Available on: http://gjetr.ep-journals.org/ E-ISSN: 3051-3782, P-ISSN: 3051-3774

Global Journal of Engineering and Technology Review

Volume: 02 Issue: 09 September 2026

Predictive Maintenance Metrics in the Minimisation of Non-Routine Flaring from Rotating Machinery Failure: A Review of Condition Monitoring, Prognostics and the Conditional Chain from Early Detection to Avoided Emergency Pressure Relief

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Published Date: September 09, 2026 **Article DOI : 10.65150/EP-gjetr/V2E9/2026-11**

ABSTRACT: Non-routine flaring in a liquefaction facility is predominantly a consequence of equipment failure, and failure in rotating machinery is predominantly preceded by a detectable degradation signature. The two propositions are individually well established and are rarely connected, with the result that condition monitoring programmes are justified on maintenance cost and availability grounds while the flaring consequence, frequently the larger cost, is attributed to a separate account. This review examines the relationship between condition monitoring performance and non-routine flaring, drawing together the diagnostics and prognostics literature, the maintenance optimisation literature, and the emissions measurement literature. The scope is restricted to rotating machinery, principally the refrigerant compressors and their drivers. Instrumentation failures and control system faults are also a material cause of non-routine flaring, but they are outside this scope, because their degradation signatures and detection routes differ and the argument developed here does not transfer to them. No data are reported. The paper is analytical throughout, and the conditional probabilities used to illustrate the chain are stipulated for exposition rather than measured or estimated; they should not be read as figures characterising any facility. Five arguments are developed. First, the causal chain from degradation signature to avoided flare event runs through four conditional steps, and the probability that a detected anomaly prevents a flare event is the product of detection probability, lead time adequacy, intervention opportunity and intervention effectiveness, each separately measurable and none ordinarily measured. Second, lead time rather than detection sensitivity is the binding constraint in a liquefaction context, because the intervention for most machinery degradation requires a load reduction or an outage and the opportunity for either is determined by the operating plan rather than the maintenance schedule. Third, the rapid development of data-driven prognostics has improved the estimation of remaining useful life without addressing the opportunity constraint, so that its practical contribution in this setting is smaller than its methodological maturity suggests. Fourth, the standard predictive maintenance metrics measure the maintenance function and not the outcome the programme is claimed to produce. Fifth, the attribution of an avoided flare event is counterfactual and therefore contestable, and a measurement approach based on the observable chain avoids the difficulty entirely. The framework is offered as a measurement proposal requiring empirical validation, not as a validated instrument.

KEYWORDS: predictive maintenance, condition monitoring, vibration analysis, prognostics, remaining useful life, infrared thermography, non-routine flaring, leading indicators, rotating machinery, maintenance optimization, liquefied natural gas.

1. INTRODUCTION

A liquefaction train flares when it cannot dispose of gas any other way, and the circumstances divide into planned operations, process upsets whose cause is external, and equipment failures. The third category dominates in most operating facilities, and within it the failure of rotating machinery, principally the refrigerant compressors and their drivers, dominates by flare volume, because the failure of a compressor removes the train's capacity to process the feed it is receiving.

Condition monitoring exists to detect the degradation preceding such failures. Its technical basis is mature: vibration analysis of rotating machinery has an extensive research literature and a well developed diagnostic vocabulary (Randall, 2011; Randall & Antoni, 2011), infrared thermography supplies a complementary detection route for thermal and electrical degradation (Bagavathiappan, Lahiri, Saravanan, Philip, &

Jayakumar, 2013), and the decision framework within which detections are acted upon has been developed over four decades of reliability-centred maintenance practice (Moubray, 1997). Operating facilities deploy these capabilities, generally to a good standard. The same detection-to-decision logic appears in adjacent asset classes and is worth holding in view, because it isolates the argument from the particular equipment: sensor-based fault detection in building services plant addresses a fault population dominated by fouling, control drift and bearing wear (Sunday & Omoegun, 2022; Sunday, Omoegun, Essien, & Oluokun, 2019), and distributed renewable assets present the same problem where instrumentation is sparse and the models must remain interpretable (Komi & Adamolekun, 2021; Komi & Adeniji, 2023).

The two are connected in principle and disconnected in practice. Condition monitoring programmes report performance in maintenance terms: findings raised, work orders generated, unplanned maintenance avoided, availability improved. Flaring is reported separately, in environmental and production terms, and its equipment-failure component is attributed to the failures rather than to the monitoring that did not prevent them. Neither report answers how much flaring the monitoring programme prevented, and the two functions have no shared metric. The general form of the problem, in which an activity reports on its own process while the outcome it is claimed to influence is accounted for by another function, is not confined to maintenance. It has been described in safety management, where observation activity and injury rate are reported separately (Obriki & Arumosoye, 2018), in procurement, where transactional efficiency and plant availability are held in different ledgers (Okoruwa, Babatope, Akokodaripon, & Akinleye, 2024), and in enterprise performance measurement more generally (Adelanwa, Basnet, & Anene, 2024).

This review examines that connection. It sets out the causal chain, surveys the detection and prognostic capability available at each link, argues that lead time rather than detection sensitivity is the binding constraint, and proposes a measurement approach avoiding the counterfactual attribution problem that has frustrated previous attempts to demonstrate the value of preventive programmes.

2. SCOPE AND METHOD

This is a narrative review. It draws on four literatures whose intersection is the subject of the paper and which are not ordinarily read together. The scope is rotating machinery, principally the refrigerant compressors and their drivers, and the paper reports no data of its own. Instrumentation and control system faults are excluded for the reason given in Section 6, and the conditional probabilities appearing later are stipulated for illustration rather than measured.

The machinery diagnostics literature addresses the detection and identification of degradation from measured signals, and is concentrated in vibration analysis with substantial supporting work in thermography, acoustic emission and lubricant analysis. The prognostics literature addresses the estimation of remaining useful life from condition information and has developed rapidly since the mid-2000s, with a pronounced shift toward data-driven and latterly deep learning methods. The maintenance optimisation literature addresses the decision problem of when to intervene given degradation information and cost structure. The emissions and flaring literature supplies the consequence against which the whole is being evaluated here. A fifth body of work is drawn on more selectively. It reports the same detection-to-intervention structure in asset classes other than rotating machinery, and is useful here for contrast rather than for content: building services plant (Sunday & Omoegun, 2022), distributed generation (Komi & Adamolekun, 2021), transmission and pipeline corridors (Dagodzo & Ahiaeke Patrick, 2020), industrial control systems (Adegbite, Adebayo, & Ahmed, 2023) and process safety monitoring (Obriki, Arumosoye, & Obogo, 2023).

The review does not attempt systematic coverage of any of these. The diagnostics and prognostics literatures in particular are very large and are served by several recent systematic reviews, which are cited and relied upon rather than duplicated (Jardine, Lin, & Banjevic, 2006; Lee et al., 2014; Lei et al., 2018). The selection here favours work bearing on the argument rather than work representative of the field.

One limitation should be stated at the outset. No operating data are reported. The conditional probabilities appearing in the chain analysis are illustrative and are present to demonstrate the effect of multiplication, not to estimate it. Where a claim is an argument from structure rather than a measured finding, this is identified.

