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A Computer Simulation Model for Reliability Estimation of a Complex System

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A B S T R A C T

In today's competitive world, preventing from probable breakdowns can be act as a powerful leverage for managers. They are faced with large complex systems. Hence, the realistic estimation of the reliability of such systems has become increasingly important and it is a vital complicated task especially in the cases where the system configuration is too complicated to present it via a Reliability Block Diagram (RBD). The focus of this research is on the reliability estimation of the complex multi-component systems; each failure mechanism is deployed from a given failure density function. Hence, due to complexity arises from unknown RBD, current research methodology is set based on computer simulation modeling. After investigating the simulation model validity, an example is examined to reveal simulation method advantages. To assess the proposed method, a typical example has also been discussed.

Keywords: System reliability estimation, Complex system, Fault Tree Analysis (FTA), Reliability Block Diagram (RBD), Simulation modeling.

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1. Introduction

Nowadays, almost all experts are willing upon the continuous functioning of a wide array of complex systems configured by components, such as machinery and equipment for our everyday security, mobility, safety, and economic welfare. We expect our systems to function whenever we need them. When they fail, the results can be catastrophic, injury or even loss of life. As our systems grows in complexity, so do the critical reliability challenges and problems that must be solved. Reliability engineering currently receives a great amount of attention from researchers and practitioners as well. Many academic researches focus on reliability engineering techniques. Some of them focus on the development of reliability estimation methods for complex system that are considered by the present paper. When the components time to failure are independent and their failure density function is known, the system reliability analysis using the Reliability

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Block Diagram (RBD) is a typical task. However, the system may embed correlated components with different time to failure density functions or it is impossible to present their configuration via a given RBD. In such cases, the reliability of the system will be difficult to estimate and still needs to develop existing methods.

Weber and Jouffe [2] research was the better complex manufacturing process that have to be dynamically modelled and controlled to optimize the diagnosis and the maintenance policies. Because of this goal, a methodology that will help developing Dynamic Object Oriented Bayesian Networks (DOOBNs) to formalize such complex dynamic models to estimate general reliability is presented. Wilson and Huzurbazar [3] used Bayesian networks for systems reliability that have binary outcomes and multilevel discrete data. These method are also suitable when system structures are too complex to be represented by fault trees. Li and Zuo [4] used Wu and Chen method and UGF for reliability evaluation of binary weighed k-out-of-n systems, and used UGF and recursive algorithm for multi-state weighted k-out-of-n systems. Ge and Asgarpoor [5] used a parallel computing environment and sequential Monte Carlo simulation for reliability of equipment and simple systems with binary structure. Simulation results are compared with the analytical approach results for the same cases. The used environment in this paper is Rock-131 from the San Diego Supercomputer Center in La Jolla, CA. Wang et al. [6] represented the reliability of the weighted k-out-of-n system, which be calculated with using component reliability based on the structure function with UGF. This method can be applied to weighted k-out-of-n systems with multi-state components and binary components, and simple series and parallel systems, too. It may also estimate complicated system reliability. Jirgl et al. [7] represented the reliability of system with four components and specific RBD that each component is two-state and follows by Exponential function, is estimated by Monte Carlo simulation and analytical method. These results are very similar. It means that the use of Monte Carlo approach for quantitative reliability analysis is suitable. Segovia and Labeau [8] presented a review to estimate the reliability of two-state and multi-state simple systems with using analytical and Monte Carlo simulation methods. Kim and Kang [9] expressed Civil infrastructures such as transportation, water supply, and electrical and gas networks that often establish highly complex networks. To understand the reliability of such complex network system under catastrophic events, the reliability analysis methods are necessary. A non-simulation-based network reliability analysis method is developed based on the Recursive Decomposition Algorithm (RDA). In this method, the intersection and union, and combinations of these processes are used for the decomposition of any general system event with multiple node pairs. Nguyen et al. [10] proposed a novel predictive maintenance policy with multi-level decision-making for multi-component system with complex structure; 14-component system is finally introduced to illustrate performance of the proposed predictive maintenance policy. Choi and Chang [11] estimated the reliability subsea production systems with two-state structure and Exponential function with FTA. Wu et al. [12] used two novel approaches for reliability prediction: One Integrating Least Square Support Vector Machine (LSSVM) and the iterated nonlinear filters for updating the reliability data accurately. In this method, a nonlinear state-space model is first formed based on the LSSVM and then the iterated nonlinear filters are employed to perform dynamic state estimation iteratively on reliability data with stochastic uncertainty. The suggested approaches are compared with the existing Neural Networks (NNs) and SVMs models. The experimental results reveal that the proposed models can result in much better reliability prediction performance than other technologies. Fan et al. [13] proposed integral equations based on the Taylor series expansion of the Probability Density Function (PDF) of a bivariate normal distribution resulted in an explicit polynomial equation of the equivalent correlation coefficient in order to estimate complex system reliability with correlated random vectors. Proppe [14] represented two Markov chain Monte Carlo simulation methods for reliability estimation, subset simulation, and the moving particles algorithm. To this end, both low-dimensional and high-dimensional test cases are considered. Both subset simulation and the moving particles algorithm seem to be well suited for off-the-shelf reliability estimations.

