

ASSESSMENT OF DYNAMIC PRA TECHNIQUES WITH INDUSTRY AVERAGE COMPONENT PERFORMANCE DATA

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ASSESSMENT OF DYNAMIC PRA TECHNIQUES WITH INDUSTRY-AVERAGE COMPONENT PERFORMANCE DATA

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ABSTRACT

In the nuclear industry, risk monitors are intended to provide a point-in-time estimate of the system risk given the current plant configuration. Current risk monitors are limited in that they do not properly take into account the deteriorating states of plant equipment, which are unit-specific. Current approaches to computing risk monitors use probabilistic risk assessment (PRA) techniques, but the assessment is typically a snapshot in time. Living PRA models attempt to address limitations of traditional PRA models in a limited sense by including temporary changes in plant and system configurations. However, information on plant component condition is not considered. This often leaves risk monitors using living PRA models incapable of conducting evaluations with dynamic degradation scenarios evolving over time. There is a need to develop enabling approaches to solidify risk monitors to provide time- and condition-dependent risk by integrating traditional PRA models with condition monitoring and prognostic techniques. This paper presents an estimation of system risk evolution over time by integrating plant risk monitoring data with dynamic PRA methods that incorporate aging and degradation. Several online, nondestructive approaches have been developed for diagnosing plant component conditions in the nuclear industry, i.e., using a condition indication index, vibration analysis, current signatures, and operational history [1]. In this work, the component performance measures at U.S. commercial nuclear power plants are incorporated within the dynamic PRA methodologies to provide better estimates of the probability of failures. Aging and degradation are modeled within the Level 1 PRA framework, are applied to several failure modes of pumps, and can be extended to a range of components, namely, valves, generators, batteries, and pipes.

Key Words: dynamic probabilistic risk assessment, component aging and degradation, Markov chain

1 INTRODUCTION

Current static probabilistic risk analysis (PRA) techniques prevalent in the nuclear industry are mainly based on event- and fault-tree analysis [3]. The static PRA techniques formulate system- and plant-level risk scenarios based on basic event probabilities that model a system's or plant's response to component failures or initiating events and compute quantities ranging from probabilities of system failure to core damage frequencies. The event- and fault-tree-based PRA is commonly performed in nuclear industry using PRA tools like Systems Analysis Programs for Hands-on Integrity Reliability Evaluation (SAPHIRE) [4] or the Computer Aided Fault Tree Analysis System (CAFTA) [5]. The current risk assessment is typically a snapshot in time, and the information on plant component condition is often not considered. This limits current PRA models from conducting evaluation of dynamic degradation scenarios.

Markov chains have long been one of the powerful techniques for reliability analysis of critical systems [6]. In the nuclear industry, Markov chains have been used for scenario-based dynamic PRAs [7-9] and for physics-based Markov models for flow-accelerated corrosion in piping [10, 11], but this work presents Markov chains being used in sync with historical component performance data to model the Markov

transitions. One major advantage of using a Markov chain for PRAs associated with component failures is its capability to define repair rates. The current static PRA techniques are limited in not only accounting for component aging and degradation but also component repair and maintenance. This limitation of current PRA techniques can be overcome using a Markov chain. This paper presents a Markov-chain-based method to incorporate dynamic degradation scenarios within the existing PRA formulation. The method is applied to failure of motor-driven pumps (MDPs) that are critical components of the main coolant flow system in every nuclear power plant (NPP).

2 NPP COMPONENT FAILURES

The failure of NPP components such as pumps, valves, and generators span a major segment of the PRA of a system, subsystem, or the entire plant. The several failure modes of NPP components are prescribed in PRA models using basic events that define the probability distribution of a failure event. Figure 1 shows a fault tree modeled in SAPHIRE for the several failure modes of an MDP. The top row defines the top event of complete failure of the MDP. The top event is connected to the following four failure modes of the MDP through OR gates: (1) Fail to Start (FS), (2) Fail to Run (FR), (3) Small Leak (LS) (1 to 50 gallons per minute), and (4) Large Leak (LL) (greater than 50 gallons per minute). The last row defines the probabilities of failure for the respective failure modes.

