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Multi-scale digital twins & AI analytics for lifecycle insights and accelerated energy solutions

Digitalizatiion, Connectivity, Artificial Intelligence & Cyber Security

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ABSTRACT

The analysis of operating profiles and highly non-linear energy prices demonstrates that asset reliability is critical, often required with relatively immature applications. It is therefore critical to analyze extensive measured data sets quickly and concisely during product definition and launches.

Leveraging INNIO Group's extensive fleet of connected assets, we understand behaviors of systems across multiple orders of magnitude. Analytics have been developed connecting microscopic material failure modes, to operational data.

By connecting these behaviors using advanced analytic techniques, multi-level digital twins provide powerful prediction machines. The massive scale of more than 13,000 active engines connected to the myplant platform and the further use of AI techniques has allowed the rapid analysis of these twins for powerful insights, enabling rapid decision making for product development.

The evolution of the system has then progressed to allow edge-based twins enabling local control of operating parameters to extend asset lifetime.

This has enabled the reduction of product maturity cycles by 70% using 30% of the analysis resource.

This paper describes the critical elements of this approach across product lifecycle.

1. INTRODUCTION

The continued evolution of the global energy markets, driven by factors such as fast-growing energy demand, the integration of renewables into the energy mix, and the emergence of new applications with high reliability requirements, is necessitating the rapid development of innovative energy solutions. These solutions must be tailored to meet the specific needs of different applications and customers and support their demands for reliability, sustainability, and efficiency in the energy sector.

In this dynamic context, the ability to accurately model and represent energy systems becomes increasingly important. Beyond traditional engineering approaches, there is a growing need to focus on system reliability, ensuring that energy solutions not only integrate seamlessly with existing infrastructures but also enhance overall performance. This comprehensive understanding of system dynamics is essential to effectively complement renewable energy sources and address the challenges posed by evolving market demands.

In this context, the key requirements for energy solutions to complement renewables can be summarized.

1. Reliable power
2. Maximum efficiency
3. Minimum emissions
4. Maximum power stability
5. Rapid starting times
6. Minimum life cycle and investment cost
7. Regulatory compliance
8. Safe operation
9. Fuel flexibility

This paper focuses on reliable power, examining how energy systems can maintain consistent and dependable performance. This is increasingly important as we observe a trend toward heightened reliability requirements that emphasizes critical operational modes and fault ride-through capabilities.

To explore this aspect, we refer to IEEE 762 [1] as the standard for defining a state machine, which models the various operational states and transitions of power systems. According to the standard, a state machine represents the system's behavior through defined states and transitions between them. The general structure of this state machine is illustrated in Figure 1.

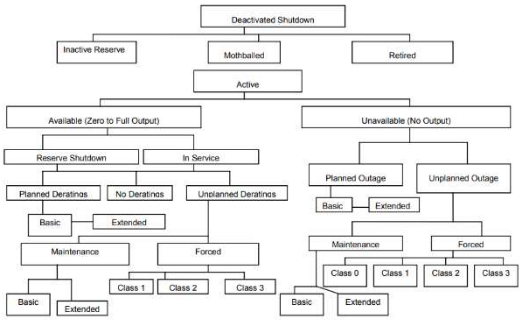

Figure 1 IEEE762-2006 [1] state machine

1.1. Innovative Integration in Energy System Development

While the individual methodologies discussed in this paper, such as digital twins, state machines, and reliability simulations, are well-established in the field, the true innovation lies in the unprecedented level of integration achieved. By seamlessly combining these advanced tools within the engineering development process, we have created a powerful system that enhances predictive accuracy and accelerates product development.

Additional innovation comes from how we integrate reliability simulations into the engineering process. Traditionally, reliability simulations are performed with proprietary software like Reliasoft and Relyence using reliability block diagrams or similar strategies. However, this method falls short in handling detailed modelling of energy demand and changing boundary conditions. To address these limitations, very high safety margins typically are introduced for boundary conditions such as required availability, emissions, and footprint.

In this paper, we discuss how the combination of advanced digital tools for reliability enables us to produce a detailed simulation of the plant. This integrated approach not only increases the reliability and efficiency of energy solutions but also helps ensure compliance with boundary conditions while enhancing safety margins to maintain cost-effectiveness for the client. This sets a new standard for adaptability in response to evolving market demands and high reliability requirements.

1.2. IEE762-2006 [1]

This standard defines a series of definitions for ratios of unit states compared to period hours (PH), which refers to the time in the active state as per Figure 1. These definitions provide clear metrics for assessing asset performance. For clarity and precision, the quantities referenced later in the document adhere to the specific formulas outlined here.

Planned outage factor (POF) gives the ratio of planned outage hours (POH) to period hours. (1) This shows the impact of planned maintenance on an asset's availability.

$$POF = \frac{POH}{PH} \times 100 \quad (1)$$

Unplanned outage factor (UOF) gives the ratio of unplanned outage hours (UOH) to period hours. This shows the impact of both unplanned outages (trips) and unplanned maintenance on an asset's availability. (2)

$$UOF = \frac{UOH}{PH} \times 100 \quad (2)$$

The forced outage factor (FOF) is a metric that represents the ratio of forced outage hours (FOH), which are unplanned shutdowns due to unexpected failures, to the total period hours. (3)

$$FOF = \frac{FOH}{PH} \times 100 \quad (3)$$

From this the overall availability factor (AF) can be derived. This is the ratio of available hours to period hours. (4)

$$AF = \frac{AH}{PH} \times 100 \quad (4)$$

The standard expands on the ratio of states and deals with multi-unit indices and derating terms.

Critically, the standard does not define reliability factor (RF) or mean time between forced outage (MTBFO). Working definitions of these are relatively straight-forward, however. (5)

$$RF = 1 - \frac{FOH}{PH} \times 100 = 1 - FOF \quad (5)$$

MTBFO is calculated as the ratio of available operating hours (AOH) to the number of forced outages from operation (NFOO). (6)

$$MTBFO = \frac{AOH}{NFOO} \quad (6)$$

By assessing availability factor, reliability factor, and MTBFO, the general performance of an asset or group of assets could be established. These methods did not, however, deal with the criticality of the demand at any given time or the availability of fuel.

