The effect of the technical level on the availability analysis: Comparison case study at equipment and component levels

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Abstract. Reliability and availability analysis is crucial at the project phase to determine whether the desired needs will be satisfied and if design adjustments, such as adding redundancy, are necessary. Reliability and availability analysis can be done at the system, equipment and component levels. Asset managers often question whether conducting availability analysis at a system level (high level) is sufficient and satisfactory or if a more detailed approach, considering individual components and failure modes is required. Thus, the purpose of this study is to model, estimate and compare availability at two different technical hierarchy levels: equipment and components. An agent-based modelling approach is used to estimate the reliability, availability of subsea safety equipment. The results show that both approaches produced similar results in terms of availability, indicating that either method can reliably predict operational availability. However, introducing more probabilistic figures, such as repair times at component and failure modes levels, makes the detailed level models more realistic compared to high-level models.

Keywords: Simulation Modelling · Agent based Modelling · System Availability · Equipment level · Component Level.

1 Introduction

Reliability, availability, and maintainability (RAM) analysis is essential in the early stages of industrial projects to ensure that system performance aligns with operational requirements [1]. These analyses help determine whether a proposed system configuration is sufficient to meet availability targets or if modifications, such as redundancy, are necessary [2]. Reliability and availability can be assessed at various hierarchical levels, including the level of the system, equipment, and components, offering different levels of detail and insight [2]. However, determining the appropriate level of detail, whether at the system level or a more granular component and the failure mode level, remains a critical challenge for asset managers and project stakeholders seeking to ensure sufficient accuracy for reliable decision making [3].

High-level analysis conducted at the system or equipment level are typically faster and less resource-intensive, but may lead to inaccurate estimates due to the use of aggregated data and oversimplified assumptions. In contrast, detailed analysis at the component level, while potentially more accurate, are time-consuming, data-demanding, and costly, especially in large and complex systems such as oil and gas platforms, where many components interact [4]. Despite these differences in approach, there is no clear consensus in industry or academia on the optimal level of detail for RAM analysis, and there is a lack of studies that compare RAM analysis at the two technical levels.

The purpose of this study is to investigate and address this issue by modeling two different levels of technical hierarchy and comparing their availability results. This includes the availability percentage, operating hours, and number of failure events. A safety-critical equipment is carefully selected for this study, where four distinct scenarios are modeled and evaluated: (1) equipment-level analysis, (2) component/failure mode-level analysis, (3) equipment-level analysis integrated with functional testing, and (4) component-level analysis integrated with functional testing. A probabilistic experiment was also performed to capture variability and provide insight into the best and worst-case performance outcomes.

In the following section, the simulation model and simulated scenarios are explained. Later, the results for the four scenarios are summarised and illustrated, followed by conclusions.

2 Materials and Methods

2.1 RAM analysis

RAM analysis is an essential aspect of system design and operation, particularly in complex industries [5]. It helps to ensure that systems perform their intended functions reliably over their expected lifespans with acceptable maintenance requirements and costs. The approach evaluates the reliability, availability, and maintainability of a component or entire system to determine the performance and any form of improvement that can be achieved. RAM analysis facilitates the identification of critical failure modes, the estimation of reliability and maintainability metrics over time, and the modeling of system behavior under various conditions [6] [7] [8]. It also informs the development of data-driven maintenance strategies and supports the calculation of key performance indicators such as MTBF and MTTR, which are essential to optimize system performance and reduce operational risks [6], [9]. Various mathematical models and techniques have been proposed, such as Markov modelling and Monte Carlo simulation [10].

2.2 Technical Hierarchy

Technical hierarchy refers to the structured organization of physical assets into multiple levels, typically including systems, subsystems, equipment units, and components. This hierarchical breakdown facilitates clear asset identification, classification, and data aggregation. It is widely used in industries such as oil and gas, manufacturing, and power generation to manage asset-related information systematically [5]. ISO 14224 [11] provides a standardized framework for developing technical hierarchies within industrial facilities. This framework also serves as a data structure for collecting and exchanging reliability and maintenance (RM) data for equipment [12]. It emphasizes the importance of consistent asset taxonomy and boundary definitions to ensure the comparability and integrity of RM data collected across operational units. The standard defines a multi-level hierarchy, beginning at the installation level and progressing through equipment classes and units down to individual components. This structure supports traceability and enables data collection at the appropriate level of detail depending on the application [11]. Studies have highlighted the role of a well-defined technical hierarchy in enhancing the consistency and usefulness of equipment data, especially for cross-functional analysis and decision support [13]. A key aspect of ISO 14224 is the delineation of equipment boundaries using boundary diagrams, which ensure clarity in asset definitions and reduce ambiguity in equipment classification. The implementation of technical hierarchy in complex systems is challenging, as incomplete or inaccurate structures can result in data inconsistencies that undermine the effectiveness of RAM analysis [14].

