Advanced Reactor Risk-Informed Licensing: Evaluation of Data Availability and Suitability

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Abstract: Advanced reactor concepts are being developed to push the nuclear energy frontier while promising enhanced safety, flexibility, and performance. In parallel, the US Nuclear Regulatory Commission is adopting a risk-informed framework for the licensing and regulation of these advanced reactor designs. Such a framework depends fundamentally on the availability of adequate and credible data to develop the necessary reliability and risk models. However, unlike existing light-water reactors (LWRs), which have accumulated more than 60 years of operational experience and empirical data, many of these advanced reactor designs currently lack well-established reliability data sources and failure data for the risk-informed licensing process. Additionally, the challenge of evaluating the credibility and suitability of data sources containing data collected from research reactors and test facilities with similar designs remains largely unanswered. To address this problem, in this paper, we define a set of 12 characteristics to evaluate existing non–light-water reactor (non-LWR) data sources and the data contained in them, enabling a structured assessment of their suitability.

1. INTRODUCTION

A new generation of advanced non–light-water reactor (non-LWR) concepts are rapidly moving from the design stage toward development and deployment. These designs span diverse coolant families—for example, sodium-cooled fast reactors (SFRs) such as TerraPower's Natrium and GE Hitachi's PRISM, high-temperature gas-cooled reactors (HTGRs) such as X-energy's Xe-100, and fluoride-salt-cooled high-temperature reactors (FHRs) and molten salt reactors (MSRs) such as Kairos Power's KP-FHR and Terrestrial Energy's IMSR. The International Atomic Energy Agency (IAEA) Advanced Reactors Information System (ARIS) [1] lists a total of 68 non-LWR designs comprising 13 SFRs, 12 lead-bismuth eutectic (LBE)-cooled fast reactors, 15 MSRs, 23 gas-cooled reactors (GCRs) and gas-cooled fast reactors (GFRs), and 5 heat pipe or other advanced reactor concepts. Collectively, these advanced reactor designs depart from light-water reactors (LWRs) in terms of coolant, fuel form, operating temperature and pressure regime, neutron spectrum, safety philosophy, and the function and configuration of many systems, structures, and components (SSCs). In the US, these designs are being licensed using a risk-informed, performance-based (RIPB) framework anchored in the guidance presented in NEI 18-04 [2] and NEI 21-07 [3], culminating from efforts over three decades such as Modular High Temperature Gas-Cooled Reactor (MHTGR) licensing [4], Next Generation Nuclear Plant (NGNP) project [5] and NUREG-1860 [6]. Central to this new licensing approach is its reliance on probabilistic risk assessment (PRA), specifically selection of licensing basis events, safety classification of SSCs, and defense-in-depth evaluations. The ASME/ANS non-LWR PRA standard RA-S-1.4-2021 [7] specifies which data must exist, which attributes the data must have (e.g., quality, traceability, uncertainty), and what must be documented in the PRA process. In particular, the high-level data analysis requirement HLR-DA-D mandates that the reliability parameters must be grounded in relevant evidence, supported by uncertainty characterization, and updated with plant-specific data as they become available.

Whereas the PRA of LWRs is supported by more than 6 decades of operational experience from commercial and research entities collected and accumulated in sources such as the US Nuclear Regulatory Commission's (NRC's) Reactor Operating Experience Data (NROD) [8], Licensee Event Report (LER) system [9], and European Industry Reliability Databank (EIReDA) [10], advanced non-LWR designs do not have access to a comparable data infrastructure. No commercial-scale non-LWR fleets have operated in the US. Although test reactors and experimental facilities such as the

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Experimental Breeder Reactor-II (EBR-II) and the Molten Salt Reactor Experiment (MSRE) provided some amount of valuable operating experience, it was collected several decades ago under conditions that differ significantly from commercial operation in scale, degree of automation, regulatory framework, staffing, and operational philosophy. Such operating experience also primarily includes qualitative discussions rather than providing enough data for statistical assessments of reliability parameters. In addition, existing data are fragmented across test facilities, decommissioned reactors (i.e., no current repositories), and proprietary vendor holdings and are often located across different countries under different accessibility regimes. This creates a fundamental challenge for advanced reactor PRA: finding "suitable" data that feed the PRA and thus the licensing and deployment of advanced reactors. The data analysis requirements DA-C1 and DA-C2 in ASME/ANS RA-S-1.4-2021 [7] explicitly acknowledge this challenge and support using any relevant and available data and experience from other facilities with justification. Addressing this challenge requires answering the following four questions about the availability, quality and credibility, and applicability of reliability data to support a given non-LWR PRA:

1. **Where are the candidate data sources?** Locate possible sources from relevant organizations.
2. **What data do they contain?** Identify available information.
3. **What is the pedigree/quality of each data source?** Appraisal of any identified source i.e., assess quality, component population, age, and assurance of data in each source
4. **How relevant and suitable are the data for a target advanced reactor design?** Evaluate how suitable a source is to a target non-LWR design whose features may be similar but not completely identical with those from which the data were originally generated.

Prior relevant work focuses more directly on the fourth question. Saignes [11] introduced the database relevancy test, based on functions, failure modes, and environment and boundary conditions for PRA of a GFR. The failure rates of identical (mostly technology neutral) and similar components were adopted and corrected using error factors from 14 state-of-the-art component failure rate databases (CFRDBs). Mean industry values were used for existing but nonreferenced components in the CFRDBs, whereas "challenging" target values were set for completely new components. The relevancy test was later applied by Grabaskas et al. [12] for PRISM SFR PRA, and the relevance of candidate reliability data was evaluated in a graded manner distinguishing between none, partial, and full relevance relative to the target reactor design. The method was demonstrated in identifying the reliability parameters for five different failure modes of an intermediate heat exchanger using data from multiple sources.

The framework developed in this work instead treats the questions 2-4 above explicitly and proceeds in the opposite direction (i.e., finding sources and the data contained, appraising sources on their own terms, and mapping them onto a design). To evaluate the databases and the individual data items contained in them and to attempt to establish their suitability for advanced reactor designs in a structured and repeatable way, we present a set of 12 characteristics. We complement the 12 characteristics with a classification of available data into 3 types to clarify what a given source actually contains. We emphasize that the current framework is intended as an evaluation aid with the objective of making reliability suitability judgement explicit and reviewable and not as an automated decision-making procedure. Also, we note that this paper is only introducing the characteristics, and a detailed demonstration is out of scope. This research focuses on data sources identified through literature reviews; proprietary datasets and other reliability data sources are excluded.

2. RELIABILITY DATA TYPES AND DATA SOURCES

The ASME/ANS RA-S-1.4-2021 standard [7] outlines 18 technical requirements for PRA analysis, including operating state, initiating event, event sequence, data analysis, and event sequence quantification. The identified reliability data are grouped as qualitative and quantitative reliability data, plus context data that augments the two types of reliability data.

Type 1: Qualitative Event Data: Qualitative event data consist of documented operational experiences and events, including definitions and descriptions of the following items:

1. Failures and failure modes (what went wrong?)
2. Root causes of failures (why did the failure occur?)
3. Event sequences (how did the failure event evolve?)
4. Hazards (what were the sources of danger)

5. Consequences (what were the end results?)

The LER database [9] detailing abnormal events in commercial LWRs, is an example collection of Type 1 data. Finding such data is essential for non-LWRs, helping to identify failure modes like salt freezing in MSRs or sodium aerosols on valve stems, as well as events with no LWR counterpart.

Type 2: Quantitative Reliability Data: Type 2 data consist of statistical information used for quantitative risk assessment, as specified in ASME/ANS RA-S-1.4-2021 [7] (DA-N-3, DA-C-1, DA-C-6 through DA-C-26). Type 2 data include the following:

1. Failure rates/frequencies per unit time or per demand
2. Human error probability values, where applicable
3. Distributional parameters such as mean values, and shape and scale parameters
4. Uncertainty bounds such as error factors and confidence intervals that establish the precision of failure rate estimates
5. Population data used for assessing the statistical power of the estimates
6. Number of maintenance activities, time durations of repair and unavailability
7. Common cause failure (CCF) parameters

These are used in fault tree and event tree quantification. NUREG/CR-6928 [13], and EIReDA [10] are good examples.

Type 1 data provide upstream operational experience raw material i.e., operational narratives and failure insights, while Type 2 quantitative data are downstream outputs that translate this experience into distributional parameters. This distinction impacts how non-LWR reliability and PRA data sources are evaluated and how data can be transferred. Type 1 data insights can generally transfer across designs with similar features, but Type 2 parameters require demonstrated similarity through formal assessment and an understanding of the conditions in which the data originated.

