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A comparison of DBN model performance in SIPPRA health monitoring based on different data stream discretization methods

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ABSTRACT

The energy and industry sectors depend upon the reliability of complex engineering systems (CESes), such as nuclear power plants or manufacturing plants; it is important, therefore, to monitor system health and make informed decisions on maintenance and risk management practices. One proposed approach is to use causal-based models such as Dynamic Bayesian Networks (DBN), which contain the structural logic of and provide graphical representations of the causal relationships within engineering systems. A current challenge in CES modeling is fully understanding how different data stream discretizations used in developing underlying conditional probability tables (CPTs) impact the DBN's system health estimates.

This paper demonstrates the impact that different time discretization strategies have on the performance of DBN models built for CES health assessments. Using simulated nuclear data of a sodium fast reactor (SFR) experiencing a transient overpower (TOP), different strategies for discretizing CES data streams are used to construct the CPTs for a health-based DBN model. This study finds that these strategies generate different models with varying levels of performance for determining different assessments of overall system health. By understanding how these design factors impact the model's health assessments, future risk models can be developed to provide a more meaningful assessment of a system's health, resulting in more informed decisions.

1. Introduction

Complex engineering systems (CESes), large-scale systems that consist of interconnected and physically distributed hardware, software, and human components, are embedded within many critical infrastructures. Failure of these systems poses significant risks to public health and safety; therefore, it is important to monitor them to avoid total system failure. One approach is to develop health monitoring models that use operational data to generate health assessments that provide necessary information for system health management. A recent modeling method proposed for CES health management is to systematically integrate currently used prognostics and health management (PHM) and probabilistic risk assessment (PRA) techniques into a single approach (SIPPRA) [1]. However, there are still many questions about how to effectively design models, such as dynamic Bayesian networks (DBNs), that are intended for SIPPRA health management.

This paper integrates results from previous research efforts to implement performance metrics to better understand how different data stream discretization strategies affect the performance of health monitoring models. Using the case study scenario outlined by Lewis and Groth [2] as a specific example for a complex engineering system, this study conducted a structured comparison of model alternatives. The results indicate that different model design choices not only affect the health value outputs, but also lead to significant variations in usability. Understanding these differences can inform different design selections under different operational conditions and restrictions. This research is distinct from other efforts to study DBNs and their performance as health monitoring models for complex systems as this work analyzes the fundamental discretization assumptions used to construct the networks. Furthermore, the comparisons are made across a wide range of performance metrics beyond model accuracy, contributing to a more holistic approach to considering model design decisions.

This paper first provides background information on SIPPRA health management and DBNs (Section 2). This is followed by a description of the general approach used to make comparisons on the performance of health monitoring models (Section 3) and the methodology used in the transient overpower (TOP) case study (Section 4). Results of the comparison are then presented (Section 5), followed by a discussion of the results (Section 7) and conclusion (Section 8). The insight from this study supports effective model designs for SIPPRA health management.

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Acronyms

BN	Bayesian Network
CES	Complex Engineering System
CPT	Conditional Probability Table
DBN	Dynamic Bayesian Network
DET	Dynamic Event Tree
DRACS	Direct Reactor Auxiliary Cooling System
PHM	Prognostics and Health Management
PRA	Probabilistic Risk Assessment
RPS	Reactor Protection System
SFR	Sodium Fast Reactor
SIPPRA	Systematic Integration of PHM and PRA
TOP	Transient Overpower

2. Background

2.1. SIPPRA health management

One approach for addressing current gaps in CES health management capabilities is to systematically integrate aspects of PHM and PRA into system health assessments. Interests in scaling up PHM for larger systems and the introduction of dynamic and forecasting elements into PRA have led to the development of system-level models. SIPPRA ties these two fields together and provides a structured form for consistently utilizing available techniques and practices for monitoring, measuring, and evaluating system health across PHM and PRA. This has largely taken the form of PHM models providing input information for PRA models [3–5] or a PHM model taking the logic structure usually used in PRA models [6,7]. Recognizing the need for a unified approach to combine PHM and PRA, Moradi and Groth [1] outlined a structured SIPPRA framework, shown in a simplified form in Fig. 1, for monitoring complex engineering systems. In their approach, a dynamic risk assessment framework identifies the system-level faults before incorporating online system data to perform health evaluation. System health management decisions made using this structure take a holistic view of the system while utilizing available and relevant data.

The biggest challenge facing SIPPRA health management is its novelty and limited use. Although there are multiple research efforts underway to model CES health using a mix of PHM and PRA techniques, it has yet to be widely applied in industry settings to support system management. This means that there are many questions left unanswered regarding effective means for representing CESes, including how to appropriately incorporate system-level data into the health models. Although there are many techniques for assessing CES health through SIPPRA, the remainder of this research will focus on one potential modeling method: the Dynamic Bayesian Network (DBN).

2.2. DBNs

DBNs are an extension of Bayesian networks, directed acyclic graphs that describe conditional probability relationships between dependent nodes connected by arcs. The "dynamic" aspect of these networks comes from the fact that the conditional probabilities considered are time-dependent. Like BNs, DBNs hold the Markov property in which only the direct parents of a node have an impact on the state of that node [8]. This assumption results in the formation of two types of relationships to consider for each dynamic node state: a "T_0" probability that exists as the initial state relationship, and a '$T_n\varepsilon$ probability that changes as the system being modeled develops over time. To calculate these probabilities, DBNs model certain system conditions as a joint probability across the dependencies captured in the model. For a given DBN with X_n variables, the underlying probability that a certain scenario would occur, P, is based on Eq. (1) [8]:

$$P(X_1, X_2, \dots, X_n) = \prod_{j=1}^{n} P\left(X_j | parents(X_j)\right) \tag{1}$$

where $parents(X_j)$ is the set of nodes with arcs into the variable X_j.

Like static BNs, DBNs share the same overall structural relationship between nodes over time; however, time-dependent relationships are now included in the model. This means that the state of a node at time t is affected not only by the inter-slice dependencies of its parents during that time, but also any parents from the previous t step. DBNs are discrete-time models, meaning they work at specified points in time rather than a continuous timeframe [8,9]. Specific node relationships are more visible when the DBN is presented as an unrolled BN, as shown in the right image in Fig. 2.

Risk-focused and reliability engineering studies have shown the versatility of DBNs for capturing system reliability and monitoring system health [10–13]. Early research connected DBN formalisms to reliability block diagrams [14], dynamic fault trees [15], and Markov Chain models [16]. As part of their extensive literature review on the use of Bayesian networks for fault diagnostics, Cai et al. [17] found that DBNs were used to support specific areas of reliability engineering research, including process, structural, and manufacturing systems. Amin et al. [18] used DBNs to determine a dynamic availability assessment of safety critical systems, Wu [19] found that DBNs could be used to make safety decisions for tunnel constructions, and Rebello et al. [20] relied on Hidden Markov Models to monitor system functionality through DBNs. These researchers wanted to capture the dynamic qualities that would otherwise not be accessible to static models. There has also been some research into whether DBNs could be used for system health prognostics [21,22]. Medjaher et al. [23] represented a small industrial system through DBNs to determine the expected prognostics of the system, and Zhao et al. [24] proposed the use of DBNs to monitor fault diagnostics and loss-of-coolant accident progression prediction in a High Temperature Gas Cooled Reactor Pebble-bed Module reactor.

DBNs are increasingly used in prognostics modeling and risk assessments for CES health management for their graphical representations of complicated causal relationships and powerful inference capabilities [17,25,26]. Lewis and Groth [27] found in their literature search on the use of BNs in reliability research that the number of articles related to DBNs published per year has been steadily growing since 2012. These include studies related to structural engineering (e.g., [28,29]), mechanical engineering (e.g., [30,31]), and risk and system safety (e.g., [10]). In these studies, the CPTs and initial value distribution used to parameterize the networks are calculated from available data or determined through expert-based opinions. A DBN's logic structure and inference capabilities make it a common alternative for causal-based system-level research. The growing interest in using DBNs to solve reliability problems places additional motivation to create models that are effective and efficient in their inference capabilities.

3. Approach

Given the novelty of SIPPRA and the limited understanding of system health management for CESes, the approach outlined in Fig. 3 supports the rigorous comparison of CES health monitoring model designs based on multi-dimensional performance metrics. Before applying the process to better understand the impact of time discretization strategies on the performance of DBN-based health monitoring models, three inputs are required: a set of performance metrics to evaluate SIPPRA methods, a list of methods used to discretize continuous time-series data for DBNs, and a real-world case study for analyzing the impact of different design choices on health monitoring models.