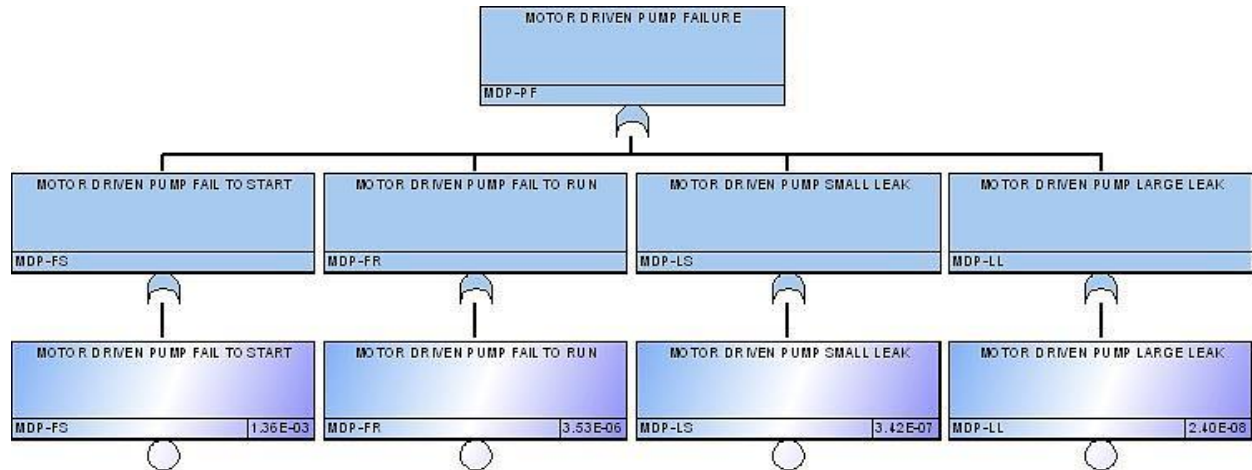


Figure 1. A fault-tree defining failure of an MDP.

Solving the fault tree in Figure 1 for the top event probability would amount to solving for the probability of failure of the MDP, which is connected to the four failure modes through OR gates. The probability of top event MDP-PF is:

$$P_{PF} = P_{FS} + P_{FR} + P_{LS} + P_{LL} \quad (1)$$

where $P_{FS} = 1.36E-03$, $P_{FR} = 3.53E-06$, $P_{LS} = 3.42E-07$, and $P_{LL} = 2.40E-08$ are the mean probability of failure of the respective failure modes. Plugging these values into Eq. (1) gives the probability of MDP failure $P_{PF} = 1.36E-03$.

The failure modes of an MDP and their probability values are obtained from the *Reactor Operational Experience Results and Databases* of the United States Nuclear Regulatory Commission (NRC) [2]. The NRC publishes the industry-average performance for components and initiating events at U.S. commercial NPPs. The probabilities of component failure modes defined by the NRC forms the basis of defining the basic event probabilities in PRA models of NPPs across the nation. The probability of failure for the four basic events for MDPs in Figure 1 is obtained from the 2014 update of the NRC industry-average component performance [2].

3 MARKOV CHAINS

A Markov chain of the MDP discussed in Section 2 with its four failure modes is shown in Figure 2. The four circles at the periphery of the figure define the four failure modes of MDP as FS (Fail to Start), FR (Fail to Run), LS (Small Leak), and LL (Large Leak). The circle labeled ‘H’ in the center indicates state corresponding to a healthy MDP. The arrows from H to each failure mode indicate the transition of a healthy MDP to the respective failed state. The transition rate indicated by Φ_i for each of the i th failed state is given by Φ_i , $i = FS, FR, LS, LL$. The transition rate Φ_{LS-LL} indicates the probability that a small leak will evolve into a large leak. The arrows from the failure modes toward the healthy state indicate the repair for each failure mode that brings a failed MDP back to the healthy state. The repair rates for each state are indicated by ω_i for each of the i th failed state.