3. LITERATURE REVIEW

3.1 Detection: Vibration Analysis

Vibration-based condition monitoring rests on the fact that mechanical degradation modifies the vibration signature in ways characteristic of the mechanism. Bearing defects, imbalance, misalignment, looseness, blade damage and rub each produce identifiable features, and the signal processing methods for extracting them are well developed (Randall, 2011).

Rolling element bearing diagnostics is the most thoroughly developed subfield and is directly relevant, since bearing failure is a common initiator of machine trips. The physical model of the vibration produced by a localised defect was established early (McFadden & Smith, 1984), and the envelope analysis techniques built on it were optimised against simulated and actual fault signals (Ho & Randall, 2000). The tutorial treatment sets out both the method and its detection limits (Randall & Antoni, 2011), and benchmark studies against widely used public datasets have established the comparative performance of competing approaches and, importantly, the conditions under which reported performance does not generalise (Smith & Randall, 2015).

Signal processing developments have extended detection into conditions where classical methods perform poorly. Spectral kurtosis and the kurtogram address the detection of transients in the presence of strong background noise (Antoni, 2006; Antoni & Randall, 2006), which is the ordinary condition in a compressor house. Time-frequency methods address non-stationary operation, where a machine changes speed or load during the measurement (Feng, Liang, & Chu, 2013). Empirical mode decomposition and wavelet approaches have been reviewed extensively for rotating machinery application (Lei, Lin, He, & Zuo, 2013; Yan, Gao, & Chen, 2014), and the general survey of signal processing techniques for bearing diagnosis maps the field (Rai & Upadhyay, 2016). Implementation accounts describe how these methods are configured in operating plant rather than in the laboratory, including the instrumented workflow by which route and continuous data are collected, screened and escalated (Omoegun, Sunday, Essien, & Oluokun, 2023). Comparable sensor-based schemes in building services plant show the same progression from raw signal to actionable finding in equipment whose failure physics is quite different, which is a useful check on how much of the method is general and how much is specific to turbomachinery (Sunday & Omoegun, 2022; Sunday, Omoegun, Essien, & Oluokun, 2019).

The measurement and evaluation of machine vibration is standardised, as is the general framework for condition monitoring programmes (International Organization for Standardization, 2016, 2018), and machinery protection system requirements for the equipment classes relevant here are specified in the applicable recommended practice (American Petroleum Institute, 2014a). The distinction between protection, which trips the machine, and monitoring, which informs a decision, is important for what follows: protection prevents machine damage and does not prevent flaring, since a machine tripped by its protection system produces the same loss of capacity as one that failed.

The specification standards for the machinery itself bear on what monitoring is feasible, since instrumentation provision is fixed at purchase (American Petroleum Institute, 2014b). A compressor train ordered without provision for permanently installed proximity and casing measurement will be monitored by periodic route-based collection, which changes the achievable detection interval by orders of magnitude. Because instrumentation provision is settled at purchase, the monitoring capability a facility will have for the following twenty years is determined by specification and vendor selection practice rather than by the maintenance function (Okonkwo, Ogunwole, & Okeke, 2018a; Okonkwo, Ogunwole, Mayo, & Okeke, 2021). The vendor evaluation literature treats this class of decision as a data problem rather than a commercial one (Ahiaeke Patrick, Okonkwo, Mayo, & Okeke, 2021; Akinleye & Adeyoyin, 2022b), which is the correct framing if the criterion is what the plant will be able to detect rather than what the machine costs.

3.2 Detection: Complementary Technologies

Vibration analysis detects mechanical degradation and detects other failure modes poorly or not at all. Three complementary technologies fill identifiable gaps.

Infrared thermography detects degradation whose signature is thermal, including electrical connection degradation, insulation failure, cooling system fouling and lubrication problems. The condition monitoring application is well reviewed (Bagavathiappan et al., 2013), and the electrical equipment application, which covers the drivers and switchgear on which compressor availability depends, has been reviewed separately (Jadin & Taib, 2012). Its limitation is that it detects a temperature difference rather than a fault, so ambient conditions, emissivity, load history and solar exposure all confound interpretation. Related non-destructive evaluation practice addresses the static equipment on which the same trains depend, where the degradation is corrosion or weld deterioration rather than a rotating fault and inspection is periodic by necessity (Atta, Tofah, Kankam, & Adenuga, 2020; Atta, Tofah, & Adenuga, 2021; Atta, Adjaklo, Asomani, & Adenuga, 2022). The materials behaviour underlying that degradation has its own literature, and it matters here because it determines whether an inspection interval is conservative or optimistic (Atta, Asomani, & Adenuga, 2018; Atta et al., 2025). Device-level work on degradation in optoelectronic and thin-film systems makes the same point in a stricter setting, since it shows how far the physical understanding of a mechanism must be developed before an observed signal can be attributed to it with confidence (Atta, 2026a, 2026b; Atta, Onyishi, Appiah, & Adenuga, 2024).

Lubricant and wear debris analysis detects degradation at the tribological interface, frequently earlier than vibration for slowly developing wear, and online sensing has developed to the point where continuous rather than sampled monitoring is practicable (Zhu, Zhong, & Zhe, 2017). Its limitation is that it localises poorly: a debris signal establishes that something is wearing without establishing what.

Acoustic emission detects the elastic stress waves generated by crack initiation, rubbing and fluid passage, and offers detection at earlier stages of damage than vibration for some mechanisms. Its application to bearing and gearbox condition monitoring has been developed extensively (Mba & Rao, 2006), and the wider treatment of acoustic methods for leak localisation in pressurised systems is directly applicable to the flare-loss problem addressed elsewhere in this series (Hu, Tariq, & Zayed, 2021).

The practical point is that no single technology covers the failure mode population of a liquefaction train, and coverage decisions determine detection probability more strongly than the sensitivity of any individual method. A programme with excellent vibration coverage and no thermographic coverage of the driver switchgear has a detection probability for driver electrical failure of approximately zero, whatever its vibration performance. Two further considerations bear on coverage rather than on the sensitivity of any technique. The first is access. Assets distributed over a corridor or a large site are inspected on a schedule set by how difficult they are to reach, and remote sensing has changed that calculation for transmission, pipeline and right-of-way assets (Dagodzo, 2018a, 2018b; Dagodzo & Ahiaeke Patrick, 2020, 2021b), with geospatial asset management supplying the record against which findings are held (Dagodzo & Ahiaeke Patrick, 2021a, 2023) and automated interpretation now extending to routine classification (Dagodzo, Ahiaeke Patrick, & Aliliele, 2022). The second is the cost of instrumenting points that were not instrumented at build. Wireless and energy-harvesting sensing was developed for exactly this case, and its reliability and latency properties are now reasonably well characterised (Asiedu & Quainoo, 2023a, 2023b, 2024; Asiedu, Quainoo, & Asiedu, 2025), including the intermittency that determines whether a measurement is available when it is needed (Asiedu & Quainoo, 2025; Asiedu, Quainoo, & Asiedu, 2026) and the link behaviour that determines whether it arrives at all (Quainoo, Ogundapo, & Asiedu, 2025a; Quainoo & Ogundapo, 2026b). A sensor reporting intermittently changes the detection probability in the first link of the chain developed below, and does so in a way that is straightforward to model and easy to overlook. Two practical constraints on such installations are worth noting because they are routinely discovered after commissioning rather than before: antenna and impedance conditions in a congested steel environment degrade the link long before the sensor itself fails (Quainoo, Ogundapo, & Asiedu, 2024), and coexistence between the several radio systems now deployed across a plant affects both power draw and delivered throughput (Quainoo & Ogundapo, 2026a). Verifying either at scale is a test automation problem rather than a sensing one (Quainoo, Ogundapo, & Asiedu, 2025b).

