Impact of Complex Engineering System Data Stream Discretization Techniques on the Performance of Dynamic Bayesian Network-Based Health Assessments

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Abstract: Critical infrastructure in the energy and industry sectors is dependent on the reliability of complex engineering systems (CESes), such as nuclear power plants or manufacturing plants; it is important, therefore, to be able to monitor their system health and make informed decisions on maintenance and risk management practices. One proposed approach is the use of a causal-based model such as a Dynamic Bayesian Network (DBN) that contains the structural logic of and provides a graphical representation of the causal relationships within engineering systems. A current challenge in CES modeling is fully understanding how different data stream discretizations used in developing the 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 assessment accuracy 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 leads to different models 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 integrated hardware, software, and human components, are imbedded 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.

The purpose of this paper is to demonstrate how one such DBN design decision, the method of discretizing operational data streams, impacts the assessment accuracy of models representing a sodium fast reactor (SFR) experiencing a transient overpower event (TOP). This paper first provides background information on SIPPRA health management and DBNs (Section 2). This is followed by a discussion of the case study (Section 3), as well as the method used to compare accuracy (Section 4). Results of the comparison are then presented (Section 5), followed by a discussion of the results (Section 6) and conclusion (Section 7). The insight from this study supports effective model designs for SIPPRA health management.

2. BACKGROUND

2.1. SIPPRA

System-level SIPPRA models address current gaps in CES health management capabilities by scaling up PHM for larger systems [2,3] and introducing dynamic and forecasting elements into PRA [4,5,6]. SIPPRA provides a structured form for consistently utilizing available techniques and practices for monitoring, measuring, and evaluating system health across PHM and PRA. The structured SIPPRA framework outlined by Moradi and Groth [1] identifies 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.

There are multiple research efforts underway to model CES health using a mix of PHM and PRA techniques; however, 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: dynamic Bayesian Networks.

2.2. Dynamic Bayesian Networks

DBNs are an extension of Bayesian networks (BNs), directed acyclic graphs that describe conditional probability relationships between dependent nodes connected by arcs. In their literature review of BNs in fault diagnosis research, Cai et al. [7] indicates that for a given BN with X_n variables, the underlying probability that a certain scenario would occur, P, is based on Equation 1:

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

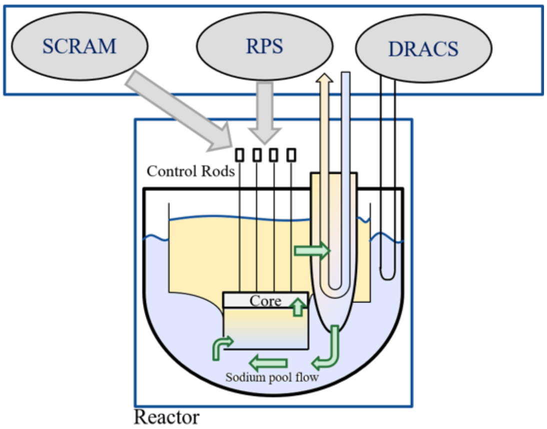
where $parents(X_j)$ is the set of nodes with arcs into the variable X_j. This relationship allows BNs to model the probability of certain system conditions as a joint probability across the dependencies captured in the model. The type of BN dictates whether the marginal probabilities used in the network are static and describe constant relationships or dynamic, in which they vary over time. The latter models are referred to as DBNs and provide a more accurate relationship for complex systems with time-dependent attributes and parameters. DBNs are discrete-time models, meaning they work at specified points in time rather than a continuous timeframe [8]. DBNs are effective in calculating inferences on the node states that are not otherwise easily observable. Using Bayes' Theorem, different inference techniques are possible with DBNs, including prediction, filtering, and smoothing. These different methods allow DBNs to be used for a wide range of system monitoring and health management applications [9].

