RELIABILITY OPTIMIZATION OF SOME INDUSTRIAL SYSTEMS USING ABC TECHNIQUE

Ph.D. THESIS

by

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A THESIS

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**RELIABILITY OPTIMIZAITON OF SOME INDUSTRIAL SYSTEMS USING ABC TECHNIQUE"** in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Mathematics of the Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from January, 2010 to June, 2013 under the supervision of Prof. S. P. Sharma, Department of Mathematics, Indian Institute of Technology Roorkee, Roorkee.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

(MONICA RANI)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date: June , 2013

(S. P. Sharma)
Supervisor

The Ph.D. Viva-Voce Examination of **Ms. Monica Rani,** Research Scholar, has been held on…………………………………………..………………………………………………..

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Abstract

With modern technology and higher reliability requirements, systems are getting more complicated day-by-day and hence job of the system analyst or plant personnel becomes so difficult to run the system under failure-free pattern. In the competitive market scenario, reliability and maintainability are the most important parameters that determine the quality of the product with the aim to estimate and predict the probability of the failure, and optimize the operation management. From a system effectiveness viewpoint, reliability and maintainability jointly provide system availability and dependability. Increased reliability directly contributes to system uptime, while improved maintainability reduces downtime. If reliability and maintainability are not jointly considered and continually reviewed, serious consequences may result. Therefore, the primary objective of any industrial system is to acquire quality products/systems that satisfy user needs with measurable improvements to mission capability and operational support in a timely manner, and at a fair and reasonable price. In determining the complexity and consequent frequent failure of the critical combination and complex integration of large engineering processes and systems, both in their level of technology as well as in their integration, the integrity of their design needs to be determined. This includes reliability, availability and maintainability (RAM) of the inherent process and system functions and their related equipments.

The main objective of the thesis is to present a technique for optimizing the reliability and availability issues of the industrial systems under different scenarios. For

this firstly, availability optimization model has been constructed for computing the optimal design parameters-MTBF and MTTR- of the system by considering manufacturing as well as repairing cost as an objective functions subject to predetermined availability constraints. Moreover, most of the data collected for analysis are taken from their historical records/sheets which are generally representing the past behavior of the system. Thus the issue of handling the uncertainties play a dominant role. For this fuzzy set theory has been used during the analysis and based on that various reliability parameters are depicted in the form of membership functions by using a proposed hybridized technique named as artificial bee colony based lambda-tau (ABCBLT). In this technique nonlinear optimization problem has been formulated by taking ordinary arithmetic operations instead of fuzzy arithmetic operations.

Apart from their behavior analysis, an investigation has been done for finding the most critical component of the system on which more attention may be given for increasing the production as well as productivity of the system. For this a composite measure of reliability, availability and maintainability named as RAM-Index has been given for a time varying failure rate components and studied their behavior in fuzzy environment. The advantage of defining this index is to analyze the impact of each component failure rate or repair time individually as well as simultaneously on its performance. Also this approach has been extended by taking degree of hesitation between the membership and nonmembership functions in terms of intuitionistic fuzzy set theory.

The present thesis is organized into nine chapters which are briefly summarized as follows:

A brief account of the related work of various authors in evaluation of system reliability by using conventional, fuzzy and optimization techniques is presented in the first chapter. The overview of the thesis is also presented in this chapter. In **Chapter 2**, the basics and preliminaries related to the reliability analysis and to be used in subsequent chapters are given.

Chapter 3 deals with performance analysis of a Butter-oil processing plant, which consists of subsystems namely Separator, Pasteurizer, Continuous butter making, Melting vats, Butter-oil Clarifier and Packaging units in series. For this an optimization model has been constructed by considering the system cost-manufacturing as well as repairing- as an objective and their system availability as a constraint. The reliability block diagram (RBD) of this system is drawn and ABC is used to compute optimal values of MTBF and MTTR. Finally computed results are shown to be statistically significant as compared to other algorithm techniques. *This work has been submitted after revision to Mathematics and Computers in Simulation, Elsevier.*

In **Chapter 4**, the computed results from the Chapter 3 are used for analyzing the behavior of their system. For this, the uncertainties which are present in the data are handled with the help of fuzzy set theory and based on that behavior of their corresponding system are analyzed in the form of fuzzy membership functions. A nonlinear optimization model has been formulated and solved by ABC algorithm for computing their reliability indices. Sensitivity as well as performance analysis on the system performance index has been analyzed which shows the effect of its component failure rate and repair time on the performance of the system. Finally the computed results are compared with the existing results as obtained by other researchers.

In **Chapter 5**, the behavior analysis of a paper mill, a complex repairable industrial system has been investigated by using ABC and fuzzy methodology. For this, time varying failure rate which follows the Weibull distribution and a constant repair time model, which follows the exponential distribution, have been taken corresponding to each component of the system. Uncertainties in the data are handled with fuzzy set theory and then behavior of the system has been analyzed in the form of various reliability parameters. To study the failure behavior of the system, crisp and defuzzified values are obtained at $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$ spreads. *This* *work has been published in International Journal of Industrial and Systems Engineering, International Journal of Performability Engineering, International Journal of Applied Mathematics and Mechanics and 16th Online World Conference on Soft computing in Industrial Application conference.*

In **Chapter 6**, performance analysis of repairable industrial systems has been done by defining a composite measure of reliability parameters called as RAM-Index. A time dependent RAM-Index as given below has been introduced in this chapter to analyze and rank the sensitive components of each unit of the system.

$$RAM(t) = w_1 \times R_s(t) + w_2 \times A_s(t) + w_3 \times M_s(t)$$

where $w_i \in (0, 1), i = 1, 2, 3$ are weights such that $\sum_{i=1}^{3} w_i = 1$. Advantage of this index is that by varying the component failure parameters, the corresponding effect on its performance has been analyzed. The presented approach has been applied to optimize the performance of a paper mill. *This work has been published in Applied Soft Computing, Elsevier and International Journal of Quality, Statistics & Reliability, Hindawi.*

Chapter 7 introduces a two-phase approach for solving the reliability-redundancy allocation problem of a series, series-parallel, complex design problems. In the first phase, an optimal reliability and their corresponding redundant component of each subsystem has been computed using ABC algorithm and the results are compared with other evolutionary algorithm results. While the improvement of their component reliability has been made in their second phase by preserving the redundant components corresponding to each subsystem. Finally the computed results during both the phases are compared to show the superbly of the proposed approach with the existing techniques.