2.3 Agent based modelling

Agent-Based Modelling (ABM) is a computational modeling approach used to simulate the actions and interactions of autonomous entities, or "agents" within a defined environment [15]. These agents are characterized by individual behaviors, rules, and attributes, enabling the modeling of complex, decentralized systems with emergent behaviors. The approach has been applied in manufacturing systems, supply chain logistics, maintenance systems, and reliability studies due to its flexibility in capturing dynamic and heterogeneous interactions [16]. ABM can represent systems as collections of interrelated agents, making it suitable for modeling complex systems with hierarchical structures such as equipment and their components. In such applications, the relationship between an equipment unit and its components is modeled as a parent–child agent hierarchy, where the parent agent (equipment) interacts with and monitors the states of its child agents (components) [17] [18]. This structure enables simulation of dependencies, propagation of failure, and aggregation of performance at different hierarchical levels [17].

ABM frameworks can incorporate multiple modeling techniques, such as system dynamics and discrete event simulation, and a state chart that captures complex system behaviors [18]. State charts are graphical representations of discrete states and transitions triggered by events or conditions and can accurately model the internal dynamics and lifecycle of agents. State charts enhance the expressiveness of Agent-Based Modelling by enabling the definition of complex agent behaviors, including failure modes, maintenance events, etc. In equipment-component systems, state charts allow each component agent to transition between operational, degraded, failed, or repair states, while the parent equipment agent can monitor these states to determine its own availability or performance level [19] [20].

3 Case study

The safety-critical equipment selected for this study is the Production Master Valve (PMV) based on a real industrial case. Its failure modes were identified and retrieved from the Failure Modes, Effects, and Criticality Analysis (FMECA) provided from this case and cross-referenced with data from the Offshore and onshore reliability data (OREDA) to obtain accurate failure rates and maintenance parameters for modeling. The PMV is a critical safety device in oil and gas wells, used to control and shut off the main flow of hydrocarbons. It is placed on the Christmas tree and ensures safe operation and isolation of the well. Its reliability is vital for safety, environmental protection, and production continuity. Table 1 shows the retrieved data from OREDA related to the production master valve.

Table 1. Obtained failure data from OREDA

Failure Modes	CODE	Failure Rate /year	MTTR /hour
Loss of Containment	LOC	0.00534	25
Fail to operate valve	FOV	0.01971	45.6
Fail to operate valve (Seal leakage)	FOV_SL	0.00919	11.4
Overload on Housing	OOH	0.0632	17.4
Fail to compensate pressure	FCP	0.07	22.9
Fail to relive overpressure	FRO	0.07	22.9
Fail to balance external (given inadequate filling of Nemis oil)	FBP	0.0072	0.3
Leak through relief valve	LRV	0.0418	19
Seizure of indicator	SOI	0.0744	16.7
Seizure of indicator due to torsion of spring retainer plate	SOI_DT	0.0744	16.7
Fail to provide thrust	FPT	0.0913	20.3
Weld Failure	WELD	0.0063	47
Fail to operate ball	FOB	0.004	15.9
Fail to operate gate	FOG	0.004	15.9
Internal Leakage	ILU	0.0704	12.2
Fail to open	FTO	0.004	15.0

The OREDA handbook is a valuable resource in the oil and gas industry because it provides reliable failure and maintenance data for offshore equipment. OREDA is a key reference in reliability engineering and integrity management, providing comprehensive data on offshore equipment performance, including failure modes, rates, mean time to repair (MTTR), equipment boundaries, and maintenance metrics. These data are collected from various operational conditions across multiple companies and regions. OREDA is based on ISO 14224 to enable collecting adequate, consistent, and valid reliability and maintainability data for specific object types. The data has been collected across various installations and equipment models under different operational conditions, hence it is considered a generic database. The data segregation and presentation approach makes it suitable for RAM analysis upon reasonable assumptions and considerations.

