CHAPTER 6

Markov and semi-Markov models in system reliability

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1. The reliability in systems

Each system has goals in which the components interact to achieve that goal. Many systems functionally include multiple, interchangeable units. These units must be active simultaneously to meet the purpose of the system. When a system is used to achieve goals, it must be reliable. Reliability is used to measure the correct performance of systems quantitatively. System reliability equals the probability of operating for a specified period under limited conditions. Reliability measures the ability of a system to provide the desired level of service against deterioration and other shocks that affect its performance. Systems can be machines, human—machine, or humans. However, reliability is usually used more for machine systems, products, engineering products, or man-made in the literature. In the past, reliability has been discussed in industries such as the military, communications, oil, gas, and aerospace. However, in recent decades, civilian sectors such as the pharmaceutical, health, transportation, medical, aviation, and home electronics industries have also focused. Therefore, in all industrial systems, one of the essential characteristics of a system is its reliability. In some systems, reliability affects security performance, so reliability is vital. Measuring the overall reliability of a system depends on the performance goals and expectations. But in general, a reliable system is a system that has continuous performance on the one hand. On the other hand, this performance is done correctly and according to the designed goals. A system with a high degree of reliability operates as it should every time used.

Reliability has two essential dimensions time and working conditions. A system must perform its desired function during several years of its useful life, despite pressures, working conditions, and other environmental factors.

As is clear from the definition above, reliability theory is related to equipment life and failure time. Therefore, if the life span of equipment is considered a random variable T,

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according to probability theory, the reliability denoted by R(t) can be calculated according to the following formula:

$$R(t) = p\{T > t\} = \int_{t}^{\infty} f(x)d(x) \tag{6.1}$$

According to the above formula, the characteristic f(x) is a failure density function, and t is also a characteristic for displaying time. This formula calculates the probability that the equipment life span is longer than the specified value.

The reliability of a system, like any other computational formula, has parameters and specifications that, by measuring each of the characteristics, can be more likely to be closer to the reliability of a set or part. Assuming that equipment can only have one of two perfect or failure states, or so-called binary, the probability of being healthy can be indicated by R, which is defined as follows:

$$0 \leq R \ < 1 \tag{6.2}$$

This means that the equipment or system will definitely fail, and there is no system that will never break down. But the probability of our equipment remaining healthy is a number between 0 and 1. So as equipment conditions get better, their reliability gets closer to 1, and vice versa, as equipment conditions worsen, their reliability gets closer to 0. Reliability is obtained using the following formula by considering the working and environmental conditions of an equipment or system:

$$R(t) = p(T > t|c_1, c_2, \ldots,) \tag{6.3}$$

The above formulae c1, c2, … are the specified operating conditions for equipment or system, usually ignored in the reliability analysis. Therefore, Eq. (6.3) defines reliability [190].

$$\mathrm{R(t) = P(T > t)} \tag{6.4}$$

The reliability of equipment R is equal to the probability that this equipment will have the required characteristics in a certain period and conditions. Otherwise, the nonreliability F equals the probability that this equipment will not achieve the required features in a given period under certain operating conditions. Nonreliability and reliability are both time-dependent. At zero time, the reliability of the equipment that starts working is 1; after some time, this value reaches 0.5, and then when it completely fails, it reaches 0. In other words, the nonreliability starts from 0 and moves upward, and when the system breaks down, the nonreliability gets 1. In general, the sum of reliability and nonreliability will be equal to 1 at any given time. In other words, reliability can be called the probability of success in a given period, which is the inverse of the probability of failure of equipment or process in that period.

$$R(t) + F(t) = 1 \tag{6.5}$$

One of the primary uses of statistics to show the behavior of random phenomena lies in Reliability Theory. Since this theory is mainly used in engineering and determining the life of equipment, it is sometimes called Reliability Engineering. According to probability theory, the degree of reliability is shown as follows:

$$\text{Reliability} = 1 - \text{Probability of Failure}$$

Failure Rate and Survival Analysis are parts of reliability theory that deal with components' life span and failure rate. The failure rate indicates the frequency of failure of a piece. It is clear that the failure rate is not constant and changes over time. It may be based on time, as an increasing or decreasing function and/or bathtub curve. Therefore, different probability functions may be used to analyze survival and determine the probability lifetime distribution of each component or system. Of course, it should be noted that since the life span is a positive number, the random variable and its distribution must contain positive values (plus zero).

There are several methods for modeling reliability: methods based on statistics and statistical information resulting from performance and determining the number of failures and the study of failure physics. In the black-box method, the system, in general, but in the transparent box method, the system's structure and components are examined. In calculating the reliability of multicomponent systems, the system is decomposed into components. The system reliability is expressed in terms of the reliability of its components. To calculate the reliability of each component based on available statistical data, a model for failure rate is selected, and its parameters are estimated based on available data or estimated by simulation or engineering knowledge or experience of experts. In engineering methods, determining the modeling and mechanism of failure is very important.

The two main functions in investigating failure behavior are failure density functions (f) and hazard rate (z). The failure density function indicates the mean (or overall velocity) speed of failures. But the hazard rate can be considered as the instantaneous speed of failures. It is usually modeled with one of the fixed, linear, or polynomial models. The constant hazard rate is sufficient in many applications and commonly indicates stochastic failure behavior (mid-life failure). In this model, the reliability and density distribution of the occurrence of failure will be exponential. But this model is not suitable for the aging system period (in which we face an increasing hazard rate). In this case, the linear hazard is used, and the density distribution of the failure will be a Rayleigh distribution. The third model (polynomial hazard) is the more general case of the above two cases, which is more accurate. In this case, the failure density will have a Weibull distribution, which is an important distribution in terms of reliability. The first two models are, in fact, special modes of this model.

The hazard rate is obtained from the following relation:

$$z(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{R(t)} \tag{6.6}$$

The hazard function is defined to analyze the life distribution with historical failure data and online status monitoring data. The hazard function is based on the failure rate, which is a function of the age and condition of the equipment. If past data on a system failure are available, Gaussian mixture models and Weibull mixture models can be used to describe time-series data.

The failure of a component affects the system in two ways: the reliability of the failed component is lost, and the reconfiguration of the system components is required. In multicomponent systems, each system consists of several independent components with a lifetime distribution, and the system's behavior depends on the behavior of the components. Component failure can cause a subsystem or the entire system to fail. Systems may have functional components that can be repaired or replaced. After working for a while, they are in various health situations due to different working conditions. In these systems, the system balance is determined based on the performance levels of the components.

Usually, in reliable models, there is a stochastic dependence between multiple system failure modes. In multicomponent systems, the probability distribution of the performance of each component must be estimated. When a system is operating in unreliable conditions, several components of that system may be involved. Different types of systems have been proposed in the discussion of reliability, which can include one component or more. In multistate systems, the components of each subsystem can have different performance rates with specific probabilities.

A multicomponent system can be a system with k independent statistical components with the same distribution. Each component is exposed to common stochastic stress, and the system fails if the level of stochastic stress created in at least a few of its components from a defined level is higher. The reliability of a system depends on all its components. Different life distributions can be defined for components that lead to different failure rates.

Systems can usually be thought of as series, parallel, or combined structures. Series systems contain components that are essential to the operation of the system, and failure of any component of the system causes failure of the entire system. For series systems, the total reliability depends on each component's reliability. It can be concluded that in series mode, because the reliability of one component is always smaller than one, with increasing components, the reliability of the whole system decreases. In parallel systems, each component can operate separately, and for system failure, both components must fail. The conclusion is that as the number n increases, the reliability of the system increases. Of course, parallel networks are not a good idea to increase reliability. Because the initial increase in reliability is negligible after a while, the system includes a combination of components in series and in parallel in hybrid systems. In addition to these systems, selectable systems can be used for emergency stop systems. With the performance of at least one system component, the entire system starts operating and is used to reduce the likelihood of system failure. In standby systems, the systems have parallel components and are operating as continuous systems and are maintained in standby mode and operate if the normal operation of the system is disrupted and fails. Standby systems include warm and cold standby systems. In warm standby systems, after a certain period of time, the parallel warm standby component replaces it as soon as a component breaks down. A component must first be converted to a warm standby component in cold standby systems and then activated.

Systems may contain one or more components, and if a system consists of several components, the components can be homogeneous or nonhomogeneous. A system can contain repairable or nonrepairable components or a mixture of repairable and nonrepairable components.

Systems can be first subdivided into subsystems. The reliability of each subsystem can be obtained separately and then combined according to the system status for the reliability of the whole system. In sequential systems, its components work independently with probabilities that may not be the same.

Systems are designed to perform different tasks in different environmental conditions. Systems can operate at different levels of efficiency; in other words, the performance rate of systems changes over time and under environmental conditions. Any system with a limited number of performance rates is called a Multistate System (MSS). The simplest systems can have two operating modes: a perfect functional state and a complete failure state. Systems usually act as multistate systems, consisting of a component or a set of components.

The linear (circular) consecutive-k-out-of-n: F systems consist of n components arranged in a line (a circular). These systems fail if at least k consecutive components fail. The m-consecutive- k-out-of-n: F systems contain n components in a line that fail when there is at least m nonoverlapping run of k consecutive failed runs.