In **Chapter 8**, a structural framework has been developed to model, analyze and predict the failure pattern of the system behavior in both quantitative as well as qualitative manner. In their framework, degree of hesitation or indeterminacy between the membership functions have been considered in which basic event are represented in the form intuitionistic fuzzy numbers of triangular membership functions. To strengthen the analysis, various reliability parameters of interest are computed and compared their results with their crisp as well as fuzzy technique results. Sensitivity analysis on the system MTBF has been computed for different combinations of reliability parameters. *The part of this chapter has been published in proceeding of International Conference on Applied Mathematics and Numerical Analysis held at Paris.*

Chapter 9 deals with the overall concluding observations of this study and a brief discussion on the scope for future work.

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List of Publications

Refereed Journals

(i) Predicting uncertain behavior of press unit in a paper industry using artificial bee colony and fuzzy Lambda-Tau methodology, *Applied Soft Computing*, Elsevier, Vol. 13, No. 4, pp. 1864 - 1881, 2013 (with S.P. Sharma and Harish Garg), (**Impact Factor: 2.612**)

(ii) A novel approach for analyzing the behavior of repairable systems by utilizing uncertain data, *International Journal of Performability Engineering*, Vol. 9, No. 2, pp. 201 - 210, 2013 (with S.P. Sharma and Harish Garg) (EI, Scopus).

(iii) Weibull fuzzy probability distribution for analyzing the behavior of pulping unit in a paper industry, *International Journal of Industrial and Systems Engineering*, Inderscience, Vol. 14, No. 4, pp. 395 - 413, 2013 (with S.P. Sharma and Harish Garg) (EI, Scopus).

(iv) Fuzzy RAM analysis of the screening unit in a paper industry by utilizing uncertain data, *International Journal of Quality, Statistics and Reliability, Hindawi Publishing Corporation*, Vol. 2012, Article ID 203842, 14 pages (with S.P. Sharma and Harish Garg) (EI, Scopus).

(v) Behavior analysis of pulping unit in a paper mill with Weibull fuzzy distribution function using ABCBLT technique, *International Journal of Applied Mathematics and Mechanics*, Vol. 8, No. 4, pp. 86-96, 2012 (with S.P. Sharma and Harish Garg).

(vi) Cost Minimization of Butter-Oil processing plant using artificial bee colony technique, *Mathematics and Computers in Simulation, Elsevier* submitted after minor revision (with S.P. Sharma and Harish Garg). (**Impact Factor: 0.738**)

Conference Proceedings

- *Reliability analysis of Press unit using vague set*, proceeding of the International Conference on Applied Mathematics and Numerical Analysis, held at Paris, France during June 27-28, 2012, Issue 66, pp. 649 – 655 (with S.P. Sharma).

- *Reliability analysis of a Press unit in a paper mill using Weibull fuzzy distribution function*, proceeding of 16th online conference World Conference on Soft computing in Industrial Application (WSC-2011), December 5-16, 2011, publishing in Soft Computing in Industrial Application, Springer (with S.P. Sharma and Harish Garg). `http://wsc16.cs.lboro.ac.uk/conference/sites/default/files/Paper_0.pdf`

- *Reliability Redundancy allocation problem of the pharmaceutical plant using artificial bee colony technique*, proceeding in International Conference on Advances in Modeling, Optimization and Computing (AMOC 2011) held at IIT Roorkee, Roorkee, India, December 5-7, 2011, pp. 560 - 567 (with S.P. Sharma and Harish Garg).

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Chapter 1

Introduction

With modern technology and higher reliability requirements, systems are getting more complicated day-by-day and hence job of the system analyst or plant personnel becomes so difficult to run the system under failure-free pattern. In the competitive market scenario, reliability and maintainability are the most important parameters that determine the quality of the product with their aim to estimate and predict the probability of the failure, and optimizing the operation management. From the view point of system effectiveness, reliability and maintainability jointly provide system availability and dependability. Increased reliability directly contributes to system uptime, while improved maintainability reduces system downtime. If reliability and maintainability are not considered jointly and reviewed continually, serious consequences may result. Therefore, the primary objective of any industrial system is to acquire quality products/systems that satisfy user needs with measurable improvements to mission capability and operational support in a timely manner, and at a fair and reasonable price. In determining the complexity and consequent frequent failure of the critical combination and complex integration of large engineering processes and systems, both in their level of technology as well as in their integration, the integrity of their design needs to be determined. This includes reliability, availability and maintainability (RAM) of the inherent process and system functions and their related equipment.

A basic and fundamental understanding of the concepts of RAM parameters, to a large extent, an empirical understanding of safety have in the main are dealt with statistical techniques for the measure and/or estimation of various parameters related to each of these concepts that are based on obtained data. However, in designing for RAM parameters, it is more often the case that the measure and/or estimators of various parameters related to each of these concepts are not based on obtained data. Furthermore, the complexity arising from an integration of engineering systems and their interactions makes it somewhat impossible to gather meaningful statistical data that could allow for the use of objective probabilities in the analysis of the integrity of engineering design. Any unfortunate consequences of unreliable behavior of such equipments or systems have lead to the desire for reliability analysis. Therefore, in recent year's system reliability has become an important issue in evaluating the performance of an engineering system by eliminating or reducing the likelihood of failures and thus increasing their desired life and operational availability.