3.3 Prognostics and Remaining Useful Life

Detection establishes that degradation is present. Prognostics attempts to estimate how long remains before functional failure, and it is the capability on which the lead time question turns.

The field has been systematically reviewed several times as it matured. Jardine, Lin and Banjevic (2006) set out the diagnostics and prognostics framework for condition-based maintenance and remains the standard entry point. Peng, Dong and Zuo (2010) survey the status of machine prognostics specifically. Lee et al. (2014) address prognostics and health management design for rotary machinery systems, which is the equipment class of interest here. Lei et al. (2018) provide the most comprehensive systematic review, organising the field into data acquisition, health indicator construction, health stage division and remaining useful life prediction, and this four-stage division is a useful analytical frame.

Methodologically the field divides into model-based, data-driven and hybrid approaches. Model-based methods represent the degradation physics explicitly, and stochastic degradation models, principally Wiener and gamma process formulations, have been developed with recursive filtering for online estimation (Si, Wang, Hu, Chen, & Zhou, 2013). Bayesian updating of residual life distributions from degradation signals was established early and remains influential (Gebraeel, Lawley, Li, & Ryan, 2005). Exponential degradation models for rolling element bearings have been refined against operating data (Li, Lei, Lin, & Ding, 2015), and unit-to-unit variability, meaning the fact that nominally identical machines degrade differently, has been incorporated explicitly (Li, Lei, Yan, Li, & Han, 2019).

Data-driven methods learn the degradation trajectory from historical run-to-failure data without representing the physics. The comparative evaluation of such techniques has been conducted repeatedly (Schwabacher, 2005; Liao & Köttig, 2014), similarity-based approaches match a current trajectory against a library of previous ones (Wang, Yu, Siegel, & Lee, 2008), and health index construction from multiple sensors by data-level fusion has been formalised (Liu, Gebraeel, & Shi, 2013). Application to bearings specifically has been reported with operating validation (Medjaher, Tobon-Mejia, & Zerhouni, 2012), and residual life prediction from monitored condition information was addressed analytically some years before the data-driven turn (Wang, 2002a). Comparable degradation modelling has been reported for asset classes where run-to-failure data are similarly scarce. Grid-connected battery storage is the clearest case, since the degradation is electrochemical, the ageing is continuous rather than event-driven, and the consequence is economic as much as technical (Komi & Ganiu, 2022). Distributed generation assets present the same estimation problem constrained by what the site happens to be instrumented to measure (Komi & Adamolekun, 2021, 2022; Komi & Adeniji, 2023).

The prognostic process is standardised in general terms (International Organization for Standardization, 2015), which is useful chiefly because it establishes a common vocabulary for a field whose terminology varies considerably between research groups. The gap between methodological development and industrial adoption has itself been examined. Sikorska, Hodkiewicz and Ma (2011) assess prognostic modelling options from the standpoint of what industry can actually implement given the data and expertise available, and reach conclusions considerably more cautious than the methodological literature; the review of data-driven approaches by Tsui, Chen, Zhou, Hai and Wang (2015) reaches compatible conclusions. The standard text on intelligent fault diagnosis and prognosis for engineering systems sets out the integrated framework (Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006), and the practitioner literature on machinery failure analysis supplies the failure mode taxonomy against which any prognostic claim must ultimately be checked (Bloch & Geitner, 2012). The statistical data-driven strand has its own review tradition (Si, Wang, Hu, & Zhou, 2011; Heng, Zhang, Tan, & Mathew, 2009; Kan, Tan, & Mathew, 2015; Elattar, Elminir, & Riad, 2016), and benchmarking against the standard public degradation datasets has been formalised so that competing methods can be compared on common ground (Ramasso & Saxena, 2014; Saxena, Goebel, Simon, & Eklund, 2008). The wider reliability engineering agenda situates prognostics among the challenges the field has set itself (Zio, 2016). Adoption is also a question of control architecture rather than only of modelling, because where an estimate is computed determines what can be done with it and how quickly (Komi & Ganiu, 2023; Komi & Adamolekun, 2022). Forecasting work in energy systems has shown repeatedly that improvements in accuracy do not by themselves produce improvements in decisions, and that the mechanism connecting the two has to be built deliberately (Komi, 2021, 2023).

3.4 Machine Learning Approaches and Their Limits

The most active recent development is the application of deep learning to both diagnosis and prognosis, and its relevance to the present argument is more qualified than its volume suggests.

The general application of machine learning to machine fault diagnosis has been reviewed with an explicit research roadmap (Lei et al., 2020). Deep learning applications to machine health monitoring have been surveyed comprehensively (Zhao et al., 2019), as has the application of deep learning to system health management more broadly (Khan & Yairi, 2018). Early demonstrations established that deep architectures could extract diagnostic features from large volumes of raw vibration data without hand-designed feature engineering (Jia, Lei, Lin, Zhou, & Lu, 2016), and remaining useful life estimation using convolutional architectures has been demonstrated on benchmark datasets (Li, Ding, & Sun, 2018). The survey literature on deep learning for remaining useful life prediction is now itself substantial (Wu, Wu, Tan, & Xu, 2024).

Three limitations bear directly on the argument of this paper. The first is data availability: these methods require run-to-failure data, and a well-maintained liquefaction facility deliberately does not generate it, since machines are intervened upon before failure. The benchmark datasets on which the methods are validated are largely from accelerated laboratory tests or from a single publicly released turbofan simulation, and generalisation from these to a refrigerant compressor is an assumption rather than a demonstration. The same scarcity is reported wherever assets are well maintained or sparsely instrumented, which is the ordinary condition in distributed energy (Komi & Adeniji, 2023) and in ageing infrastructure generally (Uduokhai, Nwafor, Sanusi, & Garba, 2025).

The second is that the methods estimate remaining useful life more precisely without changing what can be done with the estimate. If the binding constraint is intervention opportunity rather than knowledge of when failure will occur, then a better estimate improves the plan and does not avert the flare.

The third is interpretability and the associated trust problem. The wider assessment of potential and challenges for deep learning in prognostics and health management identifies the difficulty of validating such models for high-consequence decisions (Fink et al., 2020), and this connects directly to the automation reliance literature: a maintenance planner who cannot interrogate why a model predicts imminent failure will calibrate reliance on the model against its observed track record, exactly as an operator calibrates reliance on an alarm system. Applications in distributed and resource-constrained energy assets illustrate both the promise and the data constraint, since interpretable models and tiered digital twin architectures have been proposed precisely because full instrumentation and run-to-failure histories are unavailable (Komi & Adamolekun, 2021; Komi & Adeniji, 2023). Predictive safety analytics has been reviewed for liquefaction projects specifically (Arumosoye, Obriki, & Ozobu, 2026). The human-in-the-loop literature addresses this configuration directly, treating the analyst as part of the system rather than as its consumer (Ladapo, Dosunmu, Jooda, & Abolaji, 2022), and the disagreement problem, in which expert judgement and model output diverge and neither is authoritative, has been formalised (Ladapo, Jooda, Dosunmu, & Abolaji, 2026). The closest operational analogue outside maintenance is security monitoring, where anomaly detection at scale produces more candidate events than can be investigated and the discipline has organised itself around triage rather than detection (Adebayo, Adegbite, & Ahmed, 2023; Adegbite, Adebayo, & Ahmed, 2023), including the adversarial case in which the detector becomes a target in its own right (Adebayo, Adegbite, & Ahmed, 2022). The practice of auditing model-driven systems rather than trusting them approaches the validation problem from the assurance side (Aliliele, Mbonu, Uzoka, & Iwuanyanwu, 2025a).

