ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

ANALYSIS OF FAILURE MECHANISMS ON RELIABILITY OF NON-REPAIRABLE SYSTEMS

MANISH KUMAR

Research Scholar, Department of Statistics, Janta Vedic College Baraut, Baghpat.
Email: man9kumar@gmail.com

Dr. SHIV KUMAR

Associate Professor, Department of Statistics, Janta Vedic College Baraut, Baghpat.
Email: Sirshiv.kumar@gmail.com,

Dr. RAJIV KUMAR

Assistant Professor, Department of Statistics, Janta Vedic College Baraut, Baghpat.
Email: r_baliyan@yahoo.com

Abstract

The status of the failure mechanisms of other dependent components may change, rendering them worthless or preventing them from operating as a consequence of the failure of one component in a system exhibiting function-dependent behavior. There has never been a mention of the failure mechanism level in any reliability research of functional dependency. This study employs a technique for evaluating component reliability that takes into account the behavior of failure mechanisms in components that have functional dependencies. These components include the second kind of trigger and suspension. For the purpose of accurately representing the behavior of the failure mechanism, the FMT and FDEP gates are employed. This work comes to a close with the development of a BDD model of the system as well as the presentation of certain reliability curves. A case study is used to describe the behavior of the failure mechanism inside the system.

Keywords: Failure Mechanism, Suspension, Classification, Trigger Effect, Reliability

1. INTRODUCTION

Complex systems in aerospace, aviation, navy, and nuclear power plants have been the focus of substantial research into failure dependency in dependability modeling. When one part of a parallel system (such a pair of motors) fails, the other part will experience different stresses. The system's dependability decreases when the probability of joint failure rises due to a dependency failure [1]. As a result, a more accurate representation of the genuine reliability behavior of many complex systems may be achieved by a modeling method that incorporates dependent failure. The level of a system, the level of a component, and the level of a failure process or failure mechanism might all be dependent on one another in the event of a failure. A "common cause failure" (CCF) is a subset of dependent failures that occurs when two or more component functional fault states occur at the same time, or within a short period of time, due to a shared cause. This phenomenon has been the topic of substantial study on the system or component level [2].The dependability of binary systems, multi-state systems, and ulti-trigger binary systems that are prone to global impact and selective effect generated by insufficient fault coverage has been investigated. These are the three types of systems that have

ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

been explored. This has been done despite the availability of acceptable redundancy and fault coverage in each of these types of systems [3] [4].

In addition to this, the dependability of competing failures and the selected renewal policy of failures that are sensitive to failure isolation and propagation effects are researched[5][6].If the trigger in a system fails, it will render the system's dependent components useless or inoperable. Many real-world systems exhibit functional dependency characteristics. Input-output (I/O) controllers allow computers to interact with devices like monitors, keyboards, and printers that are considered peripherals. I/O controller failure renders all attached peripherals useless [7] [8].

1.1 Classification of failure mechanism correlation

As a problem develops, progresses, and ultimately causes system failure, the complexity of the system's structure and loading situation means that each potential failure mechanism will affect the others. Several correlation kinds for non-repairable system failure mechanisms are presented in Fig. 1 from an engineering perspective. Here, we use the term "independent failure mechanism" to refer to failure mechanisms that are not reliant on any other factors other than the external environment, the applied stress, and the structure and material of the failing component [9]. Failure mechanisms that are independent of one another do not have their failures caused, launched, or impacted by any other failure mechanisms. Some separate failure mechanisms have varying expansion rates. The length of time it takes for the system to collapse will be established by how long it takes for the mechanism that fails first to evolve. Or, to put it another way, this procedure is competition, or these processes have a link with competition.

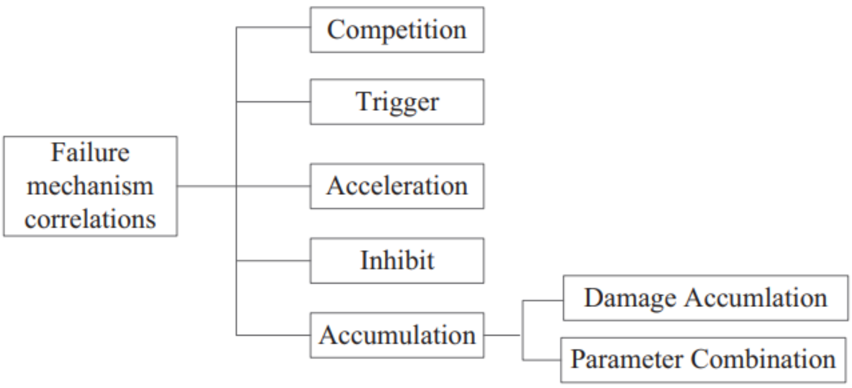

Figure 1: "Classification of failure mechanism correlations for non-repairable system."