The objective of the presented work is to analyze the behavior of some repairable process industrial systems by using vague, imprecise and uncertain data. For this, different optimization formulations for assessing their reliability parameters and characteristics are presented. A brief literature on various issues related to reliability evaluation of a system have been reviewed and are given section-wise hereafter.

1.1 Review of Literature

In this section, a brief literature review regarding reliability and availability optimization under different scenario are given.

1.1.1 Reliability with Conventional Methods

Reliability is a popular concept, being used for years as an attribute of a person, equipment or a system. Today reliability is growing into an omnipresent attribute with qualitative and quantitative connotations that pervades every aspect of our present day of technologically intensive world. As reliability deals with reducing the frequency of breakdowns, maintainability deals with the duration of breakdowns. The usefulness of the reliability analysis for the systems was discussed almost half century back by the researchers [23, 181, 206]. It has always been considered as a useful tool for risk analysis, production availability studies and design of systems.

In 1970, Buzacott [31] computed reliability measures of a system based on successive reduction of complex models and determined the intervals based on parallel and series sets, which were referred as minimal cut and path sets. Exponential distribution was used to model system failure and repair rates. Kim [134] proposed a technique for computing the reliability of complex systems and suggested a three phase approach. In the first phase, all series parallel subsystems were reduced to non series parallel subsystems. In the second stage, all the possible paths were traced from source to sink and in the third phase, system reliability is calculated based on these paths. Cherry et al. [49] performed reliability analysis of a system by calculating long run availability of plant, assuming constant failure and repair time for each of the components. Arid [10] used reliability engineering techniques in order to chalk out maintenance policies for the process plants. Dhillon [61] described application of reliability engineering principles for carrying out stochastic analysis of parallel systems with common cause failures and critical human errors by using Markovian approach. Cafaro et al. [32] explained the use of markov chains in evaluating the reliability and availability of a system with time-dependent transition rates using analytical matrix- based methods. The researchers [145–148, 151, 152] used the Markov modeling in the analysis and evaluated the performance of sugar, paper and fertilizer plants by assuming constant failure and repair rates of the systems. Now a days, system reliability evaluation has been focused by the various researchers using different methods such as Monte Carlo simulation [190, 216, 226], failure mode and effect analysis (FMEA)[214], fault tree analysis (FTA) [142, 215, 222] and Petri nets

[1–3, 200–202, 217] whereas some stochastic or statistical analysis methods included renewal process models, Markov process/analysis [9, 52, 129, 193], Poisson point process [11, 54, 205], Bayesian method [15, 109, 112, 130, 246], proportional hazard model [76, 166], redundancy allocations [53, 81, 155, 248] and combinations of these models.

Gurov et al. [97] developed a mathematical model to minimize the cost of the system under an availability constraint for partially (k-of-n) redundant repairable systems. Aghayeri and Telen [6] reported the failure frequency of repairable redundant systems and proposed an optimum production and maintenance planning model for process industry. Adamyan and David [1, 2] stressed upon the assessment of reliability and safety of a manufacturing system with sequential failures. Choi et al. [50] presented a method for minimizing the investment budget for constructing new transmission lines subject to probabilistic reliability criteria. Cochran et al. [52] developed Generic markov models for availability estimation and failure characterization of reactor regeneration system in fluid catalytic cracking unit for one of the petroleum industry. Sarhan [208, 209], Sarhan et al. [210] investigated the equivalence of different designs of simple series system, parallel systems and general series-parallel systems, based on the system reliability function and system mean time to failure. The system components are assumed to be independent and their lives to have exponential distributions. Wang [243] suggested two methods for the estimation of availability in which the allocation of MTBF and MTTR, subjected to exponential distribution, is described in first method, while in the second method estimation of the interval of availability is described when none of them is subjected to exponential distribution. The reliability and long-run availability of the process manufacturing industrial system - Butter-oil (melted butter) and Plastic-pipe plant - have been discussed by Gupta et al. [94, 95] for various choices of failure and repair rates of each component of the plant. Khan et al. [128] presented a two step risk-based methodology to estimate optimal inspection and maintenance intervals which maximize the system's availability. Isaac et al. [111] developed a model for evaluating the availability, the production rate and the reliability function of multi-state degraded systems subjected to minimal repairs and imperfect preventive maintenance.

Durga-Rao et al. [68] developed a software tool named as Dynamic Reliability with Simulation to do comprehensive dynamic fault tree analysis based on Monte Carlo simulation approach. The developed simulation approach has been validated with dynamic reliability problems. Yeh et al. [255] proposed particle swarm optimization, based on Monte Carlo simulation to solve complex network reliability by minimizing the cost of components that constituted the network under reliability constraints. Sarhan et al. [211] derived the maximum likelihood and Bayes estimators of the unknown parameters using a complete sample with the assumption that the prior distributions of the two unknown parameters follow gamma distributions.

Most of the studies assume that time-between-event is exponentially distributed. An important assumption when exponential distribution is used is that the event occurrence rate is constant. In reliability applications, this implies that the items have no aging property. But in reality this assumption is mostly violated due to wear and tear and other usage conditions, items usually have an increasing failure rate. To be able to monitor processes for which the exponential assumption is violated, Weibull distribution is a good alternative and it is a simple generalization of the exponential distribution. This flexibility and its reasonableness have made Weibull distribution probably the most useful distribution model in reliability analysis and it has been widely used by various researchers to model the failure times. There are a couple of papers where the authors have indicated the use of Weibull distribution for process monitoring in reliability [18, 249], but no detailed analysis is carried out. Related to the use of Weibull distribution in statistical process control, the authors [22, 29, 39, 57, 74, 157, 182, 223, 229, 250, 264] had discussed the use of Weibull distribution in various applications.