3.5 The Maintenance Decision

Detection and prognosis inform a decision, and the decision literature is where the operating consequence is determined.

The maintenance policy literature for deteriorating systems is mature and has been reviewed repeatedly (Wang, 2002b; Dekker, 1996; Nicolai & Dekker, 2008). The comparison between time-based and condition-based strategies in industrial application has been surveyed with attention to the conditions under which each is preferable (Ahmad & Kamaruddin, 2012), and the optimisation of condition-based maintenance for stochastically deteriorating systems has been reviewed comprehensively (Alaswad & Xiang, 2017). Programme-level treatments address the same decision at the level of the schedule rather than the individual machine (Yeboah, Enow, Ike, & Nnabueze, 2024; Uduokhai, Nwafor, Sanusi, & Garba, 2025), and the reliability-centred approach has been applied to asset classes whose failure physics differs sharply from rotating machinery, which is a useful test of how much of the framework is equipment-specific (Oyeleke, Eze, & Asiedu, 2026).

The reliability-centred maintenance tradition supplies the framework by which a detected condition becomes an intervention decision, and, importantly for this paper, the concept of the interval between the point at which failure becomes detectable and the point at which it occurs (Moubray, 1997). That interval is the paper's central quantity and the RCM literature names it without generally measuring it. The underlying reliability theory is standard (Rausand & Høyland, 2004; Rausand, 2011). The organisational conditions under which an intervention is executed are themselves a determinant of the outcome, and the occupational safety literature for maintenance work in oil and gas is explicit about the interaction between work planning, permit conditions and the quality of the restoration achieved (Obogo, Arumosoye, & Obriki, 2020b; Obogo, Obriki, & Arumosoye, 2021).

What the optimisation literature characteristically assumes, and what does not hold in a liquefaction facility operating at capacity, is that intervention can be scheduled when the model recommends it. The models take the cost of preventive intervention as a parameter. In the setting considered here that cost is dominated by the availability of an opportunity, which is determined outside the maintenance function entirely, and which is not a cost so much as a constraint. This is the analytical gap the following section develops. Restoration practice sits downstream of the decision and determines whether an intervention actually returns the machine to its prior condition, which is the fourth link in the chain developed below. The integration of designed experiments with root-cause analysis has been reviewed as the systematic route to that outcome across mechanical and process-intensive industries (Akanbi, Ganiu, & Sunday, 2023). Reliability-centred maintenance has been applied outside rotating machinery to asset classes with quite different failure physics, and those applications are instructive because they isolate the strategy from the equipment: the same logic of failure-mode analysis, consequence classification and interval derivation is applied where the dominant failure modes are thermal and electrical rather than mechanical (Oyeleke, Eze, & Asiedu, 2026). Recurrence after intervention has been examined systematically in the safety literature, where the distinction between treating an event and treating its mechanism determines whether the condition returns, and where the return of the event is treated as the primary evidence that the mechanism was not addressed (Obriki & Arumosoye, 2022, 2024b; Adeyelu, 2026).

3.6 Evidence from Adjacent Asset Classes

The argument developed below concerns a structure rather than a machine, and the structure recurs wherever a monitoring activity is expected to prevent a consequence accounted for elsewhere. Several adjacent literatures are informative for that reason rather than because their equipment resembles a refrigerant compressor, and they are cited here for the contrasts they supply.

Building services plant is the closest technical analogue at small scale, since the fault population is dominated by fouling, control drift and bearing wear, and sensor-based detection has been demonstrated against it (Sunday & Omoegun, 2022), with the thermodynamic behaviour that determines what a temperature or pressure deviation actually means set out separately (Sunday, Omoegun, Essien, & Oluokun, 2019). Electrical infrastructure supplies a second analogue, in which condition assessment is dominated by thermal and insulation signatures and the asset population is dispersed rather than concentrated (Adenuga, 2022, 2023; Dagodzo, 2018a). Distributed renewable generation supplies a third and is the most instructive of the three, because instrumentation is sparse, run-to-failure data are scarce, and the consequence of an outage falls partly on parties other than the operator (Komi & Adamolekun, 2021; Komi & Adeniji, 2023; Komi & Ganiu, 2022). Programme-level work in that sector addresses preventive maintenance design under exactly those constraints (Yeboah, Enow, Ike, & Nnabueze, 2024; Yeboah & Ike, 2020), with the compliance overlay treated separately (Yeboah, Enow, Ike, & Nnabueze, 2025).

Process and utility infrastructure outside the liquefaction train shows the same coupling between equipment condition and environmental consequence. Produced water treatment is the clearest case, since a treatment failure produces a discharge consequence rather than a production consequence and the monitoring justification is correspondingly environmental (Falegan & Aniebonam, 2022, 2024, 2025), with recent work modelling treatment performance from operating data much as prognostics models machinery (Falegan & Aniebonam, 2026). Non-destructive evaluation of static equipment occupies the same position with respect to containment loss (Atta, Tofah, Kankam, & Adenuga, 2020; Atta, Tofah, & Adenuga, 2021). High-density computing facilities present the same scheduling problem in acute form, since the intervention window is set by workload rather than by the maintenance plan (Oyeleke, Eze, & Asiedu, 2026).

A further sector is cited for its measurement practice rather than its engineering. Aviation safety oversight has developed predictive compliance monitoring from routine reporting streams, under the same constraint that the outcome being prevented is rare and its avoidance is not directly observable (Adeyelu, 2018, 2019). The oversight function there is assessed on the condition of its reporting and follow-up chain rather than on accidents avoided, which is the same measurement posture this paper proposes for condition monitoring.

4. ANALYTICAL FRAMEWORK

4.1 The Causal Chain

The proposition that condition monitoring reduces flaring conceals a chain of four conditional steps. Stating them separately clarifies where the chain breaks and what would have to be measured to know.

4.1.1 Step one: detection

The first step is detection. The degradation must produce a signature the monitoring regime observes, which requires that the machine be monitored, that the monitoring cover the relevant failure mode, and that the signature exceed the detection threshold. Detection probability is estimable retrospectively from the record of failures that occurred with and without prior detection.