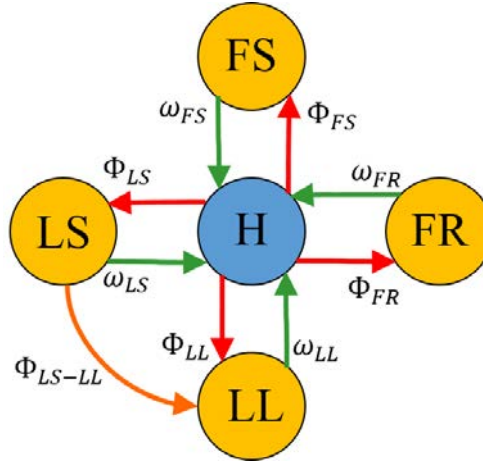


Figure 2. Markov chain for an MDP.

The four failure states and the one healthy state of the MDP result in a five-state Markov chain. The transition rates and repair rates populate the 5x5 transition matrix

$$\mathbf{M} = \begin{bmatrix} P(H|H) & \Phi_{FS} & \Phi_{FR} & \Phi_{LS} & \Phi_{LL} \\ \omega_{FS} & P(FS|FS) & 0 & 0 & 0 \\ \omega_{FR} & 0 & P(FR|FR) & 0 & 0 \\ \omega_{LS} & 0 & 0 & P(LS|LS) & \Phi_{LS-LL} \\ \omega_{LL} & 0 & 0 & 0 & P(LL|LL) \end{bmatrix} \quad (2)$$

for the five-state Markov chain. The transition rates and repair rates populate the respective matrix element, indicating the probability of transitioning from one state to another. The diagonal elements indicate the probability of staying in the same state and are given by: $P(H|H) = 1 - (\Phi_{FS} + \Phi_{FR} + \Phi_{LS} + \Phi_{LL})$; $P(FS|FS) = 1 - \omega_{FS}$; $P(FR|FR) = 1 - \omega_{FR}$; $P(LS|LS) = 1 - (\omega_{LS} + \Phi_{LS-LL})$; $P(LL|LL) = 1 - \omega_{LL}$. Similar to fault-tree analysis in Section 2, the objective of solving the Markov chain in Eq. (2) is to determine the probability of failure of the MDP.

Let $A_{n \times n}$ be the transition matrix of an n -state Markov chain populated by transition rates a_{ij} . The transition matrix after ‘ t ’ time steps is simply A^t . For the MDP Markov chain in Figure 2, the transition rates Φ_i indicate the probability of the failure mode within a time step (hence the term ‘rate’). Consider the time step to be 1 year, and then the transition matrix after ‘ t ’ years is simply the M^t that will be populated by the probabilities of failure of the four MDP failure modes. The $P_t(H|H)$ of matrix M^t will be the probability of a healthy state of MDP after ‘ t ’ years, and the probability of MDP failure will be $P_f(t) = 1 - P_t(H|H)$. Figure 3 shows the probability of failure of the four MDP failure modes along with the probability of MDP failure evolving over each time step from Year 1 to Year 20 using the Markov chain. For simplicity, the repair rates

are assumed to be 0 in order to merely illustrate the evolution of probabilities. The curves of MDP failure and the FS failure mode almost overlap, because FS has a significantly higher magnitude of the probability and is therefore the dominant contributor to the overall MDP failure.

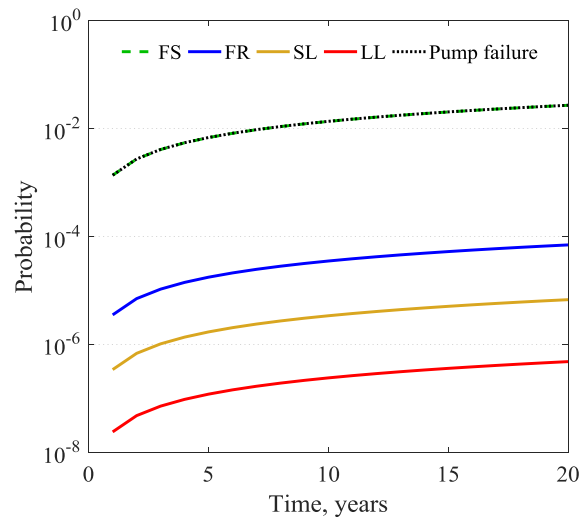


Figure 3. Probabilities of the four failure modes and probability of failure of MDP evolving from Year 1 to Year 20 using a Markov chain.

