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Reliability analysis of telecommunication networks from customer damage perspective: an overview of two techniques

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Telecommunication networks have become fundamental for our daily life, and their outages can bear large consequences and customers' economic loss. The importance of telecommunication network reliability is demonstrated by the large body of literature, but unfortunately reliability analysis of the network from customer damage perspective is scarce. To fill this gap, this paper analyses two key techniques to assess the reliability of a network. A review of reliability metrics and customer damage functions is given. The reliability metrics of telecommunication networks are summarized according to the network development. Furthermore, customer damage functions for several sectors are also categorized into six groups to cover the parties affected and various usage scenarios. We believe that this work represents an important point for academy and industry to understand and contribute to the area of telecommunication network reliability.
Keywords: telecommunication network, reliability analysis, reliability metrics, customer damage function, outage loss.

1. Introduction

In this new technological era, almost every aspect of our lives is linked to the service of telecommunication networks. Especially due to the new revolution of network use-pattern in industrial and residential sectors, the 5G cellular structure with ultra-high frequency and higher performance is aiming itself as the new generation of networks. In this regard, the number of base stations built is more than several times than previous generations of networks. The ever-rising implementation and application of 5G networks put forward a new challenge to the supply of constantly stable and non-stoppable services. In this context, telecommunication network outages not only cost millions to carriers, but may also lead to massive losses of customer loyalty.

Therefore, a main concern of telecommunication networks is to prevent the occurrence of outages and provide satisfied service to customers, i.e. to have high reliability.

In this paper, we consider the evaluation of the reliability of networks from the economic or socioeconomic perspective, which means the loss to customers. An outage considering in a telecom network can be such that the capacity of the network cannot satisfy the expected demand of customers. From this perspective, network performance must ensure signal propagation from sources to destinations, to guarantee that the capacity meets the demand. Additionally, Customer Damage Functions (CDFs) are built to quantify economic losses of customers to capture the degradation with time of the experience of users due to outages. In this paper we primarily focus on the study of CDFs and reliability metrics, the work is divided into two parts. In the first part, we provide an overview of the reliability metrics of telecommunication networks in relation to network development stages and application scenarios. In the subsequent part, the research on customer damage functions is summarized and they are categorized into six groups based on factors and scenarios considered.

The remainder of the paper is organized as follows. Section 2 discusses reliability metrics, in relation to the development of telecommunication networks. Customer damage functions associated with metrics are presented in Section 3. The last Section concludes the study with future directions of research.

2. Reliability Metrics

In this paper, we look at the reliability of telecommunication networks from the system level, and system reliability metrics are introduced The metrics are dependent on the purposes of analysis or the needs of customers.

Historically, the telecom network reliability analysis has experienced five different stages. In the early stage, the network was mainly considered as wire-connected, and K-terminal probabilistic connectivity represents the probability of connection of k-nodes in the network, was considered as a reliability metric (Jereb, 1998). Trstensky (1984) puts forward another metric related to the effectiveness of the connection considering all the states and the number of channels between vertices. Since connectivity is not able to reflect fully the degradation of the network performance, capacities-related metrics, such as normalized capacities (Rushdi 1988), simultaneous capacities transmitted and the average satisfied fraction of the capacity demands (Trstensky, 1984), have been proposed. Also some integrated metrics have been proposed. Aggarwal (1985) and Rushdi (1988) proposed a weighted reliability index of a telecommunication network by combining S-T connectivity probability and channel capacity.

In the application of call and telegraph business, metrics such as Call Setup Success Rate (CSSR) and Call Drop Rate (CDR), were adopted to evaluate the quality of service of GSM (Global System for Mobile Communication) networks (Ozovehe, 2015; Abdulkareem, 2020). CSSR is used to measure the ease with which calls are established, and CDR measures the network's ability to retain call conversation once established:

$$CSSR = \frac{S_c}{T_c} \tag{1}$$

$$CDR = \frac{N_d}{N_s} \tag{2}$$

where S_c is the number of successful call connections, T_c denotes the total number of call attempts, N_d represents the number of call drops, N_s is the number of successful call setups.