4.1.2 Step two: lead time adequacy

The second step is lead time adequacy. The interval between detection and failure must exceed the interval required to intervene. This is where the analysis departs from the maintenance framing, because the intervention preventing flaring is not the same as the one preventing machine damage. Preventing machine damage requires an outage before failure. Preventing flaring requires an outage that is planned rather than forced, which means one coinciding with a period in which the plant can accommodate the loss of the machine, and such periods occur on a schedule determined by shipping, feed availability and the wider operating plan. The operating plan against which such a window must be found is the output of a planning function with its own constraints and its own literature (Amayo, Owulade, & Isi, 2023, 2024), and the binding constraint on the intervention therefore sits outside the function that owns it.

4.1.3 Step three: intervention opportunity

The third step is intervention opportunity. Given adequate lead time, an opportunity must exist within it. In a facility running at capacity against a delivery programme, an opportunity to take a machine out of service may not occur within a lead time of several weeks, and the detection is then a warning with no corresponding action. The programme has performed correctly and the flaring occurs anyway. Materials availability enters at the same point, because an opportunity arriving before the part does is not an opportunity (Okonkwo, Agbabiaka, Ogunwole, Mayo, & Okeke, 2021; Okonkwo, Ogunwole, & Okeke, 2018b; Okonkwo, Mayo, & Okeke, 2023).

4.1.4 Step four: intervention effectiveness

The fourth step is intervention effectiveness. The maintenance performed must address the degradation. Effectiveness for machinery interventions is well below unity, and the record of repeat failures following intervention is available in most facilities' maintenance history and is rarely analysed as a performance measure of the diagnostic rather than of the repair. Recurrence tracking of this kind is standard in incident investigation practice, where a corrective action that does not address the mechanism is identified by the return of the event rather than by review of the action itself (Obriki & Arumosoye, 2024b; Adeyelu, 2026; Obogo, Arumosoye, & Obriki, 2020a).

The probability that a given degradation event results in an avoided flare is the product of these four. A programme with detection probability of 0.8, lead time adequacy of 0.7, intervention opportunity of 0.6 and intervention effectiveness of 0.85 prevents rather less than a third of the flare events its detection capability alone would suggest. The figures are illustrative; the point is that multiplication determines the outcome and that reporting only the first factor overstates the programme considerably.

4.2 Lead Time as the Binding Constraint

The chain analysis identifies steps two and three, jointly the lead time question, as the likely binding constraint in a liquefaction context, and the reasoning points to remedies quite different from those an equipment-focused analysis suggests.

Detection sensitivity is where technical effort concentrates, and improving it produces earlier detection. Earlier detection increases lead time, which increases the probability that an opportunity falls within it. So far the equipment framing and the flaring framing agree. They diverge on what to do when lead time is inadequate.

The equipment framing responds by improving detection further, and the prognostics literature surveyed above is largely an elaboration of that response. The flaring framing observes that lead time adequacy is a relationship between two quantities and that the second, the interval required to intervene, is also modifiable. That interval comprises the time to confirm the diagnosis, to obtain parts and resources, to secure an intervention opportunity in the operating plan, and to perform the work. Of these the third is frequently the longest and is entirely organisational.

This suggests an intervention unusual in practice: treating condition monitoring findings as an input to operational planning rather than solely to maintenance planning. A finding indicating that a compressor will require intervention within six weeks is information the operating plan should incorporate, because the plan determines whether an opportunity exists. In most facilities the finding goes to maintenance, maintenance schedules against equipment availability, and the operating plan is constructed independently. The coordination failure is structural and the remedy is a shared planning input rather than a technical improvement. Sector accounts of data-driven industrial control describe the same shift and identify data integration across systems, rather than sensing capability, as the practical constraint (Onyeke, Odujobi, Adikwu, & Elete, 2024). The integration point is well supported elsewhere. Records of condition, work and materials sit in systems designed independently of one another, and integration rather than instrumentation is repeatedly identified as the constraint on using them together (Okonkwo, Ahiaeke Patrick, Okeke, & Mayo, 2023; Okonkwo, Agbabiaka, Mayo, & Okeke, 2024a, 2024f). Service management platforms are the usual mechanism by which a shared planning input is operationalised, and the review literature on them is candid about the organisational preconditions that determine whether the mechanism is used as intended (Okonkwo, Agbabiaka, Mayo, & Okeke, 2024e).

A second implication concerns which machines warrant monitoring investment. The flaring framing weights machines by the flare volume their failure produces rather than by their repair cost, and these rank differently. A machine whose failure forces a train shutdown is a different proposition from one whose failure reduces rate, even where the second is more expensive to repair. Coverage decisions made on maintenance criticality will not match those made on flaring consequence, and facilities generally use the former. The general literature on the transition from reactive to predictive regimes addresses the organisational dimension of this shift (Sunday, Omoegun, Essien, & Oluokun, 2020), and implementation-level accounts describe the monitoring workflow as operating facilities encounter it (Omoegun, Sunday, Essien, & Oluokun, 2023). Programme design for preventive maintenance in energy generation settings addresses the scheduling and coverage questions directly

(Yeboah, Enow, Ike, & Nnabueze, 2024). The materials dimension of the intervention interval has its own literature and it maps directly onto the third step of the chain. Materials readiness has been modelled explicitly as a determinant of maintenance-driven supply chain performance (Okonkwo, Agbabiaka, Ogunwole, Mayo, & Okeke, 2021), inventory availability has been linked to plant uptime in energy facilities (Okonkwo, Ogunwole, & Okeke, 2018b), predictive procurement planning has been framed around sustaining operational uptime rather than around cost (Okonkwo, Agbabiaka, Mayo, & Okeke, 2024c), and supply chain resilience has been treated specifically for gas processing plants and critical infrastructure (Ogunwole, Okonkwo, Agbabiaka, Mayo, & Okeke, 2021). Where a detection has adequate lead time and the part does not exist on site, the constraint is procurement rather than diagnosis. Asset lifecycle management and inventory visibility have been modelled as a single problem, which is the correct framing here since a spare that exists but cannot be located has the same effect on lead time as one that was never purchased (Okonkwo, Mayo, & Okeke, 2023). Predictive maintenance scheduling for ageing infrastructure addresses the same optimisation from the asset owner side (Uduokhai, Nwafor, Sanusi, & Garba, 2025). The wider procurement literature supports the same point from several directions. Risk management for engineering, procurement and construction work in gas processing establishes the exposure (Agbabiaka, Okonkwo, Ogunwole, Mayo, & Okeke, 2019); regulatory conditions shape what can be bought and how quickly in a high-hazard environment (Okonkwo, Ogunwole, Mayo, & Okeke, 2021); logistics performance determines when it arrives (Okonkwo, Agbabiaka, Ogunwole, Mayo, & Okeke, 2020; Okonkwo, Agbabiaka, Mayo, & Okeke, 2024d); and supplier relationships determine whether an expedited request is honoured at all (Akinleye & Adeyoyin, 2022b; Akin-Oluyomi, Atima, & Akinleye, 2024; Ike, Ogbuefi, Nnabueze, Olatunde-Thorpe, Aifuwa, Oshoba, & Akokodaripon, 2021). Predictive approaches to the same problem have been developed on the demand side (Aifuwa, Oshoba, Ogbuefi, Ike, Nnabueze, & Olatunde-Thorpe, 2020; Tonoyan, Dada, & Ayivi-Donkor, 2024a; Akin-Oluyomi, Atima, Akinleye, & Okoruwa, 2023) and automation and negotiation practice on the transactional side (Akinleye & Adeyoyin, 2021, 2022a; Okonkwo, Ogunwole, Okeke, & Mayo, 2019). National and network-level treatments place the same problem at a scale where the reliability of energy supply is the stated objective (Okonkwo, Agbabiaka, Mayo, & Okeke, 2024b; Okonkwo, Agbabiaka, Okeke, & Mayo, 2025).