Table 1. Methods to tackle the reliability.

Author	Year	Analytical method	Simulation method
Weber and Jouffe	2006	*	
Wilson and Huzurbazar	2007	*	
Li and Zuo	2008	*	
Haifeng and Asgarpoor	2011	*	*
Wang et al	2012	*	
Jirgl et al	2013	*	*
Segovia and Labeau	2013	*	*
Kim and Kang	2013	*	
Nguyen et al	2015	*	
Choi and Chang	2016	*	
Wu et al	2016	*	
Fan et al	2016	*	
Proppe	2017	*	*

This paper is organized as follows. In Section 2, problem statement and methods to estimate reliability of system are considered. In Section 3, a simulation based reliability assessment method to analyze and predict complex system reliability is proposed. To verify the accuracy and rationale of the proposed method, one example is numerically examined in Section 4. Finally, Section 5 summarizes some conclusions.

2. Problem Statement

System reliability analysis is a quantitative method of component breakdowns in finding the probability of surviving the system. Such probability is calculated by assigning probabilities to each of components that are appeared in the Reliability Block Diagram (RBD). The probabilities of the component breakdowns are generally given by the field experience, gathering time to failure data and applying a goodness of fit test to examine failure pattern. The RBD of a system is a graphical method to reveal logical behavior of the system as function of their presented component breakdowns. This diagram often called as system configuration or architecture, and presents the effect of failure of each block on the successful functionality of the system as a whole. Every RBD diagram consists of several blocks connected in series, parallel, standby, or combinations thereof as appropriate.

Many researchers in literature remunerated to apply RBD in prediction of the system reliability. The following steps are involved in prediction of the reliability of a system [15]:

- Construction of the Reliability Block Diagram (RBD) of the system. This may involve performing Failure Modes and Effects Analysis (FMEA).
- Determination of the operational profile of each block in the diagram.
- Derivation of the time to failure distribution of each block.
- Derivation of the Life Exchange Rate Matrix (LERM) for the different components within the system.
- Computation of the reliability functions of each block.
- Computation of the reliability function of the system.

Nevertheless, mapping the complicated system configuration through a given RBD is too complicated task. Hence, the main research question is on focusing the way to predict system reliability when components deploy different statistical density functions such as a Weibull, Gamma, Lognormal, and Logistic and so on.

3. The Proposed Method

Through the current research, we propose a simulation based on reliability assessment method to analyze and predict system reliability consists of any logical order of components. We suggest a verified method for predicting system where a systematic tree construction helps prevent oversights. This methodology helps as a good decision support tool in bringing out the design and operational weaknesses in complex systems and helps the managers and engineers to efficiently uncover and prioritize component improvements.

The following steps are recommended in prediction of the reliability of a complex system where constructing the system configuration is a complicated task or impossible. Through following these sequential steps, a complicated system structure could be presented by an equivalent RBD after trimming the relevant FTA using Boolean algebra rules. They are:

- Construction of the Fault Tree Analysis (FTA) of the system. This may involve performing technical description of system failure. This method acts as a “Top-Down” approach by which each system failure mode is expanded to its required component failures. Here, the system failure is the top event and the attempt is made to find out all possible components failures responsible for the system breakdown.
- Applying of logical gates such as 'OR', 'AND', etc. to describe system failure as a logical function of their relevant component failures.
- Derivation of the time to failure distribution of each components.
- Applying the Boolean algebra rules such as associativity, commutativity, absorption, identity, distributive, and complements for trimming the tree. Each FTA that has repeated components in the last level has the ability to trim using the Boolean algebra rules. The

last trimmed tree has an equivalent RBD. Table 2 presents the most important Boolean algebra rules.

