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Evaluation of Modelling Techniques for Colocation Data Center Selection

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Abstract

According to a survey carried out by the Uptime Institute, data center outages are on an upward trend and are mainly caused by failures within electrical systems. An unreliable power grid presents a unique challenge to data center operators. To maintain uninterrupted power supply to the IT load in a data center during planned or unplanned utility outages, an open transition between the utility and generator supply will typically form part of the sequence of operations in the event of utility power loss. During the open transition, a double-conversion UPS will change modes of operation to ensure continuity of supply; the utility breaker will open, and the generator breaker will only close once the defined parameters are met, such as when the generator power supply is stable. This research study evaluates how availability modelling techniques can be used as tools to help predict and improve data center availability. Each modelling technique will be measured against a set of criteria to establish their subsequent capabilities and limitations. The concept of availability modelling is used across multiple industries, including aviation. To achieve this, the research evaluates five widely used modelling techniques.

Keywords
Markov, Reliability block diagram, Fault Tree Analysis, Stochastic Petri Nets and Failure Mode Effect and Criticality Analysis

1. Introduction
Data centers play a critical role in modern society, from the storage of personal data such as photos to industrial data processing applications. Data centers are used in diverse industries, including both the private and public sectors. Therefore, it is critical for data center operators to ensure that data centers have high availability. A data center (DC) typically comprises multiple halls, known as data halls, which house computing servers and various systems, such as power and cooling systems. These facilities represent the physical infrastructure of the "Cloud." The processing and storage of data are considered extremely valuable in the modern digital era, making cloud-based infrastructure essential (Geng, 2015).

Industries such as banking and healthcare depend on cloud services provided by DCs. The reliability and availability of DCs are of utmost importance because of the critical nature of these services operating in the cloud. Research by the Uptime Institute highlights that DC outages can disrupt vital services, resulting in financial penalties and reputational damage to service providers and end users (Lawrence & Simon, 2023). The number of data center (DC) outages continues to increase annually, matching the industry's growth rate. Unfortunately, data center operators (DCOs) often hesitate to reveal comprehensive information regarding the full scope and impact of outages. Nevertheless, a survey conducted by the Uptime Institute indicated that power is the primary cause of DC outages (Lawrence & Simon, 2023). Researchers have also outlined several data center design categories. Higher tiers, such as tiers 3 and 4, exhibit concurrent maintainability and enhanced system availability. Despite the introduction of resilient and redundant systems, power-related outages remain a concern (Madanhire & Mbohwa, 2016; Lawrence & Simon, 2023).

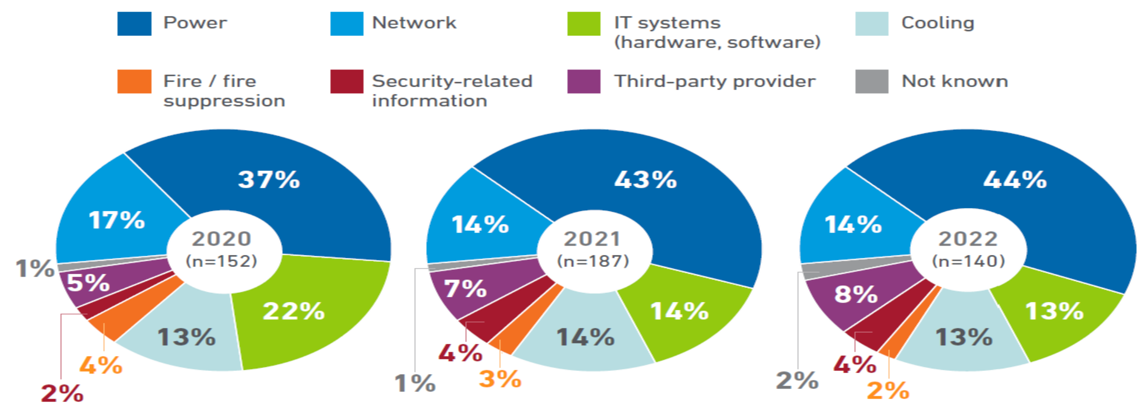

Figure 1. "Leading causes of significant outages" (Lawrence & Simon, 2023)

Therefore, it is necessary to evaluate, compare, and rank modelling techniques that can help improve the availability of electrical systems in DC environments. Furthermore, assessing how system availability is currently being conducted is particularly crucial for organizations operating or planning to operate data centers in South Africa, considering the continuous implementation of national load shedding.