The event that sets off a chain reaction of failures, whether it be a change in environmental or loading conditions or some other unexpected occurrence, is known as a trigger. An increase in the rate of development of one failure mechanism will accelerate (or hinder) the pace of growth of other failure mechanisms. It's possible that many failure modes have the same impact on the faulty component, system, or location [10]. The cumulative impact of the damage will lead to an early breakdown. There is a link between accumulation and these processes. In order to take

The Seybold Report
ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

into consideration all of the many ways to conduct harm, accumulation may be separated down into two subcategories: damage "accumulation and parameter combination." Mechanical breakdown is meant by the former. For instance, a solder junction in an electronic component might shatter due to heat wear or vibration fatigue. How long a solder junction lasts is determined by how much damage it sustains over time. In addition to damage, failure mechanisms may cause a shift in performance metrics. The same parameters may shift due to many failure modes that all operate on the same area of the component [11]. The connection between them is a collection of parameters. Evaluation of the electronic system's dependability is challenging due to the interconnectedness of its failure modes. However, failing to account for these connections may provide misleading ratings. Decoupling techniques of these correlations are required to simplify this issue.

2. REVIEW OF LITERATURE

Chen et al., (2020) [12] examined that the existence of a wide variety of system configurations, surroundings, or load circumstances over the various phases of a phased-mission system (PMS) may lead to a change in the system's behavior. The cumulative damage of each failure mechanism throughout the course of operation is a significant consideration when evaluating the system's dependability from the standpoint of the emergence of failure mechanisms. To include four unique damage accumulation criteria into PMS reliability modeling, it is recommended to adopt a hierarchical model based on the BDD. Homogeneous failure mechanisms with a constant stress or combinational profile in one phase, and inhomogeneous failure mechanisms with the same damage effect in one phase or multiple phases, both meet the inhomogeneous damage accumulation criterion. The standard BDD model was expanded to include a third failure accumulation level via the use of an extended BDD. There were three distinct tiers involved: the failure mechanism, the phase, and the objective. A case study was used to simulate and examine the consistency and reliability of a phased-mission control and drive system. The results demonstrated that the considered method successfully represented the PMS's dynamic behavior and achieved system dependability through computational modeling.

Ying et al., (2020) [13] studied that when it comes to controlling complex systems like airplanes or spaceships, fault tolerance design strategies are crucial. Even with sufficient redundancy, a system or subsystem may fail due to imperfect fault coverage (IFC). While Coverage Factor (CF) has been the primary focus of previous IFC research, system failure behaviors have been mostly absent. In the event of a low-layer failure, the upper layers may provide protection. Uncovered failure, yet, will have a functional and physical influence on the system's behavior if the coverage is inadequate. In this study, using a modeling and simulation technique that is based on BDD, the failure behavior and reliability of IFC in multi-layer systems are investigated. Additionally, a method for evaluating system reliability is proposed. An electronic controller for an aircraft engine equipped with IFC is examined to determine its failure behavior. The findings indicate that without considering the IFC, system behavior may change, maintenance intervals may be shortened, and maintenance costs would rise.

The Seybold REPORT

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

Selech et al., (2019) [4] analyzed that understanding the functional characteristics of a system's components over time is necessary in order to calculate the lifetime distributions of a technical item over time. This is because functional qualities change over time. Using a database of damage times 1for particular components, one can simply compute the average working time required to damage the element as well as the standard deviation for this time. The difficult part is selecting the appropriate sort of distribution to use.

If the kind of damage distribution that has occurred to the individual components of the technical item is incorrectly recognized, there is a possibility that the results of the reliability and durability assessment of the system may include major inaccuracies. When insufficient data is available, it is common practice to make an informed estimate as to the shape of the damage density function or the cumulative distribution. This may be done in a number of contexts. When it comes to reliability theory, the most common distributions are the ones that are used to explain how to assess the dependability of tested items based on the occurrence of their first failure. The consequences of calculations were analyzed using a variety of different situations. Calculations were carried out for various portions of the train.

Krishna et al., (2018) [15] stated that the vast majority of reliability models begin with the premise that both components and systems only ever suffer from a single kind of failure. However, many different systems, such as hardware, might fail in more than one way at the same time. Research done in the past on two-failure modes has led to the derivation of equations that may optimize reliability or reduce cost by determining the ideal number of components. The vast majority of these equations, if not all of them, are derived from models that make the simple assumption that component failures occur in a statistically independent way. In this article, models are built to evaluate the influence that correlation has on the reliability and cost of two-failure mode systems. Corresponding expressions for reliability and cost optimum designs are also given. In spite of the association, the instances we provide show that the method finds designs that are both reliable and economical to the greatest extent possible.

