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ORIGINAL RESEARCH

Reliability assessment of supply chain digital twin: an integrated Markov Chain and Bayesian Network approach

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Abstract
Fluctuations in communication networks can significantly affect the performance and reliability of a digital twin. High latency can disrupt synchronization, low bandwidth can result in loss of data or delayed, and communication networks are vulnerable to different cyber-attacks. Variability in communication networks can reduce the reliability of a supply chain digital twin. So, this study presents a reliability assessment framework for supply chain digital twin using an integrated approach of Markov Chains and Bayesian Networks. The reliability model implements Markov Chain structures to handle the three network characteristics which include latency, bandwidth, and cybersecurity. Data transmission and security in digital twin systems experience dynamic disturbances due to fluctuations in these network characteristics. A Bayesian Network developed to show communication network factor dependencies on supply chain performance indicators such as visibility, data transmission velocity and lead time using system current data status. The study highlights how varying network factors influence the performance and resilience of supply chain operations, providing valuable insights for improving decision-making and risk management in digital twin applications.

Keywords Digital twin · Supply chain · Markov Chain · Bayesian Network · Reliability

1 Introduction

Digital Twins (DTs) creates virtual replicas which enable real-time monitoring, simulation, and scenario analysis which can excel decision-making process (Huang et al. 2024; Le and Fan 2024). DTs are becoming very important in various fields including supply chain for carrying out lean strategies, enhancing the performance and improving the reliability of the systems (Guo and Mantravadi 2024a; Barykin et al. 2020). DTs facilitate monitoring, controlling and decision making in current planning, manufacturing, and delivery processes (Guo and Mantravadi 2024a; Orozco-Romero et al. 2020). Current planning, manufacturing and delivery processes can be enabled by DTs for monitoring and controlling as well as making decisions depending. DTs can enhance the certainty of supply chain by adding operational and critical risks (Barykin et al. 2020). When incorporated with agent-based models, they help present dependency relations of different aspects of a supply chain and improve the optimality of risk management (Orozco-Romero et al. 2020). DTs assist supply chain Networks to deliver higher visibility, productivity and credibility in tackling the raw risks occasioned by competition from

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worldwide and other rising forces (Ghabak and Chaugule 2024) in 2024. DTs are gaining the status of versatile solutions for solving problems related to supply chains in the food sector (Melesse et al. 2023; Huang et al. 2024). Despite the current modest number of case studies on DT applications in supply chain management published in the management literature, the prospects for enhancing efficiency, accountability, and robustness are vast (Lugaresi et al. 2023; Le and Fan 2024). Several challenges are discussed in the context of implementing of DTs and these are Technological Assessment, Performance Evaluation, and Integration complexities, according to (Huang et al. 2024; Melesse et al. 2023) Nonetheless, DTs' potential may be utilised to tackle global concerns in Agri-food value chain, however, practical implementations remain quite nascent at the current stage (Melesse et al. 2023). Future research should follow the avenue of: Innovative methods of applying establishing analytical and modelling methods, which can address the challenges or execution and use of DTs for effective supply chain management (Le and Fan 2024; Lugaresi et al. 2023). For a reliable DT, a reliable communication network is profound; however, reliable DTs encounter numerous challenges such as data quality problems pertaining to missing or conflicting real-time data, limited network qualities such as low latency, limited bandwidth, and security risks and these communication network characteristics shows the hidden interdependencies with supply chain performance metrics like resilience, forecasting accuracy, and data transmission velocity. Additionally, scalability and the synchronization of physical and digital systems add layers of complexity to reliability assessment (Tao et al. 2019). The focus of this study is to highlight the increasing importance of reliable communication systems in realizing the full potential of DTs in supply chain management. To assess the reliability of DTs in supply chain, this study has following two objectives.

1. Markov Chain Modelling to capture the dynamic state of the communication network specifically latency, bandwidth, and cybersecurity for assessing their impact on supply chain DTs.
2. To model the dependencies of the communication system on supply chain performance metrics such as Visibility, Lead Time, and data transmission velocity using Bayesian Networks (BN), enabling a comprehensive reliability analysis of DTs.

This paper offers several significant implications to the existing literature of DT reliability assessment, especially in the supply chain context. It proposes an integrated conception based on Markov Chain for modelling the dynamic states of communication system factors namely; latency, bandwidth, and cybersecurity in relation to BN for modelling dependencies of the supply chain performance in terms of resilience, forecast accuracy and data transmission velocity. This is an approach that has not been used before in analysing reliability of DTs and is innovative because it solves both the problem of temporal changes in the underlying system and accounts for probabilistic correlation in the system's behaviour. Moreover, a case study is provided based on a supply chain context to show how system performance is predicted under different conditions and how decisions are made towards improving the resilience of supply chain systems. The study encompasses a novel method for assessing and enhancing the reliability of DTs in diverse and complex working environments.

The paper first introduces DTs and its applicability in supply chain systems, then discuss the state-of-art reliability assessment techniques in literature review. The paper has its methodology focused in the integration of Markov Chain and a BN, and the case study illustrates an application of this on a supply chain system. Subsequently, it presents the findings, followed by a discussion and comparison with prior methods, as well as highlights of the study's main conclusions, limitations, and directions for further research.

2 Literature review

2.1 Reliability assessment of DTs

Mimicking of supply chain using DT brings substantial opportunities for increasing supply chain transparency, effectiveness, and robustness. These virtual systems mimic actual counterparts to allow real-time monitoring, simulation, and control purposes (Freese and Ludwig 2021). In lean supply chains, DTs enable better and unifying customization to enhance processes and cut costs in the planning, production, and distribution environments in the lean supply chains (Guo and Mantravadi 2024). They enhance organizational decision-making and teamwork, according to a pharmaceutical organization case (Marmolejo-Saucedo 2020). DTs can be classified along six dimensions: scope, actor, asset, flow reference object, performance measurement, and supply chain process, (Srai 2019). Not limited to factory operations but works well in wider supply chain environments thus holding advantages concerning control, repeatability, and cost. Nonetheless, it is seen that much more work is required in areas like Supply Chain Digital Twin Mapping, Convergence, and Cognition to fully unleash the capability (Guo and Mantravadi 2024).