- Computation of the system reliability using simulation model.

Table 2. The most important Boolean algebra rules for simplification of the FTA.

Associativity	$R_a + (R_b + R_c) = (R_a + R_b) + R_c$ $R_a.(R_b.R_c) = (R_a.R_b).R_c$
Commutativity	$R_a + R_b = R_b + R_a$ $R_a.R_b = R_b.R_a$
Absorption	$R_a + (R_a.R_b) = R_a$ $R_a.(R_a + R_b) = R_a$
Identity	$R_a + 0 = R_a$ $R_a.1 = R_a$
Distributive	$R_a + (R_b.R_c) = (R_a + R_b) + (R_a + R_c)$ $R_a.(R_b + R_c) = (R_a.R_b) + (R_a.R_c)$
Complements	$R_a + Q_a = 1$ $R_a.Q_a = 0$

3. The Computer Simulation Model

In order to establish a computer simulation model to examine k-state system reliability in ED environment following the proposed algorithm is recommended.

Step 1 (Simulation lay out planning): In the model layout put serially a set of the following atoms for each devices or components. These atoms in ED called as Product, Source, Queue, Servers (k-1 parallel server). Repeat this set of atoms individually for each machine component. For example, if the system consists of three machine or a system of three components, then the following set of atoms should be arranged three times; each set simulates any machine/component. Also, use a “Table” atom for collecting data from all final servers and a “Sink” atom to terminate all entities. So, connect the output channel of the last server to the “Table” atom.

Step 2 (Parameter setting): Set time to arrival process on the minimum amount (e.g. 1 second) to avoid any prevention of entity flow to the system. Also, set the queue capacity to a large number for preventing from blocking. In order to simulate the failure process, set time to failure process to the associated statistical density function with given parameters (e.g. exponential, Weibull, Gamma, etc.). This setting is repeated for each server based on time to transfer to the lower state. Hence, set all Time to Repair (TTR) to a big amount for preventing repairing process. Note that the readers could set TTR to the real amounts for simulating system for examining system availability. Set queue capacity to 1 for the final Queue and set their “Trigger on entry” to “cell (1, 1, out (1, c)):=Time”. This makes possibility to record arrival time of the first entity that entered to the current Queue on the first row and first column of the “Table.” Since the capacity of “Queue” is set to 1, there is no permission to enter another entity.

Step 3 (Simulation run setting): In order to achieve reliable results, we recommend to run the simulation model as long as possible for several times (more than 150 times) independent of each other and to avoid any bias in estimation the warm up period at minimum 10% of the observation period. Consequently, after running the simulation model, the time to failure for each machine/component will be recorded in the definite table. So, based on the system configuration time to failure the system, the system reliability could be calculated based on reliability calculation arithmetic.

3.1. Illustrated Example

Consider the presented system by Bently [1] that consisted of 4 components: A, B, C, and D. Each of which has 2 states: active or failure. All components are deployed from an exponential time to failure patterns with mean time to failures of 51000, 31500, 24600, and 71900 hours, respectively. Here, $Q_i = 1 - R_i$ denotes unreliability of component i; $i = A, B, C, and\ D$. Figure 1 illustrates the relevant Fault Tree Analysis (FTA) diagram for the system breakdown. Here, system configuration has not presented via a reliability block diagram.

In order to simplify the FTA, the Boolean algebra based on the logical gate probability is applied. If Q denotes the probability of system failure, then it can be calculated and simplified using the basic event rules as Eq. (1). 1.

$$Q = Q_D . Q_B \ + \ Q_A + Q_C Q_D Q_D Q_B = \ Q_D . Q_B \ + \ Q_A + Q_C \ = \ Q_A + Q_B Q_C Q_D \ . \quad (1)$$

Based on the event sequence presentation, there is a complex two-state system that its FTA is shown in Figure 2 [1]. The current system has so simple configuration. Here, B, C, and D has parallel configuration and acts in series with the A. Hence, the minimum cut sets is $\{A\}, \{B, C, D\}$. Figure 2 presents the ED layout for the relevant computer simulation model. Since the system has 4 components, based on the Step 1 of the proposed algorithm, so the layout consists of four independent serially set of atoms. Table 3 presents reported time to failure data are derived from the “Table” atom for the 1st 50 simulation runs.