3.1 Scenario 1: High-level model without functional testing

The first scenario evaluates the PMV as a single unit, with failure data aggregated and analyzed at the equipment level rather than the level of individual components. The behavior of the PMV can be described in two primary states: the working state (functional) and the failed state (under repair), as illustrated in Figure 1.

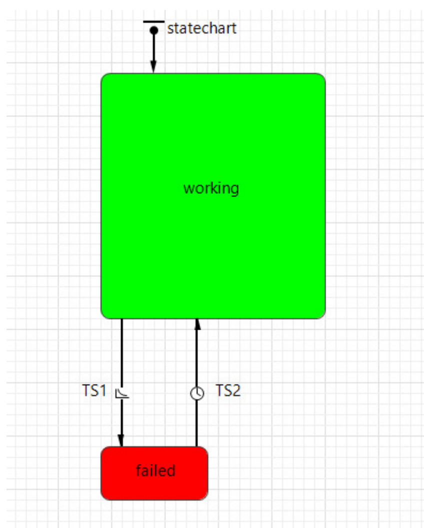

Fig. 1. Structure of the PMV at High-level (Scenario one).

In the working state, the valve is considered to actively perform its required function, serving as an emergency safety valve within the larger subsea system, therefore, it is expected to operate reliably and respond to emergency situations. When the valve is no longer able to perform its required function, it transitions to the failed state and undergoes maintenance or repair activities to restore its functionality and return it to the working state. The PMV's transition from the working state to the failed state is triggered by a failure event, which is defined as a "rate trigger" that depends on reliability metrics expressed as a function of time, illustrated in Table 2. In this case, the transition to the failed state is governed by the failure rate of the valve, typically measured per year. When the valve enters the failed state, the transition back to the working state is triggered by a "timeout", which is the time taken to perform maintenance activities. This trigger keeps the valve in the failed state for a specified duration, defined as the MTTR in Table 2. Once the timeout expires and the MTTR is fulfilled, the valve is restored to its working state.

Table 2. Model inputs for scenario 1.

States and transitions	Description	Values
Working State	The PMV is performing its function	
Failed State	The PMV has failed	
TS1 transition	Accumulated failure rate	1.3/ year
TS2 transition	MTTR	19.38 hours

3.2 Scenario 2: Detailed level model without functional testing

The second scenario models the PMV at the component level, assigning failure modes to each individual component and providing an understanding of the PMV's reliability and performance. Therefore, two levels of models shall be considered.

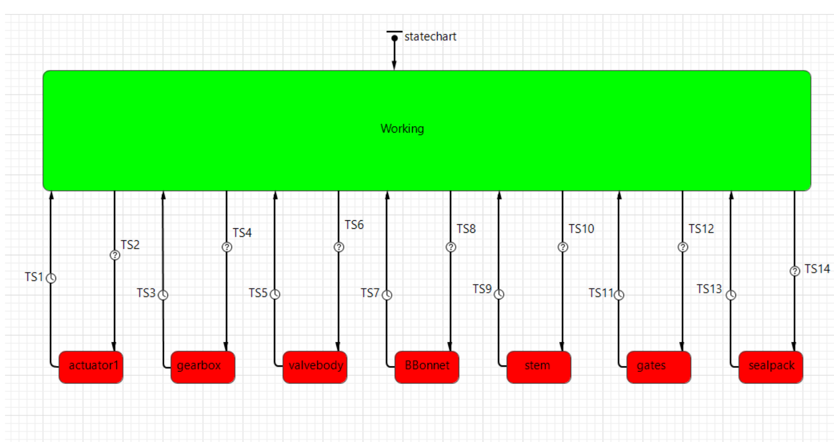

Fig. 2. Structure of PMV at Component-Level (Scenario two)

The first level is related to the equipment level, illustrated in Figure 2 shows several considered components such as actuator, gearbox, valve body, bonnet, stem, gates, and seal package. All these components were simplified and abstracted into one item in Scenario 1 (Figure 1). The second level is related to the failure mode level for each component. For example, Figure 3 represents the state chart of gearbox, where several failure modes are modelled.

