Research Article

International Journal of Advanced Technology and Engineering Exploration, Vol 10(101)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2022.10100435

Modeling downtime severity of telecommunication networks using discrete time Markov chains

Wahab A. Iddrisu[1*] and Ibrahim A. Gedel[2]
Department of Mathematics and Statistics, Ghana Communication Technology University, Accra, Ghana[1]
Department of Telecommunications Engineering, Ghana Communication Technology University, Accra, Ghana[2]

Received: 19-November-2022; Revised: 15-April-2023; Accepted: 18-April-2023

Abstract
Telecommunication network reliability remains a top priority for both customers and service providers. Downtime can result in revenue loss for providers and productivity loss for customers. Thus, accurately predicting downtime severity can help providers plan and respond effectively. This study models telecommunication network downtime severity using discrete-time Markov chains (DTMC). The data used consists of 1,211 daily network downtime records, in minutes, recorded by Ghana's national communications authority (NCA) from August 1, 2015, to April 30, 2021. The severity of daily downtime was categorized into 5 categories based on duration. Results indicate that the majority (n=905) of daily network downtime was negligible, while only 25 outages were severe. The transition probability matrix indicates that if the present network downtime severity is negligible, there is an 81% chance that the next network downtime severity may also be negligible, a 12% chance of minimal severity, a 4% chance of significant severity, a 2% chance of serious severity, and a 1% chance of severe severity. The steady-state distribution indicates that over the long term (n ≥ 17), 74% of network downtime severity is expected to be negligible, while only 2% is expected to be severe. Based on probability simulations for 12 steps, it is evident that the 'negligible' category is the most probable network downtime severity, regardless of the initial severity category. These findings can assist telecommunication providers in better planning and delivering more reliable services to their customers.

Keywords
Telecommunication, Network, Downtime, Discrete-time Markov chain.

1.Introduction
The efficient transfer of information from a source to a destination is the primary purpose of a telecommunications network. Power availability and reliability concerns have drawn more attention due to the expanding use of electronic equipments in many sectors including data centers, transmission backhaul, and internet service providers (ISPs) [1].

As used in network infrastructure performance, downtime is a metric to determine when a network, network segment, or network element is unavailable to provide service [2, 3]. More often, unplanned outages and throughput underperformance can have an enormous impact on the productivity and profitability of the network.

All downtime experienced on a network, either as a result of a planned or unplanned outage, tends to affect the overall experience of the network users [4, 5].

A network's failure to supply or carry out its main function is referred to as a network outage time [6]. Network disruptions primarily affect customers with modest to high traffic, such as banks, schools, government agencies, private ISPs, gaming establishments, etc.

Planned and unplanned outages are considered part of the outage measurement unless the system is allocated a maintenance window during which the system is not required to be in service (even though this is an uncommon phenomenon in regular telecom operations) [7].

*Author for correspondence

One of the crucial network performance issues is outage or failure, which directly relates to a network's availability [8]. Network component failures can reduce network availability and eventually lead to the termination of any services contract and sanctions by regulatory bodies due to the downtime severity.

Mobile network operators (MNOs) and tower companies (TCs) must analyze the costs and benefits of service interruptions, subpar services, and the financial impact on their business operations to avoid sanctions [9]. The MNOs and TCs have made significant investments in assuring fast throughput with relatively low latency as the demand for network reliability rises.

To reduce the negative consequences of network outages, telecommunications contracts are built around customer-centered service level agreements (SLAs), in which performance and operational goals are stated [10]. As long as clients keep their expectations for the requested service, SPs must ensure the services they offer meet the necessary performance objective.

The performance of network availability has historically been measured by two key factors used by ISPs: network availability and dependability. Network dependability refers to a device or system's ability to perform its function without error when necessary, whereas network availability refers to a network's capability to respond to requests made by users of the network [11].

The internet has developed into a crucial component of social and commercial activities. Communication networks must be more reliable and maintainable, and telecommunications providers must deliver those networks with high service availability [4].

Network design procedures, specifications, and reliability metrics were established in a study by [12] in order to increase user satisfaction with the dependability of telecommunication services. The carrier network is used by the majority of end users to access services from their ISPs and application SPs [12].

To evaluate the network's performance over a given time period and across a range of user ages, an impact metric was developed [13]. The authors of [14] proposed a more robust mobile network by concentrating on preventing downtime and achieving complete network availability in disturbance situations like accidents, natural catastrophes, etc. The international telecommunication union (ITU) defines the quality of service (QoS) as the entirety of a telecommunications service's features that have an impact on its capacity to meet the explicit and implicit needs of the service user [15]. Utilizing data traffic management technology is a must for high QoS investments in order to reduce network jitter, delay, and packet loss. Setting priorities for particular web data types allows QoS to regulate and manage network resources [6].

The authors in [16] focused on some parameters such as call set-up success rate (CSSR), call drop rate (CDR), network capacity, and bit error rate (BER) to measure the QoS for a network. Service quality can be assessed using the most relevant key performance indicators (KPIs) and key quality indicators (KQIs) for cellular networks and services [17, 18].

ITU defines the SLA as a written agreement between two or more entities that are concluded during a negotiation exercise with the aim of evaluating the service features, obligations, and priorities of each component [19].

Constantly improving QoS in the network is very important as it eliminates downtime and enhances customer experience. Outages will cause the telecommunications sector to lose money and provide poor QoS, especially while the 5th generation (5G) network is being deployed [20].

SLA is a goal that all MNOs, TCs, and SPs must reach. SLA is a legal agreement that outlines the level of service that will be offered between SPs and tenants or between only SPs [13]. SLA shall include a specific number of elements, which are called metrics of the service object. SLA shall contain technical, economic, and legal statements that cover every topic that should be discussed and agreed upon between the SPs and the tenants [9, 21].

For accountability of varying network conditions and varying user behavior over several slices, SLA administration should be automated in order to evaluate performance and accurately characterize the QoS [22].

The primary essence of regulators in the telecommunication industry is to control downtime and ensure that high-quality service is rendered by the SPs or the MNOs to the customers. In Ghana, the national communication authority (NCA) has stringent regulatory targets to which MNO and TCs are obliged to adhere, otherwise will be faced with sanctions as stated in the NCA QoS regulations draft. In the event of downtime, the SPs shall notify the authority and affected customers in any locality within an hour of any service degradation or outage, which may extend beyond an hour [23]. MNOs and TCs must ensure network reliability through suitable operational and maintenance processes [24].

Telecommunication networks' dependability is increased by effective operational divisions cooperating for better results. The network monitoring centre (NMC), and operations assurance are the key operations divisions required for higher SLA.

A network operations center (NOC) is where company information technology (IT) administrators monitor and maintain telecommunications networks [25]. It is a room containing equipments that shows network visualizations. The NOC manages and optimizes business-critical functions, including network troubleshooting, software delivery, and updating for such enterprises. Passive alarms are monitored by a specified external alarm or a remote monitoring system (RMS). Main failure (MF), site on batteries (SOB), the generator failed to start (GFS), and site on hybrid (SOH) can be monitored through the NOC [16, 26].

