j}$ is the relative weight (importance) of the j-th EHS of the i-th equipment type.
$S_{i,j}$ is the normalized score (0–100) for the j-th EHS of the i-th equipment type, and is formulized as piecewise linear equation

$$S_{i,j} = \begin{cases} s_0, & x < x_0 \\ m_1 \cdot x + c_1, & x_0 \leq x \leq x_1 \\ m_2 \cdot x + c_2, & x_1 \leq x \leq x_2 \\ \vdots & \\ m_p \cdot x + c_p, & x_{p-1} \leq x < x_p \\ s_p & x \geq x_p \end{cases} \quad \textbf{(3)}$$

where:
p is number of linear segments.
x is measured value of EHS j.
x_k is threshold breakpoints ($1 \leq k \leq p$).
s_k is value of $S_{i,j}$ at breakpoints x_k.
m_k is the gradient of the k^{th} linear equation ($m_k = \frac{s_k - s_{k-1}}{x_k - x_{k-1}}$).
c_k is the constant of the k^{th} linear equation ($c_k = s_{k-1} - m_k \cdot x_{k-1}$).
This formulation ensures that indicators with missing or unreliable data are automatically down-weighted or excluded from the final score, without skewing results.
Equation (1) becomes

$$Health_{(i)} = \left(w_{init(i)} \times H_{init(i)}\right) + \left(w_{mod(i)} \times H_{mod(i)}\right) + \left(w_{R(i)} \times H_{R(i)}\right) \quad \textbf{(4)}$$

where $w_{*(i)}$ is health component's weight coefficient, and $*$ is either initial, modifier, or reliability.
Equation (4) defines the total health score ($Health$) for each equipment type (i) as a weighted combination of three independent components: the health initial score ($H_{init(i)}$), the health modifier score ($H_{mod(i)}$), and the health reliability score ($H_{R(i)}$).

5.2. Health Score Component: Initial Score (Hinit)

$H_{init(i)}$ reflects the equipment's aging status relative to its expected service life. It is calculated based on the remaining useful life (RUL):

$$RUL_{(i)} = L_e - L_a \quad \textbf{(5)}$$

$RUL_{(i)}$ is the remaining useful life of equipment i.
$L_{e(i)}$ is expected lifetime of equipment i.
$L_{a(i)}$ is age, or elapsed time since operation/commission started of equipment i.
RUL is then normalized (by L_e) to a percentage scale to produce H_{init}.

$$\left.\begin{array}{l} H_{init(i)} = \frac{RUL_{(i)}}{L_{e(i)}} \times 100 \\ \quad \text{or} \\ H_{init(i)} = \left(1 - \frac{L_{a(i)}}{L_{e(i)}}\right) \times 100 \end{array}\right\} \textbf{(6)}$$

5.3. Health Score Component: Modifier Score (Hmod)

$H_{mod(i)}$ is calculated from operating or loading conditions. Qualitative-only condition is measured using non-numeric variable.

$$H_{mod(i)} = \left(w_{OLC(i)} \times OOC_{(i)}\right) + \left(w_{MLC(i)} \times MOC_{(i)}\right) \quad \textbf{(7)}$$

$w_{*(i)}$ is loading condition weight coefficient of equipment i.
OOC is observed operating condition that gives result in non-numeric value, e.g., visual inspection on equipment may result in {"good", "moderately degraded", "severely degraded"}, which may be translated into numerical value {90, 60, 30}.
MOC is measured operating condition (numeric)

$$MOC_{(i)} = \left(\frac{x_{n(i)} - x_{f(i)}}{x_{0(i)} - x_{f(i)}}\right) \times 100 \quad \textbf{(8)}$$

$x_{0(i)}$ is the designed value of the specified EHS variable of equipment i under operating condition.
$x_{f(i)}$ is the critical value of the specified EHS variable of equipment i under operating condition.
$x_{n(i)}$ is the measured (actual) value of the specified EHS variable of equipment i under operating condition.

5.4. Health Score Component: Reliability Score (HR)

$H_{R(i)}$ reflects the statistical probability (R) that a given equipment i will operate without failure over a defined mission time ($t_{mission}$). This probability value is then scaled to a score between 0 and 100.

$$H_{R(i)} = R_{(i,t_{mission})} \times 100 \quad \textbf{(9)}$$

where:

$t_{mission}$ is a target horizon time, where reliability score is evaluated.

$R_{(i,t_{mission})}$ is the reliability of equipment i, and is essentially the probability that equipment i will continue to perform its function without failure over the prescribed mission time ($t_{mission}$). The probability function is modelled using one of these two distribution functions: Weibull distribution (Eq.(10)), and log-normal distribution (Eq.(11)).

$$R_{(i,t_{\text{mission}})} = e^{-\left(\frac{t_{\text{mission}}}{\alpha}\right)^{\beta}} \quad \textbf{(10)}$$

$$R_{(i,t_{mission})} = 1 - \Phi\left(\frac{\ln t_{\text{mission}} - \mu}{\sigma}\right) \quad \textbf{(11)}$$

where:

α is scale parameter, which is the time at which 63.2% of the population has failed, with the exception for $\beta = 1$, α is the mean time between failure ($\alpha = MTBF$).