As referenced in Kundur's "Power System Stability and Control,"[2] the supply of power, whether within a microgrid or a national grid, can be categorized based on various operational states and stability considerations. These categories help in understanding the dynamics and control mechanisms necessary for maintaining grid stability and reliability. The basic states defined by Kundur, which outline these operational categories, are illustrated in Error! Reference source not found..

The development of IEEE762 – 2023[3] now includes critical demand period and energy metrics and a new state reflecting resource availability.

In this update the general Reliability and availability metrics remain unchanged, however there is now the option to define critical time periods and the relative metrics. Also, variable energy resources may be quantified appropriately.

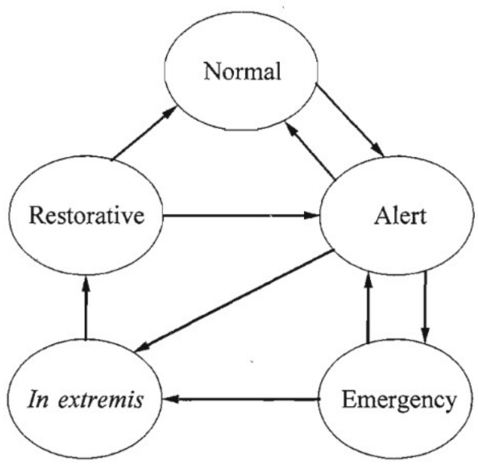

Figure 2 Power system operating states – Kundar[2]

The relative complexity of the performance metrics has increased significantly, while the usefulness to the energy market has increased.

In parallel, the deployment of digital infrastructure globally has led to the publication of the EN50600[4] series of standards.

This series of standards has a separate definition of availability and, significantly, very specific requirements for power supply development.

This standard specifies the intrinsic availability of infrastructure (A_i) under ideal operation and maintenance conditions as the ratio of MTBF to the total of MTBF and mean time to repair (MTTR). MTBF is the average time between system failures, while MTTR is the average time required to repair and restore the system to operational status. (7)

$$A_i = \frac{MTBF}{MTBF+MTT} \quad (7)$$

A critical assumption is that this is measured over 8,760 operating hours and normally refers to the infrastructure ability to provide service. It is also critical that the MTBF>>MTTR by at least one order of magnitude.

EN50600[4] does not define specific critical operating periods; instead, it specifies criticality classes for use cases and employs a 'nines' terminology, ranging from 1 to 5, to represent varying levels of reliability requirements. The availability and annual downtime requirements outlined by EN50600 are detailed in Figure 3.

Availability A	Common reference	Downtime (based on 8760 h per year)
90 %	1-nine	36,5 days
99 %	2-nines	3,65 days
99,9 % (3-nines)	3-nines	8,76 h
99,99 % (4-nines)	4-nines	52,6 min
99,999 % (5-nines)	5-nines	5,3 min
99,9999 % (6-nines)	6-nines	31,5 s

Figure 3 EN50600[4] availability and annual downtime

With one order of magnitude decrease in unreliability per nine, this serves as a useful classification of power supplies. This avoids the overreliance on MTBF statistics, which often are calculated using small numbers of failures and provide misleading comparisons.

There is still a dependency on using MTBF and MTTR figures, however. Due to the log-normal distributions normally observed, any predictions must be simulated to understand variance and necessary redundancy concepts.

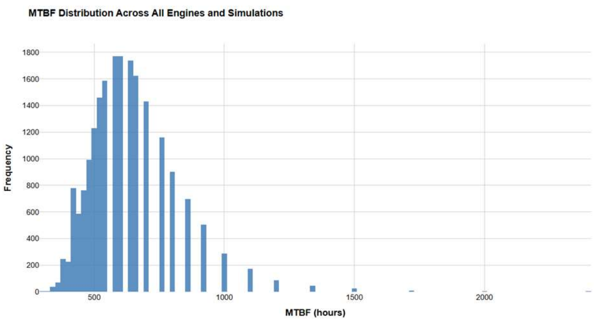

Figure 4 Annual MTBF variation

A typical distribution of TBF and TTR observed on a fleet of gensets operating with a MTBF of about 600 hours and MTTR of 5.4 hours is illustrated in Figure 4 and Figure 5 over an observation period of 8,760 hours. The results presented are calculated in accordance with the definitions introduced at the beginning of section 1.1 with the equations 1 to 7. These distributions are consistent with Poisson distributions and are as expected for this number of events. The quantization observed on the MTBF plot is explained by the number of failures being an integer.

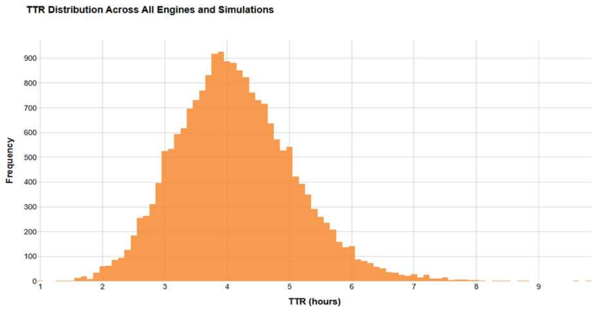

Figure 5 Annual TTR variation

It then is clear that a structured process is required to enable the development of robust plants regarding this natural variance in failures.

In the case of EN50600[4], this approach guides the specification of certain redundancy requirements. However, the standard does not offer a structured method for analyzing the resultant availability. The availability classification defined by the standard is presented in Figure 6.

The methodology for designing power solutions is increasingly moving away from single points of failure (SPOF) and toward architectures that incorporate varying levels of redundancy and independence. This shift is driven by the need to enhance reliability and lower the risk of high-consequence failures. As plant designs evolve from multiple generating assets connected to a single point of connection (SPOC) to independent chains of supply, it becomes essential to simulate the behavior of these assets. Such simulations help determine the optimal architectures that can withstand potential disruptions.

A critical aspect of this process is basing simulations on realistic operating data whenever possible, thereby avoiding an over-reliance on "black box" assumptions. This helps ensure that the simulations accurately reflect real-world conditions and provide valuable insights into the performance of the power solutions.