1.1 Objectives

The research objective was to assess various availability modelling techniques, including the common causes of power outages, and recommend the best available modelling technique in the South African context. As illustrated in Figure 1, power-related outages were significantly more frequent than other known causes of DC outages.

2. Literature Review

This study evaluated several widely used availability measurement models, primarily dissecting, comparing, and assessing them to determine their effectiveness in identifying the potential risks to data center electrical system availability (Milanovic, 2010a). However, the development, deployment, and improvement of availability modelling methods depend on the quality of equipment operational data. (Levy & Hallstrom, 2017) contend that data center components require "real-time" constant monitoring to ensure data center system health. Furthermore, the authors highlighted the need to develop modelling techniques that can be used to leverage data to improve system availability using predictive capabilities.

Constant power cuts can result in multiple switching of various electrical components, such as the generator, utility circuit breaker, and UPS batteries. IEEE std 1184-2022 provides detailed guidelines on UPS battery life, including factors that could potentially shorten battery life. These factors may include prolonged or deep battery discharge cycles. The prediction of component failure rates is one of the most widely researched topics in reliability engineering.(Jones, 2020) warns against the misconception associated with failure rates and that repairing components "will return system to its original condition." The widely accepted theory of the most probable causes of system failure includes the following:

1. Inaccurate system performance estimate
2. Unsuitable operational conditions
3. Poor manufacturing process
4. Inadequate design strategy

Failure Mode, Effects and Criticality Analysis(FMECA) enables the ranking of various failure modes to ensure that critical components within a system are identified and receive high priority when deciding on the frequency of preventative maintenance and prioritization of corrective maintenance on the critical component (Torabi & Kowal, 2022a).

According to (Jakkula et al., 2021), Reliability block diagram(RBD) does not represent a system's sequence of operation (SOO). Instead, RBD often simplifies procedures to enable mathematical quantification using RBD modelling. RBD mathematical modelling includes parallel (also referred to as "M-out-of- N") backup systems and standby (or "cold standby") and standby backup system options.

Fault Tree Analysis (FTA) assessment technique follows a "top-down" methodology as demonstrated in Figure 2, which describes a single or set of conditions that must occur to lead to subsystem or system downtime. Furthermore, the author highlights that FTA consists of capabilities similar to those of RBD (Penttinen et al., 2019; Swanepoel, 2022a).

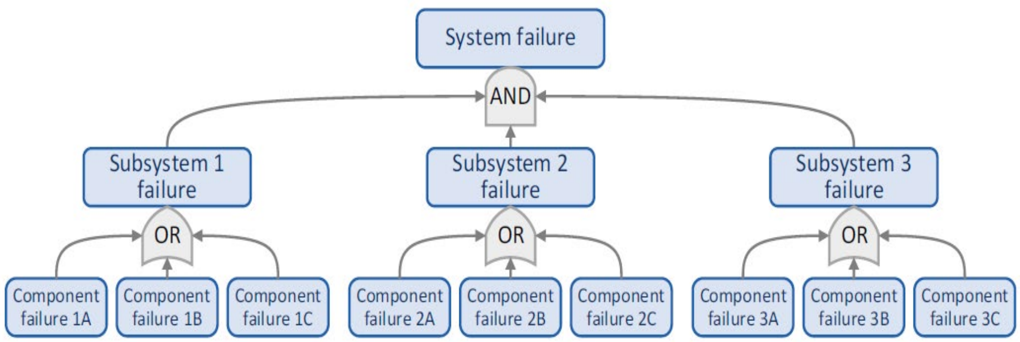

Figure 2. FTA visual system representation (Penttinen et al., 2019)

The Markov assessment technique involves a stochastic process and can evaluate the availability of a system with redundant configuration components (Milanovic, 2010b). In addition, the Markov technique can assess the probability of changing the states of a component (Penttinen et al., 2019).One of the capabilities of the “discrete Markov” method is to model the probability of state transition which can either be "PA-F,” which is the probability of changing from an available to a failed state, or "PF-A,” the probability of changing from failed to available, as shown in Figure 3. The probability of a component’s transition from availability to failure is assumed to occur over time (O'Connor & Kleyner, 2012).