A series—parallel system can consist of two identical units that are connected in series. An additional component can be placed parallel to the main component to increase the reliability of each unit, so each unit is considered as two fault-resistant components. If at least one of the series equipment fails, the whole system will fail.

The redundancy technique is often used to improve the reliability of series—parallel (hybrid) systems in the system design phase. The use of additional components depends on some limitations in the system. By placing similar subsections in a system in parallel, the overall performance of the system in the event of an error can be guaranteed.

Increased reliability leads to longer life and reduced maintenance costs. Mixing components, redundancy levels, and redundancy strategies are used to maximize reliability. In the problem of redundancy allocation, the goal is to identify the optimal design to achieve the best indicators in the system under certain constraints.

The principle of redundancy and diversity can be used to prevent stochastic failures to deploy highly reliable equipment. In this way, the system is more reliable than the components. Warm standby is one of the techniques used to reduce the risk of failure when the system is active. Switching between the active and standby components is a way to balance component degradation and increase system life.

Therefore, continuous improvement in system performance is very effective. But system failures are inevitable. Every subsystem must work in reliable conditions for a system to work without failure so that the system is reliably available over a predefined period.

Uncertainties in systems are a significant challenge for systems reliability, especially since reliability must be calculated dynamically. Reliability indicators in systems usually include the reliability function, the first failure time distribution, the mean time before failures (MTBF), mean time to failure (MTTF), the failure and repair frequency functions, the point availability, the interval availability, and the system availability. Therefore, according to these indicators, the system failure process is very important to determine their reliability, and perhaps it can be said that if the system failure process can be determined, its reliability can be predicted.

2. Failure process of systems

In assessing reliability, modeling the degradation process is an important issue. The accuracy of the indicators obtained from the models in the field of reliability depends on the quality and accuracy of the failure modeling considered.

Systems are prone to two failures: deterioration due to intrinsic failure and catastrophic failure due to shock. A system is usually exposed to internal failures and external shocks that may be stochastic. The process of deterioration and the process of shock can be interrelated. Shocks can cause a sudden increase in destruction, which increases the deterioration process.

The severity of the shock depends on the number of shocks received (the distance between the shocks). A system failure process is usually defined as a random process and can be defined as discrete or continuous. Component failure rates can be fixed or variable. Shock may cause damage to several units simultaneously. Shocks can be defined in several ways: whether the failure occurs when the accumulated damage exceeds a certain level, whether the system fails due to local damage due to successive shocks, or both happened simultaneously.

Shocks can be independent of each other, or the occurrence of shocks can be interrelated. The system fails when the time interval between two consecutive shocks is less than a predetermined level. As the degree of deterioration in shock environments increases, the failure process accelerates. Shocks may be of the same severity, but they are more severe to the system due to the deterioration of the system over time. Shock and wear processes are usually dependent on the external environment, and shocks are generated according to the Poisson process, and the rate of entry and the magnitude of damage in a random environment should be considered. The shock model can be considered in multicomponent systems in such a way that the shock potentially affects each of the components, and the system breaks down when the cumulative damage reaches a certain level.

The pure jump Levy process can model the intrinsic degradation of any component. In complex systems, failure of a component may cause a momentary and transient shock to the system. A stochastic increase can model the shock effect in the level of deterioration of each component.

Reliability analysis deals with random failures, uncertainties associated with these failures, and failure modeling. The most common assumption in reliability is to consider failures independently and with the same distribution. But these two hypotheses are unrealistic because the times between failures are related and not evenly distributed. Finding the source of the failure for each component can be used to assess the state of the system and obtain the failure probability function. Failure of hybrid system components is usually achieved using the Failure Mode and Effect Analysis (FMEA) method. The probability of small failures in reliability problems can be obtained from an integral on an uncertain parameter space with large dimensions.

Usually, the deterioration of the system itself is not reported and should be identified through inspection. The reliability of the effects of inspection errors can also be considered in the modeling. Failure of one component in the system can cause extensive damage to the system and cause a total system failure. Sometimes the failure of a component called the trigger component makes other components called dependent components inaccessible, and if the failure of any of the dependent components occurs before the trigger failure, the effect of failure propagation occurs, and the whole system will be failed.

Different models have been used to examine the failure process and system life in terms of reliability in the literature. Markov and semi-Markov models have been widely used in modeling. In Markov models, the life span of equipment is considered exponential, and since the life span of some equipment is nonexponential, semi-Markov processes are used to consider the life span of equipment as nonexponential.

3. Markov and semi-Markov models in systems reliability

Reliability modeling is based on the time-dependent Markov approach. The time-dependent behavior of the system in the intermittent state includes the healthy, defective, and failed states, which are usually described by the Markov process. The degradation process in systems is usually defined in terms of the Markov process and increases over time.

Markov and semi-Markov models have been widely used in various fields for reliability. In Markov models, the life span of equipment is defined exponentially. Unlike the Markov-based approach, which is limited to an exponential distribution, semi-

Markov models are used in systems that are subjected to certain changes of modes at predetermined times, and the duration of their stay in each mode follows from one statistical distribution. Therefore, to overcome the nonexponential consideration of equipment life, semi-Markov processes can be used assuming stochastic independence of system components. In semi-Markov models, transfer rates are used instead of transfer probabilities. Transfer rates depend on the processing time and the residence time in each case.

Markov models can easily describe the performance of a system as diagrams that show the state of system failure. Multidimensional Markov chains can be used to model the stochastic behavior of systems. In repairable systems, stiff Markov chains are used due to the sharp difference between failure and repair rates. If system components have a constant failure and repair rate, system reliability can be modeled with a continuous-time homogeneous Markov process.

Multistate homogeneous Markov (MHMM) models are optimal for approximating any failure time distribution. However, not all distributions that are linear combinations of exponential expressions can be represented exactly with multistate Markov models. Fatigue-sensitive components can be modeled based on McGill Markov and closure-lognormal stochastic processes.

The Markov renewal process technique can model a system that includes the main standby redundancy and subsystems. Markov reward models and Markov models are used to analyzing system reliability. A repairable system in a changing environment can be considered according to the intermittent renewal process, and the reliability of this system is obtained using the Markov reward theory. In repairable systems, the degradation process can be described using continuous-time Markov chain or semi-Markov models that divide the finite state space into a set of up and down states. Markov renewal process and nonhomogeneous Markov processes are commonly used for system reliability. Partially observable Markov decision processes (POMDPs) are also used for sequential decision-making in the system to analyze behavior and reliability. Markov models are used for both individual components and systems with multiple dependent components. Markov chains are widely used to model nonfunctional and performance criterion analysis in the systems. Markov models are suitable for the exponential frequency distribution of the reliability function. Exponential distribution considers the rate of risk and repair as constant.

Complex systems in which degradation phenomena are associated with uncertainty are usually modeled using Markov decision processes. Markov renewal process modeling is used to predict system failure. When the degradation process is observable by monitoring the situation, this process can be modeled using the hidden Markov model. In this system, the healthy, defective, and failure modes are the system modes where only the failure mode is visible. The whole system can be modeled using a multidimensional continuous-time Markov chain to evaluate the reliability dynamics.

Markov renewal theory is considered for redundant systems in which components are prone to failure and, in case of failure, can be replaced with a new system. Dependencies are important to system reliability and affect the distribution of system failure. There are some classic types of random processes with different dependency relationships, including Markov processes, renewal processes, and Markov renewal processes.

Modeling techniques commonly used in reliability issues include the Reliability Block Diagram (RBD), Markov Birth—Death Probabilistic approach, Petri Networks, Bayesian Networks, Markov Chains, Fault Tree Analysis (FTA), Clustering techniques, Flow Network, Failure Mode and Effects Analysis (FMEA), and Event Tree Analysis (ETA).

In the following, a literature review on reliability has been done by focusing on Markov and semi-Markov models.

Bobbio et al. [1] investigates system reliability by modeling each component with a multistate homogeneous Markov Model (MHMM). Singh et al. [2] proposes a new Markov approach for calculating production system reliability indices. Johnson [3] presents Markov models for a public availability model and a public reliability model. Rao and Balasubramanya [4] performs the Markov technique to predict the reliability, availability, and maintenance of a typical repairable Dual-VHF Omni Range (Dual-VOR).

Lindqvist [5] describes Markov models for single components and systems whose components are possibly dependent. Constantinescu [6] presents a standby system to activate industrial applications that require programmable fault-tolerant control instead of relay logic.

System reliability analysis is performed with decomposition/aggregation technique and with two homogeneous Markov models with the discrete and continuous state. Pullum et al. [7] has proposed a new Markov chain method for calculating the reliability of multipath switching networks.

Constantinescu [8] develops new closed-form solutions for the reliability, performance, and computational availability of homogeneous degrading processor arrays. Discrete and continuous-time homogeneous Markov models describe processes. Cao [9] studied a human—machine system that operates under a changing environment under a two-state Markov process, in which reliability is achieved using Markov renewal theory. Manzoul and Suliman [10] has proposed a new approach to reliability analysis based on neural networks and the discrete-time Markov model in a nonredundant digital system, the simplex system with the repair.