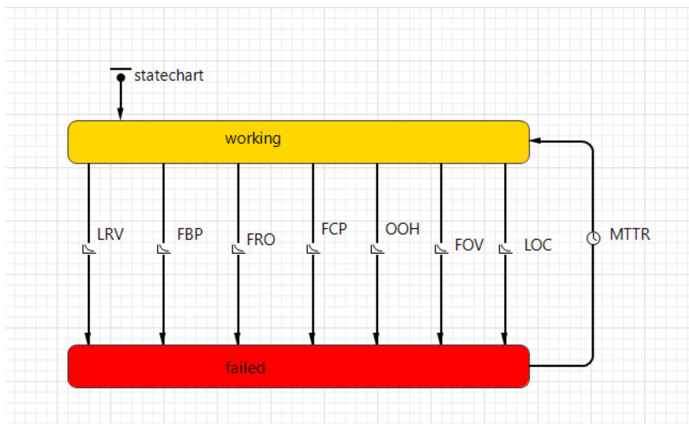

Fig. 3. Structure of the PMV's Gear Box and Failure modes.

Table 3. Model inputs for the Gear Box state chart.

States and transitions	Description	Values
Working State	The gear box is performing its function	
Failed state	The gear box is failed and not its functioning	
LRV transition	Failure mode triggered by Failure rate	0.0418/year
FBP transition	Failure mode triggered by Failure rate	0.072/year
FRO transition	Failure mode triggered by Failure rate	0.07/year
FCP transition	Failure mode triggered by Failure rate	0.07/year
OOH transition	Failure mode triggered by Failure rate	0.0632/year
FOV transition	Failure mode triggered by Failure rate	0.01971/year
LOC transition	Failure mode triggered by Failure rate	0.0534/year
MTTR transition	Failure mode triggered by Failure rate	22 hours

The behavior of the valve components (child agents) is integrated into the parent agent (PMV) using conditional logic. For instance, when a component, such as a gearbox, transitions from the working state to the failed state due to a failure event, it triggers a predefined condition in the parent agent. As a result, the PMV transitions from the working state to the failed state. Upon completion of the repair process, defined by the MTTR, the gearbox transitions back to the working state. This transition again satisfies another predefined condition in the parent agent, prompting the PMV to return to its working state. This behavior is consistently applied to all valve components to ensure an accurate reflection of the impact of the component failure. The structure and behavior of other individual components has been illustrated and explained in detail by Botsoe in his thesis [21].

3.3 Scenario 3: High-level model with functional testing

Scenario 3 is basically scenario 1 with functional testing. Two substates have been introduced to the working state of the PMV, as illustrated in Figure 4: the normal state, which is the typical operational behavior of the valve, and the testing state, where the functionality of the valve is evaluated to ensure it meets operational standards.

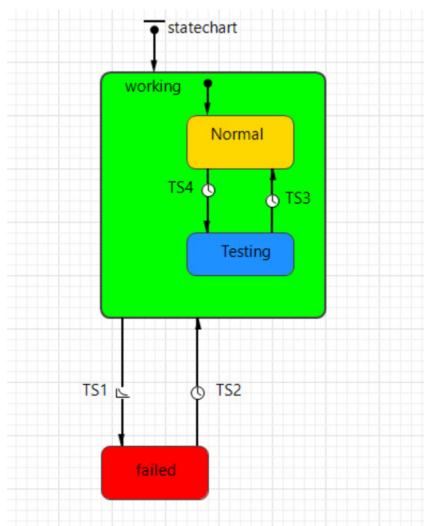

Fig. 4. Structure of the PMV at High-level with testing (scenario 3)

The introduction of these two states changes the behavior and structure of the model. These functional tests are conducted twice a year (six months apart) as part of a scheduled preventive maintenance activity. During these tests, the valve temporarily switches from the normal state to the testing state. The transition from the normal state to the testing state is a timeout trigger which is set to occur at a fixed interval every six months. The transition back to the normal state is also governed by a timeout trigger, which represents the time taken to complete the functional test.