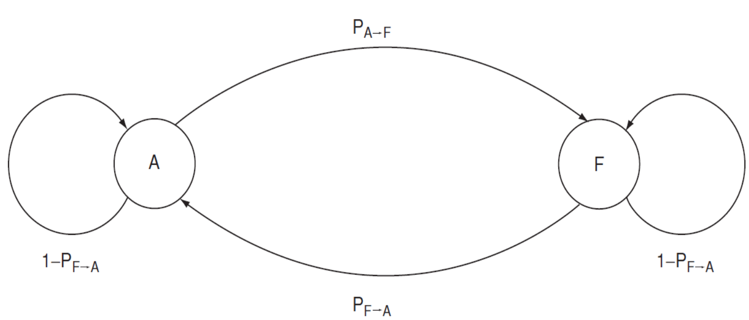

Figure 3. "Two-states Markov state transition diagram" (O'Connor & Kleyner, 2011)

The limitations of the Markov technique, as highlighted by (Bahl et al., 2018b), can be addressed using Petri Nets (PN). Some of the capabilities of Petri Nets include the ability to evaluate “dynamic” patterns within a system and visual demonstration of the change of state within a system over time. Furthermore, the following Petri Net features highlight the fundamental differences between PN and SPN:

1. The original PN excludes the time factor. This omission would make it difficult to model a "dynamic system"
2. A stochastic PN(SPN), also referred to as a time Petri net, includes the "time concept." This enables the SPN to model a wide range of systems.

3. Methods

The study used mixed research methodology to evaluate the availability modelling techniques and applied the methodology to evaluate a typical data center electrical single diagrams to measure the capability of the model among other things the ability to identify single point of failure.

3.1 Research Design

The research selected a mixed research methodology, incorporating both quantitative and qualitative approaches. Qualitative research methods were employed to investigate available knowledge from reputable academic sources, providing deeper insight into the availability of modelling techniques. This approach seeks to uncover new knowledge and address research objectives by examining specific examples and scenarios. Qualitative analysis offers a richer understanding of the capabilities and limitations of the modelling techniques under investigation. Furthermore, the capabilities of five modelling techniques were tested through their application to evaluate two distinct single-line diagrams (SLDs) from IEEE Std 493, one of which had a single point of failure (SPOF). Quantitative research methods were used to analyze data collected by the Uptime Institute global survey. Figure 4 shows the results of the survey, which primarily targeted professionals in the data center space. Among the survey participants, seven electrical components were highlighted as having played a role in data center power-related outages.

