Modelling System Availability of Unmanned Platform under Fixed Maintenance Intervals: Agent based Simulation Approach

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Abstract. The unmanned platforms offer substantial cost savings, increased operational flexibility, and enhanced safety measures, making them an attractive option for offshore industry. However, the maintenance of an unmanned platform is planned to be based on fixed time intervals, e.g. 6 to 12 months, which brings a challenge to ensure the availability with such long maintenance intervals. This study aims to solve reliability system configuration with a variable repair time model and estimate the availability and maintenance manning workload for different redundancy configurations (2, 3,4 and 5 equipment) for unmanned assets. The availability figures for the 12-month maintenance interval with several redundancy scenarios ranges from 26.50% to 87.50% for 2 to 5 equipment. However, for 6 months maintenance interval, the availability figures ranges from 67.00%, 98.10%, 99.50% to 99.70% for 2, 3, 4 and 5 pumps, respectively. These values were up to the availability of the baseline (99.00%) where two pumps are redundant and supported by direct repair policy. The applied redundancy with fixed maintenance intervals has reduced the number of maintenance visits from 188 to 20 over a 20-year lifespan. This reduction has a cascade effect on CO2 emission and operating expenses.

Keywords: Fixed Maintenance Interval · Variable Repair Time · Simulation Modelling · Agent based Modelling · System Availability · Unmanned Assets.

1 Introduction

Unmanned production platforms with single-annual maintenance interventions are expected to become standard in 5-10 years [1, 2]. Ensuring the availability of such assets is a real challenge, as no more timely repairs to maintain performance is applied [3]. Therefore, it is essential for maintenance engineers to gain insights and develop effective maintenance strategies during the design phase to ensure high system performance, minimal downtime for such complex assets [4], [5].

Among several reliability, maintainability and availability (RAM) analysis methods, reliability block diagram (RBD) models are the most commonly used

[6]. Traditional RBDs are static and exhibit several limitations when state dependency, dependent events, non-series-parallel topologies, and load-sharing aspects are involved, which complicate analysis and hinder efficiency in large-scale systems [7]. In the context of unmanned assets that are annually maintained, the mean time to repair (MTTR) is variable and depends on the annual maintenance schedule. This makes the MTTR unknown at the beginning of the availability estimation process and different for each failure event. Traditional RBDs are suitable for timely repair and a common MTTR value for all failure events and have a challenge to handle unknonw and variable MTTR. Several studies [8, 9] highlighted the flexibility of agent based modelling to analyse maintenance strategies. Therefore, the purpose of this paper is to model unmanned redundant system configuration and estimate the availability and maintenance visits for unmanned assets.

The high pressure (HP) pump in Hydraulic Power Unit(HPU) is purposefully selected as main industrial system for this study. The study covers nine scenarios. The first scenario represents the two redundant pump system under normal manned maintenance where timely repair is provided. Scenarios 2 to 5 represent redundant pump systems operating under unmanned maintenance conditions, with only a single annual visit. These scenarios consider systems with 2, 3, 4, and 5 pumps, respectively. Scenarios 6 to 9 represent redundant pump systems operating under unmanned maintenance conditions, with only a single bi-annual visit. These scenarios consider systems with 2, 3, 4, and 5 pumps, respectively. All scenarios are simulated using a well-known multi-method modelling software called AnyLogic.

In the following section, the reliability and availability theories for redundant systems are explained and the simulation model developed is presented. In Section 3, the results of the nine scenarios are illustrated and discussed. Finally, the paper concludes with conclusions, insights, and recommendations for future work.

