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Predicting Complex System Reliability Through Neural Network Considering Interval Censored Component Failure Data With Dependencies

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Abstract

This research articulates a refined approach to predicting the reliability of complex systems, integrating interval-censored component data with neural network modeling. By transforming maintenance logs into predictive insights, our methodology addresses the challenge of indeterminate system architectures, a notable gap in the current literature. The neural network's capacity to interpret intricate patterns from partial data underpins our model's novelty. This study's contributions—spanning data preprocessing, reliability estimation, and model validation with augmented datasets—advance the intersection of machine learning and reliability engineering, promising enhanced predictive accuracy and interpretability for system reliability assessment.

Keywords: multi component systems, neural network modeling, reliability, maintenance, prediction

1. Introduction

System reliability prediction is a pivotal aspect of reliability engineering, aiming to ensure systems' uninterrupted and safe functioning across various industries. In contexts where system failures can translate into substantial economic losses, safety risks, or critical mission failures, establishing an accurate understanding of system reliability is paramount. Traditional approaches in reliability prediction often necessitate a comprehensive knowledge of the system's structure and the reliability of its components. However, the complexity of modern systems, coupled with limited accessibility to their internal architectures, makes this task challenging. Moreover, detecting component failures is frequently possible only after a system-level failure has occurred.

Recent advancements in machine learning (ML) and artificial intelligence (AI) present novel opportunities in reliability prediction, enabling the construction of models capable of deciphering intricate patterns from data, even when explicit information about the system's structure is unavailable. This paper introduces a unique approach that leverages empirical reliability data derived from maintenance logs and machine-learning techniques to estimate the reliability of complex systems.

Our primary objective is to build and validate a neural network-based model that predicts system reliability using real and augmented maintenance data. The transformation of maintenance records into interval-censored data allows us to estimate the reliability of individual components, which serves as a vital input for our predictive model. Our model strives to provide accurate and reliable predictions despite the inherent uncertainties and lack of explicit system structure information.

The paper's contributions are multifaceted, encompassing the development of the predictive model, the transformation and application of real-world maintenance data, the selection of appropriate distributions for component reliabilities, and the model's validation using real and augmented data. By addressing the challenges related to unknown system structures and harnessing machine learning capabilities, this work aspires to contribute to the fields of reliability engineering and machine learning, presenting an innovative approach to reliability prediction. Furthermore, it aims to furnish practitioners and researchers with valuable insights, potentially laying the groundwork for future advancements in reliability prediction models.

2. Literature review

2.1. Reliability Prediction in Complex Systems

Reliability analysis for multi-component systems is a complex task that requires a thorough understanding of the system's components and their interactions. Researchers often use stochastic models involving a set of probability distributions describing individual components' failure rates and their dependencies. One common approach is the use of fault tree analysis (FTA). FTA is a graphical method representing the system as a series of events and their dependencies. The top event in the tree represents the system failure, and the branches represent the different paths that can lead to this event. Researchers can estimate the system's overall reliability by analyzing the probabilities of the different events in the tree. Another approach is the use of Markov models. These models represent the system as a set of states and the transitions between them. The states correspond to the system's different operational and failure modes, and the transitions represent how the system can change from one state to another. Researchers can estimate the system's overall reliability by analyzing the probabilities of the different states and transitions (Gardoni, 2017).

However, these traditional models are primarily designed for non-repairable systems and rely on precise knowledge of the system reliability model, which is often unattainable in practical scenarios such as closed-loop supply chains (Wang et al., 2013). For example, maintenance and operation teams frequently lack access to detailed spare part designs, complicating the application of classical reliability models.

Additionally, the assumption of component independence does not hold in many practical contexts, as components often exhibit dependencies. This complexity was highlighted in our previous work, which identified dependencies among components in a repairable spare part system using field data from a GE HealthCare supply chain (Boujarif et al., 2024).