β is shape parameter, where:

$\beta < 1$ corresponds to distributions where early failure dominates.

$\beta = 1$ corresponds to distributions with constant failure rate. Equation (10) is reduced to exponential distribution, and the scale parameter α is set to mean time between failures (MTBF).

$\beta > 1$ corresponds to distributions where wear-out failure dominates.

μ is mean of log-transformed failure time.

σ is standard deviation of log-transformed failure time.

Φ is cumulative distribution function (CDF) of standard normal distribution.

The selection of the distribution function is based on which between the two that best fits the historical data of equipment i 's failure time.

This approach allows equipment health scoring to reflect not only physical condition but also predicted failure behavior grounded in statistical reliability theory.

When detailed failure time datasets are not available for statistical modeling, reliability scoring may fallback to simplified metrics such as mean time between failures ($MTBF$) and mean time to repair ($MTTR$), provided that basic failure counts and repair durations are logged in CMMS systems.

$$H_{R(i)} = \left(w_{R_{MTBF}(i)} \times R_{MTBF(i)}\right) + \left(w_{R_{MTTR}(i)} \times R_{MTTR(i)}\right) \quad \textbf{(12)}$$

$w_{R_*(i)}$ is equipment i's reliability component's weight coefficient. $*$ is either $MTBF$, or $MTTR$.

$R_{*(i)}$ is reliability component of equipment i. $*$ is either $MTBF$, or $MTTR$.

$MTBF$ is mean time between consecutive failures.

$MTTR$ is mean time to repair after failure is detected.

In the complete absence of any historical data, reliability may be approximated from reference failure rate tables (e.g., ISO 14224), or subjective engineering assessment based on equipment type, age, and service conditions.

5.5. Health Score Implementation

Table 5.1. Initial Health Score for Tank in Refinery Equipment.

Subcomponent	Parameter	Data Source	Availablity	Applicability	Score	Weight
Expected Life Score	Design Estimated Life	Datasheet	True	True	0.6	5
	Residual Life	Datasheet	True	True	0.9	5
	Duty Liquid Level	Datasheet	True	True	0.6	5
	Duty Fluid Temperature	Datasheet	True	True	0.6	5
	Duty Filling Rate	Datasheet	False	True	0	5
	Duty Discharge Rate	Datasheet	False	True	0	5
Overall initial health score					**0.6**	

Table 5.2. Health Modifier Score for Tank in Refinery Equipment.

Sub component	Parameter	Data Source	Availablity	Applicability	Score	Weight
Observed Condition	Foam Chamber Installation	Operator Judgement	1	1	0.9	5
	Grounding	Filed Observation vs OSI metric	1	1	0.9	5
	Painting	Memo	1	1	0.9	2
	Roof (Cone/Floating)	Filed Observation vs OSI metric	1	1	0.9	3
	Roof seal and shoe	Filed Observation vs OSI metric	1	1	0.9	3
	Stairway/handrail/ladder/platform	Filed Observation vs OSI metric	1	1	0.9	1

	Foundation	Filed Observation vs OSI metric	1	1	0.9	3
	Roof Drain	Filed Observation vs OSI metric	1	1	0.9	2
	Insulation	Filed Observation vs OSI metric	1	1	0.9	2
	Water Sprinkle installation	Filed Observation vs OSI metric	1	1	0.9	5
	Pressure Safety Valve	Filed Observation vs OSI metric	1	1	0.9	5
	Tank Heater	Filed Observation vs OSI metric	1	1	0.9	3
	Observed Condition Score				**0.9**	**3**
Measured Condition	Annular Wall Thickness	Measurement (4.445 mm) vs OSI	1	1	0.97	4
	Bottom Plate Thickness	Measurement (6.35 mm) vs OSI	1	1	1	5
	Roof Thickness	Measurement (6.01 mm) vs OSI	1	1	1	4
	Shell Course Thickness	Measurement (10.82 mm) vs OSI	1	1	0.78	5
	Measured Condition Score				**0.93**	**5**
Overall Health Score Modifier					**0.92**	

Table 5.3. Reliability Score for Tank in Refinery Equipment.

Sub component	Parameter	Data Source	Availablity	Applicability	Score	Weight
MTBF Score	MTBF	No failure after overhaul	1	1	1	5
MTTR Score	MTTR	No failure after overhaul	1	1	1	3
Overall Reliability Score					**1**	

The overall health score of the refinery tank is derived from the structured evaluation of three complementary components: the initial health score, health modifier score, and reliability score, each reflecting different dimensions of asset condition and performance.

As shown by Table 5.1, The initial health score represents the baseline condition of the tank based on design and operational duty parameters. While core design-related parameters are available and applicable for calculation, some duty-related parameters are lacking and therefore contribute zero scores. As result, the aggregated initial health score indicates a moderate baseline condition, reflecting acceptable design integrity but partial data limitations.