The first step in carrying out such a comparison across health monitoring models is the development of relevant performance metrics. Current metrics used to evaluate model performance in PRA and PHM

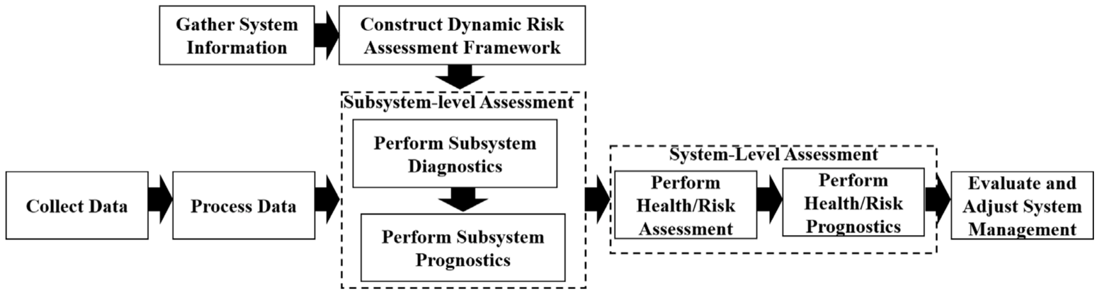

Fig. 1. General process for SIPPRA derived from Moradi and Groth [1].

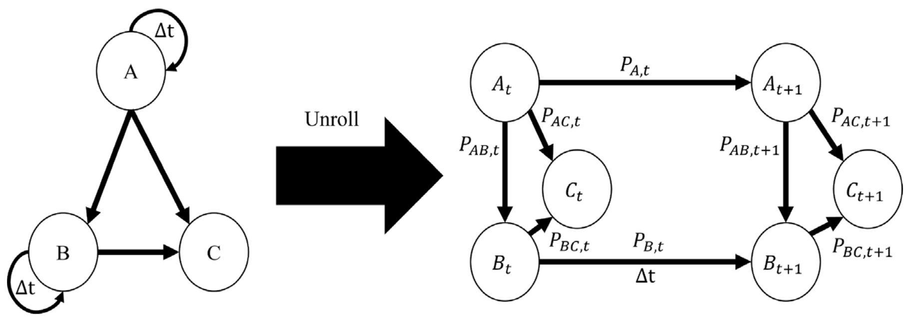

Fig. 2. Rolled (left) and unrolled (right) two-time sliced DBN. This study seeks to understand the impact of varying the "Δt" in the graph.

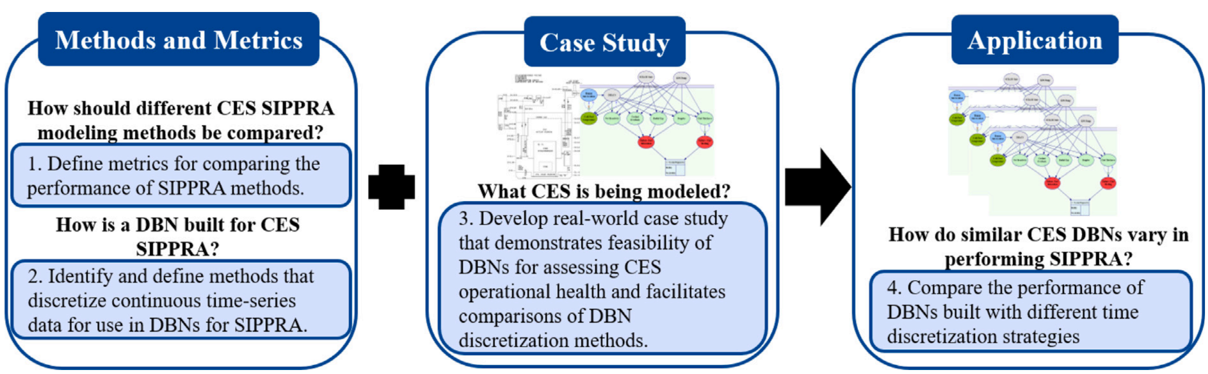

Fig. 3. Comparison of DBNs built with different time discretization strategies requires a set of preliminary questions to be already answered.

techniques are not sufficient for system-level health models that utilize SIPPRA techniques. Lewis and Groth [32] developed a rigorous process to identify performance metrics as indicators of a successful completion of SIPPRA tasks to ensure that the metrics set was comprehensive and verifiable. This produced a set of thirty-five metrics that could be used to compare the performance of different system-level health monitoring models as a multi-dimensional concept , including assessment accuracy, model construction costs, information content per sampling rate, and number of inferred data sources. These performance metrics were designed to be evaluated for a specific system or operational environment, enabling meaningful and justifiable comparisons across model designs.

The next step is to define different methods for discretizing continuous time-series data for use in DBNs. In their review of the recent reliability literature, Lewis and Groth [27] found that in constructing DBNs, researchers have relied on the use of only two discretization methods: time-based and state-based discretizations. Time-based discretizations uses system operational time as the discretizing factor, while state-based discretizations partition time by either events that affect the system or the attributes of system parameters; this is similar to the "instant-based" and "interval-based approaches described by Boudali and Dougan to categorize what they refer to as "temporal Bayesian networks [33]. However, these approaches are shown to not always respond appropriately to changes in a complex engineering system timeline. Between the capability gaps of these two discretization lies a third approach: a multi-interval hybrid discretization that adjusts its sampling frequency based on operational and environment changes. Lewis and Groth presented and verified the framework to develop a model using this discretization process through a simplified model of a CES undergoing an accident sequence [34].

The last step before the comparison of different model performances is to develop a case study in which different models could be generated to reflect the system. Lewis and Groth [2] produced a real-world case study of the operational after-effects of a SFR experiencing a transient overpower; this serves as a structured means for studying the impact of different DBN structures and designs meant to capture CES health. Structured processes were defined for converting simulated operational nuclear data into the DBN's node structure and CPTs. This work introduced a framework to use for constructing DBNs for CES health monitoring based on connecting operational environments, component health, and human interventions, to system failures and prognostics.

4. Methodology

This case study compares the performance of different DBNs designed to model the accident scenario described by Lewis and Groth

[32]; that is, an SFR experiencing a TOP and subsequent system decay, resulting in potential fuel relocation or thermal clad failures. A total of fifty-six different DBN models are constructed in GeNIe and PySmile [35], a BN software tool, using the different discretization strategies outlined by Lewis and Groth [34]. These models all have the same node structure shown in Fig. 4; however, each discretization method generates different CPTs that describe the underlying conditional probabilities of the system, as separate sets of data are considered when constructing the tables. This produces distinct models to consider as viable for system health monitoring, diagnosing system failures, or predicting current and future system states. Following a short description of the case study used in this comparison, the remainder of this section outlines the different discretization methods studied and how each metric compared is measured in this study.

4.1. Case study background

The remainder of this paper focuses on a sodium fast reactor experiencing a transient overpower event. This is a simplified version of the one studied by Jankovsky et al. [36]. SFRs can be considered a typical CES in that they feature the primary characters inherent for a CES; namely, they are composed of human, hardware and software components and generate a large amount of operational data from several data sources at varying rates. In addition to the nuclear core, the system in the case study includes a "SCRAM"process for shut down the nuclear reactions, a reactor protection system (RPS) and a direct auxiliary cooling system (DRACS). For the purposes of this case study, although there are multiple components to a sodium fast reactor that provide a significant amount of system information through sensors and operational reports, only a limited number of data sources will be considered. These are, namely, the main indicators of the automatic SCRAM process for shutting down the reactor, and are captured in Fig. 4.

The primary accident event described through the DBN model in this case study is a TOP event. TOPs can be caused by external factors, e.g., an earthquake, that results in a sudden surge of power generation in the reactor. When such an event occurs, the reactor's automatic SCRAM mechanism is expected to respond to operational changes by inserting control rods into the reactor to greatly reduce power generation; common indicators for the automatic SCRAM mechanism include changes to net reactivity, cold pool temperature, and other fuel feedback values [37]. Depending on the cause of the accident, however, SCRAM and RPS functions may be impacted, limiting their ability to prevent core reactions from further escalating. If this were to occur, the reactor would face a significant risk of fuel relocation and clad melting, resulting in a partial or full nuclear meltdown.

The accident data used in this case study to define the CPT tables in the DBN models was determined from a dynamic event tree (DET) that defined a series of accident event scenarios addressing potential failure points when responding to a TOP event [37]. Based on software-generated event scenario branching conditions, simulation modeling of the nuclear reactor under these conditions produced time sequence data for the different green measurable and derived parameters in Fig. 4 that are necessary for monitoring overall system health. CPT tables were then constructed based on the values of the simulated data as well as the underlying event conditions from that data. The models were run to simulate data readings throughout the reactor and BOP for a full day after the TOP event (86,400 simulation seconds). The scenario was considered finished when either: the cladding fraction of the core channels reached an average of 90% (representing a clad melting failure), the temperature of the cold pool had reached a significantly high temperature resulting in a fuel relocation, or the reactor had survived the simulated day without reaching those other thresholds. In those instances, it is assumed that operators would have had enough time to address any problems with the system's processes.

The nodes in the DBN in Fig. 4, represent either underlying system state conditions or the type of health monitoring data seen under those conditions. This network is dynamic in that the state values of three model nodes ("Human Intervention", "DRACS", and "Clad Thickness") are dependent on their previous states (represented with a rounded arrow). For ease of calculation, the nodes in the model are all discrete, with the table of states shown in Table 1.

4.2. Discretization practices compared

This study compares the performances of DBNs that utilize time-based, state-based, and hybrid time-based discretization methods. Table 2 provides a summary description of the discretization approach used in the models compared in this study.