To address these dependencies, several researchers have adopted advanced statistical models. Copula functions are used to model the joint distribution of random variables by capturing their dependence structure without making assumptions about their marginal distributions. Given the marginal distributions of two or more random variables, a copula function can be used to construct a joint distribution function that reflects the dependence structure between the variables. (Navarro and Durante, 2017) propose a novel approach for assessing the reliability of coherent systems with dependent components using copula-based representations for residual lifetimes. The authors consider the joint distribution of component lifetimes in a coherent system and model the dependence structure using copulas. They then derive copula-based representations for the distribution of residual lifetimes of the system, which enables the calculation of various reliability measures, such as the survival function, the mean residual lifetime, and the failure rate. (Lin et al., 2021) propose a copula-based Bayesian reliability analysis method for parallel systems with dependent components, where the component failure probability and frequency are modeled separately. The authors use copulas to model the dependency structure between the component failure probability and frequency and apply Bayesian inference to estimate the parameters of the models. The proposed method is illustrated through a case study of a hydraulic system.

Selecting the best copula function depends on the data and the application. In general, the selection process involves two steps: model selection and goodness-of-fit testing. Several copula families, such as Gaussian, t, Gumbel, Clayton, Frank, and Joe, can be considered for model selection. One approach uses statistical criteria such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) to compare the goodness-of-fit of different copula models to the data. These criteria measure the balance between the goodness-of-fit and the complexity of the model, penalizing overfitting. After selecting a copula model, it is essential to test its goodness of fit to the data. Several tests can be used, such as the Cramer-von Mises test, the Anderson-Darling test, or the Kolmogorov-Smirnov test. These tests measure the difference between the empirical and theoretical copula distributions and can indicate whether the selected copula model fits the data well.

Other papers consider a specific copula-based approach to map the correlated variable with independent ones called Nataf transformation. Nataf transformation, also known as the Rosenblatt transformation, is a method used in statistical analysis to transform a set of correlated variables into a set of independent variables, which simplifies the statistical analysis process. This transformation involves a multivariate cumulative distribution function that maps the correlated variables into independent standard normal variables. The transformation is useful in applications such as structural engineering, where correlated loads and responses must be analyzed. The Nataf transformation simplifies the analysis by reducing the correlation between the variables. However, the transformation requires the estimation of correlation coefficients, which can be challenging, especially for high-dimensional problems. (Xiao, 2014) discusses the evaluation of the correlation coefficient for the Nataf transformation. The paper analyzes the properties of the correlation coefficient in the Nataf transformation and proposes a new method to evaluate it using a series expansion. The proposed method is then compared to existing methods through numerical experiments, demonstrating its effectiveness and accuracy. (Lin et al., 2020) propose an efficient probabilistic power flow (PPF) approach for high-dimensional correlated uncertainty sources in operation based on the Nataf transformation. The approach can model the uncertainties of power system parameters with continuous and discrete probability distributions and consider their correlations. The paper presents a modified algorithm to calculate the Jacobian matrix for the transformed variables, reducing the PPF approach's computational complexity. The proposed approach is demonstrated on a 118-bus power system and compared with the Monte Carlo and Quasi-Monte Carlo simulation methods.

These advancements underscore the shift in reliability analysis from simple, independence-based models to more sophisticated approaches that incorporate the real-world complexities of component dependencies and partial system knowledge. To apply these existing models directly, however, one still needs to assume knowledge on the system reliability function. How to consider component dependencies without knowledge of system reliability function remains a difficult challenge.

2.2. Neural Network Applications in Reliability Engineering

The exploration of neural network applications within the field of reliability engineering has yielded notable advancements across various domains. (Fink et al., 2014) successfully implemented multilayer feedforward neural networks to forecast the reliability of railway turnout systems, showcasing the networks' capability to predict long-term degradation without error propagation. In chemical production, (Zhao et al., 2020) introduced a hybrid model that fuses Support Vector Machines and Random Forest algorithms, refined by the 4M1E framework, to enhance the accuracy of system reliability assessments.

Furthermore, (Colombo et al., 2020) presented a machine learning model, rooted in the Finite Element Method, to predict the reliability of downhole safety valves. Their findings suggested a superior performance over traditional statistical methods, particularly when dealing with censored data. Addressing the challenges posed by limited data availability, (Li et al., 2021) advocated for an uncertainty theory-based approach for reliability evaluation, catering to situations where conventional statistical methods are inadequate.