Twum et al., (2018)[16] suggested that in today's environment, optimizing system dependability is an absolutely necessary step in the process of assuring customer happiness, the competitiveness of enterprises, the safe and uninterrupted supply of services, and the safety of operations. When compared to other possible system configurations, complex systems are the most challenging to model in order to achieve maximum dependability.

The purpose of this study is to assess the performance of a novel optimization strategy developed by the authors in the setting of a gas transport system (GCS) with two potential points of failure and high initial dependability. The authors devised this methodology to find solutions to the challenges presented by GCSs. The fault tree methodology was used to get the minimal cut sets that included components of the system.

The reliability of these components was then formed into criteria, and both the associated cost of enhancing their reliabilities and the associated cost of maximizing their reliability were maximized. After that, Pareto optimum generic component reliabilities and system reliabilities

The Seybold REPORT
ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

were determined. The findings suggest that the optimization approach might increase the system's dependability despite the fact that it was already very high, provided that the feasibility factor for increasing the reliability of a component was already rather high.

Zhai et al., (2018) [17] studied that there are a wide variety of practical uses for phased-mission systems (PMSs). In order to complete its goal, a PMS must adapt to changing conditions in both system functioning and user demand. The inherent inter-phase dependency and dynamic system configuration (or structural function) and component behavior make reliability assessment of PMSs more difficult than that of single-phased systems. Although much work has gone into the examination of PMS reliability, gauging the dependability of a complex PMS with several phases remains challenging. To analyze the dependability of nonrepairable parallel PMSs under changing demand conditions, we provide a novel combinatorial model we call the aggregated binary decision diagram (ABDD). With the suggested method, PMSs with multiple phases may be efficiently analyzed by building a single ABDD model that accounts for failure combinations across all phases concurrently. In addition, the implications of fault-level coverage are considered within the framework of this method. In order to show how useful and effective the suggested ABDD-based method is, it is applied to examples of PMSs on a variety of scales.

Souza et al., (2017) [18] examined that it is characteristic of mission-oriented or safety systems to include components that can fail in repairable and non-repairable ways. Partially repairable systems contain components that can fail in repairable and non-repairable ways, and this allows for the possibility of partial repairs being made for the operating scenario. In this study, both analytical and numerical solutions are presented for the problem of modeling the dependability of partly repairable systems.

The modeling that has been suggested is based on Markov chains, and it consists of stand-by redundancy as well as a repair rate component. A discussion is held about the reasons for the restricted capability for repair. The modeling is used for dependability study of an electrical power system characteristic of Nuclear Power Plants. This system is supposed to be constituted of offsite power lines and redundant Diesel-generators with the goal of assessing an electrical power loss (blackout). It is shown that there is a gain as a consequence of the increase in repair capacity via the performance of a sensitivity analysis of the influence that the repairability rate has on availability and reliability.

Li et al., (2016) [19] focused on a non-repairable system with multi- and cyclic-mission sequences and multi-mode failures in its individual components. Two possible failure states for a valve system are either not closing when it should or not opening when it should. A discrete-time semi-Markov chain is built inside the time evolution framework to more accurately simulate the observable phenomena since the sojourn periods between succeeding missions may not satisfy the Markov condition. We propose an explicit form of the solution to the problem of system dependability by combining stochastic theory and the Z-transform.

This allows for easier calculation and the acquisition of distributions of various stay lengths that readers demand, including those for perfect and imperfect operations. In additionally, one

The Seybold REPORT

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

of the valve systems has three-way switching, while the other has two. In order to further demonstrate the suggested concept and strategy, numerical examples are provided.

Guo et al., (2016) [20] studied the process of mechanical systems deterioration that is caused by continuous wear and random shocks is investigated. These mechanical systems are formed of several subsystems, and they have been exposed to all of these factors. To calculate how long a sequence of systems can keep running, we developed a new mathematical model that accounts for the gradual degradation of individual components over time. In the past, researchers largely focused on simple, non-repairable systems without considering the effects of deterioration on the numerous smaller parts of the whole.

It was their belief that the threshold degree of degradation must be met before a system may function normally. This research was primarily focused on non-repairable systems. This new model expands on the prior study by taking into consideration a non-repairable system as well as a repairable system that is susceptible to numerous degradation processes. Both kinds of systems will fail when the total deterioration of the system reaches a level that is higher than the threshold level. Through the use of a Monte Carlo simulation, the model is shown with reference to a particular scenario.