4.2.1. Constructing DBNs with time-based discretization

DBNs constructed with a time-based discretization approach are built on data collected over a specified period of time, as shown in Fig. 5a. Four different data collection frequencies are evaluated in this comparison: models with data collected every 9, 60, 120, and 1,200 s. As this case study covers a period of 86,400 s, these rates roughly translate to a DBN model with 9,500, 1,440, 720, and 72 time-steps, respectively. These values were selected to provide a range of feasible monitoring time periods, with the 9 s rate equivalent to the rate in which the simulation code generates temperature data. These models were constructed using the process outlined by Lewis and Groth [2].

4.3. Constructing DBNs with state-based discretization

DBNs constructed with a state-based discretization approach are structured on data pertaining to a certain operational state; this is shown in Fig. 5b. For this case study, the reactor's net reactivity value was used as the trigger for data collection. Data is collected only when the net reactivity is evaluated over a specified threshold in a given accident scenario. Net reactivity was selected as the triggering variable as that parameter indicates whether a nuclear reaction is moving towards additional power increases.

Four net reactivity values were chosen to compare as thresholds for collecting system data: −\$0.1, \$0, \$0.02, and \$0.2. These values relate to the binning used to discretize the associated net reactivity node (\$0.02), capture baseline operations (\$0), or provide extreme bounding scopes (−\$0.1, \$0.2). To build the CPTs for these models, data is evaluated over the smallest available interval for each accident scenario. If the value of the net reactivity is evaluated as greater than the specified threshold at a given measurement, then all of the system data associated with that time is included in constructing the relevant CPTs.

4.4. Constructing DBNs with hybrid time-based discretization

Similar to those built with a time-based discretization, the CPTs for DBNs developed using a hybrid time discretization approach are built from data collected over a specified interval; however, once a threshold state is reached on a triggering variable, data is then collected at a different rate as explained by Lewis and Groth [34]. This type of model is built as a hybrid of the previous two models, shown in Fig. 5c.

For this study, different combinations of time-based discretization values are paired with a net reactivity threshold as the limit to switch from one data collection rate to another. This results in a total of forty-eight distinct models (combinations where the two rates are the same are not compared as they are equivalent to the single time-based discretization described above). Two different situations were considered when defining the threshold state: when the initial time steps are larger than the subsequent ones, and when the initial time steps are smaller than the next steps. The first describes an instance of increasing the data uptake from the system; for those models, the second time steps begin when net reactivity is greater than the specified threshold. The second situation relaxes data uptake. There, the second time steps start when net reactivity is less than the specified threshold.

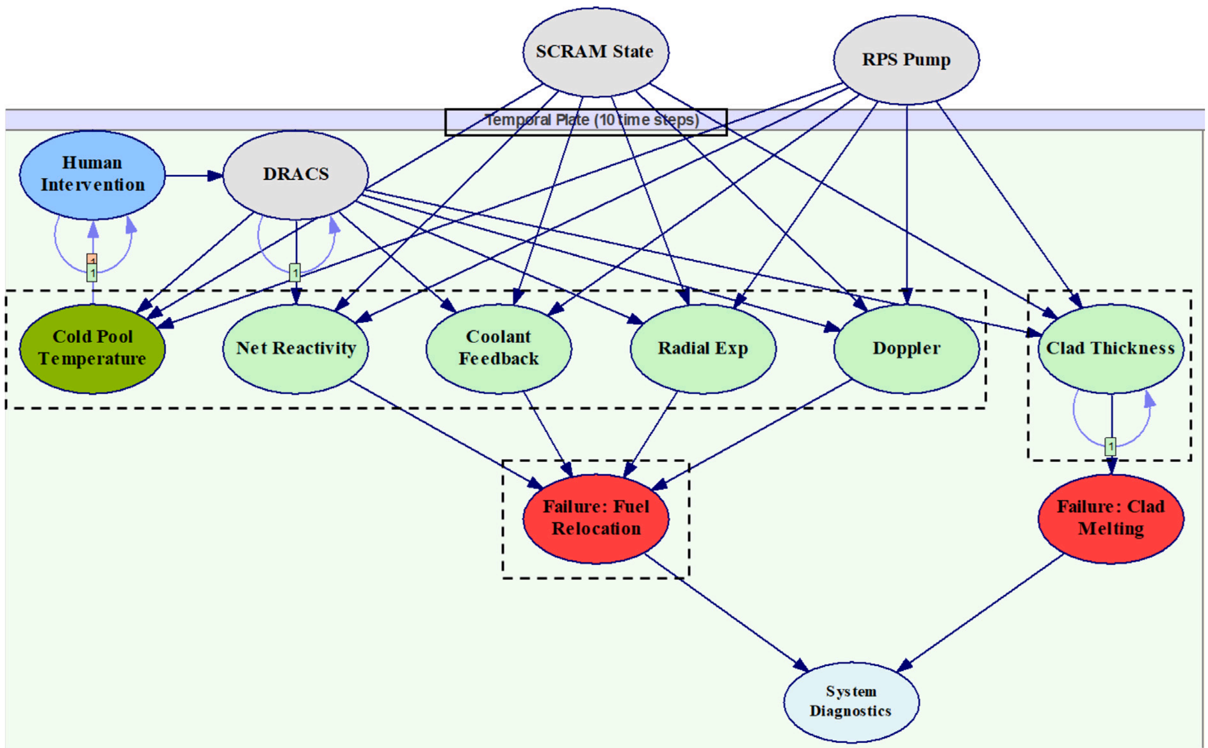

Fig. 4. Each DBN compared in this case study has the same causal graph structure. Blue — human intervention, gray — CES components, dark green — measurable parameters, light green — derived parameters, red — failure modes, light blue — system health.

Table 1
Model nodes and node states.

Node name	Type of node	Number of states	General state descriptions
SCRAM state	System Component	4	SCRAM and Trip Success, SCRAM Success and Trip Failure, SCRAM Failure and Trip Success, SCRAM and Trip Failure
RPS pump	System Component	2	Operational, Not Operational
DRACS	System Component	3	Degraded, Nominal, Enhanced
Human intervention	Human Involvement	3	Yes, No, Undecided
Cold pool temperature	System Information/ Sensor data	3	Below 753K, Above 753K
Net reactivity	System Information/ Sensor data	3	Low, Medium, High
Coolant feedback	System Information/ Sensor Data	3	Low, Medium, High
Radial expansion	System Information/ Sensor Data	3	Low, Medium, High
Doppler	System Information/ Sensor Data	3	Low, Medium, High
Clad thickness	System Information/ Sensor Data	11	90%–100% (by percent), Below 90%
Failure: fuel relocation	System Prognostics	2	Yes, No
Failure: clad fraction	System Prognostics	2	Yes, No
System diagnostics	System Diagnostics	2	Yes, No

Table 2
Summary description of discretization values used in model comparison.

Discretization	Discretization description					Number of cases
Time-based	Data collected every	9 s	60 s	120 s	1200 s	4
State-based	Data collected when reactivity greater than	−$0.1	$0	$0.02	$0.2	4
Hybrid time-based	Data collected every X sec until reactivity threshold; then, every Y sec					48

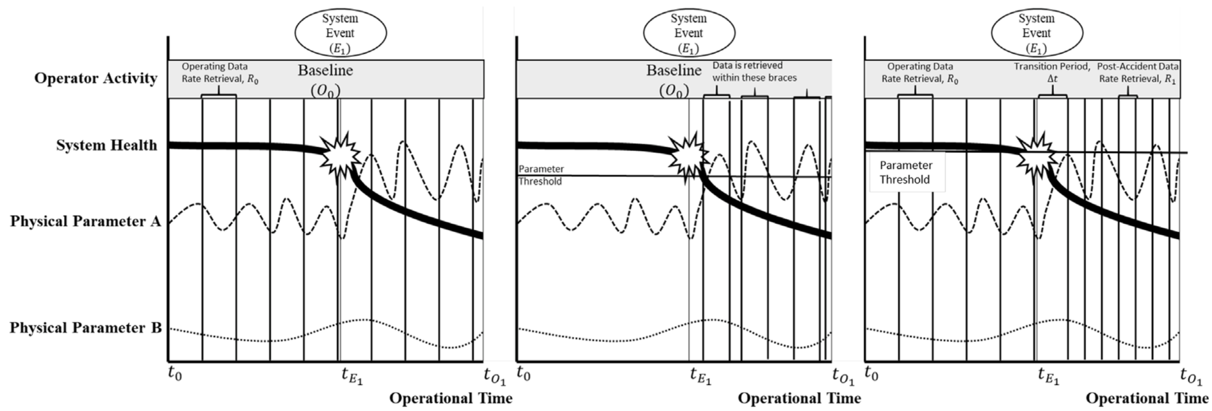

Fig. 5. The CPTs in the DBN compared in this study are generated from data derived from (a) time-based, (b) state-based, and (c) hybrid time-based data stream discretizations.

