Advancing ECLSS Reliability Modeling: Integrating ISS Data for Sustainable Long-Duration Mission Planning

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The performance of Environmental Control and Life Support System (ECLSS) technology has been a popular focus when assessing overall system maturity. Most studies have examined either the component level or the system-of-systems level. However, one crucial aspect often overlooked is sustainability, leading to limited studies addressing long-term operational efficiency and resource management. The last release of ECLSS reliability data in 2004 created a significant gap in understanding the current reliability and maintainability of today's systems, especially considering advancements in technology and mission requirements since then. This lack of updated data hinders the development of more sustainable and resilient life support systems, essential for long-duration missions such as those planned for the LEO commercial stations, Moon and Mars. This paper aims to advance reliability modeling by incorporating ISS recent data on ECLSS component replacement rates, shelf life, and throughput limits. By integrating these factors, the study seeks to create a comprehensive reliability model that accounts for all potential variables. This model will provide insights into sparing requirements for long-duration missions, enabling mission planners to better anticipate and manage the logistics of ECLSS maintenance, ultimately contributing to a more sustainable and reliable system for future space exploration.

Acronyms and Nomenclature

AR = Air Revitalization
BPA = Brine Processor Assembly
CFR = Constant Failure Rate
CCAA = Common Cabin Air Assembly
CHX = Condensing Heat Exchanger
ECLSS = Environmental Control and Life Support System
EMAT = Exploration Maintainability Analysis Tool
EVA = Extravehicular Activity
FMEA = Failure Modes and Effects Analysis
FTA = Fault Tree Analysis
HAZOP = Hazard and Operability
LEO = Low Earth Orbit
MADS = Maintenance & Analysis Data Set
MTBF = Mean Time Between Failure
MTBPMRR= Mean Time Between Preventative Maintenance Remove and Replace
MTTR = Mean Time to Repair
MTTPMRR = Mean Time to Preventative Maintenance Remove and Replace
ISMA = ISS Risk Management Application
ISS = International Space Station
IRMA = ISS Risk Management Application

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IMV	=	Intermodule Ventilation
OGA	=	Oxygen Generation Assembly
OGS	=	Oxygen Generation Subsystem
ORU	=	Orbital Replacement Unit
THC	=	Temperature and Humidity Control
PRA	=	Probabilistic Risk Assessment
PM	=	Preventative Maintenance
RBD	=	Reliability Block Diagram
R&R	=	Remove & Replace
SMP	=	Semi-Markov Process
SMP	=	Semi-Markov Process
WHC	=	Waste Hygiene Compartment

I. Introduction

The International Space Station (ISS) serves as an unparalleled testbed for scientific research and technology development, including advancing development of Environmental Control and Life Support Systems (ECLSS) which are essential for deep space human exploration missions. These systems undergo rigorous testing, validation, and refinement aboard the ISS to ensure their readiness for future missions.[1]

With the impending decommissioning of the ISS by 2030, NASA has initiated various Space Act Agreements to facilitate the establishment of new commercial space stations that will support the ongoing human presence in Low Earth Orbit (LEO).[2] Establishment of reliable ECLSS while allowing for development of improved technologies will be key to the success of these commercial enterprises.

In addition to the importance of evaluating new technologies to improve the current ECLSS design, having a good understanding on the ECLSS reliability is also essential.

The development of ECLSS, including the loop closure rate, plays a critical role in determining the configuration and efficiency of resource recovery. However, the feasibility of an ECLSS model extends beyond the development phase, encompassing the sustaining phase, which must account for potential reliability concerns and system failures during missions. The ECLSS presents a unique and critical challenge, as it is directly responsible for safeguarding the lives of crew members throughout their mission. Its reliability and performance are paramount, as the system must sustain essential life-support functions while adapting to the dynamic and often unpredictable conditions of space exploration. As human spaceflight ventures further into deep space, the pressure on ECLSS intensifies. The limitations on resupply missions and the lack of viable abort-to-safe-haven options in the event of an emergency necessitate the design of highly autonomous and resilient systems. These systems must operate reliably under extended durations and unforeseen conditions, ensuring crew safety and mission success in environments where external support is severely restricted. Achieving resilience requires balancing additional redundancies, spares, and consumable margins against their associated costs and impacts on system reliability. This trade-off ensures that the system can adapt and recover from unforeseen failures while maintaining its core functionality, ultimately supporting long-term mission success.

Another significant challenge faced by ECLSS lies in the inherent complexity of many subsystems and the extensive number of components they encompass within each subsystem, as seen in Figure 1. Rather than illustrating the system interconnection, it emphasizes the complexity of the ECLS system-of-systems, which involves a vast number of interdependent components that must function simultaneously to maintain life support. This complexity increases the likelihood of potential failures and places greater emphasis on the importance of system sustainability. Therefore, the selection of the ECLSS architecture must carefully consider the balance between system complexity, maintainability, and long-term sustainability to ensure reliable performance over extended mission durations.