Context Data: Mission type (standby or in operation), operating conditions (like temperature and pressure), and component life cycle stage add depth to both Type 1 and Type 2 reliability data. These factors influence qualitative understanding of failure mechanism and help determine the appropriate statistical model for Type 2. These context data align with ASME/ANS RA-S-1.4-2021 HLR-DA-B [7].

These three data types together form what a candidate reliability data source may include. For clarity, a *data source* refers to any report, document, or recorded experience containing reliability information, such as NUREG/CR-6928 [13]. A *database* is an organized repository that aggregates records from various facilities, components, or periods for querying, examples being RADS [14], NaSCoRD [15] and MOSARD [16]. In this paper, every database is a data source, but not all data sources are databases.

Reliability data for non-LWRs comes from various sources, each with unique features, strengths and drawbacks. Structured databases like NaSCoRD [15] and NROD [8] systematically gather component populations, operating hours, failure events, and more across multiple facilities over time. These databases are built for PRA, use consistent taxonomies, and can provide enough data for parameter estimation, but they need multi-facility participation, maintenance, and ongoing funding. At the other end of the spectrum peer-reviewed publications from academic, research, and commercial test facilities offer valuable Type 1 data, such as failure modes and root causes, even though they often cover single test loops and brief operations. For example, Burak et al. [17] present a root cause analysis of pump corrosion in a fluoride salt test loop. While these sources are usually accessible, they rarely include fleet-scale or extensive data for estimating Type 2 parameters. However, important questions arise when considering such sources – "can the data from a test loop be relevant in an advanced non-LWR PRA? If yes, what factors must be considered?". Operating records MSRE systems and components performance report [18] and the EBR-II operating experience report [19] fall between these extremes.

3. RELIABILITY DATABASE / DATA SOURCE CHARACTERISTICS

This section outlines 12 characteristics shown in Table 1 for evaluating reliability data sources and capturing distinct dimensions such as quality, scope, and relevance. Most characteristics address metadata (such as purpose or origin) and content features. Eleven of these are intrinsic, determined by the source; the twelfth is a relational one and assesses compatibility between the data source and a target system. These criteria follow requirements from ASME/ANS RA-S-1.4-2021 [7].

Characteristic 1: Objective
The purpose of data collection directly influences a data source's scope, structure, definitions, and what the data can and cannot support i.e., usability. Data sources for NRC risk models differ from those that track facility experience, so understanding their purpose helps analysts detect bias and gaps in reactor PRA data. Clearly establishing objectives ensures accurate data definitions and consistency (ASME/ANS RA-S-1.4-2021 [7]). Legacy data sources focus on system and component performances; therefore, reported failures, often referring to partial or degraded function rather than failure defined in fault trees such as "fail to run" or "failed to operate," must be carefully assessed.

Table 1. Twelve characteristics of reliability data sources.

#	Characteristic	Evaluation question (for the data source under evaluation)	Supporting requirements from ASME/ANS RA-S-1.4-2021 [7]
1	Objective	Why were these data collected? What was the intended purpose and scope?	HLR-DA-A, DA-B2
2	System design	From which system were the data collected? Specific to this effort - are there any data from non-LWR systems?	DA-A2, HLR-DA-B, DA-C1
3	Operational regime context	Under which conditions were the reliability data collected (power ranges, life cycle stage, in operation or standby, etc.)?	DA-B1, DA-C8
4	Component populations	How many different types, designs, and number of components were considered?	DA-B1, DA-B2
5	Data collection duration	How long were the data collection efforts?	DA-C11, DA-E1(e)
6	Age of the data source	How old is the data source (i.e., when was the data collected)?	DA-D10
7	Data source accessibility	Is the data source publicly available? Or is access restricted?	No direct requirement
8	Reliability data type	Which reliability data are collected and stored (Type 1, Type 2, or both)?	DA-C5
9	Data quality assurance and validation	Which standards were followed in collecting and storing the data? Are the data verified across sources? Are the data sufficient?	DA-C1, DA-E1
10	Uncertainty characterization	Does the data source include parameters/mechanisms for uncertainty quantification?	HLR-DA-D, DA-D3
11	Data use	How were these data used and who are the expected users of the data?	DA-E1
12	Data extrapolatability	Can the data be extrapolated to similar components in systems with "similar" design parameters or "similar" operating conditions?	DA-C1, DA-C2, DA-D2

