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Effects of faulty estimate in component reliability on system designing: a simulation approach

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Abstract

Component reliability is usually estimated based on economical sampling plan and historical data analysis. In such process, two types of errors may occurs. According to a conventional view, the type 1 and 2 errors respectively referred to lower and higher component reliability estimation are arisen. Generally, it is commonly thought that the first type error leads to an under-estimation of the whole system's reliability, and the second type over-estimates it, which in turn, causes false amplification or ignores the need to boost the system by using redundant components. This article is devoted to the role of component reliability estimation error in the design of a multi-state system (MSS). To this aim and from the literature survey, two optimal designed MSS evaluated by a proposed validated computer simulation model under assumption of positive and negative errors. Result revealed that any type of uncertain estimation increases with the over-designing risk and applying more number of components in the optimum system designing, but fortunately no weakness in its functionality. The greater the error, the more redundant components in MSS design.

Keywords: Component reliability, noisy estimation, system design, discrete event simulation, Multi-State System (MSS).

1-Introduction

Commonly, reliability of a system is expressed in terms of the probability that a system can accomplish the prerequisite tasks for a certain period. Many reliability engineers are devoted to examine system reliability based on binary state systems (BSSs) model which allows for just two possible states for each component: functioning well and failure. Such assumption makes it far away from their real conditions. Real-world systems are composed of components that have more levels than two. In the literature they are called as multi-state systems (MSSs). A detailed discussion on this context is presented by Lisnianski et al., (2010). He gathered many approaches to evaluated MSS reliability and their difficulties on applying them rather than using traditional binary reliability techniques. Examples of MSS are presented on power systems, communication systems, and computer systems where the system performance is measured by few metrics such as data processing speed. As an example, consider a power plant system in which states 0, 1, 2, 3, and 4 are respectively presenting the 25, 50, 75 and 100 percent of its full capacity to generate electricity. Another application of MSSs reliability could be seen in traffic systems, telecommunication networks, and satellites, (Li and Zuo, 2008).

Reliability estimation on MSS is more complicated than binary systems. Therefore, for reliability estimation such probability should cover all pre-defined states which system works sufficiently well. As the number of states, greatly increased reliability computing becomes more difficult. In order to overcome such difficulty many researchers use the Markovian chain characteristics which turns back a characteristic that refers to the next step probability distribution deploys just only to the current state. Hence the events sequence has no significance, (Lalic et al., 2005) and (Tot et al., 2003).

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This feature is known as memory less characteristic. Therefore, it is actually limited to exponential density function in life and repair time. If this condition don't happen, then applying this method cannot be useful. Nowadays the universal generating function (UGF) technique widely has been applied to MSS reliability engineering. This method lets to follow the performance distributions of its elements to calculate entire MSS performance distribution based on a given algebraic procedures.

None of the mentioned works has taken into consideration the inherent inaccuracy of the data. However, in real cases, data are never uncertainty-free and an appropriate method is desirable to face data measurement errors and their inherent randomness in problems with well-established physical constraints. Alternatively, experimental data frequently are considered as error-free for both directional search and penalty approaches, (Ibanez et al., 2016) and (Kirchdoerfer et al., 2016). Only some mathematical convergence results are derived for uncertainty free methods, which are never the case in real practice (Ayensa et al., 2018). Due to complexity arises in reliability assessment of stochastic systems, some articles focused on simulation model to analyse faults and tolerance assignment in manufacturing systems, (Yuan al., 2015) and (Singh et al., 2003). Applying simulation modelling approach to analyse complicated random mannered systems become a common task recently. Interested readers could refer to Baesler et al.(2015), Pourhassan and Raissi (2017), Ljoljic et al.(2002) and Simon et al.(2018) for applications on production systems, and Jayalath et al.(2016) and Pan et al.(2014) for others fields.

Through this paper, we focused on the multi-state system design problems carried out through classical redundancy optimization technique when dealing with uncertain component reliability. A simulation-based technique is used to examine them using different examples derived from the published papers. Section 2 gives the previous researches works of related to the MSSs reliability. Section 3 describes a proposed computer simulation model to examine the desired uncertainties. In section 4, the applicability and validity of the proposed simulation based technique is illustrated using two examples from the literatures. Finally, conclusions and further research are given in section 5.