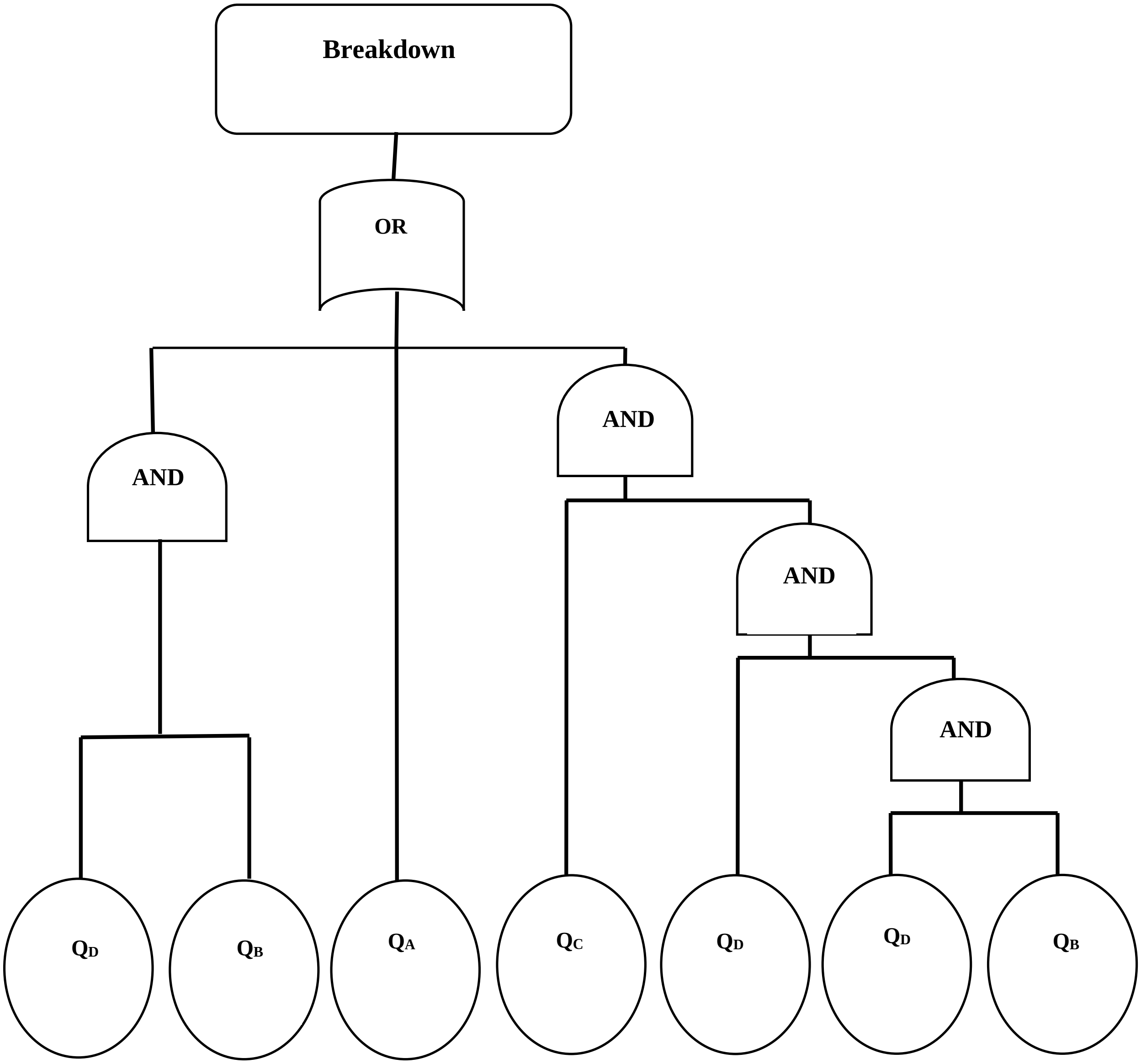

Figure 1. Fault tree analysis diagram for the Example derived from [1].