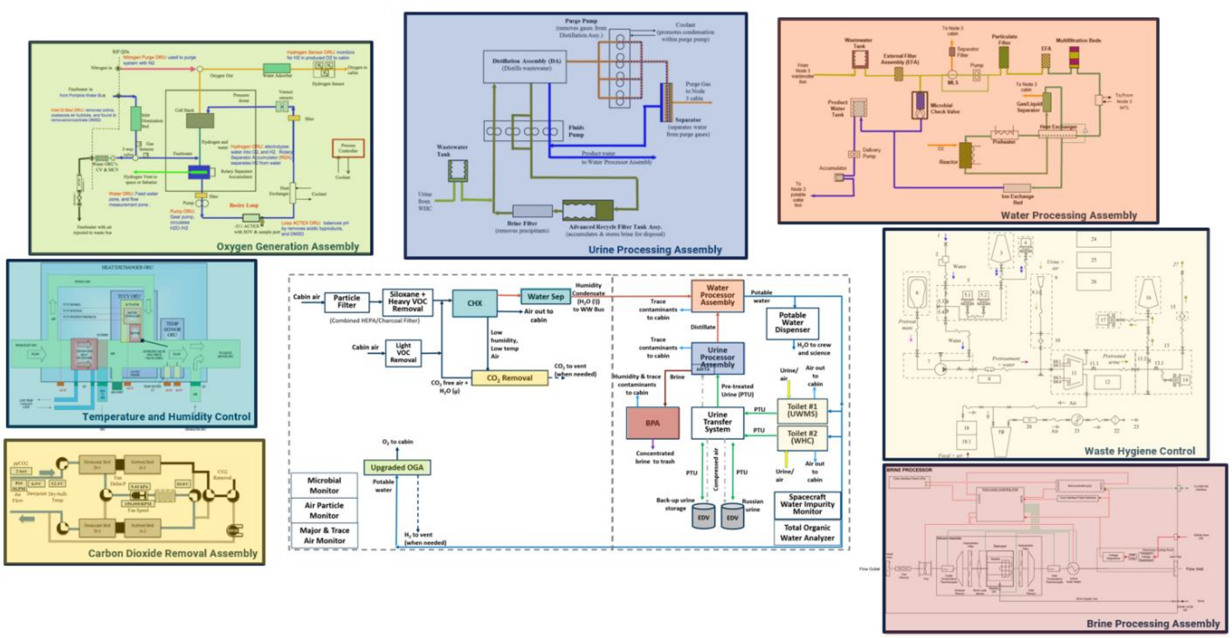


Figure 1. ISS ECLS System Composition

However, sustainability is often an overlooked aspect of ECLSS design, leading to limited studies or models in this critical area. Current NASA reliability analyses primarily rely on a "lessons learned" approach, drawing insights from historical data and expert opinions. Reliability, or failure probability, is often determined through experiments or, more commonly, through assumptions. One prominent example is the ISS Risk Management Application (IRMA), which predicts the likelihood and consequence of events using a two-dimensional risk assessment approach. This involves a scoring matrix where judgments are made by designers, operators, astronauts, and analysts. Another significant tool is the Probabilistic Risk Assessment (PRA), developed for the Space Shuttle, which identifies and evaluates failure modes based on inputs from personnel involved in design, maintenance, and operations. These methods are supplemented by industry-standard approaches like Failure Modes and Effects Analysis (FMEA), widely applied in fields such as aerospace, automotive manufacturing, and nuclear power. Additional methodologies, including Fault Tree Analysis (FTA), What-If Analysis, and the Hazard and Operability Method (HAZOP), have been adopted from analogous industries like chemical processing and nuclear energy. While effective in many contexts, these approaches exhibit notable limitations when applied to complex systems like life support systems.[5]

There are several reliability analysis approaches within the community. One of the most well-established ECLSS reliability models is NASA Langley Research Center's Exploration Maintainability Analysis Tool (EMAT). EMAT simulates daily operations over a predefined mission timeline by stochastically triggering component failures, executing repair actions, and tracking the required spare parts. While instrumental in understanding long-term mission demands, it primarily focuses on component reliability and maintainability.[9] Owen's development of a supportability module using a Semi-Markov Process (SMP)-based algorithm further enhanced spare parts prediction for selected ECLS subsystems. However, this approach was only applied at the subsystem level, and its scalability to the system-of-systems level has not been fully explored.[8] As system complexity increases, applying SMP becomes more challenging, requiring numerous assumptions and a greater modeling effort, limiting its scalability. The University of Stuttgart's Institute of Space Systems developed ELISSA, an ECLSS simulation tool, later extended by Detrell et al. into RELISSA for analyzing ECLSS reliability. RELISSA enables users to input design and reliability data, running multiple simulations with random variables to model failures, activate backups, and halt when systems fail. Results include failure data, reliability trends (via Weibull distribution and Kaplan-Meier methods), and insights for design improvement. The tool also utilizes the simulation output and ESM to evaluate the system's mass through factors such as mass, volume, power, and heat, focusing on early-stage system optimization without factoring in crew time.[6,7] One of the most complex methods for reliability analysis is using Monte Carlo simulations to model failure modes as stochastic processes. In this approach, a large number of identical stochastic systems are simulated, with random events such as failures generated based on each component's failure distribution. This method is advantageous because it can reveal insights that analytical solutions might miss. However, it has drawbacks: it requires significant computational effort, especially for large, complex systems, and the results depend on the number of simulations. Additionally, the stochastic nature of the simulations may not guarantee that all possible failure modes are sampled.[11]

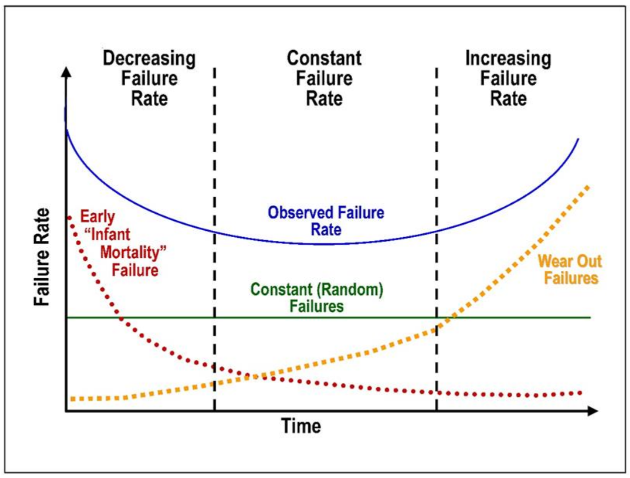
As Reliability analyses are critically dependent on a comprehensive and up-to-date database of historical data. However, the last version of the reliability dataset was released in 2004, leaving a significant gap in the availability of current and relevant information.[10] To ensure accurate and effective reliability assessments, it is imperative to establish a new version of the reliability dataset, incorporating updated and expanded ISS data to address this shortfall.