Operations assurance engineers are the core of decision-making and the momentum behind infrastructure engineering in the telecom industry. The output of the operational assurance heavily influences whether or not an MNO will succeed in the set network availability and QoS of the NCA.

In order to model the severity of the downtime experienced by Ghanaian telecommunication networks, this study adds to the body of knowledge on telecommunication network downtime by employing discrete-time Markov chains (DTMC). This approach was chosen because of the ease of use and the accuracy of out-of-sample forecasting offered by Markov chain models.

The rest of the paper is organized as follows; a review of relevant literature is presented in section 2, the methodology is presented in section 3, section 4 contains the results and key findings of the study, section 5 contains the discussion of findings, and section 6 contains the conclusions and directions for future research.

2.Literature review

One of the major elements determining customer turnover rate and one that can have a significant impact on network downtime is client retention. The efficient conveyance of information from source to destination is the main purpose of a telecommunications network. Telecommunication network customers may decide to quit a business if it cannot serve them with exceptional service around-the-clock (also known as attrition). If this occurs too frequently, the revenue loss will impact the company's stability in a highly competitive market [26, 27].

A simulation study was conducted by [28, 29] with the goal of determining how a constrained network architecture would function in terms of coverage and capacity in the presence of a mobile network. SPs employ some quantitative metrics to understand the frequency of outages and the speed at which the network is restored, such as mean time to recovery (MTTR), mean time to acknowledge (MTTA), mean time to failure (MTTF), and mean time before failure (MTBF) [30].

MTBF, which is the average amount of time between two failures, is one of the crucial variables in availability measurement. The average time for repair and testing is known as the mean time to repair [31]. The loss of business continuity, employee productivity, income, and customer goodwill are the actual costs of network failures to an organization according to a study in the Cisco white paper on network availability [31].

Using data from the network management system (NMS), a new approach based on uptime sensor downtime was suggested. The new approach tracks the duration of a device's uptime over time to evaluate service level precisely and impartially. It offers a range of distinctive visuals for every sort of failure, including transmission and power loss. The technique offers a notable increase in service level percentage. In contrast, the prior system, which was based on ping downtime, provided a 56% service level in a simulated test, while the new process provided a 97.5% service level [30, 31].

The Weibull reliability growth model also referred to as the power law model was applied to outage data by [32] to determine if the system was getting worse or better. The study showed that the intensity function increases when the scale parameter (β) is more than 1, indicating that failures are likely to happen more frequently. On the other hand, the system will operate more effectively when the intensity function is 1 [32].

A parallel system equipment availability model was also developed by [32] in order to control expected service performance and achieve steady-state outage channel signal network access. The Markov processes with related negative exponential failure and restoration time distribution were considered to represent the model's two states [32].

In a study by [33], a fresh version of the queuing model was used to depict systems with rework and process downtime. It was emphasized that rigorous comparisons between the queuing model and discrete event simulation (DES) must be made under a variety of conditions, including changing rework rates, arrival variability, and process downtime. In every scenario, the queuing model showed promise for calculating lead time [33]. The NMS data was used to calculate the SLA based on uptime sensor downtime [33]. The novel approach created in their study measures the duration of a device's uptime over time and offers distinctive visuals for various failure types, such as transmission or power failure. This made it possible to calculate service levels in a trustworthy and neutral manner [33].

In a study by [34], the efficiency of low-latency video streaming in a real standalone 5G test environment was evaluated with a particular focus on uplink latency using user datagram protocol (UDP) and transmission control protocol (TCP). The results gathered from their extensive set of evaluation with test cases indicate that 5G standalone with the right uplink-to-downlink duration ratio has the potential for low latency streaming and delay variation stays relatively satisfying level even in congested network scenarios. Also, on the efficiency of service and data handoff protocols in edge computing systems, their results showed that by being proactive, the service interruption downtime reduces by a factor of 4 times.

Conducted a reliability analysis of time slotted channel hopping (TSCH) protocol in a mobile scenario [35]. Their evaluation was performed through simulation and the results showed that mobility may cause significant network downtime where nodes are unable to associate with the network for a long period of time because of synchronization loss, especially if the environment is not fully covered by static nodes. Also, [36] developed a new framework for mobile edge caching by proposing flexible user in heterogeneous cellular networks. Their simulation results indicated that their proposed framework significantly decreases the system model's average delivery delay, which can help the network maintain its QoS in network peak-traffic duration.

Developed an intelligent data fusion algorithm based on hybrid delay-aware adaptive clustering in wireless sensor networks. Their simulation results showed that, compared with the existing delay-aware models, the proposed scheme can effectively reduce the network delay, and network energy consumption, and extend the network lifetime simultaneously [37]. Leveraged large-scale domain name system (DNS) measurement data on authoritative name servers to study the reactions of domain owners affected by the 2016 dynamic distributed denial of service (DDoS) attack [38]. They used industry sources of information about domain names to study the influence of factors such as industry sector and website popularity on the willingness of domain managers to invest in high availability of online services. Their results can inform managed DNS and other network SPs regarding the potential impact of downtime on their customer portfolio. In a study by [39], a new hybrid clustering protocol (HCP) was proposed. The new protocol consisted of two main phases; cluster formation and data forwarding. They simulated HCP and compared its performance with low-energy adaptive clustering hierarchy (LEACH) and threshold low-energy adaptive clustering hierarchy (T-LEACH). Their results showed a reduction in network power consumption and an increase in the network lifetime by 30%.

Despite the extensive research on telecommunication network downtime as reviewed above, only a few studies focused on downtime duration and severity. Furthermore, the few studies that focused on downtime duration and severity used complex mathematical and statistical models which are difficult to understand. Considering the simplicity and the out-of-sample forecasting accuracy of Markov chain models, this study contributes to the literature on telecommunication network downtime by using DTMC to model the downtime severity of telecommunication networks in Ghana.

3.Methods

3.1Data

The data used in this empirical study consist of 1,211 total daily network downtime, in minutes, recorded by the NCA of Ghana, spanning the period August

01, 2015, to April 30, 2021. The severity of the daily downtime data was categorized into 5 categories, depending on the duration of the downtime (*Table 1*).

Table 1 Severity of network downtime categories

Downtime Duration (in minutes)	**Severity Category**
Less than 200	Negligible
Between 200 and 400	Minimal
Between 400 and 600	Significant
Between 600 and 800	Serious
Greater than 800	Severe

3.2 Block diagram for the overall network downtime duration

The overall network downtime duration can be broken down into single steps of events as shown in *Figure 1*. The overall downtime duration actually starts from the time a fault is reported to the time all network is restored. The time between when a fault is captured to the time when all network is restored is termed as the measured outage duration [40]. The measured outage duration includes the dispatch time (the time when the call has been logged on the system through customer reporting or through remote terminal unit (RTU) alarms at the station and the operator has been advised to travel to the site), the travel time (the time for an operator to travel to the site), the sectionalizing time (network is partially restored during this period through back feeding and network reconfiguration), the fault finding time (the time an operator is doing a visual inspection of the components with the intent of identifying the faulted equipment), the repair time (the time to repair the faulted equipment), and the restore time (the time for the network to return to its original state) [40].