2 Reliability and Availability Modelling

2.1 Reliability Block Diagram (RBD) for a Parallel System

A Reliability Block Diagram (RBD) visually represents the components of a system and their interdependencies for successful system operation. In a parallel configuration, the system functions as long as at least one component is operational. Let $R_i(t)$ be the reliability of component i at time t. Then the system reliability $R_{sys}(t)$ for n components in parallel is:

$$R_{sys}(t) = 1 - \prod_{i=1}^{n} (1 - R_i(t))$$

Availability for a single component is given by:

$$A = \frac{MTBF}{MTBF + MTTR}$$

Where Mean Time Between Failures (MTBF) is the average time a component operates before failure, and Mean Time To Repair (MTTR) is the average time to repair a failed component. The failure rate λ and the Mean Time Between Failures (MTBF) are inversely related for systems with a constant failure rate (exponential distribution):

$$\lambda = \frac{1}{MTBF} \quad or \quad MTBF = \frac{1}{\lambda}$$

Example: If $\lambda = 0.002\, failures/hour$, then:

$$MTBF = \frac{1}{0.002} = 500\, hours$$

For a parallel system of n components with individual availability $A_1, A_2, \ldots, A_n$, the system availability is:

$$A_{sys} = 1 - \prod_{i=1}^{n} (1 - A_i)$$

Consider a system of two components, the **availability** A_1 is calculated as:

$$A_1 = \frac{MTBF}{MTBF + MTTR} = \frac{500}{500 + 20} = \frac{500}{520} \approx 0.9615$$

Similarly, if $A_2 = 0.70$, then:

$$A_{sys} = 1 - (1 - A_1)(1 - A_2) = 1 - (1 - 0.9615)(1 - 0.7)$$

$$= 1 - (0.0385)(0.3) = 1 - 0.01155 = 0.98845$$

The system is available approximately 99.8% of the time.

2.2 Agent-based Simulation modelling

Agent-Based Modelling and Simulation (ABMS) is a computational technique used to explore complex systems by simulating the behaviors and interactions of autonomous agents. Unlike conventional modeling methods that rely on aggregate-level equations, ABMS captures the system's dynamics from the bottom up—by focusing on individual components and how they interact over time. Each agent functions independently, interacting with others through messaging, interfaces, or behavioral rules. These interactions are driven by internal logic, commonly represented using state charts, which outline the conditions under which agents change states and respond to their environment or peers.

Modelling manned redundant systems Redundant systems can be modeled using a state chart, as shown in Figure 1. The system has two main states: (1) Active, (2) Downtime. However, the "active" state has internal states that represent redundant equipment, as shown in Figure 1, the "HP1 Working" state represents the first pump and the "HP2 Working" state represents the second pump. If both pumps fail, the entire system will fail and go to a "Downtime" state. The maintenance policy in Figure 1 is modelled to offer a direct repair action. This means that if one pump fails, it will be immediately repaired, and the system goes to the "Downtime" state only if both pumps fail. Therefore, the system availability is high for this configuration with a high level of maintenance service.

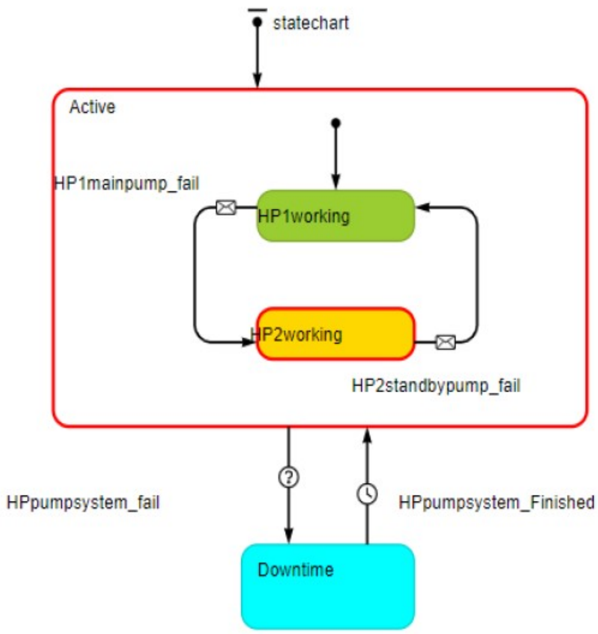

Fig. 1. State machine diagram of manned redundant systems.

The pump is also modelled as individual agent. Each pump has mainly four main states: working, standby, failure (different failure modes), and Preventive Maintenance (PM). The pump has several failure modes (5 modes are modelled, Figure 2) and each has a specific failure rate and mean repair time, as described in Table 1.