The effectiveness of machine learning models in reliability prediction was also demonstrated by (Alsina et al., 2018), who compared various models against the Weibull distribution and other traditional methods, underscoring the strengths of methods like Random Forests, especially with increasing dataset sizes. Delving into survival predictions, (Kvamme and Borgan, 2021) discussed the integration of neural networks in the face of right-censored data, proposing novel interpolation schemes for continuous-time predictions.

In the healthcare sector, (Suresh et al., 2022) introduced MultiSurv, a deep learning methodology that integrates clinical, imaging, and omics data for cancer survival prediction, noted for its capacity to manage multimodal data and accommodate missing information. (Arismendy et al., 2020) employed a multilayer perceptron neural network to predict the behavior of wastewater treatment processes with a mean absolute percentage error that aligns with industry standards. Lastly, (Qi and Majda, 2020) explored deep learning strategies to predict extreme events within turbulent dynamical systems, emphasizing the potential applicability of such models to a spectrum of complex high-dimensional systems.

The collective insights from these studies highlight the transformative potential of machine learning and neural network methodologies in enhancing predictive precision, managing complex datasets, and contributing valuable insights across diverse sectors within reliability engineering.

Despite these advancements, the application of deep learning techniques on reliability using non-continuous data, such as maintenance logs, has been relatively limited. While the field has evolved to handle complex multi-sensor signals and high-dimensional data patterns (Gebraeel et al., 2009), using non-continuous, real-world data remains less explored (Wang et al., 2018). This suggests an untapped potential in harnessing non-continuous data forms for further enhancing the field of reliability analysis.

2.3. Challenges and Gaps in Existing Approaches

Traditional methods of reliability prediction in complex systems are often limited by the inability to process incomplete or censored data, the strong requirement of precisely known system structural function, and the challenges in handling high-dimensional data with dependencies. To address these critical gaps, we develop a neural network-based approach to estimate system reliability without assuming the system structure function. Our approach first estimates the reliability of individual components from maintenance data utilizing advanced interval censoring techniques. This method circumvents the common problem of data scarcity and censored information, enabling a more robust analysis. By harnessing the power of neural networks, we further refine the reliability prediction, as these networks can uncover complex, non-linear patterns from data, even without explicit knowledge on the system structural function. Our neural network model, therefore, not only predicts system reliability with greater precision but also enhances interpretability by incorporating domain-specific knowledge. By translating real-world maintenance logs into a format that neural networks can process effectively, we bridge the gap between data-driven models and practical reliability engineering. To sum up, our work presents a significant methodological advancement that tackles the prevailing challenges in the field, laying the groundwork for more accurate, reliable, and interpretable reliability predictions for complex systems.

3. Modeling and Problem Description

3.1. Problem description

Ensuring the reliability of multi-component systems is a critical concern in systems engineering, mainly when such systems are not under continuous surveillance. This study tackles the challenge of reliability estimation for systems where the state of the components is binary and can only be observed when a system outage occurs. During these outages, components are classified simply as either functioning or failed, and any failed components are replaced. Traditional reliability models, which often rely on known system structures and continuous monitoring, are not applicable in such scenarios.

Our research seeks to address this gap by proposing a novel method to estimate the survival probability of a system over a time period t , given the known ages of its components, expressed as $R_{sys}\ (t, a_1, a_2, a_3, \dots) = P(T_{sys} \geq t \mid C_1 \geq a_1, C_2 \geq a_2, C_3 \geq a_3, \dots)$, where $C_1, C_2, \cdots$ are the ages for the components. This method is crucial for systems where component statuses are only revealed through system failures, presenting a practical solution for predicting system reliability.

3.2. Methodology

Our approach to estimating the reliability of a multi-component system without continuous monitoring unfolds through a series of methodical steps. Initially, we undertake the collection of comprehensive maintenance records across diverse systems. This data assemblage provides a historical account of component failures and repairs.

After the data collection, the computation of component ages is done. Given the binary nature of component status -- operational or failed -- and the absence of continuous monitoring, we define an age interval for each component.

The minimum age denoted as T_{min} the time post the last known operational status or zero for new installations. Conversely, the maximum age, T_{max} corresponds to the failure detection time or is considered infinite for the components yet to fail (i.e., right censored).