4 COMPONENT AGING AND REPAIR

The implementation of the Markov chain demonstrated in Section 3 was based on the fixed values of transition rates for every time step. In other words, the probabilities of the four MDP failure modes were fixed at the 2014 values obtained from the NRC industry average of component failure [2]. However, in reality, the failure rates must evolve with time, changing the transition rate values in the transition matrix for each time step. Figure 4 shows the trends from Fiscal Year 1998 through 2014 of the four MDP failure modes obtained from the component performance report for MDP published by Idaho National Laboratory [12]. The probability of MDP failure for each year is calculated by Eq. (1). The trends in Figure 4 are obtained from data based on the operating experience failure reports and do not take into account aging and degradation of the MDPs.

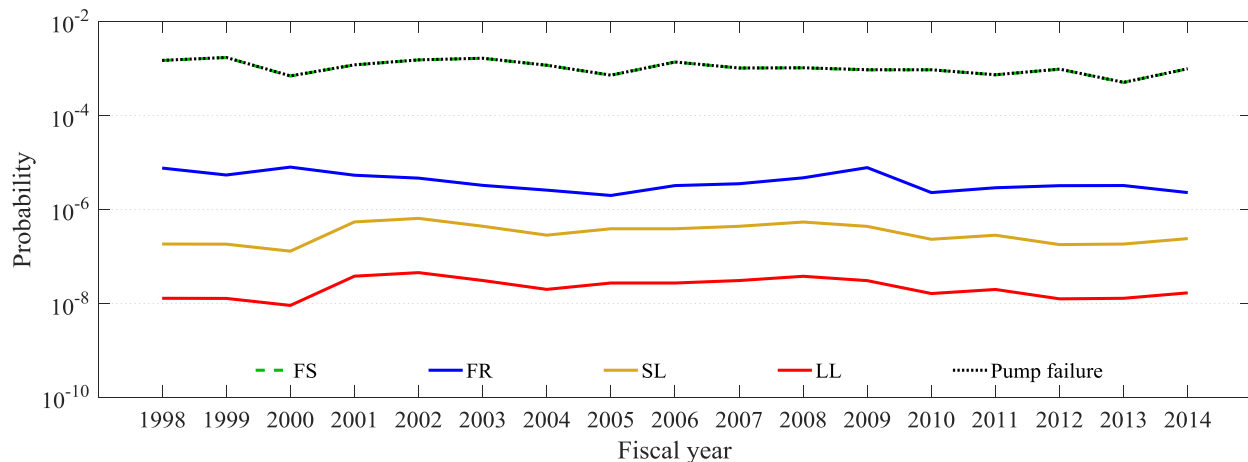


Figure 4. Industry-wide trend for the four MDP failure modes and the calculated probability of MDP failure [12].

To quantify the effect of MDP aging over probability of failure, the NRC Reactor Operating Experience Database (NROD) [13] was investigated. Based on the industry-wide License Event Reports (LERS), event notifications, and equipment reliability data collected by the Institute for Nuclear Power Operations, NROD allows NRC and nuclear industry personnel to search and view the Integrated Data Collection and Coding System and provides a user interface for searching the coded data [13]. Of the four MDP failure modes, FS is the most significant contributor to MDP failure, as seen in Sections 2 and 3. Investigating the causes of MDP-FS in NROD revealed that more than 70% of total MDP-FSs were caused by circuit breaker failure.

As part of a comprehensive study of electrical systems in U.S. NPPs, data analysis was performed for failure event data for components in the AC and DC electrical power systems consisting of circuit breakers, battery chargers, buses, batteries, and transformers. Failure data were obtained from the Reliability and Availability Data System (RADS) [14] reliability calculator found at the NROD [13] website.

To look more deeply for common threads (age, manufacturer, etc.) within the failures, data were queried directly from the Structured Query Language database that supports reliability rules. Figure 5 shows the NRC industry-wide trend obtained for MDP-FS for the 17-year period of Fiscal Years 1998 to 2014, compared with the observed industry-wide probability of failure of circuit breakers from 0 to 40 years. It is clear from the increase in the probability of the failure of breakers with time that the age of the breaker has significant impact on its probability of failure. Replacing the NRC industry-average trend for MDP-FS with the breaker failure evolving with age in the Markov chain provides a more accurate estimate of the probability of MDP failure evolving with time.

