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ABSTRACT

This report documents an analysis of the safety-related performance of the isolation condenser systems at U.S. commercial boiling water reactor plants during the period 1987-1993. Both a risk-based analysis and an engineering analysis of trends and patterns were performed on data from isolation condenser system operational events to provide insights into the performance of the system throughout the industry and at a plant-specific level. Comparisons were made to Probabilistic Risk Assessments and Individual Plant Evaluations for all the plants that have an isolation condenser system to indicate where operational data either support or fail to support the assumptions, models, and data used to develop system unreliability.

Job Code Number: E8246—Technical Assistance in Reliability and Risk Analysis

EXECUTIVE SUMMARY

This report presents a performance evaluation of the isolation condenser system (IC) at the five U.S. commercial boiling water reactors (BWRs) that have the system. The study was based on the operating experience from 1987 through 1993, as reported in Licensee Event Reports (LERs) and monthly nuclear power plant operating reports. The objectives of the study were: (1) To estimate system unreliability based on operational data, and to compare the results with the assumptions, models, and data used in Probabilistic Risk Assessments/Individual Plant Examinations (PRA/IPEs), and (2) review the data from an engineering perspective to determine the factors affecting system unreliability, and provide an analysis of the trends and patterns seen in the IC system operational data.

The reliability of the system or train to be assessed was based on the ability of the system to perform its risk-significant function under conditions that best represent those that would be expected under accident conditions. Data from unplanned demands, as a result of transient response, and from full system functional tests were used to estimate the reliability of the system. Data from component failures that did not result in a loss of reactor core cooling function of the system or train, or from tests of only portions of the system were not used to estimate reliability.

IC train unreliabilities were estimated using a fault tree model to associate fault event occurrences with broadly defined failure modes such as failure to operate or failure to provide makeup. The failure probabilities for the individual failure modes were calculated by reviewing the failure information, categorizing each failure by failure mode and then estimating the corresponding number of demands (both success and failures). IC train and component failure rates were also extracted from PRA/IPEs. These were then combined, consistent with the quantification performed using the operating experience data. The resulting failure mode probabilities were then compared to the system level unreliability estimates and failure mode probabilities calculated for this study. The following is a summary of the major findings.

The IC train unreliability (including recovery), based on operational experience data, is 0.02. The failure to operate failure-mode of the IC train and failure to provide makeup water to the isolation condenser, contributed equally to the overall unreliability. The recovery probabilities associated with these operational modes of the IC train are high, but have very broad uncertainty. With only one or two opportunities, the current operational data give little evidence to support a lower failure to recover probability. More opportunities are needed in order to reduce the uncertainty associated with the failure to recover estimates.

The recovered and non-recovered train unreliability estimates differ by a factor of five. The difference is primarily attributable to the spurious isolations of the IC train as observed in the unplanned demands. All the failures observed for the IC train failing to operate were caused by spurious isolation of the IC train.

The average of the estimates of IC train unreliability based on information contained in the PRA/IPEs was generally about a factor of 1.5 lower than the estimate of the mean probability based on operational experience data. All of the PRA/IPE estimates of IC train unreliability are within the uncertainty interval based on the operational experience data. The average of the PRA/IPE values of IC train unreliability is approximately 1.3E-2 per demand.

The PRA/IPEs show that the condensate isolation valve failing to open as the important contributor to IC train unavailability. However, this contrasts with the calculations based on operational data, which show the effect of this type of failure was not as important to IC train unreliability as the spurious isolations of the IC train. Figure ES-1 shows the train unreliabilities and comparisons to the PRA/IPEs.

The probability of maintenance out of service was not estimated in this report. The operating experience is sparse and a lack of maintenance out-of-service failures (i.e., no failures in 23 demands) relative to other failure modes does not support postulating this particular failure mode at this time. Based on PRA/IPE information, maintenance accounts for approximately 5% of the total unreliability of the IC train.

No statistically significant trends in IC train failure and unplanned demand frequencies or unreliability by calendar year were observed in the operational experience data. Further, IC train unreliability was analyzed against low-power license date for the plants to determine if unreliability was being affected by plant age. No trends were observed in the low-power license date evaluation. The results of the individual trending analyses are provided in Figures ES-2 through ES-5.

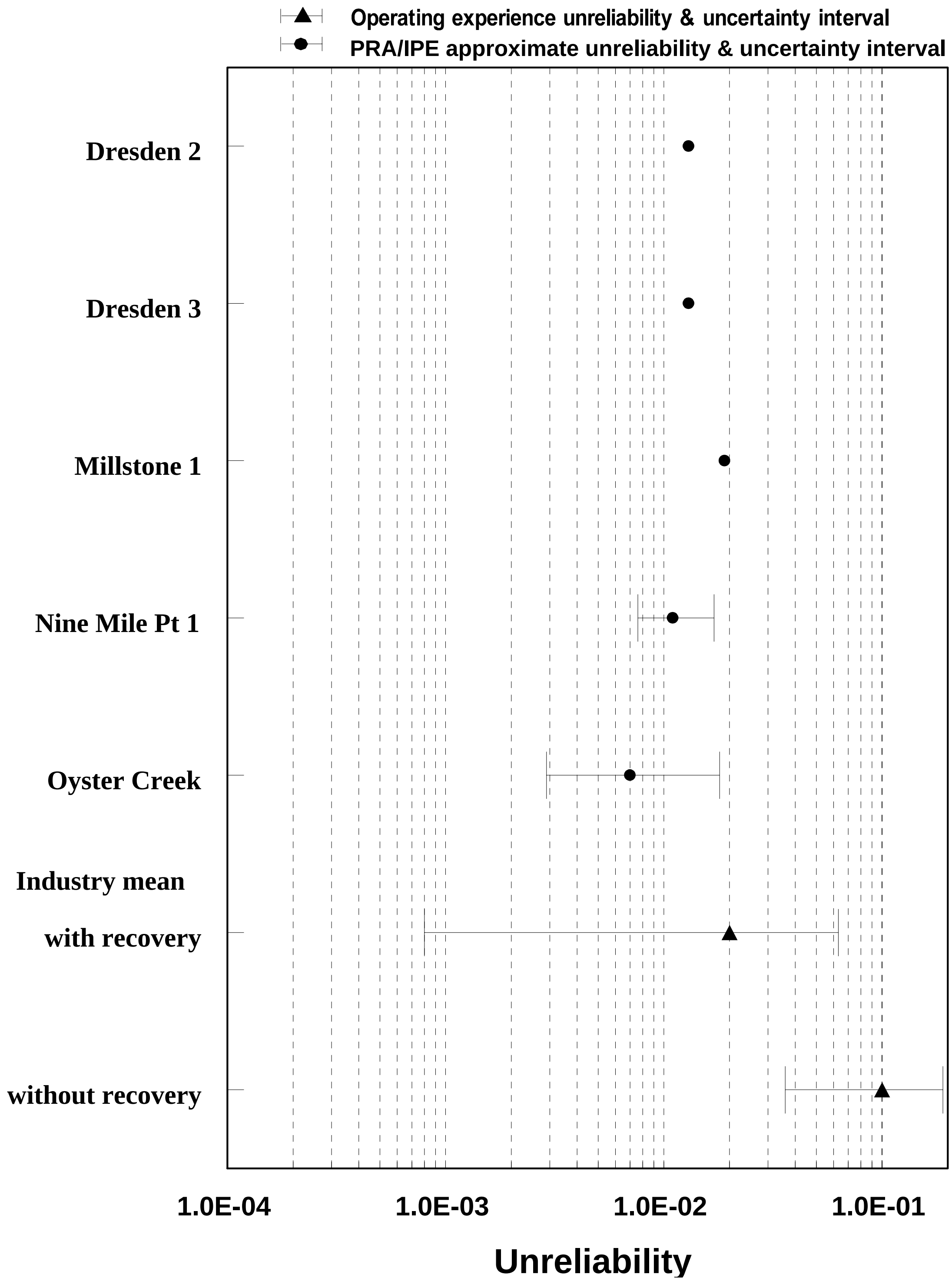

Figure ES-1. Plot of IC train unreliabilities approximated from PRA/IPE information and estimates of IC train unreliability (with and without recovery) calculated from the operational experience data. (For some plants the information documented in the PRA/IPEs was insufficient to generate uncertainty intervals.)

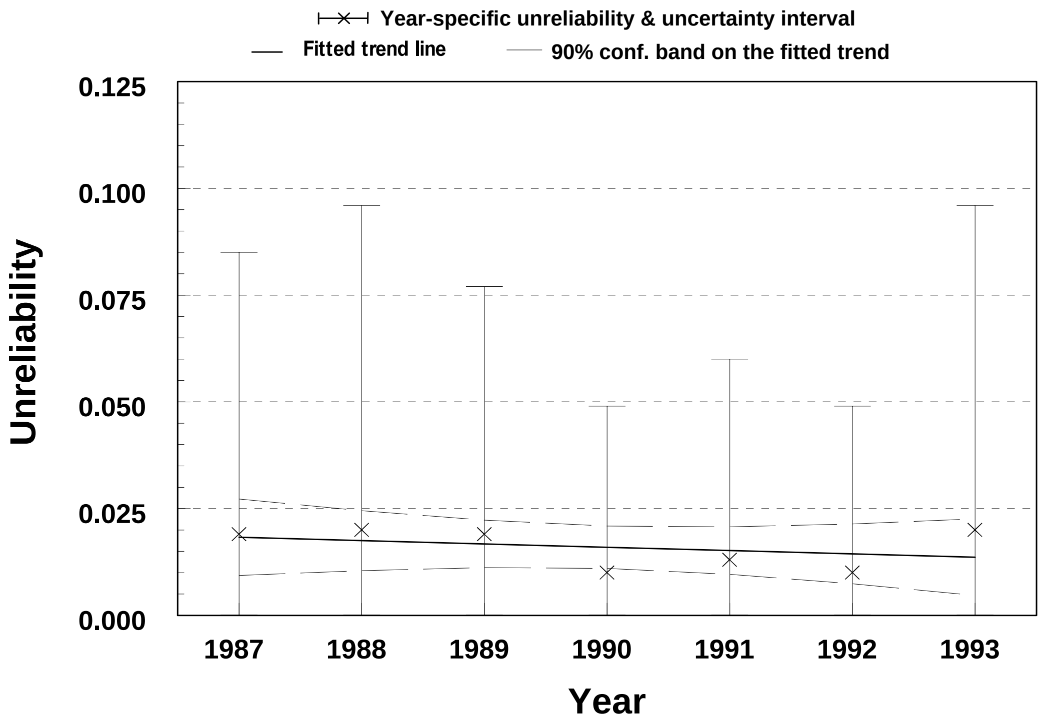

Figure ES-2. IC train unreliability by calendar year, based on a constrained noninformative prior and annual data. The plotted trend is not statistically significant (P-value = 0.43).

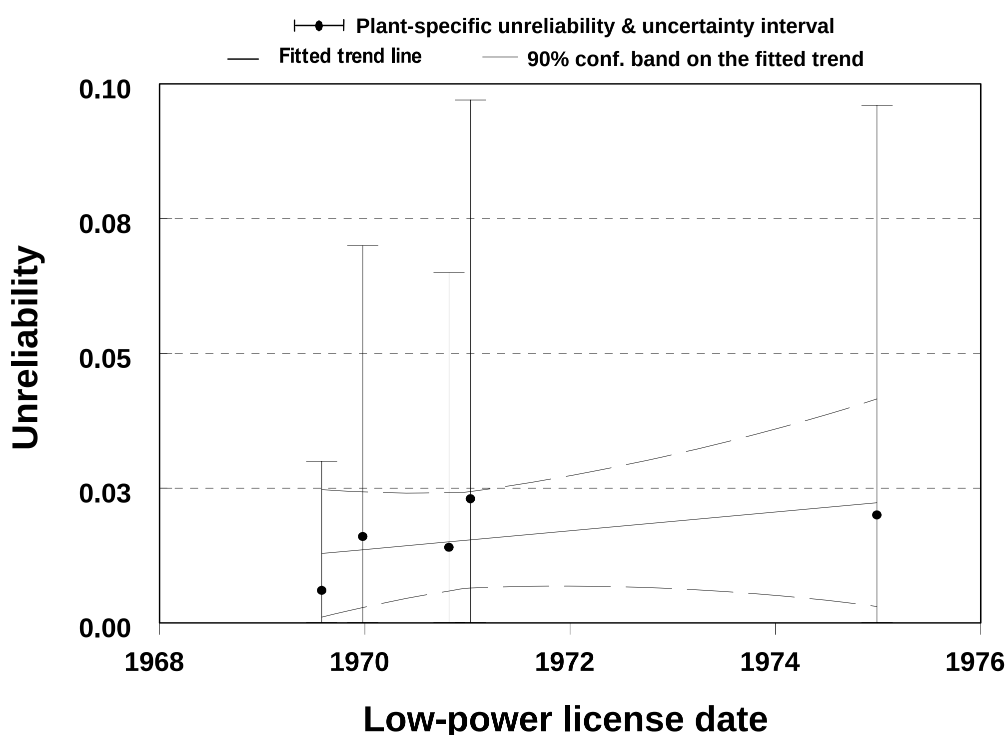

Figure ES-3. Plant-specific IC train unreliabilities based on constrained noninformative prior distributions, which include recovery actions plotted against low-power license dates. The trend is not statistically significant (P-value = 0.30).

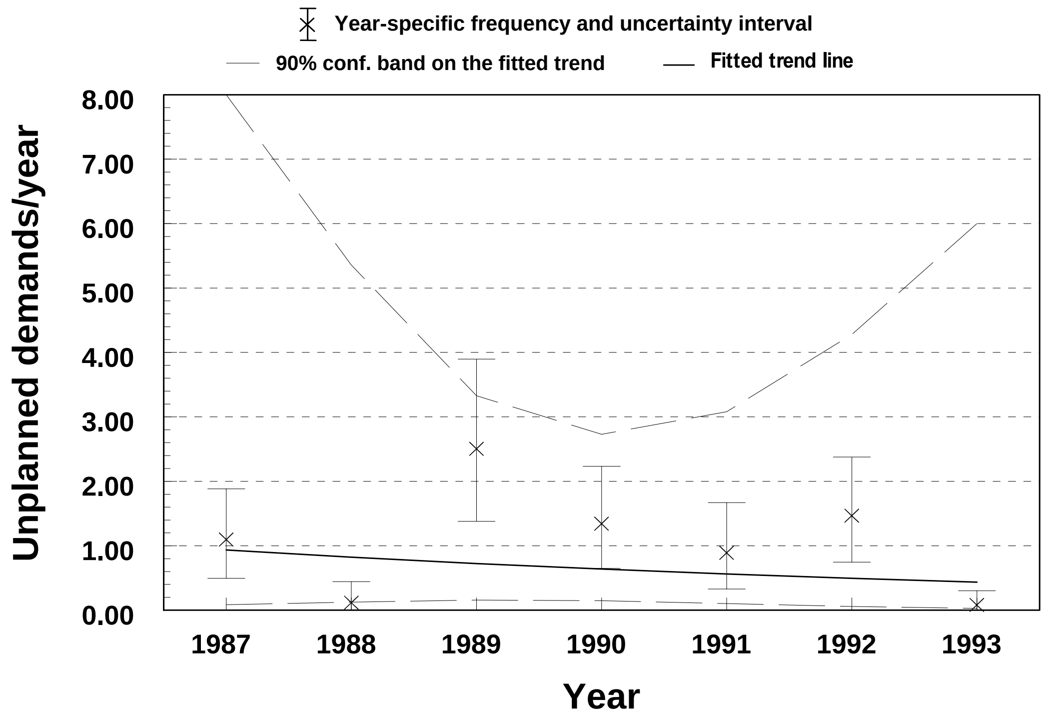

Figure ES-4. IC train unplanned demands per train operational year, with 90% uncertainty intervals and confidence band on the fitted trend. The trend is not statistically significant (P-value = 0.64).

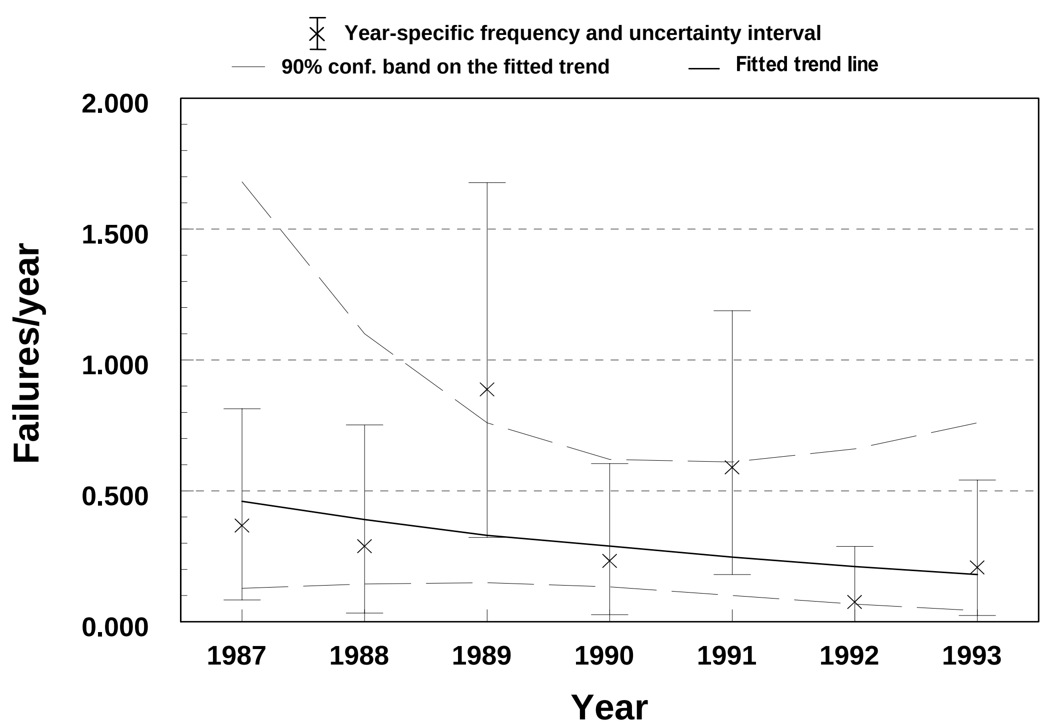

Figure ES-5. IC train failures per train operational year, with 90% uncertainty intervals and confidence band on the fitted trend. The trend is not statistically significant (P-value = 0.30).

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Technical contributions by A. J. Luptak and D. A. Prawdzik of the INEL contributed to the final report.

CONTENTS

FIGURES

TABLES

ACRONYMS

AEOD	Analysis and Evaluation of Operational Data (NRC Office)
ASEP	Accident Sequence Evaluation Program
ASP	accident sequence precursor
BWR	boiling water reactor
CCDP	conditional core damage probability
CFR	Code of Federal Regulations
CT	condensate transfer for makeup
DEP/IC	operator fails to remove noncondensible gasses during IC operation
EC	emergency condenser
ECCS	emergency core cooling systems
ESF	engineered safety feature
FR	failure to recover
FMU	failure to provide makeup
FTO	failure to operate
HELB	high-energy line break
IC	isolation condenser
ICINTA	failure of auto IC initiation
ICMU	failure of auto and manual IC makeup
INEL	Idaho National Engineering Laboratory
IPE	individual plant examination
LC1	failure of makeup to EC tank
LER	Licensee Event Report
MCC	motor control center
MOOS	maintenance out of service

MOV	motor-operated valve
MU1	operator fails to open makeup valves
MUP	failure of makeup water to isolation condenser
NRC	Nuclear Regulatory Commission
OMUP	operator action to provide makeup to shell side of the isolation condenser
OU	operator fails to initiate makeup
PRA	probabilistic risk assessment
Pt	point
RPV	reactor pressure vessel
SCSS	Sequence Coding and Search System

TERMINOLOGY

Demand frequency—The number of unplanned demands divided by the operating time, in years.

Failure—An inoperability in which the reactor core cooling function of the train was lost. Defined as the loss of the ability to remove heat and reduce reactor pressure.

Failure frequency—The number of failures divided by the operating time, in years.

Failure to provide makeup (FMU)—A failure to provide makeup water to the shell side of the IC condenser.

Failure to operate (FTO)—A failure of the IC train to automatically or manually start by opening the condensate return valve, achieving stable reactor steam flow through the condenser, and returning the resultant condensate back to the reactor.

Fault—An inoperability in which the reactor core cooling function of the train was *not* lost. This includes administrative technical specifications violations such as not performing a surveillance test when required.

Five-year surveillance test—The test of the system, typically performed once every five years, that results in a full flow test of the system equivalent to a demand of the system to function during a transient or vessel high pressure condition.

Inoperability—An event in which the IC train is not fully operable as defined by applicable plant technical specifications or Safety Analysis Reports.

Maintenance out of service (MOOS)—A failure of the IC train due to the IC system being out of service for maintenance at the time of the unplanned demand.

Operating conditions—Conditions in which technical specifications require isolation condenser operability, typically with reactor pressure >90 psig.

P-value—The probability that the data set would be as extreme as it is, if the assumed model is correct. It is the significance level (for this study, 0.05) at which the assumed model would barely be rejected by a statistical test. A small P-value indicates strong evidence against the assumed model. In most cases cited in this report, the assumed model is the null hypothesis (i.e., trends or differences do not exist in the data).

Recovery—The overcoming of a prior failure solely by operator actions without the need for any maintenance action or repair.

Safety function lost (SFL)—Loss of the ability of the IC train to provide its heat removal and pressure reduction functions; same as failure.