A further challenge arises when analyzing products for which the demand profile is not yet fully understood. As artificial intelligence (AI) continues to evolve, the demand characteristics for power solutions also change, resulting in unique power ramps that differ significantly from those observed in traditional grid supply systems. This evolution suggests that gensets may be particularly suited for AI data centers, where the demand for power can be highly variable and unpredictable.

To address these challenges, it is necessary to simulate product behavior across multiple plant configurations in parallel, even before the final demand case is known. This approach allows for a comprehensive understanding of how different configurations will perform under varying conditions, thereby helping to ensure that the power supply remains robust and reliable, regardless of the evolving demand characteristics.

item	Availability Class			
	Class 1	Class 2	Class 3	Class 4
EN 50600-2-2 Power Supply				
Availability	Low	Medium	High	Very high
Redundant sources	N	Y	Y	Y
Protected against source failure	N	Y	Y	Y
Redundant path to primary distribution	N	N	Y	Y
Protected against path failure	N	N	Y	Y
Compartmentalization	N	N	N	Y
Protected against single device failure	N	Y	Y	Y
Load operation during maintenance	N	N[1)]	Y	Y
Fault tolerant	N	N	Y[2)]	Y
EN 50600-2-2 Power Distribution				
Availability	Low	Medium	High	Very high
Redundant path	N	N	Y	Y
Protected against path failure	N	N	Y	Y
Compartmentalization	N	N	N	Y
Protected against single device failure	N	Y	Y	Y
Load operation during maintenance	N	N[1)]	Y	Y
Fault tolerant	N	N	N	Y[2)]
EN 50600-2-3 Environmental Control				
Availability	Low	Medium	High	Very high
Redundant source	N	N	Y	Y
Redundant path	N	N	Y	Y
Protected against path failure	N	N	Y	Y
Compartmentalization	N	N	N	Y
Protected against single device failure	N	Y	Y	Y
Load operation during maintenance	N	N[1)]	Y	Y
Fault tolerant	N	N	N	Y[2)]
[1)] Depending on the device being maintained. [2)] Except during maintenance.				

Figure 6 EN50600[2] summary of availability classification

This paper will explore the advanced methodologies employed to swiftly integrate these simulations into the product development process, ensuring adaptability to evolving demand profiles and enhancing the reliability of power solutions.

2. MAIN SECTION

To build a prediction machine for estimating system unreliability, INNIO Group leverages our extensive experience. The required elements are integrated into the product development cycle, drawing from historical data and operational insights. This experience-driven approach helps ensure the prediction machine is tailored to both INNIO Group and our customers' specific needs.

1. Requirements, architectures, and boundary conditions for the system to be developed.
2. Analysis of current fleets with comparable configurations and applications.
3. Definition of available simulations and quasi-real-time twins.
4. Analysis of operating fleets and twins to determine state machine behavior.
5. Abstraction of data to represent application under development.
6. Definition of necessary simulations and quasi-real-time twins.
7. Modification of development and re-simulation to minimize delta to requirements.
8. Parallel validation of both model and product during growth phase.
9. Life-cycle tracking of performance.

2.1. Requirements, architectures, and boundaries

Prior to any comprehensive understanding of a system's behavior, the appropriate requirements' flow-down and functional analysis must be executed.

The architecture(s) of the system should be defined and used to determine the appropriate transfer functions. It is critical to ensure that good system engineering practice is used and the system is appropriately specified.

The system boundary conditions are critical and need to be clearly and unambiguously defined. This may not be possible in all cases, due to the inherent uncertainty of the application, but assumptions should be made, documented, and agreed.

The use of p-chart methodology at this stage of the development is useful and facilitates the early estimation of failure modes. Interactions across domains, such as plant-level CFD analysis, is critical. In addition, climatic conditions may need to be considered as a significant input to availability studies.

The use of systems engineering methodologies, Incose[5], is critical to help ensure that the configuration and requirements remain under control during the development and that significant simulation time is not used on unrealistic combinations.

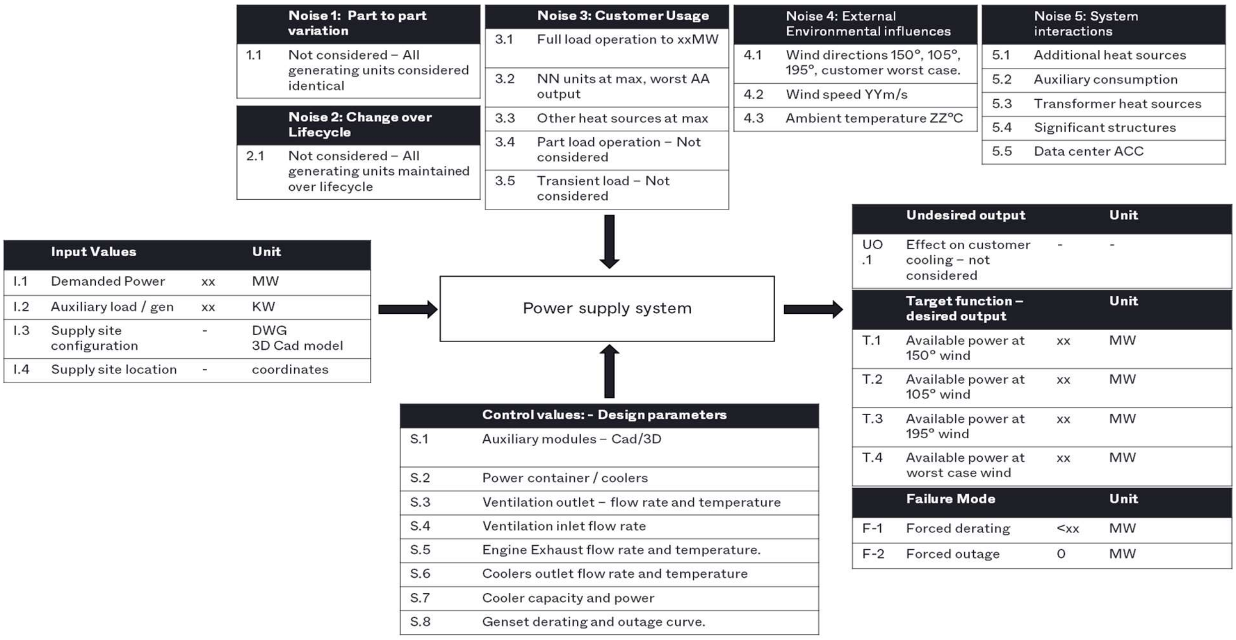

Figure 7 Power supply system cooling parameter analysis

2.2. Analysis of current fleets' comparable configurations and applications

To effectively predict unreliability of the engine, site, or fleet, understanding and representing fleet configurations and operational profiles is essential. The baseline for this is to use the extended connected fleets already available.