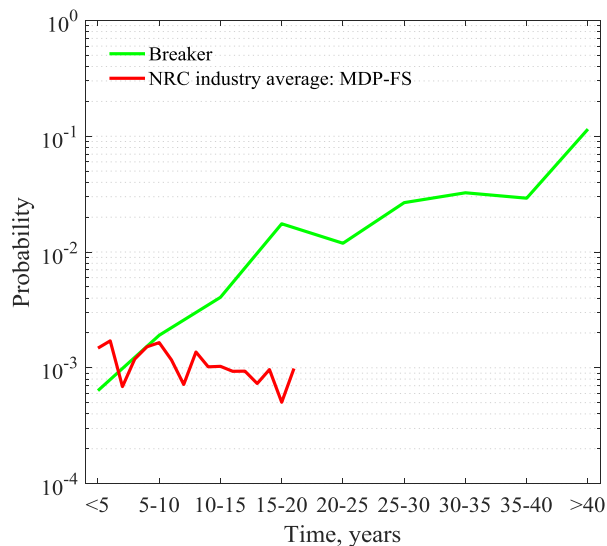


Figure 5. NRC industry-average trend for MDP-FS for 17 years from Fiscal Years 1998 to 2014, and the probability of failure with the aging effect observed for circuit breakers over 40 years of age across U.S. NPPs.

Figure 6 compares the Markov chain implemented in Section 3 along with the breaker failure substituting the MDP-FS failure mode. The transition matrix M in Eq. (2) is populated by Φ_{FS} , Φ_{FR} , Φ_{LS} , and Φ_{LL} being substituted by the respective trend values shown in Figure 4. The repair rates $\omega_{FS} = \omega_{FR} = \omega_{LS} = \omega_{LL} = 1$ indicate probability to restore a failed MDP back to its initial working condition. In addition, the probability of MDP-FS is replaced by the probabilities of failure of a breaker evolving over time, also with the full recovery effect. In Figure 6, while the probabilities from industry-average trends are anticipated as observed in Section 3, the probability of MDP-FS obtained from breaker aging shows a distinct increase over time, in spite of the full-recovery effect. Figure 7 shows the MDP failure probability obtained from three different approaches. The probability of MDP failure obtained from the NRC MDP-FS

with repair is similar to those obtained in Figure 4. The MDP failure obtained with and without incorporating full recovery or repair underlines the significant increase in MDP failure probabilities with aging, while demonstrating the capability of Markov chain to account for repairs.

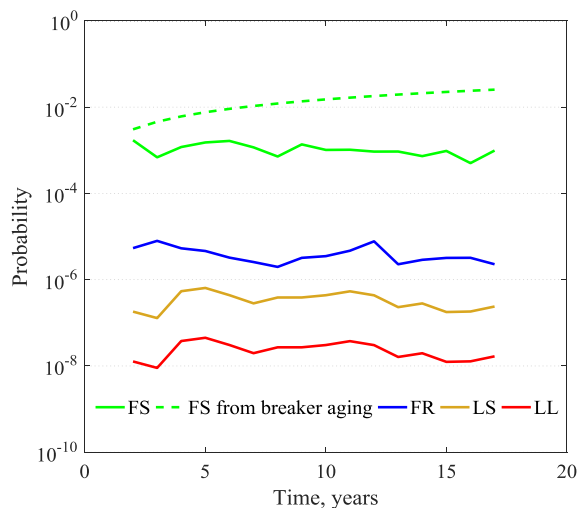


Figure 6. Probabilities of the four failure modes of an MDP evolving from Year 1 to Year 17 using a Markov chain that incorporates the NRC industry-wide trend for the failure modes and the Fail-to-Start probabilities from breaker aging analysis.