The third step in our methodology involves fitting multiple parametric distributions to the age data, governed by the assumption of interval censoring to estimate the reliability functions of the components. The statistical model that best fits the data is selected based on the Akaike Information Criterion (AIC), which is defined as:

$$AIC = 2k - 2\ln(L) \tag{1}$$

Where k is the number of estimated parameters within the model, and L is the maximized value of the likelihood function for the model. The likelihood for an interval-censored component i is then expressed as:

$$L_i(\theta) = \begin{cases} F(T_{max,i}; \theta) - F(T_{min,i}; \theta), \ if\ T_{max,i} < \infty \\ \quad 1 - F(T_{min,i}; \theta), \ if\ T_{min,i} = \infty \end{cases} \tag{2}$$

Where F is the cumulative distribution function associated with the failure time distribution of the components, and θ represents the parameters of that distribution. For a right-censored observation, $F(T_{max,i}; \theta) = 1$ and the likelihood function simplifies as $1 - F(T_{min,i}; \theta)$.

The fourth step is empirically estimating the system's reliability, as defined earlier in Section 3.1. We apply the Kaplan-Meier estimator, a non-parametric statistic used to estimate the survival function from lifetime data. In our case, it is utilized on the data subset where the components' ages exceed the age combination at which we aim to evaluate the system's reliability.

The dataset is further enriched through data augmentation, where new uniform data points are generated using the parametric distributions of component ages and the Kaplan-Meier distribution.

Finally, a neural network with multiple hidden layers, inclusive of dropout layers, is trained to predict the system's survival probability. The network's input layer receives three reliability estimates for each component: the reliability at the current age, at time t, and at the age incremented by t. The output is a single value between 0 and 1. The network is trained using a mean absolute log error loss function, adjusted to avoid the logarithm of zero:

$$Loss = Mean(\ |\log(y\_prediction + \epsilon)\ -\ \log(y\_actual + \epsilon)|) \tag{3}$$

Where ϵ is a small constant to ensure numerical stability.

3.3. Experimental set-up for Algorithm Validation

The experimental design for our reliability estimation algorithm is centered around creating a controlled environment that mimics real-world multi-component systems. This is achieved by defining four Bayesian Networks (BNs) representing different system architectures: serial, parallel, bridge, and random. These networks model the relationships between the components and the overall system status. The crux of these models lies in their Conditional Probability Distributions (CPDs), which dictate how the system's state relates to the states of the individual components.

In the serial system, the BN is set such that the system fails if any single component fails while the system stays operational as long as not all components fail for the parallel system. The bridge and random structures follow more complex dependencies reflected in their respective CPDs. The CPDs for these structures are designed to maintain the coherency of the system, meaning the system cannot be more reliable than its least reliable component.

Once the BN structures are in place, we assign a specific lifespan distribution to each component, reflecting how we expect these components to behave over time. The time of observation and the steps for the simulation are then established, with N representing the total number of systems we will simulate.

The data generation process starts by calculating the initial reliability of each component. These reliability scores serve as the initial probabilities for the BN component nodes. From here, we simulate N observations of system states at the first step.

As time progresses, for each component that has not failed, we calculate the conditional probability that it will continue to operate until the next interval, given its current age. This probability updates the component's CPD in the BN. If a component fails, we record this and update the system state accordingly. If the system is still operational, we introduce the component's failure as evidence in the BN and draw a new sample for the next step.

This process is repeated for each time step until we reach the end of our observation period. If the system fails, we reset the failed components' ages to zero and update their reliability to reflect the new components.

The resulting data set captures the various states of the system and its components over time. Our analysis focuses on the data points where system failure occurred. Using the BN and the lifespan distributions we assigned earlier, we calculate the probability that the system would have lasted longer than it did, given the ages of the components at the time of failure. This calculated probability is our benchmark, representing the 'true' system reliability we use to assess our algorithm's performance.