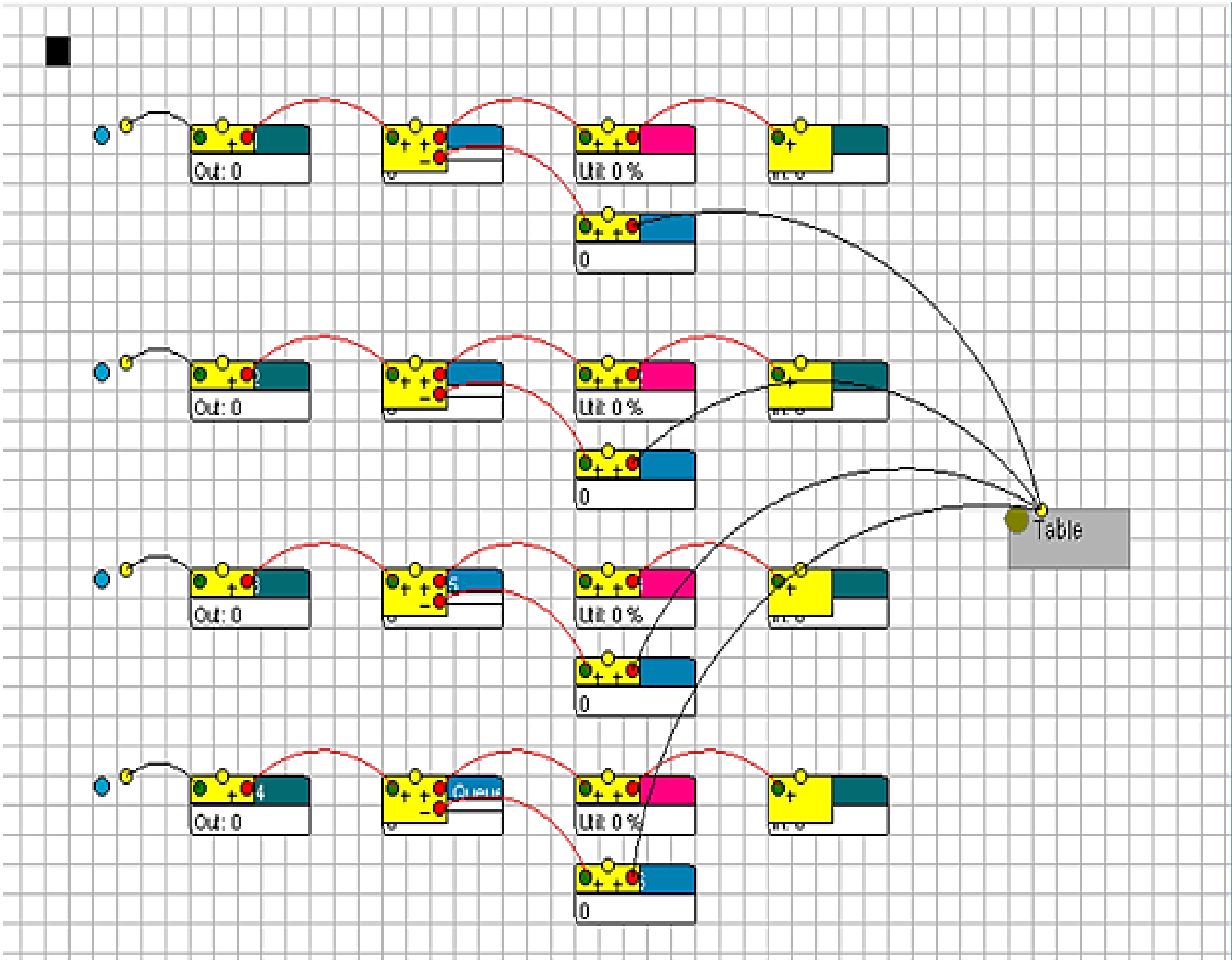

Figure 2. The simulation model layout for the Example 1.

We simulate the computer simulation model 150 times, each one at a given observation period. Then, system reliability is estimated based on the ratio of the times that the system was on active state to the number of simulation runs (150 here). Table 4 reports estimated system reliability at different target times.

Table 3. Simulated life Time to Failure (TTF) results of 50-component simulation runs of the Eexample 1.