2- Problem statement

Generally, a MSS is consists of n components. Each component i may be in one in a set of $k_i + 1$ possible states. The performance of the components downgrade gradually from state k_i to the worse state 0. k_i, k_{i-1}, ... ,1 are all operating states and 0 is the complete breakdown state. We denote λ_{is} as the state transition rate or the degradation rate of component i at time t from state $s \in \{0, 1, \dots, k_i\}$ to $s - 1 \in \{0, 1, \dots, k_i\}$.

The whole system contains subsystems that are connected in series. Each subsystem may embed components connected in parallel. Therefore, the system reliability is determined based on the minimum reliability of its subsystems. Under a certain situation component, generally the universal generating function (UGF) technique is applied to calculate system reliability. The loss of load probability (LOLP) conventionally may be applied to describe the system reliability. Such metric is the probability that the demand will not be met. According to Lisnianski et al.(1996) system reliability is defined as:

$$LOLP = \frac{\sum_{l=1}^{L} P(G_s < W_l) T_l}{\sum_{l=1}^{L} T_l} \qquad (1)$$

In which $P(G_s < W_l)$ is the probability that total system capacity, G_s, is lower than a predetermined level, W_l and T_l is duration of operating period l. In a mixed system configuration, the subsystems are connected in series and so the demand requirement is fulfilled only if each of n individual subsystem can met demand.

$$P(G_s \leq W_l) = \prod_{i=1}^{n} P(G_i \geq W_l) \qquad (2)$$

If $T_l' = \frac{T_l}{\sum_{l=1}^{L} T_l}$ the system reliability is obtained by equation 3.

$$E(x) = T_1' \prod_{i=1}^{n} P(G_i \geq W_1) + T_2' \prod_{i=1}^{n} P(G_i \geq W_2) + \cdots + T_L' \prod_{i=1}^{n} P(G_i \geq W_L)$$
$$= \sum_{l=1}^{L} T_l' \prod_{i=1}^{n} P(G_i \geq W_L) \tag{3}$$

Where $E(x)$ is the multi-state series-parallel reliability. For any subsystem, i there is X_{ij} components of type j connected in parallel. The probability that subsystem i can supply the pre-determined minimum level of W_l, $P(G_i \geq W_l)$, is calculate best on the following equations.

$$P(G_i \geq W_l) = \begin{cases} 1-(1-r_{ij})^{X_{ij}} & if\ W_l \leq g_{ij} \\ 1-Bin(X_{ij},1,r_{ij}) & if\ g_{ij} < W_l \leq 2g_{ij} \\ \dots. & \dots. \\ 1-Bin(X_{ij},K-1,r_{ij}) & if\ (K-1)g_{ij} < W \leq Kg_{ij_l} \\ \dots. & \dots. \\ (r_{ij})^{X_{ij}} & if\ (X_{ij}-1)g_{ij} < W_l \leq X_{ij}g_{ij} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$Bin(X_{ij},K,r_{ij})$ is the cumulative probability distribution for k active components. Therefore, $(X_{ij},K-1,r_{ij})$ is unavailability of a subsystem if k components are needed to satisfy the load demand. The main assumption of the UGF reliability calculation is considering the exact reliability of components. In practice, the components reliability estimation is often impossible and contaminated by errors, Consequently, the assumption of components with exact known reliability is never true in real world systems. In other word, estimating the true reliability of real world systems' components is impossible due to some uncertainty. These uncertainties arise during the component reliability estimation phase based on the collected sample data. Thus, the associated system reliability obtained by UGF method has low accuracy. In order to overcome this problem, the components uncertainties should be considered during the calculating of system reliability. Thus, in next section, a simulation-based method is proposed to model the degradation of MSS with components under uncertain reliability.

3-The proposed method

Since applying an analytical method for estimating system reliability is a crucial task and what if analysis under different error size is required, we developed a computer simulation model in the Enterprise Dynamics (ED) software. We expect that with increasing number of components and their states, the simulation models can result more efficient alternative for analyzing complex MSS.