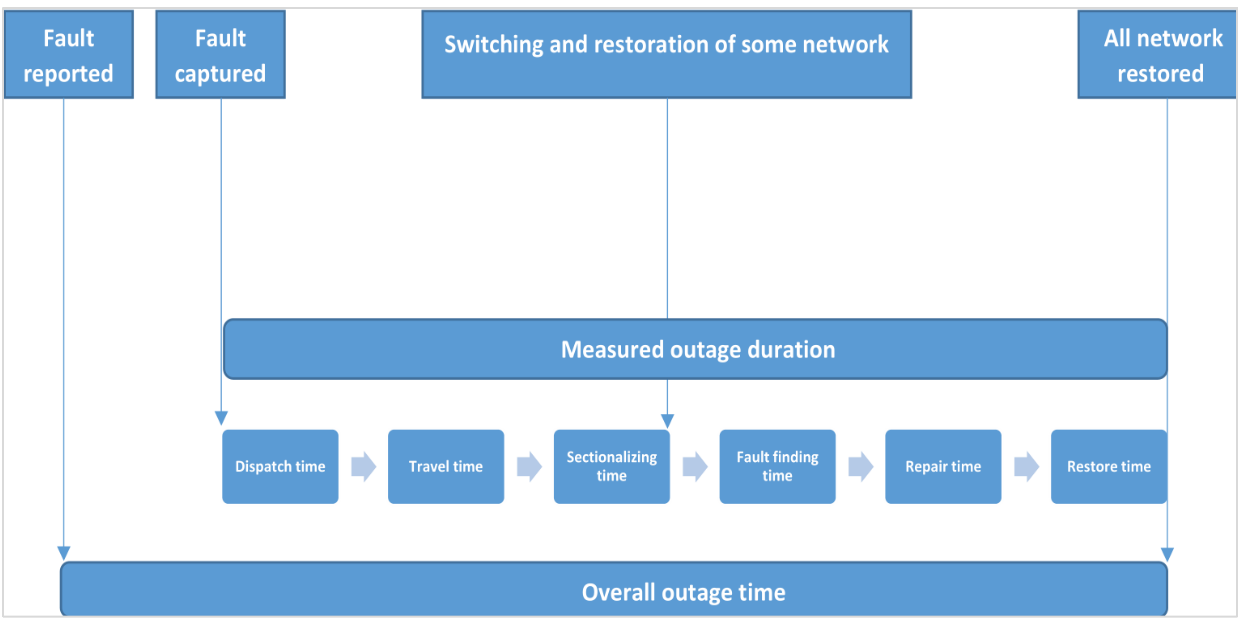

Figure 1 Key components of overall network downtime duration

3.3 Discrete-time Markov chain (DTMC) model

Markov chains are stochastic models used mainly for the analysis of stochastic processes [41]. There are basically two types of Markov chains; discrete-time and continuous-time Markov chains. The choice of either discrete-time or continuous-time Markov chain largely depends on the nature of the time series data involved. The DTMC is used in this application since the data consists of discrete network downtime severity in Ghana. Mathematically, a DTMC is defined as a sequence of random variables $X_1, X_2, \ldots$, which is characterized by the Markov property. The Markov property, also known as the memoryless property states that the distribution of the next variable (X_{n+1}) depends only on the value of the current variable (X_n) and not any of the previous variables $(X_{n-1}, X_{n-2}, \ldots, X_1)$. This definition is presented in Equation 1.

$$P(X_{n+1} = x_{n+1} \mid X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n) = P(X_{n+1} = x_{n+1} \mid X_n = x_n) \quad (1)$$

The state space of the Markov chain is the set of all possible states $S = \{s_1, s_2, \ldots, s_r\}$ of X_n, which can be finite or countably infinite. In this study, the state space consists of the 5 categories of network downtime severity classified based on the duration of the network downtime (see Equation 2).

S = {Negligible, Minimal, Significant, Serious, Severe} (2)

The Markov chain transitions from one state (say s_i) to another state (say s_j) with probability p_{ij} in one step, known as the transition probability (see Equation 3):

$$p_{ij} = \mathrm{P}\left(X_1 = s_j \mid X_0 = s_i\right) \quad (3)$$

The probability of transitioning from state i to j in n steps is shown in Equation 4.

$$p_{ij}^{(n)} = \mathrm{P}\left(X_n = s_j \mid X_0 = s_i\right) \quad (4)$$

When no change in the underlying transition probabilities is observed even as time changes, then the Markov chain is said to be time-homogeneous. A DTMC exhibits temporal homogeneity if Equation 5 holds.

$$\mathrm{P}\left(X_{n+1} = s_j \mid X_n = s_i\right) = \mathrm{P}\left(X_n = s_j \mid X_{n-1} = s_i\right) \quad (5)$$

If the DTMC exhibits temporal homogeneity, then the one-step and n-step transition probabilities are respectively given as;

$p_{ij} = \mathrm{P}\left(X_{k+1} = s_j \mid X_k = s_i\right)$ and $p_{ij}^{(n)} = \mathrm{P}\left(X_{n+k} = s_j \mid X_k = s_i\right)$, where $k > 0$

Each element, p_{ij}, of the transition probability matrix is computed using Equation 6, where n_{ij} represents the observed frequency of one-step transitions from state i to state j in the historical data.

$$p_{\mathrm{ij}} = \frac{n_{\mathrm{ij}}}{\sum_{j=1}^{k} n_{\mathrm{ij}}} \quad (6)$$

To check whether the sequence of events in the given data follows the Markov property with k states, we use the Chi-square (χ^2) test statistic with $(k-1)^2$ degrees of freedom, as shown in Equation 7.

$$\chi^2_{\mathrm{calc}} = \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{\left(n_{\mathrm{ij}} - e_{\mathrm{ij}}\right)^2}{e_{\mathrm{ij}}} \quad (7)$$

where n_{ij} and e_{ij} are the observed and expected transition frequencies respectively [42]. The expected transition frequency (e_{ij}) is computed using Equation 8.

$$e_{\mathrm{ij}} = \frac{\left(\sum_{i=1}^{k} n_{\mathrm{ij}}\right)\left(\sum_{j=1}^{k} n_{\mathrm{ij}}\right)}{\left(\sum_{i=1}^{k} \sum_{j=1}^{k} n_{\mathrm{ij}}\right)} \quad (8)$$

To investigate the long-term behavior of a Markov chain, we use the stationary distribution. The stationary or steady state distribution of the Markov chain in this study shows the long-term proportion of time each cause of network outage spends in a specific state.

4.Results

4.1Descriptive statistics

A detailed description of the data used for this study is presented in *Tables 2* and *3*. The measures of central tendency are contained in *Table 2* while the measures of dispersion are presented in *Table 3*. It is obvious from *Table 2* that the majority (n=905) of the daily network downtime recorded was negligible while only 25 of the outages were severe. 184, 59, and 38 of the recorded daily network downtime were minimal, significant, and serious respectively. The downtime data were however not normally distributed, considering the huge differences in the various measures of central tendency (mean, median, 5% trimmed mean).