In addition to the reliability of Orbital Replacement Units (ORUs), another critical factor influencing overall system reliability is the crew time required to restore the system to operational status. Many analyses assume an instantaneous transition between hardware Remove & Replace (R&R) procedures and system functionality restoration, primarily due to the lack of available data on actual repair timelines. However, in reality, delays caused by crew availability, troubleshooting, and operational constraints can significantly impact system uptime and overall mission sustainability. It is also important to highlight that crew time is a limited and valuable resource, making its efficient allocation a key consideration in the design and operation of ECLSS.

II. Methodology

To address the gap of missing up-to-date data, with the understanding of ECLSS being system of systems and provide the possibility of varying fidelity models, each subsystem is broken down into its individual major components. For components, failures can generally be classified into five major types. The first is preventive maintenance, which involves proactively replacing or servicing components to prevent failures that could result in cascading damage. The second is infant mortality, where a component fails early due to inherent defects or improper functionality from the outset. The third type is characteristic life, also known as wearout or limited life, where a component reaches the end of its operational lifespan due to aging or prolonged use. The fourth category is where failures occur unpredictably as a result of inherent or random factors which is tracked by component's mean time between failure (MTBF). Lastly, there are failures caused by external influences, such as human error, environment induced damage, false/incorrect maintenance or damage from interactions with other systems. This type failures are tracked by K-Factors. Any hardware is vulnerable to one or more of these failure modes or maintenance actions, each of which may occur over different durations depending on the specific circumstances. These components are monitored across three key categories: mean time between failures (MTBF), throughput, and shelf life (where applicable). This detailed comprehensive tracking enables a comprehensive understanding of each component's reliability and performance, forming the foundation for accurate reliability analyses.

The failure types are also closely associated with the bathtub curve as shown in Figure 2, which represents the hazard rate function of systems. This curve depicts three distinct phases: an initial period of decreasing failure rate, known as infant mortality; a middle phase with a nearly constant failure rate, referred to as the system's useful life; and a final phase with an increasing failure rate, corresponding to wearout. A simplified form of the bathtub curve, characterized by linear and constant hazard rates, is illustrated below, where c_0, c_1, c_2 and t_0 are constants determined based on the specific system and failure characteristics.



$$\lambda(t) = \begin{cases} c_0 - c_1 t + \lambda & \text{for } 0 \le t \le \frac{c_0}{c_1} \\ \lambda & \text{for } \frac{c_0}{c_1} < t \le t_0 \\ c_2(t - t_0) + \lambda & \text{for } t_0 < t \end{cases}$$

Figure 2. Simplified Bathtub Curve and Failure Rate Functions [12]

To associated it with the duty cycle, total quantity installed, K-Factor, and MTBF, the expression of annual failure rate can be seen:

$$Annual\ F/R = \frac{Duty\ Cycle * Quantity * K\ Factor * 8760\ hrs/yr}{MTBF\ Hrs}$$

In the ISS program, the average mean time between failures is used to assess reliability, and a constant failure rate (CFR) is assumed, which corresponds to an exponential probability distribution. And the well-known characteristic of the CFR model, memoryless – the time of failure of a component is not dependent on how long the component has been operating, can be utilized to simplify analysis.

To build up the complex system of systems, a fundamental method for conducting reliability analysis is the use of reliability block diagrams (RBDs), as seen in Figure 3, which represent component interactions through a network of blocks and connections. These diagrams illustrate component interactions as a network of blocks that reflect the actual physical relationships among the components within a system. For a system with n components, four common configurations are often depicted. The first is a series system, system A, where the failure of any single component results in system failure. The second is a parallel system, system B, where the system remains operational as long as at least one component is functioning. The third configuration is a k-out-of-n system, system C, where the system functions if at least k components are operational. Lastly, the fourth configuration, system D, represents a system with passive (offline) redundancy, where backup components are activated only when primary components fail.

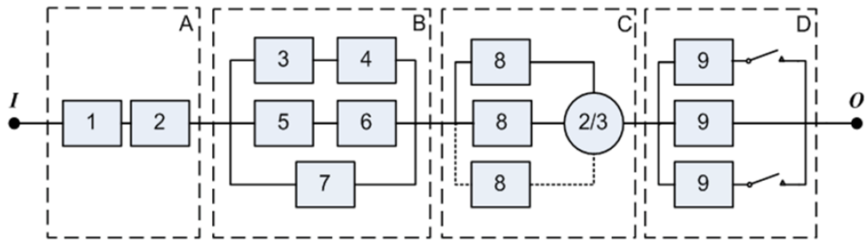


Figure 3. Reliability Block Diagram[5]

The reliability function of such system can be obtained:

$$R(\mathrm{t}) = \prod_{1}^{n} R_i(t) = \exp[-\int_0^t \lambda\,(t')]dt'$$

Where

$$\lambda(t) = \sum_{i=1}^{n} \lambda_i(t)$$

$$\lambda = \frac{Duty\ Cycle}{MTBF}$$

For most ECLS subsystems, the reliability typically follows a series system, as represented by block A. However, the overall ECLS system of systems can incorporate other configurations, such as parallel systems, k-out-of-n systems, or redundancy systems, to enhance reliability and ensure functionality under various conditions.