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 [7]. Lewis and Groth [10] 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., [11,12]), mechanical engineering (e.g., [13,14]), and risk and system safety (e.g., [15]). A DBN's logic structure and inference capabilities make these models a common method 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. CASE STUDY DESCRIPTION

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. [16]. 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 which consists of four distinct

Figure 1: Representation of the SFR System Presented in the Case Study



channels as shown in Figure 1, the system in the case study has a SCRAM and 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.

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 [16]. 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. A visual tree representation of the simplified event description is presented in Figure 2.

The accident data used in this case study is modified from the study by Jankovsky et al. [16]. In their work, a dynamic event tree (DET) was used to construct a series of accident event scenarios that addressed potential failure points when responding to a TOP event. Based on software-generated event scenario specifications, simulation models focusing on different aspects of the nuclear reactor were used to produce different parameters necessary for monitoring overall system health. 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

Figure 2: General Progression of SFR TOP Accident Event Leading to a Successful Scenario, Fuel Relocation Failure, or Clad Thickness Failure.

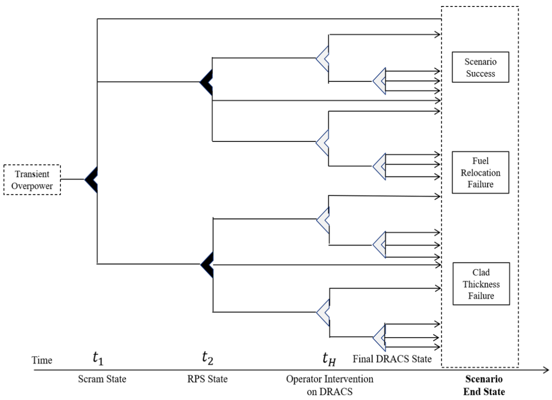
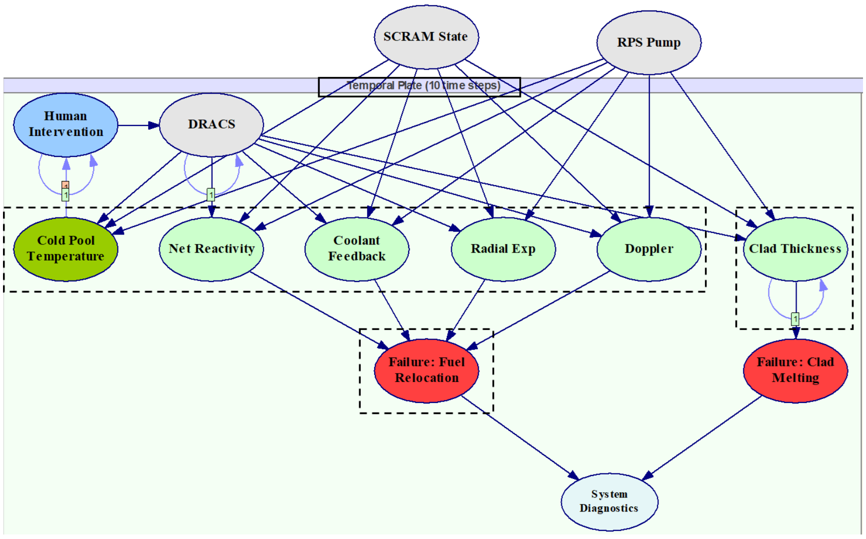


Figure 3: Node Structure for the DBN in the SFR Case Study



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.

Lewis and Groth [17] constructed the DBN model shown in Figure 3 from the case study data to cover the primary elements of the SFR relevant to TOP-induced SCRAM failures. This model, constructed using the Bayesian Network software GeNIe, helps operators identify current system health status and potential failure modes following a TOP by providing knowledge about reactor component states, system and sensor information, human involvement, system diagnostics, and system prognostics information regions. The temporal loops included in the model add temporal causality to constrain outcomes to follow logical relationships (e.g., clad thickness only deteriorates, the operator will not become undecided once he or she has decided to intervene on the DRACS, and the state of the DRACS will not revert back to nominal once it has been either enhanced or degraded). This is distinct from the other nodes which have static conditional probabilities (i.e., a prediction of the current SCRAM state is not dependent upon the SCRAM state prediction from a previous measurement). This model will be used as the basis of comparison for this remainder of this paper.