Table 2 Measures of central tendency

	N	**Mean**	**Median**	**5% trimmed mean**
Negligible	905	70.45	54	65.37
Minimal	184	277.31	268.5	273.83
Significant	59	504.29	508	504.90
Serious	38	676.34	663.5	672.94
Severe	25	6241.28	998	1102.71

Table 3 contains the measures of dispersion for the downtime severity data used in this study. The large standard deviation (SD) and mean absolute deviation (mad) values indicate that there is a lot of variation in the observed network downtime data around the mean. This, therefore, means that the observed network downtime data is quite spread out in terms of severity.

Table 3 Measures of dispersion

	sd	mad	min	max
Negligible	50.47	45.96	2	197
Minimal	54.03	56.34	200	399
Significant	60.42	77.10	402	599
Serious	52.71	44.48	602	788
Severe	25439.91	228.32	813	128336

4.2DTMC model

We started by determining if the sequence of the network downtime severity data we gathered adhered to the Markov property. *Table 4* displays the results of the Chi-square test on several contingency tables created from the order of events (network downtime severity). Large p-values indicate that the null hypothesis of the sequence following the Markov property should not be rejected. Therefore we fail to reject the null hypothesis that our data on network downtime severity follows the Markov property since the p-value is greater than 0.05 (*Table 4*). Hence, we can proceed to perform a Markov chain analysis on our data.

Table 4 Testing Markovian property

Chi-square statistic	Degrees of freedom	p-value
108.32	66	0.72

The next step in DTMC modeling, after testing the Markov property, is to generate the transition probability matrix. The state transition probability matrix presented in *Table 5*, gives the probabilities of transitioning from one state to another in a single time unit. In this case, the possibilities of moving from one category of downtime severity to another within a single time unit are provided by the transition probability matrix. Several interesting revelations are presented in the transition probability matrix. Firstly, the probabilities in *Table 5* reveal that when the present network downtime severity is negligible, then there is an 81% chance that the next network downtime severity will still be negligible, a 12% chance that the next network downtime severity will be minimal, 4% chance that the next network downtime severity will be significant, 2% chance that the next network downtime severity will be serious, and 1% chance that the next network downtime severity will be severe. Also, when the present network downtime severity is minimal, then the probabilities that the next network downtime severity will be negligible, minimal, significant, serious, and severe are 59%, 25%, 6%, 6%, and 4% respectively. Furthermore, when the present network downtime severity is significant, then the probabilities that the next network downtime severity will be negligible, minimal, significant, serious, and severe are 49%, 29%, 5%, 9%, and 8% respectively. When the present network downtime severity is serious, then the probabilities that the next network downtime severity will be negligible, minimal, significant, serious, and severe are 55%, 19%, 18%, 8%, and 0% respectively. Finally, when the present network downtime severity is severe, then there is a 32%, 24%, 2%, 8%, and 16% chance that the next network downtime severity will be negligible, minimal, significant, serious, and severe respectively (*Table 5*).

For easy understanding of the transition probability matrix in *Table 5*, the transition matrix, which gives the probabilities of transitioning from one network downtime severity category to another is presented diagrammatically in *Figure 2*. The circular arrows indicate the probability of transitioning from one downtime severity category to itself, while the directional arrows give the probability of transitioning from one downtime severity category to the other.

Table 5 Transition probability matrix for the network downtime severity

	Neg.	Min.	Sig.	Ser.	Sev.
Negligible (Neg.)	0.81	0.12	0.04	0.02	0.01
Minimal (Min.)	0.59	0.25	0.06	0.06	0.04
Significant (Sig.)	0.49	0.29	0.05	0.09	0.08
Serious (Ser.)	0.55	0.19	0.18	0.08	0
Severe (Sev.)	0.32	0.24	0.2	0.08	0.16

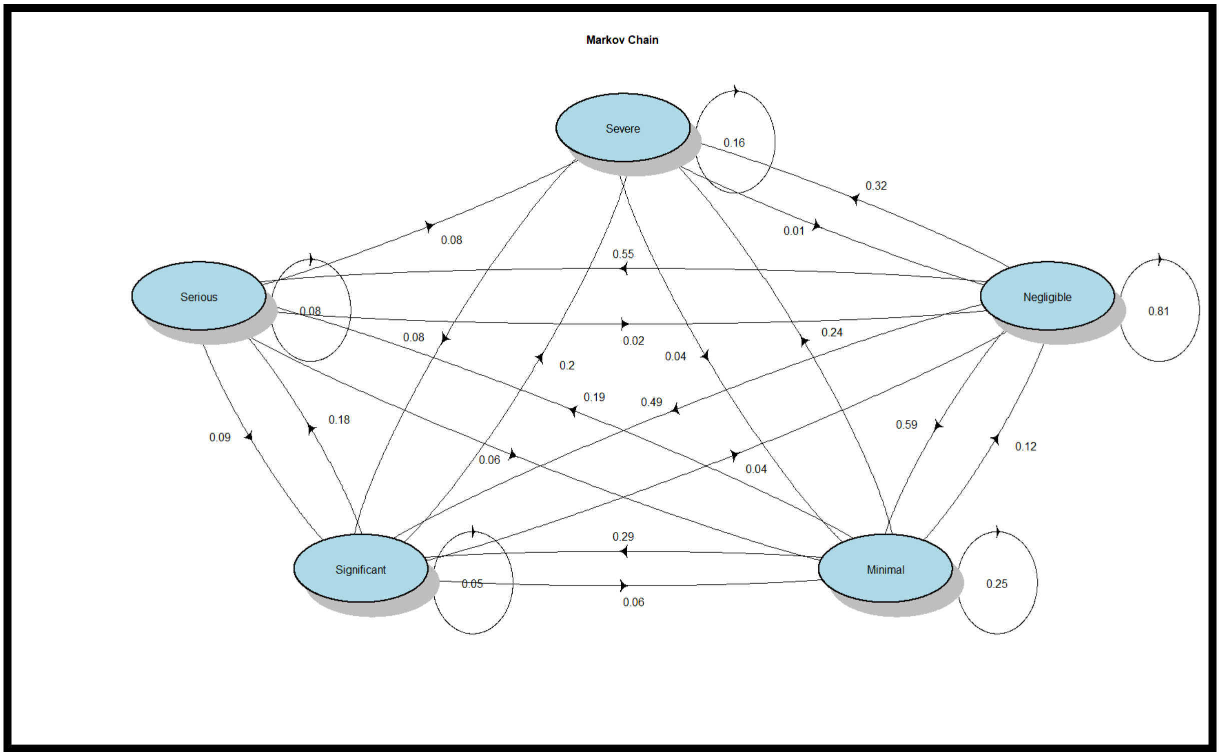

Figure 2 Transition probability diagram for the network downtime severity

The steady state distribution for the network downtime severity Markov chain is presented in *Table 6*. Also known as the stationary distribution, in the Markov chain, the steady state distribution is a probability distribution that doesn't vary over time. This indicates that in the long run ($n \geq 17$), 74% of the network downtime severity will be negligible while 16% of the network downtime severity will be minimal. In addition, in the long run, 5%, 3%, and 2% of the network downtime severity will be significant, serious, and severe respectively (*Table 5*).