While most studies focus on the subsystem level, the aforementioned method is generally applied. However, certain components, such as filters, bladders, and others, are not monitored based on hardware failure rates. Instead, these components are tracked using metrics like shelf life or operation life including throughput, as their performance is typically defined by usage limits or time-based degradation rather than failure events.

Taking the Brine Processor Assembly (BPA) as an example, its schematic and solid model can be seen in Figure 4 and 5. The hardware includes the detrusor and bladder. The detrusor has an operational life of approximately 10.8 years, while the bladder has a capacity to hold around 22 liters of brine. However, each Brine Processor Bladder must be disposed of within 35 weeks of brine fill. This disposal timeframe defines the preventive maintenance (PM) frequency and establishes the operational limited life of the component. BPA itself presents the series system as identified in the RBD.

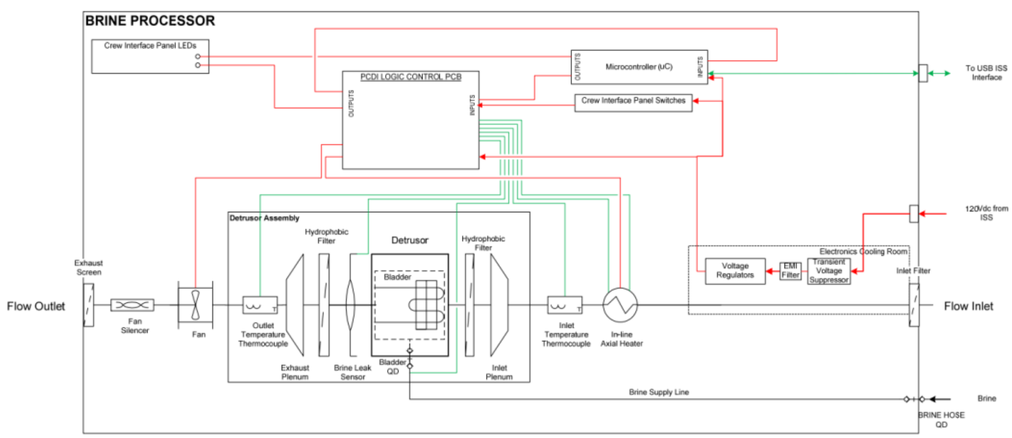


Figure 4. Brine Processor Assembly Schematic [3]

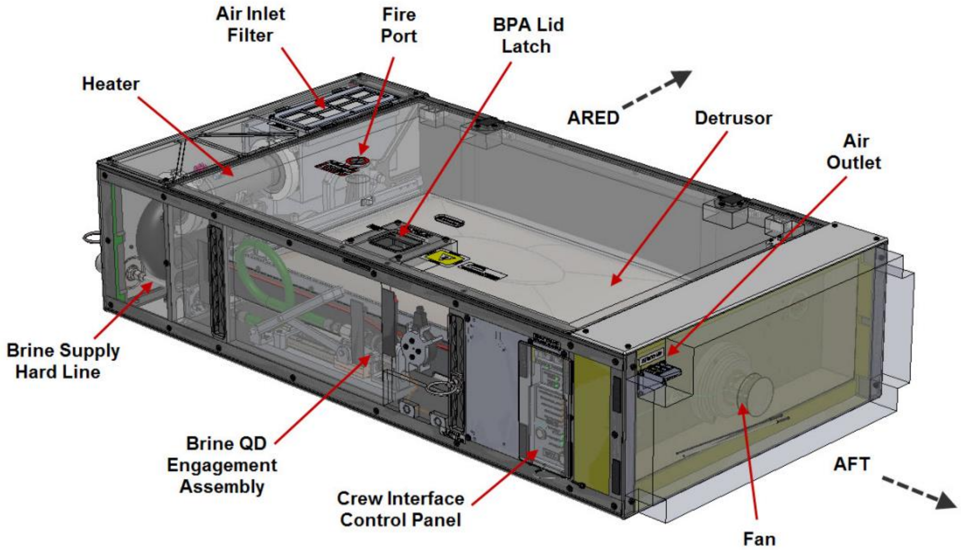


Figure 5. Brine Processor Assembly Solid Model [4]

In BPA operations, condensate is collected and condensed by the ISS Common Cabin Air Assembly (CCAA) Condensing Heat Exchanger (CHX). Several CCAA CHXs are utilized on the ISS, located in the U.S. Laboratory Destiny module (2), the Quest Airlock (1), Node 2 Harmony (1), and Node 3 Tranquility (1) modules. Excluding the airlock unit designated for Extravehicular Activity (EVA) operations, redundancy exists within the system, which can be leveraged to handle BPA's hot humid exhaust. In which, this subsystem interaction, specifically the routing and handling of BPA's hot, humid exhaust through the CCAA's redundant CHX configuration, is represented by Blocks A and D in the RBD.

To accurately model the reliability of ECLSS, it is essential to understand its system-of-systems nature and the interdependencies between its subsystems. In *Unveiling the System-of-Systems Complexity in Regenerative ECLSS: Insights from ISS,* Chen et al. deconstructed and analyzed key ECLSS subsystems, emphasizing their interconnections and resource flows to illustrate the system's inherent complexity. [13] By leveraging insights from the ISS testbed, the study underscores the importance of holistic system evaluation, which is crucial for the development of ECLSS models.