This section explores the complexities of configuration differences using the tree edit method and evaluates operational profiles and service intervals, providing insights crucial for enhancing predictive accuracy.

2.2.1. Configuration

The fleet configuration details the specific arrangement and components of each engine. With the INNIO Group fleet, we must deal with great variability in engine configurations – even among engines of the same type – because of the high level of customization that we offer to our customers.

By analyzing these differences, we can tune the analysis and tailor maintenance strategies accordingly. This section explores the importance of configuration analysis as a foundation for accurate reliability predictions.

Tracing all elements in the Bill of Materials (BOM) for engines presents significant challenges, particularly because not all activities are managed directly by INNIO Group. This often results in incomplete or inconsistent data, necessitating the use of realistic assumptions to bridge gaps. External suppliers and varying documentation standards further complicate the tracing process. Of particular importance are consumable components for which the replacement activities often are traced on site. For these components, it is important to combine the available service information with expected service and life models to best estimate when the parts are being replaced. Consequently, developing experience on how to make informed assumptions becomes essential to help ensure a comprehensive understanding of configuration differences.

Once a clear understanding — or a well-founded assumption —of the BOM for all units is available, it is crucial to ensure that the complexity of the configurations used in the prediction machine aligns with what is expected in the field. To achieve this, a method is needed to numerically assess the distance between any two configurations in terms of how many components differ and at which hierarchical level these differences appear.

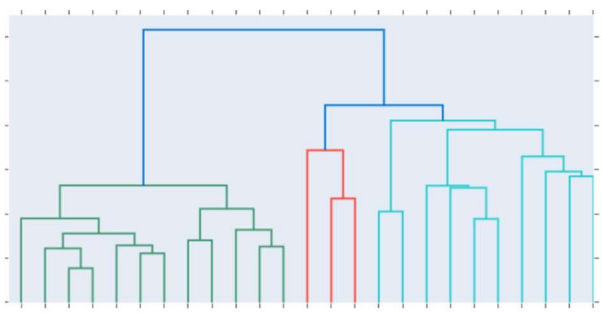

Figure 8 BOM variance tree edit diagram

The tree edit method, as detailed in Benjamin Paaßen's supplementary material for the ICML 2018 paper, "Tree Edit Distance Learning via Adaptive Symbol

Embeddings,"[6] provides a systematic approach to identify and quantify these variations, offering valuable insights into their potential impact on system reliability. A visual representation of this method applied to a small fleet of our engines is provided in Figure 8. Here, we can observe how natural clusters can be formed based on BOM similarity, illustrating the method's effectiveness in grouping engines with similar configurations.

2.2.2. Operational profiles

Operational profiles, defined primarily by the electrical and thermal demand over time from customers along with the specific requirements on engine availability, are crucial for the prediction machine to estimate fleet reliability.

Different operational environments and usage patterns significantly affect reliability and influence how units can be serviced. Similar to configuration analysis, it is essential to ensure that the prediction machine is tuned to adequately represent the way in which the units in the fleet are operated and how the operating profiles themselves differ from one another. The myplant platform, INNIO Group's advanced digital platform, plays a critical role in this process by collecting and analyzing real-time data from engines and equipment. It enables precise monitoring and management of operational parameters, ensuring alignment with actual usage patterns. Furthermore, service intervals are determined and optimized based on customer necessities, helping to ensure that maintenance schedules are tailored to enhance reliability while accommodating specific operational demands.

Once a fleet of comparable units has been identified, an initial screening for adequate operation, service history, and connectivity is critical to ensure that subsequent analysis is available.

2.3. Definition of available baseline simulations

As part of the development phase of products, several simulations are developed and executed to analyze the feasibility of the design and the compliance to the product requirements. During the design phase, the iterations between design, simulation, and validation follow the V-model. In particular, Figure 9 illustrates how field data is monitored during the validation phase. The additional step during the last phases of the validation is to develop reduced order models for key systems and critical components. The main critical systems are:

- Control system
- Thermal and energy transfer
- Structural
- Fluid-dynamics

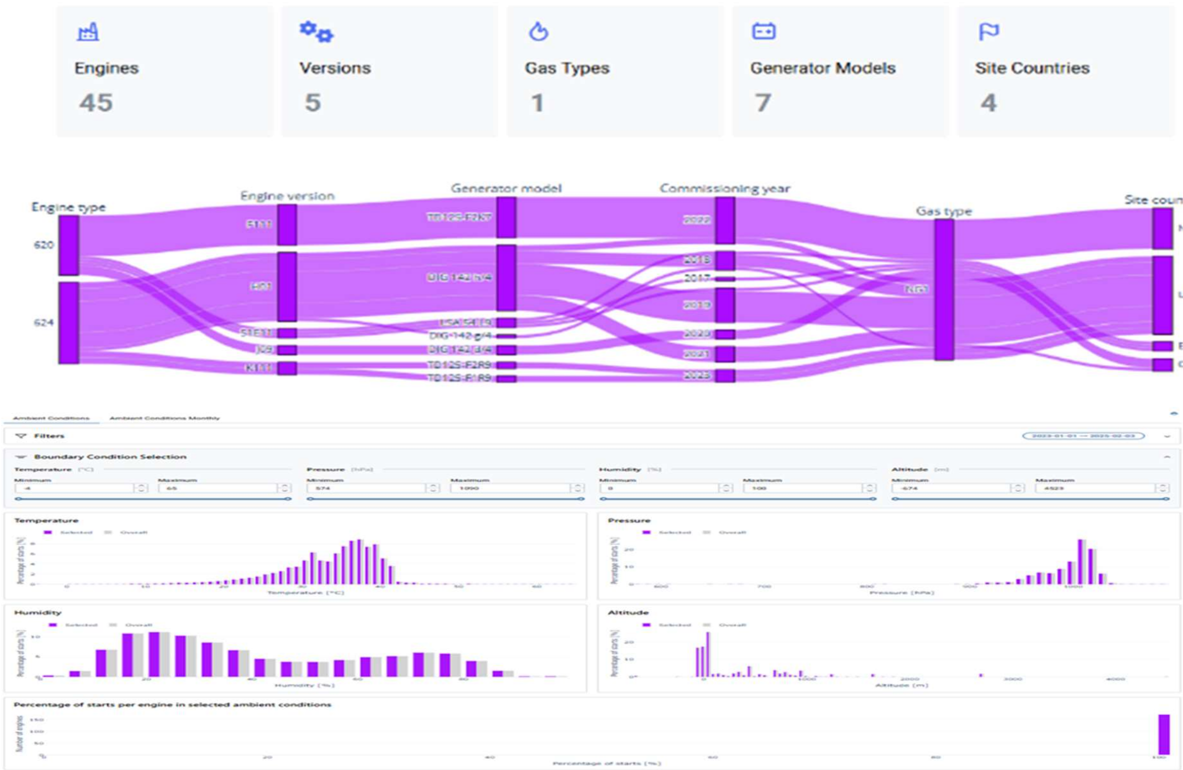

Figure 9 Application and operational analysis

The criticality of the simulations and system digital twins is driven by the results of the design failure mode and effects analysis (DFMEA) during the design phase. DFMEA defines which simulations are needed as detection and corrective actions.

2.4. Analysis of operating fleets to determine state machine behavior

A credible reliability analysis relies on accurately determining the operational states of each asset in a fleet, which requires extensive signal analysis and collaboration with controls engineers. In this work, the state machine is derived by processing a continuous stream of engine-generated messages. These messages provide detailed information on the machine performance, status, and malfunctions. Through the application of specific logics, the messages are processed into a sequence that determines the system's state at any given time. The logics define transitions between states but also identify causal alarms during forced outages. The causal alarms give information on the cause of the outage by analyzing the chain of events leading to the shutdown.

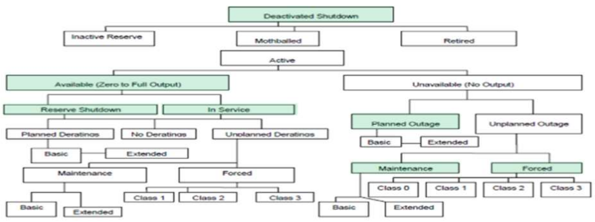

Figure 10 IEEE762[1] genset operating states structure

To further enhance our understanding of trip logic, especially in legacy systems with diverse versions of control code, we employ Large Language Models (LLMs). These models allow us to process and analyze control code, extracting the logic of trips across different software versions. This strategy needs to be combined with expert input, as it is essential to correctly characterize the logic and ensure that the interpretations align with the nuanced understanding of experienced engineers. By integrating LLMs with expert insights, we achieve a comprehensive analysis that accurately reflects the operational realities of our systems.

When deriving the state machine, certain states, such as planned and unplanned maintenance, cannot be automatically calculated and require physical input from the unit. Initially, during early development stages, this input is best gathered remotely from the asset itself, using scheduled jobs across the entire fleet. As the logic becomes more established, it can be implemented on edge devices deployed directly on individual units. These edge devices enable real-time state determination, effectively creating a digital twin that provides a virtual, real-time representation of the machine's behavior.

Once the state machine is established, it can be mapped onto other frameworks such as the one defined by the IEEE762[1] standard, thereby standardizing reliability reporting and requirement compliance efforts. While IEEE762 provides a detailed framework, other standards, such as EN50600[4], lack a specified state machine. This approach's flexibility enables the development and implementation of state machines tailored to their specific regulatory and operational environments.

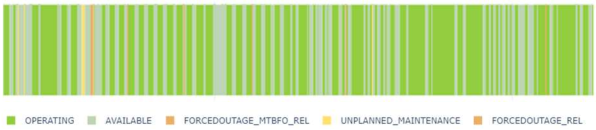

Figure 11 Genset state machine viewed as a time series per asset selected asset

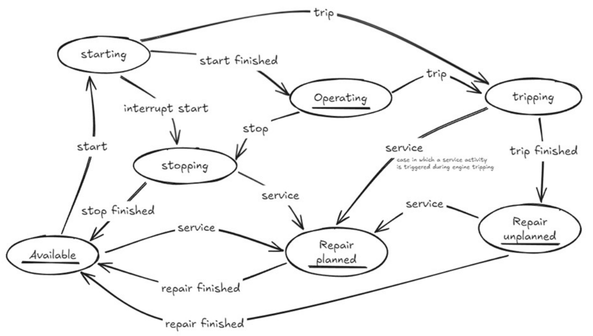

Figure 12 Markov diagram individual unit in the INNIO Group prediction machine

A semi-automatic analysis of the control system operating messages is correlated to IEEE762[1] operating states. This is supplemented by user input to the control system to determine actioned service activities.

Error! Reference source not found. highlights the set of states composing the state machine defined for the INNIO Group fleet. These states are selected among those proposed by the IEEE762 standard. Additionally, **Error! Reference source not found.** represents the resulting state machine computed for a representative asset in the fleet. Finally, based on the set of states defined by the IEEE762, Figure 12 shows the proposed Markov diagram that the INNIO prediction machine is adopting for the simulation of an asset.

2.5. Abstraction of data to represent application under development

This step consists of transforming the raw data. It involves cleaning, aggregating, and normalizing the data so that it accurately represents the application. Key information — such as boundaries, environmental conditions, and software update cycles — is consolidated into the dataset to represent the application under development. This enables the data to focus on the factors most relevant to the reliability calculations and optimization while filtering out noise or irrelevant variation.

In addition, based on the delta analysis of the baseline fleet, it is important to handle the differences in configuration and application. For configuration differences, resolved failure modes should be removed and new failure modes identified during the added DFMEA process with a clear assumption stated regarding the failure pattern. For application differences, the Parameter-Chart created should be updated with appropriate noise factors and, subsequently, updated assumptions regarding failure patterns.

A special case is when control software is updated resulting in an alternative system response, and the assumptions regarding the behavior should be validated during test phases.