Mi et al., (2016) [21] stated that modern electromechanical systems (EMSs) have become more complicated as a result of the rise of macro-engineering and mega-projects. Assessing a system's dependability becomes more challenging as its structure and failure mechanism get more complicated. Due to the complexity generated by the ever-evolving surroundings, lack of data, and random interference, engineering systems constantly exhibit uncertainty, dynamic, and nonlinear features.

An in-depth analysis of how to evaluate the dependability of complex systems is provided in this work. It takes use of the benefits offered by the dynamic fault tree (DFT) for defining system behaviors in light of the dynamic features present inside the system. By factoring in field failures, test data, and design expertise, system unit lifetimes may be described as bounded closed intervals. When trying to estimate the parameters of life distributions, the COV approach is often used. To communicate the ongoing epistemic uncertainty brought on by the lack of comprehensive evidence, it is recommended to use an expanded probability-box (P-Box).

Relevant reliability characteristics and indices have been derived by translating the DFT into an analogous Bayesian network (BN). The DFT model accounting for the system replacement strategy is then computed using the Monte Carlo (MC) simulation technique. This integrated method is shown to be more adaptable and productive in evaluating the dependability of complex dynamic systems.

2.1 Comparison of reviewed technique

There is a wide range of authors who studied on analysis failure Analysis of failure mechanisms on reliability of non-repairable systems and give their findings as seen in table 1.

The Seybold Report
ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

Table 1: Comparison of reviewed technique

Authors [Ref.]	Technique	Outcome
Chen et al., (2020) [12]	Phased-mission system	The results demonstrated that the considered method successfully represented the PMS's dynamic behavior and achieved system dependability through computational modeling.
Ying et al., (2020)[13]	Multi-layer system	The findings indicate that without considering the IFC, system behavior may change, maintenance intervals may be shortened, and maintenance costs would rise.
Selech et al., (2019)[4]	Reliability theory	The consequences of calculations were analyzed using a variety of different situations. Calculations were carried out for various portions of the train.
Krishna et al., (2018)[15]	Two-failure mode system	In spite of the association, the instances we provide show that the method finds designs that are both reliable and economical to the greatest extent possible.
Twum et al., (2018)[16]	Gas carrying system	The findings suggest that the optimization approach might increase the system's dependability despite the fact that it was already very high, provided that the feasibility factor for increasing the reliability of a component was already rather high.
Zhai et al., (2018)[17]	ABDD	With the suggested method, PMSs with multiple phases may be efficiently analyzed by building a single ABDD model that accounts for failure combinations across all phases concurrently.
Souza et al., (2017)[18]	Markov chain	It is shown that there is a gain as a consequence of the increase in repair capacity via the performance of a sensitivity analysis of the influence that the repairability rate has on availability and reliability.
Li et al., (2016)[19]	Z-transform	In order to further demonstrate the suggested concept and strategy, numerical examples are provided.
Guo et al., (2016) [20]	Monte carlo	Both kinds of systems will fail when the total deterioration of the system reaches a level that is higher than the threshold level.
Mi et al., (2016)[21]	Monte Carlo	This integrated method is shown to be more adaptable and productive in evaluating the dependability of complex dynamic systems.

3. PROBLEM FORMULATION

The rise in scientific understanding of the factors that cause electronic failure has led to an increased emphasis on reliability research for electronic systems using the physics-of-failure technique. The following presumptions are made in an effort to simplify the issue: The system is non-repairable with binary-state components, which indicates that none of the processes, elements, or items can recover from a failure or an unusable circumstance, and that the components are either working properly or have failed to do so. Additionally, the system is in one of two states: either functioning well or having failed to operate properly. In other words, the system is in a condition that may be described as binary. As a result of the inability of the effects of the dependent basic FMs to have an effect on the trigger FMs, it can be deduced that

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

after the trigger FMs have taken place, the dependent basic FMs will develop in a manner that is distinct from that of the trigger FMs. The amount of time it takes for the system to fail is defined by the first component that impacts its failure threshold.

4. RESEARCH METHODOLOGY

In a function dependent gate, the dependent components typically include a trigger and one or more dependent components. Failure of the trigger will result in failure of the dependent components; hence, failure of either the trigger or the dependent components will result in failure of the dependent components. Additionally, a failure of the trigger will result in the dependent components beginning their task. In a system in which one function is dependent on another, the failure of the trigger leads the dependent components to become worthless or inoperable. If both functions fail, the system is said to be inoperable. It is a sign that the safety mechanisms in the dependent components are currently in a state where they are either about to activate or are about to halt their operation. Following the failure of a trigger within the system, the structure of the system has been altered, which may cause some components to become inoperable while simultaneously causing others to become operational. If the components' modes of operation are different, this will inevitably result in the components' failure mechanisms being distinct. Additionally, the failure of the trigger will not instantly result in the system in a real system. The failure of one trigger component might cause certain dependent components to become useless since of the functional reliance between components. This causes the failure mechanisms of the dependent components to cease growing, which is a sort of behavior known as suspension in the context of failure mechanism behavior. The second kind of failure mechanism trigger refers to a scenario in which the failure of a trigger results in dependent components starting to function and the failure mechanisms starting to emerge. This form of failure mechanism trigger may occur in a number of different situations.