Subsequently, often metrics have been proposed for different scenarios. For scenarios where time is of significance, time-related metrics, such as delay (Chiou, 1986), latency (Li, 2017) and minimum time to transmit a certain amount of data (Lin, 2010), are presented. From the perspective of the demands of users, Carlier (1994) considers the expected loss of traffic in the rerouting process as the availability of networks in a given state. Signal-to-Interference-plus-Noise Ratio (SINR) is also applied to analyze the signal quality as the network reliability metric (Miyoshi, 2014).

In the 3G and 4G periods, wireless and wired heterogeneous networks emerged. Correspondingly Quality of Service (QoS) metrics have gradually appeared, such as network delay, jitter, loss probability, reliability, throughput and bit error rate. According to the definition of ITU (International Telecommunication Union) and ETSI (European Telecommunications Standards Institute), QoS metrics show the ability of a network or network portion to provide functions related to communications between users (Subramaniam, 1985). Based on QoS, Key Performance Indicators (KPIs) are defined and categorized into five subcategories: accessibility, retainability, mobility, integrity and availability (3GPP, 2022). In the METIS project (Popovski, 2013), through illustrating five scenarios, KPIs are classified as Traffic volume density, Experienced end-user throughput, Latency, Reliability, Availability and Retainability, Energy consumption (efficiency) and Cost. Later, Security is identified as a new KPI to address the need for security. The detailed descriptions and metrics are shown in Table 1.

Table 1 Telecommunication Network Performance KPIs

Subcategories	Qualitative Definition	Mathematical Explanation
Traffic volume density	the total user data volume transferred to/from end-user devices during a predefined time span	the sum of traffic volumes each produced and consumed by an end-user device divided by the time span and by the overall service area
Experienced user throughput	the average data throughput an end-user device achieves during a defined time span	$Th_i = E_k[L_{ik}/T_{ik}]$ L_{ik} is the size of k-th package of i-th user, T_{ik} is the E2E delay of delivering the packets, E means the expectation over a time span
Reliability	the probability that a certain amount of data from an end-user device is successfully transmitted to another peer (e.g. Internet server, mobile device, sensor) within a predefined time frame	$R=Pr(L \leqslant D)$ L is the measured E2E latency and D is the deadline, which characterizes the degree of real-time of the communication link
Latency	one trip time (OTT) latency: the time it takes from when a data packet is sent from the transmitting end to when it is received at the receiving end	$T_{OTT} = T_{A2} - T_{S1}$ T_{S1} is the start time of data transmission and T_{A2} is the time instant when messages are received
	Round trip time (RTT) latency: the time from when a data packet is sent from the transmitting end until acknowledgments are received from the receiving entity	$T_{RTT} = T_{A1} - T_{S1}$ T_{S1} is the start time of data transmission and T_{A1} is the time instant when the acknowledgment arrives at the transmitter
Availability and Retainability	availability represents the ability of a cell unit to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval	$A=Pr(R \geqslant QoE)$ R is the measured reliability and QoE is the QoE requirements in terms of reliability of the underlying use case
	retainability means a service has been made available as long as the user needs the service.	Retainability can be defined as the probability for R to remain larger than the QoE-target, QoE, given that the service has already been made available
Energy Consumption /Efficiency	data energy efficiency in operational E-UTRAN (Evolved Universal Terrestrial Radio Access Network)	Energy per information bit (the most widely accepted metric for energy efficiency, especially in urban environments) $\lambda_I = \frac{E}{I} = \frac{P}{R}$ E stands for consumed energy, P is consumed power, I is the information volume with rate R
		Information bit per energy Reciprocal of Energy per information bit
		Power per area unit (typically applicable in suburban or rural environments) $\lambda_A = \frac{P}{A}$ P is the power consumed and A is the area coverage
Cost	for a cellular network, the cost typically is related to infrastructure (capital expenditure and operational expenditure), end-user equipment and spectrum license	