4.3 The Flaring Consequence

The consequence against which the programme is being evaluated deserves its own treatment, because its magnitude is frequently understated in the maintenance business case.

Flaring is now externally observable and independently estimable at facility level through satellite radiant heat measurement (Elvidge, Zhizhin, Baugh, Hsu, & Ghosh, 2016), which means a facility's flaring performance is visible irrespective of its own reporting. The relief and disposal system design basis governs what reaches the flare and at what rate (American Petroleum Institute, 2014c, 2020).

The emissions accounting is more consequential than the hydrocarbon loss in most current regulatory environments. Combusted gas produces carbon dioxide at a rate determined by throughput and combustion efficiency, and the unburned fraction is released as methane. The supply chain literature establishes both the significance of the methane component and the wide range of published estimates for it (Balcombe, Anderson, Speirs, Brandon, & Hawkes, 2017; Balcombe, Brandon, & Hawkes, 2018), and facility-scale reconciliation work has repeatedly found component-level inventories to understate measured totals (Zavala-Araiza et al., 2015; Alvarez et al., 2018). The distribution of emissions across sources is strongly skewed (Brandt, Heath, & Cooley, 2016), which has the consequence that a single equipment failure producing sustained flaring can dominate a facility's annual figure.

The life cycle framing places facility flaring within the wider supply chain accounting by which liquefaction cargoes are increasingly judged commercially (Abrahams, Samaras, Griffin, & Matthews, 2015; Roman-White et al., 2021), and the process context is set out in the standard technical treatments (Mokhatab, Mak, Valappil, & Wood, 2014; Lim, Choi, & Moon, 2013; Kidnay, Parrish, & McCartney, 2011). Sector reviews of liquefaction technology address the recovery routes available for gas that would otherwise be flared (Ozowe, Ukato, Jambol, & Daramola, 2024; Rahimpour & Jokar, 2012). The commercial machinery through which that accounting reaches the operator is developing quickly, and the relevant work covers carbon accounting at the project decision gate (Abdulhadi & Hamdan, 2026a), the organisational capability required to manage it (Abdulhadi & Hamdan, 2026b), the contractual mechanisms by which it is priced into delivery (Abdulhadi & Hamdan, 2026c), and the reporting infrastructure through which it is verified (Abioye et al., 2023; Okojie, Filani, Ike, Okojokwu-Idu, Nnabueze, & Ihwughwavwe, 2023). Digital twin approaches to environmental compliance in oil, gas and utilities confront the same reconciliation problem this paper raises about avoided emissions, and reach a compatible conclusion that observable process measures are more defensible than modelled outcomes (Ike, Okojie, Nnabueze, Idu, Filani, & Ihwughwavwe, 2025; Okojie, Ike, Idu, Nnabueze, Filani, & Ihwughwavwe, 2023).

The implication for the maintenance business case is direct. A condition monitoring programme justified on avoided repair cost and availability has omitted the emissions consequence, which in a facility operating under a net zero commitment or a carbon price may exceed both. Two further strands complete the accounting picture: atmospheric impacts of production and use have been reviewed at sector scale (Allen, 2014), and the functional definition of a super-emitter supplies the operational criterion for the abnormal-condition category that dominates the total (Zavala-Araiza et al., 2015b; Zavala-Araiza et al., 2017; Duren et al., 2019; Cusworth et al., 2021). Two properties of the chain deserve emphasis because they bear on where improvement effort should go. The first is that the links are not independent. Improving detection sensitivity lengthens the interval between detection and failure, which raises lead time adequacy and, through it, opportunity conversion; so a gain at the first link propagates. But the propagation is bounded by the opportunity distribution, which is set outside the maintenance function entirely, and beyond a certain sensitivity the additional lead time buys nothing because the constraint has moved. The second property is that the links differ in how cheaply they can be measured. Detection rate requires retrospective examination of monitoring records against the failure record, which is laborious but requires no new data. Lead time distribution and opportunity conversion are computable directly from records the facility already keeps, at essentially no cost. Intervention effectiveness requires only that recurrence be tracked against the original finding rather than logged as a fresh event, which is a change to how work orders are coded rather than a new activity. The whole measurement set is therefore obtainable from existing systems, which distinguishes it sharply from the counterfactual estimate it replaces. A worked illustration makes the multiplication concrete, and the numbers below are stated as illustration rather than estimate. Consider a facility with four refrigerant compressor trains, each monitored continuously, experiencing on average six degradation events per year across the fleet that would progress to functional failure if unaddressed.

Suppose monitoring detects four of the six, giving a detection rate of 0.67. Of those four, suppose three are detected far enough ahead that an intervention could in principle be completed, giving lead time adequacy of 0.75. Of those three, suppose an outage opportunity actually falls within the lead time for two, giving opportunity conversion of 0.67. And suppose one of those two interventions fully arrests the degradation while the other is followed by recurrence within six months, giving intervention effectiveness of 0.50. The programme has then prevented one failure out of six, and its contribution to avoided flaring is one sixth of the fleet total rather than the two thirds its detection performance alone would suggest. Reported as detection rate, the programme looks effective. Reported as the product, it does not. The purpose of the illustration is not the arithmetic but the observation that the reporting convention determines which of those two impressions management receives, and only one of them supports a correct decision about where to invest next. The wider transition literature bears on this in a way that is easy to miss. The value attached to an avoided tonne is not a technical parameter but a policy and market one, and it varies by jurisdiction, by counterparty and over time (Adenuga, 2022; Komi & Adeniji, 2024b). A programme justified against a carbon price is justified against a variable the facility does not control, which is itself an argument for measuring the programme on quantities it does.

5. DISCUSSION

5.1 Why the Standard Metrics Do Not Measure the Outcome

Predictive maintenance programmes are measured by a standard set of indicators, and every one of them can improve while flaring is unchanged.

Findings raised measures detection activity. A programme can raise more findings by lowering thresholds, which increases false positives without increasing prevented failures. The false positive consequence is not neutral: it consumes investigation resource and, on the automation reliance evidence, degrades the credibility of the programme with the planners who must act on it. The security operations literature has quantified this effect more carefully than the maintenance literature has, because its alert volumes force the issue (Adegbite, Adebayo, & Ahmed, 2023, 2024b; Adebayo, Adegbite, & Ahmed, 2023).

Unplanned maintenance avoided is a counterfactual attribution made by the maintenance function about its own performance, and it counts avoided maintenance events rather than avoided flaring. A finding preventing a bearing failure on a spared pump has avoided unplanned maintenance and no flaring at all.

Availability improvement measures the outcome the maintenance function is accountable for and aggregates across equipment without weighting by flaring consequence. Mean time between failures measures reliability and is influenced by many factors other than the monitoring programme, with a lag long enough that programme changes are not attributable within a reasonable reporting period.