The literature analysis reveals that reliability assessment of DTs is a current area of research emphasis across diverse domains. Past researches bring out the reality that previous patterns are insufficient for compound systems such as software defined manufacturing which demands self-automated and continual reliability estimation by using hybrid models and model-to- model transformation (Grimmeisen et al. 2022). In the electrical industry generally, DT is a promising application for the evaluation of power system reliability (Biard and Abdul-Nour 2022).For example, in case of DC/DC converters the typical submarine and space applications, ripple peak-to-peak measurements in combination with Markov models and DT show how to achieve real-time reliability assessment without new measurement points (Xia et al. 2023). For DT applications, this work introduces the concept of 'Reliability-by-Design,' which posits reliability as a critical consideration at every phase of the process to optimize performance, inform decision-making, and maximize resilience while minimizing expenditures (Syrine Ben Aziza 2024). Such improvements indicate that reliability assessment becomes increasingly significant for DT applications in different sectors.

2.2 Markov chains for dynamic network modelling

The dynamic states in diverse systems have earlier been modeled using Markov chain modeling. In gas turbine engines, it has been used to condition monitoring, with both deterministic, and stochastic aspects are taken into consideration to yield better HSMS (Health and State Monitoring Systems) (Arkov et al. 2002). It encompasses the identifiability analysis and model estimation, and provide more flexibility as well as versatility than the conventional dynamic modelling technique (Jeon 2016). In automotive applications, Markovian processes have found use in the characterization of operating states and the behavior of the systems; stochastic dynamic programming and model predictive control known as the operations have also used Markov chains (Kohn 2017). The approach is also applicable to biological systems including describing pyelonephritis-associated pili expression in uropathogenic Escherichia coli. In this application, the model was shown to produce data consistent with more computationally demanding approaches whilst enabling further analysis of more regulatory characteristics (Zhou et al. 2005). Altogether, the application of Markov chain modeling is viable in ensemble of the dynamic state in numerous domains and supplies a satisfactory matching point of the system behavior in addition to its computational efficiency.

2.3 Bayesian networks for dependency modelling:

It pointed out that BNs and Dependency Networks (DNs) are two models of dependencies that can be applied to different domains. BNs are good tools for modelling the failure dependencies in the access control systems, which, in its turn, help to improve the security analysis (George 2021). To learn BNs from DNs there is an effort to make use of the effective learning algorithms of DNs that are competent to be large and used in conjunct with the convenient realization of BN inferences (Scutari 2019).This approach has been ideal for developing Bayesian classifiers since it benefits from the easy learning procedure of DNs, although it retains classification (Sucar 2021). It has been proved that the proposed DN-based classifiers can achieve the level of accuracy comparable to the other well-developed Bayesian classifiers such as Tree Augmented Naïve Bayes (TAN) or Bayesian Augmented Naïve Bayes (BAN) with the additional advantages of factorized model, extendibility, and better interpretability of relations (Sucar 2021). These studies show that DNs can be used as a training platform for learning the BNs especially where scalability is of paramount importance as it observed with large applications.

2.4 Enhancing DT reliability

DT solution is already proving its usefulness in many domains of industries, smart cities, and healthcare industry. DTs allow checking a physical system in real-time and, if necessary, perform the necessary control and optimization procedures (Groshev et al. 2021; Laaki et al. 2019). Yet, the reliable DTs are a challenge due to such parameters like latency, bandwidth, and cybersecurity. 5G and similar very reliable and very low latency data transferring networks are critically important in real-time applications and remote control (Groshev et al. 2021).Two major threats are inherent to cybersecurity: unauthorized access and data manipulation; both threats are conspicuous during the implementation of DT in smart cities (Maheshwari et al. 2024). Hence to overcome above mentioned challenges, new layers security models which include encryption, access control, and anomaly detection models have suggested (Maheshwari et al. 2024). Furthermore, the different DTs needs to satisfy several restrictions such as latency, reliability, scalability, and privacy (Qian et al. 2022). That is why future research directions should address issues related to further increase of DT performance, the creation of new services based on DT, the improvement of security and privacy, and the safe and efficient implementation of the DT technology in different areas. Despite improvements made within the field, modern scholarship related to the implementation of DTs for SCM still lacks an adequate understanding of the relationship between the reliability of the communications system and the corresponding supply chain. High quality communication solutions play a vital role for companies in getting the most out of DTs as they introduce continuous and efficient syndication of data and further improve decision making and business continuity. Therefore, the dependence between the communication network and the digital twins of supply chain assets and logistics must be defined quantitatively to ensure the proper exchange of information and increase organizational decision-making and operational redundancy.

This understanding allows the design of robust, resilient systems that can meet performance needs such as latency, bandwidth variability, and cybersecurity threats which are essential characteristics of sustainable DT solutions for SCM.

3 Methodology

The methodology involved in the current research has been shown in Fig. 1 which outline the complete research methodology employed in this paper. The methodology can be broadly categorised into four stages, as the figure illustrates: the identification of communication network factors and Supply chain performance factors and the examination of interdependency among these factors. In order to create a list of the most prevalent factors, the identification stage entails extracting factors from the body of existing literature and consulting with academics and business experts. Nonetheless, it is possible to conclude that the indicators are interdependent based on their definitions and the opinions of professionals in the field. Supply chain visibility together with coordination improve when organizations use reliable communication channels to transmit critical business data including orders alongside inventory levels production schedules and shipment status information (Giannakis et al. 2019). The incidents of security breaches or data leakages lead to multiple severe outcomes that produce both financial costs and reputational damage and generate legal responsibilities which essentially interrupt supply chain activities while diminishing stakeholder trust (Tahmasebi 2024). An expert survey questionnaire involving academics and practitioners was distributed to acquire input that produced these results. This research examined factors using Fuzzy Delphi Technique (FDT) to prioritize and rank factors while handling procedural ambiguity and uncertainty (Roldán López de Hierro et al. 2021). FDT remains a common methodology which scientific communities use throughout engineering and social sciences alongside business management and education to gain enhanced understandings of intricate decision situations (Tahriri et al. 2014). Results from FDT has been shown in the next section. After identifying the critical factors related with network characteristics and supply chain DT performance, an integrated Markov Chain and BN model was developed to assess the interdependency between communication network factors, such as latency, bandwidth, and cybersecurity, and key supply chain DT performance factors, including Visibility, Lead Time, and data transmission velocity. The integrated technique enables complete analysis of