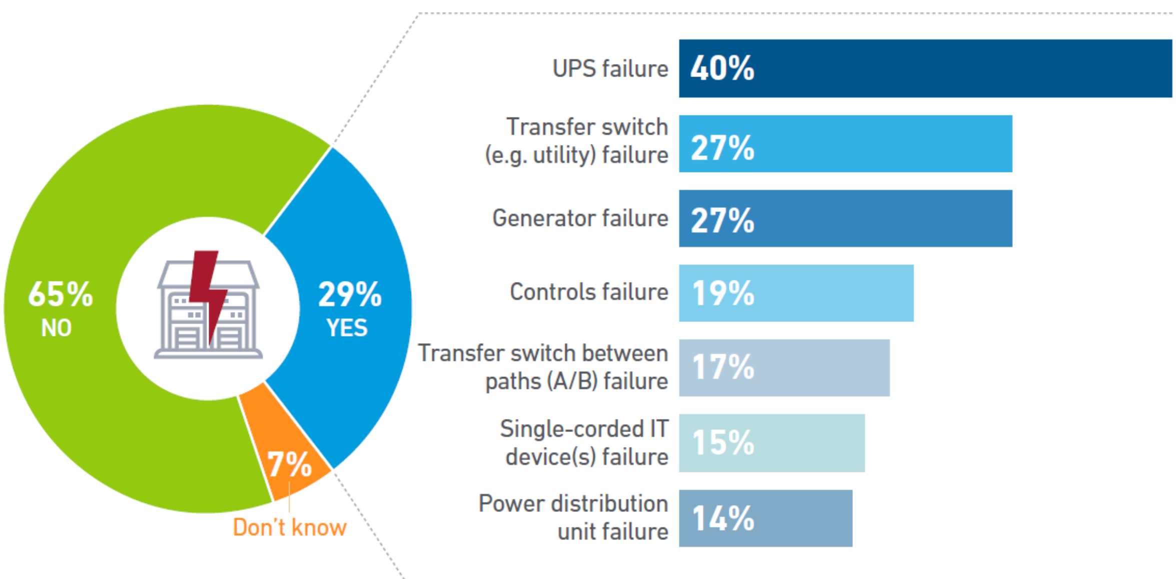

Figure 4. "Most common causes of major power-related outages" (Lawrence & Simon, 2023)

3.2 Ranking Criteria

This study proposes a list of criteria in Table 1 that can be used as guidelines when deciding which modelling technique(s) should be used to perform availability assessment or availability improvement. The criteria were measured on a scale of 1 to 5:

1. **No Capability:** The model does not meet the criteria and provides no useful information for decisions.
2. **Partial Capability:** The model meets some criteria but provides limited information for decisions.
3. **Moderate Capability:** The model meets the criteria moderately and may need to be integrated with other models or DCIM tools for complete information.

4. **Capable:** The model meets the criteria well, providing substantial information on its own, with external models or DCIM tool enhancing it further.
5. **Highly Capable:** The model fully meets the criteria and generates sufficient information for decisions without requiring external models.

Furthermore, Modern data center operations rely heavily on data center infrastructure management (DCIM) to collect, process, and store equipment data. This research suggests that an ideal modelling technique should encompass the features listed in Table 1 (Thangamani, 2011; Shafiee et al., 2019).

Table 1. Criteria listing and definitions

Criteria	Definition
Real-Time Data Processing	The model's ability in processing real-time data from sources like Data Center Infrastructure Management (DCIM) tools.
Modelling complex or dynamic systems	The model's capability to evaluate complex systems, including interdependent subsystems and failure mechanisms.
Cost-Effectiveness	Costs associated with owning the model.
State Change Probability Calculation	The model's ability to estimate the probability of a system being in either an operational (Uptime) or failed state (Downtime). .
Component failure impact assessment	The model's ability to systematically identify potential failure modes and evaluate their impact on system availability.
User friendliness and interpretability	The model's capability facilitates decision-making by providing insightful visualizations, interactive dashboards, and actionable insights.
Predictive analysis for availability associated dependability	The model's ability to utilize historical and real-time operational data to assess system reliability, maintainability, and overall supportability.

Table 2 provides ranking model sources. The authors highlighted the widely accepted characteristics of modelling techniques capabilities and lack thereof. This knowledge was used to measure and compare the capabilities of the modelling methods against the criteria

Table 2. Ranking model sources

Model	Source(s)
RBD	(O'Connor & Kleyner, 2011; Thangamani, 2011; IEEE, 2013; Park & Hanna, 2014)
FTA	(IEEE, 2013; Shafiee et al., 2019)
FMECA	(IEEE, 2013; Catelani et al., 2021)
Markov	(O'Connor & Kleyner, 2011; Ahmed et al., 2014; Swanepoel, 2022a)
SPN	(Bahl et al., 2018b) (Murad et al., 2020)

4. Data Collection

4.1 Data Assessment Method

The ranking criteria provide a numerical scale from 1 to 5, which enables comparative analysis of the overall performance of the availability modeling techniques across defined criteria. The availability modeling techniques are diverse, as some are best suited for qualitative assessment, others for quantitative assessment, and some can perform both qualitative and quantitative assessments.