Liberopoulos and Tsarouhas [163] studied the statistical analysis of failure data of an automated pizza production line, covering a period of four years, computing the most important descriptive statistics of the failure data, and investigated the existence of auto-correlations and cross-correlations in the failure data. Sartori et al. [212] did comparison between the Weibull classical distribution and the q-Weibull generalized distributions in a typical natural gas recovery plant. Their results show that the q-Weibull distribution fits better to the available data. Tan [229] studied the two-parameter maximum likelihood estimation problem for the Weibull distribution with consideration of interval data. In this, they combined the Weibull-to-exponential transformation technique and the equivalent failure and life time technique. Castet and Saleh [39] conducted nonparametric analyses and Weibull fits with the MLE procedure to the probabilities of satellite and satellite subsystems' reliability.

Tsarouhas and Arvanitoyannis [234] performed the statistical analysis of the field of failure and repair data for a bread production line. The descriptive statistics of data was performed and the parameters of the Weibull distribution that have the best index of fit among the theoretical distributions were estimated. Moreover, the reliability and hazard rate modes for all machines and the entire production line that can be a useful tool to assess the current condition, and to predict the reliability for upgrading the maintenance policy of the production line were calculated. Hoseinie et al. [103] analyzed the reliability and maintainability of electrical system of drum shearer at Parvade.1 Coal Mine in central Iran by following the lognormal and Weibull-3 parameters distribution for time between failures and time to repair respectively. Veeramany and Pandey [237, 238] presented a semi-Markov process model for evaluating the rupture frequencies and reliability of the nuclear power plant by considering Weibull failure time distribution in the model. Monte carlo simulation is used to validate the model result. El-Damcese and Tamraz [73] performed the reliability and availability analysis of parallel repairable system by considering arbitrary repair time distribution. In their model, they used the Markov and supplementary variable techniques for developing the equations for the model. Garg and Sharma [80] presented an approach for reliability and maintainability analysis of industrial system. In their approach data are fitted over several distribution namely Exponential, Weibull, Normal, Lognormal and best-fitted data are estimated by using Anderson-Darling statistic test. A case-study of crank-case manufacturing plant has been taken for demonstration of their approach.

1.1.2 Reliability with Fuzzy Methodology

Among the various paradigmatic changes in science and mathematics in this century, one such change concerns the concept of uncertainty, which occurs in any problem-solving situation in the form of some information deficiency. Information may be incomplete, imprecise, not fully reliable, vague, contradictory or deficient in some other way. In general, these various information deficiencies may result in different types of uncertainty. Conventionally probability theory is being widely used in engineering and management field for reliability analysis with the assumption that the goals of the system target or information collected from the various resources are precise, known or definite. This was true up to late nineteenth century until with the introduction of fuzzy set by Zadeh in 1966 [260]. Zadeh's work had a profound influence on the thinking about uncertainty because it challenged not only probability theory as the sole representation for uncertainty, but the very foundations upon which probability theory was based: classical binary (two-valued) logic.

As far as reliability is concerned, conventional analysis or techniques have been used which are based on the probabilistic and the binary state assumptions in which uncertainties are dealt with probabilistic approach, which is random in nature [33, 34, 239]. Moreover, the traditional technique requires large amount of data related to component of the system in the form of probabilities which are rather difficult to collect or obtain because of incomplete or non-obtainable information. Thus, it is observed that the traditional approaches of reliability analysis rely on probabilistic assumptions, which are often inappropriate, as probability theory cannot deal with uncertainty due to vagueness in data. To overcome this problem, the concept of fuzzy set theory has been used by many researchers [34, 36, 42, 47, 69, 70, 79, 89, 93, 138, 161, 165, 179, 222, 240, 246]. This concept efficiently deals with imprecise, uncertain dependent information related to system performance and provides a better, consistent and mathematically more sound method for handling uncertainties in data than conventional methods, such as Bayesian statistics, Markov process, etc. In recent times, fuzzy methodology has gained popularity and hence widely used in various reliability engineering disciplines which includes human reliability [126, 138, 266], hardware reliability [33], software reliability [35, 135], structural reliability [108, 178, 191], Bayesian reliability [109, 221, 241, 246, 247], fuzzy reliability optimization [79, 81, 169, 198, 203] etc.

Knezevic and Odoom [138] proposed a new procedure for analyzing the reliability of repairable system by using Lambda-Tau and Fuzzy methodology. In their approach, various reliability parameters are analyzed in the form of fuzzy membership functions by using fuzzy arithmetic operations. Gupta and Bhattacharya [96] proposed a methodology which employs '*hybrid data*' as a tool to analyze the fault tree. The proposed methodology estimates the failure probability of basic events using the statistical analysis of field recorded failures. The proposed methodology has been applied to a conveyor system. Ding and Lisnianski [63] proposed fuzzy universal generating functions to assess system reliability of fuzzy multi-state system. Kishor et al. [136] gave an interactive fuzzy decision making approach for solving the multi-objective reliability optimization of a life-support system in a space capsule, where system reliability is maximized while minimizing the cost. Komal et al. [141] gave a genetic algorithm based lambda-tau (GABLT) methodology for calculating the membership function of the various reliability indices for depicting the behavior of the system. Huang et al. [109] proposed a method for estimating the reliability parameters in the form of fuzzy membership functions using fuzzy arithmetic's, artificial neural network and genetic algorithms. The effectiveness of the proposed method is illustrated with normal and Weibull distributions. Rao et al. [197] presented a solution to test interval optimization problem with uncertain/imprecise parameters with fuzzy-genetic approach along with a case of application of a safety system of Indian pressurized heavy water reactor. The authors of [113, 114, 252] have analyzed the fuzzy reliability of serial and parallel systems using statistical fuzzy confidence interval methodology.