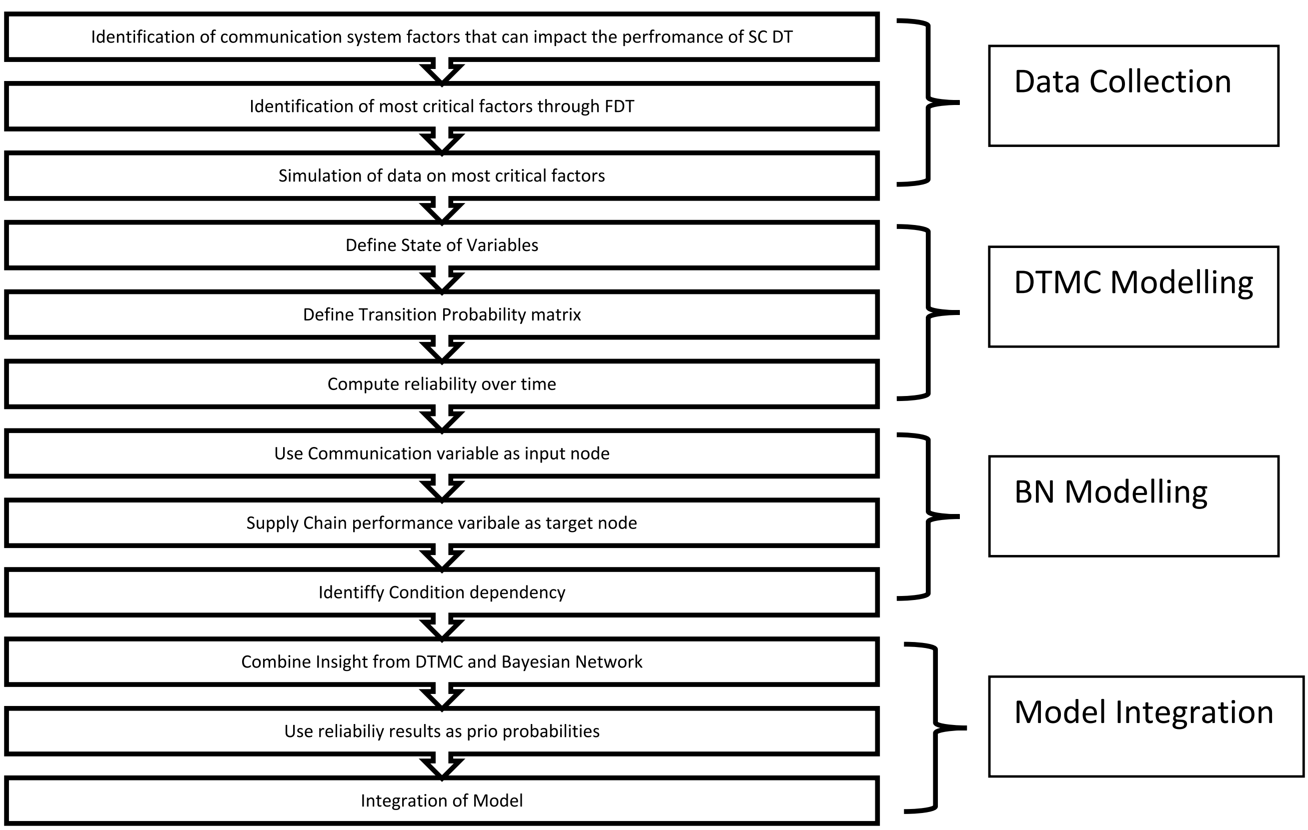

Fig. 1 Framework for reliability assessment of supply chain digital twins using Markov Chains and Bayesian Networks

shifting interplay among these factors which yields beneficial insights about supply chain DT performance and reliability.

3.1 Fuzzy Delphi technique

The Fuzzy Delphi Technique integrates traditional Delphi Technique with Fuzzy logic to bring consensus of experts on subject matter. Compared to the classic Delphi method, the Fuzzy Delphi Technique allows for a more nuanced and flexible approach to obtaining expert viewpoints. It is especially helpful in circumstances when subjectivity and uncertainty are high. Here's a detailed explanation of the steps involved.

Step-1: Define the problem and Expert Selection

Clearly define the problem, develop a questionnaire, and select a panel of experts who have knowledge and experience related to the problem.

Step-2: Define the scale of evaluation

To determine the significance of the criteria that follow the fuzzy linguistic scale shown in Table 1, experts are consulted in the first phase. Triangular fuzzy numbers (TFNs) are used in this research because of their wide range of applications in multiple-criteria decision analysis and their ease of calculation. Three elements make up the TFN: the lowest value (l), the average value (m), and the greatest value (u) (Kozarevic 2018).

Step-3: Evaluation of criteria by expert panel.

Then, the professionals and experts are consulted to assess the relative importance of factors through a survey. The Opinion of each expert per factor are obtained following the linguistic scale defined in the previous step.

Step-4 Acquire crisp values.

A crisp set that is closest to the fuzzy set as feasible is now the process of converting expert judgement into crisp values (Elmousalami 2018). Equation (1) yields crisp numbers. where C_j is the crisp value, L_j is the average of the lowest values l, M_j is the mean of the average of the values m and U_j is the average of the highest values u given by experts.

$$C_j = \frac{L_j + 4M_j + U_j}{6} \tag{1}$$

Step-5 Selection requirements.

Table 1 The linguistic scale and TFNs for Delphi Technique

Linguistic variable	Equivalent TFNs
Extreme Importance	(0.75, 1.00,1.00)
Demonstrated Importance	(0.50, 0.75,1.00)
Strong Importance	(0.25,0.50,1.00)
Moderate Importance	(0.00,0.25,0.50)
Equal Importance	(0.00,0.00,0.25)

Source: (Tseng 2018)

Choosing the criteria to be included in the study in accordance with the selection requirements is the final phase of the FDT. Equation (2), which presents the vertex approach provided by Chen (2000), is used to determine the consistency (d) of the judgements.

$$(M, m) = \sqrt{\frac{1}{3}[\left(L - l_{ij}\right)^2 + \left(M - m_{ij}\right)^2 + (U - u_{ij})^2} \tag{2}$$

where M= (L, M, U) is the average of the diffused values and m = (l_{ij}, m_{ij}, u_{ij}) are the diffused values. (Cheng, 2002) state that when the value of d is less than or equal to 0.2, the judgement is regarded as consistent. Furthermore, it is believed that a consensus greater than 0.75 is necessary (Murry, 1995). The following limitations form the basis of the criteria selection process:

- If $d \le a0.2$ and $c_j \ge 0.75$, then j is accepted as necessary.
- When $d \ge 0.2$ and $c_j \le 0.75$, the criterion j is disqualified.

Criteria will only be chosen if the consensus is more than or equal to 0.75 and the degree of inconsistency is less than or equal to 0.2; criteria that do not meet these requirements will be disqualified.