Reactor core cooling function—The ability to start and remove heat from the reactor coolant system at the rate required by the plant technical specifications for the entire mission time.

Unplanned demand—An automatic or manual signal for the IC system to start, as a result of actual need for RPV heat removal and pressure reduction. Unplanned engineered safety feature actuations of the system's vent valves or other components that do not result in the opening of the condensate return valve and flow through the condenser were not considered as unplanned demands.

Unreliability—Probability that the system will fail to complete its required mission when demanded. This includes the contributions of FTO and FMU. Recovery may or may not be included, depending on the context.

Isolation Condenser System Reliability, 1987-1993

1.0 INTRODUCTION

The U.S. Nuclear Regulatory Commission (NRC), Office for Analysis and Evaluation of Operational Data (AEOD) has, in cooperation with other NRC Offices, undertaken an effort to ensure that the stated NRC policy to expand the use of probabilistic risk assessment (PRA) within the agency is implemented in a consistent and predictable manner. As part of this effort, the AEOD Safety Programs Division has undertaken to monitor and report upon the functional reliability of risk-important systems in commercial nuclear power plants. The approach is to compare the estimates and associated assumptions as found in PRAs to actual operating experience. The first phase of the review involves the identification of risk-important systems from a PRA perspective and the performance of reliability and trending analysis on these identified systems. As part of this review, a risk-related performance evaluation of the Isolation Condenser (IC) system in the five U.S. commercial boiling water reactors (BWRs) that have an IC system was undertaken.

The evaluation measures IC system reliability using actual operating experience under conditions most representative of circumstances that would be found in response to a postulated vessel isolation event. To perform this evaluation and make comparisons to the relevant information provided in the PRA/IPEs, it was necessary to evaluate system reliability at the dual train plants on an individual train level. Therefore, the reliability estimates provided in this study are based on individual trains performing their risk-significant function. These estimates of train reliability were based on data from unplanned demands, as a result of transient response, and from full system functional tests that best simulate system response in a vessel isolation event. The data from these sources are considered to best represent the plant conditions found during accident conditions. Data from component failures that did not result in a loss of reactor core cooling function of the system or train were not utilized. Failures and associated demands that occurred during tests of portions of the system were also not used to estimate reliability because they do not represent a complete system response for accident mitigation.

The IC system reliability study was based upon the operating experience during the period from 1987 through 1993, as reported in Licensee Event Reports (LERs) found in the Sequence Coding and Search System (SCSS). The objectives of the study were to:

- Estimate unreliability based on operational data, and compare the results with the assumptions, models, and data used in Probabilistic Risk Assessment/Individual Plant Examinations (PRA/IPEs).
- Provide an engineering analysis of the factors affecting system unreliability and to determine if trends and patterns are present in the IC system operational data.

The report is arranged as follows. Section 1 provides the introduction. Section 2 describes the scope of the study, describes the IC system, and briefly describes the data collection and analysis methods. Section 3 presents the results of the risk-based analysis of the operational data. Section 4 provides the results of the engineering analysis of the operational data. Section 5 contains the references.

Appendix A provides a detailed explanation of the methods used for data collection, characterization, and analysis. Appendix B gives summary lists of the data. Appendix C summarizes the detailed statistical analyses used to determine the results presented in Sections 3 and 4 of the body of the report.

2.0 SCOPE OF STUDY

This study documents an analysis of the operational experience from 1987 through 1993 of the five U.S. commercial BWRs that have an IC system. This analysis focused on the ability of the IC system to start and provide design rated core cooling for its required mission time. The system description and boundaries, data collection, failure categorization, and limitations of the study are briefly described in this section.

The data used in this report are limited to the set of plants listed in Table 1. Table 1 also provides the associated number of operating years and other plant-specific IC system information. Operating years for each plant were estimated by calendar time minus all periods when the main generator was off-line for more than two calendar days. LER data were not collected for a given calendar year if there was no operating time in that year. Details of the calculation of operating time are provided in Appendix A.

This analysis focused only on the isolation condenser's emergency core cooling system (ECCS) function to reduce reactor pressure and remove fission product decay heat. The containment isolation function of the system was not evaluated in this study.

2.1 System Operation and Description

The IC system is a standby high-pressure system that removes residual and decay heat from the reactor vessel in the event of a scram in which the reactor becomes isolated from the main condenser, or if any other high pressure condition exists. Also, at most plants, the IC system aids in reactor vessel depressurization in the event that either (depending on plant design) the feedwater coolant injection or high-pressure coolant injection system fails. Because of its role in emergency core cooling, the IC system is designated as an emergency core cooling system (ECCS). The IC system is a single-train system in three plants and dual-train system in the other two plants. Figure 1 provides a simplified single train IC system diagram. This configuration is typical of the single train plants and is effectively doubled for the dual-train plants. Four plants have a single dual pass isolation condenser per train, while one plant (Nine Mile Pt. 1) has two single-pass isolation condensers per train.

Table 1. BWR plants with a dedicated IC system.

Plant name	Docket	Operating years	Trains	Total number of IC condensers	Number of condensers per train	Condenser design	Time before make-up is required (min)
Dresden 2	237	5.09	1	1	1	Dual-pass	20
Dresden 3	249	5.42	1	1	1	Dual-pass	20
Millstone 1	245	5.66	1	1	1	Dual-pass	30
Nine Mile Pt. 1	220	3.67	2	4	2	Single-pass	90
Oyster Creek	219	5.21	2	2	1	Dual-pass	45

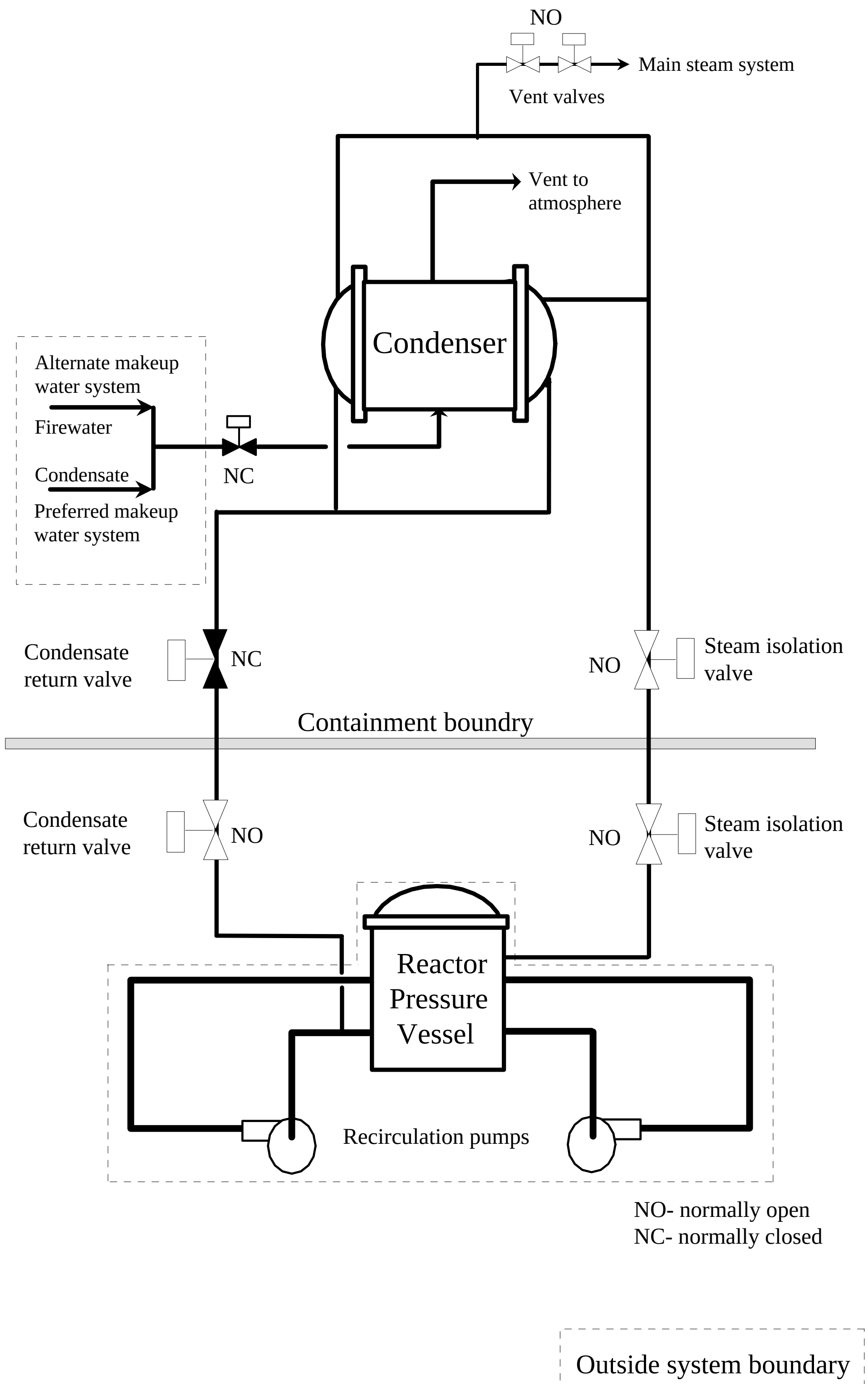


Figure 1. Simplified single train isolation condenser system schematic.

2.1.1 System Operation

The IC system transfers residual and decay heat from the reactor coolant to the water in the shell side of the heat exchanger resulting in steam generation. The steam generated in the shell side of the heat exchanger is then vented to the outside atmosphere. The system employs natural circulation as the driving head from the reactor steam side, through the isolation condenser tubes, and back to the reactor.

A typical IC system is designed to handle three percent reactor power, which means that five minutes after a scram and initiation of the IC system, the heat removal capacity of the system equals the decay heat production rate of the shutdown reactor. Therefore, reactor water inventory will only be lost through the relief valves for five minutes following a scram and isolation. This represents a minor loss relative to the vessel inventory.

The IC system is typically required to be operable when there is fuel in the reactor vessel and steam is being produced. During normal operation the isolation condensers are in standby, and are placed in service automatically when needed to provide heat transfer to the environment. In the stand-by condition, the steam isolation valves are open so that the condenser tube bundles are at reactor pressure. Condensate builds up in the condenser and condensate return piping; the condensate is prevented from returning to the reactor by having one of the condensate return valves for that train closed. The steam lines contain vent valves which are open to vent air and noncondensibles to the main steam system. Collection of air or noncondensible gases in the IC system could prevent natural circulation flow. The initiation signal places the IC system into operation by opening the condensate return isolation valve. This valve can also be remotely operated from the control room.

The IC system operates in a closed loop mode. Steam rises from the reactor vessel to the condenser where it is condensed by boiling the water in the condenser shell. As the reactor steam condenses, it returns by gravity flow through the condensate return valve to the suction of a reactor recirculation pump and thus to the reactor vessel. The water inventory on the shell side of the condenser will provide heat removal for between 20 and 90 minutes depending on the plant design, at which time makeup water must be provided to prevent uncovering the condenser tubes. The sources of makeup water are a combination of condensate water, demineralized water, or the fire water system depending on individual plant design. One plant (Nine Mile Pt. 1) has gravity fed makeup water tanks which can supply enough water for eight hours of operation before additional makeup is required.

The IC system instrumentation and control consists of initiation and containment isolation circuitry. These circuits provide different functions, both of which are important to system reliability. The initiation circuitry provides for automatic and manual start of the system. The purpose of the containment isolation circuitry is to initiate closure of appropriate primary containment isolation valves to limit fission product release should a steam line rupture occur.

The IC system is automatically initiated if a high reactor pressure condition is sustained for 15 seconds. The time delay prevents unnecessary system initiation during turbine trips. Also at most plants, the IC system automatically initiates on a low vessel water level to aid in reducing reactor pressure for small line breaks. The isolation condenser system can be operated manually by opening the condensate return valve. The IC system is designed to provide core cooling regardless of whether electrical power is available.

The IC system is automatically isolated if high IC steam flow or condensate return flow is sensed indicating a line break (Group V isolation). This isolation shuts all the steam and condensate isolation valves and the steam line vent valves, rendering the IC system inoperable. The steam line vent valves will also automatically shut on a low vessel water level condition (Group I isolation). Isolation of the vent valves for a prolonged period of time could render the heat exchanger inoperable due to the buildup of noncondensible gases. However, failure of this circuit to close the vent valves would not preclude operation of the system.

2.1.2 System Boundaries

For this study, the IC system includes all steam piping from the reactor vessel penetration to the condenser, the isolation condenser, condensate piping back to the reactor, and all valves and valve operators. Additional components that are considered to be part of the IC system are the circuit breakers at the motor control centers (MCCs), but not the MCCs themselves, the dedicated DC power system that supplies IC system power, and the initiation and isolation logic circuits with their associated detectors.

The ability to provide makeup water to the isolation condenser was included in this study. The makeup capability was limited to the IC system makeup water supply valve. This valve must be operable in order to supply water to the IC tank level control valve for long term cooling.

2.2 Operational Data Collection

The IC system operational data used in this report are based on LERs residing in the SCSS database. The SCSS database was searched for all IC system records as reported in LERs for the years 1987-1993 that identified any failure of the IC system within the system boundaries defined previously in Section 2.1.2. The SCSS database was also searched for all unplanned engineered safety feature (ESF) actuations associated with the IC system during the study period. The information encoded in the SCSS database, and included in this study, encompasses both actual and potential IC system failures during all plant operating conditions and testing. However, differences may exist among plants interpreting what is a valid IC system actuation and failure and hence what is reportable. These potential differences in what a plant may or may not report are not evaluated in this report. It was assumed for this study that every plant was reporting IC system ESF actuations and failures consistently as required by the LER Rule, 10 CFR 50.73, and the guidance provided in NUREG-1022, *Event Reporting Systems 10 CFR 50.72 and 50.73.*[1] IC system events that were reported in accordance with the requirements of 10 CFR 50.72 (Immediate Notification Reports) were reviewed and compared to the 50.73 reports. However, the 50.72 reports were not explicitly used in this study because the LERs (i.e., 50.73 reports) provided a more complete description of the event which is needed to determine successful operation or failure of the IC system, associated failure mode, and failure mechanism. In addition, all of the failures and ESF actuations identified in the Immediate Notification Reports were captured by the LERs.

Because several of the plants have an IC system consisting of redundant trains, the reporting requirements are also different. The IC system is required by technical specifications to be operational, therefore any occurrences where the system was not fully operable (inoperabilities), as defined by plant technical specifications or the Safety Analysis Report, are required by 10 CFR 50.73 to be reported in LERs. However, not all train level malfunctions are captured in the LER data. For example, at Nine Mile Pt. 1 and Oyster Creek the systems are a dual train configuration. Plants with a dual train system would not report single train malfunctions unless the malfunction resulted in a train outage time in excess of technical specification allowable outage times or resulted in a unit shutdown required by technical specifications. Otherwise, any occurrences where a train was not fully operable would not be reported. For example, no LER would be required if a single train malfunction occurred at Nine Mile Pt. 1 or Oyster Creek, and was repaired with operability restored prior to expiration of the technical specification limiting condition for operation.

Because of the redundant train configurations, not all independent train failures resulting from testing are available in the LERs found in the SCSS database for Nine Mile Pt. 1 or Oyster Creek. Specifically, surveillance test failures of a single train would not be required to be reported, if the redundant train was operable and the limiting condition for operation not exceeded as required by plant technical specifications. This effectively removed the surveillance test data results from being considered for these two plants in the unreliability estimate. However, for the unplanned demand all train failures are assumed to be reported. Because all ESF actuations are reportable as required by 10 CFR 50.73, the plants having only a single train provides a data source that is assumed to be complete with respect to failures observed during both testing and unplanned demands.

2.2.1 Methodology For Data Collection and Characterization

Failure Classifications—The identified LERs from the above mentioned SCSS database search were read completely and independently by a team of engineers with U.S. commercial nuclear power plant experience with care taken to properly classify each event and to ensure consistency of event classification. The LERs were reviewed to determine the types of failures, the causes of the event, the method of discovery, and the component that contributed to the failure. The information encoded in the SCSS database was used only to identify the LERs for screening. The information necessary for determining IC system reliability such as failure modes, system demands, failure mechanism, etc., in this report were based on an independent review and classification from a risk and reliability perspective of the information provided in the LERs.

As stated previously, not all IC events reported in the SCSS database resulted in actual failure of the IC system. The term *inoperability* is used to describe any occurrence in which the plants reported any IC system problem in accordance with the requirements of 10 CFR 50.73. The term failure, which is also an inoperability, is an event for which the ECCS function of the system was lost. Failures include such problems as failure to operate and failure to provide makeup water. Inoperabilities include failures as well as problems related to seismic design, and administrative events such as late performance of a test. Because analysis of the containment isolation function of the isolation condensers is not included in this study, events relating to the inability to isolate the IC system were classified as inoperabilities, not failures. The failures identified in this study represent actual malfunctions that would have prevented the successful operation of the system in performing its ECCS function of removing heat from the reactor core.

To understand the operational factors affecting reliability of the IC train, the failure events were classified by failure mode. The review of the operational data identified that when the IC system receives an automatic or manual start signal, the system functions successfully if the condensate return valve opens, stable steam flow is obtained from the reactor to the IC system condenser, and condensate is returned back to the reactor until the system is no longer needed. Failure may occur at any point in this process including a loss of makeup water to the IC system condenser. The loss of makeup water will stop the condenser heat removal process and thus fail the IC system even though the reactor steam/water cycle would otherwise remain operable. For the purposes of this study, failure modes that can occur in response to an actual IC system demand are defined below:

- Maintenance out of service (MOOS) occurs if, due to maintenance, the IC system is prevented from starting automatically or manually. (As explained in Section 3, based on the operational data, MOOS was not considered as an explicit failure mode in the calculation of IC system unreliability.)

- Failure to operate (FTO) occurs if the system is in service but fails to operate, either automatically or manually, by opening of the condensate return valve and achieving stable reactor steam flow to the IC system condenser and condensate return flow back to the reactor.

- Failure to provide makeup (FMU) occurs if, at any time during the operation of the system, the capability to provide makeup water to the shell side of the condenser is lost when makeup is required.

The criteria used for estimating the reliability of the IC system was the ability of the system to perform its ECCS function in conditions as close as can be found in the plant operating experience to those circumstances that would be obtained under accident conditions. The operating data for the IC system indicated that the system was typically demanded in the event of a scram in which the reactor was isolated from the main condenser, or if a high pressure condition existed. This is the primary reactor core cooling function of the IC system, and the operational experience was evaluated to determine those events that completely demonstrated the system's reactor core cooling function (or its inability to demonstrate its reactor core cooling function).

The operational data used for this report also contain events relating to the recovery of a failed IC train. Recovery of an IC train was only considered in the unplanned demand events, since these are the types of events where recovery of core cooling is necessary. To recover an IC train from a FTO event, operators have to recognize that the IC train was in a failed state, and manually start the train to provide core cooling. Recovery from a FMU was defined in a similar manner. Each failure reported during an unplanned demand was evaluated to determine whether recovery of the IC train by operator actions had occurred. Further details of the failure characterization, including additional measures taken to ensure completeness and correctness of the coded data, are included in Section A-1 of Appendix A.

Demand Classifications—For the purposes of estimating reliability, demand counts must be associated with failure counts. The first issue is the determination of what types of demands and associated failures to consider. Two criteria are important. First, each unplanned demand must reasonably approximate conditions observed during a vessel isolation event. Any surveillance test selected to estimate reliability must be at least as stressful on the train as a demand in response to a vessel isolation event. For this study, this requirement meant that the entire IC train must be exercised in the test. Second, counts or estimates of the number of the demands and associated failures must be reliable. Because the criteria used for estimating the reliability of the IC train was the ability of the train to proved adequate core cooling, unplanned demands as a result of a vessel isolation and the 5-year surveillance test demands were used to estimate IC train reliability.

The LERs that identified an ESF actuation from the above mentioned SCSS database search were screened to determine the nature of the ESF actuation. Many of the ESF actuations were demands of only a part of the system. The partial demands included vent valve closures and relay actuations related to plant maintenance actions, such as removal of a fuse or shorting of test leads. These partial demands did not exercise the IC system in response to an actual need for the ECCS function of the system and therefore, would not provide an adequate measure of system performance relative to completing its reactor core cooling function in an accident condition. As a result, these records were excluded from the count of IC system unplanned demands.

Other types of partial demonstrations (e.g. cyclic or quarterly surveillance testing) of the system's capability were also not considered representative of the system's performance under accident conditions.

Testing that did not demonstrate the reactor core cooling function completely or result in flow through the heat exchanger(s) were not utilized in the assessment of IC reliability. These tests (e.g. cyclic and quarterly surveillance testing) are considered to be partial demonstrations of the system capability, because they did not result in flow through the condenser and heat removal from the core. These tests typically verified system operability and functionality on a component level, however, flow through the system was not required for any of these tests. Therefore, quarterly and cyclic test data were excluded from the system reliability analysis. However, the information on the types and causes of failures observed during these tests were reviewed in the engineering analysis section of this report.

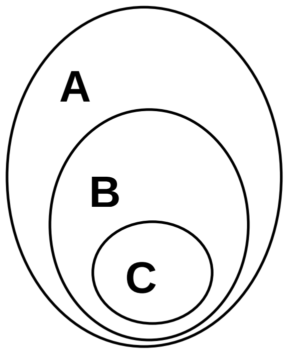
A review of several plant technical specifications indicated that plants are required to manually start the IC system with a periodicity of once every 5 years (referred to as 5-year surveillance tests). The 5-year periodic test completely demonstrates the system's heat removal capability and the ability to manually initiate the system. This test is assumed to represent system response during a plant transient and the associated risk-related reactor core cooling function. Therefore, the 5-year surveillance test data were considered for estimating system unreliability. For more details on the counting of unplanned demands and surveillance test demands, see Section A-1.2 in Appendix A.