Gil et al. [11] studied Markov models for studying the safety, reliability, and availability of a watchdog processor. Bulleit [12] describes the development and use of a Markov model to estimate the lifetime reliability of structural systems. Shao and Lamberson [13] provides a complete Markov model for analyzing the reliability and availability of k-out-of-n: G systems with the Built-In-Test technique (BIT). Lassen [14] describes a model of probabilistic cumulative fatigue damage based on the simple Markov chain approach to evaluate the reliability of welded joints in marine steel structures.

Limnios and Cocozza-Thivent [15] studied two types of the stochastic reservoir, including uncontrolled reservoirs and other reservoirs controlled by fully controlled computers, to assess their reliability criteria. The stochastic behavior of reservoirs with two Markov chains is modeled in three and five dimensions, respectively. Senegacnik and Tuma [16] presents a Markov model for power plant operations and shows that this model is a successful tool for determining time-dependent reliability. Tan et al. [17] describes a computerized reliability model based on evolving Markov processes. Guo and Cao [18] examines the reliability of a multistate repairable system under a changing environment with a two-state Markov process.

Singh and Sharma [19] studied analytical techniques for assessing reliability, availability, and a combination of performance and reliability metrics. They also calculated the state probabilities of the Markov model behavior. Stavrianidis [20] studied the performance evaluation of Programmable Electronic Systems (PES) in safety applications and used Markov modeling techniques to develop a reliability model. Yamada et al. [21] studied a software reliability growth model considering imperfect debugging. This model is described by a semi-Markov process. Sculli and Choy [22] tested the reliability of pump sets that supply water to boilers in large power plants. Failure and repair rates are estimated from historical data, and the system is modeled as a Markov process to calculate its reliability. El-Damcese [23] presents a generalized Markov model to test the reliability of multiple systems, consisting of n-identical/nonrepairable components.

Csenki [24] studied the semibrand reliability models of repairable systems. Moustafa [25] studied Markov models for transient analysis of reliability with and without repair for K-out-of-N: G systems subject to two failure modes. Farhangdoost and Provan [26] has studied reliability analyses to predict the life of fatigue-sensitive components. McGill—Markov models and closure-lognormal stochastic processes have been presented. Yoo et al. [27] proposed a Markov process approach for analytically extracting the mission reliability of an automated fault tolerance control system with distributed Built-in-Test. Chandra and Kumar [28] introduced a Markov reliability model for a transputer-based fail-safe and fault-tolerant node for use in a network of critical distributed safety rail signaling systems. Mustafa [29] studied a Markov model for analyzing the reliability of K-out-of-N: G systems that are prone to dependent failures with incomplete coverage and concluded that failure rate dependencies significantly reduce system reliability.

Ouhbi and Limnios [30] estimated the reliability and availability of a turbo generator rotor. The rotor is modeled by a semi-Markov process used to estimate the reliability and availability of the rotor. Mustafa [31] studied Markov models for transient analysis of reliability with and without repair for K-out-of-N: G systems subject to M failure modes. Chang et al. [32] considered a system (n, f, k) consisting of n components arranged in a line or a cycle. This system fails if at least f component is damaged or at least k component; there are consecutive failures. They obtain system reliability formulas for linear and circular systems with the reliability of various components using the Markov chain method.

Beshir et al. [33] presents a new framework for assessing probabilistic reliability. Seven operating modes are considered for power system conditions, and a Markov model defines these modes. Lisnianski and Jeager [34] proposes a redundant system in which the task of the whole system is a sequence of n phases, and the whole work must be performed in a limited time. For the reliability of the system, a suitable model is presented, and a semi-process Markov has been used as a mathematical technique. Whittaker et al. [35] used the Markov chain model to predict the reliability of multibuild software. Knegtering and Brombacher [36] offers a method that greatly reduces the computational effort required to obtain quantitative safety and reliability assessments to determine safety integrity levels for applications in the process industry.

The method integrates all the advantages of Markov modeling with the practical advantages of Reliability Block Diagrams. Yan and Wang [37] analyzed the reliability of the train's automatic protection system to achieve high reliability and safety. The failure rate is first divided into several parts, and the reliability and safety are analyzed using the Markov model. Tokuno and Yamada [38] provides a software reliability model that assumes there are two types of software failure. They use a Markov process to formulate this model and derive several quantitative criteria for evaluating its software reliability. Becker et al. [39] studied a nonhomogeneous semi-Markov process for modeling the reliability properties of components or small systems with complex experiments. Lassen and S0rensen [40] studied stochastic models to analyze the fracture reliability of welded steel plate joints. A Markov chain is defined that shows discrete damage modes related to the selected crack depth at the joints.

Zupei and Xiangrui [41] studied the application of the Goal-Oriented (GO) method to a repairable system described by the Markov model. Ouhbi and Limnios [42] defined reliability and availability estimators in semi-Markov processes and showed uniformly highly consistent. Grabski [43] presents the reliability function properties of an object with a failure rate modeled by a semi-Markov process defined in the maximum countable state space. Bouissou and Bon [44] proposed a modeling formalism called Boolean logic Driven Markov Processes (BDMP). This formalism has two advantages: it is possible to define complex dynamic models and easy to build as fault trees compared to the conventional models used in reliability evaluation. Goda [45] proposes a strong Markov process-based reliability model for unidirectional composites with fibers in a hexagonal array.

Wu and Patton [46] suggests using Markov models to analyze the reliability of fault-tolerant control systems. Tokuno and Yamada [47] discusses a software reliability model for an incomplete debugging environment in which detected errors are not always corrected and removed from the system. Given the cumulative number of corrected errors, the uncertainty of the debugging activities is related to the increasing complexity of the corrected errors. A Markov process describes the random behavior of the error correction phenomenon with incomplete debugging. Several quantitative criteria have been derived from this model to evaluate software reliability.

The level of reliability of power systems varies from time to time due to weather conditions, power demand, and accidental errors. It is essential to obtain an estimate of the reliability of the system under all environmental and operational conditions [48]. Tanrioven et al. [48] used fuzzy logic in the Markov model to describe both transfer rates and temperature-based seasonal variations. El-Gohary [49] presents maximum likelihood and Bayesian estimates of parameters in a three-state semi-Markov reliability model. Wang [50] introduces two reliability criteria, which are Markov-chain Distributed Program Reliability (MDPR) and Markov-chain Distributed System reliability (MDSR) for reliability modeling of Distributed Computing System (DCS). A discrete-time Markov chain with an absorption mode is constructed for this problem. Dobias et al. [51] provides a reliability assessment method for TTP/C-based distributed systems. This method is based on the Markov reliability model.

Sadek and Limnios [52] studied nonparametric statistical inference problems for the reliability/survival, availability, and failure rate of continuous-time Markov processes. They assume that state space is limited. Azaron et al. [53], using the shortest path analysis in stochastic networks, proposed a new approach for the reliability function of time-dependent redundancy systems. The shortest path distribution of this newly constructed network is obtained using continuous-time Markov processe. Bai [54] provides a Bayesian Markov network developed to model software reliability prediction with operational specifications.

Wang et al. [55] extended the white box to an architectural approach, and a state machine is made from a discrete-time Markov model and is used to calculate the reliability of the software. Li and Zhao [56] used stochastic modeling to investigate the reliability assessment of Fault-Tolerant Control Systems (FTCS). System errors are described by a Markov chain, while the Fault Detection and Isolation (FDI) and system operations for reliability assessment are described by two semi-Markov chains. Ajah et al. [57] presents a hierarchical modeling approach that overcomes the exponential explosion in the size of the Markov model by increasing the number of components for modeling deterioration and system repair and in screening and accurate analysis of the reliability and availability of components of such infrastructure systems.

Li and Zhao [56] used a stochastic modeling method to investigate the problem of assessing the reliability of FTCS. System errors are described by a Markov chain, while the FDI and system operation for reliability assessment are described by two semi-

Markov chains. Kucera et al. [58] calculated the reliability of a turbine protection system used in Siemens Industrial Turbomachinery products. The Markov model of the system is introduced, and the analysis of the Markov model is presented. Tanrioven and Alam [59] provides a method for modeling and calculating Proton Exchange Membrane Fuel Cell Power Plants (PEM FCPP) reliability. This method involves the development of a state-space method for calculating the reliability of the standalone PEM FCPP using the Markov model. Platis [60] studied a general form of the performance criterion defined for the reliability of fault-tolerant systems and present various formulas using a homogeneous Markov chain and a cyclic nonhomogeneous Markov chain and their asymptotic expression.

Csenki [61] considers Markov reliability models whose finite state space is divided into a set of up and down states. Fei and Hong-yue [62] described a set of Markov stochastic processes with finite state space to illustrate the FDI decision in the active FTCS. In addition, system stability and reliability are discussed. Dominguez-Garcia et al. [63] proposed an integrated method for reliability and dynamic performance analysis of fault-tolerant systems. This method uses a behavioral model of system dynamics. Markov chains are used to model the random process associated with the different configurations that a system can adapt in the event of a failure. Li et al. [64] studied a reliability monitoring scheme for active FTCSs. A semi-Markov model is developed to assess reliability based on the safety behavior of each regime model. El-Nashar [65] studied the combination of equipment reliability in the optimal design of cogeneration systems for power and desalination. The Markov process performs design optimization using hermoeconomic theory and equipment reliability using the state-space method.