3.2 Bayesian network

A directed acyclic graph as Pearl (2014) called Bayesian Network appears in the Fig. 2 depict probabilistic connections between multiple variables. The network contains nodes to represent variables that follow random distributions

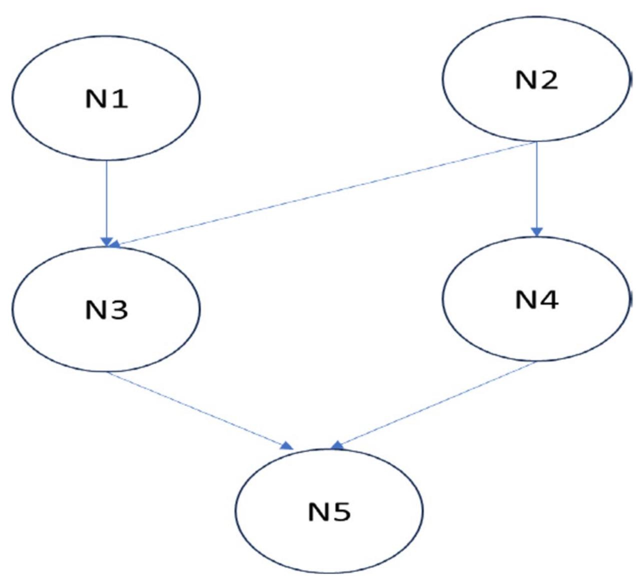

Fig. 2 Simple Bayesian Network

and links express dependencies between those variables. In this particular network: Random variable is represented by nodes (N_k) and edges represent dependencies between variables. Each node k within the network represents a random variable (N_k) that describes a specific system component (e.g., Latency (C1): Delay in communication, representing the time it takes to transmit information between locations. in the context of this study). Immediate predecessor of Node (N_k) is the parent node represented as P_a (N_k), as shown in Fig. 2 N1 is parent node of N3. The Joint Probability distribution is denoted by equation given below:

$$P(U) = \prod_{k=1}^{n} P\left[N_k | P_a(N_k)\right] \tag{3}$$

The odds that something will occur become known through conditional probability computations once another specific event has already taken place. Every connection in a BN shows the conditional probability between the corresponding linked nodes [e.g., P (N3| N2, N1) in Fig. 2]. Bayesian Network uses its Conditional Probability Tables or CPTs to display how different parent node values combine for computing node distribution probabilities. Those nodes without parental components refer to prior probabilities located within the CPT (Wang and Zhang 2017). Quantitative aspects within a Bayesian Network are encoded through CPTs thus allowing joint probability calculation and inference execution (Zhang 2016). A Bayesian Network appears as a figure that displays random variables through nodes while edges represent dependency relations between them. Through the marginalization rule applied to P(U) experts can determine each variable's marginal probability (Ren et al. 2008).

3.3 Discrete Time Markov Chain (DTMC)

DTMC helps us model how a system moves between different states through time by showing transitions at fixed period intervals (Škulj 2009) as in Fig. 3. We use a transition probability function to describe the likelihood of transitioning between states across discrete points in time as given in equation 4.

$$\begin{aligned} &P\left(X_k(n+1) = j | X_k(n) = i, X_k(u) = w\right) \\ &= P\left(X_k(n+1) = j | X_k(n) = i\right) = P_{ij}(n) \end{aligned} \tag{4}$$

where i, j, and w represent the different variable states at time steps n, n+1, and u respectively n, u ≥ 0 and u < n. For a DTMC model to be valid, P_{ij}(n) must exhibit time homogeneity, meaning the transitions are assumed to be independent of the initial state at n=0. This property can be quantified

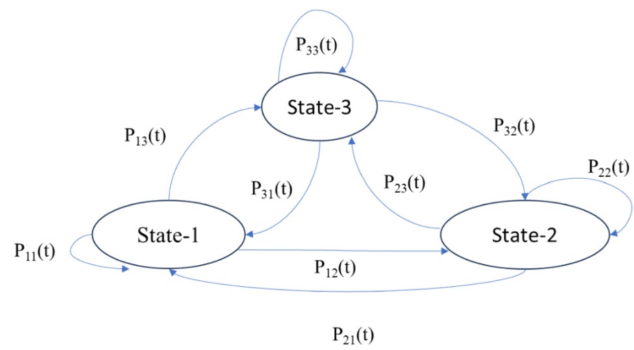

Fig. 3 Discrete time Markov chain

using the Chapman-Kolmogorov equation (Hachigian 1963) as follows:

$$P(n+1) = P(n).Q \tag{5}$$

where P(n) is the transition probability matrix at time step n $\{P_{ij}(n)\}$ and Q is the transition matrix that defines the probabilities of variable transitions between different states.

3.4 Integrated Markov chain and Bayesian network

A discrete Markov Chain brings temporal state transitions to BNs by using Markov Chains for state development together with BNs that show variable probabilistic connections within states. Through this integration researchers can merge both time-dependent patterns and advanced relationship systems. The Markov Chain-BN approach separates the structural components since it maintains independent temporal transitions whereas Dynamic Bayesian Networks require explicit extension of BNs through temporal nodes across time slices. In practical terms DBNs offer greater flexibility yet they use significant computational power to compute large systems (Fig. 4) (Rebello et al. 2018).

4 Case study and results

A real-world example which shows the critical interdependence of Communication network on supply chain is the 2017 NotPetya cyberattack on Maersk. The attack had seriously harmed the communication system of the Maersk and thus its digital twin models were useless because the digital twin models were not able to run in a real time sync. This event resulted in a substantial loss of finances and operational turmoil, indicating the potential of a domino effect on supply chains due to cybersecurity risk changes in network characteristics (latency, bandwidth, etc.). Our case study is simulating these conditions in order to measure and evaluate this vulnerability.