4. METHOD

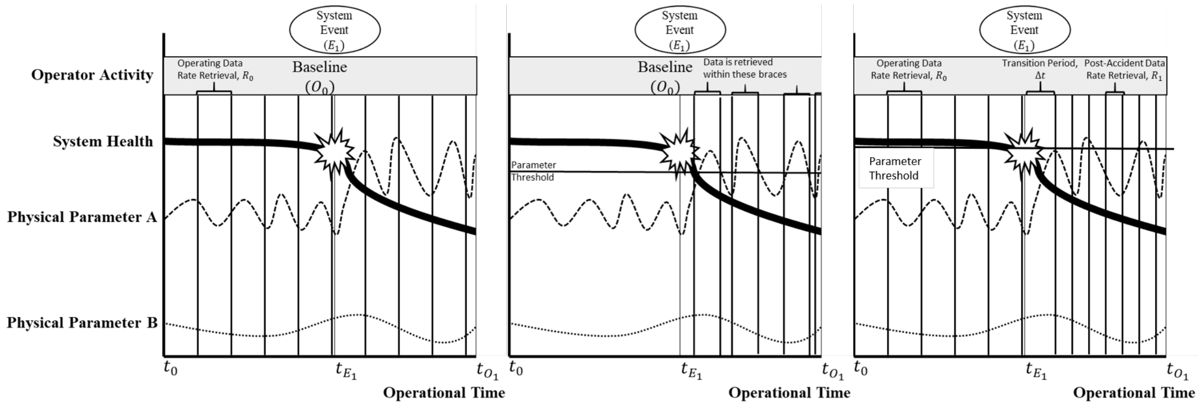
To evaluate the impact that different discretization strategies have on model performance, a total of fifty-six different DBN models (summarized in) are constructed using different discretization strategies defined by Lewis and Groth [18] and described in Sections 4.1-4.3. These models all have the same node structure shown in Figure 3; 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 alternatives for monitoring system health.

4.1. Constructing DBNs with Time-based Discretization

Table 1: Summary Description of Discretization Values Used in Model Comparison

Discretization	Descretization Description (Data collected…)					Number of Cases
Time-based	Every	9s	60s	120s	1200s	4
State-based	when reactivity greater than	-\$0.1	\$0	\$0.02	\$0.2	4
Hybrid-based	every X seconds until reactivity threshold; then, every Y sec					48

Figure 4: The CPTs in the DBN Compared in this Study are Generated from Data Derived by a) Time-based, b) State-based, and c) Hybrid Time-based Data Stream Discretizations.



(a) Time-based discretization (b) State-based discretization (c) Hybrid time-based discretization

DBNs constructed with a time-based discretization approach are built on data collected over a specified period, as shown in Figure 4a. Four different data collection frequencies are evaluated in this comparison: 9, 60, 120, and 1,200 seconds. As this case study covers a period of 86,400 seconds, these rates translate to DBN models 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 second 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 [17].

4.2. 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 Figure 4b. 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 each accident scenario. Net reactivity was selected as the triggering variable because 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. 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 system data associated with that time is included in constructing the relevant CPTs.