We can also see how the probabilities change as the number of steps rises using the DTMC model created in this study to compare the actual number of steps. So, we calculated the likelihood of a network downtime. severity for 12 steps. From the plots in *Figures 3 – 7*, it seems apparent that the most likely network downtime severity category is ‘negligible’, irrespective of whether the initial network downtime severity is negligible, minimal, significant, serious, or severe. However, the likelihood decays with time.

Table 6 Steady state distribution

Downtime severity category	**Limiting probabilities**
Negligible	0.74
Minimal	0.16
Significant	0.05
Serious	0.03
Severe	0.02

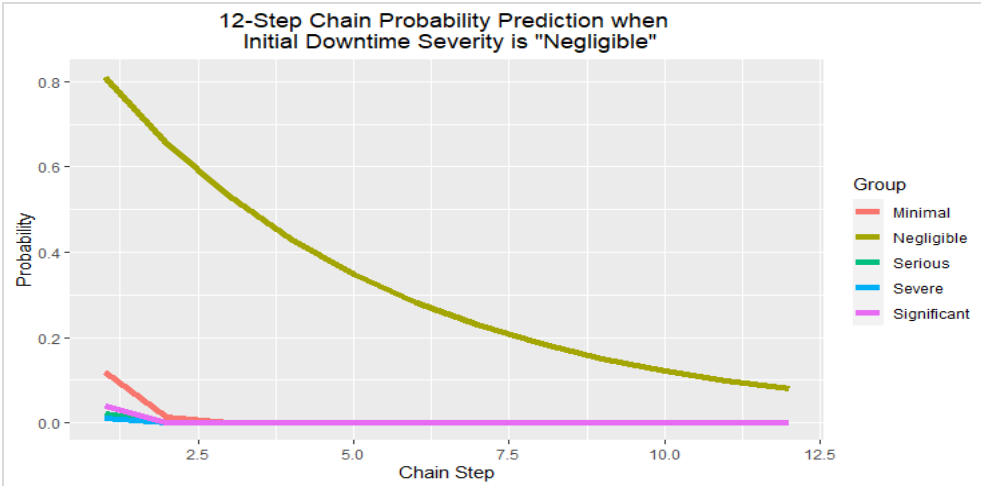

Figure 3 12-Step chain probability predictions when initial network downtime severity is 'Negligible'

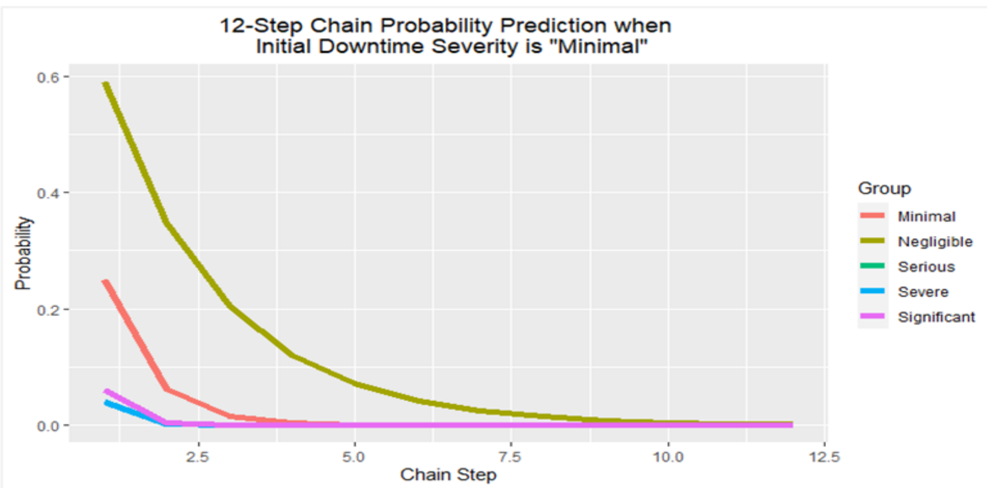

Figure 4 12-Step chain probability predictions when initial network downtime severity is 'Minimal'

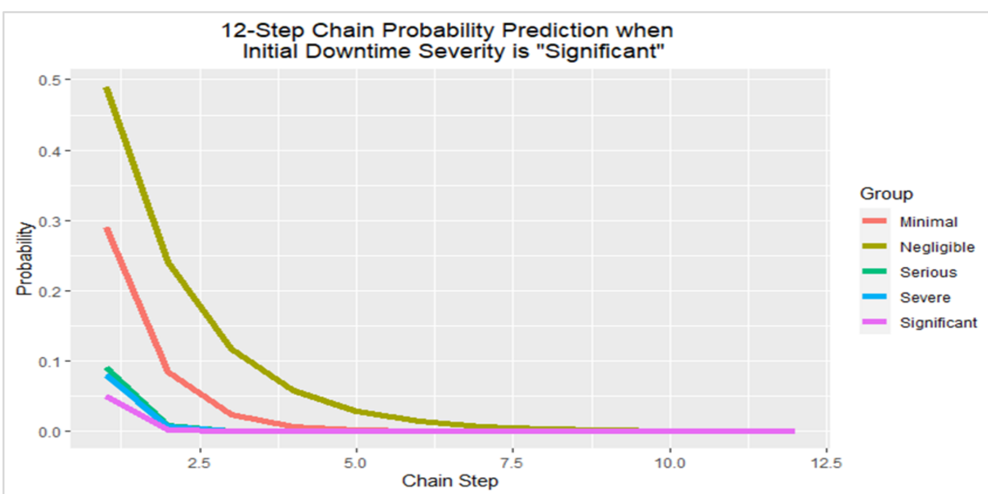

Figure 5 12-Step chain probability predictions when initial network downtime severity is 'Significant'

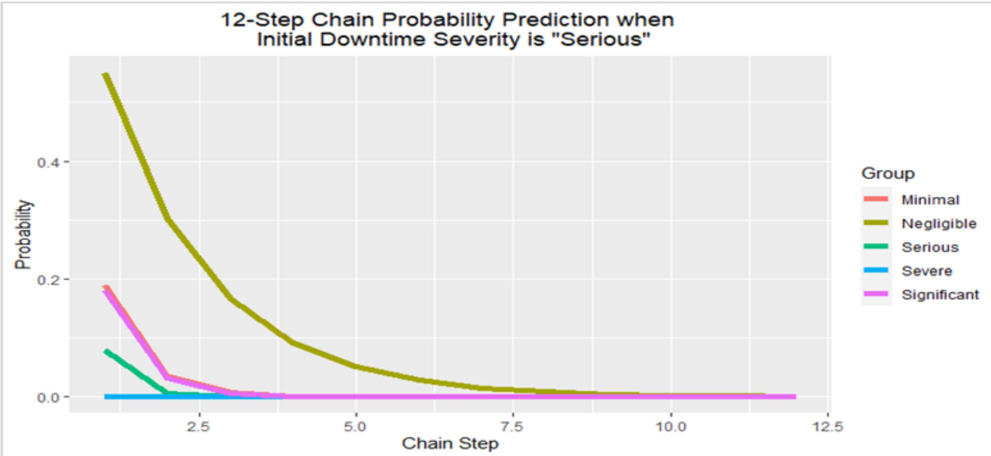

Figure 6 12-Step chain probability predictions when initial network downtime severity is 'Serious'