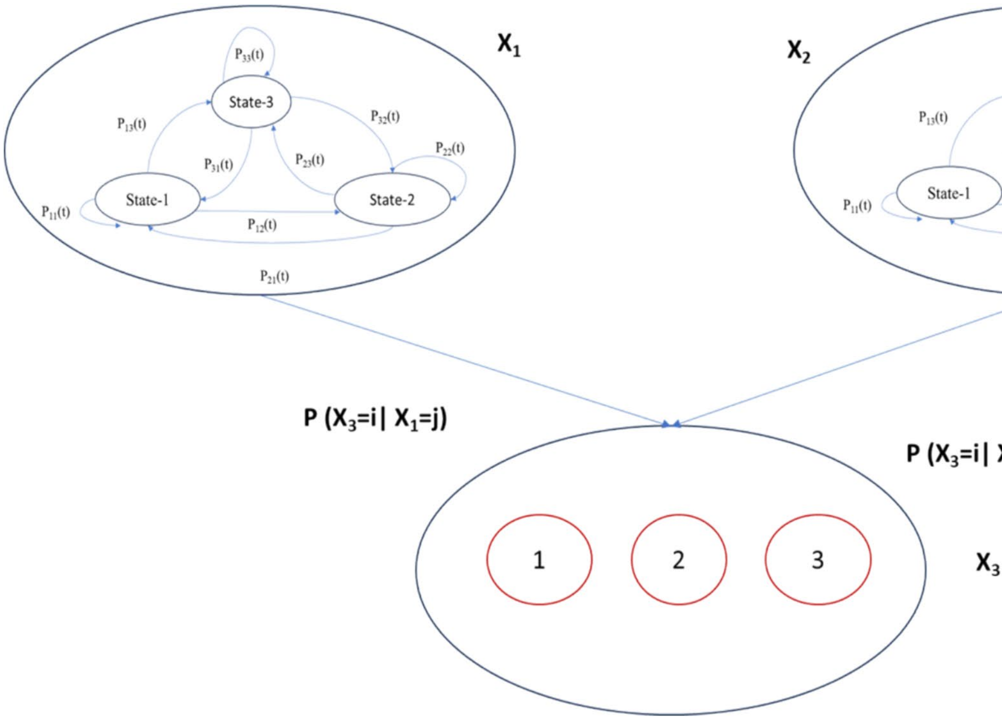

Fig. 4 Integrated DTMC and BN

4.1 Assessment of important factors

From the Literature review, a total of 8 factors were identified for reliable communication network and 10 performance factors were identified for supply chain DT which depends on reliable communication network. After identification of these factors a survey was sent to panel of experts consists of member from industry and academia working in the field of supply chain or communication to evaluate the relative importance of factors identified. In order to draw conclusion, the average of the responses was calculated. The demography of experts can be seen in Table 2. Using Eq. (1), the assessment was defuzzied to obtain crisp value, next the value of inconsistency (d) was calculated using Eq. (2). At last, acceptance criteria were defined as having a consensus of at least 0.85 and an inconsistency of less than 0.2. As a result, 5 factors were selected for reliable communication network as shown in Tables 3 and 7 factors were selected for resilient supply chain network as shown in Table 4. According to expert most important factor for reliable communication network is cybersecurity, because it guarantees that the data and information being communicated are secured from numerous risks and vulnerabilities, cybersecurity is essential for reliable communication. For supply chain decision-makers to make well-informed decision, accurate data is crucial. Cybersecurity enhances the entire resilience of the supply chain by safeguarding data integrity, which guarantees that choices are made using true and unaltered

Table 2 Experts profile for Fuzzy Delphi Technique

Field	No. of experts	Year of experience	Percentage (%)
Industry	3	>10	15
	5	5-10	25
	2	<5	10
Academia	5	>10	25
	3	5-10	15
	2	<5	10
Total	20		100

Table 3 Factors accepted after FDT for reliable communication network

Factors	FDT	d	Outcome	Ranking
Latency (C1)	0.87	0.13	Accept	2
Bandwidth (C2)	0.86	0.14	Accept	3
Network coverage (C3)	0.80	0.21	Reject	–
Network topology reliability (C4)	0.83	0.22	Reject	–
Cybersecurity (C5)	0.89	0.15	Accept	1
Quality of service (QoS) (C6)	0.74	0.23	Reject	–
Redundancy (C7)	0.73	0.22	Reject	–
Fault tolerance (C8)	0.79	0.24	Reject	–

Table 4 Performance factors accepted after FDT for supply chain DT

Factors	FDT	d	Outcome	Ranking
Lead time (S1)	0.87	0.13	Accept	2
Collaboration (S2)	0.81	0.23	Reject	–
Visibility (S3)	0.89	0.14	Accept	1
Agility (S4)	0.80	0.25	Reject	–
Information sharing (S5)	0.78	0.22	Reject	–
Velocity (S6)	0.86	0.11	Accept	3
Transparency (S7)	0.76	0.25	Reject	–
Trust (S8)	0.73	0.22	Reject	–
Anticipation (S9)	0.77	0.23	Reject	–
Risk management culture (S10)	0.72	0.24	Reject	–

Table 5 Model specifications for the states of the three basic variables

Variable	State level	State range	Distribution
Latency	Low	0–0.1 seconds	Normal
	Medium	0.1–0.2 seconds	
	High	0.2–0.4 seconds	
Bandwidth	Low	0.3–0.5 Gbps	Log-normal
	Medium	0.5–0.7 Gbps	
	High	0.7-1 Gbps	
Cybersecurity	Low	–	Categorical
	Medium	–	
	High	–	

information (Wong 2022). In this study, Visibility is identified as most important factor for a resilient supply chain, data and information from diverse locations in the supply chain are guaranteed to be transmitted without delay due to a reliable communication network. Since it enables stakeholders to keep an eye on shipments, inventory levels, manufacturing plans, and other crucial supply chain elements, real-time data sharing is crucial for visibility (Mantravadi 2018).

From the results of FDT and Literature survey it is found out that factors like latency, bandwidth and cybersecurity are important to evaluate the performance or reliability of Supply chain DT in terms of lead time, visibility, and data transmission velocity. Inspired from a real-world scenario a simulated model of a supply chain was build to show the interdependency of Supply chain DT factors on communication network characteristics, simulated model was used as the dataset combining these factors are not readily available.