2.3 Methodology For Operational Data Analysis

The risk-based and engineering analysis of the operational data were based on two different data sets. The Venn diagram in Figure 2 illustrates the relationship between these data sets. Data set A represents all the LERs that identified an IC system inoperability from the above-mentioned SCSS database search. Data set B represents the subset of inoperabilities that resulted in a loss of the reactor core cooling function (failure) of the IC system. Data set C represents those actual failures identified from LERs for which the corresponding demands (both failures and successes) could be counted. Data set C provides the basis for estimating the unreliability of the IC system. Data set C contains the failures that occurred during either an unplanned operational experience or a 5-year surveillance test (referred to as operational experiences). The only criteria are the occurrence of a *real* failure and the ability to count all corresponding operational experiences (i.e., both failures and successes). Data set C represents the minimum requirements for the data used in the risk-based analysis of the operational experience.

To ensure the completeness and appropriateness of the failure data for performing risk-based analyses, three additional selection criteria on the data were imposed. These criteria were: (1) the reporting requirements for identifying independent train failures must be the same for all the plants, (2) the failure data for the plants must be from the same population (i.e., homogeneous statistically), and (3) the data must be consistent from a operational viewpoint (i.e., does it make sense from an engineering perspective). Even though these three criteria are tabulated separately, the criteria are not totally independent of each other. Each of these three criteria must be met and understood to ensure the results of the analysis are not biased and incorrectly interpreted. As a result, the failure and demand data that comprise data set C were not analyzed strictly on the ability to count the number of failures and associated demands for a risk-based mission, but also to ensure each of the above three criteria were met.

The purpose of the engineering analysis was to provide qualitative insights into IC train performance and not calculate quantitative estimates of reliability. Therefore the engineering analysis utilized all of IC train inoperabilities appearing in the operational data. That is, the engineering analysis focused on data set A, which includes data set C. The engineering analysis is intended to identify the factors affecting IC train reliability.



A The IC train was inoperable as defined by applicable technical specifications.

B The safety function of the IC train was lost (failure).

C The safety function of the IC train was lost (failure) and the demand count could be determined or estimated.

Figure 2. Illustration of the relationship between the inoperability and failure data sets.

3.0 RISK-BASED ANALYSIS OF THE OPERATIONAL EXPERIENCE DATA

In this section, the data pertaining to the capability of IC system to remove decay heat from the reactor (referred to as operational experience data for the purposes of this section of the report) were extracted from LERs and analyzed in two ways. First, estimates of IC train unreliability were calculated from the operational experience data. The estimates of IC train unreliability are analyzed to uncover trends and patterns within IC systems in U.S. commercial nuclear power plants. Plant-specific and industry-wide trend and pattern analyses provide insights into the reliability performance of the IC system. Second, comparisons are made between the IC unreliabilities based on the operational experience data and those reported in the selected PRAs and IPEs. The objective of the comparisons is to indicate where operational experience data tend to support the assumptions, models, and data used in the PRA and IPEs.

Four plant risk information reports (i.e., PRAs and IPEs identified in References 2 through 5) for the five plants with an IC system were reviewed for information pertaining to IC train unreliability. Estimates of IC train unreliability were approximated from the information contained in the PRAs and IPEs. (For the purposes of this study, the source documents will be referred to collectively as PRA/IPEs.) The information extracted from the source documents contain IC train statistics for all of the operating BWR plants with a IC system. The PRA/IPE estimates were compared to the IC train unreliability results obtained in this study.

IC train unreliabilities were estimated using a fault tree model to combine broadly defined failure modes such as failure to operate or failure to provide makeup into an overall IC train unreliability model. The failure probabilities for the individual failure modes were calculated by reviewing the failure information, categorizing each failure event by failure mode and then estimating the corresponding number of demands (both success and failures). Approximate PRA/IPE-based unreliabilities were calculated from the failure data for the operating, providing makeup, and maintenance phases of the IC train. The IC train-level unreliabilities and failure probabilities extracted from the PRA/IPEs are compared to the estimates based on the operational data (i.e., operational experience failure data). A summary of the major findings are presented here.

- The IC train unreliability (including recovery), based on operational experience data, is 0.02. The failure to operate failure-mode of the IC train and failure to provide makeup water to the isolation condenser, contributed equally to the overall unreliability. The recovery probabilities associated with these operational modes of the IC train are high, but have very broad uncertainty. With only one or two opportunities, the current operational data give little evidence to support a lower failure to recover probability. More opportunities are needed in order to reduce the uncertainty associated with the failure to recover estimates. Since only five plants have an IC system, relatively few demands occur, and since the system is mostly passive, obtaining better estimates based on operational data may not be feasible in the near future.

- The recovered and non-recovered train unreliability estimates differ by a factor of five. The difference is primarily attributable to the spurious isolations of the IC train as observed in the unplanned demands. All the failures observed for the IC train failing to operate were caused by spurious isolation of the IC train.

- The average of the estimates of IC train unreliability based on information contained in the PRA/IPEs was generally about a factor of 1.5 lower than the estimate of the mean probability based on operational experience data. All of the PRA/IPE estimates of IC train unreliability are within the uncertainty interval based on the operational experience data. The average of the PRA/IPE values of IC train unreliability is approximately 1.3E-2 per demand. The PRA/IPEs show that the condensate isolation valve failing to open as the important contributor to IC train unavailability. However, this contrasts with the calculations based on operational data, which show the effect of this type of failure was not as important to IC train unreliability as the spurious isolations of the IC train.

- The probability of maintenance out of service was not estimated due to the sparseness of the operational experience data and lack of failures to support postulating this particular failure mode (i.e., no failures in 23 demands). Based on PRA/IPE information, maintenance accounts for approximately 5% of the unreliability of the IC train.

- No trends in IC train unreliability by calendar year were observed in the operational experience data. Further, IC train unreliability was analyzed against plant-specific low-power license date to determine if unreliability was affected by plant age. No trends were observed in the low-power license date evaluation.

3.1 Unreliability Estimates Based on Operational Experience Data

Estimates of IC train unreliability were calculated using the unplanned demand and 5-year test information reported in the LERs. The failure data identified in the LER information were used to develop failure probabilities for the observed failure modes defined in Section 2. The types of data and counts used for estimating probabilities for each of the IC train failure modes are identified in Table 2.

In calculating failure rates for individual failure modes, the operational experience data were analyzed and tested (statistically) to determine if significant variability were present in the data. All data were initially analyzed by plant, by year, and by source (i.e., unplanned and 5-year test demands). Each data set was modeled as a binomial distribution with confidence intervals based on sampling uncertainty. Various statistical tests (Fisher's exact test, Pearson chi-squared test, etc.) were then used to test the hypothesis that there are no differences between the types and sources of data.

Table 2. Failure data sources and counts used for estimating IC train failure mode probabilities.

Failure mode	Unplanned demands		5-year tests	
	failures	demands	failures	demands
Failure to operate (FTO)	2	35	0	3[a]
Failure to provide makeup (FMU)	1	34	0	3[a]
Failure to recover from a FTO (FRFTO)	0	2	—	—
Failure to recover from a FMU (FRFMU)	0	1	—	—
Maintenance out of service (MOOS); while not in a shutdown condition	0	23	—	—

a. Because Nine Mile Pt. 1 and Oyster Creek have dual train systems, single train failures would not be required to be reported in accordance with the 10 CFR 50.73 reporting requirements. As a result, only the surveillance tests from the remaining three plants were used in this estimate.

Because of concerns about the appropriateness and power of the various statistical tests, and an engineering belief that there are real differences between plants, an empirical Bayes method to model variation was attempted regardless of the results of the statistical tests for differences. The simple Bayes method was used if no empirical Bayes could be fitted. [For more information on the statistical approach to evaluate the data, see Appendices A and C (Sections A-2.1 and C-1.1)]. In the simple Bayes case, the uncertainty in the calculated failure rate was dominated by random or statistical uncertainty (also referred to as sampling uncertainty). The simple Bayes method essentially pools the data into one, assuming homogeneous data set. If, on the other hand, the uncertainty was dominated by the plant-to-plant (or year-to-year) variability, then the data were not pooled, and individual plant or year-specific failure rates were calculated based on the factor that produced the variability.

The operational experience failure data from 5-year test and unplanned demands were used to estimate the FTO and FMU probabilities. Because Nine Mile Pt. 1 and Oyster Creek have dual train systems, single train failures would not be required to be reported in accordance with the 10 CFR 50.73 reporting requirements during surveillance tests. As a result, only the surveillance test data from the remaining three plants were used to estimate these two probabilities (see Section 2.2 and Appendix A-1.2.2 for more details). No plant-to-plant variability (i.e., statistically significant) was detected in either the FTO and FMU failure modes.

For the MOOS failure mode, pooling of the unplanned demand data with 5-year test data was illogical when estimating unreliability, since the plant is unlikely to initiate an IC system test if the IC system is out of service for maintenance. Only MOOS events that occurred while the plant was not shutdown are included.

Table 3 contains the estimated probabilities and associated uncertainty intervals calculated from the operational experience data for each of the failure modes with the exception of MOOS. The overall unreliability calculated for the IC train requires special attention because of the sparseness of failure data for several of the failure modes (e.g., no failures in 23 demands for MOOS). The mean probability estimate of MOOS derived from the unplanned demand data would likely be conservative. The estimate is the result of calculating the mean of the simple Bayes distribution assumed in this analysis. Therefore, the MOOS estimate may not reflect actual system performance. Furthermore, partitioning the overall data into sparse data sets representing the failure modes typically modeled for the IC train is not appropriate in all situations. In general, when dealing with sparse data, the estimate of the overall unreliability derived from the failure modes will result in an estimate that is higher than an estimate based on the aggregated data. For example, the estimate of IC train unreliability (with no recovery) based on the aggregated data and a simple Bayes distribution results in a mean probability estimate of 0.09 (3.5 failures divided by 39 demands). An unreliability estimate based on the individual failure modes is 0.12 (FTO, FMU, and MOOS). Clearly the latter estimate makes the system look much worse than it likely is. Since MOOS is based on no failures in a small number of demands, including this failure mode estimate into the overall estimate is not reasonable.

Table 3. IC train failure mode data and Bayesian probability information.

Failure mode	Failures	Demands	Modeled variation	Distribution	Bayes mean and 90% interval (per demand)
Failure to operate (FTO)	2	38	Sampling	Beta (2.5, 36.5)	1.5E-2, 6.4E-2, 1.4E-1
Failure to recover from FTO (FRFTO)	0	2	Sampling	Beta (0.5, 2.5)	9.0E-4, 1.7E-1, 5.7E-1
Failure to provide makeup (FMU)	1	37	Sampling	Beta (1.5, 36.5)	4.8E-3, 4.0E-2, 1.0E-1
Failure to recover from FMU (FRFMU)	0	1	Sampling	Beta (0.5, 1.5)	1.5E-3, 2.5E-1, 7.7E-1

However, recovery probabilities are included in the overall estimate and they are based on sparse data. The recovery failure modes are included since the operational data does show that IC train failures were recovered. However, as indicated in Table 3, the probabilities of failing to recover from an FTO and FMU event are high. With only one or two opportunities, the current operational data gives little evidence to support a lower failure to recover probability, even though the actual probabilities may be lower. More opportunities are needed for the operational data to reduce the uncertainty associated with the failure to recover estimates. Since only five plants have an IC system, relatively few demands occur, and since the system is mostly passive, obtaining better estimates based on operational data may not be feasible in the near future.

Overall, the estimates for the individual failure modes are based on sparse data; therefore, only weak inferences can be made. Drawing conclusions about the unreliability of IC train based solely on these statistical estimates should be done with caution.

3.1.1 IC Train Unreliability

The IC train unreliabilities were estimated from the operational experience data using the fault tree model depicted in Figure 3. Table 4 contains the estimated IC train unreliability and associated uncertainty intervals resulting from quantifying the fault tree using the Bayesian probability estimates in Table 3. Also included in Table 4 are the probabilities for the two sets of failure combinations that cause train failure along with their percentage contribution.

The estimates of train unreliability provided in Table 4 include the recovery failure modes for FTO and FMU. The estimate of IC train unreliability without recovery based on operational experience data is 0.10. The associated lower and upper 90% uncertainty bounds for the without recovery estimate are 0.036 and 0.19, respectively. The effect of recovery on IC train unreliability is about a factor of five improvement in the overall IC train unreliability.

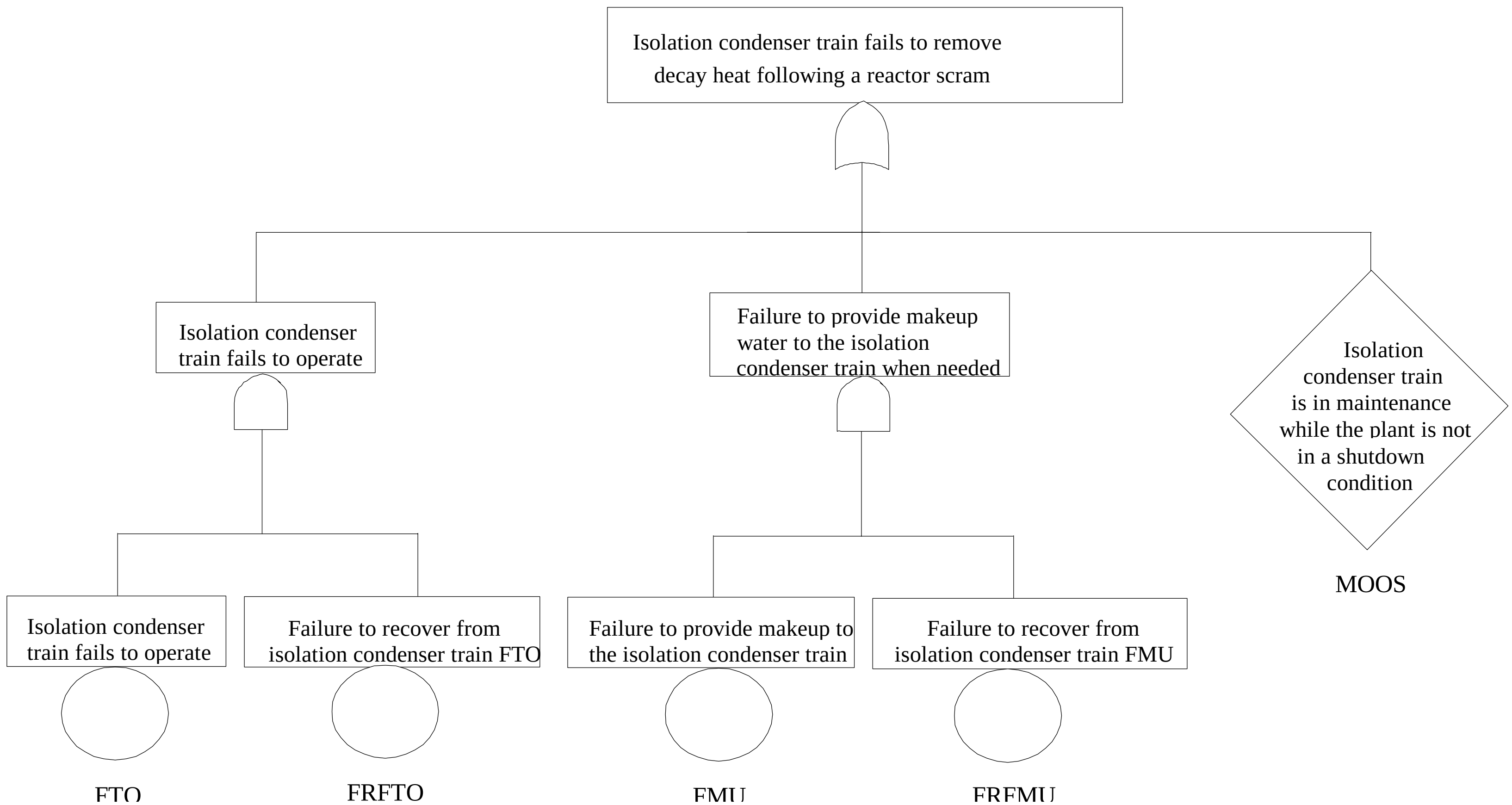


Figure 3. Fault tree model of isolation condenser train utilized for estimating train unreliability.

Table 4. Estimates of IC train unreliability and associated failure modes based on operational experience data.

Contributor	Failure probability	Percentage contribution
FTO*FRFTO	0.01	50
FMU*FRFMU	0.01	50
Unreliability (mean)	0.02	—
90% Uncertainty interval	0.0008, 0.063	—

3.1.2 Investigation of Possible Trends

No trend of IC train unreliability by year is evident, based on the operational experience data (P-value = 0.43). IC train unreliability on a per year basis was calculated to reveal if any overall trend exists within the industry. Figure 4 displays the unreliability trend of the IC train by year. The unreliability for each year was obtained using the constrained noninformative prior for each failure mode pooled across plants for each calendar year as described in Appendix A and in Appendix C. The annualized unreliabilities include the probability of recovering failed IC trains (i.e., operator recovery of IC train from FTO or FMU).

To give some indication of the effect of the passage of time (i.e., older plants versus newer plants) on IC performance, plant-specific unreliability was plotted against the plant low-power license date. The plot is shown in Figure 5 with 90% uncertainty bars plotted vertically. A trend line and a 90% confidence band for the fitted trend line are also shown. The slope of the trend line is not statistically significant (P-value = 0.30).

3.2 Comparison to PRAs

The operational experience-based unreliabilities were compared to the results documented in the PRA/IPEs utilized in this study. The IC train unreliabilities were estimated from the operational experience data using the fault tree model shown in Figure 3. The estimates are presented with and without the FRFTO and FRFMU recovery events to illustrate the effects of recovery on the probability estimate. The recovery failure modes identified in the operational experience data are of such a nature that actual diagnosis and repair of the IC train is not required to make the train operational. Generally, the events listed in these categories require a restarting of the train if the automatic function was lost. Most PRA/IPEs model recovery at the event tree or scenario level since actual diagnosis and repair of the failed equipment is required. This type of recovery is significantly different from the recovery failure modes identified in the operational experience data and utilized in the calculations of this report.

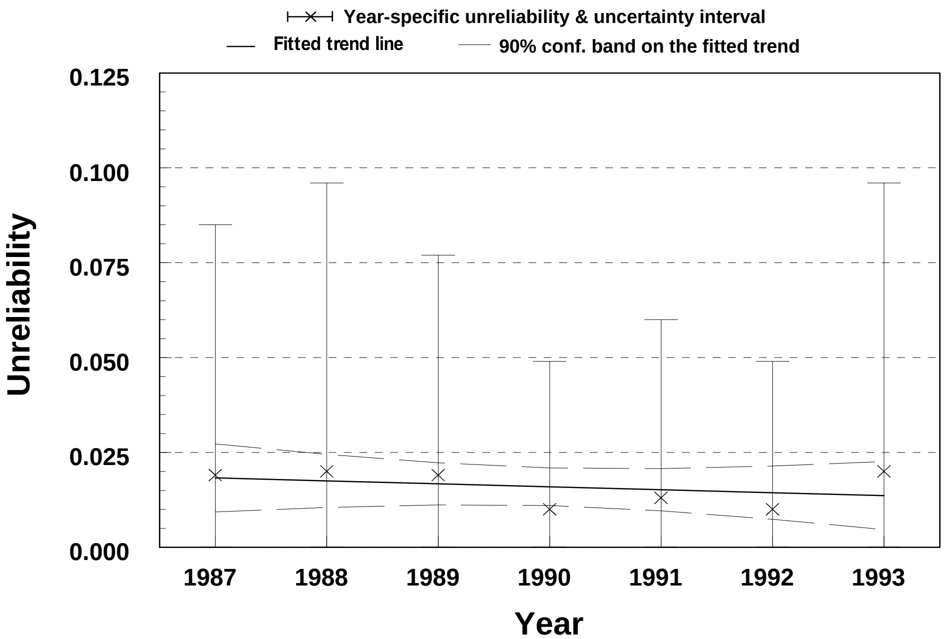


Figure 4. IC train unreliability by calendar year, based on a constrained noninformative prior and annual data. The plotted trend is not statistically significant (P-value = 0.43).

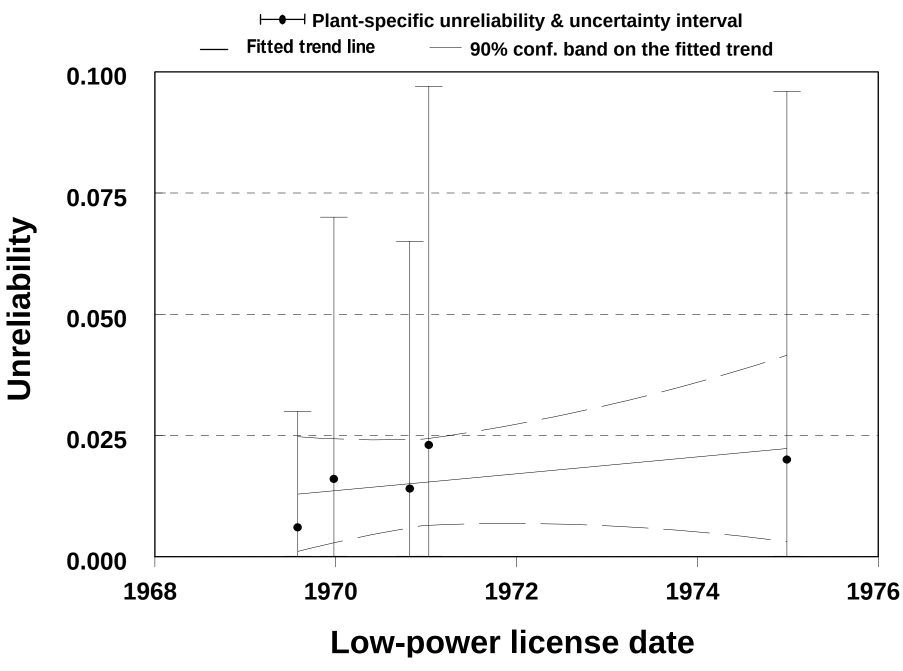


Figure 5. Plant-specific IC train unreliabilities based on constrained noninformative prior distributions, which include recovery actions plotted against low-power license dates. The trend is not statistically significant (P-value = 0.30).