All assumptions regarding changes must be clearly documented as part of the development process as validation of these assumptions is critical.

2.6. Definition of necessary simulations and quasi-real-time twins

To effectively predict system reliability and performance, the integration of simulations and quasi-real-time digital twins is essential. These tools provide an accurate, dynamic representation of the system's behavior and allow the incorporation of real-world operating conditions into the development process. The following components form the foundation of the required simulations and twins:

2.6.1. Asset configuration and part swaps

A quasi-real-time update of the BOM is critical to maintaining an accurate record of the asset configuration that incorporates maintenance activities and part swaps. This helps ensure that the predictive model reflects the current state of the system, accounting for component-level changes and their potential impact on performance. By integrating these updates, the simulation framework adapts dynamically to represent the true operational state, which is vital for reliable performance and failure analysis.

2.6.2. Controls twin

The controls twin is a quasi-real-time simulation model focused on the control system of the asset. It provides insights into the marginal distance to trips and deviations from optimal performance. This twin enables precise monitoring of control parameters and their interaction with other systems, helping to ensure that the asset operates within safe and efficient boundaries. Early detection of deviations allows for pre-emptive adjustments to avoid potential failures or suboptimal performance.

2.6.3. Thermal and energy twin

The thermal and energy twin models the thermal dynamics and energy flows within the asset under varying operating conditions. It captures the impact of environmental factors, load variations, and operational profiles on system performance and temperature distributions. By understanding these thermal and energy characteristics, this twin helps optimize cooling systems, prevent overheating, and enhance overall efficiency, particularly in demanding applications with fluctuating thermal loads.

2.6.4. Structural twin

The structural twin evaluates the impact of environmental and operating conditions on vibrations and component life. This twin is essential for understanding the long-term structural integrity of the asset, particularly under harsh conditions or high-stress scenarios. It incorporates real-time data on environmental influences, such as temperature fluctuations and mechanical loads, to predict wear and fatigue. This predictive capability is crucial for designing maintenance schedules and identifying potential failure points before they manifest in the field.

Beyond their role in simulating current asset performance, these quasi-real-time models also serve as powerful tools for optimizing the behavior of applications under development. By incorporating real-world data alongside artificial changes representing potential design or operational modifications, these models enable accurate prediction of new asset behaviors. This capability significantly enhances the development process by allowing iterative optimization grounded in realistic scenarios.

2.6.5. Integration of real data and artificial changes

The models leverage extensive real-world data collected from operating fleets to enable predictions that are based on actual asset performance under various conditions. This data is supplemented by artificial changes, such as simulated adjustments to control parameters, altered component configurations, or hypothetical operating conditions. By exploring the combined effects of real data and controlled modifications, the models provide a deeper understanding of how proposed changes might influence system reliability, efficiency, and performance.

2.6.6. Enhanced prediction accuracy

The integration of real data and artificial changes enhances prediction accuracy by accounting for complex interactions between system components and environmental conditions. For instance, the thermal twin can simulate the impact of introducing new cooling technologies under specific ambient conditions, while the structural twin can predict how different load profiles affect component life. This detailed insight enables the identification of potential bottlenecks or vulnerabilities that might not be apparent through conventional testing methods.

2.6.7. Optimization of application behavior

Using these enhanced predictive capabilities, the models facilitate optimization in several key areas:

- Design refinement: By simulating the effects of various design adjustments, the models help identify configurations that increase performance while lowering risks.
- Control strategy optimization: The controls twin enables fine-tuning of algorithms to improve stability and efficiency, reducing the likelihood of trips or operational deviations.
- Maintenance planning: The asset configuration and structural twins inform more precise maintenance schedules, helping to ensure reliability while lowering life-cycle costs.
- Operational strategy development: The thermal and energy twins allow for improved operating conditions, such as load management or thermal cycling, to enhance performance under specific application scenarios.

2.6.8. Continuous feedback loop

The iterative nature of this approach creates a feedback loop between the model predictions and actual operational data. Initial simulations guide the development of the application, while subsequent field data validates and refines the models. This continuous improvement process helps ensure that the predictions remain accurate and relevant, even as the application evolves or faces new operational challenges.

By leveraging these models for optimization, developers can confidently make data-driven decisions, accelerating the development process and ensuring that new applications achieve their performance and reliability objectives with minimal risk.

2.7. Modification of development and re-simulation to minimize delta to requirements

The optimization of the system behavior to enhance reliability then can be done using simulations and structured available data.

This step combines statistical modelling insights with design trade-offs to optimize operational modes, maintenance schedules, and resource allocations for the specific application and requirements. This collectively reduces the likelihood of failure. Feedback loops from quasi-real-time digital twins and ongoing field data collection helps to verify the optimization under realistic scenarios.

Possible solutions tweaking design variables, control algorithms, or usage parameters drive improvements that balance performance requirements, cost considerations, and reliability objectives.

As an example, the selection of power node becomes critical in a multi-unit plant development with a redundancy concept. As the number of independent units increases, the observed plant reliability tends to increase once adequate redundancy is achieved.

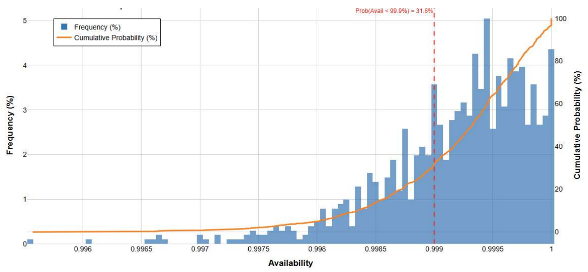

Figure 13 Intrinsic availability Monte Carlo distribution 1

Figure 13 presents some significant results derived from a Monte Carlo simulation. The x-axis illustrates the resulting availability for the simulated fleet, while the y-axis, labelled "Frequency," indicates the percentage of simulations that exhibit a reliability value within each specific bin. This visualization effectively highlights the distribution of reliability outcomes across the simulated scenarios, providing valuable insights into the fleet's performance under the tested conditions. In the example, given a redundancy strategy of $n + 2$ assets, the simulation results in a 30% chance of not meeting 99.9% over a year of plant operation. In this case, and as shown in Figure 14, the use of assets with a lower probability to trip can be seen to yield a much lower probability to not meet availability targets.