Run No.	**TTF (hours)**				**Run No.**	**TTF (hours)**			
	A	**B**	**C**	**D**		**A**	**B**	**C**	**D**
1	145611	56916.7	37861.1	139472	26	4361.11	138056	69861.1	28694.4
2	113639	4055.56	32472.2	29027.8	27	78472.2	59444.4	75638.9	138972
3	18472.2	45111.1	32777.8	57777.8	28	21250	12694.4	2138.89	8750
4	185500	1833.33	611.111	28361.1	29	33250	1583.33	22555.6	14916.7
5	12611.1	10555.6	4861.11	138667	30	81416.7	1750	2472.22	18694.4
6	22888.9	102722	6805.56	14138.9	31	47111.1	116806	24638.9	70361.1
7	1972.22	28222.2	8083.33	15305.6	32	98388.9	10527.8	9472.22	59111.1
8	53972.2	8722.22	28583.3	162472	33	170222	32722.2	11222.2	48166.7
9	98305.6	1944.44	42194.4	40944.4	34	22694.4	14916.7	56305.6	178194
10	76500	65000	67138.9	38861.1	35	3111.11	40972.2	11083.3	42250
11	41250	16638.9	8222.22	38861.1	36	45500	27000	30472.2	127389
12	2722.22	78444.4	12861.1	91944.4	37	28694.4	1083.33	7194.44	22861.1
13	31916.7	8194.44	12472.2	134389	38	37222.2	22750	14027.8	108667
14	33777.8	40527.8	5861.11	165778	39	3916.67	10250	111333	7638.89
15	3166.67	5583.33	55.5556	133694	40	16972.2	13861.1	1972.22	68583.3
16	70611.1	36194.4	18472.2	133694	41	159361	17750	16527.8	5333.33
17	7861.11	1250	47888.9	40027.8	42	9611.11	14250	23111.1	144639
18	6361.11	36750	277.778	6888.89	43	17027.8	11722.2	178444	4166.67
19	53805.6	2000	7583.33	28555.6	44	5194.44	1388.89	16722.2	13777.8
20	27333.3	154111	1555.56	23611.1	45	1638.89	1027.78	777.778	125556
21	1111.11	36055.6	40722.2	36638.9	46	43361.1	39027.8	9388.89	65194.4
22	15750	361.111	83694.4	39472.2	47	40055.6	56694.4	20361.1	37888.9
23	81250	12305.6	27388.9	176083	48	17166.7	76055.6	29750	13527.8
24	92083.3	944.444	11111.1	47722.2	49	15055.6	6277.78	722.222	2750
25	86888.9	37805.6	23361.1	11333.3	50	7555.56	26833.3	12027.8	2750

Table 4. Reliability of system for Example 1 in 40 different times with analytical method.

Observation Period	System Reliability	Observation Period	System Reliability
2000	0.9614	12000	0.7755
2500	0.9519	12500	0.7663
3000	0.9425	13000	0.7572
3500	0.9331	13500	0.7481
4000	0.9237	14000	0.7390
4500	0.9143	14500	0.7299
5000	0.9050	15000	0.7209
5500	0.8956	15500	0.7119
6000	0.8863	16000	0.7030
6500	0.8770	16500	0.6940
7000	0.8678	17000	0.6851
7500	0.8585	17500	0.6763
8000	0.8492	18000	0.6675
8500	0.8400	18500	0.6587
9000	0.8307	19000	0.6500
9500	0.8215	19500	0.6413
10000	0.8123	20000	0.6327
10500	0.8030	20500	0.6241
11000	0.7938	21000	0.6156
11500	0.7847	21500	0.6071

In order to examine the simulation model validity, we calculated the system reliability analytically based on Eq. (2) at 40 different target times and the reliability of components and system reported in Table 5.

$$R_{system} = R_A\big(1 - (1 - R_B)(1 - R_C)(1 - R_D)\big), \tag{2}$$

where based on the relevant example assumption:

$$R_A = e^{-(\frac{1}{51000}*t)} \tag{3}$$

$$R_B = e^{-(\frac{1}{31500}*t)} \tag{4}$$

$$R_C = e^{-(\frac{1}{24600}*t)} \tag{5}$$

$$R_D = e^{-(\frac{1}{71900}*t)} \ . \tag{6}$$

Table 5. Results of system reliability estimation based on the proposed simulation model.