The failure mode probabilities that were used in the unreliability calculations are those listed in Table 3. Since no plant-to-plant variability exists, plant-specific estimates based on the operational experience data are not provided. The estimate of IC train unreliability for the overall population apply to all plants.

The PRA/IPE estimates used for comparison were based on the information contained in four PRA/IPEs (References 2 through 5) that document the five plants with an IC system. Due to the nature of the IPE reports, fault tree models were not readily available in these documents. However, the failure data associated with quantifying the IC train unavailability were generally available in the IPEs. To allow comparison of PRA/IPE results to operational experience-based reliability parameters in the most efficient manner, only the PRA/IPE failure mode data that were major contributors to the IC system unavailability were used.

The PRA/IPE estimates provided within this report are approximate values and should not be interpreted as the exact estimate of IC train unreliability utilized in the IPEs. Furthermore, several IPEs did not report uncertainties, therefore, only a point estimate of IC train unreliability is provided for these plants. The information extracted from the PRA/IPEs to approximate IC train unreliability is shown in Table 5.

The PRA/IPE estimates provided within this report include both the short term and long term contributions to the unreliability of the IC system. The short term operation encompasses the initial opening and subsequent cycling of the condensate return valves and operation of the system exclusive of adding makeup water to the IC condenser. Long term operation encompasses the ability to provide makeup water to the IC condenser train. Long term includes the operator action to initiate makeup as well as the opening of the makeup valves.

The PRA/IPE estimates and the estimates based on the operational experience data are plotted in Figure 6 for comparison. The operational experience estimates are calculated with and without the failure to recover probabilities included in the overall unreliability estimate of the IC train. The PRA/IPE estimates of IC train unreliability range from 0.007 to 0.019. The operational experience uncertainty bounds of IC train unreliability (with recovery) are 0.0008 and 0.063. All of the PRA/IPE estimates of IC train unreliability are within the uncertainty interval based on the operational experience data. However, all of the PRA/IPE estimates are smaller than the estimated mean derived from the operational experience data. The average of the PRA/IPE values of IC train unreliability is approximately 1.3E-2 per demand. The mean IC train unreliability based on operational experience data is 2.0E-2 per demand.

Table 5. The IC train failure probabilities approximated from PRA/IPE failure mode information (major single train failure information extracted from the PRA/IPE.)

PRA/IPE	PRA/IPE Estimates	PRA/IPE Basis Information[a]
Dresden 2 & 3	0.013	IC1 or IC2 —fails, all supports available (2.5E-3); MUP—failure of makeup to EC tank, all supports available (2.6E-3); and OMUP—operator action to provide makeup to shell side of the IC (7.9E-3)
Millstone 1	0.019	ICINITA—failure of auto IC initiation (1.6E-2); ICMU—failure of auto and manual IC makeup (1.3E-3) DEP/IC—operator fails to remove noncondensible gasses during IC operation (1.3E-3)
Nine Mile Pt. 1	0.011	EC1—single IC train failing (6.3E-3); LC1—failure of makeup to EC tank (2.7E-3), and OU—operator fails to initiate makeup (2.0E-3)
Oyster Creek	0.007	IC2—single train failing to automatically actuate (3.0E-3); CT—condensate transfer for makeup (1.3E-4); and MU1—operator fails to open makeup valves (4.0E-3)

a. The acronyms listed in this table are those reported in the PRA/IPEs and are provided for traceability.

Comparing the train unreliability estimates, with and without recovery, shows a factor of five difference. The difference is directly attributable to the spurious isolations of the IC train as observed in the unplanned demands. All the failures observed for the FTO mode were due to spurious isolation of the IC train and all were recovered. Based on PRA/IPE results, spurious isolation is not important to IC train unavailability. The PRA/IPEs generally modeled spurious isolation of the IC train. However, the effect of this type of failure on IC availability was not important based on the PRA/IPE information. The PRA/IPEs show that the condensate isolation valve failing to open is the important contributor. Section 4 provides additional detail on the IC failures due to spurious isolation.

3.3 Additional PRA Insights

Because of the sparseness of the operational data, the ability to make inferences with a high degree of confidence is limited. Therefore, the reader is cautioned when interpreting the results of the comparisons provided in this section. The failure modes of the IC system defined for this report were compared to their counterparts in the PRA/IPE models. To make the comparisons, the basic events from the PRA/IPEs were grouped into the same system failure mode categories defined by operational experience data. The major basic event descriptions from the PRA/IPEs are:

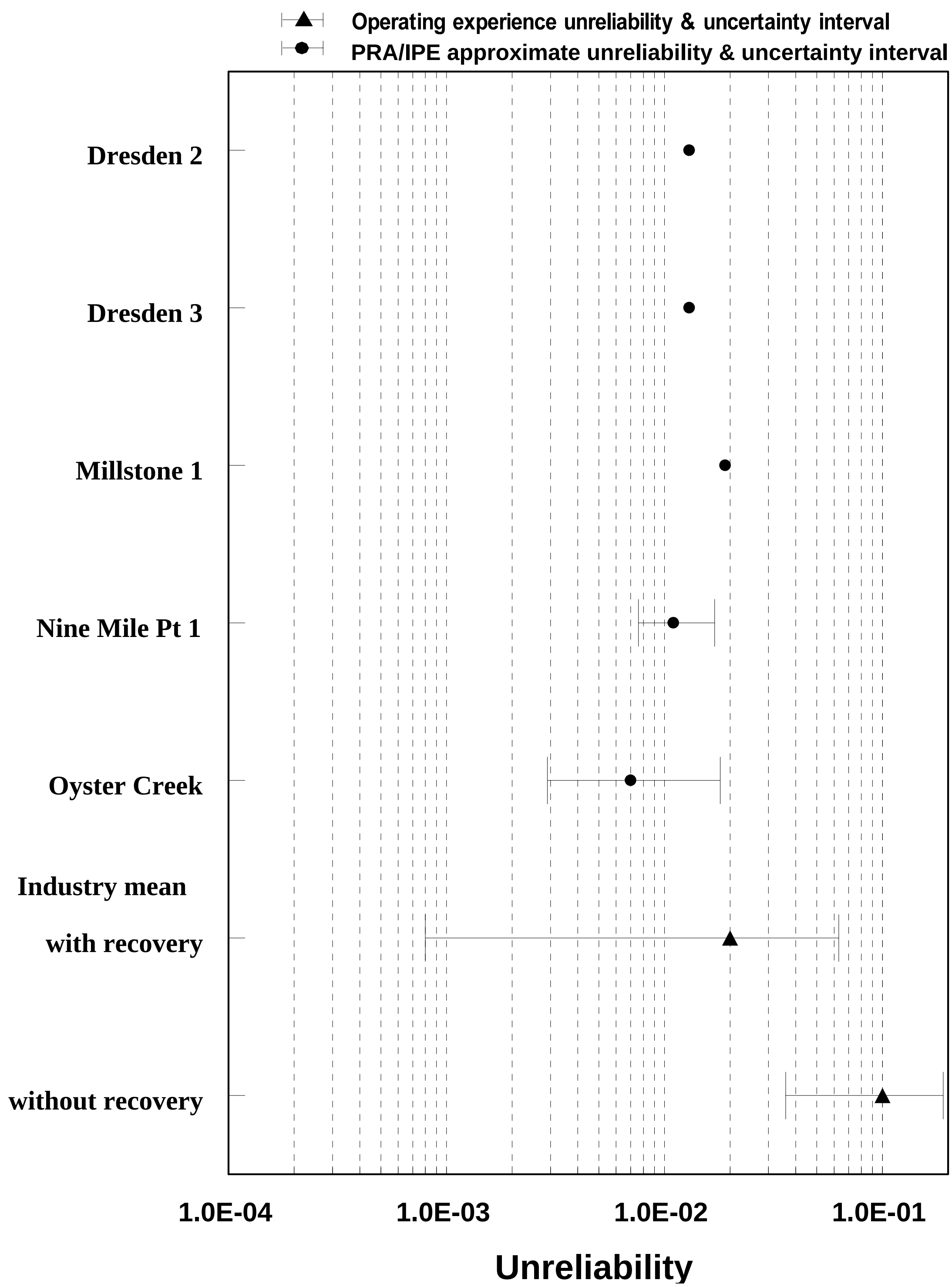


Figure 6. Plot of IC train unreliabilities approximated from PRA/IPE information and estimates of IC train unreliability (with and without recovery) calculated from the operational experience data. (For some plants the information documented in the PRA/IPEs was insufficient to generate uncertainty intervals.)

FTO: Failure of isolation condenser to remove decay heat exclusive of providing makeup water to the isolation condenser.

FMU: Failure to provide makeup water to the isolation condenser (includes both operator and hardware faults) when makeup is required.

MOOS: Maintenance that renders the IC train unavailable.

3.3.1 Failure to Operate

Figure 7 is a plot of the operational experience and PRA/IPE FTO estimates. The FTO contribution to IC train unreliability based on operational experience data without recovery is 62% compared to the recovered FTO contribution of 50%. The average value for the PRA/IPE failure to operate probability is 5.4E-3. The average of the PRA/IPE values is about a factor of twelve lower than the corresponding FTO estimate (0.064) derived from the operational experience data. However, all the plant-specific FTO probabilities approximated from the PRA/IPEs lie below the lower 5% uncertainty bound based on operational experience data. Keep in mind that the failure to recover from FTO are not included in these observations.

Based on limited information, the IPE for Dresden identified the condensate return valve failing to open as the major contributor to the IC train failure to operate probability. The Dresden IPE further reported that plant-specific data for motor-operated valves was utilized in the IC system model. The data consisted of 86 failures in 45,840 demands—1.9E-3 per demand.

Nine Mile Pt. 1 reported the air-operated valve in the condensate return line as a dominant contributor for failure of the IC train to operate (failure probability estimate of 1.7E-3 per demand). The IPE also reported the steam line isolation motor-operated valve as a major contributor to IC train unavailability. Even though this valve is a normally open valve, it was modeled as necessary for cooldown control (i.e., MOV cycling for cooldown control—3.6E-3 per demand).

The dominant contributor at Oyster Creek for FTO is the motor-operated valve on the condensate return failing to open. The failure probability estimate for this motor-operated valve is 1.8E-3 per demand. The IPE reported the estimate is based on plant-specific data (32 failures in 18,230 demands).

Millstone 1 reported the highest failure probability of failure to operate of the PRA/IPE’s. The Millstone 1 IPE reported that the failure rate for the condensate return valve was treated separately from the other motor-operated valve estimates utilized by the IPE. The reasons, as stated in the IPE, for separate treatment of this valve are: 1) the risk importance of the valve, 2) a design change in 1985 to replace the motor operator, and 3) a procedure change in 1987 which significantly reduced the failure probability to open on demand. The failure data utilized in the IPE were 0 failures in 44 demands (7.6E-3 per demand). The operational experience data utilized in this study for Millstone 1 are 0 failures in 4 demands.

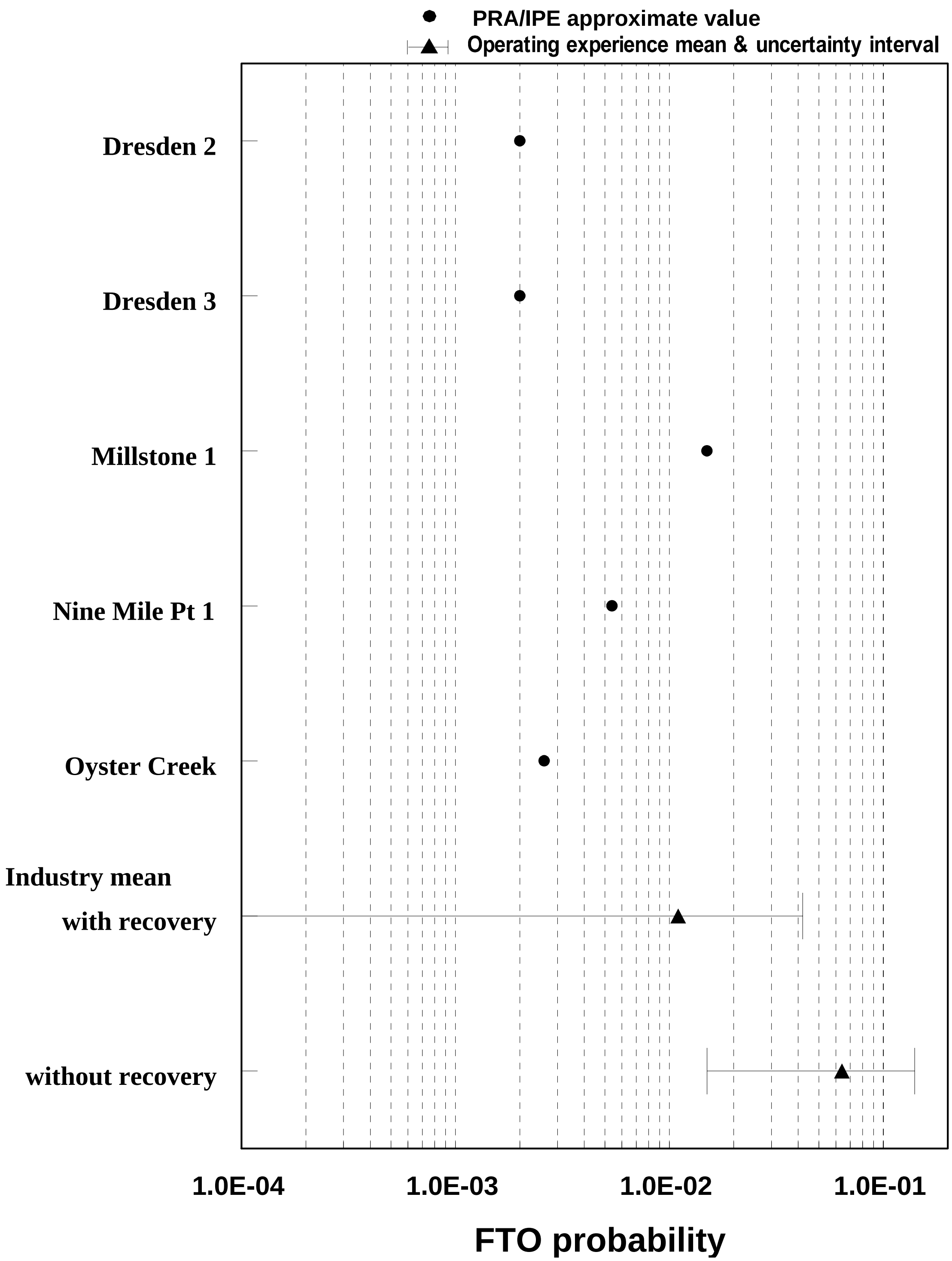


Figure 7. Plot of IC train failure probabilities for failure to operate based on PRA/IPE information and estimates (with and without recovery) calculated from operational experience data.

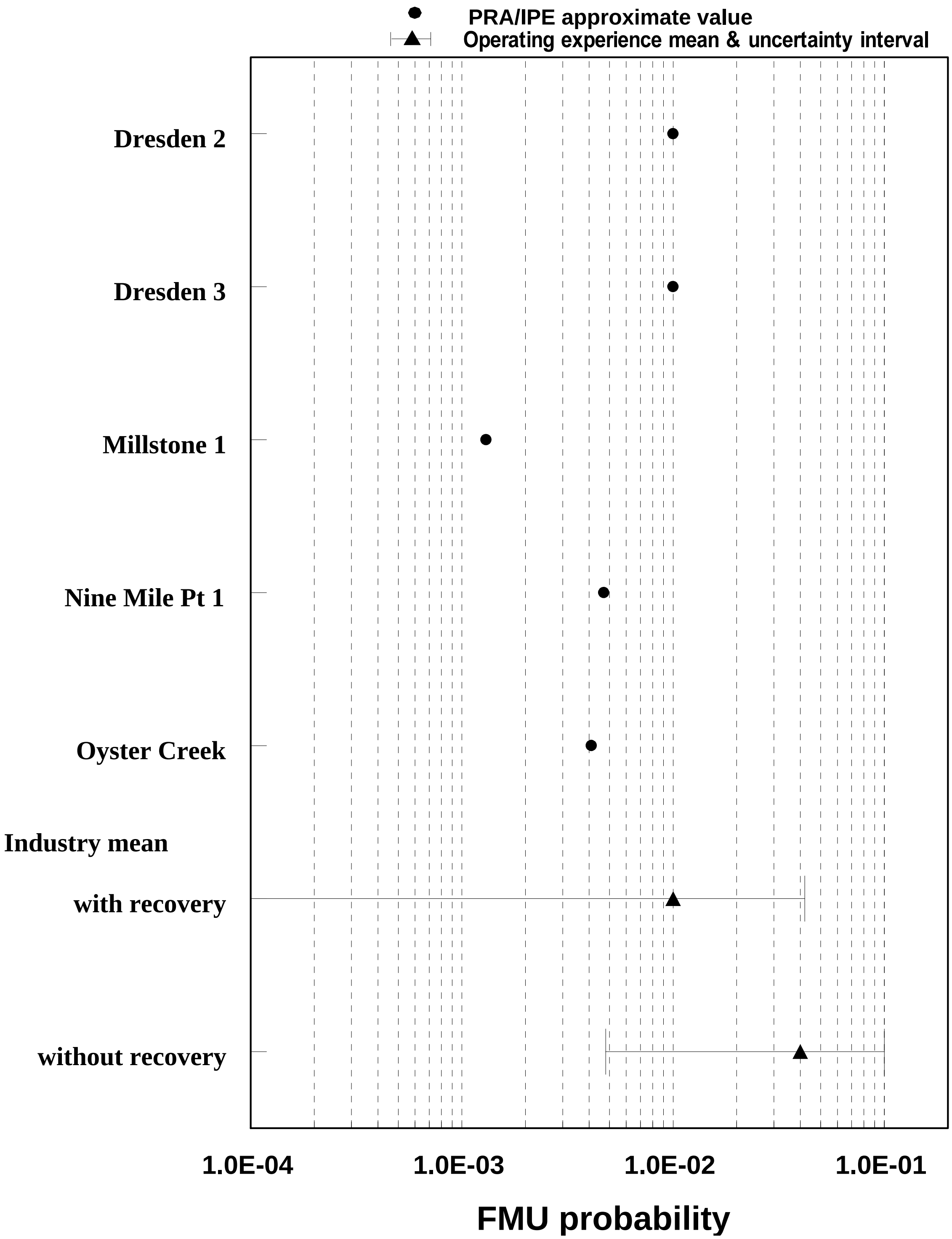


Figure 8. Plot of IC train failure probabilities for failure to provide makeup based on PRA/IPE information and estimates (with and without recovery) calculated from operational experience data.

3.3.2 Failure to Provide Makeup

Failure to provide makeup contributes 38% to IC train unreliability based on operational experience data and with no recovery considered. Since the only failure to provide makeup event was recovered, the contribution of failure to provide makeup to the overall IC train unreliability is 50%. Figure 8 displays the IC train failure probabilities associated with failure to provide makeup. The average value for the PRA/IPE failure to provide makeup probability is 6.0E-3 per demand. The average of the PRA/IPE values is about a factor of 13 lower than the corresponding estimate derived from the operational experience data when considering no recovery.

3.3.3 Maintenance Out of Service

The MOOS contribution to IC unreliability based on operational experience data was not included in the unreliability estimate. Based on the simple Bayes distribution, the mean is the number of failures plus 0.5 divided by the number of demands plus one. Therefore, the estimate of the mean probability of MOOS is 0.02 based on operational experience data. However, because of the lack of failures the inclusion of this failure mode could not be supported at this time. The average value of the PRA/IPE estimates of MOOS is 0.0006. The MOOS estimate based on operational experience data is a factor of 33 greater than the average of the PRA/IPE estimates. The reasons for this significant difference can be explained. First, due to the sparseness of the operational experience data (i.e., no failures in 23 demands), the statistical methods utilized in this study provide estimates that are likely conservative. The PRA/IPE estimates are generally calculated according to the frequency and duration of the maintenance activities. Therefore, risk analysis generally account for the MOOS probability as an unavailability estimate (i.e., fraction of IC down time compared to total plant operating time). In this study, the MOOS probability only considers maintenance failures and demands when the train was required to remove decay heat from the reactor (i.e., a reliability parameter) following an unplanned demand. In theory (i.e., infinitely large sample) these two estimates should be equivalent. However, the IC MOOS data set is small.