Characteristic 2: System Design
This characteristic determines which systems are covered in the data source, with a focus on non-LWR designs. Data sources without relevant reactor data are limited to generic components not tied to specific technologies, like electrical switchgear or certain digital instrumentation. The Hydrogen Component Reliability Database (HyCReD) requirements [20] explicitly outline three system design categories: fluid properties, component configuration, and facility configuration. These are relevant to non-LWR PRA data sources as well. System design consists of multiple aspects that inform reliability assessment.

The following features are intrinsic to the system being described and will be updated and ranked for reliability importance based on expert input.

1. **Coolant family:** Determines main degradation mechanisms (e.g., corrosion chemistry, freezing behavior) and is a discriminating factor for applicability of advanced reactor reliability data.
2. **Neutron spectrum:** (Thermal, fast, intermediate) Affects radiation damage rates, activation, and material behavior in service.
3. **Materials of construction:** Metals, alloys, ceramics, and their specifications influence failure mechanisms and rates.
4. **Instrumentation and control type:** Analog/digital systems and sensor technology define possible failure modes that are possible and that can be captured, as well as monitoring accuracy.
5. **Physical scale:** Dimensions, volumes, flowrates etc., matter as some failures such as corrosion rates depend on scale, while others do not.
6. **System and facility configuration:** Component layout, containment, support systems, and plant context that shape operational outcomes.

Characteristic 3: Operating Regime Context

This characteristic focuses on the conditions under which the data were collected and whether the data source covers events beyond normal power operation, such as start-ups, shutdowns and transients. It also considers if the data span key physical and chemical conditions (temperature, pressure, flow, mixture) and represent components in various service modes like standby or intermittent operation, since failure rates can differ between states. While Characteristic 2 specifies system design, this characteristic checks if reliability data reflect operation throughout the design range. For instance, NUREG/CR-6928 [13] excludes startup and shutdown-related events. Multiple regime context features are proposed here and will be refined in future studies.

1. **Operating mode and mission profile:** Operating, standby, intermittent.
2. **Physical conditions regime:** The operating temperature and pressure ranges range over which the data were generated. Example ranges: MSRs: ~600–750 °C and low pressure (< 1 MPa); HTGRs: ~700–950 °C and high-pressure (~7 MPa).
3. **Chemistry control regime:** Corrosion and material degradation in non-LWR systems such as MSRs depend on chemistry, including redox potential, impurity levels (moisture, oxygen), and control measures. Test loops with continuous redox monitoring and purification experience different degradation rates than those with limited chemistry control. For sodium systems, factors such as cover gas purity and cold trap effectiveness are similarly important. Shahbazi et al. [21] review ORNL MSR Program data showing that corrosion mechanisms in fluoride salts are strongly influenced by chemistry control.
4. **Life cycle stage:** Whether the data cover burn-in, useful life, or wear-out periods of the components.
5. **Operational context:** Data is influenced by the environment and personnel involved. Research staff in test loops follow experimental protocols and operate differently from licensed operators in commercial plants under technical specifications. Test loops often require manual interventions not seen in automated plants, making failure pathways highly context dependent. Failures linked to support systems or human factors unique to the test environment should be filtered or adjusted before using the data in reactor PRA. However, qualitative insights from human errors, such as incorrect salt loop operation can still provide valuable information, even if error rates aren't directly transferable.

ASME/ANS RA-S-1.4-2021 [7] requires PRA for advanced reactors to consider multiple plant operating states beyond full power. Generic estimates cannot be reused across these states unless their relevance is confirmed (DA-C25), although the process for this evaluation is not specified in [7]. NaSCoRD [12] stands out for incorporating normal, abnormal, and transient operation data, along with engineering data.