Time	Calculated Reliability					Time	Calculated Reliability				
	R_A	R_B	R_C	R_D	R_{system}		R_A	R_B	R_C	R_D	R_{system}
2000	0.924	0.888	0.883	0.992	0.924	12000	0.718	0.596	0.581	0.847	0.699
2500	0.911	0.866	0.862	0.984	0.911	12500	0.710	0.586	0.570	0.840	0.689
3000	0.899	0.846	0.842	0.977	0.899	13000	0.701	0.576	0.559	0.833	0.680
3500	0.887	0.827	0.823	0.969	0.886	13500	0.693	0.566	0.549	0.827	0.670
4000	0.875	0.809	0.805	0.962	0.874	14000	0.685	0.557	0.538	0.820	0.660
4500	0.864	0.792	0.788	0.954	0.862	14500	0.677	0.547	0.528	0.814	0.650
5000	0.853	0.775	0.771	0.947	0.851	15000	0.670	0.538	0.518	0.807	0.641
5500	0.842	0.759	0.754	0.939	0.839	15500	0.662	0.530	0.509	0.801	0.631
6000	0.831	0.744	0.739	0.932	0.828	16000	0.654	0.521	0.499	0.794	0.622
6500	0.821	0.729	0.723	0.924	0.816	16500	0.647	0.513	0.490	0.788	0.613
7000	0.811	0.715	0.709	0.917	0.805	17000	0.639	0.504	0.481	0.781	0.603
7500	0.801	0.702	0.694	0.910	0.794	17500	0.632	0.496	0.473	0.775	0.594
8000	0.791	0.688	0.680	0.903	0.783	18000	0.625	0.488	0.464	0.769	0.585
8500	0.781	0.676	0.667	0.896	0.772	18500	0.618	0.481	0.456	0.763	0.576
9000	0.772	0.663	0.653	0.888	0.762	19000	0.611	0.473	0.447	0.757	0.568
9500	0.762	0.651	0.640	0.881	0.751	19500	0.604	0.466	0.439	0.751	0.559
10000	0.753	0.640	0.628	0.874	0.741	20000	0.597	0.459	0.432	0.745	0.550
10500	0.744	0.628	0.616	0.867	0.730	20500	0.591	0.452	0.424	0.739	0.542
11000	0.735	0.617	0.604	0.861	0.720	21000	0.584	0.445	0.416	0.733	0.533
11500	0.727	0.606	0.592	0.854	0.710	21500	0.578	0.438	0.409	0.727	0.525

To compare significant difference between the theoretical system reliability with the simulation results, we apply a nonparametric Mann-Whitney hypothesis testing for the true means using Minitab statistical software. Here, the null and alternate hypothesis is set as:

Mean of the theoretical system reliability = Mean of the estimated system reliability using simulation model.

Mean of the theoretical system reliability ≠ simulated life Time to Failure (TTF) results of components.

H_0: Mean of the theoretical system reliability = Mean of the simulation model.

H_1: Mean of the theoretical system reliability $\neq$ Mean of the simulation model.

Result shows that the interval estimate for the two populations mean at 95 % confidence interval is (0.01861, 0.1255). Hence, the Mann –Whitney statistic (W) is equal 1888 and the test is significant at 0.0101. Consequently, we conclude that there is no significant difference between two means and we could not reject simulation model validity.

4. Conclusion

Computing systems are widely used today, and in many areas, they serve the key function in achieving highly complicated and safety-critical mission. At the same time, the size and complexity of computing systems have increased, which make its performance evaluation more difficult than ever before. The main focus of this paper was to provide a descriptive method rather than common analytic techniques for estimating the reliability of systems in which the role of components in the proper functioning of the system is well-defined; but the system configuration cannot be presented using reliability block diagram. The proposed method was based on using fault tree analysis. Through analyzing of every breakdown structure, it was possible to construct a preliminary FTA. The proposed method suggested for applying trimming process using the Boolean algebra tools. We suggested that the final reduced FTA had no repeated component in last level of the tree. A method for simulating the final FTA was presented in which the components' failure density functions can had any potential functions. Therefore, the proposed validated discrete event simulation method had the following advantages rather than technical methods:

- The method had capability to apply it on any complicated system configuration.
- There was no restriction in applying the method based on any stochastic process or time to failure density functions.
- What if analysis in the simulation method was an appropriate key tool for sensitivity analysis on component importance and system configuration?

Future research on the present topic can include investigating on applying simulation method of dealing with complicated multi-state systems. The results from application of such method can be compared with that of this paper in the cases of two states. Examining similar system under accelerated stress factors can be followed as future research.

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