The health modifier score, shown by Table 5.2 , refines this baseline by aggregating observed and measured condition data obtained from inspections and thickness measurements. Observed conditions is obtained from operator direct observation such as foam chamber installation, grounding, painting, roof condition, foundation, insulation, and safety installations. From the table, observation values consistently show high condition score indicating that visible and functional aspects of the tank are in good condition. Measured conditions, including annular wall, bottom plate, roof, and shell thickness, also demonstrate strong structural integrity with scores close to optimal values. The resulting overall modifier score is high, confirming that current physical condition and inspection results positively reinforce the tank's health status.

Lastly, as shown by Table 5.3, the reliability score reflects historical operational performance based on MTBF and MTTR indicators. Since no failures have occurred after the last overhaul, both MTBF and MTTR achieve the maximum score. This results in a perfect reliability score, signifying strong operational dependability and effective maintenance practices.

Taken together, from the focus group discussion of the experienced refinery users, the priority of tank health factor is the health score modifier since refinery tank is most likely be altered on overhaul if the physical condition is worsened. So, remaining life score are not significant than observation and measurement score. Hence, it is decided that the weighted value of initial health score, health score modifier, and reliability score are 1, 5 and 3 respectively. So, the final health score of tank refinery are shown by

Table 5.4. Overall Health Score for Tank in Refinery Equipment.

	Health Score	Value	Weight
1	Initial Health Score	60%	1
2	Health Score Modifier	92%	5
3	Reliability Score	100%	3
	Overall Health Score	91%	

The three scoring components demonstrate that, although the tank exhibits a moderate design-based baseline condition, its overall health is significantly enhanced by excellent present condition and outstanding reliability performance. This integrated evaluation confirms that the equipment is currently in a healthy operational state, characterized by low short-term failure risk and strong maintenance effectiveness, thereby supporting its continued serviceability within refinery operations.

6. DISCUSSION

The health scoring framework demonstrates a structured, data-integrated approach to reliability assessment in refinery environments. Using Equipment Health Scores (EHSs) derived from both real-time monitoring and historical performance, the system captures equipment health dynamically and comprehensively. The integration of DCS, CMMS, and PdM tools facilitates a multi-dimensional understanding of asset conditions, while the weighting of EHSs ensures that more critical indicators, such as age, MTBF, inspection findings, and operational stress, have a proportionate influence on the final score.

The application of this model to static, rotating, and electrical/instrumentation assets reveals several key insights. For static equipment like tanks and heat exchangers, the availability of offline inspection reports and structural thickness measurements is generally sufficient. However, online monitoring capabilities remain limited and must be improved to support continuous assessment. For rotating assets, real-time condition monitoring (e.g., vibration and lubrication quality) is more mature, though reliability metrics like MTBF and MTTR are inconsistently recorded across systems. Electrical systems present unique challenges, as EHSs such as insulation resistance and breaker trip history are often not captured in structured databases, limiting their integration into the health score.

The gap analysis, particularly for assets like refinery tank and piping systems, highlights challenges in data completeness and standardization. While certain categories such as design data and offline inspections are well-documented, critical real-time parameters and reliability history are often unavailable or manually stored. These gaps not only reduce the accuracy of the health score but also hinder predictive maintenance efforts. Addressing data availability, particularly at Level 2 (engineering required) and Level 3 (manual acquisition needed), will be essential for improving score precision and asset readiness evaluation. The discussion reinforces the need for a robust digital infrastructure to fully realize the potential of health-based maintenance.

7. CONCLUSION

The implementation of a EHS-based health scoring system offers a promising advancement in asset reliability management. By combining historical, real-time, and reliability-based data streams, the system provides a quantitative and adaptive method for assessing the condition of refinery equipment. The modular scoring logic, supported by weighted indicators and normalization strategies, ensures consistency across different asset types and operational scenarios.

The framework effectively distinguishes health characteristics for static, rotating, and electrical assets, allowing for tailored assessments that reflect real-world degradation patterns. Case studies, particularly the in-depth review of refinery tank, validate the framework's capability to incorporate inspection data, operational duty, and age-based factors into a unified health index. Nevertheless, the analysis also reveals that data limitations, especially in online condition monitoring and automated reliability tracking, pose significant constraints to scoring accuracy and effectiveness.

To enhance the system's reliability and practical utility, future efforts must focus on improving sensor coverage, integrating real-time data pipelines with CMMS and historian systems, and enforcing consistent data structuring. A clear mapping between health score modifiers, reliability metrics, and maintenance outcomes will also be critical to operationalizing the scores for decision-making. Moreover, the relational database model proposed in the report offers a scalable foundation for digital integration and predictive analytics.

In conclusion, the health scoring framework represents a foundational step toward reliability-centered, data-driven maintenance in refinery operations. By institutionalizing EHSs into routine monitoring and planning processes, organizations can transition from reactive maintenance to proactive asset management, thereby improving operational continuity, safety, and cost-efficiency.

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