None of these is a bad metric for its own purpose. The observation is narrower: a facility justifying a condition monitoring programme partly on flaring reduction and then measuring it entirely on maintenance indicators has no evidence for the part of the justification that concerns flaring, and will not detect a programme that has ceased to deliver it. The general form of this problem in organisational measurement is long established (Kerr, 1975). The general problem of measuring the activity rather than the outcome recurs in performance management across sectors (Adelanwa, Basnet, & Anene, 2024; Tonoyan, Dada, & Ayivi-Donkor, 2024b), and the assurance literature has approached it from the audit side by asking what evidence would support the claim being made rather than what data happen to be collected (Akomolafe & Agu, 2018; Akomolafe, Agu, & Bello, 2023, 2025).

5.2 A Measurement Approach That Avoids the Counterfactual

The direct measure, flaring avoided, is a counterfactual and is contestable in every individual case, because the claim that a failure would have occurred and would have caused flaring cannot be verified once the intervention has been made. This is the fundamental difficulty in demonstrating preventive value and it is not soluble by better estimation.

The proposal is to measure the observable chain instead. Each of the four steps produces observable events and each admits a rate computable from records the facility already holds. Each rate is computed from records held in systems the facility already operates, so the practical obstacle is integration and data quality rather than collection (Okonkwo, Ahiaeke Patrick, Okeke, & Mayo, 2023; Aliliele, Mbonu, Uzoka, & Iwuanyanwu, 2025b; Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2021). Where the underlying records are of uneven quality, classification and traceability practice supplies the necessary discipline (Aliliele, Mbonu, & Iwuanyanwu, 2024; Mbonu, Aliliele, Iwuanyanwu, & Uzoka, 2022).

Detection rate is computed retrospectively from equipment failures that caused flaring, by examining whether a detectable signature was present in the monitoring record before failure. This is the most informative single exercise available, because it distinguishes failures that were not detectable from failures that were detectable and not detected, and only the second indicates a programme deficiency.

Lead time distribution is computed from detections followed by intervention, recording the interval between finding and intervention. The distribution rather than its mean is the quantity of interest, since the failures that matter are in the tail.

Opportunity conversion is the proportion of findings with adequate lead time that received an intervention within it. This measure exposes the coordination failure between maintenance and operational planning, and is the measure most likely to be organisationally unwelcome for exactly that reason. Visibility measures of this kind are familiar from supply chain practice, where end-to-end traceability is valued precisely because it exposes handovers that each function separately reports as successful (Nnabueze, Ike, Olatunde-Thorpe, Aifuwa, Oshoba, Ogbuefi, & Akokodaripon, 2021; Okoruwa, Babatope, Akokodaripon, & Akinleye, 2024, 2025; Babatope, Akokodaripon, Akinleye, & Okoruwa, 2023).

Intervention effectiveness is the proportion of interventions not followed by recurrence of the same degradation within a defined period. This measures diagnostic and repair jointly and is computable from maintenance history without additional collection.

Reporting these four alongside the flaring record allows the relationship to be examined without any individual counterfactual claim. A facility whose opportunity conversion is low knows where its programme is losing value irrespective of whether it can attribute a specific avoided event.

5.3 Relation to Leading Indicator Practice

The measures proposed here are leading indicators in the process safety sense, and the relationship to established indicator practice is worth stating.

Indicator guidance distinguishes lagging indicators recording outcomes from leading indicators recording the condition of the systems intended to prevent them, and requires that leading indicators be selected for their relationship to the outcome rather than for availability (American Petroleum Institute, 2016; Health and Safety Executive, 2006). The risk based process safety framework situates mechanical integrity and asset reliability within the wider management system (Center for Chemical Process Safety, 2007). The applied safety literature has produced a large body of work on this selection problem: the relationship between an observation activity and the outcome it is meant to predict (Obriki & Arumosoye, 2019, 2023; Obriki, Arumosoye, & Ozobu, 2025), the use of near-miss and hazard observation data as an indicator stream (Arumosoye & Obriki, 2019; Obogo, Arumosoye, & Obriki, 2021), continuous monitoring as an alternative to periodic inspection (Obriki, Arumosoye, & Obogo, 2023), and predictive analytics applied to the resulting data (Obogo, Ozobu, Garba, & Adio, 2026; Arumosoye, Obriki, & Ozobu, 2026). The organisational maturity conditions under which such indicators are used rather than merely reported have been modelled explicitly (Arumosoye & Obriki, 2021; Obriki & Arumosoye, 2020).

The chain measures satisfy the selection requirement in a specific way: each corresponds to a link whose failure breaks the chain, so their relationship to the outcome is structural rather than statistical. This is a stronger basis than the correlation-based selection indicator programmes frequently use, and it means the measures remain interpretable in a period with no flaring events, which correlation-based indicators do not.

The counterpart caution applies. Any measure carrying consequence will be managed, and each of the four is manageable: detection rate improves if thresholds fall, opportunity conversion improves if findings with poor lead time are not raised. Reporting them as a set rather than individually is the available control, since manipulations improving one degrade another. The organisational analyses of major accidents supply the general warning about audit regimes that measure process compliance while the underlying hazards go unexamined (Hopkins, 2000, 2008; Reason, 1997; Hollnagel, 2004). A final observation concerns who should own the measurement. The four rates span three functions: detection sits with condition monitoring, lead time and opportunity conversion sit at the interface between maintenance planning and operations, and intervention effectiveness sits with the maintenance execution function. No single one of those functions can compute the set, and each has an interest in the link it owns appearing favourable. That is the ordinary condition under which a measure becomes an advocacy instrument rather than a diagnostic one. The structural remedy is the same one the alarm management literature reaches for the equivalent problem: locate ownership of the reported set with a role that is accountable for the outcome rather than for any single link, and report the four together so that a gain in one purchased at the cost of another is visible on the face of the report. It is worth being explicit about what the four measures would and would not settle, because a measurement scheme that promises more than it delivers invites the same overclaiming this paper criticises. They would settle where in the chain a given programme is losing value, which is the question that determines what to do next and which no current reporting answers. They would not establish the absolute quantity of flaring avoided, because that remains counterfactual, and they would not by themselves justify the programme against an alternative use of the same resource. What they permit is comparison over time within one facility and, where counting conventions are agreed, between facilities. That is a narrower claim than programme justification and a considerably more defensible one. The wider indicator literature makes the same distinction between measures that describe the condition of a protective activity and measures that establish its effect, and it is consistent in holding that the first is achievable and the second usually is not (American Petroleum Institute, 2016; Health and Safety Executive, 2006; Hopkins, 2009). Governance arrangements for contractor and subcontractor performance face an identical incentive problem and have converged on the same remedy of reporting a set rather than a headline (Arumosoye & Obriki, 2020; Obriki & Arumosoye, 2024a; Obogo, Uduokhai, & Ozobu, 2021). Executive-level reporting of a technical posture has been treated most explicitly in cyber risk quantification, where converting a set of process measures into a single defensible statement is the central difficulty of the field (Adegbite, Adebayo, & Ahmed, 2024a, 2025). The problem takes its strongest form where a measure is attached to remuneration, since a measure that determines reward will be optimised against, so the design question is not whether the measure can be gamed but whether the set is constructed such that optimising it and improving the outcome are the same act. This is the strongest argument available for reporting the four rates together and for locating their ownership with a role accountable for the outcome rather than for any single link.