Mahapatra and Mahapatra [168] analyzed the reliability and cost of the series system models using fuzzy parametric geometric programming by considering two types of the non-linear cost function models. The former one is to find out the optimum system reliability with cost constraint and the latter is to minimize the system cost model with targeted reliability goal in fuzzy environment. Donighi and Khanmohammadi [65] presented an approach for evaluating the reliability of series-parallel system, based on the use of beta type distribution as membership function. Kumar et al. [150] analyzed the reliability of system using real coded genetic algorithms and fuzzy methodology. Hadi-Vencheh et al. [99] proposed a fuzzy risk priority numbers (FRPNs) for prioritization of failure modes by treating the risk factors as fuzzy variables and evaluate them using fuzzy linguistic terms and fuzzy ratings.

1.1.3 Reliability, Availability and Maintainability (RAM)

With the advance in technology, a designer always wants to manufacture the equipment and systems of greater capital cost, complexity and capacity which results in increasing the reliability of the system. Also at the same time the unfortunate penalty of low availability and high maintenance cost need to be improved for their survival. To achieve this end, availability and reliability of equipment in the process must be maintained at the higher order. However, to improve the quality and quantity of a manufactured associated prospectus, there is a need to accentuate more on operational management. For this reason and to reduce the number of likelihood failures, there is a great interest in dealing with the main feature of the reliability parameters which affects the system performance directly i.e. reliability, availability and maintainability (RAM) . Also with the growing complexities of the system, the job of the system analyst becomes more tedious to analyze their simultaneous effects on the system performance. In that direction, various researchers have addressed the issue of RAM analysis by adapting the suitable maintenance strategies for increasing the performance of the system [67, 110, 167, 207, 244, 263].

Markeset and Kumar [172, 173] have discussed the application of reliability, maintainability and risk analysis methods to minimize life cycle cost of the system. Sun and Li [227] have proposed a truncated bathtub curve for failure rate by considering their exponential and Weibull distributions failure rate. Barabady and Kumar [20, 21, 22] had presented a methodology for improving the availability of a repairable system by using the concept of importance measures. The empirical data of two crushing plants at the Jajarm bauxite mine of Iran are used as a case study for reliability and availability analysis. The reliability and maintainability analysis of strudel, peach, bread production line at machine, workstation and entire line level was developed in [233–235]. The descriptive statistics of the failure and repair data was carried out and the best index of fit among the common theoretical distribution and their corresponding parameters were determined.

Nepal et al. [186] presented an integrated and analytical approach to modularise the product architecture by focusing on reliability and maintainability (R & M) issues upfront at conceptual stage so that the redesign problems at the later stage can be minimized. In addition, they also considered cost as criterion for modularisation and fuzzy logic was used to evaluate the candidate modules with respect to R & M and cost metrics. Sharma and Kumar [216] presented the application of RAM analysis in a process industry by using Markovian approach as a tool to model the system behavior. In their approach, crisp historical data are utilized in the analysis without quantification of involved uncertainties. Rajpal et al. [196] explored the application of artificial neural networks to model the behavior of a complex, repairable system. A composite measure of RAM parameters called as RAM-Index has been proposed for measuring the systems performance by simultaneously considering all the three key indices which influence the system performance directly. But disadvantage of their indices is that they are static in nature i.e. their values are specified at a fixed time. As the industrial system performance varies from time to time and hence the performance index must be improved. In that direction, Komal et al. [142] introduced time dependent RAM-Index in which historical uncertain data are used for its evolution. In their formulation, constant failure-rate and repair-time model has been used for analysis while uncertainties occurring between them were removed by using fuzzy set theory. Their membership functions were computed by formulating a non-linear optimization problem. Barabadi et al. [19] studied the effect of time-dependent covariates on the analysis of maintainability performance. The proportional repair model based on proportional hazard model was developed for analyzing the time-dependent covariates, instead of time-independent covariates, by using Cox regression model in the maintainability field. The applicability of the method has been demonstrated with a case study of crushing plants of Jijarm Bauxite Mine.

1.1.4 Reliability-Redundancy Allocation Problem

The system reliability optimization has its importance in variety of engineering yields. A design engineer has several options to improve the reliability of a system with a given basic design. The reliability of a system can be enhanced by either providing redundancy at the component level or increasing components' reliabilities or both. The utilization of redundancy is assumed to be one of the main attributes to meet high level reliability. The problem is then to select the feasible design configuration (i.e., optimal redundancy levels) that maximizes system reliability. This problem is called redundancy allocation problem (RAP) which was first introduced by Misra and Ljubojevic in 1973 [176]. A series-parallel system is basically characterized through a predefined number of sub-systems which are connected serially. However, redundancy and component reliability enhancement lead to increase in system cost. Thus, a tradeoff between these two options is necessary for budget-constrained reliability optimization [155]. Besides the above two ways, the combination of the two approaches and reassignment of interchangeable elements are another feasible ways for increasing the system reliability [100, 155]. Such problem of maximizing system reliability through redundancy and component reliability choices is called "reliability-redundancy allocation problem (RRAP)" [155]. In this problem the aim is to find simultaneously the optimal redundancy levels and optimal component reliabilities that maximize system reliability subject to resource constraints such as cost, weight and volume of the system. This problem is an NP problem [48] and belongs to the category of constrained nonlinear mixed-integer optimization problems.

Several researchers since 1960s have solved reliability optimization problems with single objective in which reliabilities of the system components are assumed to be known at fixed positive levels which lie between zero and one [5, 55, 98, 100, 155, 156, 177, 184, 185, 232]. However, in real-life situations, the reliability of a component varies due to several reasons, such as improper storage facilities, the human factor and other factors related to environment. Due to the non-availability of their distribution function at the product design, the reliability of each component is sensible and hence it may be treated as a positive imprecise number between zero and one instead of a fixed real number. Hence, a more general problem is one where both the optimal component reliability and the optimal redundancy at each stage are determined to obtain the maximum system reliability i.e. RRAP.