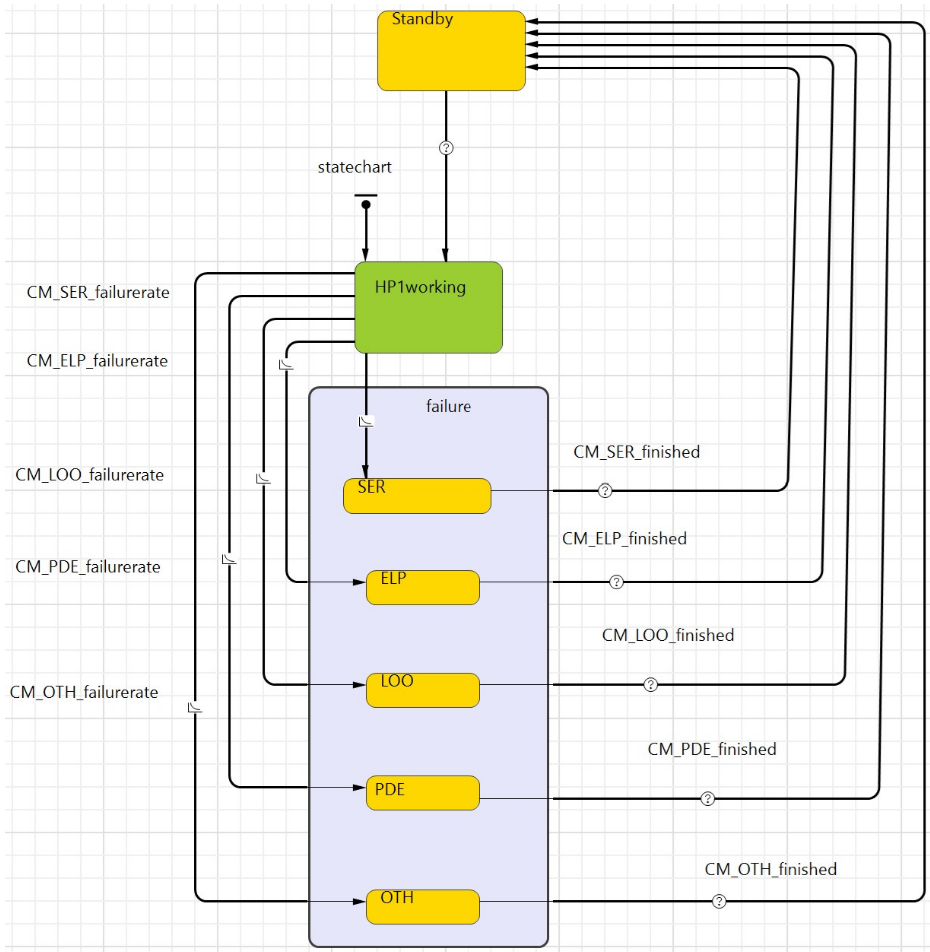

Fig. 2. State chart of a redundant pump.

Table 1. Failure rates and mean repair times for the pump equipment.

Failure mode	Description	Failure rate per year	MTTR in Hrs
SER	Minor in-service problems	3.66	2.45
ELP	External Leakage-Process Medium	1.67	5.40
LOO	Low Output	0.33	6.00
PDE	Parameter Deviation	0.67	3.00
OTH	Other: Breakage, Instrument Failure	1.33	8.00

Modelling unmanned redundant systems The unmanned systems are modeled using a state chart, as illustrated in Figure 3. It has the same states as the manned systems. However, the main difference is the transition between the "Downtime" and "Maintenance" states, where a condition rule has replaced a time out rule. The condition rule keep the system in the downtime state until a planned maintenance visit is triggered.

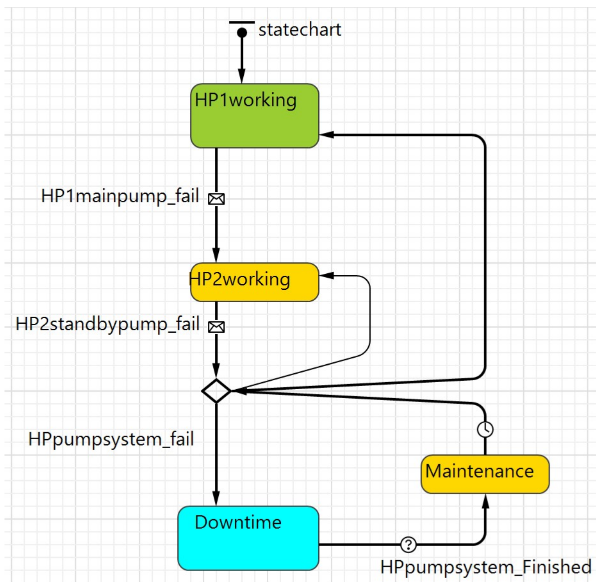

Fig. 3. State machine diagram of unmanned redundant systems.