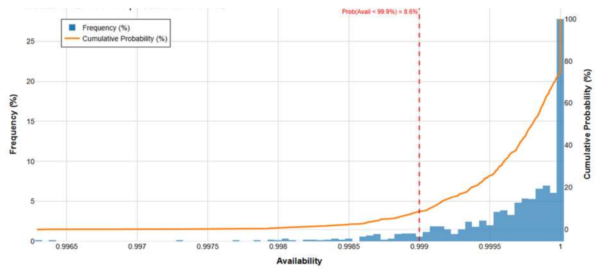

Figure 14 Intrinsic availability Monte Carlo distribution 2

2.8. Parallel validation of both model and product during growth phase (reduced order models)

As documented extensively by Duane[7] and Crow-AMSSA[8], it is critical to correctly design the launch of new products. Too rapid an introduction and discovery of new failure modes will outstrip the ability to update products, while with too slow an introduction, new failure modes will remain hidden.

Figure 15 Duane model of reliability growth

An estimation of the growth co-efficient based on similar developments is useful to plan ramp strategies. With assets that are being commissioned in large power plants, it is critical to determine a rapid method to apply changes from launch learnings while remaining in configuration control.

2.9. Life-cycle tracking of performance

As plants are commissioned, it is crucial to ensure continuous performance tracking. This is most effectively achieved through the development of analytics portals for connected assets. These systems enable real-time interrogation, allowing for the display of corresponding control system messages that indicate state changes during outages.

From this analysis and corresponding service events, rapid root cause analysis can be executed. It is critical that all failure modes are understood, particularly in the early stages of a product's life cycle where it is impossible to estimate the frequency of events. At this stage, the organization must already be in place to rapidly deploy fixes to the fielded fleet, and it is critical to have a pragmatic and open approach.

The use of a failure reporting and corrective action (FRACAS) database correlating specific actions to observed outages is critical, and cycle time to retirement of issues must be such that failure fix rate is significantly greater than failure discovery rate.

Care also is required with respect to wear out failure modes as the failure mode will not happen until a large fleet of units also may be deployed. In this case, it is critical that appropriate actions are specified in the DFMEA with outcomes validated on fleet leaders.

3. APPLICATION OF METHODS AND BENEFITS

3.1. Infrastructure

It is obvious that for this methodology to work there must be the ability to capture the operating data of the assets as part of an internet of things architecture. The specific sampling frequency, sensor signals, and controls messages will vary, depending on the product. Within this architecture it is important also to determine the processing of the measurements toward the state machine and ensure that timing issues are resolved.

3.2. Product architecture

To ensure reliability growth, the product itself must be able to be modified rapidly. The modularity and testability of subsystems plays a vital role.

With independent and testable sub-functions, software twins and hardware in the loop testing can be used to simulate outcomes.

The application of system engineering to subsystem boundaries also significantly reduces the cycle time to resolve issues as less time is spent on fault trace through activity.

3.3. Organization

The adoption of agile methodologies during product launch phase has been shown to massively simplify and accelerate launches.

With a clear availability requirement, the epic performance standard is set, normally with stories relating to launch stages. Sprints then are used to accelerate problem identification and fixing. Daily scrum helps ensure the launch team communicates.

It also is critical that the organization is available to support during this phase with appropriate controls in place to ensure the team has a stable methodology including appropriate response to inevitable failure mode discovery.

Figure 16 Genset outage pareto analysis

Communication of root cause analysis should be centralized in a single system that has a direct connection to the observed unit events.

A key aspect of the organization is also the clear acceptance that the aim of the growth phase is to discover and resolve hidden failure modes. A pragmatic and positive approach is required, with launch teams prepared and available to work quickly on solutions.

It is critical to establish acceptance test phases, with clear outcomes and appropriate planning.

3.4. Benefits

3.4.1. Product development acceleration

The journey from the concept phase to achieving availability targets is a critical aspect of product development. The integration of a digital engineering reliability process has significantly accelerated program timelines and equipped us with the tools necessary to quantify this acceleration.

Key to this advancement is the automation of state machines and metrics at the fleet level, enabling comprehensive daily analysis of entire fleets. This capability allows for the prompt detection of failures and effective resolution on a first-event basis. Furthermore, the state machine facilitates tracking the reliability growth process by employing tools such as the Duane model.

In addition to these advancements, the implementation of fleet-level reliability simulation serves as a powerful enabler for accelerating product development. This simulation capability allows for the prediction of fleet behavior in scenarios where historical data is unavailable, thereby identifying critical areas for reliability improvement. Moreover, it supports a better response to detected failures by enabling simulations of the impact that proposed solutions will have on the fleet.

In 2018, a typical program aimed at halving product unavailability required approximately three years and substantial engineering efforts. However, by 2024, an equivalent program was completed in just six months, and it used only 60% of the resources. This remarkable achievement represents a reduction to 10% of the total man-hours previously spent, with the launch time decreased by an impressive 85%.

By enabling daily analysis of the fleet state machine, issues were effectively addressed on a first-event basis, thereby eliminating the potential costs of future failures. As a result, the cost of quality at product launch, relative to sales, was reduced by a factor of 90%.

Moreover, the accelerated pace of improvement helps ensure that the launch phase is both dependable and plannable within the organization. This newfound efficiency not only enhances the reliability of product launches but also significantly optimizes resource allocation and cost management.

A list of the main tools that INNIO Group leverages to achieve the results described in this section is provided in

Table 1. A brief description of short- and long-term impact of the tools is provided.