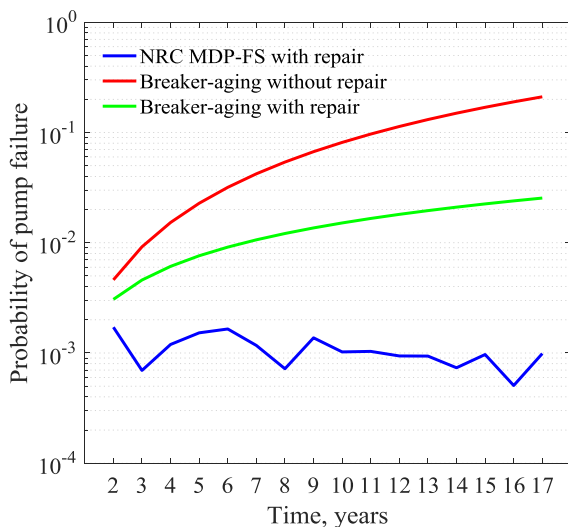


Figure 7. Probability of failure of an MDP obtained from a Markov chain evolving over a 17-year period with the effects of aging and repair.

5 CONCLUSIONS

This paper presents the Markov chains that were applied to model the evolution of the probability of NPP component failure over time. The technique is demonstrated by applying it to four failure modes of MDPs widely used as part of coolant flow systems across NPPs. The probability values of the MDP failure modes are obtained from the NRC's published industry-wide trends for component reliability. Investigating the FS mode of an MDP showed more than 70% of failures occurred due to circuit breaker failures. The aging of circuit breakers is used for modeling the evolution of the FS mode of MDPs. Aging effects and the

full recovery effect are incorporated in the Markov chain to obtain MDP failure probabilities. The results show that aging and repair have a significant impact on the evolution of MDP failure rates with time.

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7 REFERENCES

1. Vivek Agarwal, Nancy J. Lybeck, Binh T. Pham, Richard Rusaw, and Randall Bickford, "Online monitoring of plant assets in the nuclear industry," *In Annual Conference of the PHM Society*, New Orleans, pp. 1-7 (2013).
2. S. A. Eide, T. E. Wierman, C. D. Gentillon, D. M. Rasmuson, and C. L. Atwood, *Industry-Average Performance for Components and Initiating Events at U.S. Commercial Nuclear Power Plants*, NUREG/CR-6928, U.S. Nuclear Regulatory Commission (2007).
3. Enno Ruijters and Mariëlle Stoelinga, "Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools," *Computer Science Review*, **15**, pp. 29-62 (2015).
4. K. J. Kvarfordt et al., "Systems Analysis Programs for Hands-On Integrated Reliability Evaluations (SAPHIRE), Version 8" (2011).
5. "Computer Aided Fault Tree Analysis System (CAFTA)," <http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000003002004316>, (2014).
6. Paul Pukite and Jan Pukite, *Markov Modeling for Reliability Analysis* (1st Edition), Wiley-IEEE Press (1998).
7. Dana L. Kelly and Curtis L. Smith, "Bayesian inference in probabilistic risk assessment—the current state of the art," *Reliability Engineering & System Safety*, **94.2**, pp. 628-643 (2009).
8. J. S. Schroeder and R. W. Youngblood, *Integration of Reliability with Mechanistic Thermalhydraulics: Report on Approach and Test Problem Results*, INL/EXT-11-23600, Idaho National Laboratory (2011).
9. P. Bucci, J. Kirschenbaum, L. A. Mangan, T. Aldemir, C. Smith, and T. Wood, "Construction of event-tree/fault-tree models from a Markov approach to dynamic system reliability," *Reliability Engineering & System Safety*, **93**, pp. 1616-1627 (2008).
10. Karl N. Fleming, Stephen D. Unwin, Dana Kelly, Peter P. Lowry, Mychailo B. Toloczko, Robert F. Layton, Robert Youngblood et al., *Treatment of Passive Component Reliability in Risk-Informed Safety Margin Characterization*, INL/EXT-10-20013, Idaho National Laboratory, pp. 1-210 (2010).
11. A. Guler, J. Hur, R. Denning, T. Aldemir, "Aging Effects on Safety Margins of Passive Components In Seismic Events", Proc. PSAM 13, Paper A-380, International Association for Probabilistic Safety Assessment and Management, California (October 2016).
12. J. A. Schroeder, *Enhanced Component Performance Study: Motor-Driven Pumps*, INL/EXT-16-37937, Idaho National Laboratory (2016).
13. Shawn Walter St. Germain, "NRC Reactor Operating Experience Data," *Proceedings of Probabilistic Safety Assessment and Management* (2014).
14. "Reliability and Availability Data System (RADS)," <https://nrod.inl.gov/> (2017).