In the 5G era, some ground-breaking solutions are appearing to transform the world, such as the digitalization of industries. In order to satisfy the new requirements for telecom networks, ITU has envisaged three important usage scenarios eMBB (enhanced mobile broadband), mMTC (massive machine-type communications) and URLLC (ultra-reliable and low latency). For these scenarios, the corresponding quantitative KPIs of 5G networks are also set forth (3GPP 2018; 3GPP, 2022). Salman (2017) summarizes the available literature and categorizes metrics as energy and power, QoS, QoE (Quality of Experience), security and reliability and resilience metrics. Further QoS metrics are classified as application-based QoS for end-to-end quality of real-time applications and network-based QoS for traffic quality enabled by the network equipment, QoE as subjective and objective metrics based on whether human perception is evaluated directly.

For telecom networks, the aforementioned metrics mostly are local indices or focus on a certain specific performance which cannot reflect the system reliability comprehensively. In some cases, the stakeholders have the need to evaluate whether the network can satisfy end-users' demands based on reliability metrics from a system view of point. Using metrics of the power grid industry for reference, Yan-FU LI (2021) identifies three system reliability metrics to statistically evaluate the probability that the network capacity meets the demand, which are Expectation Consumers Not Satisfied (ECNS), Expectation Consumers Satisfaction Rate (ECSR) and Expectation Demand Not Satisfied (EDNS):

$$ECNS = \sum_i P(G_i - D_i) \tag{3}$$

$$ECSR = \frac{N - \sum_i P(G_i - D_i)}{N} \tag{4}$$

$$EDNS = \sum_i E(max(D_i - G_i, 0)) \tag{5}$$

where G_i is the network supply for customer i under the current network state, D_i denotes the demand of customer i and N represents the number of customers served during operation.

Because of the similarity of the two service systems (power and telecommunication), some system-level reliability metrics of power grid systems are also applied to represent the performance adequacy of telecommunication systems. Billinton (1984; 1988) presented Energy Not Supplied (*ENS*) and Expected Energy Not Supplied (*EENS*) as system metrics to reflect the ability of the system. *ENS* is estimated as the amount of energy that would have been supplied to the customers if the interruption did not occur:

$$ENS = \sum_j L_{a(j)} U_j \tag{6}$$

$$EENS = \sum_k ENS_k p_k \tag{7}$$

where $L_{a(j)}$ is the average load connected to load point j, U_j is the annual outage time, p_k is the probability of system state k.

Based on *EENS*, an extended index *IEAR* (Interrupted Energy Assessment Rate) is put forward for capacity adequacy assessment and defined as the ratio of the total cost and the total expected unserved energy. *IEAR* can also be expressed with expected values which are Expected Customer Interruption Cost (*ECOST*) and *EENS*:

$$IEAR = \frac{ECOST}{EENS} = \frac{Total\ cost}{Total\ expected\ unserved\ energy} \tag{8}$$

3. Customer Damage Functions

Broadly speaking, the damage of an outage from the customers' perspective is related to the degree to which the customer activities interrupted are dependent on the service not delivered by telecommunication networks. Usually, customer damage is represented by economic losses experienced by customers as a result of network service reliability or quality problems, which is described by a Customer Damage Function (CDF). Customer damage functions are applied in power grid systems, whereas applications on telecommunication systems are rare. Due to the similarity of these two service distribution systems, customer damage functions can also be applied to evaluate the cost of outages induced by the failure of telecommunication networks.