4.2 Data Strength and Limitation

The evaluation of the capabilities and limitations of the availability modelling techniques was carried out without any operational data from data centers operating in South Africa. Due to the sensitivity associated with data center operations, the research study used random data in Table 3 to calculate component and system availability. The use of random data is not unique to this academic research; it was necessary in the absence of real-time operational data. Component failure rate estimations are often provided by the original equipment manufacturer (IEEE Std 493, 2007). Jones (2020) argued that component failure rates are often theoretical and may not reflect real-life situations

5. Results and Discussion

5.1 Numerical Results

Table 3 shows how the individual availability models performed against the seven criteria. The models demonstrated various levels of capabilities.

Table 1. Criteria weight and ranking

Criteria	**Capability Rank**	**Weight**	**Model(s)**
Real-Time Data Processing	No Capability	1	None
	Partial Capability	2	None
	Moderate Capability	3	RBD, FTA, FMECA
	Capable	4	Markov, SPN
	Highly capable	5	None
Modelling Complex systems	No Capability	1	None
	Partial Capability	2	RBD
	Moderate Capability	3	FTA
	Capable	4	FMECA, Markov, SPN
	Highly capable	5	None
State change probability calculation	No Capability	1	RBD, FMECA
	Partial Capability	2	FTA
	Moderate Capability	3	None
	Capable	4	Markov
	Highly capable	5	SPN
Component failure impact assessment	No Capability	1	None
	Partial Capability	2	None
	Moderate Capability	3	RBD, SPN, Markov
	Capable	4	FTA, FMECA
	Highly capable	5	None
User friendliness and interpretability	No Capability	1	None
	Partial Capability	2	Markov, SPN
	Moderate Capability	3	FMECA
	Capable	4	None
	Highly capable	5	FTA, RBD
Predictive analysis of availability associated dependability	No Capability	1	None
	Partial Capability	2	RBD, FTA
	Moderate Capability	3	None

	Capable	4	FMECA
	Highly capable	5	Markov, SPN
Cost effectiveness	No Capability	1	None
	Partial Capability	2	None
	Moderate Capability	3	Markov, SPN
	Capable	4	RBD, FTA, FMECA

5.2 Graphical Results

SPN and Markov models were the overall best performing models when measured against the seven criteria. FMECA and FTA yielded similar results as indicated in Figure 5. RBD scored the lowest among the five models.

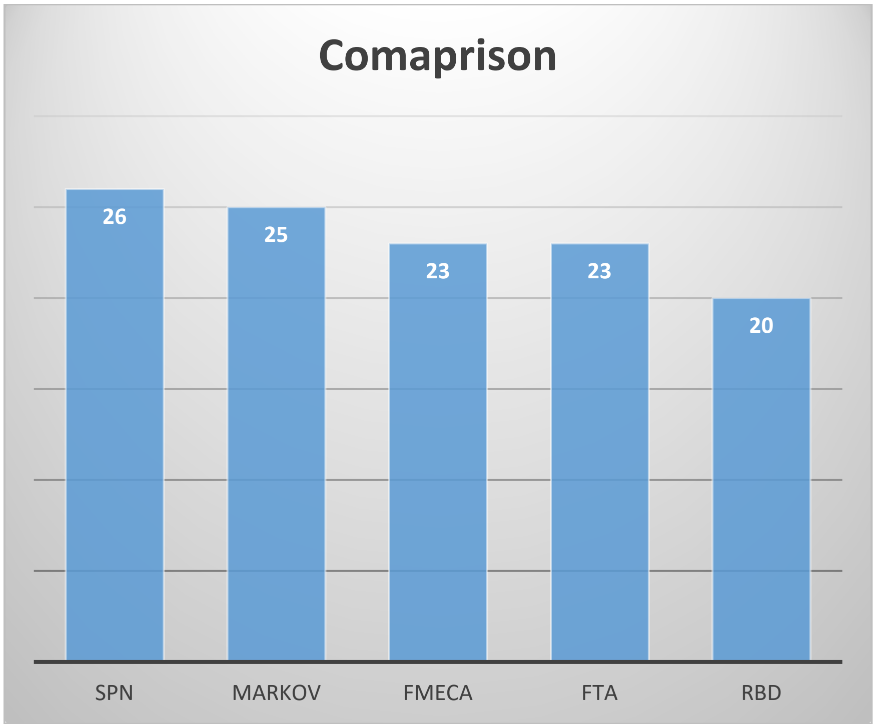

Figure 5. Model comparison results

5.3 Proposed Improvements

The FTA, RBD, and FMECA models are predominantly quantitative and do not easily adapt to changes in operational environmental conditions. Consequently, the initial system availability prediction obtained from these models during the design phase becomes the only system availability data until the assets are decommissioned.