Characteristic 4: Component Populations

This characteristic measures coverage breadth (horizontalness), evaluating the diversity and quantity of component types and populations in a data source. Broad databases with sufficient counts enable reuse across multiple systems. Larger component populations increase statistical confidence. Also, Bayesian estimates NUREG/CR-6823 [22] are sensitive to the number of failures, and zero-failure datasets require special treatment (Jeffreys prior). The HyCReD framework [20] defines two specific

subcategories: **System data** – component counts: the number of individual components of each type. **Facility data** – population count: number of facilities or plants contributing the data.
NUREG/CR-2641 [23] outlines how to define component populations, groupings, and boundaries, including specifications for hierarchies and counting operating hours and demands. For advanced reactor PRA, the limited component population is a key issue. While NUREG/CR-6928 [13] uses US commercial LWR fleet data, non-LWR sources like NaSCoRD [15] rely on only a few sodium facilities (such as EBR-II and FFTF), resulting in much smaller populations.

Characteristic 5: Data Collection Duration
This characteristic asks how long the data collection efforts lasted. This duration affects the completeness of the data source—that is, a longer collection period captures more operating hours, more demands, and potentially more failure events, yielding more precise Type 2 estimates. A longer duration also aids in collecting data across different life cycle contexts (burn-in vs aging).

Characteristic 6: Age of the Data
The relevance of collected data depends on its age, as changes in manufacturing, materials, QA programs, and operations affect component and system reliability. For example, MSRE data from the 1960s may not apply directly to modern MSR designs because technology has evolved. While sodium technology boasts over 400 years of accumulated operating experience, most NaSCoRD [15] data are from early development (1960s–1980s). Using these failure rates for current SFR designs should be done carefully, treating them as informative but potentially conservative priors. Age complements and does not duplicate design specifications by indicating *whe*n they were in effect; both factors are critical when assessing a data source. Characteristic 2 checks if source specifications align with the target system, while Characteristic 6 assesses whether the era matches. For instance, a 316H pipe from 1980 may have different defect distributions than one from 2025, reflecting temporal differences. Age captures this without duplicating specifications. This effort proposes four sub aspects:

1. **Calendar age:** The time gap between the source's data window and the target system's design period.
2. **Manufacturing-era practices:** Standards in effect when components were made, such as earlier ASME Boiler and Pressure Vessel Code (BPVC) rules, determine a component's manufacturing profile.
3. **QA program generation:** Regulatory QA requirements like 10 CFR 50 Appendix B vary over time; data from previous regimes may need special justification for current use. This refers to the era of data generation, not system specs.
4. **Record keeping practices:** Data drawn from historical operation records (e.g., MSRE 1960s) depend on what was documented, which may differ from actual events due to varying event definitions.

Analysts can use these subfactors in evaluating the usefulness of a data source i.e., identify when a data source's calendar age is high, but specifications are suitable, or when age is moderate, yet specifications differ. A systematic review of these characteristics is needed for better fitness assessments in advanced reactor reliability studies. Distinguishing collection duration (Characteristic 5) from age (Characteristic 6) is crucial: a data source with extensive collection duration may still be outdated. For instance, IAEA research reactor data in TECDOC-930 [24] were collected between 1986–1988 across various systems with collection durations from 2 to 28 years, so its relevance for current applications in 2020s should be evaluated separately.

Characteristic 7: Data Accessibility
This characteristic considers whether data sources and documentation are openly accessible or restricted. The ASME/ANS RA-S-1.4-2021 [7] standard mandates reliability estimates be documented, traceable and reviewable. Access-controlled data sources may hinder such reviews. Accessibility can be of the following types:

1. **Publicly available data (PAD):** Information approved for unlimited public release (e.g., published reports, open literature).
2. **Access controlled data:**
    a. Applied technology (AT) data: nonpublic technical information developed under DOE programs that offer technical advantages, such as design specifications or vendor-sensitive

details. While not classified, AT data is controlled, requiring marking, approved access, and nondisclosure procedures.

b. Export controlled (EC) data: information whose dissemination is limited by US export control laws and needs formal review, restricted access, and sharing controls. NaSCoRD [15] contains both AT and EC data; MoSARD [16] hosts EC data, integrating sources from PAD reports and non-EC data.

It should be noted that accessibility by itself does not make a data source and the data contained within it high quality/credible. However, accessibility makes traceability and the PRA review process easier.