CDF is traditionally referred to as the outage or interruption cost for a given type of customer and it is a function of outage or interruption attributes, customer characteristics and other factors. Understanding the nature and variety of customer impacts resulting from network outages is the essential preliminary step before assessing the reliability cost from the customer point of view (Mohammoud et al., 2012). In most situations, the cost functions are built based on data. The methods that have been used to obtain interruption cost data can be grouped into three categories: indirect analytical evaluations, case studies and customer surveys (Billinton, 2002). Among the three methods, the most preferred and extensively used technique is customer surveys. In the customer surveys, a questionnaire is prepared and distributed to customers from various sectors. The survey includes questions about different outage scenarios. Because zero responses, extreme responses and strategic responses are introduced in the survey, making the results less reliable and bringing more uncertainties, some data preprocessing, such as logarithmically transformation, and standardization, is performed to eliminate the impact of outliers and data anomalies. Analytical methods analyze the outage costs from a theoretical economic perspective. Case studies allow to estimate losses associated with actual outage events(Billinton, 2003).

When gathering cost data, different attributes and characteristics are considered, and CDFs can be derived with different independent variables based on the cost data. A general form of CDFs can be expressed as:

$$CDF = f(outage\ attributes, customer\ characteristics, other\ attributes) \tag{9}$$

The outage attributes might include duration, frequency, season, time of day, day of week and advance warning. The customer characteristics could comprise the type of customer, nature of the customer's activities, various demands or loads as a function of time, size and other firmographic or demographic characteristics. Others may refer to geographical information, climate, etc. Among all these, the interruption duration is normally considered to be a primary variable and widely applied to evaluate the loss (Teansri, 2013).

Lawton et al. (2003) conducted a survey for seven customer sectors defined in SIC (Standard Industrial Classification). Considering the customer sectors, interruptions number and duration at each load point in the network, the interruption cost function can be expressed by the following expression, where the damage function, which is also regarded as cost rate, is interpolated based on the data collected in the survey:

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^\tau} \sum_{s=1}^{nr_S} \sum_{j=1}^{nr_C^S} c_{ref}^S(r_i)\, P_{ref,j} \tag{10}$$

where lp = load point, nr_{LP} = number of load points in the network, nr_I^τ = number of interruptions in year τ for lp, nr_S = number of customer sectors at lp, nr_C^S = number of customers of sector S in lp, $c_{ref}^S(r_i)$ = customer damage function for sector S with interruption duration r_i, $P_{ref,j}$ = load or power or energy for customer j (for power grid applications).

According to the factors considered above, CDFs render different sector-related levels. All the individual customer damage functions of the various customers within a sector (e.g. industrial, residential, commercial, agricultural and others) can be joined into a representative cost function for that sector, referred to as the Sector Customer Damage Function (SCDF). Here two different ways can be widely implemented to get the SCDF by weighting CDFs:

- the averaging process: CDFs are normalized either by annual peak load (or capacity) of the customer or annual power consumed by customers. Then, the individual cost functions are summed to get the SCDFs (Teansri, 2011),

- the aggregating process: the alternative is to sum the cost functions before they are normalized and divide by the sum of the normalizing factors.

However, SCDFs neglect the service utilization characteristics with quite distinct consequences of outage scenarios among the same sectors. In some cases, to obtain more specific evaluations, the service sector is divided into sub-sectors, and correspondingly sub-sector customer damage functions (SSCDF) are introduced.

Further to evaluate the cost comprehensively, a Composite Customer Damage Function (CCDF) is used and can be obtained by weighting the SCDFs for all sectors in a studied service area (Bassiouny, 2017). This function represents the total costs associated with interruptions for mixed users in the studied service area. For the customers of residential, commercial and industrial sectors, Billinton et al. (1985; 1986; 1987) provide a composite customer damage function which is a combination of interruption losses of various customer categories, weighted in proportion to their energy or power consumption within the service area considered.

Customer damage functions must then be converted to a metric. Depending on the data collected and the purpose of the analysis, different metrics are given to represent the cost. To the best of the authors' knowledge, almost all cost models in the literature are presented for evaluating outage losses of power grid systems. Due to the similarities between power systems and telecommunication systems, these models can be leveraged to apply to telecom systems. Here we summarize the cost models associated with indices that can be utilized for the reliability evaluation of telecommunication networks.