If the parameters of components reliability in a system are known and the terms of the assumptions have been provided, then analytical methods could be applied to calculate system reliability. Considering the uncertainties in components reliability may lead to loss the real system reliability. In order to examine MSS reliability, we presented a computer simulation model to examine system reliability based on components reliability. For this purpose, we introduced a computer simulation model to calculate the reliability of the system based on its component lifetime parameters. The proposed model may be applied for any system configuration and it does not depend on limiting presumptions over the components life density function.

The main logic of the computer simulation program is shown in flowchart in figure 1. As mentioned, it is based on the fact that a system consists of l subsystems and each of them has $m_i; i = 1,2,\dots.,m_l$ components, which are calculated through applying any optimum redundancy allocation method in such a way that the system could achieve the desired reliability. Therefore, the simulation model works based on 1) the optimal structure of a system with respect to it's subsystems and the relevant components 2) Reliability of each components; r_{ij}, 3) A certain amount of error size in component reliability estimation. The MSS simulation model runs for long times say $B > 10000$ days to occur system fully breakdown. In order to remedy the bias, 25 days of simulation period considered as warmup period and simulation method set as separate runs. As fully mentioned in the simulation logic, a procedure generates a random amount of component reliability (r_{ij}^*)within the range of lower and upper bound from continuous uniform distribution (UNF). Detail of the simulation model depicted on Fig. 3 based on the ED standard. The model replicated $n > 30$ times each one for long observation period to estimate MSS reliability each time, the average of n replication could be considered as the system reliability namely R_S^*. Final results compared with the expected analytic value to examine deviation raised from estimation uncertainty.

1) Estimate r_{ij} the reliability of the j^{th} component in the i^{th} subsystem using any analytic method; $i = 1, 2, \ldots, l \quad and\ j = 1, 2, \ldots, m_l$
2) Consider any fluctuation size of e as the amount of estimated error on r_{ij}
3) Calculate the upper bound (UB) and lower bound (LB) of r_{ij} from:

$$UB(r_{ij}) = r_{ij}(1 + e)\ and\ \ LB(r_{ij}) = r_{ij}(1 - e)$$

4) Generate a random number from UNF $[LB(r_{ij}), UB(r_{ij})]$ and called it as r_{ij}^* or from:

$$r_{ij}^* = LB(r_{ij}) + (1 - R)[UB(r_{ij}) - LB(r_{ij})];\text{ where } R \sim UNF[0,1]$$

5) Estimate the system reliability (R_S^*) based on r_{ij}^* using the proposed simulated model which have run to occur system break down.
6) Go back to step 4 and repeat the process.
7) Estimate mean value of the simulated system reliability based on the n estimated R_S^*

Fig. 1. The computer simulation logic

As mentioned the ED simulation layout shows a typical model for a series-parallel system with five subsystems and up to seven components on them. In order to evaluate the uncertainties raised weakness on parameter estimation, the reliability of the components is fluctuated under different sizes.

Fig. 2. A graphical representation of simulation model

In order to examine simulation model validity, analytic system reliability might be compared with the simulated amount and no significant difference should be revealed.

4- Results and discussion

4-1- Numerical example

Consider the example derived from Ramirez-Marquez and Coit (2004) which is a SP-MSS system consists of five subsystems connected to each other in series. Each subsystem configured by 4 up to 9 different parallel components. The target MSS reliability E_0 is set to three different values, 0.975, 0.980, and 0.990 and so three separate problems are created. Table 1 presents the component information for each subsystem in which the components feeding capacity is represented according to the system nominal capacity. Table 2 presents the operation intervals of the system and the demanded performance levels. In 2, W_l is system supply of demand level requirement during T_l units of time.