Characteristic 8: Reliability Data Collected

This characteristic refers to the actual content of the data source, distinguishing it from previous metadata-related characteristics. It shows whether a data source offers Type 1, Type 2, or both types of data, as each serves unique roles in PRA with distinct extrapolation properties. Data sources can thus be classified into three types based on this feature:

1. **Primarily Type 1 sources:** These primarily contain qualitative event data and provide failure descriptions, and phenomenological insights. For example, NRC's LER database [9].
2. **Primarily Type 2 sources:** These provide parameters such as failure rates, their distributions, etc. For example, NUREG/CR 6928 [13].
3. **Mixed sources:** These contain both engineering/event data and quantitative estimates. For example, NaSCoRD [15].

Characteristic 9: Data Quality Assurance and Validation

Data QA and validation is the most critical and complex of the 12 characteristics. We use six metrics informed by the IAEA [25] and Gitzel et al. [26] to further detail this aspect. The focus is on the data itself (i.e., the records of failure rates, distributional parameters, event narratives, and context fields). Quality is inherent to the data whereas validation reflects the analyst's or user's assessment.

1. **Level of detail:** Assesses the granularity of recorded information (i.e., whether the data source contains detailed descriptions of failure events and modes or aggregate counts).
2. **Data collectors:** Represents the human factors element *of* (and not in) reliability data. Quality of the data is impacted by who collects it. The data in NUREG/CR-6928 [13] were collected directly from the operating commercial LWR fleet, while Burak et al. [17] Type 1 data was collected in an academic setting from a test loop operated by students.
3. **Standards and codes:** Evaluates adherence to reliability standards like ISO 14224:2016 [27].
4. **Consistency:** Reviews if uniform definitions, formats, and coding were applied over time and across locations since inconsistent practices cause systematic errors, and if there were duplicate entries. Establishing clear definitions is a requirement in ASME/ANS RA-S-1.4-2021 [7].
5. **Quantity and significance:** Determines if collected data are sufficient to accurately evaluate failure parameters and establish uncertainty bounds of those parameters. Characteristic 4 establishes the population (numbers) from which the data are reported, and this sub metric determines whether what is reported is adequate.
6. **Cross validation:** Type 1 data are verified across facilities for matching failure modes and Type 2 data are benchmarked with comparable sources.

Table 2 presents a mapping (shaded cells) that shows which of the above six metrics are applicable to the different elements of the collected data. This mapping will be updated to include more details in future research.

Table 2. Mapping the six data QA and validation features to the two types of reliability data.

		Sub metrics					
		1	**2**	**3**	**4**	**5**	**6**
Type 1 data (definitions and descriptions)	Failures and failure modes						
	Root causes of failures (initiators)						
	Event sequences						
	Hazards						

	Consequences						System-dependent
Type 2 data (failure/ reliability/ statistics)	Failure rates/frequencies per unit time or per demand						
	Human error probability values						
	Distributional parameters						
	Uncertainty bounds						
	Population data						
	Number of maintenance activities, time durations of repair and unavailability						
	CCF parameters					Limited availability	

Characteristic 10: Uncertainty Characterization
This characteristic evaluates whether a database includes uncertainty quantification mechanisms, such as distribution parameters, error factors, or confidence intervals. ASME/ANS RA-S-1.4-2021 [7] (HLR-DA-D) requires significant events to include both mean values and probabilistic uncertainty and nonsignificant events require point estimates with characterized ranges. NUREG/CR-6928 [13] and EIReDA [10] provide failure data fitted to beta and gamma distributions, compatible with Bayesian updating frameworks [22]. Many non-LWR sources lack clear support for uncertainty quantification, posing challenges for Bayesian analysis and requiring analysts to assess uncertainty through expert judgment or sensitivity analysis. Our framework identifies three states of uncertainty characterization:

1. **Explicit:** Source provides distributional parameters directly compatible with NUREG/CR-6823 [22] and the analyst transcribes them.
2. **Implicit:** Source does not provide distributional parameters but gives sufficient statistics (e.g., failure count) to compute distributional parameters via conjugate prior analysis [22] procedures. The analyst computes the parameters.
3. **Absent:** Source only offers point estimates and analyst assigns a default uncertainty distribution based on assumptions.

The implicit case is far closer to the explicit case than to the absent case, and the implicit case depends on sub metric 9.5.