4.1 Failure Mechanism Suspension

Assuming that in a system with "k out of n components, all of the Bi components (i = 1, 2,..., n) are the same and are independent of one another. In addition, components A and Bx (where A is the trigger component and Bx are the dependent components) are connected with one another. Bx may have any value for x between 1 and n. In Figure 2, one can see both the failure mechanism suspension (MSPS) and the failure mechanism tree."

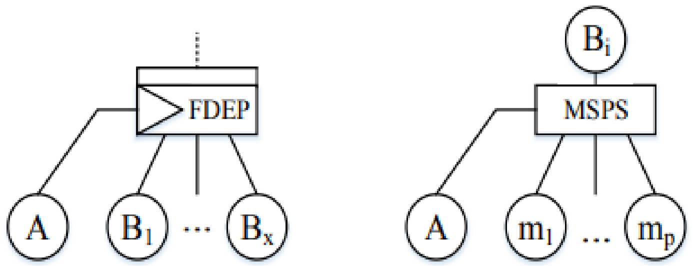

Figure 2: Logic diagram of failure mechanism suspension and FMT

ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

The failure of any one of the p dependent components will result from the failure of any one of the p failure mechanisms. If we suppose that the component has a life of ς,, then there will be a competing connection between the various failure modes. Ti to be the time of failure mechanism mj"(j = 1, 2, …, p) from initiating to resulting in component failure, so component lifetimeς, can be expressed by,"

$$\zeta = \min\,(T1, T2, \ldots, Tp) \tag{1}$$

Then failure probability of component

$$F_{Bi}(t) \text{ is,} F_{Bi}(t) = P(\xi \leq t) = 1 - P(\xi > t) \tag{2}$$

And ζ can obtained in equation (1), then

$$F_{Bi}(t) = 1 - P(\min(T1, T2, \ldots, Tp) > t) \tag{3}$$

$$= 1 - P(T1 > t, T2 > t, \ldots, Tp > t)$$

The event of $Ti > t(i = 1,2, \ldots, p)$ are independent, then

$$F_{Bi}(t) = 1 - \prod_{j}^{p} P(Tj > t) \tag{4}$$

$$= 1 - \prod_{j=1}^{p} (1 - Fj(t)) \tag{5}$$

$$= 1 - \prod_{j=1}^{p} \left(1 - \int_{j=1}^{t} fi(t)\, dt\right) \tag{6}$$

In the above formula, $f_i(t)$ is the failure density function of mechanism mj.

"Assume trigger A failure at Ttr, failure probability of this k-out-of-n system is"

When $t < T_{tr}$,

$$F_s(t) = 1 - R_s(t) \tag{7}$$

Only if both trigger A and the system inherently are operating would the system be operational. As a result, the chance of the system failure is,

$$F_s(t) = 1 - \begin{bmatrix} \Pr(component\ \ A\ doesn'tfaily)\ x \\ \Pr(system\ doesn'tfail\ inherently) \end{bmatrix} \tag{8}$$

4.2 Generation of Failure mechanism Trees

A failure in MIU1 caused the development of a mechanism in M1, M2, and M3, which caused those mechanisms to be paused. A failure in MIU2 will cause the mechanism in M4 to come to a halt. Failure mechanism suspension is shown in Figure 3, parts a and b. In addition to this, MIU1 causes MIU2 to become activated, and the failure mechanisms of M4 begin to emerge. The second sort of failure mechanism trigger is shown in Figure 3's (c) and (d) subfigures.

ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

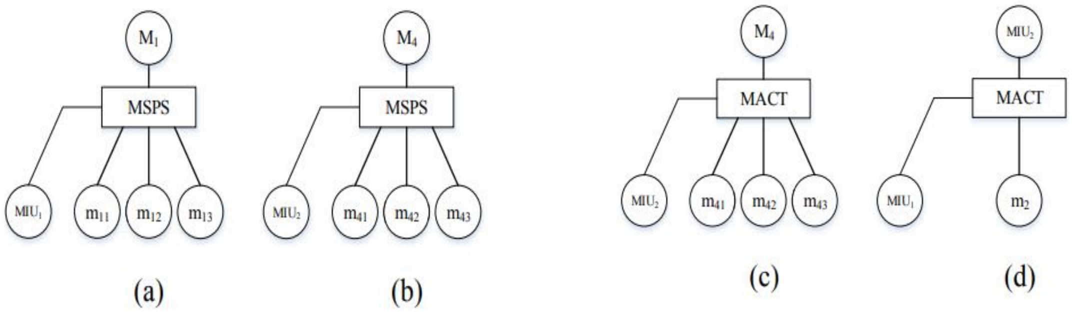

Figure 3: "Failure mechanism trees of components"

4.3 Generation of Dynamic fault tree model

The dynamic fault tree model shown in Figure 4 illustrates the particular connection that exists between the units. As can be seen in Figure 4, the DFT model has a total of four functional dependency gates; to put it another way, the system is comprised of a total of four functional connections. In the event that MIU1 fails, M1, M2, and M3 will either become inaccessible or useless, which would halt the development of the mechanisms. In the meanwhile, its failure will cause the MIU2 to develop its failure mechanisms, and M2, M3, and M4 will begin to function. After then, the rest of the memory units are activated by MIU2. In point of fact, due to the fact that the time gap between the transitions from the functional state of the main interface to the standby interface being so short, it is disregarded here.

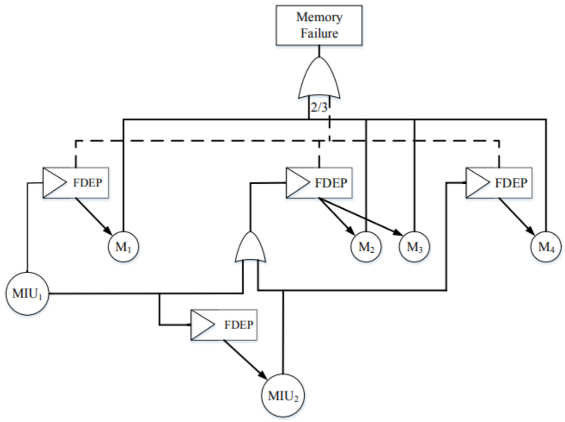

Figure 4: "DFT of the computer memory system"

4.4 Generation of BDD model

A channel from a no-sink node in the BDD model, which is seen in Figure 5, is given a label of either a "1" or a "0," indicating whether or not the component is operating properly. If the sink node for a route is marked with a '1' or a '0', then it will result in the system failing to operate or successfully doing so.

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

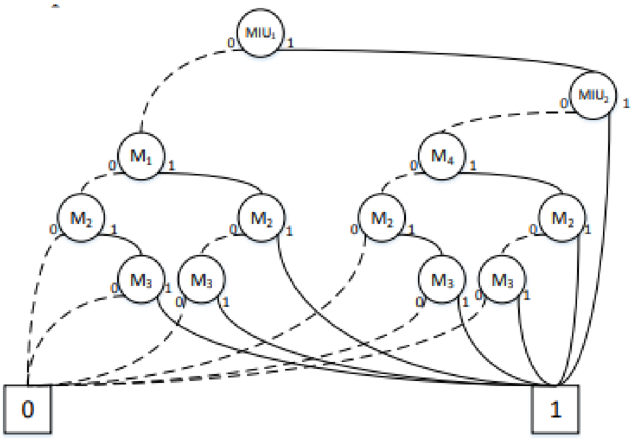

Figure 5: "BDD model of the system."

5. RESULT AND DISCUSSION

After the three models have been established, it will be possible to receive some of the findings that were anticipated from the simulation. Because it was assumed in the previous section that M1, M2, and M3 are all the same thing, we will refer to them collectively as M from here on. RM (t) does not take into account the impact that the trigger has on the dependent components; instead, it displays the reliability function of M in three different scenarios as three separate curves in Figure 6. In addition, the reliability function of M is denoted by RM-1(t) when MIU1 serves as the trigger, and RM-2(t) when MIU2 serves in that capacity. When examining the functional dependency, as shown in Figure 6, RM-1(t) reductions more quickly than RM (t), and the dependability of the same dependent component will change depending on the trigger used.