From a standpoint of reasonableness, the MOOS estimate based on operational experience data is not consistent with the information provided in the LERs. The outage information reported in some of the LERs indicates about an average of 6 hours per train-year for non-routine maintenance and surveillance testing. The outage time based on the operational experience MOOS estimate is approximately 124 hours (0.02 probability of MOOS times 8760 hours/year times 0.71 average yearly plant availability). The PRA/IPE average MOOS estimate correlates to about 3.7 hours assuming an average plant availability of 71%. Based on the outage time comparisons, the MOOS estimate based on operational experience data does not seem reasonable.

For the reasons stated above, the inclusion of MOOS as a parameter in the unreliability estimate is not appropriate. Further, the reader is cautioned when making absolute comparisons of the PRA/IPE estimates to the operational experience estimate of MOOS calculated above. The PRA/IPE estimates for MOOS failure probability are plotted in Figure 9.

3.3.4 Common Cause

Common cause failure is not addressed in this study. This is because of the scarcity of any common cause failure data. Three of the five plants in the study have single train IC systems and common cause failures are not applicable to the single train system. At the two dual train plants, there were very few actuations where a common cause failure could occur. No common cause failures occurred at Oyster Creek. No failure/test data for the unreliability analysis were recorded for Nine Mile Pt. 1 since no full system demands occurred during the study period. Because of these complications, it was decided not to include a common cause failure analysis of the operational experience data**.**

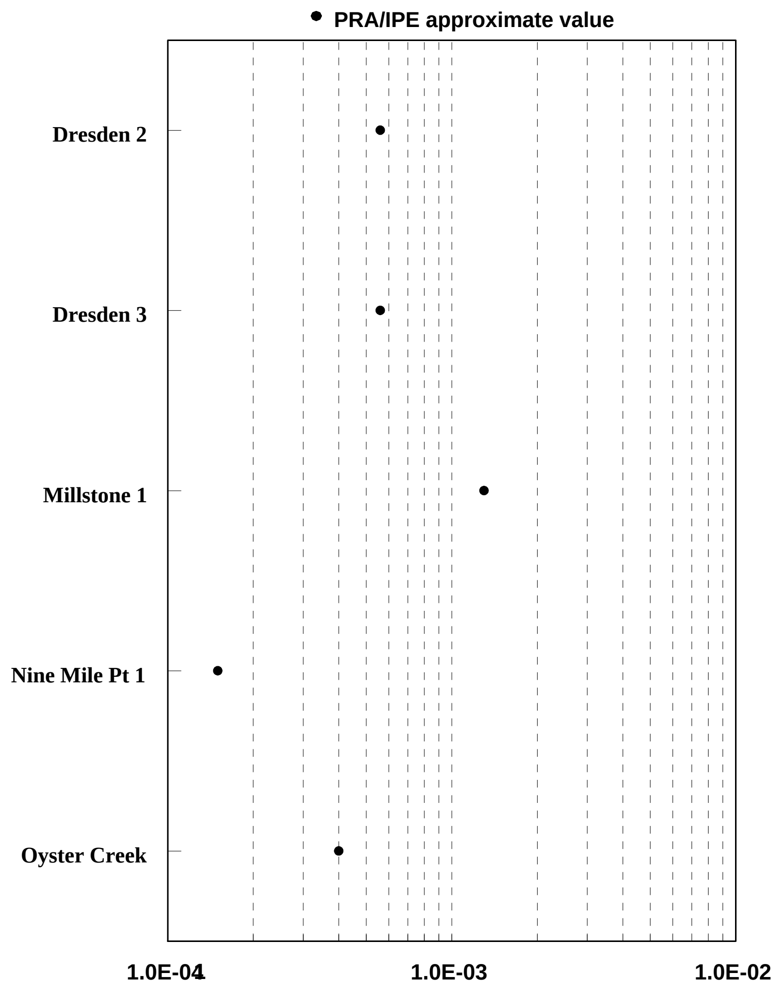


Figure 9. Plot of IC train failure probabilities for maintenance out of service calculated from PRA/IPE information.

4.0 ENGINEERING ANALYSIS OF THE OPERATIONAL DATA

This section documents the results of an engineering evaluation of the IC system operational data derived from LERs. The objective of this analysis was to analyze the data and provide insights into the performance of the IC system throughout the industry and at a plant-specific level. Unlike the risk assessment provided in Section 3, all LERs submitted during the evaluation period and the accident sequence precursor (ASP) events that mentioned the IC system were considered as part of this analysis; no data were excluded. The data include 35 IC unplanned train demands and 43 IC train inoperabilities.

The engineering data analysis provides qualitative insights into the performance of the IC system throughout the industry and on a plant-specific basis. These qualitative insights characterize the factors contributing to the quantitative estimates of IC reliability presented previously in Section 3. The reader is cautioned when comparing the individual plant data to the unreliability estimates provided in Section 3. A plant-specific estimate derived solely from the failure data at a particular plant may result in a different estimated unreliability than an estimate derived from the population as a whole, especially when the data are sparse. In addition, the effects of recovery will influence any comparisons to the results shown in Section 3. See Appendix A for additional information into the effects of performing plant or group-specific investigations.

The results of the operational data review are:

- There were no statistically significant trends in the rate of failures or unplanned demands per operational year.

- The cause of unreliability was primarily the result of spurious IC isolations that were recovered by operator actions. The isolations were found to be a failure mechanism of low probability in the PRA/IPEs reviewed for this study. However, the failure data utilized in this study are sparse, and conclusions regarding IC failure characteristics based on the sparse failure data may not be indicative of true performance. Overall based on all available operational data, there were no situations where the IC system or train failed and was not subsequently restored to an operable condition to remove heat and control reactor pressure during an unplanned demand.

- Spurious IC isolations account for most of the observed failures observed during the performance of surveillance tests and routine plant operations. These failures primarily were caused by either spurious (false) high flow signals, or personnel error in performance of surveillance testing or restoring the system to standby following surveillance testing.

The following subsections provide a comprehensive summary of the operational data supporting the above results as well as additional insights derived from: (a) an assessment of the operational data for trends and patterns in system performance across the industry and on an individual plant basis, (b) the identification of the causes that contribute to the system failures, and (c) the Accident Sequence Precursor events involving the IC system.

4.1 Industry-wide Evaluation

4.1.1 Trends by Year

Table 6 provides the IC train level inoperabilities, failures, and unplanned demands that occurred in the industry for each year of the study period. Figures 10 and 11 display the failure and unplanned demand frequencies with 90% uncertainty intervals for each year of the study. The frequencies are the number of train level events that occurred in the specific calendar divided by the IC train operational years. The IC train operational year is calculated as the number of IC trains multiplied by the plant operational years for a given calendar year. Included with the figures are a fitted trend line and a 90% confidence band for the fitted trend. As shown in the Figures 10 and 11, trend analysis of the failure and demand frequencies per IC train operational year showed, in general, no statistically significant trend over the past 7 years.

4.1.2 Factors Affecting System Reliability

The IC failures and inoperabilities were reviewed to determine the factors affecting overall unreliability. Since the focus of this study is on the reliability of the IC system in performing its reactor core cooling function, inoperabilities that do not result in a loss of reactor core cooling function (i.e., faults) are not discussed. Only inoperabilities that result in a loss of the IC system reactor core cooling function (i.e., failures) are discussed. To direct the review, the failures were partitioned by method of discovery for each major component. The results of the data partition are provided in Table 7.

As shown in Table 7 the isolation logic for the IC system contributed a majority of the failures. These failures of the isolation logic circuit all resulted in an isolation. The remaining four failures were distributed among the other components with the exception of the steam isolation valves in which no failures were observed. The one observed failure associated with the makeup valves contributed to failure to provide makeup water to the condenser. The remaining failures were categorized as IC train failure to operate.

Table 6. Number of IC system inoperabilities, failures, and unplanned demands by year.[a]

Classification	1987	1988	1989	1990	1991	1992	1993	Total
Inoperabilities	5	8	8	5	8	8	1	43
Failures	2	1	4	1	3	0	1	12
Unplanned demands	6	0	10	7	4	8	0	35
Plant operational years[b]	3.86	3.19	3.13	3.81	3.13	3.80	4.13	25.05

a. Each entry consists of train level events that occurred that year while the plant was operational.
b. Shutdowns longer than two calendar days are excluded from plant operational years.

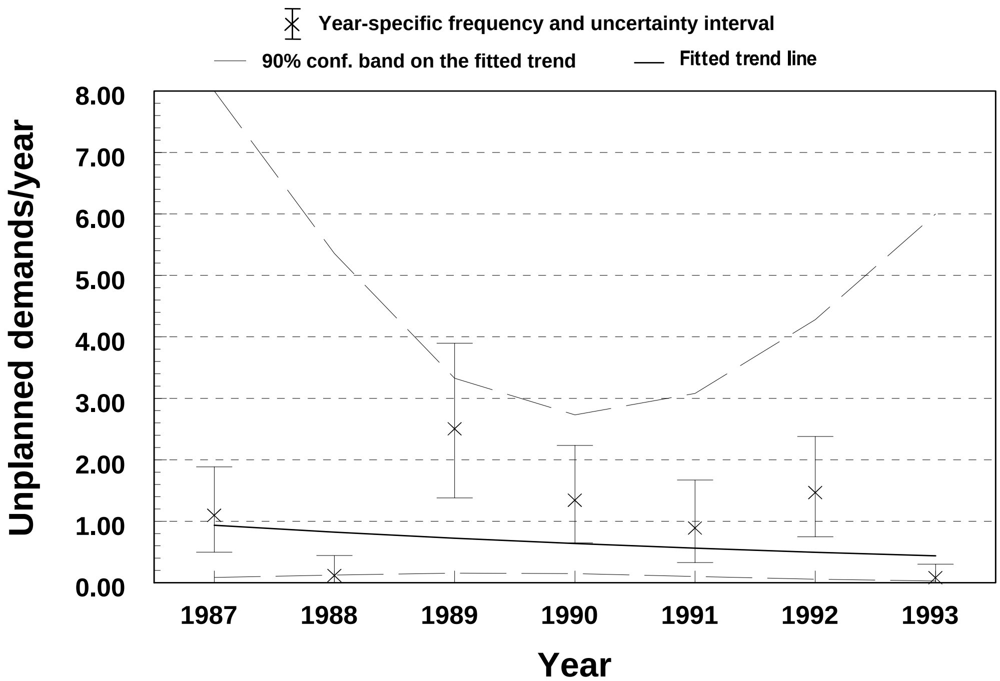


Figure 10. IC train unplanned demands per train operational year, with 90% uncertainty intervals and confidence band on the fitted trend. The trend is not statistically significant (P-value = 0.64).

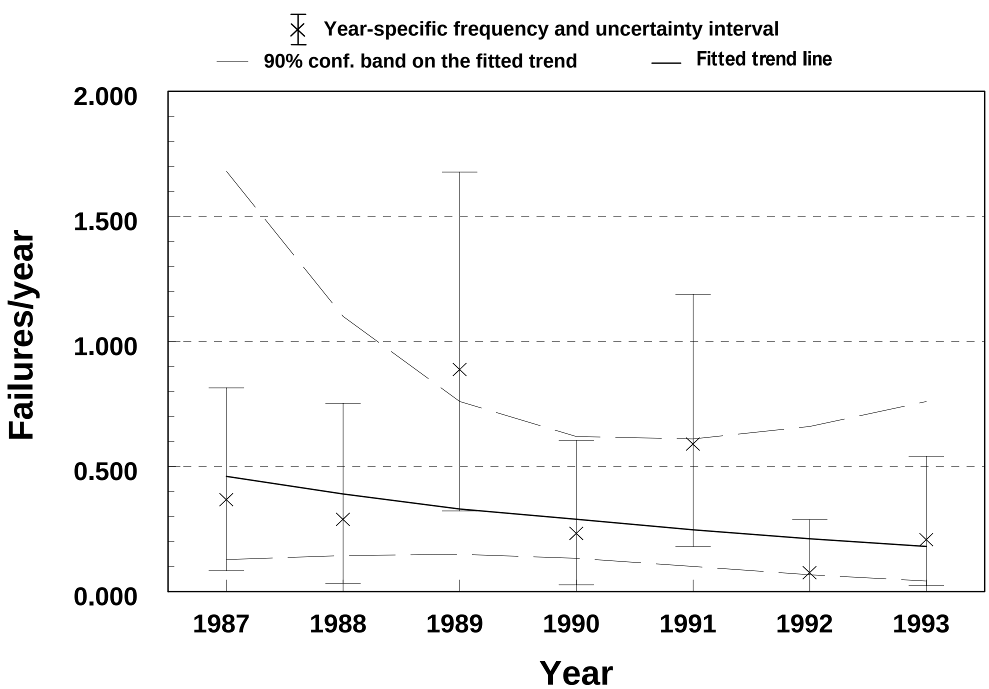


Figure 11. IC train failures per train operational year, with 90% uncertainty intervals and confidence band on the fitted trend. The trend is not statistically significant (P-value = 0.30).

Table 7. Component failure contribution for the IC system, by method of discovery.

Component	Method of discovery		
	Unplanned demand	Surveillance test	Other
Actuation logic circuit	—	1	—
Condensate return valves	—	—	1
Isolation logic circuit	2	2	4
Makeup valves	1	—	—
Steam isolation valves	—	—	—
Vent valves	—	—	1

Unplanned Demands—There were three train failures observed during unplanned demands that contributed to the overall unreliability estimate presented in Section 3. These three failures occurred during events in which the vessel was isolated (main steam isolation valves closed). Two of the failures were the result of spurious isolations and the third was the result of the inability to provide makeup water to the condenser. Each of the three failures were recovered by operator actions. The spurious isolations were found to be a failure mechanism of low probability in the PRA/IPEs reviewed for this study. However, the failure data utilized in this study are sparse, and conclusions regarding IC failure characteristics based on the sparse unplanned demand failure data may not be indicative of true performance.

The spurious isolations were the result of a false high flow signal and a personnel error, each resulted in a complete isolation of the system. The high flow isolation occurred approximately 3 hours after the initial start. The system was being used to cooldown the plant during an unplanned shutdown. The spurious isolation was recognized by plant operators, the logic reset, and the system was returned to normal operation within a few minutes. The second spurious isolation was the result of an operator inadvertently isolating the system during a ground detection procedure (not pre-planned maintenance). A few minutes later a reactor scram occurred as a result of a high vessel pressure condition which subsequently demanded the isolation condenser system. However, because the isolation valves were still closed (23 minutes after the isolation) the system could not initiate. Plant operators quickly reset the isolation logic and the system automatically initiated as required.

The remaining unplanned demand failure event was the result of a failed makeup isolation valve during system operation. Multiple electrical problems at the plant resulted in a reactor scram and the need to use the isolation condenser to cooldown the plant. However, the electrical problems also resulted in the isolation of the normal makeup to the condenser. Operators recognized the problem and used an alternate source of makeup water during the event before IC system performance was degraded. In addition, when power was restored to the normal makeup isolation valve, the normal makeup supply flow rate through the valve was inadequate for the demand. Investigation following the event by plant personnel determined that the normal makeup valve was undersized for plant cooldown.

Surveillance Tests—The surveillance test failure data are sparse with only three failures observed during all types of testing. However, none of the failures were observed during the 5-year test. Therefore, these three failures were not part of the unreliability estimate presented in Section 3.

Two of the surveillance test failures were the result of personnel error and the third attributed to a false high flow signal in the condensate flow sensing circuit. The two isolation logic failures resulted in spurious isolations. One was caused by a false high flow signal in the condensate flow sensing circuit, and the other was the result of personnel error in the operation of a selector switch. The single actuation logic failure was the result of an isolated instrument concurrent with the redundant instrument in the same channel being out of service for a routine calibration check. Both instruments inoperable in the same channel would have prevented the IC system from initiating on high pressure.

Other Failures—Six failures were detected by means other than during an unplanned demand or surveillance test. Four of these were caused by spurious isolations, one was the result of isolated system vent valves, and the remaining failure was a failed condensate return valve.

The four spurious isolations were caused by a blown fuse, a lug wire failure, and two instances of spiking in the flow sensing circuitry for the isolation logic. The longest of the spurious isolations caused the system to be non-functional for less than six hours, which was well within the technical specification limiting condition for operation. The other spurious isolations were of very short duration (a few minutes).

The most significant failure (i.e., in terms of the duration of the failure) occurred as a result of the steam side vent for one train of the system being closed for 21 days. This effectively gas bound the condenser after three days thus making the train non-functional for the remaining 18 days. This condition was discovered when the redundant train was inoperable for maintenance. All other failure events were significantly shorter in duration.

The failed condensate return valve occurred after cycling the valve during a normal plant cooldown. The condensate return valve cycling was required after every 100^{o}F change in plant temperature. The motor operator tripped on overcurrent when the valve was being shut. The overcurrent condition was the result of a roll pin failure that caused excessive friction in the motor operator. The cycling of the valve was to prevent thermal binding.

The LERs that identified failures of an IC train contained information pertaining to the length of time the train was not functional. The time that an IC train was failed or manually removed from service due to an inoperability was used to calculate the average time per operational year that the train was not functional. Only those periods for which the IC train was unable to perform its intended function were considered in the calculation.

Based on the operational data, an IC train was not available to perform its reactor core cooling function on the average of 18 hours per operational year for reasons other than surveillance testing or routine maintenance. This calculation does not consider down time due to surveillance testing or routine maintenance because these are not reported under the LER reporting requirements. If the one event with an 18 day out of service time period was excluded, the average down time per operational year would decrease to approximately 6 hours per train.

4.2 Plant-specific Evaluation

Table 8 shows the following information for each plant: operating years, number of inoperabilities, the number of failures, the number of demands, and the failure and demand frequencies. As used here, a *frequency* is simply the number of events divided by the number of operating years. It should be noted that 50% (19 of 38) of the demands for an IC train occurred at one plant, Oyster Creek; however, Oyster Creek has two trains, so IC system automatic actuations result in two train demands. The other dual train plant, Nine Mile Pt. 1, had no unplanned demands during the study period.

Because the dual-train plants in this study do not have to report single-train failures (discussed previously in Section 2), and the dual-train plants' automatic system actuations result in two train-level demands, no plant-to-plant comparisons for demand and failure frequencies, or failure frequency versus low-power license date are made in this section. However, a plant-specific discussion of the events are provided in an effort to understand the types of failures and demands that occurred. The failure and unplanned demand frequencies shown provide insights that can be used to characterize the factors contributing to the quantitative estimates of unreliability presented previously in Section 3.

The reader is cautioned when comparing the individual plant data to the reliability estimates provided in Section 3. Plant-specific estimates derived solely from the failure and demand data at a particular plant may produce results that differ from those presented in Section 3. There are several reasons for this, two of which are the sparse data associated with IC system performance at individual plants and the ability to recover from IC system failures. However, sparse data alone does not create differences between the best estimates of unreliability presented in Section 3 (which are calculated using Bayesian statistics) and what can be calculated if only the individual plant data were used (that is, using classical statistics). Sparse data provide the opportunity for rare or atypical performance to overly influence any unreliability estimate that is based solely on the plant-specific data. (Note that in the long run the atypical low unreliability will be balanced out by atypical high unreliability. "Sparse data" is defined such that the IC system experience is not long enough to allow the data to converge on the true unreliability.) This atypical data can result in the unreliability estimate either over predicting or under predicting the true unreliability of the IC system. Of course it is impossible to determine absolutely whether or not the sparse data are atypical of the true system performance; maybe the system really is as unreliable or reliable as the data suggests. Nevertheless, to minimize the chance of producing non-representative estimates based on sparse data, the best estimates presented in Section 3 are calculated using Bayesian statistics that utilize all knowledge of IC performance across the industry.

Table 8. IC train level inoperabilities, failures, and unplanned demands differentiated by plant.

Plant name	Operating years	Inoperabilities	Train failures	Failure frequency	Train demands	Demand frequency
Dresden 2	5.09	12	3	0.59	8	1.57
Dresden 3	5.42	9	5	0.92	6	1.11
Millstone 1	5.66	5	1	0.18	3	0.53
Nine Mile Pt. 1[a]	3.67	1	1	0.27	0	0.00
Oyster Creek[a]	5.21	16	2	0.38	18	3.45
Industry	25.05	43	12	0.48	35	1.40

a. The plant has a dual-train system. Therefore, failure and demand frequencies are listed in units of train-failures/year and train-demands/year, respectively.

The second issue to consider when reviewing the individual plant experience is the possibility of recovering from a IC system failure. Industry-wide, there were three opportunities in which plant personnel, due to circumstances of the particular events, had to recover the IC system from a failure to operate/makeup event. In all three instances, the recovery was successful. Consequently, the unreliability estimates presented in Section 3 include the likelihood that the failure events will be successfully recovered. Whereas the results of individual plant-specific comparisons presented in Section 4 do not necessarily include consideration of recovery.

The Dresden plants account for two thirds (8 of 12) of all failures, and all three unplanned demand failures. Unit 2 experienced one unplanned demand failure, and Unit 3 experienced two unplanned demand failures, all of which were successfully recovered. The Dresden plants also experienced 14 of the 35 unplanned demands, with Dresden 2 accounting for 8 and Dresden 3 accounting for 6. Of all the Dresden IC system unplanned demands only one was automatically initiated, the remaining 13 were manual initiations with some of these being multiple initiations during the same event. The multiple initiations were the result of operational considerations for pressure and cooldown control. The failures and unplanned demands were generally distributed throughout the evaluation period with the exception of Dresden 2 having six unplanned demands in 1990.