3.4. Results and analysis

In our investigation, we simulated the lifespan of 500 systems over a period equivalent to five years, measured in unit time intervals of 30 days. Each system comprised six components, with their time-to-failure (TTF) following an exponential distribution characterized by mean values of $(365, 1000, 450, 1600, 470, 800)$ respectively, to mirror a realistic variance in component longevity. We split the generated data into train and test data sets, where we used the train set to derive the components' reliability and train our NN model and the test set for performance evaluation.

To quantify the predictive accuracy of our model, we employed two error metrics: *Mean Absolute Error* (MAE) and *Mean Absolute Percentage Error* (MAPE). These were chosen for their ability to capture average deviations and relative discrepancies from the true reliability values, respectively. To mitigate the distortion of error metrics due to small denominators, we incorporated a shift of 1 into the MAPE calculation, as described by the following equations:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \widehat{y_i}| \tag{4}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left|\frac{y_i - \widehat{y_i}}{y_i + 1}\right| \tag{5}$$

where y_i represents the true reliability values estimated using our generated bayesian network model under the assumption of known structure and known component's reliability and $\hat{y}_i$ denotes the estimated reliability from our developed approach.

The outcomes of this evaluation are succinctly encapsulated in Table 1, which delineates the MAE and MAPE across various system structures.

Table 1. Summary of Model Error Metrics Across Different Structures.

Error Metrics	Series Structure	Parallel Structure	Bridge Structure	Random Structure
MAE%	12	36	0.08	19
MAPE%	7.7	20.18	5.2	12.43

The analysis of the model's performance in predicting system reliability demonstrates varied error magnitudes contingent upon the structural archetype in question. This variation underscores the model's sensitivity to distinct system configurations. A synthesis of the results indicates a MAPE that fluctuates significantly, with a modest 5% in the bridge configuration and a more pronounced 20% in parallel systems. Generally, the model's predictions fall within a tolerable error range, affirming its practical value for reliability assessments. Nonetheless, the disparity in error magnitudes across various structural paradigms calls for an in-depth analysis to identify and understand the underlying causes of these discrepancies.

In our in-depth examination of the model's performance, we have attributed variability to several sources of uncertainty inherent in our methodological approach. This method relies on interval-censored data to estimate component reliability and construct an empirical multivariate survival distribution for system reliability labeling. Subsequently, this labeled data trains a neural network to predict the system's reliability. Our scrutiny reveals three principal sources of uncertainty:

- The uncertainty in the reliability estimates of individual components.
- The uncertainty embedded in the system reliability assessment process.
- The uncertainty inherent to the predictions generated by the deep neural network.

A critical aspect of our evaluation involved contrasting the neural network's predictions against those derived from the Kaplan-Meier estimator, considered the standard for true system reliability. This juxtaposition evaluated our model's adeptness under the hypothetical scenario where we could ideally ascertain the system's empirical reliability.

Table 2. Comparison of Model Error Using Kaplan-Meier Estimates vs Theoretical Reliability.

Error Metrics	Baseline R	Series Structure	Parallel Structure	Bridge Structure	Random Structure
MAE%	Kaplan-Meier	9	28	7	1
MAE%	Bayesian network	12	36	8	19
MAPE%	Kaplan-Meier	7.17	17.85	5.15	7.95
MAPE%	Bayesian network	7.7	20.18	5.2	12.43

Table 2 showcases the error metrics when using the Kaplan-Meier as a proxy for the true system reliability against theoretical reliability computations. Notably, the error margins contracted in all scenarios when benchmarked against the empirical reliability standard, suggesting that a refined approximation of true empirical reliability could significantly improve the model's accuracy. This is particularly evident in non-parallel structures, where the MAE and MAPE are markedly reduced. This insight propels us to suggest future research directions focused on enhancing the labeling process for training data and exploring training methodologies that incorporate confidence intervals. Delving into deep learning models adept at managing aleatory uncertainty could also yield more resilient predictive performance.

On the other hand, the use of interval-censored and right-censored data introduces another layer of uncertainty. These types of censoring can lead to inaccuracies in estimating component failure distributions and, subsequently, the system's survival distribution. Such inaccuracies are reflected in the model's Mean Absolute Error (MAE) when predicting the reliability of individual components within each structure. Specifically, the inherent data pattern of parallel structures — where system failure is predicated on the concurrent failure of all components — could inadvertently lead to the presumption that components share a uniform failure distribution.