4.5. Performance metrics used to compare model designs

For this study, relevant performance metrics were selected and then framed based on the specifications of the case study. The metrics used to compare the different model designs were selected from the list generated by Lewis and Groth [32]. After reducing the list to consider metrics relevant for inspection, the following metrics were identified as providing different ranges of performance: assessment accuracy (as the alignment of risk assessment), prelimary model construction costs (as CPT development time) and information content per sampling rate (as average information content). Since this work studies how different discretization methods impact model performance, these metrics are model characteristics that are affected by changes data quantity. The remainder of this section outlines how each metric is measured in this study.

4.5.1. Assessment accuracy: Alignment of risk assessment

The first metric used to compare the different discretization approaches is assessment accuracy; in this study, that means how well the model's prior estimate of system health, represented by the "System Diagnostics" node's "Healthy" state, matches the underlying system safety of the accident scenario. Model accuracy is a common metric for evaluating model performance; if a monitoring model is unable to provide an appropriately reflective health assessment, it is limited in its ability to be used as a health management tool.

Joint prior probability for the "System Diagnostics" node is calculated using a model's generated CPTs. The value of the node's "Healthy" state at the model's last time step (86,400 s or equivalent) is then compared by both magnitude and percent error to the calculated system health assessment from the underlying DET used to generate the system data. As an event tree, DET system health is determined from the summation of failure probabilities. The closer the assessment is to the baseline estimate ($2.77 * 10^{-7}$), the more aligned the model is to the DET assessment. In terms of percent error, those values should be as close to zero as possible.

4.5.2. Model construction costs: CPT development time

The next metric studied is the model construction cost; in particular, the time required to develop the CPTs for the DBN models. For networks representing complex engineering systems, CPTs are often calculated through processing online data associated with specific parent and child node configurations. Timing how long it takes for CPT-generating programs to process the data and then construct the CPT through internal software timers can provide model builders a sense of CPT development time. Understanding the length of time required to develop a model prior to use is important when considering appropriate model designs to pursue.

This metric is evaluated as the summation of time taken to construct network CPTs that vary in response to the different discretization methods. These CPTs describe the causal relationships for the four unobservable parameters (net reactivity, coolant feedback, radial expansion, and doppler), observable parameter (cold pool temperature), dynamic clad thickness, and fuel relocation failure. For this metric, models that take a shorter amount of time to construct are preferable to those that take longer to develop.

4.5.3. Information content per sampling rate: Average information content per measurement

The last metric compared in the study is the average information content of each model. At the beginning of an accident scenario, there are many unknowns beyond the probabilities of occurrence that are assigned to the potential accident timelines. As new system information becomes available from different data sources over time, there is greater certainty about the nature of the current accident sequence as well as its outcome. This new knowledge can ultimately lead to better preparation and risk management for expected outcomes.

Information content for each measurement from the "Cold Pool Temperature" node is quantified using information theory. Eq. (2) shows how the information content for a collection of scenario outcomes X based on the previous knowledge about Y data measurements can be expressed as the sum of the conditional entropies of the potential operational sequences that resulted in those measurements:

$$H(X|Y) = -\sum_{y \epsilon Y} Pr(y)\left(\sum_{x \epsilon X} Pr(x|y) log\left(\frac{1}{Pr(x|y)}\right)\right) \quad (2)$$

The total information entropy is then averaged to better approximate the information content for a given set of cold pool temperature measurements. As entropy describes the amount of overall uncertainty or information required to identify a current scenario from all possible events, lower values for this metric are preferable (e.g., a value of 0 indicates complete certainty) to larger values.

5. Results

This section presents the results from evaluating the performance metrics described above for DBN models built using different data stream discretization strategies. For a cleaner discussion and analysis, this section will feature either sample values or summarizing figures. The summary figure common across the performance metrics is a heat map of metrics values. Shown in Fig. 6, these maps can be divided into the four regions for the discretization approach used: the lower-left section (hybrid time-based discretization where the first time step rate is less than the secondary rate), the diagonal (standard time-based discretization), the upper right part (hybrid time-based discretization

Table 3
Sample DBN model prior safety estimates (vs. DET baseline safety estimate of $2.77 * 10^{-7}$).

	Time-based		State-based		Hybrid time-based	
	120 s	1200 s	Net Reac. >= 0	Net Reac. >= 0.02	1200→120 @ Net Reac. <= 0.02	120→1200 @ Net Reac. >= 0.02
Prior risk	2.59*10E−07	2.68E−07	5.16E−08	8.00E−08	8.65E−08	2.47E−07
% Difference	−6.36%	−3.21%	−81.4%	−71.1%	−68.8%	−10.73%

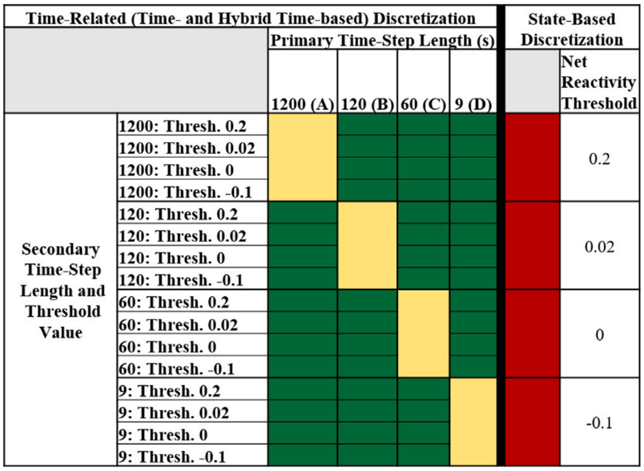

Fig. 6. Heat maps like this one summarize the results from the metric studies. Green indicates a preferable metric value, while red squares indicates less preferable values.

where the first time step rate is greater than the secondary rate), and the separate right-side column for state-based discretization. Model designs with more preferable values appear closer to dark green, while those with less desirable values are a darker shade of red.

5.1. Results of risk assessment alignment study

Table 3 shows a sample of estimated priors from example models for the different discretization approaches and their similarity with the underlying DET's baseline estimate of $2.77 * 10^{-7}$. The values lie roughly within an order of magnitude to the baseline estimate. The models that collect more data (120s time step vs. 1200s time step, and reactivity threshold greater than 0 vs. greater than 0.02) appear to produce more conservative safety estimates with greater percent error from the baseline estimate. This trend is further expressed in Fig. 7, which plots the calculated safety assessment for each state- and time-based values (the DET value is included as reference). Even though both time- and state-based discretization strategies have a similar trajectory, the state-based discretization cover a wider range of values.

The percent errors for the hybrid discretization are compared alongside the time- and state-based discretization results in the heat map in Fig. 10. The percent difference for the diagonal region is consistently better than the other two regions, but gets progressively larger with smaller time step lengths. The upper-right region is slightly worse than its diagonal counterparts, but improves with lower threshold states. On the other hand, the models represented in the lower-left region are significantly further off from the baseline DET estimate but worsens with lower threshold states (see Fig. 8).

5.2. Results of CPT development time study

Table 4 presents the amount of time it took to develop the CPTs for the example models described previously in Table 3. Overall, the CPTs that required the most amount of time to construct described the causal relationships for the non-observable and observable parameters. This is largely in part due to these variables changing over time, while the other nodes relate to system aspects that occur less frequently or at the end of the accident scenario.

As expected, the models with CPTs constructed with more data, either by shortening the time step length or lowering the threshold value, took longer to build that those with longer time steps or higher threshold values. Since the number of CPT entries for a given node remained constant across the models, the CPT development time is dependent upon the quantity of data that was required to be processed during each discretization process. The construction times for the four time-based and state-based models are plotted in Fig. 9 and compare the increases in computational time requirements with the increases in available data for either discretization strategy (either through shorter time-steps or lower thresholds). The CPT construction times associated with the DBNs built from a time-based discretization follow a power curve. While the state-based models also require more time to develop CPTs at lower thresholds, the increase in time is not easily modeled through a curve. This can easily be seen by the sharp jump in computational time between the model measuring data at $0.02 to $0 threshold. The model construction time for these two discretization times appears to intersect somewhere between $0.02–0 reactivity threshold and, using the power curve to determine boundaries similar to the time for the state-based discretization strategies, somewhere between 240 to 3500 s.

The CPT construction times for the hybrid time-based models presented in Table 4 lie between the construction values for the two discretization rates when used in a time-based discretization. The remaining computational times for the hybrid strategies are captured and compared to the times from the other models in the heat map in Fig. 10. For the most part, hybrid-time discretization construction times lie between the values of the two time-based methods used, presented along the diagonal of the heat map. That is not always the case, however; for some models, like the one built with a primary time step length of 120 s that transitions over into a new rate of 60 s following a reactivity measurement above $0.02, the computational time required for developing the hybrid CPTs were longer than that for the time-based model built with a time-based discretization of 60 s time steps (46,278.3 vs 46,053.5 s).

5.3. Results of information content study

The charts in Figs. 11 and 12 show the progression of average conditional entropy, or information content, for the models built using the state- and time-based discretization strategies across the different model time steps. Each model begins with an entropy of 4.32; this is derived from the failure probabilities from the DET branches. The figures show that additional system information can affect the value of information for the particular scenario.