During the last two decades several heuristic as well as global optimization methods have been introduced by the researchers to solve these problems which can be classified as heuristic methods, Lagrangian multiplier method, branch and bound method, linear programming, and so on [87, 100, 133, 177, 177, 183, 192, 218, 230, 251, 258]. These approaches do not guarantee exact optimal solutions, but they achieve reasonably good solutions for hard problems in relatively short time periods. Specially, heuristics have been popular for solving reliability-redundancy allocation problems, because global optimal solutions to these problems are not obtainable in reasonable amounts of time. However, the heuristic techniques require derivatives for all non-linear constraint functions, that are not derived easily because of the highly computational complexity. Due to the non-convexity, non-smoothness and high-dimension of the problems, many classical mathematical methods fail to obtain satisfactory solutions. To overcome this difficulty meta-heuristic methods, based on swarm intelligence, have shown great potential in solving the reliability optimization problem and gained increasing attention. These heuristics include genetic algorithm [83, 106, 174, 188, 257], particle swarm optimization [53, 81, 248], evolutionary algorithm [85, 204] ,ant colony algorithm [175], harmony search algorithms [242, 267], neural network [56], immune algorithm [46, 107] and artificial bee colony algorithm [105, 253] etc.

1.1.5 Reliability with Artificial Bee Colony optimization

The last few decades have witnessed the introduction of several optimization algorithms, based on nature-inspired ideas. Some examples of such algorithms include ant colony optimization [66], evolutionary algorithm [85, 204] genetic algorithm [86, 102], particle swarm optimization [72, 127] etc. Most of these algorithms are meta-heuristic-based search techniques and generally referred to as multipurpose optimization algorithms because of their applicability to a wide range of problems. In a similar context, Artificial Bee Colony algorithm (ABC) was initially published by Karaboga in 2005 as a technical report for numerical optimization problems [116] and with its co-authors for optimizing numerical problems [116, 118, 124]. Its development was motivated by simulating the intelligent foraging behaviour of honey bees in their colony and its performance was initially measured using benchmark optimization function. In recent times, however, the attention of researchers in the engineering and optimization domains have been drawn to adopt the use of ABC for a variety of decision making problems such as for constrained optimization [28, 117], in engineering [7, 224], economic dispatch problems [225], neural network [104, 123, 213, 254], software engineering [58, 171], multi-objective [187, 265, 269] and many others.

Karaboga and Basturk [119] extended ABC algorithm for solving constrained optimization problems and applied it to a set of constrained problems. Brajevic et al. [27] presented an improved version of ABC for constrained optimization problems, which has been implemented and tested on several engineering benchmarks which contain discrete and continuous variables. Li et al. [160] used ABC for reliability analysis of engineering structures and their study was demonstrated by four examples to show the present method is reliable and accurate. Dongli et al. [64] proposed a modified ABC algorithm for numerical optimization problems and tested its performance on a set of benchmark problems. Rajasekhar et al. [194] proposed an improved version of ABC algorithm with mutation based on Levy probability distributions. Yeh et al. [256] presented an approximate model for predicting the network reliability by combining the ABC algorithm and Monte Carlo simulation. Yeh and Hsieh [253] presented the penalty guided ABC for solving the reliability redundancy allocation problem. Four benchmark reliability allocation problem has been solved and found that ABC algorithm perform better than the well known solution given by other meta-heuristic technique results. Hsieh and Yeh [105] presented a penalty guided artificial bee colony algorithm to solve system reliability allocation problems with a mix of components. For more details about the application and methodology of ABC algorithm, we may refer to [7, 8, 118, 121–123]

1.1.6 Reliability with Intuitionistic fuzzy set theory

The theory of fuzzy sets proposed by Zadeh [260] has achieved a great success in various fields to handle the uncertainties in the data by defining the fuzzy set which accommodate the various degree of membership on the real interval [0,1] by the membership function $\mu_{\widetilde{A}} \in [0, 1]$. After the introduction of the concept of fuzzy sets, several researches were conducted on the extensions of the notion of fuzzy sets. Among these extensions the one that has drawn the attention of many researchers during the last decades is the theory of intuitionistic fuzzy sets (IFSs) introduced by Attanassov [13, 14]. IFS adds an extra degree called as degree of non-membership function in order to model the hesitation or indeterminacy between the degree of membership functions belonging. In fuzzy set the degree of non-membership or degree of hesitation is simply considered as one minus the degree of membership function and hence it is fixed. However, in IFS theory, the characteristic function of an element in the universe is expressed by the degree of membership (or acceptance) and the degree of non-membership (or rejection) simultaneously such that sum of their membership function is less than 1. Thus, the introduced IFS is more suitable for dealing with fuzziness and uncertainty than the ordinary fuzzy set, and has received more and more attention since its appearance. Gau and Buehrer [82] gave the notion of vague set, which is another generalization of fuzzy sets. But Bustince and Burillo [30] showed that it is an equivalent of the IFS. Therefore, it is expected that IFSs could be used to simulate any activities and processes requiring human expertise and knowledge, which are inevitably imprecise or not totally reliable.

In many complex decision making problems, the decision information provided by the decision maker is often imprecise or uncertain [137] due to time pressure, lack of data, or the decision maker's limited attention and information processing capabilities. Thus, IFS is a very suitable tool to be used to describe imprecise or uncertain decision information. In that direction, Chen [43, 45] presented the arithmetic operations and analyzing the fuzzy system reliability based on vague sets. Shu et al. [220] proposed an algorithm to calculate the fault interval of system components by integrating both expert knowledge and experience in terms of providing the possibilities of failure of bottom events using intuitionistic fuzzy fault tree analysis. They applied their method to the failure analysis problem of printed circuit board assembly. Kumar et al. [144] developed a method for analyzing system reliability by using interval valued vague sets, and applied it for the reliability analysis of a marine power plant. Chang et al. [40] proposed a vague fault-tree analysis procedure to determine the weapon system's reliability. Mahapatra and Roy [170] presented a method for fuzzy system reliability analysis using the idea of interval valued vague sets and intuitionistic fuzzy numbers respectively. Chang and Cheng [41] obtained fault interval and reliability interval of the printed circuit board assembly with different membership function using fault-tree analysis. Taheri and Zarei [228] investigated the Bayesian system reliability assessment in vague environment. Kumar and Yadav [149] presented an approach for constructing the membership and non-membership of reliability index using non-linear programming problem using different types of intuitionistic fuzzy numbers. As far as reliability field is concerned, IFSs have been proven to be highly useful to deal with uncertainty and vagueness, and a lot of work has been done by researchers [12, 17, 40, 45, 90–92, 144, 149] to develop and enrich the IFS theory.