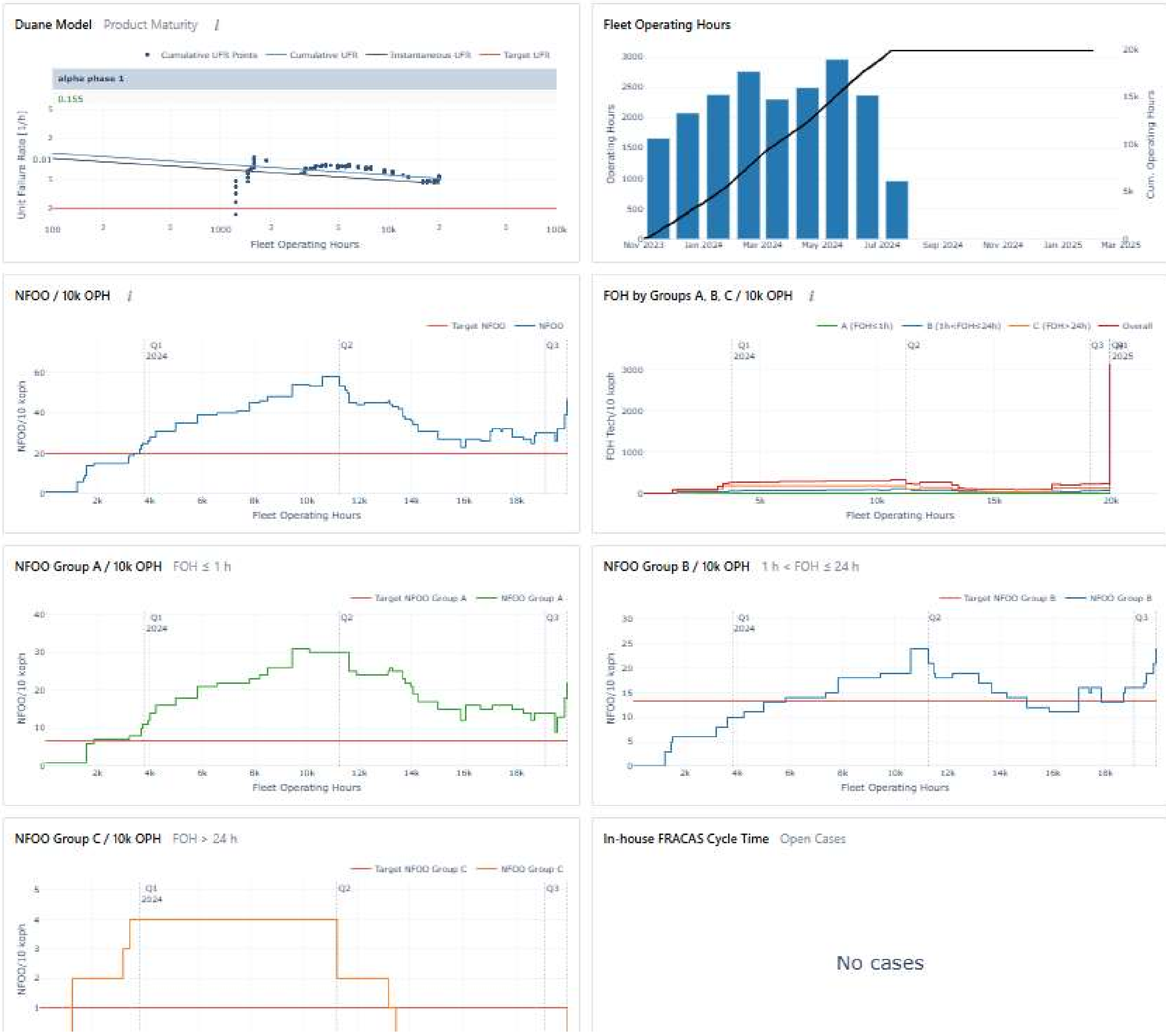

Figure 17 Life-cycle outage tracking tool

3.4.2. Development of organizational and systemic learning

The correlation of events to measured system behavior and rapid resolution also then builds the engineering knowledge of the design space. This reduces the probability of future design having repeat issues.

By coding the state patterns, alarms, and signal behavior directly into a learning system, both development and customer support diagnostics are accelerated.

4. CONCLUSIONS

The development of large, connected systems of generating assets is a powerful resource for accelerating product development. Traditional design-for-reliability methods must be updated to align with this evolution. The field has firmly moved into the digital engineering domain, employing baseline comparisons, quasi-real-time digital twins, synchronous state machines, and machine learning for engine diagnosis.

By incrementally adding capabilities and tools, we have achieved significant launch accelerations. This methodology does not eliminate the need for expert engineering but helps ensure maximum focus on the physics of failure.

Culturally, the most significant transformation is observed in the creativity of engineers, whose problem-solving abilities have become evident, fostering a pragmatic and positive approach to product development as the norm. The integration of additional digital twins into this methodology also is under development, with power system analytics yielding energy management results.

	Short-Term Impact	Long-Term Impact
Prediction Machine	Enhances immediate reliability predictions, improving the way we react to unexpected failures.	Builds a comprehensive reliability database, improving future predictions.
State Machine	Standardizes reliability reporting, improving immediate compliance efforts.	Establishes a consistent framework for long-term reliability analysis.
Quasi-Real-Time Digital Twins	Provides real-time insights into system performance, allowing for quick adjustments.	Facilitates ongoing optimization of system design and operation.
myplant Engineering Platform	Enables precise monitoring and management of operational parameters.	Supports continuous improvement in operational efficiency and reliability.
Tree Edit Method	Improves understanding of configuration differences, aiding immediate maintenance strategies.	Enhances long-term reliability predictions by refining configuration analysis.
FRACAS	Provides rapid root cause analysis, reducing downtime in the short term.	Builds a knowledge base for long-term failure prevention and corrective action planning.

Table 1 Impact and effect of main tools

5. FIGURES, TABLES AND EQUATIONS

6. DEFINITIONS, ACRONYMS, ABBREVIATIONS, (EQUATIONS)

AF:	Availability factor (4)
AH:	Available hours
A_i:	Intrinsic availability (7)
AI:	Artificial intelligence
AOH:	Available operating hours
BOM:	Bill of material
CFD:	Computational fluid dynamics
DFMEA:	Design failure mode and effects analysis
FOF:	Forced outage factor (3)
FRACAS:	Failure reporting and corrective action system
MTBFO /MTBF:	Mean time between failure / forced outage (6)
MTTR:	Mean time to repair
NFOO:	Number of forced outages from operation
PH:	Period hours
POF:	Planned outage factor (1)
POH:	Planned outage hours
RF:	Reliability factor (5)
SPOC:	Single point of connection
SPOF:	Single point of failure
TBF:	Time between failures
TTR:	Time to repair
UOF:	Unplanned outage factor
UOH:	Unplanned outage hours (2)

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