With the constructed ECLS system, its interdependencies, and the selected reliability model in place, the next step involves data extraction and utilization. The ISS Maintenance & Analysis Data Set (MADS) serves as the primary source for data collection, as it provides up-to-date reliability data on ECLSS hardware. By leveraging MADS, failure rates, and maintenance insights can be analyzed to refine reliability assessments and enhance the predictive accuracy of ECLSS performance. The complete ECLSS reliability dataset comprises with the ORU mass, operational kfactor, MTBF, operational Mean Time to Repair (MTTR), Mean Time Between Preventative Maintenance Remove and Replace (MTBPMRR), Mean Time to Preventative Maintenance Remove and Replace (MTTPMRR), operational limited life, and throughput limited life where applicable. Due to the nature of the ORU, some hardware is built with limited life characteristics, governed either by operational duration or throughput capacity. Recognizing these constraints is crucial for accurately modeling the lifecycle and maintenance requirements of ECLSS components. Operationally limited life items are tracked by calendar or operational hours, whereas throughput limited life components depend on the quantity of processed material or fluid. Most hardware components are tracked and operated until they reach their maximum allowable life. However, some components are proactively replaced based on a preventative maintenance schedule.

Following data, as shown in the Appendix, extraction from MADS, the reliability information can have a great potential to be integrated into a simulation framework, enabling detailed assessments of system performance over mission timelines. The development of such simulation framework is in work and will be presented and demonstrated in future ICES paper. This integration facilitates comprehensive reliability predictions, supporting the identification of critical failure points and enhancing preventive maintenance strategies. Moreover, by continuously updating the model with real-world operational data from MADS, the predictive reliability assessment remains dynamic, reflecting the most current operational insights and anomalies. Next, sensitivity analyses are performed using the integrated reliability model to determine the impact of individual ORU failures on the overall system robustness. This step highlights system vulnerabilities, enabling targeted design improvements and risk mitigation measures. Finally, outcomes from these analyses inform decision-making processes regarding spare parts inventory, maintenance scheduling, and operational readiness, ultimately contributing to increased mission success probability and crew safety. However, it should be noted that the reliability database is not yet complete. If specific data is required but unavailable in the current dataset, assumptions based on analogy can be employed to estimate potential failure rates.

Taking Oxygen Generation Assembly (OGA) as an example, the hardware is decomposed into a list of major ORUs which are tracked by ORU's replacement rate, Life Limit, and throughput limit where applicable. The decomposition can be seen in the Figure 6 with the reliability data in Table 10.

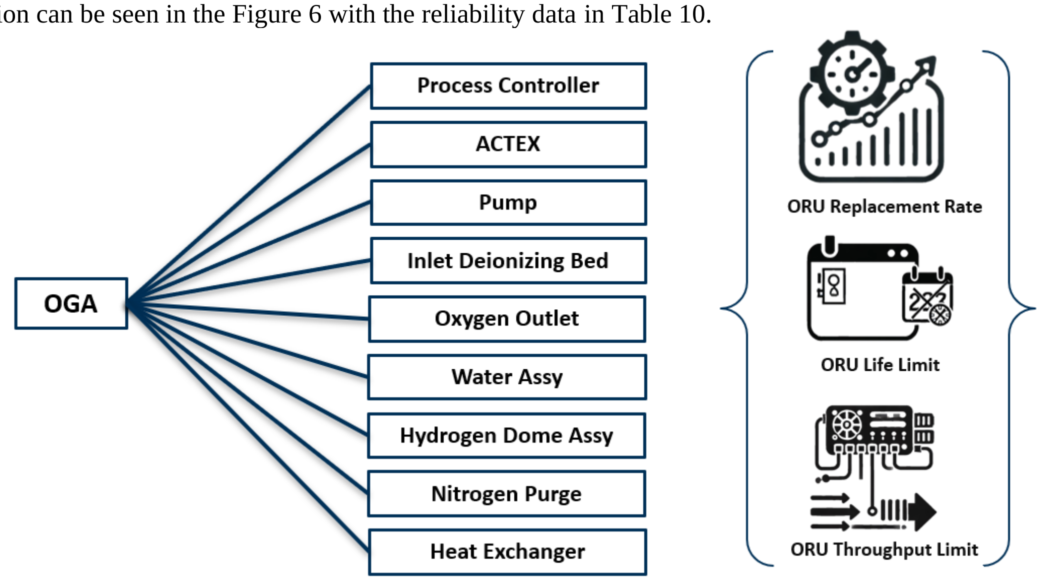


Figure 6. OGA Decomposition

Another critical factor significantly impacting reliability analysis is crew time. Many studies assume no gap between hardware failure and replacement due to the lack of available data. However, this assumption may not accurately reflect real-world scenarios, where crew availability, scheduling conflicts, training requirements, and operational constraints can introduce substantial delays. Such delays can markedly influence system performance and reliability, potentially exacerbating the consequences of hardware failure events.

This paper aims to assist in the advancement of reliability analysis by explicitly providing the crew time required for major ISS ORUs. Metrics such as MTTR and MTTPMRR offer valuable estimates of the hours needed for crew members to remove and replace an ORU, restoring system functionality. These metrics facilitate the calculation of necessary resource reserves and enhance preparedness for potential system failures.