Table 1. Main technical data for components in the 1st example

Subsystem	Component	Cost	Nominal capacity	Estimated reliability
1	1	0.59	120	0.980
	2	0.535	100	0.977
	3	0.47	85	0.982
	4	0.42	85	0.978
	5	0.4	48	0.983
	6	0.18	31	0.920
	7	0.22	26	0.984
2	1	0.205	100	0.995
	2	0.189	92	0.996
	3	0.091	53	0.997
	4	0.056	28	0.997
	5	0.042	21	0.998
3	1	7.525	100	0.971
	2	4.72	60	0.973
	3	3.59	40	0.971
	4	2.42	20	0.976
4	1	0.18	115	0.977
	2	0.16	100	0.978
	3	0.15	91	0.978
	4	0.121	72	0.983
	5	0.102	72	0.981
	6	0.096	72	0.971
	7	0.071	55	0.983
	8	0.049	25	0.982
	9	0.044	25	0.977
5	1	0.986	128	0.984
	2	0.825	100	0.983
	3	0.49	60	0.987
	4	0.475	51	0.981

Table 2. System feeding requirements for Example 1

W_l	1	0.8	0.5	0.2
T_l(hours)	4203	788	1228	2536

To support the target reliability, the best solutions for each scenario found by Ramirez Marquez and Coit (2004) are listed in table 3. In general, consider a tuple of $(n_1, n_2, \dots n_i)_j$ presents the optimal redundancy structure to attain the target system reliability where n_i refers to number of redundant in the i^{th}component of subsystem j; $(j = 1,2, \dots ,5)$. For example, in the case of E_0=*0.975* the system reliability is equal to 0.977 and $(n_1, 2, n_3, n_4, n_5,)$ there must be two of the second component type in subsystem one, two of the third component type in subsystem two, three of the second component type in subsystem three, three of the seventh component type in subsystem four and one of the second component type in subsystem five. The system reliability related to the optimum solutions, presented in table 3.

Table 3. Optimum redundancy structure for example No. 1

Minimum system reliability	Reliability	Total cost	System Structure
0.975	0.977	16.45	[0,2,0,0,0,0,0]-[0,0,2,0,0]-[0,3,0,0]-[0,0,0,0,0,0,3,0,0]-[0,1,0,0]
0.980	0.980	16.52	[0,2,0,0,0,0,0]-[0,0,0,0,6]-[0,3,0,0]-[0,0,0,0,0,0,3,0,0]-[0,1,0,0]
0.990	0.993	17.05	[0,2,0,0,0,0,0]-[0,0,2,0,0]-[0,3,0,0]-[0,0,0,0,0,0,3,0,0]-[0,0,0,3]

Hence due to get more reality, consider that components reliability embeds over or lower estimation. Although the chance for lower estimation has low functional operational risk, but both issue has been addressed in this paper. Table 4 shows a confidence bounds for each components reliability based on three size of fluctuation, they are $\pm 0.1\%$, $\pm 0.3\%$ and $\pm 0.5\%$ over the point estimation. Under any given amount, the reliability of the system lies between the two lower and upper bound denoted respectively by LB and UB. A computer simulation in Enterprise Dynamics (ED) generated and is applied to calculate the system reliability upon different scenarios that defined in table 4. To this aim, three simulation models are developed based on the redundancy structures showed in table 3. Fig 4 illustrates the layout of the designed ED simulation model in the case of minimum system reliability is equal to 0.975. In the layout, a SERVER atom is applied to model components. Consequently, we have the possibility to set time to failure statistical patterns. The SERVER atoms are arranged according to the system configuration. In the simulation model there is a QUEUE atom between each component. A PRODUCT atom as an entity flows through the system. When it enters to a QUEUE, based on FIFO discipline will be sent to the next SERVERs. In the case of subsystem failure, the product will have blocked and this is a signal for the system failure. This procedure repeated many times, time to system failure documented, and probability of surviving system as system reliability calculated.

Table 4. Confidence bound for true components reliability under different estimation errors