Chiquet and Limnios [66] studied the time evolution of an increasingly stochastic process by a first-order stochastic differential system. They consider a Markov renewal process (MRP) associated with the piecewise deterministic Markov process (PDMP) and its Markov renewal equation (MRE), which is solved in order to obtain a closed solution of the PDMP transfer function. It is then used in the context of survival analysis to evaluate the reliability function of a given system. Sisworahardjo et al. [67] presents a method for modeling and calculating the reliability and availability of low portable direct methanol fuel cells (DMFCs). A state-space method is proposed to calculate system availability using the Markov model (MM).

Guo and Yang [68] presents a new technique for automating Markov models to evaluate the reliability of safety instrumentation systems. Many safety-related factors, such as failure modes, self-diagnostics, repairs, common cause, and voting, are included in Markov models. A framework is first created based on voting, failure modes, and self-diagnosis. Then, repairs and failures are included in the framework to build a complete Markov model. Ehsani et al. [69] proposes an analytical probabilistic model to assess the reliability of competitive electricity markets. A Markov state-space diagram is used to assess market reliability. Since the market is a system that operates continuously, the concept of absorber modes is applied to evaluate reliability. Pil et al. [70] describes the reliability assessment of reliquefaction systems for boil-off gas (BOG) in LNG carriers with a focus on redundancy optimization and maintenance strategies. Reliability modeling is based on the time-dependent Markov approach.

Do Van et al. [71] presents the development of Differential Significance Criteria (DIM), which have recently been proposed for use in risk-based decision-making in the context of Markov reliability models. Soszynska [72] presents a semi-Markov model of system operation processes and uses a model of system operation process and multistate system reliability to assess the reliability and risk of the port oil pipeline transportation system. Veeramany and Pandey [73,74] provide a general model for evaluating the rupture frequencies and reliability of the piping system in a nuclear power plant based on the semi-Markov process theory. Wei et al. [75] proposes a Markov-based model for estimating the reliability of a hierarchical architectural system. This model is proposed to replace the traditional RBD. Comparative studies between the Markov-based model and RBD have been performed. Experimental results show that Markov techniques can improve the predictive value of system reliability. Jiang et al. [76] suggests a reliable Markov model for effectively reducing manpower abnormal events in the high-security digital main control room of nuclear power plant (NPP).

Veeramany and Pandey [73,74] have studied the reliability analysis of nuclear component cooling water systems (NCCWs). A semi-Markov process model is used in the analysis. Mathew et al. [77] presents the modeling and reliability analysis of a two-unit system of continuous casting (CC) plant using semi-Markov processes and regenerative point techniques. Grabski [78] considers the failure rate of a random process with continuous nonnegative and right continuous trajectories, and the reliability function is defined as a functional expectation of that random process. In particular, the failure rate is defined by semi-Markov processes. Theorems related to the renewal equations for the conditional reliability functions with the semi-Markov process as the failure rate are presented.

Gupta and Dharmaraja [79] proposes an analytical reliability model for VoIP. The reliability model is analyzed using the semi-Markov process, which shows the effects of the non-Markovian nature of the time spent in different system modes. Liu and Rausand [80] examined this classification by studying the safety instrumented system's reliability for different demand rates, demand durations, and test intervals. This approach is based on Markov models. Haghifam and Manbachi [81] proposes a reliability model based on state space and continuous Markov method for combined heat and power (CHP) with power generation, fuel distribution, and heat generation subsystems. Yuan and Meng [82] studied a warm standby system consisting of two dissimilar units and a repairman. In this system, using Markov process theory and Laplace transform, they obtain some important reliability indicators and some steady-state indicators. Hosseini et al. [83] discusses the effects of considering the reliability of equipment for thermal analysis of a combined and multistage flash water desalination plant. Equipment reliability is entered into thermoeconomic analysis to improve cost values using state space and the continuous Markov method.

Cai et al. [84] examines the effects of stack configuration and types of mount on subsea BOP systems from a reliability perspective. A model based on the Markov method for performance evaluation is presented. The availability and reliability of the system are assessed by integrating Markov stand-alone models with the Kronecker product approach. Rosset et al. [85] has developed reliability models for a group membership protocol designed for TDMA networks such as FlexRay. Models are based on time-based Markov chains. Hosseini et al. [86] studied multiobjective optimization for the design of a combined gas turbine and multistage flash desalination plant. They also incorporate equipment reliability into the optimization approach using state space and the continuous Markov method. Gilvanejad et al. [191] propose a new Markov model for the reliability analysis of the fuse cutouts, which considers the hidden failures of the fuses.

Wang and Liu [87] has developed an automated air traffic control system (ATCAS) and the Markov model, which collects 36-month ATCAS failure data. A method for predicting s1, s2, s3 ATCAS is based on the Markov chain, which confirms the reliability of ATCTS according to the inference theory of reliability. Lisnianski et al. [88] presents a multistate Markov model for a coal power generating unit. The proposed multistate Markov model is used to calculate important reliability indicators such as the Forced Outage Rate (FOR), the Expected Energy Not Supplied (EENS) to consumers, etc. Selwyn and Kesavan [89] used the concept of Markov analysis (MA) to model the failure characteristics of the main components to calculate the probability, availability, and reliability of different modes of a wind turbine (WT) system with capacities of 225 kW, 250 kW, and 400 kW.

Cao et al. [90] presents a model using Markov to examine the quantitative relationship between software testing and software reliability in the presence of imperfect debugging. Zhang et al. [91] proposes a Markov modeling approach for system reliability analysis. Wang et al. [92] provides redundant design of the BCHP (Building Cooling, Heating, and Power) system and its mode of operation. The space-state method is combined with probabilistic analysis of the Markov model and is used to analyze the reliability of three forms of energy supply, including electricity, heat, and cold, in the BCHP system. Montoro-Cazorla and Perez-Ocon [93] studied an n-component system, one online and the rest in standby and repairable mode, to assess reliability by considering the Markov process governing the system, as well as Markovian failure shocks and repair times.

Liu et al. [94] proposes a reliability model to evaluate the reliability and life span of laser diodes in a space radiation environment. The degradation process is divided into discrete states, and the reliability model is subsequently developed based on the Markov process. Karami- Horestani et al. [95] analyzed the role of different SVC (Static VAR

Compensator) components in system availability and proposed a reliability model for a typical SVC. The Markov process is used to analyze the proposed model. They present an equivalent three-state model for SVC. Guilani et al. [96] evaluated the reliability of nonrepairable three-state systems and proposed a new method based on the Markov process for which a suitable state definition is provided. Malefaki et al. [97] considered a semi-Markov setting to study the main criteria for the reliability of a repairable continuous-time system under the hypothesis that the time evolution of its components is described by a continuous-time semi-Markov process. Mattrand and Bourinet [98] studied the reliability of cracked components under stochastic amplitude loads modeled by discrete-time Markov processes. Galateanu and Avasilcai [99] studied the reliability analysis of a business ecosystem based on the probabilities of its elements. This analysis is based on Markov chain theory.

Soleymani et al. [100] studied wind farm modeling in assessing the reliability of power systems. The mechanical behavior of each wind turbine generator (WTG) is modeled by the sequential Monte Carlo method, and the Markov model is used for wind farm output power. Aval et al. [101] used the Markov method based on state-space analysis to investigate the effects of BCHP system performance on the reliability of power systems. Wu and Hillston [102] studied two types of mission reliability for mission systems that do not require routine work throughout the mission. The first type is related to the mission requirement that the system must be continuously active for a minimum period of time during a certain mission period, while the second type is related to the mission requirement that the total operating time of the system in the mission time window must be more than a certain value. Based on the Markov renewal properties, matrix integral equations for semi-Markov systems are obtained. Petroni and Prattico [103] studied the issue of power production by wind turbines using the semi-Markov chain as a wind speed model and calculated some of the main reliability criteria. Fazlollahtabar et al. [104] proposes an integrated Markovian and back-propagation neural network approach to calculate the reliability of a system.

Timashev and Bushinskaya [105] described pipeline degradation—the simultaneous growth of many corrosion defects and the reduction of residual pipe resistance (burst pressure) by Markov processes of pure birth and death type, respectively. Based on Markov models, a method has been suggested for assessing the probability of failure (POF)/reliability of a defective pipeline cross section and a pipeline as a distributed system. Pham et al. [106] presents a reliability modeling scheme for a component-based software system whose models are automatically converted to Markov models for reliability prediction by the reliability prediction tool.