Scenario 3 was explored because (1) the PMV is a part of the Safety Instrumented System (SIS), and its performance must comply with safety standards such as IEC 61508, IEC 61511, NOG 070, and NORSOK D-010. These standards define the requirements for ensuring the Safety Integrity Level (SIL) of the valve's safety instrumented functions. Regular functional testing is required to confirm the valve's proper response under specific fault conditions or to maintain its integrity over time. Three primary types of tests are typically carried out: Partial Stroke Test (PST), Full Stroke Test (FST) and Internal Leak Test. (2) Functional testing performed on the valve introduces an additional analytical dimension, as the duration and frequency of these tests could impact the availability and the number of hours the valve is in operation. (3) This approach provides insights into the possibility of opportunistic maintenance, where situations in which lengthy functional testing-induced downtime could be leveraged as a window to perform PM tasks to address potential failures pre-emptively.

3.4 Scenario 4: Detailed-level model with functional testing

Scenario 4 is basically scenario 2 with functional testing, as illustrated in Figure 5.

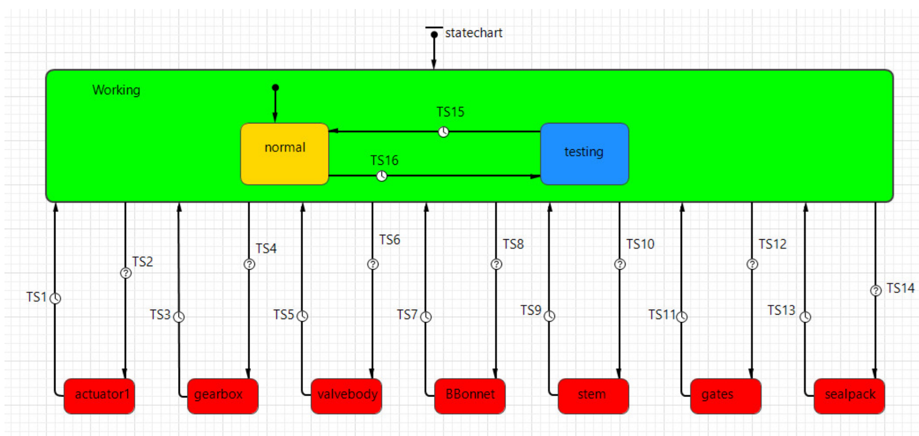

Fig. 5. Structure of the PMV at component level with testing (Scenario 4)

3.5 Simulation Experiment: Probabilistic Repair Time

In all scenarios considered, a constant MTTR was used to represent the time needed to restore the valve to operational status after a failure. However, MTTR values usually vary with a wide range due to delays and different levels of damage. To improve the robustness and realism of the model, the constant MTTR was replaced by a triangular distribution to allow a range of MTTR values. This adjustment recognizes the inherent uncertainties and variabilities in the repair process, where repair times can vary due to factors such as the complexity of the failure, availability of spare parts, or accessibility to failed components. In contrast to a constant value, a triangular distribution is defined by minimum, maximum, and most likely repair times, which allows the model to account for a range of possible repair durations, from the best-case scenario to the worst-case scenario. This experiment better represents real-world scenarios where repair times rarely adhere to a single average value, yet there is limited data to capture actual system behaviour. This experiment makes the analysis more relevant to decision-makers who must manage and account for uncertainty for accurate risk assessment and strategic planning.

In the probabilistic approach, it is assumed that MTTR is a minimum of 11.4 hours, a mean of 22 hours, and a maximum of 45.6 hours. After running the probabilistic model, the resulting MTTR distribution shows a higher mean of 24.52 hours, as shown in Figure 6.

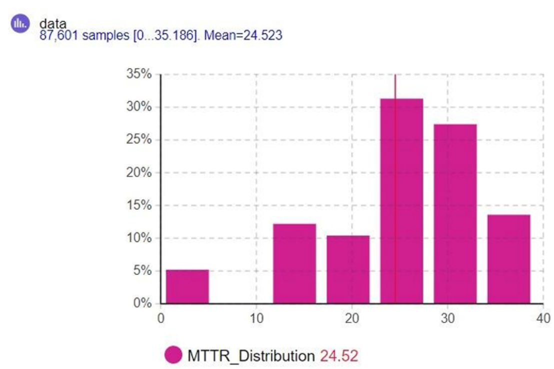

Fig. 6. Histogram of the MTTR.