The failures at the Dresden plants were primarily caused by equipment-related problems (5) and personnel error (3). Six of the failures were either: an inadvertent isolation of the system, as a result of personnel error, or spurious isolations as a result of hardware-related problems. Two isolations were caused by personnel error, and the other four isolations were caused by hardware-related problems. The hardware-related problems were: two instances of instrument flow spikes, a blown fuse in the isolation control circuit, and a failed wiring lug in the isolation logic power lead. The remaining two failures were caused by: a loss of power to the makeup supply valve that was later determined to be undersized for a normal plant cooldown, and a personnel error during a surveillance test in which one channel of the automatic initiation circuit was rendered inoperable.

Although Oyster Creek experienced the highest number of inoperabilities and IC demands (16 inoperabilities and 18 demands), it did not experience a high number of failures (2). The demands are high because the system consists of two trains, and as a result any event involving system initiation generally effects both trains and was therefore counted twice in the demand total for the plant. The inoperabilities and demands were distributed throughout the study period, with the exception of one year (1988) where five inoperabilities were observed, and two years (1989 and 1992) with a high number of demands, six and eight respectively. Unlike at Dresden, 14 of the 18 demands at Oyster Creek were automatically initiated.

The two failures observed at Oyster Creek were the result of the steam side vent for a condenser for one train being closed for 21 days and a failed condensate return valve. The closed steam side vents effectively gas bound the condenser after three days thus making the system non-functional for the remaining 18 days. This condition was discovered when the redundant train was already inoperable. The failed condensate return valve occurred after cycling the valve during a plant cooldown (required every 100^{o}F). The motor operator tripped on overcurrent when the valve was being shut. The overcurrent condition was the result of a roll pin failure that caused excessive friction in the motor operator. The repeated cycling of the valve was to prevent thermal binding during the plant cooldown.

Millstone 1 experienced two inoperabilities, one of which was a failure from a spurious high flow isolation while using the system to cool the reactor head following a plant cooldown. Three IC system demands occurred during the evaluation period. These events were distributed throughout the study period.

Nine Mile Pt. 1 experienced only one event, a failure from a spurious IC system isolation during a surveillance testing of instrumentation. No IC system demands or other inoperabilities have occurred.

4.3 Accident Sequence Precursor Review

Five IC events identified by the Accident Sequence Precursor (ASP) Program (NUREG/CR-4674) were reviewed. The purpose of this review was to relate the operational data to the types of events that resulted in a conditional core damage probability (CCDP) of greater than 1.0E-6. The search for ASP events was limited to the 1987-1993 study period, and included all ASP events in which the isolation condenser system was identified in the ASP database.

The CCDP for the ASP events ranged from 3.1E-6 to 8.8E-5. Only one of the ASP events involved a malfunction where the isolation condensers would not have functioned, this resulted in a CCDP of 3.6E-6. The remaining ASP events involved loss of power events. In one of these events, the normal makeup water supply to the IC tank was initially lost due to the loss of power but backup water supplies were available and power was later restored. In the remaining events the isolation condensers either operated as designed or would have if called upon.

The ASP events occurred at 3 different plants, Oyster Creek accounted for 3 events, and Dresden 2 and Dresden 3 accounted for 1 event each. Of the 5 ASP events related to the IC system; 1 identified a system failure during an IC system demand, 2 were demands with no corresponding failure, and 2 were system inoperabilities with no demand. Three of the five events were used in this study to estimate IC system unreliability (two unplanned demands and one failure during an unplanned demand). A brief discussion of these five events are provided in Table 9.

Table 9. Summary of the ASP events identifying an isolation condenser malfunction.

Plant Name	LER	Event	CCDP	Description

	Number	Date		
Dresden 2	23790002	01/16/90	3.1E-6	A reactor scram occurred from a loss of feedwater, it was followed by a loss of offsite power due to a transformer internal fault. The isolation condenser was manually actuated to control pressure immediately following the scram and several times subsequently during the cooldown.
Dresden 3	24989001	03/25/89	1.3E-5	A loss of offsite power was caused by a fault in a circuit breaker, resulting in a reactor scram. The isolation condenser was manually initiated three times during the shutdown to control pressure. Shortly after the first manual initiation it was discovered that the demineralized water make-up valve had been de-energized due to the LOOP. Mildly contaminated condensate was used as a makeup water supply for the IC shell. Power was restored to this valve, however, on the second initiation of IC the steaming rate exceeded the demineralized water makeup supply, so again condensate was used to supplement the demineralized water makeup supply.
Oyster Creek	21988019	09/02/89	3.6E-6	Both trains of isolation condenser were concurrently out of service for 10 days. This occurred when it was discovered that the vent valve for the "A" Isolation condenser had been shut for the past 21 days and during this time the "B" Isolation condenser had been taken out of service due to a failed motor operated valve and leakage past the condensate return valve.
Oyster Creek	21990005	04/21/90	8.8E-5	A ground fault caused a loss of power rendering numerous safety systems inoperable including the "B" isolation condenser. Although administratively inoperable, the "B" isolation condenser would still have been able to perform its reactor core cooling function. During the plant cooldown the "A" isolation condenser was declared inoperable when one of the isolation valves became thermally bound while attempting to cycle the valve.
Oyster Creek	21992005	05/03/92	7.1E-5	A forest fire caused a loss of offsite power and a reactor scram. Both isolation condensers automatically actuated on high reactor pressure and operated as designed. Both isolation condensers were later manually actuated to control pressure as the plant was cooled down.

5.0 REFERENCES

1. Event Reporting System 10 CFR 50.72 and 50.73, NUREG-1022

2. GPU Nuclear Corporation, Oyster Creek Probabilistic Risk Assessment, November 1991.

3. Northeast Utilities, Millstone Nuclear Power Station, Unit No. 1 Individual Plant Examination for Severe Accident Vulnerabilities, NUSCO-174, March 1992.

4. Commonwealth Edison Company, Dresden Station, Individual Plant Examination Submittal Report, January 1993.

5. Niagara Mohawk Power Corporation, Nine Mile Pt. Unit 1 Individual Plant Examination, July 1993.

Appendix A

Isolation Condenser System Data Collection and Analysis Methods

Appendix A

Isolation Condenser System Data Collection and Analysis Methods

To characterize isolation condenser (IC) system performance, operational data pertaining to the IC system from U. S. commercial nuclear power plants from 1987 through 1993 were collected and reviewed. For the five boiling water reactor (BWR) plants having IC systems, all the reported system inoperabilities and unplanned demands were characterized and studied from the perspective of overall trends and the existence of patterns in the performance of particular plants. Only the demands requiring a complete response of the IC system and/or train are utilized in the unreliability calculation (herein referred to as operational experiences). The inoperabilities included such problems as isolated vent paths, late performance of surveillance tests, and missing seismic restraints, as well as failures of the IC's emergency core cooling design safety function. After considering inoperabilities, the subset of failures (losses of safety function) was analyzed from an engineering perspective to identify major system performance issues. A quantitative analysis then focused on the failures for which system demands could also be estimated. From a knowledge of these failures and the associated demands, occurrence probabilities for each failure mode and the system unreliability were estimated. Finally, IC failure probabilities from probabilistic risk assessments (PRAs) or individual plant examinations (IPEs) for the five plants with IC systems were evaluated by comparing them to the estimated unreliability.

Descriptions of the methods for the basic data characterization and the estimation of unreliability are provided below. The descriptions give details of the methods, summaries of the quality assurance measures used, and discussion of the reasoning behind the choice of methods.

A-1. DATA COLLECTION AND CHARACTERIZATION

IC system operational data used in this report were based on LERs found using the Sequence Coding and Search System (SCSS). The SCSS database was searched for all IC system records as reported in LERs for the years 1987-1993. Since the IC system at each plant is part of the emergency core cooling system (ECCS), any malfunctions or occurrences where the system was not fully operable (inoperabilities) as defined by plant technical specifications or by the plant’s Safety Analysis Report are required by 10 CFR 50.73 to be reported in LERs. However, because the IC system has two trains at Nine Mile Point 1 and at Oyster Creek, the reporting requirements for these two plants differ from the Dresden units and Millstone (see Section 2, Table 1 in the text for further information about the system configurations). Nine Mile Point and Oyster Creek are not required to report single-train malfunctions unless the malfunction occurred on an unplanned demand for the IC system’s safety function, resulted in either a train outage time in excess of technical specification requirements or a unit shutdown required by technical specifications, or had a system level impact affecting both trains. Reporting of single-train malfunctions at these units is not required if none of these conditions are met. This uncertainty about the completeness of the data (i.e., the possibility of not identifying some failures) effectively precludes using surveillance test data from these two plants, in the unreliability calculations.

In subsections below, methods for acquiring and screening the basic operational data used in this study are described in more detail. The data are inoperabilities and failures, and the associated operational experiences.

A-1.1 Inoperabilities and Failures

The identified IC system inoperabilities reported in the LERs in the SCSS database were read completely (full text) by engineers having U.S. commercial nuclear power plant experience, with care taken to properly classify each event and to ensure consistency of the classification for each event. The LERs were reviewed to determine the types of failures, the causes of the event, the method of discovery, and the component that contributed to the failure. The information encoded in the SCSS database was used only to identify the LERs for screening. The identification of attributes necessary for event analysis, such as failure classification, failure modes, system demands, and failure causes, was based on an independent review of the information provided in the LERs from a risk and reliability perspective.

As stated previously, not all IC events reported in the SCSS database resulted in actual failure of the IC system. The term, *inoperability*, is used to describe any LER-reported IC event in which the system did not meet the operability requirements identified in applicable plant technical specifications or the Safety Analysis Reports. The term, *failure*, describes an inoperability for which the ECCS function of the system was lost. Failures include such problems as failure to operate and failure to provide makeup for the IC system condenser. Inoperabilities include these, and also problems such as events related to seismic design, and administrative events such as late performance of a test. Because analysis of the containment isolation safety function of the ICs is not included in this study, events such as failures to isolate the system were classified as inoperabilities, not failures.

The IC events identified in this study as failures represent actual malfunctions that would have prevented the successful operation of the system in response to a severe reactor accident. Closed vent valves or slow valve opening times were not considered failures, since facility analyses stated that a sufficient safety margin was present to preclude core damage. System events reported as potential failures because of inadequate seismic design, environmental qualification, or other similar administrative technical specification concerns were not considered failures. System events related to troubleshooting activities, such as occurrences immediately after maintenance and prior to the post maintenance test, were not considered failures.

The IC system failures were classified to the system failure mode observed at the time of failure. When the IC system receives an automatic or manual start signal, the system functions successfully if the condensate return valve opens, stable steam flow is obtained from the reactor to the system condenser, and condensate is returned back to the reactor until the system is no longer needed. Failure may occur at any point in this process including failure from loss of makeup water to the system condenser. A loss of makeup water will stop the condenser heat removal process and thus fail the IC system, even though the reactor steam/water cycle would otherwise remain operable. For purposes of this study, failures that can occur in response to an actual IC system operational experience are classified into the following two failure modes:

- Failure to operate (FTO) occurs if the system is in service but fails to open the condensate return valve and achieve and maintain stable reactor steam flow to the system condenser and condensate flow back to the reactor. This failure mode occurs when the system fails to automatically or manually start after a demand, and whenever reactor steam/condensate flow is inadvertently interrupted by closure of the condensate return or steam supply valves.

- Failure to provide makeup (FMU) occurs if, at any time during the operation of the system, the capability to provide makeup water to the shell side of the IC train condenser is lost when makeup is required.

Other plant system studies based on LERs have also considered the possibility of a system being out of service for maintenance (MOOS) at the time of an unplanned demand. In this failure mode, the system is unavailable due to preexisting preventive or corrective maintenance. This failure mode was not quantified and included in the unreliability estimates for the ICs because the operational data contain relatively few demands and no failures. The point estimate and bounds calculated using such sparse data tend to be unrealistically high.

The operational experience used for this report identified events pertaining to the recovery of a failed system. To recover from an FTO event, operators have to recognize the failed state of the system and manually restart it without performing maintenance (e.g., without replacing components). Recovery from an FMU event is defined in a similar manner, with plant operators recognizing a problem and restoring the IC train's heat removal capability from the control room. Each failure reported during an unplanned operational experience was evaluated to determine whether recovery of the system by an operator had occurred.

In addition to the failure mode and recovery data captured for each inoperability, the following information from each failure was entered into a data base:

- The run time prior to failure, if given.

- The subsystem and component involved, and the time the system was out of service to repair the component, if given.

- The cause (hardware malfunction, personnel error, system design, administrative problems).

- The method of discovery of the event (unplanned demand, surveillance test, normal plant operations, or design review); and, for surveillance tests, the test frequency.

Identification of the test frequency was important, because failures must be matched with associated demands for the estimation of unreliability. For the IC system, the LER information clearly distinguished whether a failure during testing occurred during a full test of the system's safety function.

A-1.2 Demands

To estimate unreliability, information on the frequency and nature of IC system demands was needed. The operational experience was evaluated to determine those events that completely demonstrated the system's capability (or inability) to provide adequate core cooling. Two criteria were utilized in identifying what types of demands and failures to consider in this process. First, each demand must reasonably approximate conditions for required accident/transient response. Any test data used to estimate unreliability needs to be at least as stressful on the tested portion of the system as a full unplanned demand. For this study, this requirement led to the identification of particular failure modes tested by various types of demands. Second, counts or reliable estimates of the number of demands and associated failures must be available.

A-1.2.1 Unplanned Demands

As with the inoperabilities, the SCSS database was used to identify all LERs describing unplanned IC engineered safety feature (ESF) actuations for the years 1987-1993. Since the IC system is a safety system, unplanned ESF actuations are reportable as defined by 10 CFR 50.73 reportability requirements. Therefore, all the unplanned IC ESF actuations should be included in the identified LERs.

Each identified LER was screened to determine the nature of the IC ESF actuation. Among the IC ESF actuation events, some were unplanned operational experiences following plant transients that resulted in an actual high reactor pressure vessel (RPV) pressure conditions or vessel isolation. These events required the heat removal safety function of the IC system. These unplanned operational experiences were used in the estimation of system unreliability.

In addition to the unplanned operational experiences, many of the ESF actuations were demands of only a part of the system. The partial demands included vent valve closures and relay actuations related to plant maintenance actions, such as removal of a fuse or shorting of test leads. A partial demonstration of the system's ECCS safety function was not considered as being representative of performance under actual conditions. These types of demands would not provide an adequate measure of system success relative to completing the ECCS safety function in an accident condition, they were excluded from the count of IC system unplanned operational experiences.

The criterion that operational experiences of interest must demonstrate the success or failure of the IC ECCS safety function resulted in the exclusion from the system unreliability assessment of events associated just with the containment isolation function. For example, events leading to an isolation of the system's vent valves were not counted as full system demands. However, ESF actuations resulting in the closure of the condensate return or steam supply valves were included and also were classified as a loss of the system's ability to provide core cooling (failure).

Database records were created for initial full system demands. A field in the unplanned demand data base indicated the number of IC train demands associated with each event. This number was a multiple of two for the dual-train plants. Several of the events, however, consisted of a series of separate system demands in response to the RPV pressure being restored and then later rising again. The demand records show the total time of operation, summed across the separate train demands, whenever that information is available. The unplanned demands identified in this review are listed in Appendix B.

Among the full IC train demands, makeup water for the IC condenser was not required for demands of short duration, typically less than 10 minutes. The events were therefore screened for their duration and the likelihood of makeup. Depending on the particular plant, the condensers are designed to provide 20 to 90 minutes of cooling before makeup is absolutely required. However, normal system operation would provide makeup flow to the condenser before the condensers run dry. Short duration events were marked as such and not treated as demands for makeup. Depending on the plant, events with an average of ten minutes or more per train demand were judged as requiring makeup for each demand. Two events were uncertain. Because 97% of the know demands were judged as long enough to require makeup, the two uncertain events were included in the count of demands for makeup.

It is noteworthy that Nine Mile Point 1 did not have any reportable unplanned demands of the IC system during the study period.

A-1.2.2 Surveillance Tests

Data from the surveillance tests that are performed on a periodic basis may be used to estimate selected aspects of IC system unreliability. For reasons described below, just those surveillance tests that are conducted on a 5-year frequency were used to estimate unreliability for the IC system.

For the IC system, a detailed review of plant technical specifications found that the quarterly and cyclic surveillance tests provide only a partial demonstration of the system's ECCS safety function. The quarterly surveillance tests were found to only functionally test and calibrate the system's relays and switches. The cyclic surveillance tests (performed during refueling outages) were found to only check the system's automatic actuation logic. Overall, these tests verified system operability and functionality on a component level but do not demonstrate the complete system response needed to mitigate or prevent a reactor accident. The partial demonstrations (e.g., cyclic, quarterly, monthly, and other more frequent surveillance testing) of the system’s capability were not considered representative of the system’s performance under accident conditions. Therefore, these tests and associated demand count estimates were excluded from the system reliability analysis. The engineering analysis section of this report does contain a review of the types and causes of failures observed during these tests.

The review of plant technical specifications indicated that the plants are required to manually start and run the IC system with a periodicity of once every 5 years (referred to as 5-year tests). The running time for this test was found to be long enough to also test the capacity of the system to maintain level in the shell side of the IC condenser and thus maintain the heat transfer capability of the system. Since the 5-year tests were found to completely demonstrate the system's heat removal capability, they were used in estimating system unreliability whenever complete failure information was also available.

Lack of completeness of failure information resulted in the exclusion of the 5-year test data for the two plants with two-train IC systems (Nine Mile Point 1 and Oyster Creek). These plants are not required to report single-train failures on the test if the other train performed properly. Therefore, only the test demands from Dresden 2 and 3, and Millstone 1 were included, resulting in only three surveillance test demands for the study period.

Since Nine Mile Point 1 had neither unplanned demands during the study period nor reportable single train failures based on the 5-year test, it effectively contributed no data to the study. Industry-wide data results are applied to this plant.

A-1.3 Plant Operational Time

The reported system inoperabilities, failures, and unplanned operational experiences were studied from the perspective of overall trends and the existence of patterns in the performance of particular plant units. These assessments were based on frequencies of occurrence per operational year. Thus, estimation of the operational time for each plant and year was also part of the data collection.

Operational time, ideally, is the time when the system is required to be operable, in accordance with plant technical specifications (i.e., reactor temperature greater than 350°F and irradiated fuel in the vessel). This time was not known exactly. Therefore, the NRC's *OUTINFO* database was used to estimate operating time. This database, based on plant Monthly Operations Reports, lists the starting and ending dates of all periods when the main generator is off-line. During short generator off-line periods, the reactor may remain critical and pressurized; therefore, the starting and ending days of such outages were treated as operational periods. The outages likewise were treated as operational if they spanned 2 calendar days or less. The operational time for a plant was estimated by calendar time minus all periods when the main generator was off-line more than 2 calendar days.

A-2. ESTIMATION OF UNRELIABILITY

As discussed in Section 3.1, four failure modes were identified for the estimation of IC unreliability: failure to operate (FTO), failure to recover from failure to operate (FRFTO), failure to provide makeup (FMU), and failure to recover from failure to provide makeup (FRFMU).

As stated in Section A-1, maintenance out of service (MOOS) failures were not addressed in this study. No such failures were observed in the operational data, and not enough successful unplanned operational experiences were observed to determine a realistic estimate of the MOOS failure probability from the data. Therefore, the unreliabilities calculated from the operational data excluded MOOS.

Common cause failure was likewise not addressed in this study. Such failure data would only be applicable for the two plants that have dual-train systems; the other three have just single trains. No demands during the study period were found for one of the two dual-train plants. Data from just the one remaining plant are insufficient for estimating reasonable uncertainty bounds that include possible between-plant variation. Developing a point estimate for this plant was not worthwhile due to the sparsity of data.

The included individual probabilities were combined to estimate the total unreliability given a demand. Estimating the unreliability and the associated uncertainty involves two major steps: (a) estimating probabilities and uncertainties for the different failure modes, and (b) combining these estimates. These two steps are described below.

A-2.1 Estimates for Each Failure Mode

Estimating the probability for a failure mode requires a decision about which data sets (unplanned demands, 5-year tests, or both) to use, a determination of the failure and demand counts in each data set, and a method for estimating the failure probability and assessing the uncertainty of the estimate.

A-2.1.1 A Priori Choice of Data Sets

Since recoveries are typically not attempted after a failure on a test, the FRFTO and FRFMU failure modes were found only in the unplanned operational experiences, not in the 5-year tests. For the FTO and FMU modes, both the unplanned operational experiences and the 5-year tests were considered as possibly relevant, and the data were examined as described below to show which sets to use.

A-2.1.2 Demand and Failure Counts

Unplanned Demands. The unplanned demands were counted by failure mode as follows. The total demand data set was obtained as described in Section A-1.

The number of FTO demands is simply the number of ICs fully demanded, as obtained from the LERs. The number of demands for recovery from fail to operate (FRFTO) was the total number of failures to operate. The number of demands for makeup of the condenser was the number of long demands to operate minus the number of unrecovered FTO events among the long demands to operate (recall from Section A-1.2.1 that no demand for makeup was associated short duration demands, less than 10 minutes). The number of demands for recovery from failure to provide makeup (FMU) was the number of failures to provide makeup.

Five-Year Tests. The above discussion considered only unplanned operational experiences. Five-year surveillance tests are described in Section A-1.2.2. Demand counts for the 5-year tests for the IC system were estimated as follows. The plants are required to perform the test at their initial startup, i.e., their low-power license date. Then they must repeat this test every 5 calendar years after that. So the number of tests for each plant was simply calculated by counting forward in multiples of 5 calendar years from their low-power license date and tracking how many fell within the study period (1987-1993). The INEL database UNITINFO lists the low-power license date and the decommissioning date for each plant. It worked out that, for each of the plants, only one test was done within the study period. As noted in section A-1.2.2, the dual-train IC plants' surveillance data were not used because reporting a failure of one of the two trains is not required.