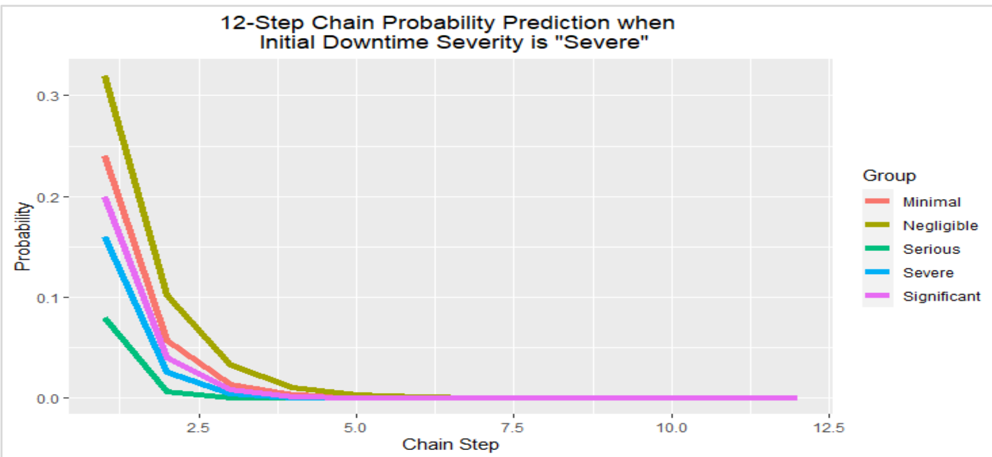

Figure 7 12-Step chain probability predictions when initial network downtime severity is 'Severe'

5.Discussion

The implications of this study are quite clear. The results reveal that the majority (n=905) of daily network downtimes recorded were negligible, while only 25 outages were severe. Of the recorded daily network downtimes, 184, 59, and 38 were classified as minimal, significant, and serious, respectively. The study's results indicate the network's availability and dependability, which every operator of a telecommunications network wants to ensure [43]. The amount of network downtime demonstrates the effectiveness of preventative maintenance, which increases the lifespan of telecommunications equipment and generates high revenue. Telecom providers can reduce network downtime by adhering to industry best practices for energy supply [44, 45]. This research finding suggests that while most of the recorded incidents of telecommunication network downtime are not severe and have little impact on users, there are still a few incidents that are severe enough to cause disruptions and affect users' ability to access communication services.

There could be several reasons why most recorded downtime incidents are negligible. One possible explanation is that telecommunication network providers have implemented robust infrastructure and backup systems to minimize the risk of service disruptions. Additionally, advancements in technology and network monitoring tools may have enabled providers to detect and address issues quickly before they escalate into severe downtime [45]. It is worth noting that although most downtime incidents may be negligible, they can still have a cumulative impact on the overall network's reliability. Therefore, telecommunication network providers must continue to closely monitor their systems and invest in infrastructure upgrades and maintenance to minimize the risk of downtime, even for relatively minor incidents [44].

Secondly, the results reveal that when the present network downtime severity is negligible, then there is an 81% chance that the next network downtime severity will still be negligible, a 12% chance that the next network downtime severity will be minimal, 4% chance that the next network downtime severity will be significant, 2% chance that the next network downtime severity will be serious, and 1% chance that the next network downtime severity will be severe. The analysis reveals a very low severity of downtime, which should be the goal of every MNO, as well as a minimal level of call drop, excellent QoS, low operational costs, and good profitability [46, 47].

This research finding suggests that when the present network downtime severity is negligible, there is a high probability (81%) that the severity of the next network downtime incident will also be negligible. This implies that most telecommunication network downtime incidents are not likely to escalate into severe or serious incidents.

The research finding further suggests that if there is another downtime incident after a negligible incident, there is a 12% chance that it will be minimal, meaning that it will cause minor disruptions but not severely impact users. Additionally, there is a 4% chance that the next downtime incident will be significant, meaning that it will cause moderate disruptions that may affect a significant number of users. There is a 2% chance that the next downtime incident will be serious, meaning that it will cause significant disruptions that may affect a large number of users. Finally, there is only a 1% chance that the next downtime incident will be severe, meaning that it will cause a complete service outage for an extended period.

It is important to note that while the probability of a severe downtime incident is low, it is not impossible. Telecommunication network providers must remain vigilant in monitoring their systems and addressing even minor incidents promptly to minimize the risk of severe downtime incidents [46]. This research finding provides valuable insights into the likelihood of various levels of downtime severity in telecommunication networks. It emphasizes the importance of proactive measures and infrastructure upgrades to prevent downtime and ensure uninterrupted access to essential communication services.

Furthermore, the DTMC's steady state distribution shows that in the long term ($n \geq 17$), 74% of the network downtime severity will be negligible while 16% of the network downtime severity will be minimal. In addition, in the long run, 5%, 3%, and 2% of the network downtime severity will be significant, serious, and severe respectively. The steady-state distribution of the DTMC outcome demonstrates that the MNO possesses a reliable network and is in compliance with all of the NCA, FCC, and ITU network QOS standards [47, 48]. To determine the impact of network downtime and reliability, evaluating the severity of individual outages and the network's overall performance over time is essential [10, 6, 49].

The finding that 74% of network downtime incidents will be negligible in the long term is consistent with the idea that telecommunication network providers have implemented robust infrastructure and backup systems to minimize the risk of service disruptions. This suggests that most minor incidents are quickly resolved before they escalate into more severe downtime incidents.

The finding that 16% of network downtime incidents will be minimal indicates that some incidents may cause minor disruptions that can be quickly resolved but may still affect users' ability to access communication services. This highlights the importance of prompt incident response and effective communication with users to manage their expectations and minimize the impact of downtime incidents [50]. This research finding provides valuable insights into the long-term distribution of network downtime severity in telecommunication networks. It underscores the importance of continuous monitoring and proactive measures to minimize downtime incidents and ensure uninterrupted access to essential communication services [50, 51].

5.1Limitations

The study's main limitation is that the downtime data used is not system-based; instead, the majority of it is determined by the NOC engineer. Weak network connections also impact remote monitoring software, and some alarms are discarded, resulting in data loss that may alter the study's findings. Furthermore, the categorizations of downtime are also founded on field experience. Another limitation concerns the DTMC model. The DTMC only depends on the current state to determine the probability of transitioning to the next state, and not on any previous states. This means that the future state is independent of the past states given the present state. A complete list of abbreviations is shown in *Appendix I*.