1.2 Objective of the Thesis

The main objective of the thesis is to present a technique for optimizing the reliability and availability issues of the industrial systems under different scenarios. As most of the data collected for analysis are taken from their historical records/sheets which generally represent the past behavior of the system. Thus the issue of handling the uncertainties play a dominant role. For this fuzzy set theory has been used during the analysis for handling such type of vagueness, limited or imprecise data. Based on that, behavior of an industrial system is analyzed in terms of various reliability parameters, which affects the performance of the system directly, in the form of various fuzzy membership functions such as failure rate, repair time, MTBF etc. For computing the membership functions of these parameters, a hybridized technique named as artificial bee colony based lambda-tau (ABCBLT) technique has been proposed in which nonlinear optimization problem has been formulated by taking ordinary arithmetic operations instead of fuzzy arithmetic operations. ABC technique has been used for solving this problem. The major advantages of proposed technique is that it gives compressed range of prediction for all computed reliability parameters by utilizing uncertain data as compared to other techniques. Sensitivity as well as performance analysis on the system performance have also been done for showing the effect of various reliability parameters on its performance.

Apart from their behavior analysis, a time varying index named as RAM-Index, which is a composite measure of reliability, availability and maintainability parameters, are studied in fuzzy environment. Advantage of this index is that by varying the component failure parameters, the corresponding effect on its performance has been analyzed. Based on their analysis, critical component of the system, as per preferential order, has been given to the system analyst for analyzing the impact of failure rate and repair time of each component on its system. Based on that plant maintenance personnel may decide the best suited action and to assign the repair priorities as per the system requirements. In addition to these, an approach has been suggested for analyzing the behavior of complex repairable industrial systems in terms of membership and nonmembership functions by defining their interminancy between the membership functions in terms of vague set theory. Sensitivity analysis on the system MTBF has been computed for different combinations of reliability parameters. Finally, an approach has been given to enhance the reliability of the redundant component of a series, series-parallel or complex (bridge) system.

1.3 Overview of the thesis

The present thesis is organized into nine chapters including the present one that contains mainly the literature review. The rest of chapters are described below:

In **Chapter 2**, the basics and preliminaries related to the reliability analysis which are to be used in subsequent chapters are given.

Chapter 3 deals with performance analysis of a Butter-oil processing plant, which consists of subsystems namely Separator, Pasteurizer, Continuous butter making, Melting vats, Butter-oil Clarifier and Packaging units in series. For this an optimization model has been constructed by considering the system cost-manufacturing as well as repairing- as an objective and their system availability as a constraint. The reliability block diagram (RBD) of this system is drawn and ABC is used to compute optimal values of MTBF and MTTR. Finally computed results are shown to be statistically significant as compared to other algorithm techniques.

In **Chapter 4**, the computed results from the Chapter 3 are used for analyzing the behavior of their system. For this, the uncertainties which are present in the data are handled with the help of fuzzy set theory and based on that behavior of their corresponding system are analyzed in the form of fuzzy membership functions. A nonlinear optimization model has been formulated and solved by ABC algorithm for computing their reliability indices. Sensitivity as well as performance analysis on the system performance index has been analyzed which shows the effect of its component failure rate and repair time on the performance of the system. Finally the computed results are compared with the existing results as obtained by other researchers.

In **Chapter 5**, the behavior analysis of a paper mill, a complex repairable industrial system has been investigated by using ABC and fuzzy methodology. For this, time varying failure rate which follows the Weibull distribution and a constant repair time model, which follows the exponential distribution, have been taken corresponding to each component of the system. Uncertainties in the data are handled with fuzzy set theory and then behavior of the system has been analyzed in the form of various reliability parameters. To study the failure behavior of the system, crisp and defuzzified values are obtained at ±15%, ±25% and ±50% spreads.

In **Chapter 6**, performance analysis of repairable industrial systems has been done by defining a composite measure of reliability parameters called as RAM-Index. A time dependent RAM-Index as given below has been introduced in this chapter to analyze and rank the sensitive components of each unit of the system.

$$RAM(t) = w_1 \times R_s(t) + w_2 \times A_s(t) + w_3 \times M_s(t)$$

where $w_i \in (0, 1), i = 1, 2, 3$ are weights such that $\sum_{i=1}^{3} w_i = 1$. Advantage of this index is that by varying the component failure parameters, the corresponding effect on its performance has been analyzed. The presented approach has been applied to optimize the performance of a paper mill.

Chapter 7 introduces a two-phase approach for solving the reliability-redundancy allocation problem of a series, series-parallel, complex design problems. In the first phase, an optimal reliability and their corresponding redundant component of each subsystem has been computed using ABC algorithm and the results are compared with other evolutionary algorithm results. While the improvement of their component reliability has been made in their second phase by preserving the redundant components corresponding to each subsystem. Finally the computed results during both the phases are compared to show the superbly of the proposed approach with the existing techniques.

In **Chapter 8** a structural framework has been developed to model, analyze and predict the failure pattern of the system behavior in both quantitative as well as qualitative manner. In their framework, degree of hesitation or indeterminacy between the membership functions have been considered in which basic event are represented in the form of vague fuzzy numbers of triangular membership functions. A vague set theory over fuzzy set theory has been used, as the vague sets separates the trueness and falseness evidence for membership of an element in a set. Further, in vague set, the level of confidence of domain experts lies between [0,1] instead of 1 as in fuzzy set theory. To strengthen the analysis, various reliability parameters of interest are computed and compared their results with their crisp as well as fuzzy technique results. Sensitivity analysis on the system MTBF has been computed for different combinations of reliability parameters.