Generally speaking, the average conditional entropy decreases over time across all discretization methods studied, with greater decreases more likely to occur towards the earlier time steps for each model. In instances where the time-steps overlap (i.e., data would have been collected at the same time), the average conditional entropy is greater for models with more time steps. The difference between entropies at the same point in time however, appears to be reduced over smaller distances than larger ones. This is further seen, when at approximately 70,000 s into the simulation for the time-based discretizations, differences in the conditional entropy across the models eventually decrease, leading to roughly consistent entropy values from then on.

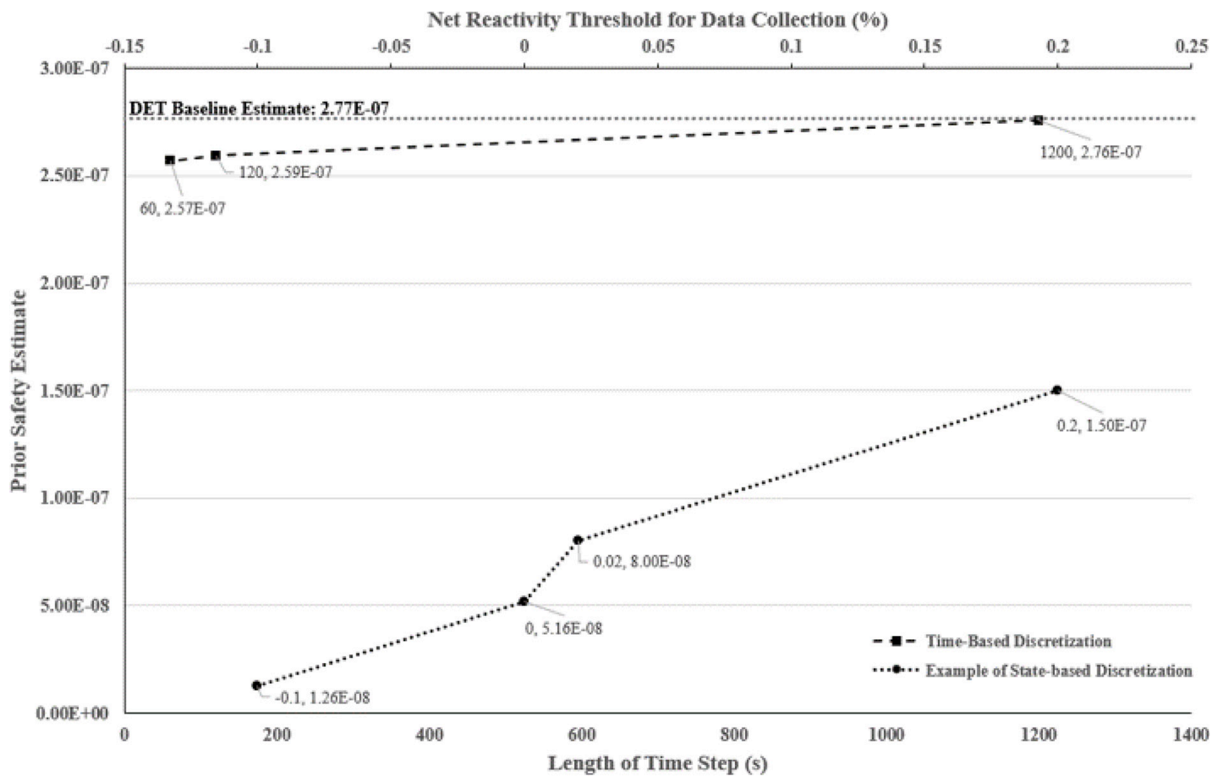

Fig. 7. Prior safety estimates for DBN models constructed using a time- and state-based discretization approach compared to the baseline DET estimate. The two trends are plotted on different x-axes: the time-based values (dashed line) align with the lower axis, while the state-based values (dotted line) are graphed according to the upper axis.

Time-Related (Time- and Hybrid Time-based) Discretization							State-Based Discretization	
		Primary Time-Step Length (s)						
		1200	120	60	9			Net Reactivity Threshold
Secondary Time-Step Length and Threshold Value	1200: Thresh. 0.2	-3.21%	-10.77%	-11.61%	-6.05%		-46%	0.2
	1200: Thresh. 0.02		-10.72%	-11.46%	-8.42%			
	1200: Thresh. 0 0		-10.73%	-11.42%	-7.92%			
	1200: Thresh. -0.1		-3.47%	-4.17%	3.22%			
	120: Thresh. 0.2	-65.86%	-6.36%	-11.05%	-5.23%		-71%	0.02
	120: Thresh. 0.02	-68.77%		-11.05%	-5.49%			
	120: Thresh. 0	-68.76%		-11.05%	-5.45%			
	120: Thresh. -0.1	-65.85%		-7.94%	2.42%			
	60: Thresh. 0.2	-79.53%	-33.33%	-7.21%	-5.18%		-81%	0
	60: Thresh. 0.02	-82.11%	-34.00%		-6.21%			
	60: Thresh. 0	-82.11%	-33.12%		-5.30%			
	60: Thresh. -0.1	-79.52%	-33.05%		1.08%			
	9: Thresh. 0.2	-25.50%	-45.85%	-22.81%	-1.28%		-95%	-0.1
	9: Thresh. 0.02	-99.69%	-50.74%	-62.76%				
	9: Thresh. 0	-99.68%	-53.26%	-25.50%				
	9: Thresh. -0.1	-99.66%	-47.34%	-25.49%				

Fig. 8. Comparison of percent error of safety estimates across models and discretization strategies.

The heat map presented in Fig. 13 captures the averages of each model's average information content. In general, those values were larger for models with larger time steps and more inclusive thresholds, validating the observations made before. The values for the hybrid time-based models lay between the values of the two time-based methods used.

6. Analysis

The structure of the metrics studies allowed for an initial evaluation of the difference between modeled system safety and the "ground truth" system safety captured by the DET. For the most part, the models provide roughly the same level of performance with respect to prior assessment accuracy, with time-based models providing slightly more similar results than either the state-based or hybrid time-based models. From this metric alone, the discretization strategies appear comparable in model performance; however, the results from the other metrics studies indicate that there are substantial differences in the performances of DBN SIPPRA health monitoring models derived from the discretization approach used to derive model CPTs. The rest of this section expands upon more findings from this study with respect to the different discretization strategies.

Table 4
Sample development time for CPTs.

	Time-based		State-based		Hybrid time-based	
	120 s	1200 s	Net Reac. >= 0	Net Reac. >= 0.02	1200→120 @ Net Reac. <= 0.02	120→1200 @ Net Reac. >= 0.02
Non-observable parameters	383.3	3,420.1	838.2	838.2	4,068.6	1,223.0
Observable parameter	2,035.6	19,590.1	9,958.6	9,958.6	2,610.3	2,229.9
Fail: fuel relocation	58.7	28.7	15.1	15.1	16.4	17.1
Dyn. clad thickness	1.0	10.2	21.8	21.8	31.9	338.4
Total (s)	**2,478.6**	**23,032.9**	**10,833.7**	**10,833.7**	**6,727.2**	**3,808.4**

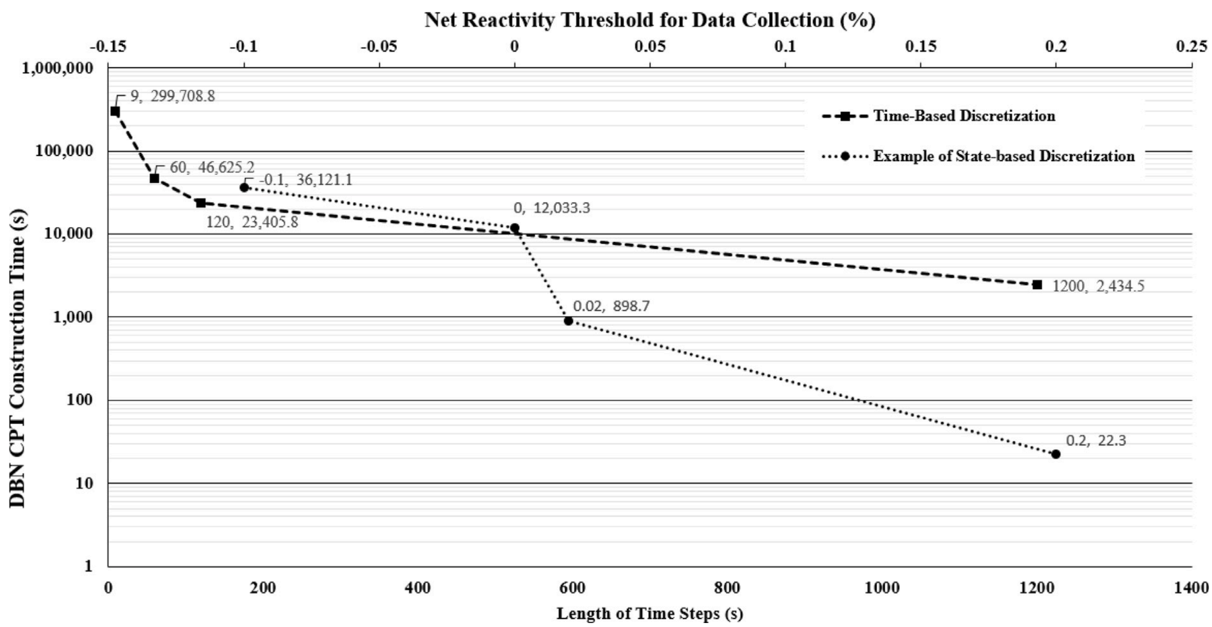

Fig. 9. Comparison of the construction time of DBN CPTs based on the length of time steps and threshold values.