4.2 Data collection

RIPE Atlas measurements helped obtain data about network status across different region of world. Our method of data collection included regular ping and traceroute tests between network probes in different regions. We assessed bandwidth and latency performance from these tests. Cybersecurity metrics emerged from security configurations and incident reports when necessary. The system automatically recorded measurement results at different times to generate a time-based dataset. To create realistic simulations of network interactions the probability distribution was fitted on the data that best describe the network behaviour. Most latency measurements showed a normal distribution pattern because they group tightly near the mean with exceptions. The unequal bandwidth data points demonstrated better results when treated using log-normal distribution. Our security assessment data pointed to three distinct security conditions that we measured using categorical probability distributions. For Each variable there is three state level in a particular state range as described in the table below. These ranges were designed to categorize different levels of Latency, Bandwidth and cybersecurity effectiveness and their potential impact on supply chain performance metrics like resilience, data transmission velocity, and forecasting accuracy. In order to measure the performance fluctuation of the communication networks and how they influence the behavior of the supply chain DT, all the network features, latency, bandwidth, and cybersecurity, were discretized into three conditions, Low, Medium, and High as shown in Table 5. These state levels were established on the empirical data characteristics and domain specific thresholds that are previously observed in other studies and technical requirements. In case of latency, it was decided that 0.1 and 0.2 seconds are the thresholds of standard user-perceived delays on real-time systems with 100ms defined as optimal. The pattern of normal distribution of data also supported bringing together the data in terms of the standard deviations surrounding the mean (Iorio 2021). In the case of bandwidth, skewness in measurements was best characterized by a log-normal distribution and state thresholds were decided at 0.5 Gbps and 0.7 Gbps which is commonly found in enterprise and industrial settings (Akbari 2024). The state for cybersecurity was determined through categorical ratings (of known security incidents, patching policies, and vulnerabilities score) which is Low, Medium, and High, and it is qualitative, not numeric. These ranks are related to industry frameworks like National Institute of Standards and Technology, US (NIST) and Open Worldwide Application Security Project (OWASP) categorization at large. Monte Carlo sampling used to generate simulated data on fitted distribution that is aligned with real world scenario. In case of latency, the values were sampled according to the normal distribution, where parameters have been determined on the basis of the observed RIPE Atlas readings, and categorized into three states. Values of bandwidth were sampled based on log-normal distribution with their empirical mean and variance, turned into discrete scale by the specified thresholds. The random assignment of

Table 6 Sample of data simulated

Latency	Latency category	Bandwidth	Bandwidth category	Cyber-security category
0.341718	High	0.736178	High	Low
0.202358	High	0.977073	High	Medium
0.153184	Medium	0.840003	High	High
0.114465	Medium	0.876914	High	Low
0.049522	Low	0.651337	Medium	Medium
0.172973	Medium	0.638525	Medium	Medium
0.034608	Low	0.694939	Medium	Low
0.141947	Medium	0.3877	Low	High

Table 7 Transition probabilities for latency

	High	Low	Medium
High	0.354	0.354	0.290
Low	0.343	0.375	0.281
Medium	0.222	0.277	0.500

Table 8 Transition probabilities for bandwidth

	High	Low	Medium
High	0.281	0.500	0.218
Low	0.309	0.380	0.309
Medium	0.440	0.360	0.200

cybersecurity states was performed with categorical probability distribution according to the probability of an incident available in security bulletins and configuration audit.

The simulation involved three different stages, each designed to emulate different network states as shown in Tables 5 and 6.

4.3 Transition probability calculations

For transition probabilities calculations involves three states, first identify the distinct sates in each variable, such as latency which have states like "High", "Medium" and "Low". Next step is to count the no. of transition from one state to another for example determine how often the system transit from low latency to high latency to medium latency. To calculate the transition probability, divide the count of transitions from a given state i to another state j by the total number of transitions originating from state I, as shown in Eq.uation (6).

$$P(X_{t+1} = j|X_t = i) = \frac{Count\ of\ transitions\ from\ state\ i\ to\ state\ j}{Total\ transitions\ from\ state\ i} \tag{6}$$

Results of Transition probability matrix for the variables, Latency, Bandwidth, and cybersecurity are given in Tables 7, 8, and 9.

Figure 5 showing the convergence behaviour of transition probability over time, showing how state probabilities evolve and converge to their steady state value. The probability distributions demonstrate stability as time progresses which indicates equilibrium is more likely to be achieved by the system. Throughout all three parameters the medium state always achieves dominance which demonstrates typical operational behaviour in the system. Between them the Latency and Bandwidth states reach equilibrium quickly but Cybersecurity takes longer to stabilize. The observed pattern confirms both system stability and resilience through different situations which enables better resource optimization decisions and improved reliability outcomes.

Table 9 Transition probabilities for cybersecurity

	High	Low	Medium
High	0.406	0.312	0.281
Low	0.303	0.363	0.333
Medium	0.294	0.294	0.411

4.4 Model structure

A Markov-integrated Bayesian Network (MIBN) as shown in Fig. 6 has three layers, first layer consists nodes like Latency, Bandwidth, and Cybersecurity which shows their influence on second layer nodes like Data Transmission Velocity, Lead Time and Visibility while these three second-level nodes then connected with Reliability state. Our framework shows both random connection changes