A-2.1.3 Data-Based Choice of Data Sets

At this point, failures and demands had been counted or estimated for two sets of data; unplanned demands and 5-year tests. To determine which data to use for FTO and FMU failure modes, each mode failure probability and the associated 90% confidence interval were computed separately for unplanned demands and 5-year tests. The confidence intervals assume binomial distributions for the number of failures observed in a fixed number of demands, with independent trials and a constant probability of failure in each data set. A comparison of the plotted confidence intervals gave a visual indication of whether the data sets could be pooled.

The hypothesis that the underlying probability for unplanned demands and for 5-year tests is the same was tested for each failure mode. Fisher's exact test (described in many statistics books) was used, based on a contingency table with two rows corresponding to failures and successes and two columns corresponding to unplanned demands and 5-year tests. For the FTO and the FMU failure modes, this hypothesis could not be rejected and the two sources of data were pooled.

To further characterize the failure probability estimates and their uncertainties, probabilities and confidence bounds were computed in each data set for each year and plant. The hypothesis of no differences across each of these groupings was tested in each data set, using the Pearson chi-square test. Often, the expected cell counts were so small that the asymptotic chi-square distribution was not a good approximation for the distribution of the test statistic; therefore, the computed P-values were only rough approximations. However, they are useful for screening.

As with Fisher's exact test, a premise for these tests is that variation between subgroups in the data be less than the sampling variation, so that the data can be treated as having constant probabilities of failure across the subgroups. When statistical evidence of differences across a grouping is identified, this hypothesis is not satisfied. For such data sets, confidence intervals based on overall pooled data are too short, not reflecting all the variability in the data. However, the additional between-subgroup variation is likely to inflate the likelihood of rejecting the hypothesis of no significant systematic variation between years, plant, or data sources, rather than to mask existing differences in these attributes.

A-2.1.4 Estimation of Failure Probability Distributions

Three methods of modeling the data for the unreliability calculations were employed. They all use Bayesian methods, with the unknown probability of failure for each failure mode represented by a probability distribution. An updated probability distribution, or posterior distribution, is formed by using the observed data to update an assumed prior distribution. One important reason for using Bayesian methods is that the resulting distributions for individual failure mode probabilities can be propagated easily, yielding an uncertainty distribution for the overall unreliability.

In all three methods, Bayes Theorem provides the mechanics for this process. The prior distribution describing failure probabilities is taken to be a beta distribution. The beta family of distributions provides a variety of distributions for quantities lying between 0 and 1, ranging from bell-shape distributions to J- and U-shaped distributions. Given a probability (p) sampled from this distribution, the number of failures in a fixed number of demands is taken to be binomial distributed. Use of the beta family of distributions for the prior p is convenient because, with binomial data, the resulting output distribution is also beta. More specifically, if a and b are the parameters of a prior beta distribution, a plus the number of failures and b plus the number of successes are the parameters of the resulting posterior beta distribution. The posterior distribution thus combines the prior distribution and the observed data, both of which are viewed as relevant for the observed performance.

The three methods differ primarily in the selection of a prior distribution, as described below. After describing the basic methods, a summary section describes additional refinements that are applied in conjunction with these methods.

Simple Bayes Method. Where no significant differences were found between groups (such as plants), the data were pooled and modeled as arising from a single binomial distribution with a failure probability p. The assumed prior distribution was taken to be the Jeffreys noninformative prior distribution.[A-1] More specifically, in accordance with the processing of binomial distributed data, the prior distribution was a beta distribution with parameters, a = 0.5 and b = 0.5. This distribution is diffuse and has a mean of 0.5. Results from the use of noninformative priors are very similar to traditional confidence bounds. See Atwood[A-2] for further discussion.

In the simple Bayes method, the data were pooled, not because there were no differences between groups (such as years), but because the sampling variability within each group was so much larger than the variability between groups that the between-group variability could not be estimated. The dominant variability was the sampling variability, and this was quantified by the posterior distribution from the pooled data. Therefore, the simple Bayes method used a single posterior distribution for the failure probability. It was used both for any single group and as a generic distribution for industry results.

Empirical Bayes Method. When between-group variability could be estimated, the empirical Bayes method was employed.[A-3] Here, the prior beta(a, b) distribution is estimated directly from the data for a failure mode, and it models between-group variation. The model assumes that each group has its own probability of failure, p, drawn from this distribution, and that the number of failures from the group has a binomial distribution governed by the group's p. The likelihood function for the data is based on the observed number of failures and successes in each group and the assumed beta-binomial model. This function of a and b was maximized through an iterative search of the parameter space, using a SAS routine.[A-2] In order to avoid fitting a degenerate, spike-like distribution whose variance is less than the variance of the observed failure counts, the parameter space in this search was restricted to cases where the sum, a plus b, was less than the total number of observed demands. The a and b corresponding to the maximum likelihood were taken as estimates of the generic beta distribution parameters representing the observed data for the failure mode.

The empirical Bayes method uses the empirically estimated distribution for generic results, but it also can yield group-specific results. For this, the generic empirical distribution is used as a prior, which is updated by group-specific data to produce a group-specific posterior distribution. In this process, the generic distribution itself applies for modes and groups, if any, for which no demands occurred (such as plants with no unplanned demands).

A chi-square test was one method used to determine if there were significant differences between the groups. Because of concerns about the appropriateness and power of the chi-square test, discomfort at drawing a fixed line between significant and nonsignificant, and an engineering belief that there were real differences between the groups, an attempt was made for each failure mode to estimate an empirical Bayes prior distribution over years and over plants. The fitting of a nondegenerate empirical Bayes distribution was used as the index of whether between-group variability could be estimated. The simple Bayes method was used only if no empirical Bayes distribution could be fitted, or if the empirical Bayes distribution was nearly degenerate, with smaller dispersion than the simple Bayes posterior distribution. Sometimes, an empirical Bayes distribution could be fitted even though the chi-square test did not find a between-group variation that was even close to statistically significant. In such a case, the empirical Bayes method was used, but the numerical results were almost the same as from the simple Bayes method.

When more than one empirical Bayes prior distribution was fitted for a failure mode, such as a distribution describing variation across plants and another one describing variation across years, the general principle was to select the distribution with the largest variability (highest 95th percentile). Exceptions to this rule were based on engineering judgment regarding the most logical and important sources of variation, or the needs of the application.

Alternate Method for Some Group-Specific Investigations. Occasionally, the unreliability was modeled by group (such as by plant or by year) to see if trends existed, such as trends due to time or age. The above methods tend to mask any such trend. The simple Bayes method pools all the data, and thus yields a single generic posterior distribution. The empirical Bayes method typically does not apply to all of the failure modes, and so masks part of the variation. Even when no differences can be seen between groups for any failure mode, so that the above methods would pool the data for each failure mode, the failures of various modes could all be occurring in a few years or at a few plants. They could thus have a cumulative effect and show a clearly larger unreliability for those few years or plants. Therefore, it is useful to calculate the unreliability for each group (each year or plant) in a way that is very sensitive to the data from that one group.

It is natural, therefore, to update a prior distribution using only the data from the one group. The Jeffreys noninformative prior is suitably diffuse to allow the data to drive the posterior distribution toward any probability range between 0 and 1, if sufficient data exist. However, when the full data set is split into many groups, the groups often have sparse data and few demands. Any Bayesian update method pulls the posterior distribution toward the mean of the prior distribution. More specifically, with beta distributions and binomial data, the estimated posterior mean is (a + f)/(a + b + d). The Jeffreys prior, with a = b = 0.5, thus pulls every failure probability toward 0.5. When the data are sparse, the pull toward 0.5 can be strong, and can result in every group having a larger estimated unreliability than the population as a whole. In the worst case of a group and failure mode having no demands, the posterior distribution mean is the same as that of the prior, 0.5, even though the overall industry experience may show that the probability for the particular failure mode is, for example, less than 0.1. Since industry experience is relevant for the performance of a particular group, a more practical prior distribution choice is a diffuse prior whose mean equals the estimated industry mean. Keeping the prior diffuse, and therefore somewhat noninformative, allows the data to strongly affect the posterior distribution; and using the industry mean avoids the bias introduced by the Jeffreys prior distribution when the data are sparse.

To do this, the "constrained noninformative prior" was used, a generalization of the Jeffreys prior defined in Reference A-4 and summarized here. The Jeffreys prior is defined by transforming the binomial data model so that the parameter p is transformed, approximately, to a location parameter,. *r*. The uniform distribution for *r* is noninformative. The corresponding distribution for p is the Jeffreys noninformative prior. This is generalized using the maximum entropy distribution[A-5] for *r*, constrained so that the corresponding mean of p is the industry mean from the pooled data, (f + 0.5)/(d + 1). The maximum entropy distribution for *r* is, in a precise sense, as flat as possible subject to the constraint. Therefore, it is quite diffuse. The corresponding distribution for p is found. It does not have a convenient form, so the beta distribution for p having the same mean and variance is found. This beta distribution is referred to here as the constrained noninformative prior. It corresponds to an assumed mean for p but to no other prior information. For various assumed means of p, the noninformative prior beta distributions are tabulated in Reference A-4.

For each failure mode of interest, every group-specific failure probability was found by a Bayesian update of the constrained noninformative prior with the group-specific data. The resulting posterior distributions were pulled toward the industry mean instead of toward 0.5, but they were sensitive to the group-specific data because the prior distribution was so diffuse.

Additional Refinements in the Application of Group-Specific Bayesian Methods. For both the empirical Bayes distribution and the constrained noninformative prior distribution, beta distribution parameters are estimated from the data. A minor adjustment[A-6] was made in the posterior beta distribution parameters for particular plants and years to account for the fact that the prior parameters a and b are only estimated, not known. This adjustment increases the group-specific posterior variances somewhat.

Both group-specific failure probability distribution methods use a model, namely, that the failure probability p varies between groups according to a beta distribution. In a second refinement, lack of fit to this model was investigated. Data from the most extreme groups (plants or years) were examined to see if the observed failure counts were consistent with the assumed model, or if they were so far in the tail of the beta-binomial distribution that the assumed model was hard to believe. Two probabilities were computed, the probability that, given the resulting beta posterior distribution and binomial sampling, as many or more than the observed number of failures for the group would be observed, and the probability that as many or fewer failures would be observed. If either of these probabilities was low, the results were flagged for further evaluation of whether the model adequately fitted the data. This test was most important with the empirical Bayes method, since the empirical Bayes prior distribution might not be diffuse. No strong evidence against the model was seen in this study. See Atwood[A-2] for more details about this test.

Group-specific updates were not used with the simple Bayes approach because this method is based on the hypothesis that significant differences in the groups do not exist.

A-2.2 The Combination of Failure Modes

The results for each failure mode must be combined to obtain the unreliability. For the primary results, stated in the body of this report, the logic depicted in a simple fault tree was used to quantify the failure probability. For the IC system, the fault tree considered two failure modes, FTO and FMU, and their associated recoveries (FRFTO and FRFMU).

For the plant and calendar-year specific investigations reported in Appendix C, the following algebraic approximation, presented in more generality by Martz and Waller in Reference A-7, was used. According to the logic model, the unreliability is given by

Unreliability = Prob{(FTO and FRFTO) or (FMU and FRFMU)}.

This can be rewritten by repeatedly using the fact that

Prob(A or B) = 1 - Prob(not A)*Prob(not B) = 1 - [1 - Prob(A)]*[1 - Prob(B)]

where A and B are any independent events. The resulting algebraic expression is linear in each of the four failure probabilities.

The estimated mean and variance of the unreliability are obtained by propagating the means and variances of the four failure probabilities. These means and variances are readily available from the beta distributions. Propagation of the means uses the fact that the mean of a product is the product of the means, for independent random variables. Propagation of variances of independent factors is also readily accomplished, based on the fact that the variance of a random variable is the expected value of its square minus the square of its mean. In practice, estimates are obtained by the following process:

- Compute the mean and variance of each beta distribution.
- Compute the mean and variance of the unreliability for each case using simple equations for expected values of sums for "or" operations and of products for "and" operations.
- Compute parameters for the beta distribution with the same mean and variance.
- Report the mean of the unreliability and the 5th and 95th percentiles of the fitted beta distribution.

The calculated means and variances are exact. The 5th and 95th percentiles are only approximate, however, because they assume that the final distribution is a beta distribution. Monte Carlo simulation for the percentiles is more accurate than this method if enough Monte Carlo runs are performed. This is due to the output uncertainty distribution is empirical and not required to be a beta distribution. Nevertheless, the approximation seems to be close in cases where comparisons were made. Therefore, the beta approximation was used when many unreliabilities needed to be calculated and compared. In particular, the method was used for the unreliabilities by plant and by year in Appendix C.

A-3. ESTIMATION OF FREQUENCY DISTRIBUTIONS FOR TREND ANALYSIS

In addition to the analyses used to estimate system unreliability, the overall frequencies of inoperabilities, failures, and unplanned demands were analyzed by plant and by year to identify possible trends and patterns. Two specific analyses were performed for these three occurrence frequencies. First, the frequencies were compared to determine whether significant differences exist among the plants or among the calendar years. Frequencies and confidence bounds were computed for each type for each year and plant unit. The hypotheses of simple Poisson distributions for the occurrences with no differences across the year and plant groupings were tested, using the Pearson chi-square test. The computed P-values are approximate since the expected cell counts were often small; however, they are useful for screening.

Regardless of whether particular years or plants were identified as having different occurrence frequencies, the occurrence frequencies were also modeled by plant and by year to see if trends exists. For plants, trends with regard to plant age are assessed, as measured from the plant low power license date. For years, calendar trends are assessed. Least-squares regression analyses are used to assess the trends. The paragraphs below describe certain analysis details associated with the frequency trend analyses.

With sparse data, estimated event frequencies (event counts divided by time) are often zero, and regression trend lines through such data often produce negative frequency estimates for certain groups (years or ages). Since occurrence frequencies cannot be negative, log models are considered. Thus, the analysis determines whether log (frequency) is linear with regard to calendar time or age. An adjustment is needed in order to include frequencies that are zero in this model.

Using $0.5/t$ as a frequency estimate in such cases is not ideal. Such a method penalizes groups that have no failures, increasing only their estimated frequency. Furthermore, industry performance may show that certain events are very rare, so that $0.5/t$ is an unrealistically high estimate for a frequency. A method that adjusts the frequencies uniformly for all the grouping levels (plants or years) and that uses the overall frequency information contained in the industry mean is needed for sparse data and rare events.

Constrained noninformative priors similar to those constructed for probabilities (see Section A-2.1.4) can be formed for frequencies. This method meets the requirements identified above. Because it also produces occurrence frequencies for each group (each year or plant) in a way that is very sensitive to the data from that one group, it preserves trends that are present in the unadjusted frequency data. The method, described in References A-4 and A-8, involves updating a prior distribution using only the data from a single group. For frequencies, such distributions are gamma distributions rather than beta distributions. Since industry experience is relevant for the performance of a particular group, a practical prior distribution choice is a diffuse prior whose mean equals the estimated industry mean, $(0.5+N)/T$, where N is the total number of events across the industry and T is the total exposure time. This specification for the prior distribution mean is the constraint. Keeping the prior diffuse, and therefore somewhat noninformative, allows the data to strongly affect the posterior distribution. This goal is achieved by basing the modeling on a maximum entropy distribution. The details are explained in Reference A-4; the resulting prior distribution is a gamma distribution with shape parameter 0.5 and scale parameter $T/(2N+1)$. The mean of the updated posterior distribution is used in the regression trending. This process thus adds 0.5 uniformly to each event count and $T/(2N+1)$ to each group exposure time.

In practice, an additional refinement in the application of the constrained noninformative prior method adjusts the posterior gamma distribution parameters for particular plants and years to account for the fact that the prior distribution gamma scale parameters are only estimated, not known. This adjustment, explained in Reference A-6, increases the group-specific posterior variances somewhat.

A-4. REFERENCES

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Appendix B

Isolation Condenser System Operational Data, 1987-1993

Appendix B

Isolation Condenser System
Operational Data, 1987-1993

In the subsections below, listings of the data used for the isolation condenser (IC) system reliability study are provided. First, the plants used are listed. Then their inoperabilities and unplanned demands are described.

B-1. PLANTS USED

Each of the data listings is restricted to the period from 1987 to 1993 and to the set of plants listed in Table B-1 below. Table B-1 includes all the boiling water reactors (BWRs) with an IC system.

The operating years for each plant during the study period are shown in Table B-1. Operating years were estimated from information in the OUTINFO database. This database is developed from monthly operating reports submitted to the NRC by the licensees. The database provides starting and ending dates for generator off-line periods. To estimate operating time for this study, the starting and ending days themselves are treated as operational periods. Periods between these dates that are at least 2 calendar days long are treated as outage periods and subtracted from the total number of operational days in a year for a plant.

Table B-1. BWR plants with a dedicated IC system.

Plant name	Docket	Operating years	Trains	Number of ICs	Number of condensers per train	Condenser design	Time before makeup is required
Dresden 2	237	5.09	1	1	1	Dual pass	20 minutes
Dresden 3	249	5.42	1	1	1	Dual pass	20 minutes
Millstone 1	245	5.66	1	1	1	Dual pass	30 minutes
Nine Mile Pt. 1	220	3.67	2	4	2	Single pass	90 minutes
Oyster Creek	219	5.21	2	2	1	Dual pass	45 minutes

B-2. IC INOPERABILITIES

The search for IC inoperabilities resulted in the identification of 43 inoperabilities during the period 1987 through 1993. In 12 of these events, the inoperability was severe enough that the system would not have been able to perform its design function. These are classified as failures. Table B-2 provides a breakdown of the inoperabilities. A breakdown of the counts according to the method of discovery for all inoperabilities is provided. The failures are further classified according to failure mode. The three failures that occurred during unplanned demands were used to estimate unreliability.

Table B-3 defines the column headings used in Table B-4. Table B-4 is a listing of the IC inoperability events. The "Failure" column identifies the inoperabilities that were classified as failures. Only those failures that occurred during an unplanned demand or during the performance of the 5-year surveillance test were used in the unreliability calculations. Each of the three failures found during an actual unplanned demand have a matching record in the IC unplanned demand database. No additional failures were found during the 5-year surveillance tests. Table B-5 provides a description of the failure events that were used to estimate unreliability.

Table B-2. IC inoperability counts.

	Method of discovery				
	Unplanned full demands	5-year surveillance tests	Other surveillance tests	Other[a]	Total
Failures					
Maintenance out of service (MOOS)	0	NA	NA	NA	0
Failure to operate (FTO)	2	0	3	6	11
Failure to provide makeup (FMU)	1	0	0	0	1
Subtotal, Failures	3	0	3	6	12
Inoperabilities[b]	0	0	6	12	18
Grand Total	3	0	9	31	43

a. Plant tours, control room annunciators/indication, design review, etc.
b. Excludes failures.

Table B-3. Column heading abbreviations and definitions used in Table B-4.

Field	Definition
Failure	Failure: T, true—the deficiency was significant enough to prevent the system from providing sufficient cooling capability to the reactor pressure vessel to maintain the core cooled for the length of time needed; F, false—no loss of the safety function as defined here.
Fail. mode	Failure mode: FTO, failure to operate, FMU, failure to provide makeup, NA, no specific category applies.
Disc. Meth.	Method of discovery: O, other, an inoperability is discovered through operator tours, annunciators, other control room indication, and design reviews; S, surveillance test; A, on demand from an actual plant transient.

Table B-4. IC system inoperabilities.

Plant name	LER number	Event date	Failure	Fail. mode	Disc Meth.
Dresden 2	23787005	02/20/87	F	NA	O
Dresden 2	23787024	08/21/87	F	FTO	O
Dresden 2	23788022	11/14/88	F	NA	O
Dresden 2	23789012	03/04/89	T	FTO	A[a]
Dresden 2	23789019	07/12/89	F	FTO	O
Dresden 2	23789021	08/09/89	T	FTO	O
Dresden 2	23790005	07/30/90	T	FTO	O
Dresden 2	23791017	08/25/91	F	FTO	O
Dresden 2	23791023	08/07/91	F	NA	O
Dresden 2	23792006	02/21/92	F	NA	O
Dresden 2	23792025	07/17/92	F	FTO	O
Dresden 2	23793001	12/23/92	F	NA	O
Dresden 3	24987013	08/07/87	T	FTO	A[a]
Dresden 3	24987014	09/05/87	T	FTO	S
Dresden 3	24988003	03/23/88	F	NA	O
Dresden 3	24989001	03/25/89	T	FMU	A[a]
Dresden 3	24989002	03/30/89	F	FTO	O
Dresden 3	24990005	03/10/90	F	FTO	O

Table B-4 continued.