Subsystem	Component	Estimated reliability	±0.1%		±0.3%		±0.5%	
			LB	UB	LB	UB	LB	UB
1	1	0.980	0.97902	0.98098	0.97706	0.98294	0.97510	0.98490
	2	0.977	0.97602	0.97798	0.97407	0.97993	0.97212	0.98189
	3	0.982	0.98102	0.98298	0.97905	0.98495	0.97709	0.98691
	4	0.978	0.97702	0.97898	0.97507	0.98093	0.97311	0.98289
	5	0.983	0.98202	0.98398	0.98005	0.98595	0.97809	0.98792
	6	0.920	0.91908	0.92092	0.91724	0.92276	0.91540	0.92460
	7	0.984	0.98302	0.98498	0.98105	0.98695	0.97908	0.98892
2	1	0.995	0.99401	0.99600	0.99202	0.99799	0.99003	0.99998
	2	0.996	0.99500	0.99700	0.99301	0.99899	0.99102	1.000
	3	0.997	0.99600	0.99800	0.99401	0.99999	0.99202	1.000
	4	0.997	0.99600	0.99800	0.99401	0.99999	0.99202	1.000
	5	0.998	0.99700	0.99900	0.99501	1.000	0.99301	1.000
3	1	0.971	0.97003	0.97197	0.96809	0.97391	0.96615	0.97586
	2	0.973	0.97203	0.97397	0.97008	0.97592	0.96814	0.97787
	3	0.971	0.97003	0.97197	0.96809	0.97391	0.96615	0.97586
	4	0.976	0.97502	0.97698	0.97307	0.97893	0.97112	0.98088
4	1	0.977	0.97602	0.97798	0.97407	0.97993	0.97212	0.98189
	2	0.978	0.97702	0.97898	0.97507	0.98093	0.97311	0.98289
	3	0.978	0.97702	0.97898	0.97507	0.98093	0.97311	0.98289
	4	0.983	0.98202	0.98398	0.98005	0.98595	0.97809	0.98792
	5	0.981	0.98002	0.98198	0.97806	0.98394	0.97610	0.98591
	6	0.971	0.97003	0.97197	0.96809	0.97391	0.96615	0.97586
	7	0.983	0.98202	0.98398	0.98005	0.98595	0.97809	0.98792
	8	0.982	0.98102	0.98298	0.97905	0.98495	0.97709	0.98691
	9	0.977	0.97602	0.97798	0.97407	0.97993	0.97212	0.98189
5	1	0.984	0.98302	0.98498	0.98105	0.98695	0.97908	0.98892
	2	0.983	0.98202	0.98398	0.98005	0.98595	0.97809	0.98792
	3	0.987	0.98601	0.98799	0.98404	0.98996	0.98207	0.99194
	4	0.981	0.98002	0.98198	0.97806	0.98394	0.97610	0.98591

According to table 3 and table 4, there are two number of component type two which its reliability is a random variable between 0.97602 and 0.97798. Therefore, two server atom are placed in subsystem one and the reliability of these SERVER atoms is set to uniform (0.97602, 0.97798). The other subsystems are constructed just like this and then the simulation model is run. An atom named product moves among the servers. As soon as all the servers of a subsystem are failed, the product atom cannot pass that subsystem and the whole system is locked. Consequently, the system reliability can be measured. The simulation model is run for a 100 hours period. Since the simulation model is stochastic, each example is replicated to 30 times and the averaged results are considered. The results are presented in Table 5. As shown in Table 5, if there is an error of one percent in the estimation of components reliability, the system reliability will be equal to 0.976. While the accuracy in estimating the components reliability is decreased the difference between reliability obtained by analytical methods and simulation in increased so the under a 0.005 fluctuation there is a high error of 0.977-0.966=0.011.

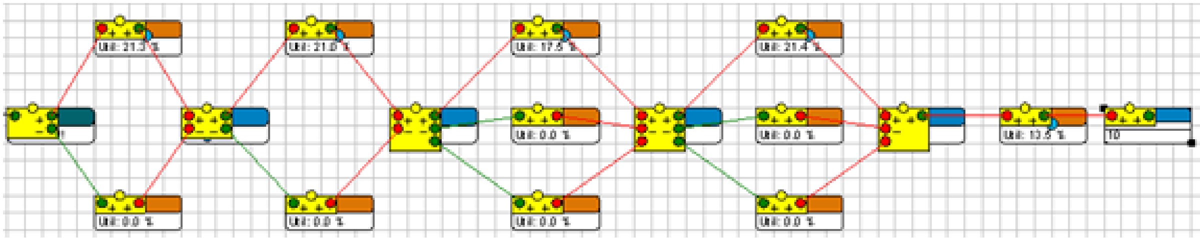

Fig.3. The structure of the ED layout on the best solution

Table 5. Simulation results under different level of uncertainty example 1

Minimum system reliability	Analytical Reliability	Simulation Reliability		
		0.001 Fluctuation	0.003 Fluctuation	0.005 Fluctuation
0.975	0.977	0.976	0.973	0.966
0.980	0.980	0.979	0.977	0.975
0.990	0.993	0.992	0.989	0.986