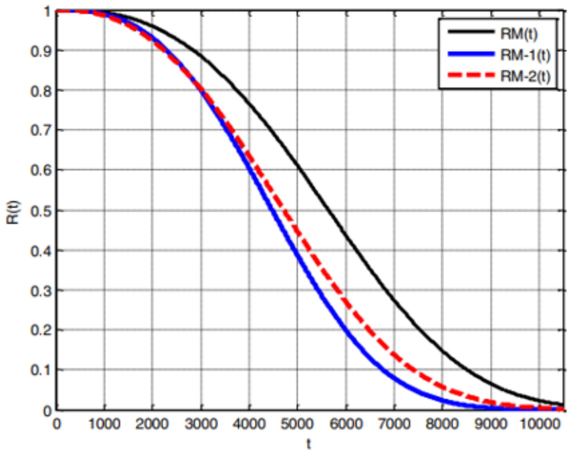

Figure 6: Reliability function of memory units

ISSN 1533-9211
DOI 10.17605/OSF.IO/9F46H

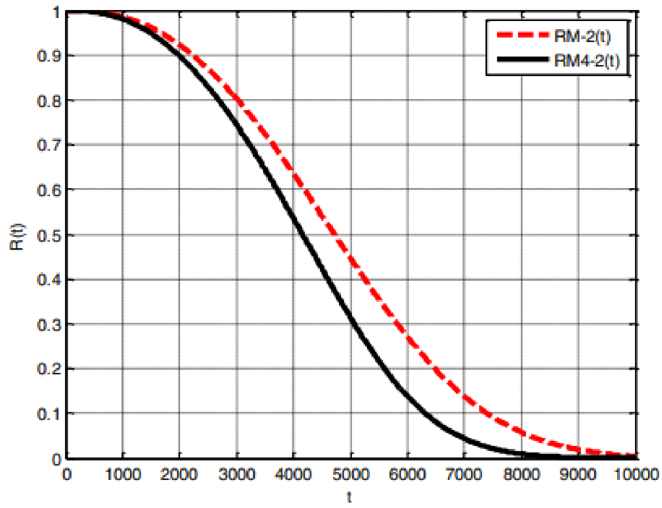

Figure 7: Comparison of reliability function of M and M4

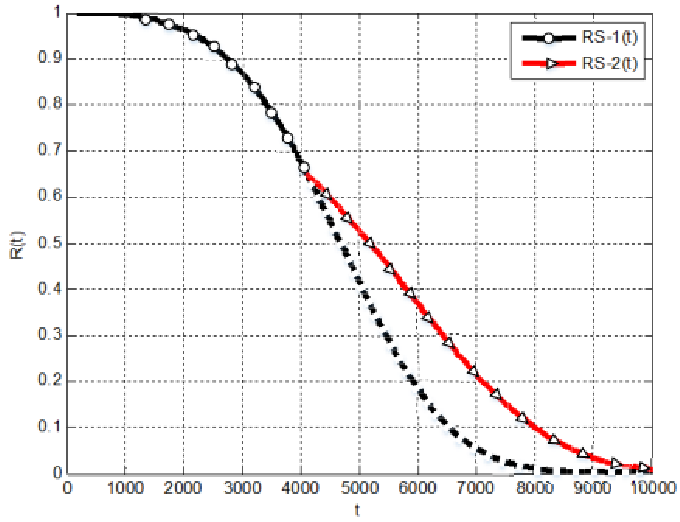

Figure 8: Reliability function of system

When both triggers are MIU2, the RM4-2(t) and RM-2(t) values are distinct from one another due to the disparate failure processes of the two components, as seen in Figure 7. The mechanism may be broken down into two distinct stages, as seen in Figure 8. The reliability function of this stage is denoted by the symbol RS-1 (t), and it is performed by the interface unit MIU1 while it is operating in the first phase as a trigger. The memory units M1, M2, and M3 that are attached to it serve as dependent components. At the second stage, MIU1 has failed; after this, MIU2 begins to operate, which enables M2, M3, and M4 to function; the reliability curve is denoted by the symbol RS-2 (t). When we associated the two stages, we discovered that the triggers and the components that were reliant on them were distinct from one another.

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

6. CONCLUSION

In this study of research, the failure mechanisms are investigated on the presumption that there is a functional reliance in a system. In addition, the failure mechanism trigger of the second type and the failure mechanism suspension are also proposed as suitable solutions. Through this research, the BDD model, failure mechanism tree models of components, and a dynamic fault tree model for the computer memory system are all developed. We were successful in obtaining the reliability curves of both the components and the system, which not only supplied more information but also demonstrated the presence of a different sort of failure mechanism trigger in addition to failure mechanism suspension.

References

1) Levitin, Gregory, and Liudong Xing. "Reliability and performance of multi-state systems with propagated failures having selective effect." *Reliability Engineering & System Safety* 95, no. 6 (2010): 655-661.

2) Peruzzi, L., F. Salata, A. de LietoVollaro, and R. de LietoVollaro. "The reliability of technological systems with high energy efficiency in residential buildings." *Energy and Buildings* 68 (2014): 19-24.