3.1. *Interruption Frequency Based Models*

Sjoberg et al. (2010) built a composite customer damage function (CCDF) on the national level, based on energy not supplied (*ENS*) and loss of load obtained from a customer survey. Customer interruption cost *cic* for year *t* is estimated using *SAIDI* (System Average Interruption Duration Index) and *SAIFI* (System Average Interruption Frequency Index) as shown in Eq.(11):

$$cic(t) = P_{av} \cdot SAIFI \cdot c_{ref}^{C}(r) + P_{av} \cdot SAIDI \cdot \frac{dc_{ref}^{C}}{dr}|_{r=r_a}$$
$$SAIFI = \frac{CI}{N_T}(interruption/costomer)$$
$$SAIDI = \frac{CMI}{N_T}\left(\frac{hour}{costomer}\right) \tag{11}$$

where $c_{ref}^{C}(r)$ is CCDF on a national level for interruption duration *r*, dc_{ref}^{C}/dr refers to the slope of CCDF, r_a represents the average interruption duration and P_{av} defines average hourly load estimated on the annual energy consumption of networks, *CI* is the total number of customers interrupted, N_T is the total number of customers served, *CMI* represents the total time of customers' interruption.

3.2. *Interruption Energy/Power Based Models*

One of the earliest approaches used was simply to ascribe a cost for the total energy not supplied, which can reflect the overall performance of the system. For each customer category, interruption cost is acquired through the product of *ENS* and average specific interruption costs, which differ depending on customer sectors and the situation of notification in advance (Langset, 2001):

$$cic(t) = \sum_{S=1}^{nr_S^{syst}} ENS^S \cdot c^S \tag{12}$$

where nr_S^{syst} is the number of customer sectors in the system, c^S denotes the average interruption costs in a specific sector obtained from customer surveys. This cost model has been applied in the new Swedish quality regulation since 2012.

In Eq.(12), *ENS* is calculated based on the expected load curve in the interruption period. The expected *ENS* for customer category *K* connected to node *N* is determined according to Eq.(13), for an interruption lasting from *T1* to *T2* (Heggset et al., 2009):

$$ENS_{N,K} = \int_{T_1}^{T_2} P_{N,K}(t)dt \approx \sum_{h=1}^{h=i+n} P_{N,K,h} \tag{13}$$

where *n* is the number of intervals included in the outage, $P_{N,K,h}$ signifies the average load for customer category *K* at node *N* in any hour *h*.

Individual, subsector and composite customer damage functions are given based on *CENS* (Cost of Energy Not Supplied) computed from the surveyed data of six customer sectors about average interruption duration and general price increases (Kjolle et al., 2006). The individual *CENS* and sector *CENS* are shown as Eq.(14) and Eq.(15), which are related to outage duration and time:

$$c_{ENS,i}(r,t) = \frac{C_i(r,t)}{ENS_i(r,t)} \tag{14}$$

where $C_i(r,t)$ is a continuous cost function based on interpolation between the discrete surveyed interruption data with duration *r* occurring at time *t*, $ENS_i(r,t)$ denotes energy not supplied for respondent *i* for an interruption of duration *r* occurring at time *t*.

$$c_{ENS,s}(r,t) = \frac{1}{m}\sum_{i=1}^{m} c_{ENS,i}(r,t) \tag{15}$$

where $c_{ENS,i}(r,t)$ is the customer damage function (CDF) for respondent *i* for an interruption of duration *r* occurring at time *t*, and m is the number of respondents in sector *s*.

Then, the composite cost function as Eq.(16) is obtained through the product of sector cost functions and weights, defined as the sector's proportion of total annual power consumption.

$$c_{ENS,comp}(r,t) = \sum_{s=1}^{S} c_{ENS,i}(r,t) \cdot W_s \tag{16}$$

where W_s is the weight for each sector, and S defines the number of sectors.