Time-Related (Time- and Hybrid Time-based) Discretization		Primary Time-Step Length (s)				State-Based Discretization	
		1200	120	60	9		Net Reactivity Threshold
Secondary Time-Step Length and Threshold Value	1200: Thresh. 0.2	2,478.6	3,545.1	4,791.9	17,645.1	58.30	0.2
	1200: Thresh. 0.02		3,808.4	4,831.1	17,147.0		
	1200: Thresh. 0		3,735.4	4,796.1	17,179.5		
	1200: Thresh. -0.1		18,820.6	36,783.1	229,696.3		
	120: Thresh. 0.2	2,780.0	23,032.9	26,513.9	38,295.7	813.20	0.02
	120: Thresh. 0.02	6,727.2		26,202.7	38,234.9		
	120: Thresh. 0	12,791.7		26,797.3	39,515.8		
	120: Thresh. -0.1	24,134.4		44,420.4	236,564.0		
	60: Thresh. 0.2	2,632.1	26,159.5	46,053.5	61,993.4	11,117.20	0
	60: Thresh. 0.02	10,884.9	46,278.3		62,689.6		
	60: Thresh. 0	24,947.4	48,627.0		62,689.4		
	60: Thresh. -0.1	47,889.3	49,458.4		249,578.4		
	9: Thresh. 0.2	2,725.0	26,930.4	53,125.0	299,708.8	35,319.80	-0.1
	9: Thresh. 0.02	62,493.2	295,423.2	281,304.2			
	9: Thresh. 0	155,729.9	304,475.5	312,017.7			
	9: Thresh. -0.1	312,802.7	313,412.6	318,069.3			

Fig. 10. Comparison of the different CPT construction times across models and discretization strategies.

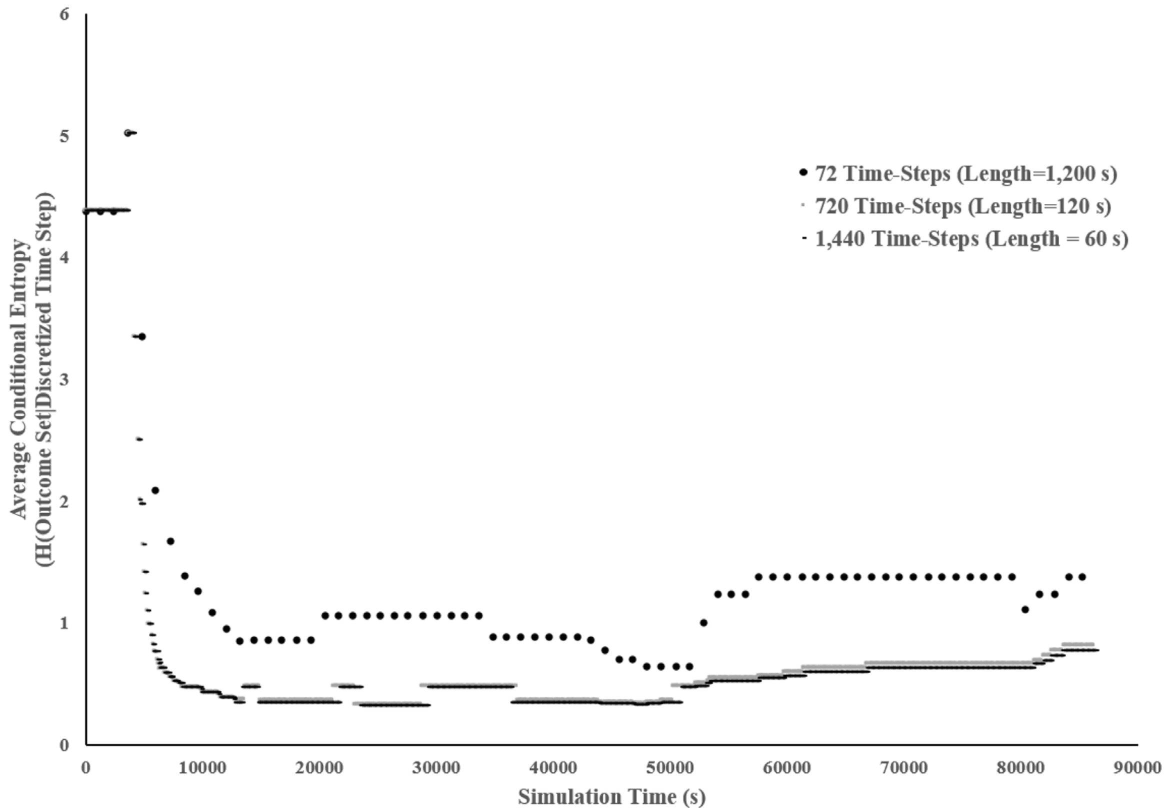

Fig. 11. Progression of information content in the form of conditional entropy across simulated time for models built with time-based discretization.

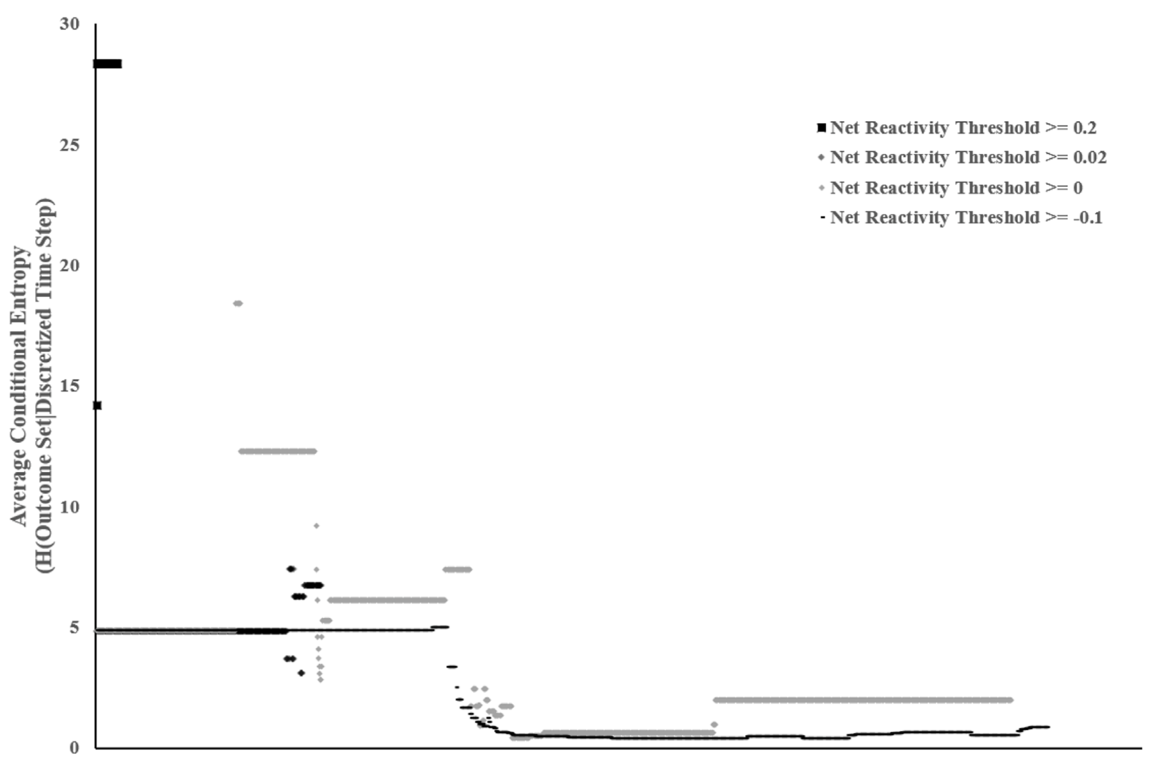

Fig. 12. Progression of information content in the form of conditional entropy across time steps for models built with state-based discretization.

Time-Related (Time- and Hybrid Time-based) Discretization		Primary Time-Step Length (s)				State-Based Discretization	
		1200	120	60	9		Net Reactivity Threshold
Secondary Time-Step Length and Threshold Value	1200: Thresh. 0.2	2,478.6	3,545.1	4,791.9	17,645.1	58.30	0.2
	1200: Thresh. 0.02		3,808.4	4,831.1	17,147.0		
	1200: Thresh. 0		3,735.4	4,796.1	17,179.5		
	1200: Thresh. -0.1		18,820.6	36,783.1	229,696.3		
	120: Thresh. 0.2	2,780.0	23,032.9	26,513.9	38,295.7	813.20	0.02
	120: Thresh. 0.02	6,727.2		26,202.7	38,234.9		
	120: Thresh. 0	12,791.7		26,797.3	39,515.8		
	120: Thresh. -0.1	24,134.4		44,420.4	236,564.0		
	60: Thresh. 0.2	2,632.1	26,159.5	46,053.5	61,993.4	11,117.20	0
	60: Thresh. 0.02	10,884.9	46,278.3		62,689.6		
	60: Thresh. 0	24,947.4	48,627.0		62,689.4		
	60: Thresh. -0.1	47,889.3	49,458.4		249,578.4		
	9: Thresh. 0.2	2,725.0	26,930.4	53,125.0	299,708.8	35,319.80	-0.1
	9: Thresh. 0.02	62,493.2	295,423.2	281,304.2			
	9: Thresh. 0	155,729.9	304,475.5	312,017.7			
	9: Thresh. -0.1	312,802.7	313,412.6	318,069.3			

Fig. 13. Comparison of mean values of average conditional entropy across models and discretization strategies.