Wan et al. [107] proposes a stochastic process prediction model for estimating the thermal reliability of an electronic system based on Markov theory. A stochastic model of thermal reliability analysis and prediction for the whole electronic system is constructed based on the Markov process. Ossai et al. [108] described how to use Markov modeling and Monte Carlo simulation to determine the reliability of internally corroded pipelines. Shariatkhah et al. [109] proposes an analytical method for modeling the dynamic behavior of thermal loads in MCEB reliability analyses. The proposed method is based on the Markov chain by integrating thermodynamic equations. Honamore and Rath [110] proposes Hidden Markov Model (HMM) and fuzzy logic prediction model to predict service (web) reliability. Honamore et al. [111] used the HMM and Artificial Neural Network (ANN) to model the web service failure model and predict the reliability of web services.

Adefarati and Bansal [112] studied the effects of renewable energy resources (RERs) on a microgrid system. Stochastic properties of the main components of RERs and their effects on the reliability of a power system have been presented using the Markov model. Zhu et al. [113] studied an m-consecutive-k, l-out-of-n system with nonhomogeneous Markov-dependent components. Using the probability generator function method, closed-form formulas is used for the reliability of the m-consecutive-k, l-out-of-n system. Li et al. [114] studied the development of reliability criteria for a repairable multistate system operating under discrete-time dynamic regimes. The process of regime change is governed by one Markov chain, and the system operation process follows another Markov chain with different probability transfer matrices under different regimes.

Du et al. [115] presents a model based on aggregated stochastic process theory to describe history-dependent behavior and the effect of neglected fractures on Markov history-dependent repairable systems. Based on this model, instant availability and steady state are obtained to determine the reliability of the system. Zeygolis and Bourdeau [116] proposes a new method for reliability evaluating the internal stability of reinforced soil walls, taking into account the very high strength-redundant properties of these structures. Redundancy is formulated based on transfer probabilities and Markov random processes.

Kabashkin and Kundler [117] presents a Markov model for analyzing sensor node reliability in wireless sensor networks. Snipas et al. [118] offers solutions for Markov chain reliability models with a large state space. Li et al. [119] proposes a multistate decision diagram algorithm for Phased Mission System (PMS) and a multistate decision diagram model for the PMS to model nonrepairable multistate reliability. Based on the semi-Markov process, a method based on the Markov renewal equation has been presented to deal with nonexponential multistate components. For reliability design, Ye et al. [120] introduces a systematic approach to modeling the random process of system failures and repairs as a continuous-time Markov chain, which incorporates the maintenance effect to find the optimal choice of parallel units. Rebello et al. [121] presents a new method for estimating and predicting the functional reliability of a system using system functional indicators and component condition indicators. The proposed method uses both hidden Markov models and a dynamic Bayesian network to estimate and predict the operational reliability of the system.

Sonal et al. [122] considers the reliability study of series/parallel systems of vibrating systems under multicomponent random excitations. An experimental protocol, based on a subset simulation with Markov chain splitting, is proposed to estimate the failure probability with a relatively smaller number of samples, thus reducing the test time. Montoro-Cazorla and Perez- Ocon [123] studied a reliability system exposed to shocks, internal failures, and inspections, and a Markov process has been developed for this system. For the first time, Yi et al. [124] addresses two new reliability criteria, the availability of point coverage and the availability of interval coverage for discrete-time semi-Markovian systems. Kabir and Papadopoulos [125] provides an overview of fuzzy set theory methods used in safety and reliability engineering, including fuzzy Fault Tree Analysis (FTA), Failure Mode and Effects Analysis (FMEA), and Event Tree Analysis (ETA), fuzzy Bayesian networks, fuzzy Markov chains, and fuzzy Petri nets.

Gunduz and Jayaweera [126] studied the power system reliability assessment of an integrated physical-cyber system operation with multiple photovoltaic (PV) system configurations combining Markov chain transmissions for PV system components. Ardakan and Rezyan [127] proposes a two-objective reliability-redundancy allocation problem that uses a Markov-based approach to calculate exact values of reliability. Alizade and Sriramula [128] introduces a new reliability model for redundant safety-related systems using the Markov analysis technique. Su et al. [129] studied a systematic method for assessing the reliability of natural gas pipeline networks. The supply capacity of a pipeline network depends on the unit states and network structure, both of which change randomly. Thus, a random capacity network model is developed based on Markov modeling and graph theory.

Steurer et al. [130] proposes a new Systems Modeling Language (SysML)-based method for the analysis of the reliability of unmanned aerial vehicles (UAVs). This method consists of three main stages, one of which the Dual-Graph Error Propagation Model (DEPM)-based evaluation of system reliability criteria using Markov chain models and advanced techniques for probabilistic model evaluation is the third stage. Cheng et al. [192] present a Markov model to mimic a solar-generating system with series inverters, unreliable bypass switches, and common cause malfunctions. They obtain quantitative reliability models of the system using renewal point analysis technique and semi-Markov process theory. Gao et al. [131] studied a new repairable balanced k-out-of-n: F system with m sectors. The characteristic of this balanced system is that the number of active components in the m sectors must remain constant at all times. The excellent Markov imbedding method is used to obtain system reliability and availability.

Zhao et al. [132] introduces a Markov model for modeling hybrid DC circuit breaker reliability to calculate steady-state availability, failure rate, and average time between failures. Agrawal et al. [133] presents a Markov model for the reliability analysis of an EPBTBM (Earth Pressure Balance Tunnel Boring Machine) used in an irrigation tunnel. Wang et al. [134] integrated the Maximum Entropy Markov Model (MEMM) with time series motifs to achieve a new prediction model to address the problem of predicting component system reliability in a dynamic and uncertain environment. Yang et al. [135] provides a framework of the Markov/(Cell-to-Cell Mapping Technique) CCMT search engine platform for dynamic system modeling and reliability analysis.

Honarmand et al. [136] proposes a new mathematical model for evaluating the reliability of distribution networks integrated with process-oriented intelligent monitoring systems. This model uses the Markov method and considers the effect of process failure factors on the overall reliability of the system. Che et al. [137] created piecewise-deterministic Markov process modeling that can combine machine degradation and human error to evaluate system reliability. Wang et al. [138], to evaluate reliability and operational availability (OA), proposes a Markov model with a Reliability Block Diagram method.

Zhao et al. [139] proposes the overlapping finite Markov chain method for the first time to derive the system reliability and the expected shock length. Kabashkin [140] presents a way to increase the independence time of sensors in cluster-based wireless sensor networks (WSNs) prolongation using battery redundancy and proposes a Markov model for analyzing sensor node reliability in cluster-based WSNs with the proposed method. Wang et al. [141—143] studied the problem of multiobjective optimization by considering the optimal redundancy strategy, whether in active or cold standby mode. The exact reliability of additional cold standby redundant subsystems with incomplete detector/switch is determined by the introduction of a continuous-time Markov-chain-based approach.

Son et al. [144] presents an integrated reliability assessment model of the reactor protection system in nuclear power plants based on the Markov model. Zhao et al. [145] studied multistate balanced systems and derived the corresponding probability functions and some other reliability indices using the two-stage finite Markov chain imbedding approach. Cheng and Yang [146] proposes a reliability model for multistate phased mission systems (MS-PMS) by sharing common bus performance taking into account transmission loss and performance storage. They present a new Markov model for multistate components to solve the problem of interdependence between phases. To demonstrate the importance of a total battery energy storage system (ABESS) in microgrid (MG), Pham et al. [147] examines the reliability of its operation and presents an analytical approach based on Markov models to evaluate the reliability of the overall operation of ABESS.

Liu et al. [148] has proposed a modified one-dimensional Markov chain model for stratigraphic boundary uncertainty (SBU) modeling in slope reliability analysis considering soil spatial variability. Chakraborty et al. [149] has introduced a new coverage-reliability index, CORE, to quantify specific coverage-based reliability. CORE provides measurement of the ability of the sensor network with multistate nodes to satisfy the needs of the application-specific coverage area by delivering reliable data to the mobile sink. Wu and Ciu [150] proposes two Markov renewal shock models with multiple failure mechanisms. Shock size and time dependence between inputs are studied assuming that the magnitudes and times between inputs of shocks are controlled by an absorbing Markov chain with finite state space. Methods for calculating reliability functions and other reliability indices are presented under two Markov proposed renewal shock models.

Jiang et al. [151] provides a framework that emphasizes quantitative analysis and increased reliability of kick detection sensor networks. They use the Markov chain to obtain a reduction in the reliability of measurement sensors over time. Wu and Cui [152] investigated the reliability of multistate systems under Markov renewal shock models with multiple failure levels. In these models, the times between the arrival and the magnitude of the shock are controlled by an ergodic Markov chain and an absorption Markov chain. Chiachico et al. [153] studied that the prognostic method relies on a stochastic degradation model based on Markov chains, which is embedded in the framework of sequential mode estimation to predict remaining useful life and time-dependent reliability estimation.

Raghuwanshi and Arya [154] offers two methods for evaluating the reliability indicators of an independent hybrid photovoltaic (PV) energy system. Markov model and frequency-duration (F- D) reliability techniques have been used to evaluate the reliability indicators. Guilani et al. [155] tried to apply heterogeneous components in a subsystem. A mathematical model based on the continuous-time Markov chain (CTMC) method has been developed, which allows the system reliability to be accurately calculated because it is sensitive to component sequencing. Anand et al.[156] has proposed a possible new approach to evaluate the impact of electric vehicles on the performance of power distribution systems. A dynamic hidden Markov model is used to record the movements of an electric vehicle in the traffic layer.