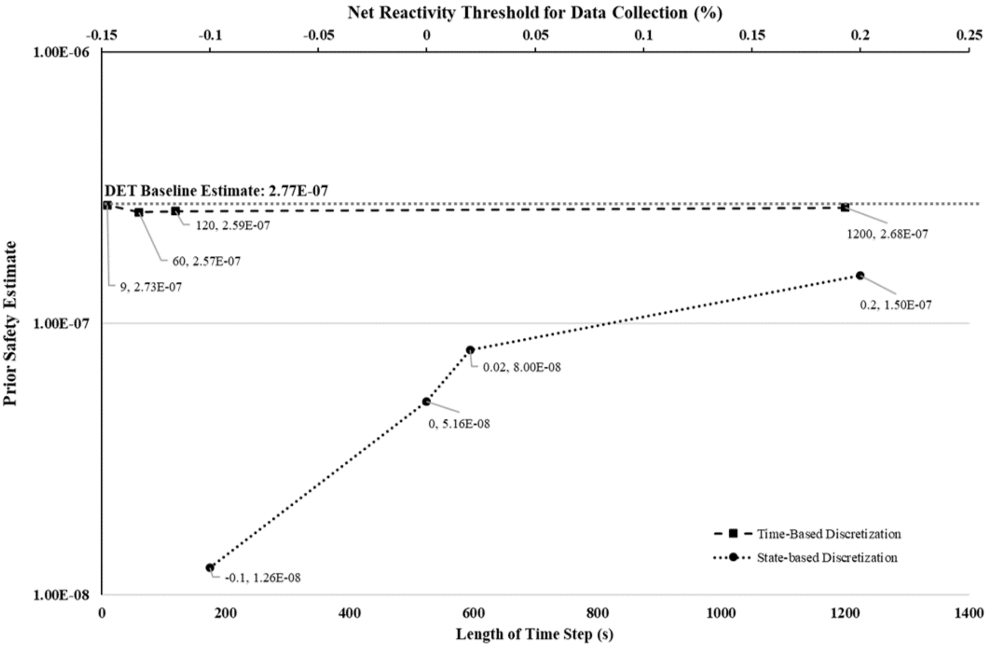
4.3. Constructing DBNs with Hybrid Time-based Discretization

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. This type of model is shown in Figure 4c.

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. 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.

4.4. Evaluating Assessment Accuracy

Figure 5: Prior Safety Estimates for DBN Models Constructed Using a Time- and State-based Discretization Approach Compared to the Baseline DET Estimate. Time-based Values (Dashed Line) Align with the Lower Axis, while State-based Values (Dotted Line) Align with the Upper Axis.



In this study, assessment accuracy means how well the model's prior estimate of system health matches the underlying system safety of the accident scenario. This is a common approach to 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.

This alignment estimate is determined by calculating the joint prior probability for the "System Health Diagnostics" node derived from the model's CPTs. The prior measurements for the last model step (86,400s or equivalent) are then compared in magnitude and by percent error to the DET assessment, calculated by the summation of failure probabilities, for the health of the system. 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.

5. RESULTS

Table 2 shows a selection of estimated priors from models built using the different discretization approaches and their similarity with the underlying DET's baseline health estimate of $2.77 * 10^{-7}$ following a TOP. The values lie roughly within an order of magnitude to the baseline estimate. The models that collect more data (1200s time step vs. 120s time step, and reactivity threshold greater than \$0.2 vs. greater than \$0) appear to produce more conservative safety estimates with greater percent error from the baseline estimate. This trend is further expressed in Figure 5, which plots the calculated safety assessment for each state- and time-based values (the DET value is included as reference). The exception to this is the model built with 9s time steps, which has the value most similar to the baseline

Table 2: Select DBN Model Prior Safety Estimates (vs. DET Baseline Safety Estimate of $\mathbf{2.77 * 10^{-7}}$)

	Time-based		**State-based**		**Hybrid Time-based**	
	120s	1200s	Net Reac. >=\$0	Net Reac. >=\$0.02	1200→ 120 @ Net Reac. <=0.02	1200→ 120 @ Net Reac. <=0.02
Prior Risk	2.59E-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%

Figure 6: Heat Map Comparison of Percent Error of Safety Estimates Across Models and Discretization Strategies.

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		-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%			

estimate. 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 Figure 6. The percent differences for time-based models (represented in the diagonal region) are consistently greater than the hybrid-based discretization models (the remaining values in the time-related portion of the table), but get progressively larger with smaller time step lengths. The upper-right hybrid model region is slightly worse than its diagonal counterparts, but the lower-left region is significantly further off from the baseline DET estimate and worsen with lower threshold states.