6.1. Analysis of state-based discretization model performance

The DBN literature search by Lewis and Groth [27] found that examples of time-based and state-based discretization methods were being used to develop DBNs for research. When applied to constructing DBNs for SIPPRA, both approaches seem to offer a way to reduce the overwhelming amount of CES data to consider when developing CPTs. Where the data is reduced, however, varies significantly. While adjusting time-based discretizations changes how many measurements are taken across all potential scenarios equally, a change in the threshold for state-based discretization alters the number of scenarios considered for as usable system information. If the measurement threshold would not be reached during a potential scenario, that scenario is not considered in building out the underlying conditional probabilities of that model.

The elimination of certain scenarios during model construction distinguishes the metrics results for the models built with state-based discretization from those built with the time-based discretization. First, the range of prior assessment values is considerably larger for state-based models as only similar data are considered for use in constructing the CPTs; adjusting the threshold value changes what data are deemed "relevant". With respect to computational time requirements, DBNs constructed with state-based discretization could not be plotted along a similar power curve like the time-based discretization. Rather, it is the amount of system data above the threshold value that indicates the time required for CPT construction; for this accident space, there are far more instances across more scenarios where net reactivity was measured between \$0 and \$0.02 than \$0.02 and \$0.2. This explains the large increase in computational time when the threshold was lowered from \$0.02 to \$0. Lastly, DBNs discretized with a state-based approach had the widest range of average entropy values. Although lowering the number of time steps for these models tended to lower average entropy, and therefore reduce the uncertainty, of the accident scenario's identity for any specific point in time, the information content values associated with these models were greater than either time-based or hybrid-based. One reason for this is that net reactivity can be associated with values of cold pool temperature. As such, the threshold selected for the net reactivity also impacts the range of different cold pool temperatures available for constructing model CPTs.

Another effect of eliminating any data from certain scenarios is the transformation of CPTs across models and discretization values. Table 5 shows the same portion of a CPT across different time-steps and threshold values considered for this studies. As the threshold and length of time steps get lower, the CPTs begin to approach a similar value; this is to be expected as with the smallest possible steps and no threshold for collecting data, both approaches would capture the same data. Moving away from that point, however is when the CPTs vary drastically. With a reactivity threshold value placed at \$0.2, system data collected for that model would suggest that a scenario in which DRACS could be enhanced or degraded is not possible. With this albeit unrealistic threshold value, model designers are left to figure out an appropriate uninformed relationship to place in the empty spaces of the CPTs. As the threshold is lowered, however, evidence is made available about those scenarios, and the CPT can be filled in using available system data. This contrasts from the time-based discretization models, where even at the largest time step studied, the time-based discretization had access to available data for those scenarios.

For these reasons, constructing a DBN health monitoring model using a state-based discretization is not a recommended approach. Although they were often faster to construct than their time-based counterparts, DBNs constructed with state-based discretization have too much uncertainty and variability associated with the amount of data above or below different threshold values to consistently predict their performance across the different metrics studied. Eliminating scenarios that do not meet a threshold also presents significant challenges in ensuring that the health monitoring model has appropriate scenario coverage; that is, the model is applicable for different scenarios of system operation. If the model is unusable in certain situations, i.e. when there is a SCRAM failure but not high net reactivity, then it will be not helpful in predicting the system's progression of system health. This problem is only exacerbated if sensors that are used to determine whether a threshold has been reached are inaccurate or broken.

6.2. Analysis of time-based discretization model performance

Although models built with the time-based discretization approach were shown to have the most similar safety assessments relative to the baseline estimates, the other results from the multi-dimensional performance study indicate that models built with the time-based discretization also face limitations of their own. The placement of CPT construction time on a power curve greatly restricts the ability for the model to capture on-line time. For example, in some instances, the SAS4 A data set also used to develop this case study, provided data about the reactor simulation at a rate of 0.1 s. Using the modeled power curve as an estimate for predicting computational time, the amount of time require to construct a 8,640,000 time step model would be approximately 24.5 million seconds, or about 284 days. For modeling

Table 5
Portion of radial expansion CPT (SCRAM: SCRAM failure, trip success; RPS pump: operational) over different State- (upper table) and Time-based (lower table) discretizations.

React. thresh.	0.2			0.02			0			−0.1		
DRACS	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.
Low	No Evid.	0.306	No Evid.	0.209	0.079	0.208	0.068	0.018	0.095	0.084	0.002	0.083
Middle	No Evid.	0.575	No Evid.	0.791	0.371	0.792	0.932	0.184	0.905	0.916	0.061	0.917
High	No Evid.	0.119	No Evid.	0	0.550	0	0	0.797	0	0	0.937	0
Time step	1200 s			120 s			60 s			9 s		
DRACS	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.
Low	0	0	0	0.0004	4.3E−06	0.0004	0.001	6.2E−06	0.001	0.001	1.3E−05	0.001
Middle	1	0.011	1	0.9996	0.01	0.9996	0.999	0.010	0.999	0.999	0.010	0.999
High	0	0.989	0	0	0.990	0	0	0.990	0	0	0.990	0

a CES with even more components and failure modes, this would be an overwhelming amount of time and computational requirements. There were even challenges in calculating CPTs for models with larger time steps; even building a model with a realistic monitoring of every two minutes took a considerable amount of time to construct. Time-based discretization models are also constrained by the length of time that they cover; for instance, given the limited capability for GeNIE to tackle models greater than 3,000 time steps, the models with the 9.5 s had to be split up over subsequent models. This space requirement is a major concern for time based models over long forecasting periods; reducing the time of interest to focus on more upcoming events and scenarios may be beneficial for improving the performance of these models.

As shown in Table 5, the CPTs for time-based models quickly converge; this is a product of the data from this study, as most of the accident scenarios have relatively constant data over the length of the simulation time. This also helps to explain the stabilizing average information content per model as the simulation progresses. However, as these CPTs become relatively similar, the only noticeable difference becomes the amount of time steps present to represent the 86,400 s time period. As the model CPTs reflect a degrading system, more time steps indicate a greater likelihood of system failure. This explains why the time-based discretization models with more time steps have lower safety assessments than those with fewer. Furthermore, with fewer time steps, the beginning of the simulation time (where most of the data volatility occurs), is weighted more heavily against the more constant data of the success scenarios; this helps capture why, in this instance, the system safety assessment of the models utilizing larger time steps are closer to the underlying baseline estimate. It should be noted that in more volatile scenarios, larger time-step values could overstep available information that indicated a SCRAM failure event had occurred. Without that information, the model would provide an incorrect assessment. Furthermore, increasing the number of time steps for time-based models tended to lower average entropy for any specific point in time. With only a set number of scenarios addressed in this case study, providing more information about the branching from “High” to “Low” cold pool temperature restricts the range of possibilities that could occur. This allows the user of these models to limit his or her attention to the possible scenarios based on the available information. Smaller time steps capture more data variations and data trends earlier, which, when incorporated into a CPT, help to create DBNs that are better aligned with the scenario; however, this results in increased computational requirements.

6.3. Analysis of hybrid time-based discretization model performance

The hybrid time-based discretization approach was introduced to address some of the challenges faced by the previous two discretization strategies, The aim of this approach is to reduce the computational costs of the time-based discretization strategies by emphasizing scenarios relevant to the model user while minimizing, but not eliminating the scenarios that do not meet the specified interests.

The metrics results from the hybrid models indicate a discretization approach that provides comparable performance while reducing computational requirements. Table 6 shows how the probability values from CPTs for a hybrid time-based discretization for a given parent-node “operational context” compare to the same CPT conditions for the two related time-based discretization scenarios. Depending on the threshold, some columns of the table may align more to one time-step length or another as the threshold value restricts data from certain scenarios. This is similar to the state-based discretization approach, which is built from data of predetermined scenarios; however, unlike that discretization approach, all scenarios are considered in building the CPTs. This is shown in the computational time required to build a hybrid time-based model’s CPTs. In most instances studied, the computational time for these models lie between the computational time for the two measurement rates as they remove a number of excess measurements from scenarios that are of lower interest. However, it should be noted that as the number of scenarios meet the specified threshold, the additional time required to check scenario data causes these models to become equivalent, or even become greater than, the time required for a model constructed using single time-based discretization with the smaller time steps.