Postnikov and Stennikov [157] performed probability modeling of district heating systems (DHS) states based on a Markov random process under conditions that can be specified for real systems. This method is based on Markov theory of stochastic processes and the basic principles of probability theory. Li et al. [158] developed the Markov-based dynamic fuzzy fault tree analysis method to solve the uncertainty of the failure rate in the hydraulic system of wind turbines, to model the reliability by considering the dynamic failure characteristics. Wang et al. [141—143] have proposed a multistate reliability modeling method based on the performance degradation process of the pipeline system considering the failure interaction. Also, the Markov model of the degradation process was proposed to determine the relationship between the probability of occurrence of each state and the path of decay.

Zhou et al. [159] proposes an integrated supply reliability assessment method for multiproduct pipeline systems and used the discrete-time Markov process to describe stochastic failure and the Monte Carlo method to simulate the transition of system states. Wang et al. [141—143] have proposed a Markov process imbedding approach for analyzing the reliability of balanced systems. Roy and Sarma [160] analyzed the performance on energy efficiency, throughput, and reliability of a synchronous duty-cycled reservation-based MAC protocol named Ordered Contention MAC (OCMAC) protocol by modeling the OCMAC queuing behavior with the Markov chain process.

Wu et al. [161] considered a balanced performance-based system by sharing the performance of a common bus consisting of n components. When the system goes out of balance after a performance share or the performance of the whole system is less than a predetermined value, the system fails, whichever comes first. A Markov process is used to describe changes in the performance of each component and the global production function technique is used to obtain an analytical solution for system reliability. Wang [162] presents a method for evaluating the time-dependent reliability of aging structures. In this regard, a closed solution for structural reliability has been developed that models the sequence of load effects as a Markov process. Wang et al. [163−165] considered a component reassignment problem (CRP) for a balanced system with multi-mode components operating in a shock environment. In such a balanced system, the components are multistate and the balance of the system is defined based on the performance levels of the components. Some reliability indicators have been obtained with the two-stage Markov chain imbedding approach.

Based on most practical systems, Fang and Cui [166] has developed an automated balancing mechanism for an innovative multistate balanced system consisting of two subsystems for theoretical and practical demands. Aggregated stochastic processes and semi-Markov processes are used to obtain reliability criteria. Peirayi et al. [167] created a continuous-time Markov chain model for mixed and K-mixed strategies. The proposed model estimates reliability under different redundancy strategies more effectively and in a simple way. In Tarineiad et al. [168], first, using Markov chain, a method for modeling the self-healing behavior of a component is proposed. Then, with different combinations of Taylor series expansion and self-repair, several criteria are proposed to evaluate the reliability of a software system.

Yi et al. [169] developed a belief reliability analysis method for transportation systems based on traffic performance margin. They developed an uncertain percolation semi-Markov (UPSM) model to describe the essential physical properties of traffic accidents, taking into account random and epistemic uncertainties. Yi et al. [170] introduced two new reliability indicators including multipoint-bounded coverage availability and multidistance-bounded coverage availability for discrete time systems. Their explicit formulas are derived for first- and second-order discrete aggregated semi-Markov systems, whose state spaces are divided into three subsets of perfect states, imperfect states, and failure states, respectively. Wang et al. [164] proposes a new reliability method by combining relevance vector machine and Markov-chain-based significance sampling (RVM- MIS). Jun et al. [171] provides an integrated Markov/CCMT analysis platform for the dynamic reliability of a digital process control system.

Farzin et al. [172] presents a Markov model that shows the different effects of harmonics on the reliability of overcurrent relays. Jiang and Li [173] developed the computational framework and modeling of multistate physics to evaluate the dynamic reliability of a multicrack structure through the implementation of piecewise deterministic Markov processes (PDMP). Wu and Cui [174] developed a reliability and maintenance model for a periodic inspection system with competitive risks exposed to a randomly changing operating environment, which is modeled as a continuous-time homogeneous absorption Markov process. Tahmasebzadehbaie and Sayyaadi [175] studied the water—energy—environment linkage in a city for burner gas recovery while considering downstream installation reliability. The Markov technique has developed a new integrated model for evaluating various proposed scenarios.

Jagtap et al. [176] provides a framework for reliability, availability, and maintenance (RAM) analysis to evaluate the performance of a water circulation system (WCS) used in a coal-fired power plant (CFPP). WCS performance is assessed using the Reliability Block Diagram (RBD), Fault Tree Analysis (FTA), and Markov Possible Birth—Death Approach. Mathebula and Saha [177] modeled the reliability and availability of the multi-mode IEC-61850-based Substation Communication Networks (SCN) using the structure—function and Markov process to combine defective repairs and diagnostic coverage of the system. Li et al. [178] studied a Markov Regenerative Process (MRGP) model to consider the effect of shocks on PMS reliability modeling.

Wang et al. [163—165] present a mathematical model for the reliability of a repairable (k1, k2)-out-of- n: G system consisting of two different types of components. The repair time of each failed component is exponential and the repairman's break time follows the phase-type distribution. The system works if at least the components of k 1 type 1 and k 2 components of type 2 work simultaneously. System reliability criteria are analyzed using Markov process theory and matrix analytical method.

Haghgoo and Damchi [179] proposes a new Markov model for assessing Capacitor Voltage Transformer (CVT) reliability. To obtain the model, first, a Markov model is presented for each CVT subsystem. Then, by merging these models, a 10-state Markov model is obtained, and finally, by combining similar modes, they obtain a three-mode model, including healthy, low-quality, and fault modes. Yin et al. [180] studied models for linear and circular k-out-of-n systems with common components consisting of subsystems. Using the Markov chain technique, the n-step transition rate matrix is obtained. Finally, system reliability is achieved by summing the reliability of all items with a limited Markov chain approach. Wu and Ding [181] provides a reliability model for systems that are exposed to multiple dependent competitive failure processes under the influence of Markovian environments.

Markov reward models are analytical tools for stochastic processes. Systems that ultimately suffer irrecoverable failure are modeled with absorption Markov chains, while repairable systems are modeled with irreducible chains. In the first case, the mode space is divided into two parts, which are a set of up and a set of down from modes of the system. In repairable systems, transient behavior in such systems is described by values of reliability and point and interval availability. Markov models can be used for transient reliability analysis with and without repair for K-out-of-N:G systems. The Built-In-Test technique with Markov model is used to analyze the reliability and availability of k -out-of-n:G systems.

Methods for solving reliability problems mainly include analytical techniques and stochastic simulations. Each of these methods has advantages and disadvantages. One of the important analytical techniques is the Markov method for reliable problem-solving. Markov analysis is a powerful and flexible technique for measuring system reliability. In the Markov method, state space is used to consider the states that may occur for the system, and an appropriate definition of system states must be considered. Process state space can be general, discrete, continuous, finite, and infinite. Due to the high number of states defined in Markov methods, or in other words, due to the exponential explosion in the size of the Markov model with the increasing number of states, or in other words, the curse of dimensionality, this method of solution may be limited. And these methods are usually time-consuming.

There are several ways to overcome this limitation in using the Markov method to solve complex systems. One of these methods is to simplify these models to reduce the number of state-space modes or to merge the modes. In Markov methods, the probabilities of state transfer are not definite and are calculated probabilistically. In semi-Markov systems, system states are defined, which are usually divided into healthy, defective, and failure states, in which the failure state is absorption and the system cannot come out after entering it. In semi-Markov processes, future behavior depends on current states as well as residence time. Markov reliability models have the ability to consider statistical correlations between failure events in dynamic systems. Reliability of systems is often a function of component failure, some of which are independent of components and others are interdependent. In using the Fault Tree (FT), the faults must be independent of each other. If the faults are interdependent, Markov analysis must be used, although the performance of the Markov model also largely depends on the size of the model. Of course, the Markov model is not suitable when the state space is large and when the time distribution is not exponential.

Semi-Markov chain approaches are based on considering the length of the process stays in each case. Hidden semi-Markov models are used to obtain the probabilities of transition between modes and the length of stay in each mode. In semi-Markov reliability models, the state space is divided into two sets of up and down modes. The probabilities of state transfer can always be the same or change with age.

Renewal equations are used for reliability functions in semi-Markov processes and conditionally in discrete state space. Non-Markovian models can be approximated by phase-type distribution. Markovian complex systems can also be analyzed. In system analysis, time is an important and influential factor in system capability and Markov models are suitable for analyzing these systems.

Reliability theory uses various mathematical and statistical tools for calculations. These tools include total positivity, majorization and Schur functions, renewal theory, Bayesian statistics, isotonic regression, Markov and semi-Markov processes, stochastic comparisons and bounds, convexity theory, rearrangement inequalities, and optimization theory Boland and Proschan [182].

In reliability theory, the replacement of items in case of failure is defined by the renewal process. The renewal function is defined as the expected number of replacements at a given moment. When it is assumed that the lifetime distribution of items is in one of the reliability classes of lifetime distributions, lower and upper bounds can be obtained for the renewal function. Reliability in standby systems that are prone to failure and are replaced by a new system after failure can be calculated using Markov renewal theory.