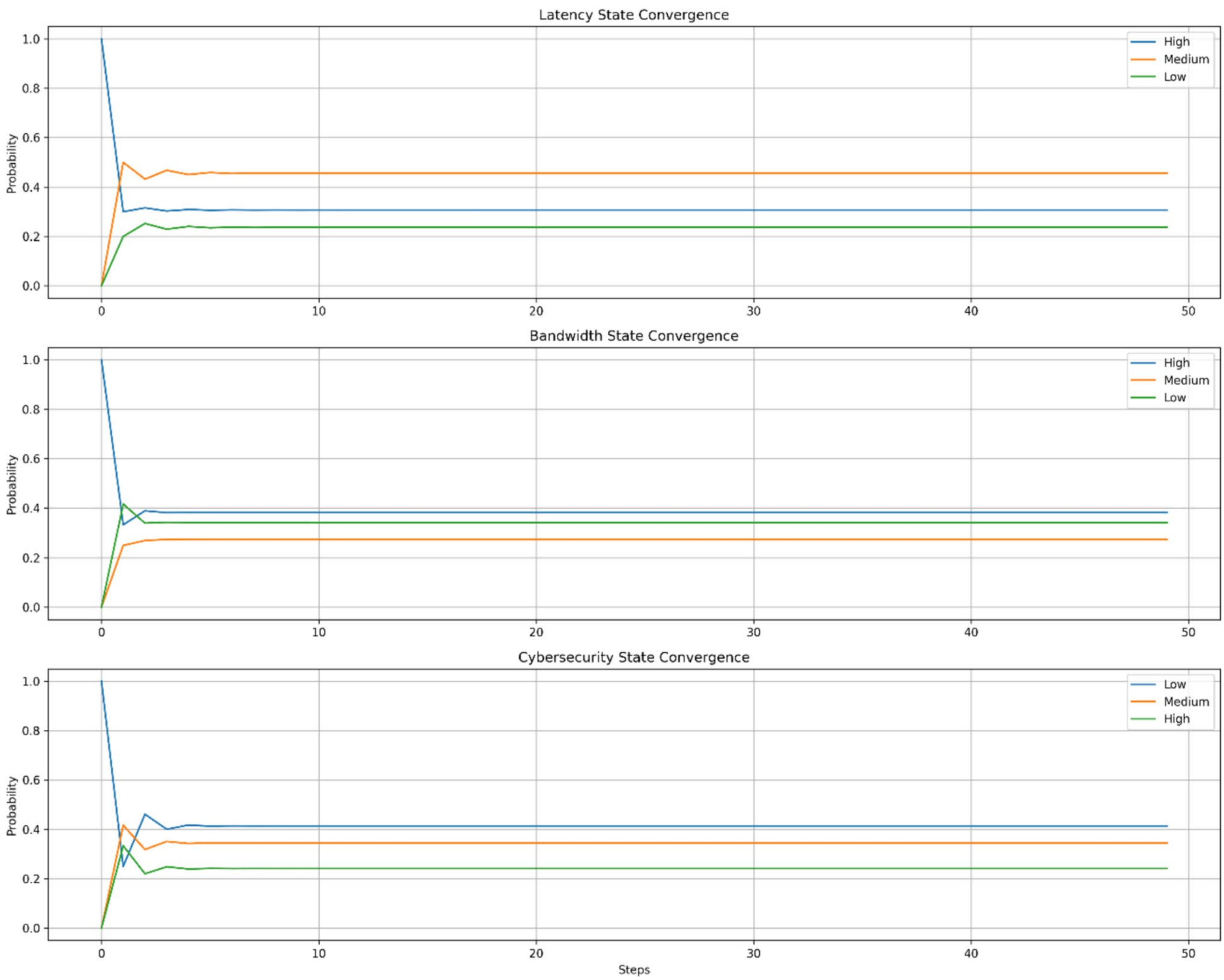

Fig. 5 Transition probabilities convergence over time **a** latency convergence, **b** bandwidth convergence, **c** cybersecurity convergence

and time effects while estimating how system reliability changes with network conditions. The model below shows that supply chain DT performance undergoes significant changes because of latency variations along with bandwidth changes and inadequate cybersecurity affect both data transportation speed and visibility and total lead time durations thus reducing reliability levels. The transmission speed of data suffers from delays caused by high latency thus bringing reduced visibility detection capability to disruptions while making lead times longer. Limited bandwidth simultaneously reduces the amount of processed supply chain data which leads to poorer visibility accuracy while extending lead times and making forecasting more difficult. Cybersecurity weaknesses make systems more vulnerable to attacks such as unauthorized data breaches and unauthorized access which both impede data transmission and diminish user confidence in the DT's visibility capabilities. Multiple factors drive digital twin systems towards degraded or failed operation states thereby affecting their reliability level. Robust cybersecurity and high bandwidth combined with low latency result in faster data transmission and enhanced visibility that shortens lead times while elevating the reliability of DTs (Table 10).

The graphical representation demonstrated in Fig. 7 reveals that the reliability trend transversing over the time can be divided into three regions such as Failed (red), Degraded (orange), and Fully Reliable (green). These regions refer to various configurations of the base variable states of the network-Latency, Bandwidth and Cybersecurity. The model takes discrete step time and at each time of the day the state of the system would be established by taking sampled values of these three variables taking into consideration the distributions and transition probabilities of the reservoir. A Failed Zone occurs when both variables are at low levels (e.g., high latency, low bandwidth, and insecure cybersecurity), which causes

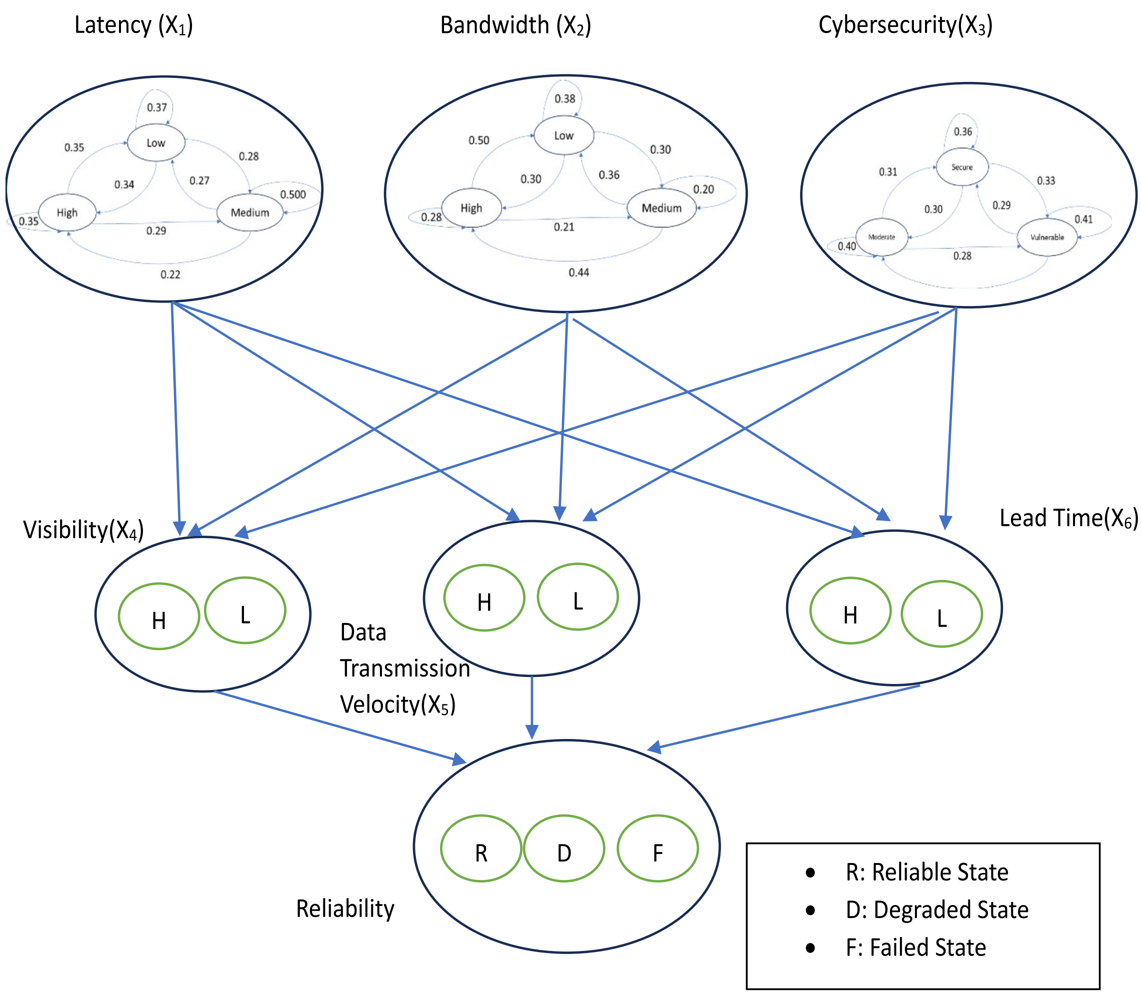

Fig. 6 Integrated DTMC and BN Model of communication network with supply chian digital twin factor