The performance of the hybrid time-based models vary based on the time-step lengths used as well as the threshold value assigned to switch from one rate to another. This can be seen in the stark difference in the models’ system safety estimates. Here is another instance in which the discretization of the operational data is affecting model performance. For models whose primary time-step length is smaller than the secondary rate, more emphasis is placed on data after the threshold value has been met. In this situation, where an accident has already occurred, this switch gives data further away from the accident more weight in the CPTs. On the other hand, time step rates that are smaller immediately following an accident prioritize data closer to an accident that can offer a better picture of what is going on. These rates can be relaxed once more normal values have been met. This is also shown in the average conditional entropies for these models, in which the two scenarios present different amounts of knowledge about the current situation.

6.4. Comparison across model performances

Ultimately, the results from the study show that in this scenario, models built with a hybrid time-based discretization method provide a useful compromise between the operationally dependent but often incomplete state-based models, and the all-inclusive but time-consuming

Table 6
Comparison of "Radial Exp" node CPTs for time-based discretization and sample hybrid-time discretizations across select specific system state "operational contexts".

Select portion of radial CPT	Operational context / "Radial expansion" node state	1	2	3	4	5	6	7
Time-based disc.: 120 s time steps	Low	0.0004	4.3E−06	0.0004	0.0004	0.006	0.0002	0.006
	Medium	0.9996	0.010	0.9996	0.002	0.845	0.028	0.831
	High	0	0.990	0	0.998	0.149	0.971	0.162
Time-based disc.: 60 s time steps	Low	0.001	5.6E−06	0.001	0.0002	0.006	0.0002	0.006
	Medium	0.999	0.010	0.999	0.002	0.845	0.028	0.831
	High	0	0.990	0	0.998	0.148	0.971	0.162
Hybrid time-based disc.: 120 s until net reactivity >0.02, then 60 s time steps	Low	0.001	9.3E−06	0.001	0.0002	0.006	0.0004	0.006
	Medium	0.999	0.017	0.999	0.001	0.845	0.055	0.831
	High	0	0.983	0	0.999	0.148	0.945	0.162
Hybrid time-based disc.: 120 s until net reactivity >0 s, then 60 s time steps	Low	0.0005	5.6E−06	0.0005	0.0002	0.006	0.0002	0.006
	Medium	0.9995	0.01	0.9995	0.001	0.845	0.028	0.831
	High	0	0.990	0	0.999	0.148	0.971	0.162
Hybrid time-based disc.: 60 s until net reactivity <0, then 120 s time steps	Low	0.0004	4.3E−06	0.0004	0.0005	0.006	0.0002	0.006
	Medium	0.9996	0.010	0.9996	0.003	0.845	0.028	0.831
	High	0	0.990	0	0.997	0.149	0.971	0.162

Table 7
Metric summary comparisons.

	Time-based	State-based	Hybrid time-based
Risk alignment with underlying DET assessment	Comparable (More Accurate)	Comparable (Less Accurate)	Comparable (In-Between)
Description of CPT Development time	Defined power curve	Disjointed step function	Bounded between Time-based values
Information content: Avg. conditional entropy	Lowest	Highest	In-Between

time-based models. If model selection was solely based on time or assessment accuracy, the model constructed with 72 time steps would be the top choice. However, because it fails to provide meaningful knowledge assessments, the hybrid time-based model that starts at 120 s time steps and transitions over to 72 following a reactivity threshold of $0 might also be another choice to consider. These decisions require understanding the model user's needs and subsequent consequences for system failure.

7. Discussion

7.1. Applying different discretization strategies to other CES health management scenarios

Table 7 summarizes the broad findings of applying the three performance metrics on DBN models constructed using each of the different data-stream discretization approaches. The differences in metric values across the three discretization strategies highlight the variations in model performance that arise when DBN CPTs are parameterized using data collected over different time windows and system characteristics. These findings serve as an initial step towards better understanding the impact of the decisions the dynamic risk model developers make when determining what time discretization to use for a particular health monitoring scenario.

Ultimately, the range of values provided by these metrics indicate that the performance of SIPPRA health monitoring models is multidimensional, and cannot be narrowly constrained to a single metric. This is important when considering an appropriate discretization approach for developing, as there exists opportunities for trade-offs based on different risk model user preferences, needs, and requirements. For example, in the SFR case study, larger time steps may result in shorter computational time to develop the CPT, but this comes at a loss of information per model step. Likewise, smaller time steps and more relaxed thresholds provide more information about the current scenario, but require significantly more time to construct the model. A hybrid time-based model may address some of these limitations, but it is still often bounded in performance between time-based models constructed using either rate. Considering these trade-offs, as well as additional ones from other performance metrics mentioned in Lewis and Groth [32], will provide better understanding on how DBN discretization strategies impact SIPPRA model performance and allow risk model developers clearer insight for designing improved system health assessment models.

It should be noted that although these results are valid for this particular scenario and CES, inherently, conclusions cannot be separated from the purpose behind building a model and the assumptions that went into constructing it. This SFR TOP scenario has a number of unique features that may have contributed to these results. First, the scenario outlined in this case study is the aftermath of a external disaster that has damaged the system; as a result, the focus of this scenario is not the prevention of a disaster (that has already happened), but rather a better understanding of whether the system will be able to return to normal operations. To that end, the time period covered for this accident sequence is skewed far beyond most operational changes would occur to the system. As a result, the volatility of the parameters lessens over time, making inspection beyond a certain point unnecessary. This is seen in the relatively constant CPTs constructed over time. Despite the additional information, the data was still incorporated into the CPTs at the same rate (as in, doubling the time steps over the period of time would just double the count of data to consider).

Understanding CES operational scenario nuances is important when considering discretization strategies for a health monitoring model design, particularly in the case for hybrid time-based discretization. As previously mentioned, models built to assess system health within the context of the scenario in this study are intended to reflect the health of a system that has already experienced damage. Given that insight, the hybrid-time structure best suited for this study is one that collects more system data early on, gradually loosening restrictions once a certain threshold has been reached. Other CES operational data may appear differently than the accident data used in this study, however. For example, the scenario of interest may be the lead-up to a potential system failure based on component degradation or human intervention. In that instance, system parameter values begin as baseline values but become more abnormal over time. There, it is reasonable to increase measuring rates once an abnormal threshold is met, as the aim there is to identify the likelihood of system failure as early as possible. To determine which discretization approach would be best suited for that example would require a similar study to the one carried out here that takes into consideration the operational nuances and requirements of the CES of interest.

7.2. Applying study methodological process to other SIPPRA model design decisions

The results from this study provide further insight into how discretization strategies affect different aspects of model performance, and also serve as a validation for the use of the methodological process applied in this study to investigate aspects of CES health monitoring model design decisions. Effectively discretizing data streams is just one open question in the area of SIPPRA and CES health management; there are many others that would greatly benefit from a similarly structured comparison study. These potential research areas may be focused, like studying the impact of different data binning discretization practices on DBN health assessments, or broad, like comparing different approaches to health monitoring. Tackling these research questions would require a similar approach: identifying the different model designs for the comparison, selecting the performance metrics used to compare the model designs, and then applying them on a specific CES health monitoring scenario and analyzing the results of the comparison. The continual process of studying the impact of different SIPPRA approaches on model performance would support a richer understanding of CES health and provide better approaches for effectively monitoring and managing them.

7.3. Future work

As an initial investigation into the impact that applying different time-discretization strategies has on the performance of SIPPRA-based DBNs, there are several areas to further our understanding of CES health management. The first approach would be to expand the current SFR case study. The model used in this research can be expanded by adding additional nodes and arcs to the structure to provide a more detailed representation of SFR system operations following a transient overpower. Incorporating information about other reactor components could provide either more understanding about the current scenarios explored in the case study, or provide more information about the impact that time discretization strategies have on DBNs constructed for dynamic PRA.

The second area for future work would be to perform additional CES case studies. In this study, a number of conclusions were drawn on the contrast of performance of models utilizing different time discretization strategies from the model comparisons made in the SFR case study. Carrying out another case study on a different system would help to validate the applicability of these findings across CESes. This secondary case study could be on another accident scenario for a different nuclear reactor, other systems within the nuclear power plant, or even in a completely separate system domain. Other metrics could be selected to analyze the differences of each DBN model built, including prognostic and diagnostic model metrics like outcome accuracy and prognostic horizon or model uncertainty [38].

8. Conclusion

This paper presented the results of comparing fifty-six DBN-based SIPPRA health models for a sodium fast reactor experiencing a transient overpower using different discretization techniques and compared across different performance metrics identified by Lewis and Groth [32, 34]. Although the risk assessments for each model are comparable to one another, the computational time and information content for each model vary drastically. This indicates that the modeling decisions one makes in the formation of health monitoring models have an impact on their performance. Ultimately, the results of the study show that other performance metrics are needed outside of considering assessment accuracy in determining appropriate discretization parameters for optimal performance. This study helps to provide better understanding on how DBN time-step discretization impacts model performance through the variations of these metrics; prioritizing certain metrics over others will allow risk model developers to design useful tools to provide risk managers clearer insight into potential accident scenarios and help to develop improved risk management strategies for CESes.

CRediT authorship contribution statement

Austin D. Lewis: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Katrina M. Groth:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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