2.3 Model and result validation

The model comprises three components: input, logic, and output. The inputs were chosen on the basis of historical data and expert involvement to ensure their validity. The conceptual model was derived from the case study and confirmed by experts. The results were partially validated. The results of the simulated scenarios were qualitatively validated by the case study experts, as these scenarios have not yet been implemented and no data have been collected. The considered lifetime for these scenarios is 20 years (175,200 h).

3 Results

The results are summarised in Table 2, where nine scenarios are compared. Scenario 1 represents the baseline estimates, where the system is modeled as a parallel configuration of two pumps and a direct repair policy (direct after failure and has a deterministic repair time). Scenario 2 presents the redundant two pump system with fixed maintenance interval (once every 12 months). When comparing the availabilities of scenarios 1 and 2, the effect of the direct maintenance policy can be observed, as it ensures 99% availability compared to 26.5% if maintenance is performed annually. In terms of maintenance visits and associated expenses (manning, vessel rent, CO2 taxes), the direct repair policy is definitely high to ensure such high availability level.

The second set of results is related to the effect of redundancy in a fixed maintenance interval (once every 12 months). It is obvious that availability increases whenever more redundant equipment is introduced. The availability of a two-pump system is about 26.50%, while it is 35.70%, 62.60% and 87% for a three-pump system, a four-pump system and five pump systems, respectively.

Table 2. Results of modelled scenarios

Scenario	Availability in %	No. maintenance visits
Scenario 1, (baseline) two pumps with direct repair policy	99.00	188
Experiment 1: Unmanned, 12 month maintenance interval		
Scenario 2: two unmanned pumps	26.50	20
Scenario 3: three unmanned pumps	35.70	20
Scenario 4: four unmanned pumps	62.60	20
Scenario 5: five unmanned pumps	87.00	20
Experiment 2: Unmanned, 6 month maintenance interval		
Scenario 6: two unmanned pumps	67.00	40
Scenario 7: three unmanned pumps	98.10	40
Scenario 8: four unmanned pumps	99.50	40
Scenario 9: five unmanned pumps	99.70	40

The third set of results is related to the effect of the fixed maintenance interval. For experiment 2, the fixed maintenance interval was reduced from 12 months to 6 months. It is obvious that availability increases whenever shorter maintenance intervals are introduced. With 6 month maintenance interval, availability of two-pump system is about 67%, while it is 98.10%, 99.50% and 99.70% for three-pump system, four-pump system and five pump systems, respectively.

These sets of results provide several insights for maintenance engineers in designing an unmanned system with high availability with a lower level of maintenance service. For example, a four-pump system (scenario 8) provides better availability and maintenance demand compared to a two-pump system with a direct repair policy (scenario 1). It clearly helps to reduce maintenance visits from 188 to 40 throughout the lifetime.

4 Conclusions

This study provides an agent-based simulation model that estimates the availability of unmanned assets. The main challenge to estimate availability of unmanned asset is the variable repair time; as the next possible maintenance visit might happen in two weeks, three months, etc. The repair time depends on when the failure occurred and when the possible maintenance visit is planned. Agent-based simulation modeling is flexible enough to enable setting the repair time as a condition that keeps checking when the next maintenance visit is active.

It can be concluded that availability increases whenever more redundant equipment and shorter maintenance intervals are introduced. Definitely, redundancy is an effective design strategy to ensure availability for unmanned assets. There might be better policy to handle the yearly maintenance interval and make more flexible, e.g. maintenance is done whenever three pumps out of four is failing. The flexible maintenance interval policy shall be further explored.

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