3) Wang, Chaonan, Liudong Xing, and Gregory Levitin. "Reliability analysis of multi-trigger binary systems subject to competing failures." *Reliability Engineering & System Safety* 111 (2013): 9-17.

4) Wang, Chaonan, Liudong Xing, Rui Peng, and Zhusheng Pan. "Competing failure analysis in phased-mission systems with multiple functional dependence groups." *Reliability Engineering & System Safety* 164 (2017): 24-33.

5) Maaroufi, Ghofrane, Anis Chelbi, and NidhalRezg. "Optimal selective renewal policy for systems subject to propagated failures with global effect and failure isolation phenomena." *Reliability Engineering & System Safety* 114 (2013): 61-70.

6) Wang, Chaonan, Liudong Xing, and Gregory Levitin. "Propagated failure analysis for non-repairable systems considering both global and selective effects." *Reliability Engineering & System Safety* 99 (2012): 96-104.

7) Zhao, Guilin, and Liudong Xing. "Competing failure analysis considering cascading functional dependence and random failure propagation time." *Quality and Reliability Engineering International* 35, no. 7 (2019): 2327-2342.

8) Xing, Liudong, Chaonan Wang, and Gregory Levitin. "Competing failure analysis in non-repairable binary systems subject to functional dependence." *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 226, no. 4 (2012): 406-416.

9) Baccar, D., and D. Söffker. "Identification and classification of failure modes in laminated composites by using a multivariate statistical analysis of wavelet coefficients." *Mechanical Systems and Signal Processing* 96 (2017): 77-87.

10) Levitin, Gregory, Liudong Xing, Suprasad V. Amari, and Yuanshun Dai. "Reliability of non-repairable phased-mission systems with propagated failures." *Reliability Engineering & System Safety* 119 (2013): 218-228.

11) Lu, Ji-Min, and Xiao-Yue Wu. "Reliability evaluation of generalized phased-mission systems with repairable components." *Reliability Engineering & System Safety* 121 (2014): 136-145.

12) Chen, Ying, YingYi Li, Rui Kang, and Mosleh Ali. "Reliability analysis of PMS with failure mechanism accumulation rules and a hierarchical method." *Reliability Engineering & System Safety* 197 (2020): 106774.

ISSN 1533-9211

DOI 10.17605/OSF.IO/9F46H

13) Ying, C. H. E. N., Y. A. N. G. Song, and K. A. N. G. Rui. "Reliability evaluation of avionics system with imperfect fault coverage and propagated failure mechanisms." *Chinese Journal of Aeronautics* 33, no. 12 (2020): 3437-3446.

14) Selech, Jaroslaw, and Karol Andrzejczak. "Identification of Reliability Models for Non-repairable Railway Component." In *Reliability and Statistics in Transportation and Communication: Selected Papers from the 18th International Conference on Reliability and Statistics in Transportation and Communication, RelStat'18, 17-20 October 2018, Riga, Latvia 18*, pp. 507-518. Springer International Publishing, 2019.

15) Krishna Murthy, Anusha, Saikath Bhattacharya, and Lance Fiondella. "Optimal Reliability and Cost of Non-Repairable Systems Subject to Two Failure Modes Considering Correlated Failures." *International Journal of Reliability, Quality and Safety Engineering* 25, no. 05 (2018): 1850024.

16) Twum, Stephen Boakye, and Elaine Aspinwall. "Multicriteria reliability modeling and optimisation of a complex system with dual failure modes and high initial reliability." *International Journal of Quality & Reliability Management* (2018).

17) Zhai, Qingqing, Liudong Xing, Rui Peng, and Jun Yang. "Aggregated combinatorial reliability model for non-repairable parallel phased-mission systems." *Reliability Engineering & System Safety* 176 (2018): 242-250.

18) Souza, Gilberto FM, and Cesar A. Gabe. "Reliability modeling of partially repairable systems applied on electrical power system." In *2017 Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1-6. IEEE, 2017.

19) Li, Yan, Lirong Cui, and He Yi. "Reliability of non-repairable systems with cyclic-mission switching and multimode failure components." *Journal of Computational Science* 17 (2016): 126-138.

20) Guo, Shuyang, Yufeng Sun, Guangyan Zhao, and Zhiwei Chen. "Degradation process and lifetime evaluation of repairable and non-repairable systems subject to random shocks." In *2016 11th International Conference on Reliability, Maintainability and Safety (ICRMS)*, pp. 1-5. IEEE, 2016.

21) Mi, Jinhua, Yan-Feng Li, Yuan-Jian Yang, Weiwen Peng, and Hong-Zhong Huang. "Reliability assessment of complex electromechanical systems under epistemic uncertainty." *Reliability Engineering & System Safety* 152 (2016): 1-15.