Billinton (2003) also collected costs and losses data of five customer sectors by virtue of the questionnaire survey and formulated three levels of customer damage functions. Different reliability metrics were then applied. Combining with cost weight factors, which are calculated with values at the worst time as a base and reflect the time variation, expected customer outage cost (*ECOST*) and total expected unserved energy (*EUE*) are given. Correspondingly, the reliability index *IEAR* is evaluated. The equations are shown below:

$$EUE = \sum_{i=1}^{N} m_i f_i d_i$$
$$ECOST = \sum_{i=1}^{N} m_i f_i c_i(d_i)$$
$$IEAR = \frac{\sum_{i=1}^{N} m_i f_i d_i}{\sum_{i=1}^{N} m_i f_i c_i(d_i)} \quad (17)$$

where m_i is the capacity or load not supplied, f_i represents the frequency of outage events, c_i is customer damage function, d_i is outage duration.

3.3. *Time-varying Cost Models*

The interruption costs vary by season, weekdays and time of day. The time dependency on the interruption cost can be significant, especially for industrial, commercial and public sectors.

The cost of an interruption (C_j) at any time j for customer category K supplied by node N in the network is calculated according to Eq. (18):

$$C_{N,K,j} = c_{N,K,ref}(r) \cdot f_{Ch} \cdot f_{Cd} \cdot f_{Cm} \cdot P_{N,K,ref} \quad (18)$$

where $C_{N,K,j}$ is the cost of an interruption in DP at time j, $c_{DP,K,ref}(r)$ is the cost rate at reference time for customer category K and duration r at time j, $P_{N,K,ref}$ represents interrupted power at reference time, f_{Ch}, f_{Cd}, f_{Cm} are correction factors for cost at time j, i.e. in hour h, on weekday d and in month m.

To reflect the time-varying characteristic of costs, Gerd et al. (1998) give two customer damage functions with average and more specific correction factors to consider the cost change with hour, week and month. Below are for average time-dependent cost model and specific time-dependent cost model:

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{\tau}} \sum_{s=1}^{nr_S} \sum_{j=1}^{nr_C^S} E(\tilde{f}_h^S) E(\tilde{f}_d^S) E(\tilde{f}_m^S)\, c_{ref}^S(r_i) P_{ref,j} \quad (19)$$

$$\begin{aligned} cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{\tau}} \sum_{s=1}^{nr_S} \sum_{j=1}^{nr_C^S} [&\tilde{f}_h^S(t_i^1) \tilde{f}_d^S(t_i^1) \tilde{f}_m^S(t_i^1) c_{ref}^S(t_i^1) \\ &+ \tilde{f}_h^S(t_i^2) \tilde{f}_d^S(t_i^2) \tilde{f}_m^S(t_i^2) \left(c_{ref}^S(t_i^2) - c_{ref}^S(t_i^1)\right) + \ldots \\ &+ \tilde{f}_h^S(t_i^K) \tilde{f}_d^S(t_i^K) \tilde{f}_m^S(t_i^K) \left(c_{ref}^S(t_i^K) - c_{ref}^S(t_i^{K-1})\right)] P_{ref,j} \end{aligned} \quad (20)$$

where $\tilde{f}_h^S$, $\tilde{f}_d^S$, $\tilde{f}_m^S$ are time-varying factors for hourly, daily and monthly deviation from the reference time for Sector S, $E(\tilde{f}_j^S) = \frac{[\tilde{f}_j^S(t_i^1) + \tilde{f}_j^S(t_i^2) + \cdots + \tilde{f}_j^S(t_i^K)]}{K}, j = \{h, d, m\}$ signifies the average time-varying factor, t_i^K is the hour k of interruption i occurring at time t, K is the closest whole hour to interruption duration r_i, $P_{ref,j}$ represents the load or power or energy at reference scenario for customer j.