6. ANALYSIS

6.1. Analysis of State-based Discretization Model Performance

A DBN literature search by Lewis and Groth [18] 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 discretizaton. 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." The elimination of any data from certain scenarios is the transformation of CPTs across models and discretization values.

Table 3 shows the same portion of a CPT across different time-steps and threshold values considered for this study. 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

Table 3: Portion of “Radial" Node CPT over Different State- (Upper Table) and Time-based (Lower Table) Discretizations (“SCRAM" Node: “SCRAM Failure, Trip Success"; “RPS Pump" Node: “Operational"

React. Thresh.	**0.2**			**0**			**-0.1**		
DRACS	Enh.	Nom.	Deg	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.
Low	No Evid.	0.306	No Evid.	0.068	0.018	0.095	0.084	0.002	0.083
Middle	No Evid.	0.575	No Evid.	0.932	0.184	0.905	0.916	0.061	0.917
High	No Evid.	0.119	No Evid.	0	0.797	0	0	0.937	0
Time Step	1200s			60s			9s		
DRACS	Enh.	Nom.	Deg	Enh.	Nom.	Deg.	Enh.	Nom.	Deg.
Low	0	0	0	0.001	6.2E-06	0.001	0.001	1.3E-05	0.001
Middle	1	0.011	1	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

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. 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. 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

Models built with the time-based discretization approach were shown to have the most similar safety assessments relative to the baseline estimates. However, there were challenges in calculating CPTs for models with larger time steps; 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 second 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 3, 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. However, as these CPTs become relatively similar, the only noticeable difference becomes the amount of time steps present to represent the 86,400s 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

Table 4: Comparison of "Radial" Node CPTs for Time-based Discretization and Sample Hybrid-time Discretization

Select Portion of Radial CPT	Operational Context	1	2	3	4	5	6	7
Time-based Disc.: 120s time steps	Low	0.004	4.3E-06	0.0004	0.0004	0.006	0.0002	0.006
	Medium	0.996	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.: 60s 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: 120s until net reactivity >0.02, then 60s 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	0.999	0.148	0.945	0.162
Hybrid Time-based Disc: 120s until net reactivity >0.02, then 60s time steps	Low	0.0005	5.6E-06	0.0005	0.0002	0.006	0.0002	0.006
	Medium	0.9995	0.010	0.9995	0.001	0.845	0.028	0.831
	High	0	0.990	0	00.999	0.148	0.971	0.162
Hybrid Time-based Disc: 120s until net reactivity >0.02, then 60s time steps	Low	0.004	4.3E-06	0.0004	0.0005	0.006	0.0002	0.006
	Medium	0.996	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

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 approaching the same estimate as the time-based model that had a data rate measurement equivalent to the data generation rate. 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. 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 4 shows how the CPTs for a hybrid time-based discretization compare to the same CPT 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 select 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 affects 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.

6.4. Implications of Comparison Results

The differences in assessment accuracy 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 decisions made by dynamic risk model developers when determining what time discretization to use for a particular operational scenario.

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 an 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 present in Table 4 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).

6.4. Future Work

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 other metrics studies could indicate that there are substantial differences in the performances of DBN SIPPRA health monitoring models based on the discretization approach used to derive model CPTs. Considering other performance metrics for SIPPRA health models identified by Lewis and Groth [19] 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.

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 CES scenario 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. CONCLUSION

This paper presents the results of comparing assessment accuracy of fifty-six DBN-based SIPPRA health models for a sodium fast reactor experiencing a transient overpower built using different discretization techniques. The variations in assessment accuracy indicate that the modeling decisions one makes in the developing health monitoring models impacts this aspect of performance. State-based discretization resulted in less accurate models, while models built with a time-based discretization approach provided safety assessments that aligned more with the underlying data. Hybrid time-based models had the widest range of safety assessment predictions, making them potential design choices under the right conditions. Considering these differences 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.

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