Each system has subsystems that have different levels of fault tolerance. The subsystems have dependencies. Each subsystem has several multistate components whose behavior can be analyzed using Markov models. To analyze the reliability of multicomponent systems, the components are not considered separately and are examined by considering the effect of component failure on each other. System status is assessed based on the failure level of all components. The system fails when the failure level of a component reaches a critical value or the difference in the deterioration level of the two components in symmetrical positions is higher than a certain limit. The occurrence of system failures in transition and stationary regimes can be obtained by using the matrix analytical method and probabilistic properties of phase-type distribution and Markov process theory.

The more complex the structure of systems and their multistate characteristics, the more difficult it is to assess their reliability. Due to the various techniques available for analyzing multistate systems, simulation is the only applicable approach for these systems. However, simulation requires counting the number of possible system states and defining the cutting sets associated with each state. Therefore, in large complex systems, counting the states and defining the cutting set make the simulation problem difficult and require a detailed understanding of the failure mechanism. Each component in the system can be defined as a semi-Markov random process and the system performance can be imitated through discrete simulation.

4. Conclusions and future research

System reliability can be defined as the system being able to operate continuously over a specified period of time with a certain level of performance. In some writings, instead of system reliability, they use functional reliability because reliability actually shows the level of system performance. Reliability is also defined as the frequency of a system failure. Reliability analysis is therefore usually dependent on the failure rate. In addition to time, the reliability of systems also changes due to environmental and operational conditions. Many systems deteriorate. This deterioration includes both natural degeneration and stochastic shock. Intrinsic deterioration and shock both cause the system to fail. There is usually a correlation between degradation and stochastic shocks, and both increase degradation. The time between two consecutive shocks can follow any distribution. Continuous phase-type distribution can be a suitable distribution. The times between consecutive shocks can be considered as a geometric distribution, and it can be assumed that shocks occur based on a binomial process. The shock process can be described by the Poisson process. Shock models with self-healing mechanisms can be used. Cumulative shock models and delta shock models are also used for shock modeling.

Usually, during the life of equipment, different periods can be described in which the system configuration and failure criteria change. There are several models for evaluating longevity in terms of reliability, including models based on Markov's reward theory and continuous phase-type distributions. Equipment life can be predicted using time series. The life span of your equipment is generally exponential. However, the longevity of many systems follows nonexponential distributions, including Weibull, and Markov modeling cannot be used for system behavior. Weibull distribution is one of the most important distributions in the reliability of systems.

Therefore, in these systems, the semi-Markov process was used, in which the lifetime of the components in dynamic systems follows the nonexponential distribution. Phase-type distribution can be suitable for equipment life. This distribution increases the flexibility of the systems. Markov chains are commonly used to model the degradation process. In Markov models, exponential distributions are used for failure times, but the number of modes in complex problems can be reduced by assuming the Weibull distribution for failure times. Negative exponential distribution and geometric distribution can also be used for failure times. The gamma process can be used to describe the random behavior of degeneration. Thus natural degradation behavior can be explained by the gamma process. In reliability models, it can be assumed that components break down based on a multivariate gamma process with dependence on the Levy copula. The Wiener process can be used to model component degradation. The failure rate in the equipment is proportional to the number of faults in the system and the failure correction rate has two components, either an error is corrected at a certain rate or an error is corrected, but a new error is created with a new correction rate.

Markov models are suitable for the exponential frequency distribution of the reliability function. The exponential distribution considers the hazard rate and repair to be constant. However, the Weibull model is one of the most widely used distributions to describe the frequency distribution in reliability and failure. Weibull distribution can be approximated to exponential distribution by linearization. Therefore, even if the Weibull distribution is considered for the reliability function, the Markov models can still be used for it by considering this approximation.

The pattern of degradation in systems is usually nonlinear. In some systems, transient regeneration events can affect the rate of degradation. For the degradation process, a Bayesian inference exponential model is usually used that ignores transient behaviors and local fluctuations. As a result, they do not perform well. However, models must be presented in which transient behaviors are also considered, so a general model must be presented that considers both transient behaviors and the pattern of gradual degradation. A model based on the Poisson process can record transient behaviors.

The rank regression method is used to determine the most appropriate failure distribution function. Semi-Markov continuous-time processes with distributed Weibull transmission times can also be used to model system failure. Dynamic Bayesian networks are also used to model degradation and reliability in cases where space is discrete and limited. Dynamic Bayesian networks integrate conditional stay time distributions with multiple dynamic degradations. Hidden Markov models are also included in the reliability. Bayesian inference can be used to reveal the unknown dimension of hidden Markov models.

Uncertainty parameters are usually entered as random variables in reliability models and their distribution must be specified. Past data are usually used to estimate distribution parameters. Real data between failures can be used to infer model parameters using the Monte Carlo Markov chain simulation method. For reliability in mechanical systems with continuous-state degradation process, the gamma process with nonconstant degradation is often used, and the matrix-based approximation method is used to calculate the average residual life and the residual life distribution.

It can be assumed that the system fails when the level of deterioration reaches a critical threshold. Sudden shocks are triggered at random times following a heterogeneous Poisson process, and the system fails when a sudden shock occurs. A nonhomogeneous continuous-time Markov chain is used to describe the state evolution process, and the nonhomogeneous Poisson process is used to model the number of external shocks. The probability of staying in any state of the Markov process is obtained through a recursive.

Reliability should be defined quantitatively, which can be done using the regenerative point techniques and semi-Markov process theory. Statistical methods based on the Bayesian approach can be used to quantitatively evaluate the failure process. To estimate the reliability of a system, indicators should be used to check the status of each component. The Chapman—Kolmogorov differential equations are used to obtain reliability criteria. In systems that are prone to deterioration or impact, self-healing action is less considered. Assessing reliability by considering the self-healing effect of components will be an interesting topic, although systems with self-healing mechanisms are used in many areas.

Due to the exponential explosion in the size of the Markov model with the increasing number of cases, or in other words, the curse of dimensionality, the Markov method may be limited in solving complex and large problems. There are several ways to overcome this limitation in using the Markov method to solve complex systems. Either these models need to be simplified to reduce the number of state space modes, or they can be combined to reduce the number of modes.

Korolyuk's method is a method of integrating state space into Markov models. Another solution is to use hierarchical modeling, which overcomes this increase in states in the Markov model. And you can use classical Markov methods or simulation techniques in Markov method. The Lz-transform can also be used. Reinforcement learning (RL) is used to improve Markov decision processes with large state spaces.

The probabilities of state transfer in Markov methods are not definite and are calculated probabilistically. Fuzzy logic can be used in Markov models to determine the transfer rate. Most failures cannot be shown by Markov chain methods and the Poisson process. These methods are not suitable for analyzing non-Poisson failures.

The Event tree (ET)/Fault tree (FT) method is one of the approaches used to assess reliability. Simple reliability problems are solved easily and quickly using error tree models. But in more complex problems, the state space increases exponentially and these models are prone to error, and this approach has not worked efficiently in modeling the reliability of dynamic systems. A dynamic FT with the definition of additional gates called Dynamic gates is able to solve complex systems using Markov models. Stochastic reward networks, which are a type of Petro-Stochastic networks, can be used for these models. The FT is commonly used to specify how the failure of individual components can lead to system failure. The dynamic FT shows the probability dependencies between the components and how these probabilities change over time.

Reliability is often complex due to system dynamics and existing uncertainties, and statistical methods are usually used to calculate it. Statistical methods focus on past system data and do not consider system dynamics and change over time. Markov reliability models have the ability to consider statistical dependencies between failure events in dynamic systems. Markovian and non- Markovian models are used for dynamic equipment reliability.

Markov models are not useable for fault detection and identification (PDI) in FTCS due to the inherent memory of these tests. But semi-Markov models can be used for these tests. Markov chains can be used to describe system faults. The metamodel method is also used in reliability analysis and the limitation of this method is to quantify the uncertainty of the model.

Numerical algorithms are another analytical technique used to solve reliability problems. The Monte Carlo Markov simulation method has been widely used in solving reliability problems. This method is suitable for modeling the dynamic behavior of the system but is stochastic. The Hamiltonian Monte Carlo (HMC) method, which is a nonstochastic simulation method, can be used to solve problems. Riemannian Manifold Monte Carlo Simulation (RMHMC-SS) is used to overcome the limitations of Monte Carlo approaches to solving reliability problems in highly curved non-Gaussian spaces. Markov chain simulation is used with the Metropolis—Hastings algorithm to estimate reliability. Bayesian methods can be incorporated into Monte Carlo Markov simulations and facilitate the inference of evaluation.

The shortest path analysis in stochastic networks can be used in reliability where systems are time-dependent. Regenerative point techniques are also used for analysis. Common universal generating function (UGF) such as Lz-transform and recursive algorithm are used in systems with many components. Of course, universal generating function techniques are commonly used to analyze steady-state reliability.