6.Conclusion and future work

In this paper, we utilized a DTMC to model and analyze the severity of downtime in telecommunication networks in Ghana. The duration of downtime was categorized into 5 levels based on severity: negligible, minimal, significant, serious, and severe. Descriptive statistics revealed that the majority (n=905) of daily network downtime was negligible, while only 25 of the outages were severe. The transition probability matrix showed that when the current network downtime severity is negligible, there is an 81% chance that the next severity will also be negligible, a 12% chance of minimal, a 4% chance of significant, a 2% chance of serious, and a 1% chance of severe. The steady-state distribution indicated that in the long run ($n \geq 17$), 74% of the network downtime severity will be negligible, while only 2% will be severe. We also simulated the probabilities of network downtime severity for 12 steps and found that the most likely severity category was "negligible," regardless of the initial severity category. The study's DTMC model was simple and accurate in out-of-sample forecasting. Future research may compare the results of continuous-time Markov chains (CTMC) and DTMC for predicting telecommunication downtime duration.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Dr. Wahab A. Iddrisu: Conceptualization, data curation, writing-original draft, analysis and interpretation of results. **Dr. Ibrahim A. Gedel:** Conceptualization, writing introduction, literature review and discussion, data curation, and writing-original draft.

References

[1] https://www.seo-e.com/seo-advantage. Accessed 04 April 2023.
[2] https://www.sustainalytics.com/esg-research/resource/investors-esg-blog/telecom-network-outages-the-esg-risks-of-a-connected-world. Accessed 04 April 2023.
[3] Yeshalem MT, Khan B. Design of an off-grid hybrid PV/wind power system for remote mobile base station: a case study. Aims Energy. 2017; 5(1):96-112.
[4] Matsukawa T, Funakoshi H, Koshiji K. Evaluating downtime and maintenance time in communication networks. In proceedings-annual reliability and maintainability symposium 2011 (pp. 1-6). IEEE.
[5] Haggarty L, Shirley MM, Wallsten S. Telecommunication reform in Ghana. Available at SSRN 636345. 2002:1-40.
[6] Tollar ES, Bennett JM. Network outage impact measures for telecommunications. In proceedings IEEE symposium on computers and communications 1995 (pp. 120-6). IEEE.
[7] Osei-owusu A. The analysis of the Ghana telecom industry. 26th European regional international telecommunications society conference, Madrid, 2015 (pp 1-20).
[8] Mazidi P, Baltas GN, Eliassi M, Rodríguez P. A model for flexibility analysis of RESS with electric energy storage and reserve. In 7th international conference on renewable energy research and applications 2018 (pp. 1004-9). IEEE.
[9] Quaye HA. Data and telecommunication problems in Sub-Saharan Africa. 2016; 6(4):11-4.
[10] Biggar DR. Competition and regulation issues in telecommunications. Available at SSRN 318779. 2002:1-416.
[11] Oduro-gyimah FK, Boateng KO, Adu PB, Quist-aphetsi K. Prediction of telecommunication network outage time using multilayer perceptron modelling approach. In international conference on computing, computational modelling and applications 2021 (pp. 104-8). IEEE.
[12] Oduro-gyimah FK, Azasoo JQ, Boateng KO. Statistical analysis of outage time of commercial telecommunication networks in Ghana. In international conference on adaptive science and technology 2013 (pp. 1-8). IEEE.
[13] Akanbasiam JA, Ngala DK. The study of quality of service on a major mobile network operator in Ghana. IOSR Journal of Electronics and Communication Engineering. 2017; 12:21-5.
[14] Nungu A, Olsson R, Pehrson B. On powering communication networks in developing regions. In symposium on computers and communications 2011 (pp. 383-90). IEEE.
[15] Frimpong SK, Boateng AK. Quality service delivery in the telecommunication industry of Ghana: the perspective of MBA students of Sikkim Manipal University. International Journal of ICT and Management. 2014; 2(2):163-70.
[16] Alashaikh A, Gomes T, Tipper D. The spine concept for improving network availability. Computer Networks. 2015; 82:4-19.
[17] Teshnizi SH, Aghamolaei T, Kahnouji K, Teshnizi SM, Ghani J. Assessing quality of health services with the SERVQUAL model in Iran. A systematic review and meta-analysis. International Journal for Quality in Health Care. 2018; 30(2):82-9.
[18] Ghotbabadi AR, Feiz S, Baharun R. Service quality measurements: a review. International Journal of Academic Research in Business and Social Sciences. 2015; 5(2):267-86.

[19] Tests ON. National communications authority telcos sanctioned GHC34 million for Failing Quality. NCA Ghana. 2018; 6:4-7.

[20] Säe J, Lempiäinen J. Maintaining mobile network coverage availability in disturbance scenarios. Mobile Information Systems. 2016:1-11.

[21] https://www.epa.gov/system/files/documents/2022-06/TelecomGuide_508c.pdf. Accessed 04 April 2023.

[22] Al-Mhasnah A, Salleh F, Afthanorhan A, Ghazali PJ. The relationship between services quality and customer satisfaction among Jordanian healthcare sector. Management Science Letters. 2018; 8(12):1413-20.

[23] https://bcp.gov.gh/acc/registry/docs/ELECTRONIC%20COMMUNICATIONS%20REGULATIONS,%202011%20(LI%201991).pdf. Accessed 04 April 2023.

[24] Snow AP. Network reliability: the concurrent challenges of innovation, competition, and complexity. IEEE Transactions on Reliability. 2001; 50(1):38-40.

[25] Panajotovic B, Odadzic B. Design and "inteligent" control of hybrid power system in telecommunication. In MELECON, 15th Mediterranean electrotechnical conference 2010 (pp. 1453-8). IEEE.

[26] Schmidt RR, Shaukatullah H. Computer and telecommunications equipment room cooling: a review of literature. In eighth intersociety conference on thermal and thermomechanical phenomena in electronic systems 2002 (pp. 751-66). IEEE.

[27] Ciardo G, Blakemore A, Chimento PF, Muppala JK, Trivedi KS. Automated generation and analysis of Markov reward models using stochastic reward nets. In linear algebra, markov chains, and queueing models 1993 (pp. 145-91). Springer New York.

[28] Tsadimas A, Kapos GD, Dalakas V, Nikolaidou M, Anagnostopoulos D. Simulating simulation-agnostic SysML models for enterprise information systems via DEVS. Simulation Modelling Practice and Theory. 2016; 66:243-59.

[29] Vegunta SC, Milanovic JV. Estimation of cost of downtime of industrial process due to voltage sags. IEEE Transactions on power Delivery. 2009; 26(2):576-87.

[30] Samuels CI, Syambas NR, Edward IJ, Shalannanda W. Service level measurement based on uptime data monitoring for rural internet access services in Indonesia. In 11th international conference on telecommunication systems services and applications 2017 (pp. 1-5). IEEE.

[31] Brown AJ, Badurdeen F. A queuing model for systems with rework and process downtime. In international conference on automation science and engineering 2013 (pp. 789-94). IEEE.