4-2- Discussion

A graphical representation of the reliability estimation by the analytic and the proposed simulation method presented in Fig. 6-8. The Fig. 4. is related to the example. According to this figure for the $E_0=0.975$ and under a 0.001 of fluctuation the reliability obtained by both analytical and simulation methods can satisfy the minimum required system reliability. Nevertheless, for 0.003 and 0.005 fluctuation the reliability obtained by simulation cannot satisfy the minimum required system reliability. This is an evidence to show that the due to a small deviation in the pre-determined the components reliability, the real system reliability may be lower than minimum required. For $E_0=0.980$ and under a 0.001, 0.003 and 0.005 of fluctuation the reliability obtained by simulation is lower than E_0. At last, for $E_0=0.990$ only under a 0.005 of fluctuation the reliability obtained by simulation is lower than E_0.

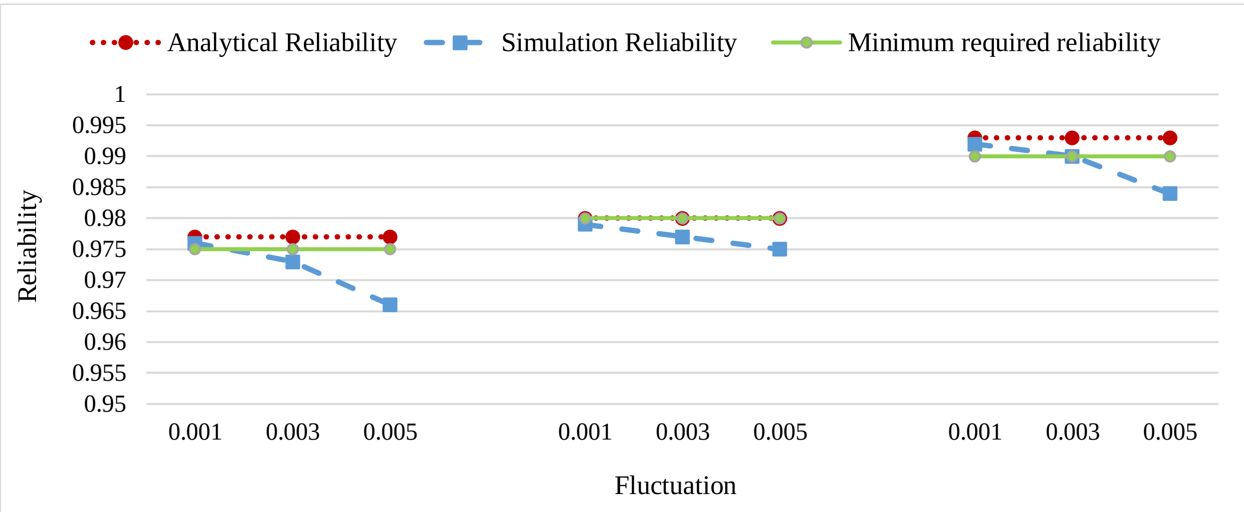

Fig. 4. Comparison on results of the analytical and simulation method for example No.1

Not satisfying the minimum system reliability requirements is illustrated well in figure 5 and figure 6. According to these figures it can be say than if a 0.005 of fluctuation is applied to the components reliability, the obtained reliability by analytical methods will reduced so that the minimum system reliability requirements is not met. This lack of consistency between analytical based reliabilities and real reliability happens for 0.003 of fluctuation except for example one and when $E_0=0.990$.

All of these are evidence that the results obtained using analytical methods are reliable only in certain conditions. In other word, considering the fact that there is some error in per-measured components reliability, the results obtained by using the analytical methods will differs of those happens in real world. Therefore, to find a real reliability, the system should be simulated and uncertainty in components reliability must be considered.