A detailed graphical analysis, as shown in Figure 1, compares estimated reliability functions against actual data for selected components within various structural configurations. The divergence between the estimated and true reliability of components in each structure shows a mixed level of accuracy from the model. In series and bridge structures, the model estimates are pretty close to the true reliability, with only minor divergences, suggesting a good fit. The parallel structure exhibits a significant divergence, particularly as time progresses, indicating the model's challenges in accurately capturing the system's behavior where the failure of all components is required for system failure. The model demonstrates a slight but consistent underestimation across components in the random structure, reflecting a partial capture of the system's complex structure.

We utilize the Kullback-Leibler (KL) divergence in addition to MAE and MAPE to quantify this divergence. KL is a measure of the discrepancy between two probability distributions. For discrete distributions P and Q, the KL divergence is defined as:

$$D_{KL}(P||Q) = \sum_i \log\left(\frac{P(i)}{Q(i)}\right) \quad (6)$$

where $P(i)$ represents the true probability and $Q(i)$ represents the estimated probability of the i-th event. This statistical measure is particularly effective in highlighting the differences in expected versus observed outcomes.

Table 3 provides a quantitative assessment of this divergence. The Kullback-Leibler (KL) divergence and Mean Absolute Error (MAE) values are generally low in the bridge and series structures, suggesting a closer match between the estimated and true reliability distributions. The MAPE is also relatively low, indicating a more minor relative error. Conversely, the parallel structure shows notably higher values in all three metrics, particularly the MAPE, which indicates a significant relative error in the model's reliability predictions. The random structure exhibits moderate divergence and error values, with the MAPE indicating more substantial relative errors than the bridge and series but less than the parallel. Across all structures, there is a discernible variation in error rates, with the average divergence reflecting the aggregated disparity between the estimated and true distributions for each structure.

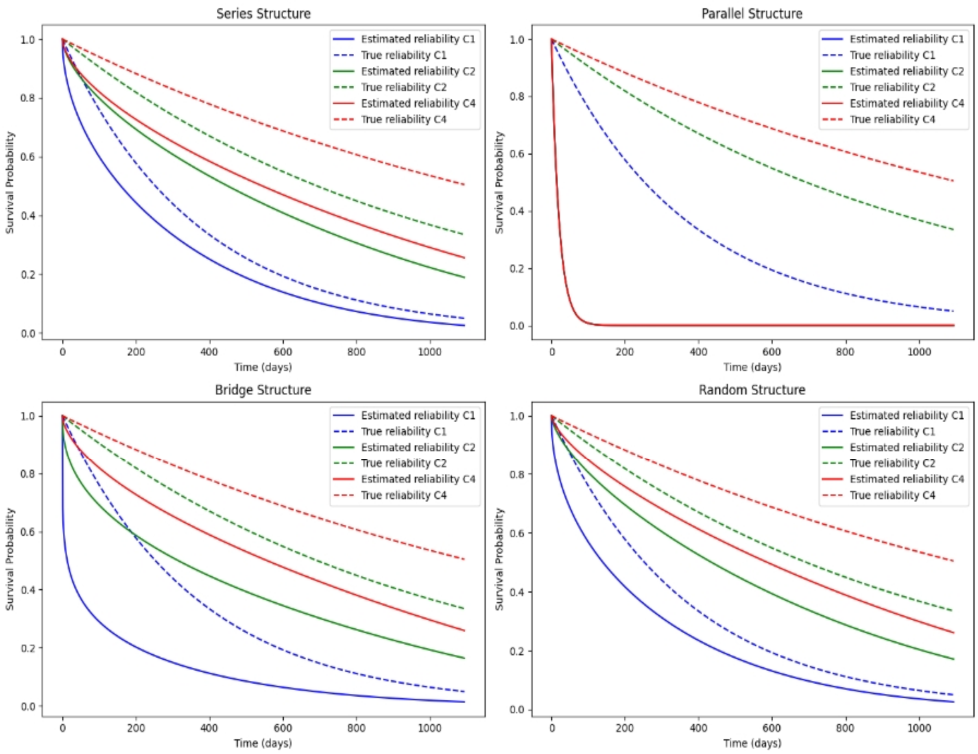

Fig. 1. Estimated vs. True Reliability Functions for Components in Different Structures.