[32] Jackman J, Johnson E. The role of queueing network models in performance evaluation of manufacturing systems. Journal of the Operational Research Society. 1993; 44(8):797-807.

[33] Uitto M, Heikkinen A. Evaluating 5G uplink performance in low latency video streaming. In joint European conference on networks and communications & 6G summit (EuCNC/6G Summit) 2022 (pp. 393-8). IEEE.

[34] Scotece D, Fiandrino C, Foschini L. On the efficiency of service and data handoff protocols in edge computing systems. In global communications conference 2021 (pp. 1-6). IEEE.

[35] Raza S, Van DLT, Exarchakos G, Güneş M. A reliability analysis of TSCH protocol in a mobile scenario. In 16th annual consumer communications & networking conference 2019 (pp. 1-6). IEEE.

[36] Eslami P, Amerimehr MH, Shariatpanahi SP. A new framework for mobile edge caching by proposing flexible user in heterogeneous cellular networks. IEEE Access. 2020; 8:188938-50.

[37] Liu X, Zhu R, Anjum A, Wang J, Zhang H, Ma M. Intelligent data fusion algorithm based on hybrid delay-aware adaptive clustering in wireless sensor networks. Future Generation Computer Systems. 2020; 104:1-4.

[38] Haq MY, Jonker M, Van RR, Claffy KC, Nieuwenhuis LJ, Abhishta A. No time for downtime: understanding post-attack behaviors by customers of managed DNS providers. In European symposium on security and privacy workshops 2022 (pp. 322-31). IEEE.

[39] Masoud MZ, Jaradat Y, Zaidan D, Jannoud I. To cluster or not to cluster: a hybrid clustering protocol for WSN. In Jordan international joint conference on electrical engineering and information technology 2019 (pp. 678-82). IEEE.

[40] Dumakude GC. Evaluation of smart technology for the improvement of reliability in a power distribution system (Doctoral Dissertation). Research Space. 2015.

[41] Mo J. Performance modeling of communication networks with Markov chains. Synthesis Lectures on Data Management. 2010; 3(1):1-90.

[42] Wilks DS. Time series. In international geophysics 2011 (pp. 395-456). Academic Press.

[43] Andrade EC, Machida F, Kim DS, Trivedi KS. Modeling and analyzing server system with rejuvenation through SysML and stochastic reward nets. In sixth international conference on availability, reliability and security 2011 (pp. 161-8). IEEE.

[44] Snow AP, Chatanyam K, Weckman GR, Campbell P. Power related network outages: impact, triggering events, and root causes. In NOMS 2006:1-7.

[45] Rauf H, Khan HA, Arshad N. Optimized power system planning for base transceiver station (BTS) based on Minimized power consumption and cost. In international conference on renewable energy research and applications 2019 (pp. 773-9). IEEE.

[46] Siemer K, Wolf D. TCO-optimized solar system dimensioning in BTS applications. In international telecommunications energy conference 2015 (pp. 1-6). IEEE.

[47] https://sgp.fas.org/crs/misc/R45338.pdf. Accessed 04 April 2023.

[48] Pai GJ, Dugan JB. Automatic synthesis of dynamic fault trees from UML system models. In 13th

international symposium on software reliability engineering, Proceedings 2002 (pp. 243-54). IEEE.
[49] Pachauri RK, Chauhan YK. Hybrid PV/FC stand alone green power generation: a perspective for Indian rural telecommunication systems. In international conference on issues and challenges in intelligent computing techniques 2014 (pp. 802-10). IEEE.
[50] Macmillan M, Wilson K, Baik S, Carvallo JP, Dubey A, Holland CA. Shedding light on the economic costs of long-duration power outages: a review of resilience assessment methods and strategies. Energy Research & Social Science. 2023.
[51] Lin D, Zhang W. Evaluation method of power loss for distribution network fault handling based on distribution transformer outage and restoration information matrix. In journal of physics: conference series 2023 (pp. 1-7). IOP Publishing.

Dr. Wahab A. Iddrisu obtained a four-year Bachelor's degree in Statistics and Mathematics from the University of Ghana in 2008, a Master of Philosophy degree in Applied Mathematics from the Kwame Nkrumah University of Science and Technology in 2012, and a Doctor of Philosophy degree in Applied Statistics from the University for Development Studies in 2017. For the past 10 years, Dr. Iddrisu has been working as a university lecturer and consulting statistician, collaborating with renowned researchers from various disciplines to provide statistical support and research guidance. He has co-authored over 30 peer-reviewed journal articles, where he has been the sole contributor of statistical content.
Email: widdrisu@gctu.edu.gh

Dr. Ibrahim A. Gedel received his Bachelor's degree in Applied Electronics and Systems Engineering, with a major in Computer Engineering, from Regent University in 2011. He obtained his first Master's degree in Telecommunications Engineering from the Ghana Telecommunications University in 2013, and a second Master's degree in Business Administration with a focus on project management from the Ghana Institute of Management Studies in 2018. In 2021, he earned his Doctorate in Electrical and Electronics Engineering, specializing in 5G technology implementation, from the University of Johannesburg. He has attended about five conferences in Ghana and Johannesburg. In 2019, Dr. Ibrahim became a certified member of the Ghana Institute of Engineers, with over 15 years of working experience in the telecommunications industry. He joined academia as a university lecturer in 2021 and has co-authored about four articles. He is a telecommunications O&M specialist and consultant.
Email: igedel@gctu.edu.gh

Appendix I

S. No.	Abbreviation	Description
1	5G	5th Generation
2	BER	Bit Error Rate
3	CDR	Call Drop Rate
4	CSSR	Call Set-Up Success Rate
5	CTMC	Continuous-Time Markov Chains
6	DES	Discrete Event Simulation
7	DTMC	Discrete-Time Markov Chain
8	DDoS	Distributed Denial of Service
9	DNS	Domain Name System
10	GFS	Generator Failed to Start
11	HCP	Hybrid Clustering Protocol
12	IT	Information Technology
13	ITU	International Telecommunication Union
14	ISPs	Internet Service Providers
15	KPIs	Key Performance Indicators
16	KQIs	Key Quality Indicators
17	LEACH	Low Energy Adaptive Clustering Hierarchy
18	MF	Main Failure
19	MTBF	Mean Time Before Failure
20	MTTA	Mean Time to Acknowledge
21	MTTF	Mean Time to Failure
22	MTTR	Mean Time to Recovery
23	MNOs	Mobile Network Operators
24	NCA	National Communication Authority
25	NMS	Network Management System
26	NMC	Network Monitoring Centre
27	NOC	Network Operations Center
28	QoS	Quality of Service
29	RMS	Remote Monitoring System
30	RTU	Remote Terminal Unit
31	SLAs	Service Level Agreement
32	SPs	Service Providers
33	SOB	Site on Batteries
34	SOH	Site on Hybrid
35	T-LEACH	Threshold Low Energy Adaptive Clustering Hierarchy
36	TSCH	Time-Slotted Channel Hopping
37	TCs	Tower Companies
38	TCP	Transmission Control Protocol
39	UDP	User Datagram Protocol