4-3- Statistical analysis

Comparison of simulation results with analytical methods showed that increasing error in component reliability estimation actually increases the pessimistic perspective on system design due to lower system reliability estimation. Results of simulation model show that under various error size and direction, the reliability curve shows smaller values and the higher the error, the more the system reliability will be reduced. Table 6 depicted differences of the two curves. Figure 5 presents a Tukey 95% simultaneous confidence interval for such differences. As show in the figure as the fluctuation is increasing the effect of error of analytical method is getting larger. For a 0.001 of fluctuation there is no statistical difference between analytical and simulation methods. Although, analytical and simulation methods are statistically similar in 0.003 of fluctuation, but the gap is relatively positive. For a 0.005 of fluctuation there is a significant statistical difference between two curves.

Table 6. The gap between system reliability estimation on the analytic and simulation model

Example	E_0	Fluctuation	Analytical	Simulation	% GAP
1	0.975	0.001	0.977	0.976	0.1024
		0.003	0.977	0.975	0.2047
		0.005	0.977	0.972	0.5118
	0.980	0.001	0.98	0.979	0.1020
		0.003	0.98	0.977	0.3061
		0.005	0.98	0.975	0.5102
	0.990	0.001	0.993	0.992	0.1007
		0.003	0.993	0.99	0.3021
		0.005	0.993	0.984	0.9063

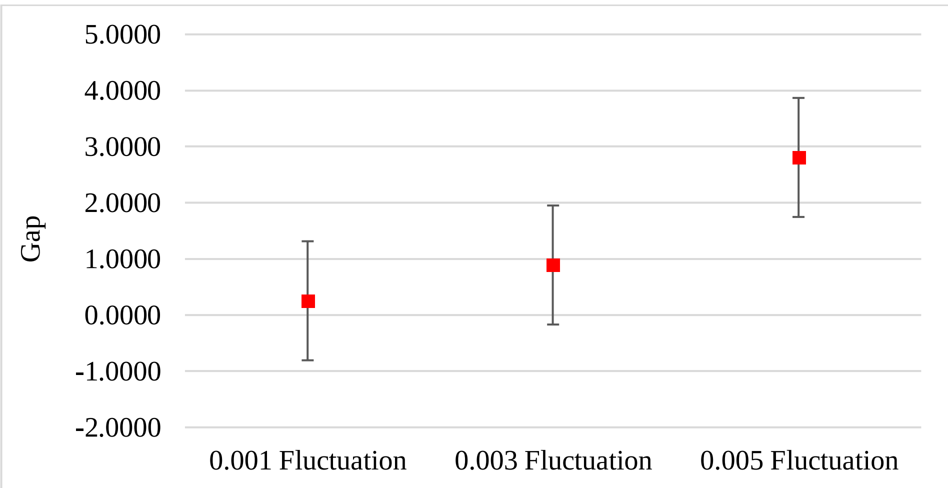

Fig. 5. A 95% Tukey confidence interval for the gap between the analytic and the simulation model

5-Conclusion

This paper examined the effects of uncertainties arises on component reliability estimation. To this aim, three well-known multistate examples with different configuration derived from the literature and optimum redundancy allocation compared with a computer simulation model. Validity of the simulation model examined with the analytic method and based on what if analysis on the simulated model, effects of over or lower component reliability estimation evaluated on the system reliability. Simulation model revealed that weak component reliability estimation tends to increase system design costs. The lower component reliability estimation effects on lower estimation of system reliability and trusted designers to inevitably seek for alternatives to increase the subsystem reliability using redundant components to achieve the desired level of reliability.

The results of this study can provide more confidence for critical system designers who are engaged on the proper system performance beyond economic design. Hence conclusions can be viewed from two perspectives.

1- Since in the real cased, uncertainty in component reliability estimation cannot completely be eliminated; the design of the systems is always pursued in a pessimistic manner.
2- Lower components' reliability estimation are as detrimental to deterrence as their over estimation.
3- Getting the optimum system design requires a more accurate estimation on component reliability using more sample size or elongation sampling time and spending more sampling cost. The more unreliable estimation leads to more overdesigning of the system.
4- The proposed computer simulation model could be applied for carrying out more "what if analysis" on the inputs such as component dependencies, complex system configuration, availability analysis and so on.

Current research focused on the system consisted of multiple independent components each one works on different states. Carrying out similar method for dependent model such as load sharing systems is on appeal as further research.

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