Characteristic 11: Data Use
This characteristic considers data usage and target users. Usage history offers indirect evidence of quality, acceptance, and regulatory suitability. Data sources used in NRC-accepted PRA models have greater regulatory precedent than those used mainly for research. Knowing the user base aids in identifying potential biases. ASME/ANS RA-S-1.4-2021 (HLR-DA-C, supporting requirement DA-C2) [7] requires past facility experience to be reviewed, including how previous users applied the data and any noted limitations. While Characteristic 1 represents why the data was collected, this represents how the data was used after collection.

Characteristic 12: Data Extrapolatability
Data extrapolatability is the most analytically challenging of the 12 characteristics, and is uniquely relational. It determines if reliability data from one source can credibly apply to a new reactor design PRA with similar but different conditions. We introduce a quantitative metric based on Gower's distance [28] that uses features such as system design, operational regime, age (Characteristics 2, 3, and 6), and expert opinion, as shown in Eq. (1).

$$S_{ij} = \frac{\sum_{k=1}^{p} w_{ijk} s_{ijk}}{\sum_{k=1}^{p} w_{ijk}} \tag{1}$$

where S_{ij} is the similarity between two objects i and j; p is the number of descriptors/features, both continuous such as temperature and discrete (or qualitative); w_{ijk} are non-negative weights, obtained from experts; and s_{ijk} is the similarity between the two objects regarding the kth feature. For binary or descriptive features such as coolant types, s_{ijk} is either 0 or 1, whereas for continuous features,

$$s_{ijk} = 1 - \frac{|x_{i,k} - x_{j,k}|}{R_k} \quad (2)$$

where $x_{i,k}$ is the magnitude of the kth feature of object i, and R_k is the range of the kth feature. The three characteristics used are defined as vectors with multiple dimensions. The similarity value s_{ijk} in Eq. (1) is applied over these individual dimensions, and the score S_{ij} represents the aggregate over all the dimensions. Considering the characteristic system design, the individual features can be coolant types (binary), operating temperature range (continuous), pressure range (continuous), etc. A full list of system representative features relevant for reliability data will be defined in future research.

4. EXAMPLE DATA SOURCES AND THEIR CHARACTERISTICS

Two data sources relevant to molten salt technology are considered and their characteristics are listed. The data sources are:

1. Molten Salt Reactors Reliability Database (MOSARD) [16]: This is a structured database currently under development at ORNL with consolidated data from the MSRE operating experience from the 1960s. Reported incidents from both publicly available and restricted component performance and maintenance reports are analyzed and sorted based on the types of components, types of failures encountered and any contributing factors.
2. Experimental investigation of flow accelerated corrosion in FLiBe loop [29] at the University of New Mexico (UNM): This document presents initial results from an experimental study of flow accelerated corrosion in a stainless steel molten salt loop and a validated Multiphysics corrosion model. Additional failures such as salt leaks and sensor failure are also discussed. This is primarily Type 1 data source – an academic report with limited scope.

Table 3 presents the characteristics of these two data sources.

Table 3. Example non-LWR reliability data sources and their characteristics.

#	Characteristic	**MOSARD** [16]	**UNM FLiBe loop document** [29]
1	**Objective**	Build a structured MSR component database by methodical extraction of key data like initiating events and their frequencies from MSRE operational records.	Characterize flow accelerated corrosion in FLiBe molten salt loop.
2	**System design**	MSRE. Approximately 12000lbs of molten FLiBe coolant with ZrF_4-UF_4 fuel, molten salt pumps, air cooled heat exchangers, Hastelloy-N molten salt tank.	316 stainless steel forced circulation loop - 36” in length and 1.2 L operating volume. The loop was designed for 600°C - 700°C operating temperature with laminar flow and to expose the metal to 1000-3000hrs under these conditions.
3	**Operational regime context**	Covers MSRE operating history including cover-gas system. Coolant temperature was in the range 635°C - 665°C.	A few hours (unspecified) of shakedown test with HITEC salt, a close alternative to FLiBe, was run at a temperature of 500°C.
4	**Component populations**	Limited population (compared to large fleets) from a single MSRE system.	The loop consisted of a pump, melt and expansion tanks, 9-coupon holder and 22 Swagelok fittings. Instrumentation included 3 thermocouples, 3 electrodes and a flowmeter.
5	**Data collection duration**	Data was collected and recorded during the entire MSRE operation (1965–1969).	Realtime data collection lasted only a few hours. Relevant reliability data is only from system initialization and burn-in. Experiments did not last long