3.6 Validation Process

The model comprises input, logic, and output. The failure data retrieved from the OREDA handbook and the participation of experts were used to ensure the validity of the input data. The logic was derived from the generic maintenance concept (GMC) of a case study and was confirmed by experts for precision. The results obtained from the simulated scenarios were qualitatively validated by engaging the case study experts.

4 Results

The results of the four scenarios are summarised in Table 4. When comparing the availability percentages of scenarios 1 and 2, it can be observed that the high-level and detailed-level models provide very close results; the difference, in this case, was about 0.1% and 53 operating hours. Comparison of availability percentages for Scenarios 1 and 3, to observe the effect of functional tests, a marginal decrease in availability (from 99.7% to 99.6%) and the number of operating hours recorded. Although the functional test shows an observable impact on system availability, it emphasized that in systems where functional tests require significant amounts of time and will induce longer downtime, it can be leveraged for opportunistic maintenance.

Table 4. Results of modelled scenarios under deterministic MTTR.

Criteria	Scenario 1/High Level	Scenario 2/Detailed Level	Scenario 3/ High Level with testing	Scenario 4/ Detailed Level with testing
Availability in %	99.7%	99.6%	99.6%	99.5%
Availability in hours	87,348.06	87,295	87,208.06	87,175
Number of failure	13	14	13	14

Table 5. Results of modelled scenarios under probabilistic MTTR.

Criteria	Scenario 1/ High Level	Scenario 2/Detailed Level	Scenario 3/ High Level with testing	Scenario 4/ detailed Level with testing
Availability in %	99.7%	99.4%	99.5%	99.2%
Availability in hours	87,292.97	87,072.41	87,162.96	86,932.40
Number of failure	12	17	12	17

Table 5 provides the availability figures for the four scenarios under probabilistic MTTR values. In the probabilistic approach, MTTR is assumed to be a minimum of 11.4 hours, a mean of 22 hours, and a maximum of 45.6 hours. Compared to the deterministic MTTR conditions, it can be observed that all scenarios explored have have been affected by the probabilistic MTTR values. For example, the availability estimated for Scenario 3 has decreased from 99.6% under deterministic to 99.5% under probabilistic MTTR conditions. Similarly, for Scenario 4, there is a drop in availability from 99.5% under deterministic MTTR to 99.2% under probabilistic MTTR conditions. However, this drop is mainly related to the number of failure events (which increased from 14 to 17) and partially related to the probabilistic MTTR.

The increase in the number of failures for the detailed technical level in probabilistic MTTR is largely due to the frequent transitions between operating and failed states in situations where the repair times are shorter than average in the probabilistic model. Each transition back to the operational state after a repair introduces a new opportunity for failure, hence increasing the likelihood of occurrence within each uptime period. This phenomenon in reliability theory, where systems that undergo more frequent start-stop cycles due to variable repair times, can experience cumulative stress, which can accelerate the occurrence of failures within each operational cycle [22]. However, the decrease in the number of failures at the high technical level under probabilistic MTTR highlights a limitation of deterministic models, as they may provide oversimplified and sometimes pessimistic reliability predictions due to their inability to account for variability and favorable (or unfavorable) deviations from the mean[10][23].

5 Conclusions

Based on the results, it can be concluded that both approaches (high- and detailed-level modeling) produced similar availability estimates. It can be also concluded that high-level model at the system and equipment level is sufficient for availability evaluation during the early project phase. However, component-level breakdown provided more detailed insight into system behavior by capturing the contribution of individual components and failure modes.

Although the equipment-level approach effectively captures essential reliability metrics without the complexity of system decomposition, it lacks the granularity needed to assess specific failure behaviors. This limitation reduces its usefulness for informing proactive maintenance decisions or tailoring maintenance strategies during operational phases. The component-level approach supports more informed asset management by enabling precise failure identification and providing data to support the prioritisation of monitoring efforts to component and failure modes that have a significant impact on the overall system performance.

The introduction of probabilistic variation in the MTTR highlighted the limitations of fixed-value assumptions in deterministic models. Although deterministic models offer a simplistic approach to establishing a baseline, they fail to capture the inherent variability and uncertainty of real-world maintenance activities. The probabilistic approach, although it produces slightly lower availability and operational time, aligns more closely with the realistic nature of industrial systems and provides a more accurate basis for reliability assessment and maintenance planning [24].

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