Table 1 includes the crew time needed to R&R major ORUs. However, it does not include the gathering and stowing time needed for the R&R. It is essential to acknowledge that crew time estimates are highly dependent on hardware installation locations, accessibility, and the complexity of tasks involved. Therefore, these estimates should serve as reference points within reliability models rather than definitive values. Furthermore, the provided data is not exhaustive; the table presented includes crew time estimates specifically for major ORU removal and replacement tasks, highlighting the need for comprehensive data collection to refine future analyses.

Table 1. Major ORU R&R Crew Time

Subsystem	ORU R&R	Crew Time
AR	TCCS – Catalytic Oxidizer, Sorbent Bed, and Charcoal Bed	4 hrs
AR	CDRA – CO2 Selector Valve	4 hrs
AR	CDRA – Blower and Precooler Assembly	6 hrs
AR	CDRA – Chassis and Bed	2 hrs
AR	CDRA – Heat Controller	5 hrs
AR	CDRA – Motor Controller	1 hr
AR	CDRA – Two Stage Pump	1 hr and 30 mins
AR	Four Bed – Bed Filter	3 hrs and 35 mins

OGS	OGA – Deionizing Bed	2 hrs and 50 mins
OGS	OGA – Pump	1 hr and 5 mins
OGS	OGA – ACTEX	2 hrs and 30 mins
OGS	OGA – Process Controller	2 hrs and 10 mins
OGS	OGA- Oxygen Outlet	2 hhrs
OGS	OGA – Water	2 hrs and 15 mins
OGS	OGA – Power Supply Module	2 hrs and 10 mins
OGS	OGA – Hydrogen	14 hrs
THC	Lab CCAA – Water Separator	2 hrs and 15 mins
THC	Lab CCAA – Heat Exchanger	5 hrs and 30 mins
THC	Lab CCAA – Electrical Interface Box	2 hrs
THC	Lab CCAA – Water Separator Liquid Check Valve	4 hours and 20 mins
THC	Nod 3 CCAA – Inlet	1 hr and 45 mins
THC	IMV Valve	3 hrs and 25 mins
THC	AAA	2 hrs
THC	High Speed IMV Fan	3 hrs and 5 mins
AR	MCA – Series Sample Pump Assembly	2 hrs
AR	MCA – Verification Gas Assembly	2 hrs and 30 mins
AR	MCA – Mass Spectrometer	4 hrs
WHC	Urine Hydraulic Components	5 hrs
WHC	Dese Pump and Pre-Treat Tank	2 hrs and 55 mins
WHC	Water Hydraulic Components	3 hrs and 50 mins
Water	WPA – Multifiltration ORU	3 hrs
Water	WPA – Separator Filter	2 hrs and 40 mins
Water	WPA – Waste Water Filter	3 hrs
Water	WPA - Pump/Separator	3 hrs
Water	WPA – Waste Water	3 hrs
Water	UPA - Pressure Control and Pump Assembly	2 hrs and 25 mins
Water	UPA – Fluids Control and Pump Assembly	4 hrs
Water	UPA – Wastewater Storage Tank Assembly	4 hrs
Water	UPA – Distillation Assembly	3 hrs
Water	UPA – Firmware Controller Assembly Data and Power Module	3 hrs and 30 mins
Water	WPA- Gas Separator, Water Delivery, Ion Exchange and AAA	19 hrs and 15 mins

III. Conclusion

This paper presents a structured methodology to advance ECLSS reliability modeling, addressing a critical need for updated and comprehensive reliability data in the post-2004 era. By leveraging recent data from the ISS MADS, the study integrates key hardware characteristics—such as MTBF, limited life constraints, throughput capacities, and operational k-factors—into a system-of-systems reliability framework tailored for long-duration mission planning.

Another major inclusion of this work is the ORU crew time estimates for R&R tasks. Traditional models often assume immediate component replacement following failure, neglecting the operational and logistical constraints experienced in spaceflight. By introducing crew time data (e.g., MTTR and MTTPMRR), this paper provides an opportunity for the community to enhance the realism of ECLSS reliability simulations and provides actionable insights into the human factors that impact system availability and recovery timelines.

The paper also emphasizes the use of analogies to estimate failure rates when data gaps exist, allowing for continuity in modeling while acknowledging uncertainties. A preliminary dataset for key ISS ECLSS components was compiled and presented, covering a broad range of subsystems including water recovery, atmospheric revitalization, temperature and humidity control, and waste management.

This foundational framework supports future efforts to develop integrated simulation environments that combine reliability analysis with resource planning and logistics management. Such models will be instrumental in designing resilient and autonomous ECLSS architectures capable of supporting lunar, Martian, and commercial LEO missions where repair windows, spares logistics, and crew resources are tightly constrained.

Overall, this paper lays the groundwork for the upcoming simulation model by establishing key assumptions, identifying data gaps, and introducing a preliminary reliability framework. The reliability model developed here will be integrated into the larger simulation architecture to enable system-level performance evaluations, assess failure impacts, and support trade studies across different ECLSS configurations. This integration will enhance the fidelity of future simulations by accounting for both functional behavior and probabilistic system reliability over mission timelines.

In conclusion, the integration of updated ISS operational data, ORU-specific lifecycle characteristics, and maintenance timelines could provide a significant step forward in the fidelity of ECLSS reliability modeling. These contributions support the transition toward sustainable, long-duration human exploration beyond low Earth orbit.