3.4. *Probability Distribution Based Models*

In an outage event, the factors that affect the cost of interruption are uncertain and introduce large variance and skewness in the cost. However, conventional average or aggregate CDF methods cannot express this cost variation. A probability distribution method (PDM) to capture the dispersed nature of interruption cost is presented (Chan, 1993; Ghajar, 1996) and formulated as Eq. (21):

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{\tau}} \sum_{s=1}^{nr_S} \sum_{j=1}^{nr_C^S} cost_{i,j}\, P_{ref,j}$$
$$cost_{i,j} = \begin{Bmatrix} 0 & if\ u \leq P_z(r_i) \\ \exp(c_{i,j}) & u > P_z(r_i) \quad otherwise \end{Bmatrix} \quad (21)$$

where $u \in U(0,1)$ and $c_{i,j} \in N(\mu^S(r_i), \sigma^S(r_i))$, and the parameters μ and σ perform a regression analysis to get the relationship with outage duration r_i.

In these methods, in order to reduce the variance, normalization based on peak demand or annual consumption, and Box-Cox transformation of data are often implemented. Hypothesis testing is also performed to ensure the transformed data conform to the desired distribution.

Nazineh (2011) collected cost data through a survey that considers the interruption duration, location, frequency and other social effects, and adopt the *IEAR* as the index to evaluate the cost of customer damage. Additionally, while calculating the *EENS* and *ECOST*, failure rate, repair rate and probability of outage were considered as shown in Eq.(22) and (23):

$$EENS = \sum_{si \in F} p_{si}(\mu_{si} + \lambda_{si}) d_{si} L_{csi} \quad (22)$$

where p_{si} is the probability of existence of outage state *si*, μ_{si} is the total repair rates of the failed components in system state *si*, λ_{si} represents the total failure rates of the operating components in system state *si*, d_{si} is the expected duration at system state *si*, L_{csi} is the load curtailed of the system in state *si*, F is the set of system failure states in which load curtailment occurs:

$$ECOST = \sum_{si \in F} p_{si}(\mu_{si} + \lambda_{si}) c(d_{si}) L_{csi} \quad (23)$$

where $c(d_{si})$ is the cost which is a function of duration d_{si}.

3.5. *Tobit Regression Based Model*

For evaluating the interruption cost accurately, often variables including customer characteristics and outage characteristics should be considered in building the customer damage function. In this regard, a Tobit regression model and extended Tobit models have been proposed (Bilias, 2000; Chib, 1992; Lawton, 2003). The general expression is as below:

$$cic(\tau) = \sum_{lp=1}^{nr_{LP}} \sum_{i=1}^{nr_I^{\tau}} \sum_{s=1}^{nr_S} \sum_{j=1}^{nr_C^S} cost_{i,j}\, P_{ref,j}$$
$$cost_{i,j} = \max\{0, cost_{i,j}^*\}$$
$$cost_{i,j}^* = \alpha + \beta \boldsymbol{r_i} + \gamma \boldsymbol{x_i} + \epsilon_{i,j} \quad (24)$$

where α is a constant, β and γ are regression coefficients for interruption characteristic vector r_i and socio-economic characteristics vector x_i for customer j, $\epsilon_{i,j}$ is the normally distributed error term with *N(0,* σ^2*)*.

Carlsson et al. (2011; 2007) use a random parameter Tobit model and a random effects Tobit model to assess the damage cost respectively, which is regarded as WTP (Willing to Pay). The Tobit model is shown as Eq.(25). The parameters α, β, γ in the model capture a random characteristic and comprise two parts, mean and deviation which is assumed to be normally distributed with mean zero and standard variance:

$$\ln(WTP_{i,j}^*) = \alpha + \beta \ln(t_i) + \gamma x_i + \epsilon_{i,j}$$
$$\ln(WTP_{i,j}) = \max\{0, \ln(WTP_{i,j}^*)\} \quad (25)$$

where t is the outage duration and x is a vector of socio-economic characteristics which are age, gender, income, household type and geographic location.