Traditional approaches such as simulation, Markov chains, and probability techniques are usually not capable of analyzing the reliability of complex systems. Petri net theory can be used to analyze reliability. Petri nets due to their visual nature can provide insight into the nature of the system being modeled. But the Petri model also has the problem of exploding mode space with increasing model complexity.

Stochastic Petri nets have different types that can be used as modeling tools for system reliability. Stochastic Petri Nets (SPNs) and Generalized Stochastic Petri Nets (GSPNs) are used for continuous-time stochastic processes (continuous-time Markov chains), Extended Stochastic Petri Nets (ESPNs) with semi-Markov processes, and Deterministic and Stochastic Petri Nets (DSPNs) for Markov regenerative processes. Stochastic Petri net can be used for this modeling Choi et al. [183]. This approach calculates the probabilities of their transfer instead of evaluating or assuming them. The Markov renewal process can be used to increase the analytical power of Petri nets.

There are limitations to reliability calculations in complex systems. These limitations include the curse of dimensionality with the exponential increase of the set of states with the number of components. Another limitation is the curse of history with the exponential increase of decision trees with increasing decision steps. Uncertainty is another limitation due to the inherent stochastic nature of system change. Also in complex systems, there are stochastic constraints related to resource scarcity Andriotis and Papakonstantinou [184].

Partially Observable Markov Decision Processes (POMDP) and multiagent Deep Reinforcement Learning (DRL) are used in reliability. Eigenvectors and eigenvalues can also be used to analyze system reliability. The reliability function can be obtained using the Laplace method. In semi-Markov systems with finite state space, algebraic calculus in convolution algebra can be used for reliability analysis. Differential equations can be used to solve reliability problems. Bayesian estimation can be used for system reliability using the Lindley approximation. Reliability models can be solved analytically in the form of Laplace transforms. Also, closed-form probability solutions are used to obtain reliability and mean failure time.

Bayesian networks can be used in systems reliability. The growing use of Bayesian networks is due to the advantages that Bayesian networks offer compared to other classical methods of reliability analysis such as Markov chains. Bayesian models have been successful in analyzing complex systems. These models have good ability to predict and detect failure. Information can also be updated using the Bayesian network based on the observations obtained. Bayesian inference techniques are effective in assessing the reliability of complex systems. In this technique, using previous system performance data and other information, different probabilities of reliability hypotheses can be obtained. Due to the fact that real failure data may not be available, it is necessary to perform test designs at the subsystem level. The Bayesian hypothesis test can be used to determine the number of tests that can be performed to show that a reliability target is estimated in a system with a certain level of probability. Update on Bayesian networks is a powerful tool for quantifying model uncertainty using new observations. Bayesian models also have the ability to use multimodal variables. Bayesian networks also have the ability to accurately calculate the probability of an event occurring, which is one of the advantages of these networks in solving reliability problems.

Today, in industrial systems, there is a set of components with dependencies between components and environmental conditions. System reliability can be achieved by influencing external variables on system degradation modes based on Bayesian dynamic networks. To effectively model the dependence between component degradation modes, a hierarchical structure must be defined. Dynamic programming is also used in solving reliability models. Traditional methods can also be used dynamically. Dynamic FTs, considering the characteristics of dynamic failure, can replace the traditional Markov-based FT, which may have the mode explosion constraint. Algebra of logics can be used to evaluate the reliability of large multicomponent systems if the use of differential equation-solving approaches or semi-Markov processes is problematic.

As described above, the use of classical approaches to solving reliability problems is limited by the diversity and behavioral uncertainty of existing systems and data, as well as the functional dependence between components and multiple failure modes. Solution approaches can be developed that can analyze the reliability of a system if performance specifications and failure data are not available.

Statistical solution methods and reliability Markov models need to be integrated with other modern problem-solving methods such as machine learning, artificial intelligence, and artificial neural networks. Intelligent monitoring systems can be used in smart networks to improve reliability, which indicates the amount of exposure to system components failure.

FT analysis and reliability block diagrams are static methods that are not able to record the redundancy and dynamics of the system. But Markov models are dynamic models; they are not suitable for very large and unsolvable models, and the time to stay in any case in these models is exponential. Most failures cannot be demonstrated by Markov chain methods and the Poisson process. These methods are not suitable for analyzing non-Poisson failures. Markov modeling can be combined with the advantages of other modeling techniques such as reliability block diagrams.

When man works with a machine, man also has an effect on the deterioration of the machine. The deterioration of the machine also causes fatigue and human error and accelerates the process of deterioration, so when examining the deterioration of the machine, manpower, environmental conditions, and raw materials must also be considered. By considering the human—machine system, the reliability of the system can be analyzed under a Markov process.

There is usually not much statistical data on component failure to probabilistic risk assessment (PRA). To overcome this limitation, fuzzy set theory is used.

The solution approaches used to probabilistic risk assessment should be considered fuzzy. Reliability models must be flexible to be up-to-date. Bayesian networks are a powerful tool that can adapt to a variety of factors in complex problems. Bayesian methods including Bayesian networks and dynamic Bayesian networks are used to analyze the reliability of complex systems. Dynamic Bayesian networks (DBNs) are used in multicomponent systems to determine the deterioration dependence between different system components and the complex structural behavior of the system.

The redundancy allocation problem (RAP) is used in many reliability optimization problems. To improve system reliability, component redundancy and component maintenance play an important role. Redundancy or standby is a technique used to improve reliability in system design. Reliability and availability analysis must be performed to decide on redundancy in the event of equipment failure. Systems can be interconnected and multistate, and demand in systems is usually random. Auxiliary resources can be used to improve system reliability. The reliability of multimode systems with redundancy should be studied. Standby system components are usually assumed to be statistically identical and independent. While in practical applications, not all components in standby mode can be considered the same because the failure rate and repair rate are not the same. A system that includes the main standby redundancy and subsystems can be considered and modeled with the Markov renewal process technique.

There are many studies on the RAP, but few of them consider designing systems that work for a certain period of time. In these systems, checking reliability in infinite time will not be useful. In the redundancy allocation problem, nonrepairable components including standby, cold or warm subsystems are usually used. Repairable components can be used in the RAP. Also, in the RAP, subsystems containing homogeneous components are generally included in the system. Nonhomogeneous components in a subsystem can be used to develop the RAP. Since RAP is in the NP-hard class of optimization problems, new solution approaches to this problem can be proposed.

Traditional reliability estimation methods, including reliability prediction methods, do not consider the impact of fault detection on the system. Models for estimating reliability can be proposed based on new approaches that take into account the impact of fault detection on the system.

In calculating the failure rate, the repairman repair operation can also be considered as an effective factor in the equipment failure rate after repair. Failure and repair rates change with the operating age of the equipment, so the transfer rate also changes with the age of the equipment. This rate can be obtained based on fuzzy set theory or using the knowledge of experts.

In systems, the failure rate can be defined independently of time and based on operational and environmental conditions. Probability modeling for Bayesian inference and quantification of uncertainty is one of the problems in determining the reliability of systems. New approaches can be proposed in this field.

Hybrid processes can be modeled in which components that act as discrete parts interact with continuous components. In evaluating high-dimensional systems, these systems can be hierarchically decomposed into several levels, and each level can be described by one of the reliability approaches, such as FT, Reliability Block Diagram, and state transfer diagram. Systems are usually considered statically for analysis. Systems described by hybrid reliability models are usually dynamic. In dynamic systems, there is a functional interdependence between components.

Reliability models often focus on fundamental faults while the reliability of transient faults must also be considered in predicting reliability. The numerical solution of a set of linear differential equations can be used simultaneously to calculate the transient state of repairable systems. For nonrepairable systems, transient probabilities for reliability can be obtained from closed-form solutions. Most reliability models assume that all failures are detectable and correctable. A reliability model in which not all failures can be identified and corrected can be analyzed.

During a software debugging operation, there is a possibility that an additional fault will be entered into the program when deleting an existing fault. So complete debugging is an ideal assumption but in reality, it is impractical. Models can be provided for these systems that consider the debugging operation to be incomplete. The Internet of Things (IoT) connects a large number of objects to the Internet, which can be used to achieve a higher level of control in terms of reliability.

The challenge in assessing reliability is the lack of failure data. The nonlinear least-squares regression-based method uses past degradation data to predict longevity. The Bayesian method can be used to estimate useful life. In the discussion of reliability, the binary assumption (completely failed or completely intact) for the system in the theory of reliability is not acceptable. In this case, the fuzzy state assumption must be considered for the state of a system, and the fuzzy assumption must be taken into account in the calculation of the function of reliability, lifetime, and failure rate.

Built-In-Test techniques are used in standby systems. This technique can be used with the Markov model in systems with nonidentical components to calculate reliability. Bivariate gamma process and fuzzy process can be used for stochastic modeling and reliability.

The decision to replace faulty components is made based on the condition of the components and the system, and there is a limit to the inventory level in this decision. Both maintenance and refill decisions affect system performance. Integrated models can be proposed by considering reliability and inventory decisions in multicomponent systems. Models can be provided for the reliability of systems with regard to environmental conditions. Gray Markov chains can be an interesting and new approach to system reliability.

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