IV. Appendix. ECLSS Reliability Data

Table 2. Water Processor Assembly Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR (hr)	Kfactor (-)
Catalytic Reactor	57.43	27,077	6	1.05
Gas Separator	39.28	61,182	1.18	1.09
Ion Exchange Bed	12.02	442,478	0.65	1.38
Microbial Check Valve	3.72	178,447	0.63	1.18
Multfiltration Bed	50	349,650	0.62	1.2
Particulate Filter	26.76	560,695	1.5	1.38
Processor Controller	36.83	70,745	1.61	1.1
Pump/Separator	27.58	39,429	1.15	3.26
Reactor Health Sensor	8.62	134,077	1.13	1.15
Sensor	3.63	184,618	1.12	1.18
Separator Filter	7.26	641,342	0.31	1.38
Start-up Filter	9.44	226,850	0.01	1.38
Wastewater	87.36	43,669	1.14	2.17
Water Delivery	39.15	61,797	1.13	1.09
Water Storage	49.17	40,463	1.13	1.06

Table 3. Urine Processor Assembly Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)
Distillation Assembly	75.57	41,376	7	1.84
Firmware Controller Assembly	-	13,453	1.54	1.02
Fluids Control and Pump Assembly	45.59	22,759	1.93	1.19
Pressure Control and Pump Assembly	44.77	59,221	1.19	1.28
Advanced Recycle Filter Tank Assembly	52.62	1,321,000	1	1.38
Separator Plumbing Assembly	172.72	88,993	1.04	2.63
Wastewater Storage Tank Assembly	47.76	82,200	1.48	1.11
	Mass (kg)	**MTBPMRR (d)**		**MTRPMRR (hr)**
Brine Filter	5.35	60		0.17
Purge Filter	1.61	545		0.17
Distillate Filter	1.61	545		0.17

Table 4. Brine Processor Assembly Reliability Data

Component	Limited Life
Brine Processor	10.8 years life time
Brine Processor bladder	Each bladder must be disposed of within 35 weeks of Brine fill. The BPA batch processes 24 L of brine every 26 days.

Table 5. Water Storage System Reliability Data

Component	Mass (kg)	MTBF (hr)	Kfactor (-)	R&R (hr)	Limited Life
Water Storage Tank Assembly	75.57	279,558	1.21	0.33	-
Potable Water Manifold	6.1	49,733	1.14	0.67	-
ACTEX Filter	1.46	469,469	1.15	0.5	Throughput: 6750 lbs Or 4 yrs wetted life
Double Isolation Valve Assembly	8.03	94,066	1.32	-	-
Microbial Check Valve	0.91	178,447	1.38	0.5	-
Controller Shelf Assembly	20.77	26,320	1.07	0.67	-
Resupply Air Manifold	20.77	99,570	1.32	0.33	-
Resupply Water Tank Manifold	-	49,733	1.14	0.67	-
Controller	1.68	130,000	1.17	0.67	-
Nitrogen Manifold	-	58,708	1.16	0.67	-
Single Isolation valve	-	204,184	1.32	-	-
N2 Isolation Manifold	-	259,905	1.32	0.67	-
Power Supply	2.98	1,089,998	1.38	-	-

Table 6. Waste Hygiene Compartment Reliability Data

Component	Mass (kg)	MTBPMRR (Days)	MTTPMRR (hr)
Pretreat Tank with Hose	11	71	2.167
Water Sensor Unit	1.9	1,095	0.58
Urine Sensor Unit	1.48	365	0.83
Flush H2O Tank Full Pressure Sensor	.	1,095	0.58
Urine Interface Sensor Unit	1.9	365	0.83
H2O High Pressure Sensor Unit	.	1,095	0.58
Pipeline	1	180	1.42
Filter Insert	0.24	42	0.33
T-Joint Hose	0.79	365	0.83
Urine Valve/Tank Hose	0.6	365	0.83
ACY Urine Filter Hose Assembly	3.35	180	2
Hose, Dose Pump Flush Water	0.8	1,095	0.58
Water Interface Valve Unit	7	1,095	0.58
Wring Collector (WHC)	.	365	0.75
Flush Water T-Hose	.	1,095	0.58
Air Filter	.	730	0.66
Urine Receptacle	.	42	1
Liquid Indicator	0.6	540	0.18
ACTEX	1.46	1,460 or 6750 lbs throughput	0.33
Urine Valve Block Interface	4.8	365	0.83
Flexible Hose	.	540	0.18
Hose (A1-A8T)	.	540	0.18
Hose (A7-A9)	.	540	0.18
Hose (A10-A11)	.	540	0.18
Corner Fitting	.	540	0.18
T Adapter		540	0.18
Liquid Pressure Regulator Hose	3.3	1,095	0.58
Pretreat Tank with Cap	10.88	71	0.5
E-K Hose	0.7	240	0.1
EDV Cover	.	2,440	0.33

Table 7. Atmosphere Control and Supply Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)
Valve, Manual Pressure Equalization	1.06	4,291,000	0.5	1.4
Tank Assy, Oxygen	-	300,000	14	1.04
Electronics Unit	-	21,832	1.2	1.31
Tank Assy, Nitrogen	-	300,000	14	1.04
Pressure Sensor, 3500 PSIA	0.236	5,000,000		1.31
O2 Manual Iso Valve	-	1,000,000	1.5	1.18
N2 Manual Iso Valve	1.04	1,000,000	1	1.18
O2 Relief Valve Assy	1.91	400,000	1.5	1.4
Regulator/Relief Valve Assy, Low Pressure O2	1.81	300,000	8	1.1
Regulator/Relief Valve Assy, Medium Pressure O2	1.81	300,000	8	1.1
Regulator/Relief Valve Assy, Low Pressure	1.81	300,000	2	1.1
O2 Latching Motor Valve	1.63	500,000	2	1.12
N2 Latching Motor Valve	1.63	500,000	2	1.12
Valve, Vent & Relief	-	79,100	1.4	2.17
Control Panel, Pressure	-	107,000	0.77	1.04
Non-propulsive Vent Assy, Vacuum System	-	200,000,000	-	1.2