Table 10 Condition probability table for reliability node

X4	X5	X6	R	D	F
Low	Low	Low	0.2	0.3	0.5
Low	Low	High	0.1	0.4	0.5
Low	High	Low	0.4	0.4	0.2
Low	High	High	0.3	0.5	0.2
High	Low	Low	0.5	0.4	0.1
High	Low	High	0.5	0.4	0.1
High	High	Low	0.6	0.3	0.1
High	High	High	0.8	0.2	0.1

serious communication breakdown and sync loss to the digital twins. Degraded Zone happens when one or more variables become medium in one or more levels such that there is partial inability to communicate the data or even see one another. The Fully Reliable Zone would be associated with conditions leaving nothing to chance: i.e., low latency, high bandwidth, and secure cybersecurity, and as a result, precise real-time performance can be expected of the digital twin. Therefore, the graph proves the dynamic effects of the changing network conditions in time on the reliability of the supply chain digital twins.

5 Conclusion

This study provides a reliability assessment methodology by integrating the DTMC with BN to model and assess how the different network conditions can impact the performance of a supply chain DT. The Markov chain model the different state for network characteristics like latency, bandwidth, and cybersecurity for which the data was simulated with the help of RIPE Atlas. These Network states control important aspects of how digital twin data travels securely so that operations can run properly. The BN connects different network components to supply chain features such as Data transmission velocity, Lead Time and Visibility in supply chain while

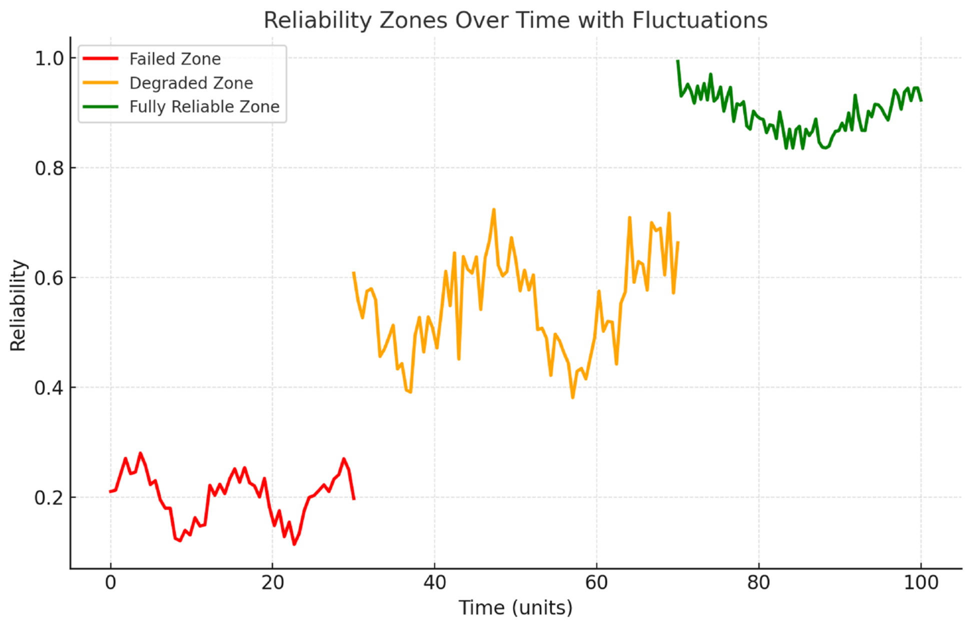

Fig. 7 Reliability variation over time

showing how network performance affects these features. The research design includes network relationships to show how network status and supply chain feature affect the DT reliability. The study finds out that when latency is in low state, bandwidth is high and cybersecurity is secure then system is highly reliable, when one of the state's degrades, system fall into degraded state signifies potential risk to digital twin reliability. A failed state is declared when all the variable is in their low state that indicate digital twin is not reliable anymore. The Study uses a combined approach to help us better understand how changes in network conditions lead to disruptions in a supply chain performance. DTs depend on network model analysis to build stronger Reliable systems that protect companies better in today's complex data-centric supply chains. The use of Markov chains and Bayesian Networks on the basis of our proposed method shows a high level of computational efficiency, since the approach utilizes the discrete states representation and finds the probability in closed form. Each variable has a manageable state space (Low, Medium, High) whose transition probabilities are to be calculated and this creates substantial simplification of the model as compared to when transition probabilities for continuous-state or high dimensions are to be used. The modular nature of our model also enables it to be scaled up to support more network parameters (e.g. jitter, packet-loss) or supply-chain performance measures (e.g. flexibility, visibility) without too much additional computing costs being incurred. Also, parallel processing and inference optimization is possible when using probabilistic graphical models, and so the method is applicable in bigger simulations and real-time applications.

5.1 Limitations

Future research should aim to overcome the limitations of this study by making this model better and more usable for practical purposes. The present model that runs with a DTMC which assumes a fixed time interval for a state change with only three states in future continuous time Markov chain can be employed to better capture real time fluctuations in network with multi state.

5.2 Future scope

Future researchers should bring real-time data from IoT sensors and digital technology into their models to automatically update network performance measurements. Findings of this study can improve reliability assessment quality when they combine with live sensor data to enable better supply chain disruption prevention. In future, researchers can also focus on combining other business and environmental factors into their reliability model. This research approach enables businesses to identify linkages between economic and environmental influence on supply chain operations while building more sustainable digital solutions. Further work may also be performed to numerically compare the proposed Markov-Bayesian framework with other existing reliability modelling methods like Universal Generating Function (UGF) or semi-Markov processes to determine any relative performance relating to accuracy, scalability and computational capacity.

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Data availability Data will be made available on request.

Declarations

Conflict of interest The authors declare that there is no conflict of interest.

Research involving human participants and/or animals All research involving human participants in this study was conducted in accordance with relevant guidelines, regulations, and ethical standards and there is no involvement of animals for conducting this research.

Informed consent Informed consent was obtained from all individual participants included in the study. Participants were provided with detailed information about the purpose and procedures of the study, and they voluntarily agreed to participate.

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