#	Characteristic	MOSARD [16]	UNM FLiBe loop document [29]
			enough to collect data from other life cycle stages.
6	**Age**	Source data is from 1965–1969, i.e., almost 6 decades old.	The experiment was conducted during 2017-19. The observations are more age relevant.
7	**Data availability and accessibility**	Access is anticipated through DOE GAIN.	The documentation and results are open access.
8	**Reliability data collected**	Mixed Type 1 and Type 2 i.e., descriptions of recorded failures and relevant statistics.	Only Type -1 data. 3 failure events were observed – salt leak from expansion tank, melt tank and a Swagelok fitting, and a flowmeter failure. Mechanistic corrosion model was validated from the experiment as well.
9	**Data QA and validation**	High quality – The MSRE was run and the data was collected by trained researchers. ORNL is the custodian of the data and is commonly used as benchmark for MSRs.	Limited detail and data were collected in an academic setting. Cross-validated using ORNL MSRE data. Given the objective of the experiment, no reliability standard was applied in data collection.
10	**Uncertainty characterization**	Limited: Aim is to extract distributional parameters from structured data. However, the efforts are constrained by MSRE's limited statistical basis.	Not directly applicable for reliability data. However, the corrosion metal loss mechanistic model was validated against ORNL MSRE to within 30%.
11	**Data use**	Intended for MSR PRA and RAM support.	Intended use – corrosion model validation.

Three salt leak (failure) events were observed by Weitzel et al. [29] during the course of their experiment. These include salt leak from the expansion tank "around" a gasket, through a Swagelok socket joint and around the melt tank lid. The root causes identified were of small gasket size, insufficient tightening of the fitting and improper salt loading – highlighting the characteristic 3.5 – who operated the loop – and the need for evaluating data sources.

The 12th characteristic is a relational one and is evaluated with respect to a relevant advanced reactor design. The Kairos Power Hermes reactor with FLiBe coolant is chosen as an example, and three features – two categorical - coolant type and chemistry control and one continuous - operating temperature range (650-750℃) were chosen. Observe that material types, neutron spectrum, radiation effects, age etc. are not considered and these features require establishing further details. For the categorical features, both data sources got a score of 1 for having the same coolant. MOSARD and UNM loop scored 1 and 0 for chemistry control respectively. Mean operating temperatures were considered for $x_{i,k}$ in Eq. (2), with R_k representing the operating temperature span of Hermes. The scores for different weighting schemes are presented in Table 4. Note that these scores represent the suitability/ extrapolatability of the data sources at a high level and are not correction factors of individual reliability parameters. These are intended to only aid the PRA analyst in identifying and selecting relevant data sources.

Table 4. Sensitivity of Gower similarity scores to selected weighting schemes

Weights	MOSARD	UNM Loop
Baseline - Equal weights (0.33, 0.33, 0.33)	0.833	0.50
Coolant type dominant (0.6, 0.2, 0.2)	0.9	0.7
Chemistry dominant (0.2, 0.6, 0.2)	0.9	0.3
Temperature dominant (0.2, 0.2, 0.6)	0.7	0.5

5. CONCLUSIONS

Advanced reactor PRA and RIPB licensing depend on reliability evidence, yet much of the available non-LWR operating experience is fragmented across legacy reactors, experiments, and test facilities and is not packaged in a form that is immediately usable for PRA parameterization. In summary, this paper presents a characteristic-based approach to assessing reliability data sources. By outlining 12 distinct characteristics that are traceable and aligned with ASME/ANS RA-S-1.4-2021 expectations, we provide a framework that enables analysts and reviewers to capture the strengths and weaknesses of a data source, facilitating its appropriate use in PRA. The motivation is that real sources are rarely uniformly good or bad: A source may be excellent on quality and uncertainty but weak on extrapolatability. Some sources exhibit specific strengths (e.g., phenomenological insight and failure mode identification) alongside limitations that matter for PRA use (e.g., incomplete exposure statistics, limited uncertainty characterization). Further work involves finalizing the framework with expert opinion and the assessment of weights for the extrapolatability metric. Future work will focus on translating these descriptive characteristics into a graded, design-specific assessment process, including formalization of similarity/extrapolation treatment and guidance for consistent application across analysts and reactor concepts

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