5.4 Organisational Preconditions

The measurement scheme proposed here is cheap in data and expensive in coordination, which places it among organisational changes rather than technical ones, and the literature on such changes is consistent about what determines whether they hold. Procedure design determines whether a new coding convention for work orders survives contact with the execution function (Eyetsemitan, Oyeleye, Ambali, & Fadayomi, 2022; Ambali, Eyetsemitan, Oyeleye, & Fadayomi, 2021). Governance alignment across functions that do not report to one another is the specific difficulty here, and it has been treated directly in joint venture and multi-contract settings, which is the configuration most liquefaction facilities are in (Eyetsemitan, Ambali, Oyeleye, & Fadayomi, 2020; Amayo, Owulade, & Isi, 2023; Ike, Aifuwa, Nnabueze, Olatunde-Thorpe, Ogbuefi, Oshoba, & Akokodaripon, 2024). And the human factors literature is a reminder that the people who must act on a finding have their own workload and their own working model of how reliable the finding is (Onche, Adegbite, & Ogbonna, 2026; Onche, Ogbonna, & Adegbite, 2024).

Where a facility elects to build the reporting itself rather than buy it, the relevant experience is in analytics delivery rather than in maintenance engineering: lifecycle performance management of infrastructure data (Adelanwa, Basnet, & Anene, 2023a), the construction of forecasting and risk models on transactional records (Adelanwa, Basnet, & Anene, 2023b; Tonoyan, Dada, & Ayivi-Donkor, 2021, 2022), and the governance arrangements that keep such systems trustworthy once they begin to influence decisions (Akomolafe, Agu, & Bello, 2025; Aliliele, Mbonu, Uzoka, & Iwuanyanwu, 2025a). Lean and continuous improvement practice supplies the discipline for acting on what the measures reveal, and in particular for resisting the temptation to act on the measure rather than on the constraint it identifies (Efobi, Akinleye, & Fasawe, 2022; Ike, Ogbuefi, Nnabueze, Olatunde-Thorpe, Aifuwa, Oshoba, & Akokodaripon, 2022; Efobi, Akinleye, & Fasawe, 2023).

6. LIMITATIONS

This paper presents an analytical framework and reports no data. The illustrative conditional probabilities are not measurements and should not be read as estimates.

The claim that lead time rather than detection sensitivity is the binding constraint is an argument from the structure of the liquefaction operating context and would be falsified by measurement showing high opportunity conversion and low detection rate. That measurement is available to any facility with a condition monitoring history and a flaring record.

The analysis addresses rotating machinery and generalises poorly to other failure modes producing flaring, notably instrumentation failures and control system faults, whose degradation signatures are different in kind. Instrumentation and control failures are better addressed by the industrial control systems literature, where anomaly detection operates on process data rather than on machinery signals and the architecture of the monitoring is itself a security question (Adegbite, Adebayo, & Ahmed, 2020, 2022; Ahmed, Adegbite, & Adebayo, 2021; Jimoh, Abolle-Okoyeagu, Ahmed, & Lawal, 2023).

The paper treats flaring as the outcome of interest, reflecting a framing in which emissions and hydrocarbon loss dominate. A facility whose principal concern is production continuity would construct the consequence weighting differently, though the chain structure would be unchanged. Consequence weightings of this kind have been constructed in other settings for environmental, safety and financial outcomes, and it is generally the weighting rather than the analysis that determines the resulting priorities (Arumosoye, Obriki, & Ozobu, 2025; Ike, Aifuwa, Nnabueze, Olatunde-Thorpe, Ogbuefi, Oshoba, & Akokodaripon, 2024; Akin-Oluyomi, Atima, & Akinleye, 2023).

Finally, the retrospective detection analysis recommended here has a selection problem that should be acknowledged. Examining monitoring records after a failure, knowing a failure occurred, makes signatures easier to identify than they were prospectively. The analysis therefore establishes an upper bound on what could have been detected rather than an estimate of what would have been, and blind review by an analyst not told which records precede failures is the available correction. A further boundary concerns generalisation across facility configurations. The chain was developed with a multi-train liquefaction facility in view, where a compressor failure removes a discrete and large block of capacity and the flaring consequence is correspondingly sharp. In a single-train facility the same failure produces a total shutdown and the consequence is different in kind rather than in degree. In a facility with substantial intermediate storage the consequence is buffered and may not reach the flare at all. The four rates remain computable in each case, but the weighting by flare volume that the paper recommends for selecting monitoring coverage would produce quite different priorities, and the argument that machines should be ranked by flare consequence rather than repair cost is strongest precisely where the configuration makes those two rankings diverge.

7. CONCLUSION

Non-routine flaring from equipment failure and the condition monitoring that could prevent it are managed by different functions, measured on different indicators, and connected by no shared metric. The connection is analytically straightforward and the obstruction is organisational.

The causal chain from degradation to avoided flaring runs through four conditional steps whose probabilities multiply, so a programme reporting only its detection performance substantially overstates its effect. Lead time adequacy and intervention opportunity are the likely binding constraints in a facility operating at capacity, and both are organisational rather than technical.

The rapid maturation of prognostics has improved remaining useful life estimation without addressing the opportunity constraint. Where the limiting factor is whether an outage window exists rather than whether the failure date is known, a better estimate improves the plan and does not avert the flare. This is not an argument against prognostics; it is an argument about where the marginal effort returns most.

The counterfactual problem that has frustrated demonstration of preventive value is avoidable. Measuring the four links, each of which produces observable events, permits the programme to be assessed without any claim about what would have happened. The retrospective examination of monitoring records preceding flare-causing failures is the single most informative exercise available and requires no new data. This is a measurement claim of a kind made routinely in adjacent disciplines, where a protective activity is assessed on the condition of the chain it maintains rather than on the events it is credited with preventing (Obriki, Arumosoye, & Ozobu, 2025; Adegbite, Adebayo, & Ahmed, 2025).

And machines should be selected for monitoring investment by the flare volume their failure produces rather than by their repair cost. These rank differently, and most facilities use the wrong one.

Competing Interests

O. A. Akano is employed by Chevron Nigeria Limited, F. E. Adikwu by Waltersmith Refining and Petrochemical Company Ltd, and C. Amarahobu by NNPC Energy Services Ltd (EnServ). All three are employed in the oil and gas sector, which is the sector this paper examines, and each therefore has a professional interest in the condition monitoring and flaring management practices the paper discusses. O. Ekelemu is an independent researcher and declares no competing interests. No author holds a financial interest in any condition monitoring vendor, instrumentation supplier, analytics product or service named or implicated in this review, and no author has received consultancy income, honoraria or equity from any such party. The paper draws on no proprietary operating data from any employer. The views expressed are those of the authors alone and do not represent the positions of their employers, none of which reviewed, approved or otherwise influenced the content of the manuscript or the decision to submit it.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors. The authors received no financial support for the research, authorship or publication of this article, and no employer provided material support for the work.

Data Availability

No datasets were generated or analysed during this study. The paper is an analytical review and reports no primary or secondary data. The conditional probability values used in the worked illustration in Section 4 are stipulated for exposition rather than derived from any dataset, are stated in full in the text, and require no separate deposit. All literature on which the review draws is listed in the References and is available from the cited publishers.

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