Table 3. Summary of MAE, MAPE and KL divergence metrics.

Structure	Metric	C1	C2	C3	C4	C5	C6	Average divergence
Bridge	KL Divergence	0.023	0.7636	0.0456	1.2803	0.0605	0.2481	0.4035
	MAE%	0.0638	0.127	0.0287	0.2014	0.0586	0.0897	0.0949
	MAPE%	5.9374	10.3767	2.6246	14.8782	5.3369	7.6271	7.7968
Parallel	KL Divergence	8.9907	13.4423	10.1267	14.5871	10.3513	12.6974	11.6992
	MAE%	0.0943	0.2612	0.1176	0.3879	0.1231	0.2112	0.1992
	MAPE%	8.7758	21.3416	10.7547	28.6556	11.2111	17.958	16.4495
Random	KL Divergence	0.0195	0.3157	0.0515	0.644	0.0622	0.1639	0.2095
	MAE%	0.0294	0.107	0.0373	0.1934	0.0367	0.0797	0.0806
	MAPE%	2.736	8.7426	3.4111	14.2872	3.3424	6.7768	6.5494
Series	KL Divergence	0.026	0.322	0.0283	0.5329	0.0274	0.149	0.1809
	MAE%	0.0259	0.1015	0.0363	0.198	0.0372	0.0742	0.0788
	MAPE%	2.4103	8.2932	3.3197	14.627	3.3879	6.3091	6.3912

The comparison of the average divergence in MAE from Table 3 with the MAE for the baseline *Bayesian network* in Table 2 suggests that the uncertainty in the reliability estimates of individual components is the primary error source affecting the model accuracy. For the bridge structure, the average divergence in MAE was low, and this aligns with a low MAE for the baseline in the bridge structure, indicating consistent and accurate predictions. However, in the parallel structure, the average divergence in MAE was relatively high, mirrored by a high MAE value, underscoring significant predictive discrepancies. This pattern reflects the model's relative reliability and areas where improvements are needed, especially in the parallel structure where predictive performance is notably weaker.

In summary, the devised methodology demonstrates a competent capacity to estimate the reliability of complex systems within an acceptable margin of error. This model is particularly adept when applied to systems characterized by intricate structures or varied failure mechanisms. Nonetheless, the accuracy diminishes notably when addressing systems with parallel structures. The precision of predictions is considerably influenced by the breadth of interval censoring and the fidelity of empirical survival function estimates for system reliability. For future endeavors, it is suggested that research explores the application of autoencoder algorithms, which can discern the distributions of component and system reliability intrinsically, thereby obviating the requirement for separate data point labeling.

4. Conclusion

Concluding this paper, we have presented a novel approach for predicting the reliability of complex systems, leveraging neural network modeling in conjunction with interval-censored data on the component level. Our model showcases a robust predictive ability for various system structures, delivering estimates within a reasonable error threshold. This is particularly noteworthy in systems with diverse and intricate failure dynamics, where traditional predictive methods may not work well.

However, the model's performance indicates a limitation in accurately capturing the behavior of parallel system structures, where the interdependencies and collective failure modes present substantial challenges. The accuracy of our predictions is closely tied to the precision of interval censoring and the quality of the empirical system reliability estimates, which are pivotal factors in the model's training and subsequent performance.

Looking ahead, further advancements in this domain are crucial. A promising direction for future research lies in the utilization of autoencoder algorithms. These algorithms can directly learn the underlying distributions of component and system reliability from the data. They could streamline the modeling process, reducing the dependence on separately labeled data points and enhancing the model's ability to generalize across various structures.

This work's implications extend beyond academic inquiry, offering tangible benefits for complex systems' design, maintenance, and operation. By improving the accuracy and reliability of predictive models, we can better anticipate system failures, optimize maintenance schedules, and mitigate potential risks. Consequently, this contributes to the advancement of reliability engineering and has the potential to inform more resilient system designs in the future.

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