Plant name	LER number	Event date	Failure	Fail. mode	Disc Meth.
Dresden 3	24991008	08/30/91	T	FTO	O
Dresden 3	24992022	10/20/92	F	FTO	O
Dresden 3	24993009	05/12/93	T	FTO	S
Millstone 1	24587022	07/02/87	F	NA	S
Millstone 1	24591008	04/07/91	T	FTO	O
Millstone 1	24591020	07/12/91	F	NA	O
Millstone 1	24592005	02/07/92	F	NA	O
Millstone 1	24592023	09/02/92	F	FTO	S
Nine Mile Point 1	22091010	09/09/91	T	FTO	S
Oyster Creek	21988018	08/28/88	F	FTO	O
Oyster Creek	21988019	08/24/88	F	FTO	O
Oyster Creek	21988019	08/29/88	F	FTO	O
Oyster Creek	21988019	09/02/88	T	FTO	O
Oyster Creek	21988021	09/29/88	F[b]	FTO	O
Oyster Creek	21989010	03/16/89	F[b]	NA	O
Oyster Creek	21989013	05/08/89	T	FTO	O
Oyster Creek	21990005	04/21/90	F	FTO	O
Oyster Creek	21990005	04/21/90	F	NA	O
Oyster Creek	21990015	12/21/90	F	NA	O
Oyster Creek	21991006	10/01/91	F[b]	NA	S
Oyster Creek	21992008	06/08/92	F	NA	O
Oyster Creek	21992011	08/26/92	F	NA	O

a. This event was used in the estimation of unreliability.
b. This event indicated two inoperabilities for the same date and cause.

Table B-5. Summary of IC train failure events used for unreliability calculations.

Plant name	Failure mode	LER number	Event date	Description
Dresden 2	FTO Recovered	23789012	03/04/89	The IC systems was inadvertently isolated when an operator inadvertently caused a spurious isolation signal during a ground detection procedure (not pre-planned maintenance). A few minutes later a reactor scram occurred as a result of a high vessel pressure condition which subsequently demanded the isolation condenser system. However, because the isolation valves were still closed (23 minutes after the isolation) the system could not initiate. Plant operators quickly reset the isolation logic and the system automatically initiated as required.
Dresden 3	FTO Recovered	24987013	08/07/87	A spurious isolation occurred owing to a false high flow signal. The high flow isolation occurred approximately 3 hours after the initial start. The system was being used to cooldown the plant during an unplanned shutdown. The spurious isolation was recognized by plant operators, and the logic reset and the system was returned to normal operation within a few minutes.
Dresden 3	FMU Recovered	24989001	03/25/89	Multiple electrical problems at the plant resulted in a reactor scram and the need to use the isolation condenser to cooldown the plant. However, the electrical problems also resulted in the isolation of the normal makeup to the condenser. Operators recognized the problem and used an alternate source of makeup water during the event before IC system performance was degraded. In addition, when power was restored to the normal makeup isolation valve, the normal makeup supply flow rate through the valve was inadequate for the demand. Investigation following the event by plant personnel determined that the normal makeup was undersized for a plant cooldown.

B-3. IC UNPLANNED DEMANDS

The data search for unplanned demands of the IC system's design function identified 16 LERs in the SCSS data file. Detailed review of each of the LERs showed that there were 35 full train-level demands of the IC system's design function. These events are listed in Table B-6 with the plant name and event date.

Table B-6. IC unplanned demand events.

Plant	LER number[a]	Event date	Plant	LER number[a]	Event date
Dresden 2	23787032	10/20/87	Oyster Creek	21987011^{2}	02/14/87
Dresden 2	23789012	03/04/89	Oyster Creek	21989015^{2}	05/18/89
Dresden 2	23790001	01/05/90	Oyster Creek	21989016^{2}	06/25/89
Dresden 2	23790002^{5}	01/16/90	Oyster Creek	21979021^{2}	09/22/89
			Oyster Creek	21991005^{2}	08/22/91
Dresden 3	24987013^{2}	08/07/87	Oyster Creek	21992005^{6}	05/03/92
Dresden 3	24989001^{3}	03/25/89	Oyster Creek	21992009^{2}	08/22/92
Dresden 3	24990005	03/10/90			
Millstone 1	24587007	03/22/87			
Millstone 1	24591008^{2}	04/07/91			

a. The superscript number following the LER number is the number of unplanned demands identified in the LER (when the number of demands was greater than one).

Appendix C

Failure Probabilities and Unreliability Trends

Appendix C
Failure Probabilities and Unreliability Trends

This appendix displays the relevant isolation condenser (IC) event counts and the estimated probability for each failure mode, including distributions that characterize any variation observed between portions of the data. It then evaluates whether trends exist in the IC system data. Three types of detailed analyses are given: (1) a plant-specific analysis of probabilities for individual failure modes; (2) an investigation of the possible relation between plant low-power license date and IC performance as measured by unreliability, by the rate of unplanned operational experiences (i.e., demands) and by the rate of failures and inoperabilities; and (3) an investigation of whether overall performance as measured by these attributes changed during the seven years of the study.

C-1. FAILURE PROBABILITIES

In the two subsections below, generic and then plant-specific results are given for the four failure modes modeled in this study. The modes are failure to operate (FTO), failure to recover from failure to operate (FRFTO), failure to provide makeup (FMU), and failure to recover from failure to provide makeup (FRFMU).

C-1.1 Analysis of Individual Failure Modes

Table C-1 contains results from the initial assessment of data for the four IC failure modes, including point estimates and confidence bounds for the probability of failure for each mode. Note that the point estimate and bounds do not consider any special sources of variation (e.g., year or plant). These results are plotted in Figure C-1.

Table C-2 summarizes the results from testing the hypothesis of constant probabilities across groupings for each failure mode based on data source, calendar years, and plants.

Statistical evidence of differences (chi-square tests) across these groupings was not found. The data were either too sparse to detect differences, or there were no significant differences in the occurrence probabilities.

More specific descriptions of the particular data used to estimate unreliability for each failure mode and the rationale for choosing that data are discussed in subsections below. The type of modeling selected to calculate the distributions that characterize sampling and/or between-group variation is discussed. The resulting distributions, summarized in Section C-1.1.2 (Table C-3), were used to compute uncertainty bounds for the overall unreliability estimates of the IC train.

Table C-1. Point estimates and confidence bounds for IC failure modes.

Failure mode	Demand source	Failures	Demands	Probability[a]
Failure to operate (FTO)	Unplanned	2	35	(0.010, 0.057, 0.169)
	5-year test	0	3	(0.000, 0.000, 0.632)
	Pooled	2	38	(0.009, 0.053, 0.157)
Failure to recover from FTO (FRFTO)	Unplanned	0	2	(0.000, 0.000, 0.776)
Failure to provide makeup (FMU)	Unplanned	1	34	(0.002, 0.029, 0.132)
	5-year test	0	3	(0.000, 0.000, 0.632)
	Pooled	1	37	(0.001, 0.027, 0.122)
Failure to recover from FMU (FRFMU)	Unplanned	0	1	(0.000, 0.000, 0.950)

a. The middle number is the point estimate (# of failures divided by # of demands). The two end numbers form a 90% confidence interval.

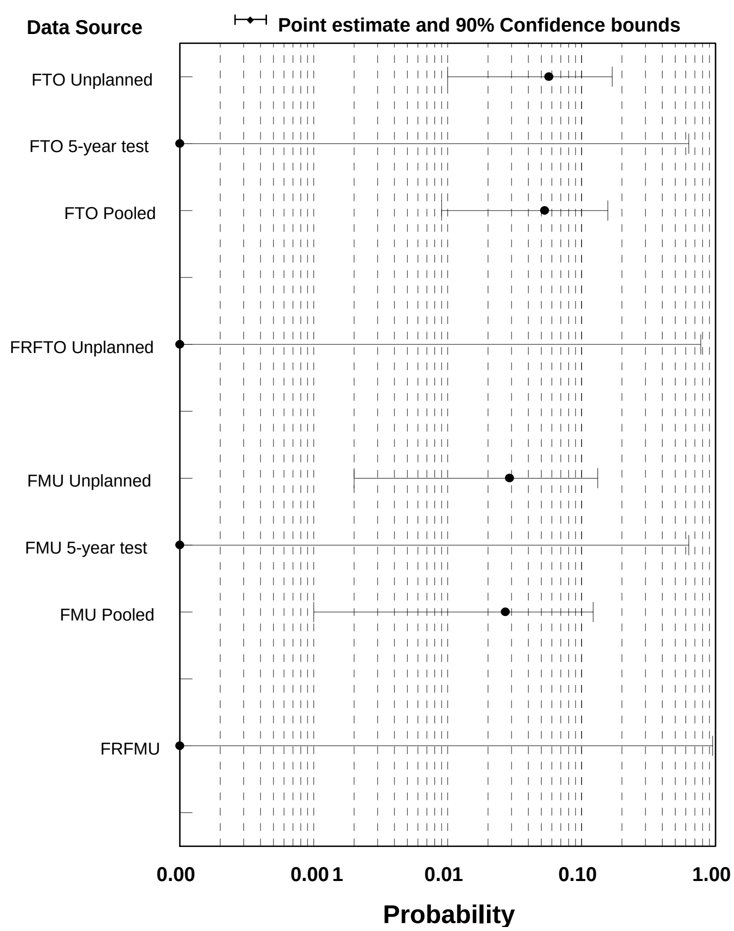

Figure C-1. Point estimates and 90% confidence bounds for the IC train failure modes.

Table C-2. Evaluation of differences between groups for IC failure modes.

Failure mode	Demand source	P-values for test of variation[a]: Between demand sources	Between years	Between plants	Entities with relatively high chi-square statistics[b]
Failure to operate (FTO)	Unplanned	—	NS	NS	—
	5-year test	—	0F	0F	—
	Pooled	NS	NS	NS	None
Failure to recover from FTO (FRFTO)	Unplanned	—	0F	0F	—
Failure to provide makeup (FMU)	Unplanned	—	1F	1F	None
	5-year test	—	0F	0F	—
	Pooled	1F	1F	1F	None
Failure to recover from FMU (FRFMU)	Unplanned	—	0F	0F	—

a. NS, not significant (P-value >0.05); 0F, no failures (thus, no test); 1F, only one failure (thus, no test).
b. Years and plants with an unusual failure rate (compared to others in the group) would be flagged. Unusual means statistically significant at the 10% level.

C-1.1.1 IC Failure Modes

Failure to Operate. There were two failures to operate (FTO) in 35 unplanned demands. One of the failures occurred at the start of the demand, while the other occurred after over three hours of running. Both events, however, involved valve closure and inadvertent isolation of the IC system. No FTO failures occurred in the three 5-year test demands. The difference between the FTO probabilities of these two data sets was not significant; therefore, the two data sources were pooled and used in the analysis. No significant differences were found between years or plants in this pooled FTO data set. Therefore, a simple Bayes beta distribution for FTO was estimated from the pooled data.

Failure to Recover from Failure to Operate. Both failures to operate were recovered, i.e., there were no failures to recover from failure to operate. Therefore, a simple Bayes beta distribution was estimated for this recovery.

Failure to Provide Makeup. One failure to provide makeup (FMU) occurred among the 34 unplanned demands. The makeup demands were of sufficient duration to require makeup of the cooling water in the IC train condenser. No failures occurred in the three 5-year tests. The failure probabilities from these two sources of demands were not significantly different. Therefore, the two data sources were pooled and used in the analysis. No significant differences were found between years or plants in this pooled FMU data set, and a simple Bayes beta distribution for FMU was estimated from the pooled data.

Failure to Recover from Failure to Provide Makeup. Since the makeup isolation valve closure that caused failure of makeup was recovered, no failures to recover from failure to provide makeup were found in the operational data. Therefore, a simple Bayes beta distribution was used to model this recovery, as with the other failure modes.

C-1.1.2 Summary of Beta Distributions for Individual Failure Modes

Table 3 in the body of the report describes the beta distributions selected to model the statistical variability observed in the data used to model IC unreliability. The results are plotted in Figure C-2. For all failure modes, a simple Bayes beta distribution was used as the model. The Table 3 results differ slightly from Table C-1 (and Figure C-1) because Table C-1 gives traditional confidence intervals rather than Bayes distributions and intervals. This choice allows the results for the failure modes to be combined to give an uncertainty distribution on the unreliability.

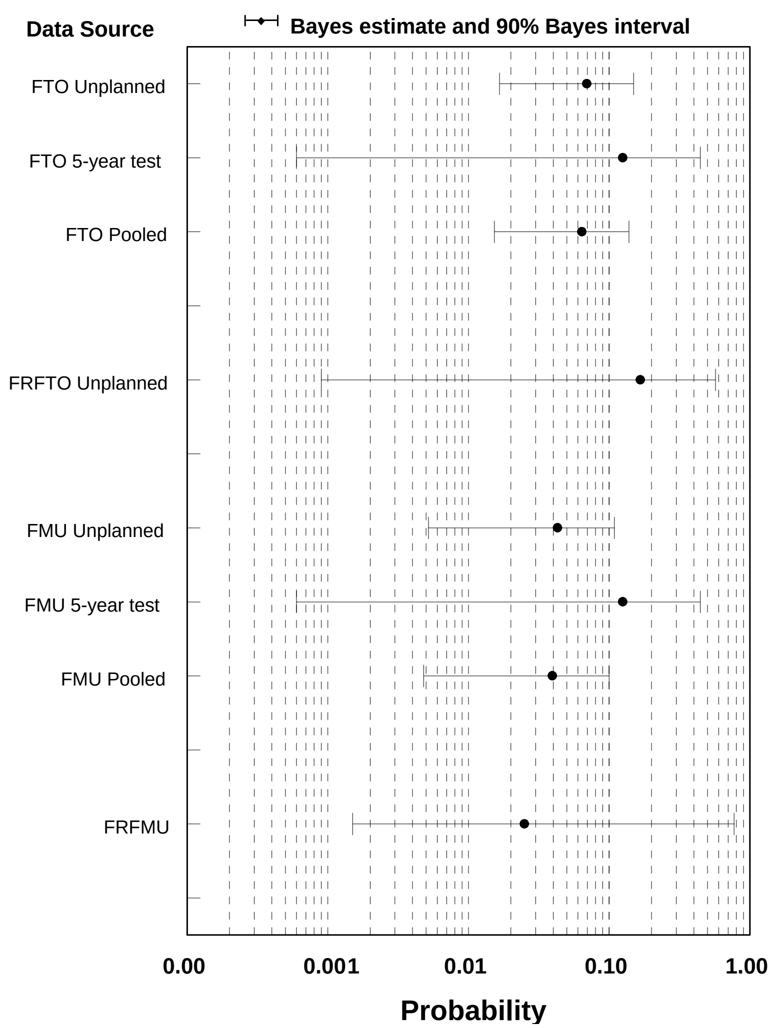

Figure C-2. Summary of Bayes estimates and 90% uncertainty intervals for the IC train failure modes.

C-1.2. Plant-Specific Failure Probabilities

This section exists to provide plant-specific basic event failure probabilities for the failure modes where such variation could be modeled. However, for all IC failure modes and data groupings considered in this study, the data were too sparse to estimate nondegenerate empirical Bayes distributions. Therefore, the data were pooled across plants and years to form generic simple Bayes distributions for each failure mode. Note also that Nine Mile Point 1 provided no plant-specific data for the IC unreliability analysis. This is due to no unplanned operational experiences reported during the study period for Nine Mile Point 1. Further, the reporting of single train failures during the 5-year surveillance test is not required for plants with dual trains.

C-2. INVESTIGATION OF RELATION TO PLANT LOW-POWER LICENSE DATES

The data were analyzed to determine if statistical differences exist between the plants with regard to IC train unreliability and with regard to IC frequencies for unplanned demands, failures, and inoperabilities. The data were also analyzed to see if IC performance was significantly changing as a function of plant age (as measured by a plant's low-power license date).

C-2.1 IC Unreliability

Table C-3 shows the IC unreliability by plant, along with the plant low-power license date. The estimates were obtained by pooling the industry data for a failure mode, thus forming a constrained noninformative prior as described in Section A-2.1.4 for each failure mode. For each plant having data, the constrained noninformative prior for each failure mode was updated with plant-specific failures and demands from the study period to obtain plant-specific posterior distributions. The failures used to estimate the unreliability were those for which failure opportunities (demands) could be counted. The resulting updated distributions were combined for each plant as described in Section A-2.2 to yield plant-specific unreliabilities that were very sensitive to the plant data.

Linear regression (least squares fitting) was used to see if there was a trend, here and in the work described in the next section. A plot of plant-specific unreliability against low-power license date is shown in Figure 5 of the body of this report, with 90% uncertainty bars plotted vertically. The 90% intervals were not used in the trend calculations, but are shown as a matter of interest. A straight line was fitted to the unreliability (shown as dots in the plot), and a straight line was also fitted to the log (unreliability). The fit selected was the one that accounted for more of the variation, as measured by R^2, provided that it also produced a plot with regression confidence limits greater than zero. The regression-based confidence band shown as dashed lines on the plots applies to every point of the fitted line simultaneously; it is the band due to Working, Hotelling, and Scheffé, described in statistics books that treat linear regression.

The slope of the trend line was not statistically significant for the IC unreliabilities with regard to plant age.

Table C-3. Unreliability by plant, based on constrained noninformative distributions.

Plant	Low-power license date	90% interval[a]
Dresden 2	12/22/69	(3.86E-06, 0.016, 0.070)
Dresden 3	01/12/71	(1.62E-05, 0.023, 0.097)
Millstone 1	10/26/70	(3.40E-07, 0.014, 0.065)
Nine Mile Point 1	12/26/74	(1.09E-06, 0.020, 0.096)
Oyster Creek	08/01/69	(2.60E-07, 0.006, 0.030)

a. The middle number is the Bayes mean, and the end numbers form a 90% interval. The calculations use a diffuse prior, updated by plant-specific data, for each failure mode. Therefore, the intervals are wide and the means vary greatly between plants.

C-2.2 Unplanned Demand, Failure, and Inoperability Frequencies

For the frequency analyses, plant-specific event counts for the study period were normalized by the number of operating years during the study period. Unplanned demand frequencies were normalized first by plant operating years, then by train operating years, each summed across the seven years in the study period. Failures and inoperabilities were normalized just by train operating years since the opportunity for such events to occur increases with the number of trains. Plant operating years were multiplied by two to obtain train operating years for Oyster Creek and Nine Mile Point 1. The resulting frequencies were trended against plant low-power license date using basically the same linear regression method as for the unreliabilities.

An additional detail of the methodology for frequencies deserves mention. The log model cannot be used directly when a frequency is zero. Rather than simply use an (arbitrary) fraction of a failure or demand divided by exposure time to estimate a nonzero frequency for these cases, all the data for a particular frequency were adjusted uniformly. The constrained noninformative prior distribution described in Section A-3 was updated with plant-specific data, and the resulting plant-specific mean was used for the frequency. It was strictly positive; therefore, its logarithm was defined. For the IC frequencies, this adjustment effectively added approximately 0.5 to each failure count and, depending on the frequency under consideration, from 0.4 to 1.4 years to each exposure time. (As explained in Section A-3, the exposure time increment is relatively large when industry event counts for a frequency are few.) This process results also in the calculation of 90% Bayesian uncertainty bounds for each frequency; these bounds are shown in the plots as a matter of interest.

The normalized frequency analysis showed a nearly significant difference among plants for the frequency of unplanned demands per plant operating year. The number of plant IC system operational experiences varied from zero at Nine Mile Point 1 to nine at Oyster Creek. The P-value for this test was 0.0558. The logarithms of these frequencies formed a significantly decreasing trend with plant age (the regression slope P-value was 0.0232).

The unplanned demand frequency per train year was even more significant. The P-value for differences in the train unplanned demand frequency was 0.0041. Unplanned demand counts at the train level varied from zero to 19. The decreasing frequency trend was also more significant, with a P-value of 0.0092 for trends in the logarithms of the unplanned train demand frequencies. The newer plants experienced fewer unplanned demands.

No significant differences between plants nor trends with plant age were found for the normalized failure frequencies. For the inoperability frequencies, however, between plant differences were significant (P-value = 0.0070). Nine Mile Point 1 had just one inoperability, while Oyster Creek had 16. A nearly significant decreasing trend (P-value = 0.0560) was identified for the inoperability frequency.

C-3. ANALYSIS BY YEAR, 1987-1993

The analyses of Section C-2 were modified to see if there was a time trend during the period of the study, i.e., a trend in calendar time instead of plant age. As in Section C-2, the analyses apply to unreliability and to four frequencies: unplanned demand events per plant operating year; unplanned train demands per train operating year, failures per train operating year, and overall inoperabilities per train operating year.

Table C-4 tabulates the unreliability by calendar year. The estimates were obtained in the same manner as in Section C-2, except that the data used to update the constrained noninformative prior for each failure mode were pooled across plants for each calendar year instead of across calendar year for each plant. Similarly, the linear model method to test for a trend was the same as described in Section C-2, except that the time variable was calendar year instead of low-power license date.

The logarithmic fit was selected in preference to the linear model for the IC unreliabilities, but the slope of the trend was not statistically significant in either case. A plot of the unreliability by calendar year is provided in Figure 4 of the main report.

Frequencies for each calendar year were also analyzed by pooling the data from all the plants during each calendar year. The adjustment described in Sections C-2 and A-3 was used to account for zero frequencies, and logarithmic models were selected to ensure positive trend lines.

The results of the unplanned demand and failure frequency analyses showed no significant calendar year trends for the IC system frequencies (Figures 10 and 11 of the main body of the report illustrate the unplanned demand and failure frequencies).

Table C-4. Unreliability by year including recovery, based on diffuse prior distributions and annual data.

Year	90% interval[a]
1987	(3.14E-06, 0.019, 0.085)
1988	(1.09E-06, 0.020, 0.096)
1989	(1.78E-05, 0.019, 0.077)
1990	(3.51E-07, 0.010, 0.049)
1991	(3.52E-07, 0.013, 0.060)
1992	(3.51E-07, 0.010, 0.049)
1993	(1.09E-06, 0.020, 0.096)

a. The middle number is the Bayes mean, and the end numbers form a 90% interval. The calculations use a diffuse prior, updated by year-specific data, for each failure mode.