Mo Se Kim et al. (2020) also use WTP as the damage cost index and propose a Bayesian Tobit quantile regression model to overcome the inaccurate cost estimates for prolonged outages based on the standard Tobit regression model and outliers' influence in the survey for short durations. The model also introduces a square variable to capture the nonlinear feature and two additional customer characteristics as control variables, which are employees' number E_i and annual energy consumption C_i. $\epsilon_{\theta ij}$ is the θth quantile of the error term:

$$\ln\left(1+WTP_{i,j}^{*}\right)=\beta_0+\beta_1 t_i+\beta_2 t_i^2+\beta_3 E_i+\beta_4 C_i+\epsilon_{\theta ij}$$
$$\ln\left(WTP_{i,j}\right)=\max\left\{0,\ln\left(WTP_{i,j}^{*}\right)\right\} \quad (26)$$

3.6. *Machine Learning Based Models*

Currently, applications of artificial intelligence algorithms in the area of telecommunication systems are gaining attention. Many advantages of these algorithms are related to their structure, including robustness, excellent noise immunity and non-linearity. Artificial Neural Networks (ANNs) based methods (Chen, 1993; Mohammoud, 2012) are increasingly studied and applied to analyze the reliability of telecommunication networks. A basic ANN-based CDF structure is shown as Figure 1.

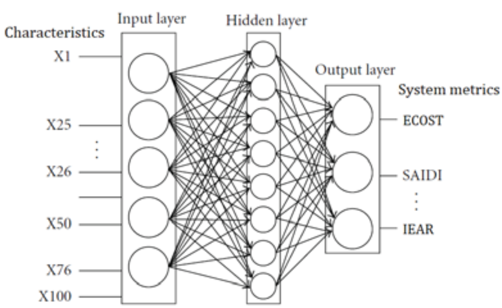

Figure 1 Structure of a basic NN CDF

Umesh et al. (2022) propose an ANN model to predict the *CCDF* at various failure intervals to identify the reliability metric *ECOST* which comprises failure rate through considering the aging effect of the distribution system's components for a thorough analysis of system reliability:

$$ECOST=\sum_{i=1}^{n}\lambda_i C_i L_i \quad (27)$$

where *CCDF* C_i is an ANN model with interruption characteristics as input and CDF as output, the failure rate λ_i for node point *i* including all contingencies is derived based on Weibull distribution.

In an attempt to improve the robustness and noise immunity, a Radial Basis Function (RBF) neural network model has been introduced to integrate PDM (Langset, 2001) and AAM (Heidari, 2013) to evaluate the reliability worth *ECOST* and *IEAR* of a distribution system. In the network model, the input variables are customer and interruption characteristics, the outputs are the parameters of PDM or sector interruption cost.

4. Conclusion

This study provides a systematic review of reliability metrics and customer damage functions for telecommunication networks. The reliability metrics applied experience a transition period as the functions provided by telecom networks evolve and the principal applications for customers progressively shift. The customer damage functions are classified into six groups based on factors and usage scenarios, with reference to the reliability analysis of power grids.

On the basis of the work of this paper, future studies can be conducted to evaluate the reliability of telecommunication networks:

- performance models should be built to analyze whether the capacity of the network meets the demand varies with time and customer sectors, including channel capacity model under a certain network architecture, handover process and signal attenuation algorithms under miscellaneous environments during the signal propagation;
- telecommunication networks are complicated systems composed of multiple subnetworks and components with different properties. The probability distribution model of the system should be built and the failure rate should be derived to evaluate the loss of customers by integrating with customer damage functions and performance models;
- reliability metrics and customer damage functions need to be contained for a specific usage scenario to analyze the reliability of networks.

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