Stochastic Petri Nets and Markov models are complex to develop and require specialized knowledge to operate and maintain. Furthermore, due to the complexity of these models, it is highly improbable to develop and manage them for complex system availability assessments without the use of computerized tools. Certain key capabilities cannot be achieved independently using a single availability model. One solution to this problem is to use hybrid models that may consist of two or more techniques. The initial cost of developing a hybrid model may be high, but the benefits of such a model may outweigh the associated cost.

5.4 Validation

FTA is effective in identifying the relationships between system and subsystem failures. It provides a top-down overview of critical components and potential failure scenarios that could lead to overall system failure. RBD, on the other hand, offers a graphical representation of the system's configuration, particularly its redundancy and dependencies. RBD can facilitate the calculation of system availability using data from OEM specifications or actual operational performance. Together, FTA and RBD techniques can be used to identify system vulnerabilities, such as SPOF, and enhance overall system reliability and resilience. FMECA is a systematic analytical technique used to identify potential failure modes, evaluate their causes and effects, and quantify their probability and criticality. When conducted thoroughly, FMECA provides numerical values such as RPN or critical indices that help assess the relative importance of components within a system or subsystem. This insight can be instrumental in developing effective maintenance strategies. FTA and FMECA can be used to identify components or subsystems whose failure would have the most significant detrimental impact on overall system availability.

Markov modelling is a probabilistic technique used to analyze systems by determining the likelihood of transitioning between different states over time. It is also highly data-driven and relies on accurate, reliable input data to produce meaningful reliability and availability estimations. However, a key limitation of Markov modelling is the state space explosion problem, which arises when modelling complex systems with various states such as operational, degraded, failed, or under repair. To address this limitation, the SPN technique can be used. SPN offers a more compact and flexible representation of complex systems. Unlike traditional Markov models, SPN can represent state transitions and system dynamics more efficiently without experiencing state explosion. Markov and SPN models are valuable tools for assessing the probability of system availability. These techniques offer detailed insights into the behavior and failure probabilities of systems, subsystems, and components. Furthermore, these techniques can model the impact of non-technical factors, such as the availability or unavailability of critical spare parts, on system availability or the probability of state changes. These models can be utilized to perform various functions, including providing early warnings of potential system failures, informing maintenance strategies, and identifying design flaws.

6. Conclusion

In conclusion, system availability modelling is essential during both the design and operational phases. Crucially, availability modelling should not be a static exercise; rather, it must be treated as a continuous and adaptive process that incorporates real-time data and operational feedback for data center operators. This dynamic approach ensures that proactive actions are taken to safeguard electrical uptime. FTA and RBD are favored for their simplicity and adherence to standardized engineering methodologies, while Markov and SPN models offer more advanced capabilities for capturing uncertainty and system variability. FMECA plays a key role in identifying interdependencies and failure propagation, and when used in hybrid configurations, such as FMECA-FTA, it can support more robust availability forecasting for complex systems.

The research identified SPN as the overall best-performing model. However, considering the cost implications and complex nature of deploying SPN, this study recommends a hybrid model, such as FMECA-FTA, to mitigate the costs and complexities associated with advanced models such as SPN. The research demonstrated that a reduction in the probability of system availability does not directly imply an immediate state change. Instead, it reflects a higher likelihood of transitioning from an available state to a failed state. Consequently, it is crucial to manage the probabilities of state changes effectively.

Acknowledgment

Section in the document	AI tool used	Function/Purpose	Description/explanation of the used function	Dates used
Article	Paperpal	Grammar & language	The AI tool was used to improve grammar and language. The AI tool was installed as "Add-Ins" in Word.	September 2025

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