Table 8. Air Revitalization Subsystem Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)
Low Voltage Power Supply Assy (MCA ORU 04)	5.67	199,000	0.75	1.15
Verification Gas Assembly (MCA ORU 08)	5.54	52,100	2.5	2.16
EMI Filter Assy, (MCA ORU 07)	-	1,160,000	0.5	1.31
Sample Distribution Assy (MCA ORU 06)	2.11	70,900	0.75	1.08
Major Constituent Analyzer Assy (MCA)	13.93	8,180	5	1.1
Data and Control Assembly, (MCA ORU 01)	9.24	43,500	3.73	2.12
Sample Pump Assy, Series, (MCA ORU 05)	3.13	11,900	0.75	1.02
Blower Assy, TCCS	5.72	121,500	0.38	1.1
Sorbent Bed Assembly	4.94	241,000	4	1.63
Charcoal Bed Assy ORU	38.44	215,000	1.2	1.07
Catalytic/Oxidizer Assy	12.62	89,500	1.5	2.19
Blower/precooler Assy, CDRA	5.58	129,700	12	1.68
Transducer, Pressure	-	493,000	0.62	1.17
Sensor, Immersion, Temperature	-	2,542,000	1.5	1.29
Sensor, Pressure, 20 PSIA	0.48	1,250,000	1.5	1.32
Sensor, Pressure, Differential	0.48	1,250,000	1.5	1.32
Desiccant/Adsorbent Assy	42.91	77,100	17.7	1.19
Coldplate Assy	-	3,600,000	2.5	1.4
Valve, Selector, Assy	2.94	117,000	2.5	1.09
Pump Assy, Two-stage	-	156,200	3	2.29
Controller, Pump Motor	2.94	2,272,000	3	1.9
Controller, Heater	2.52	242,700	1	1.49

Electrical Interface Assy	3.42	483,000	0.59	1.31
Element, Filter	-	200,000,000	0.25	1.16

Table 9. Temperature and Humidity Control Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)	MTBPMRR (Days)	MTTPMRR (hr)
Valve Assy, 2.5 inch, Internal Vacuum	-	347,425	0.91	1.12	-	-
Valve, Intermodule Ventilation	3.084	139,000	3.6	1.01	-	-
Flow Meter Assy	1.34	936,000	0.35	1.32	-	-
Supply Diffuser, Cabin Air	-	200,000,000	0.63	1.4	-	-
Damper Assy, Cabin Air	-	200,000,000	0.43	1.4	-	-
Damper Assy, Perforated, Cabin Air	-	200,000,000	0.43	1.4	-	-
Damper Assy, Actuator, Cabin Air	-	200,000,000	0.34	1.4	-	-
Check Valve Assy, Temperature Control	7.45	92,600	2.3	2.1	-	-
Electrical Interface Box (EIB)	4.08	2,350,600	2.3	1.23	-	-
Liquid Sensor, Heat Exchanger	0.499	1,136,300	1.9	1.17	-	-
Fan Assembly, Air - IMV	-	429,737	2.4	2.13	-	-
Avionics Air Assy	12.5	429,700	8	3.2	-	-
Inlet, Cabin Air	-	332,900	2.6	1.06	-	-
Heat Exchanger, Cabin Air-ORU	54.22	832,600	6	1.19	-	-
Separator Water, ORU	11.93	130,800	3.3	1.57	-	-
Sensor, Temperature	0.25	37,593,900	1.3	1.31	-	-
Fan Assembly, Air - IMV	-	429,737	2.4	2.13	-	-
Velocicalc Probe	0.26	-	-	-	670	.
Velocicalc	0.28	-	-	-	1643	0.08
HEGA Filter	2.2	-	-	-	2190	1
HEPA Filter	1.5	-	-	-	913	1

Table 10. Oxygen Generation System Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)	MTBPMRR (Days)	MTTPMRR (hr)
Avionics Air Assy	12.23	429,700	8	3.2	-	-
Sensor, Hydrogen ORU	4.63	57,803	0.98	2.24	201	0.75
ACTEX Unit Assembly (ISS) (Silver Removal Cartridge)	1.5	469,469	-	1.15	675	3.5
Power Supply Module	46.49	49,202	1.65	1.08	-	-
Pump ORU-OGA	10.52	189,433	1.01	1.21	-	-
Inlet Deionizing Bed	1.36	442,478	1.03	1.38	2569	0.75
Oxygen Outlet	32.613	99,252	1.26	1.14	-	-
Process Controller	36.83	75,677	1.61	1.11	-	-
Hydrogen Dome Assembly ORU	136.69	29,551	1.59	1.06	-	-
Water Assembly ORU	34.56	37,885	4.19	1.07	-	-
Nitrogen Purge ORU	23.13	140,195	1.02	1.18	-	-

OXYGEN GENERATOR ASSEMBLY-RACK 3	-	-	-	-	201	1.5
Detector, Smoke, Area	1.14	748,313	0.5	1.71	-	-

Table 11. Vacuum System Reliability Data

Component	Mass (kg)	MTBF (hr)	MTTR(hr)	Kfactor (-)
Non-propulsive Vent Assy, Vacuum System	-	200,000,000	-	1.2
Valve Assy, 2.5 inch, Internal Vacuum	-	347,425	0.91	1.12
Valve Assy, 1 in., Vacuum System	-	428,700	3.57	1.03
Pressure Transducer Assy, Vacuum System	-	682,611	1	1.17

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