Chapter 9 deals with the overall concluding observations of this study and a brief discussion on the scope for future work.

Chapter 2

Preliminaries

This chapter presents some of the fundamental definitions and mathematical theory for reliability. The focus is on the reliability and unreliability functions, the probability density function, the hazard rate, the conditional reliability function, and some time-to-failure metrics.

2.1 Reliability metrics

2.1.1 Reliability

Reliability in engineering problems is concerned with whether a system can operate properly without failure. System reliability is a measure of how well a system meets its design objective. In the probability context it can be taken as a quantitative and is defined as the probability that the product or a system performs the intended function adequately for a specified period of time, under stated operating conditions or environment. Mathematically, if we define $T \geq 0$ to be the continuous random variable that represents the time to failure of a system and $F(t)$ the distribution of the system life time, then the basic reliability function $R(t)$, is defined [25] for time to failure of the system (or subsystem) as

$$R(t) = Pr(T > t) = 1 - F(t) = \int_t^{\infty} f(x)dx \tag{2.1.1}$$

where $R(0) = 1$ and $R(\infty) = 0$ and $f(t)$ failure probability density function. The function $R(t)$ is a non increasing function of t. The reliability function is also called the survivor function in literature. The cumulative distribution function of T is also called the unreliability function and is defined as

$$F(t) = Pr(T \leq t) = \int_{-\infty}^{t} f(x)dx \tag{2.1.2}$$

In addition to the probability function, there is another function, called the failure rate or hazard rate function which is often used in reliability. It provides an instantaneous (at time t) rate of failure. The conditional probability of a failure in the time interval from t to $t + \delta t$ given that the system has survived to time t is

$$Pr\{t \leq T \leq t + \delta t \mid T \geq t\} = \frac{R(t) - R(t + \delta t)}{R(t)} \tag{2.1.3}$$

then $\dfrac{R(t) - R(t + \delta t)}{R(t)\delta t}$ is the conditional probability of failure per unit of time (failure rate). The rule of conditional probability therefore dictates that:

$$\lambda(t) = \frac{-dR(t)}{dt} \cdot \frac{1}{R(t)} = \frac{f(t)}{R(t)} \tag{2.1.4}$$

then $\lambda(t)$ is known as the instantaneous hazard rate or failure rate function. Based on these hazard rate function, the reliability function can be derived as

$$R(t) = \exp\left[-\int_{0}^{t} \lambda(u)\, du\right] \tag{2.1.5}$$

The mean time to failure(MTTF) of the system is defined as

$$MTTF = \int_{0}^{\infty} R(t)dt \tag{2.1.6}$$

2.1.2 Availability

Availability is one of the most important measures in reliability theory. Some authors have defined various kinds of availabilities. A good survey and a systematic classification of availabilities were given in [164] and is defined as the probability of a product or system working satisfactorily at any given point of time when used under the given conditions of use [71]. Thus availability signifies the probability that the system is available and is working satisfactorily at a given point of time. Availability is a more meaningful parameter of performance of a maintained system than reliability. For defining the availabilities of the system, let

$$X(t) = \begin{cases} 1 & \text{if the system is up at time } t \\ 0 & \text{if the system is down at time } t \end{cases} \tag{2.1.7}$$

(a) *Pointwise availability:* It is the probability that the system will be up at a given instant of time. This availability is given by

$$A(t) = Pr(X(t) = 1) = E\{X(t)\} \tag{2.1.8}$$

(b) *Interval availability:* It is the expected fraction of a given interval that the system will be able to operate, which is given by

$$A(t) = \frac{1}{t} \int_0^t A(u)\ du \tag{2.1.9}$$

(c) *Limiting interval availability:* It is the expected fraction of time in the long run that the system will be able to operate, which is given by

$$A(t) = \lim_{t \to \infty} \frac{1}{t} \int_0^t A(u)\ du \tag{2.1.10}$$

(d) *Steady State Availability:* The steady state availability of the system is the limit of the instantaneous availability function as time approaches infinity and is given as

$$A(t) = \lim_{t \to \infty} A(t) = \frac{MTBF}{MTBF + MTTR} \tag{2.1.11}$$

where $MTBF$ and $MTTR$ are the mean time between failure and mean time to repair of the system respectively.

2.1.3 Maintainability

Maintainability refers to the measures taken during the development, design, and installation of a manufactured product which ensure that the product meets the requirements for its intended use [71]. When it is observed that a system or piece of equipment fails to perform its function satisfactorily, all or part of it is taken out of operation to locate and correct the fault. The fault may be corrected by a repair or a part may be replaced by a spare. From a qualitative point of view, maintainability is defined as the probability that an item will be restored to specified conditions within a given period of time when maintenance action is performed in accordance with prescribed procedures and resources. Maintainability is characterized by specifying a repair-time probability distribution. Let T_D denote the item downtime random variable, distributed according to a density function $g(t)$. Then, the probability that a repair will be accomplished within time t i.e., maintainability ($M(t)$) can be written as

$$\mathrm{P}(T_D \leqslant \mathrm{t}) = M(t) = \int_0^t g(u)\ du \tag{2.1.12}$$

and the mean downtime i.e., mean time to repair (MTTR) is defined as:

$$\mathrm{MTTR} = \int_0^\infty t\ g(t) dt = \int_0^\infty (1 - \mathrm{M}(t)) dt \tag{2.1.13}$$

2.2 Fault Tree Analysis

For complex multi-component systems, for example nuclear, chemical, paper, process and aerospace industries, it is important to analyze the possible mechanisms of failure and to perform probabilistic analyses for the expected frequency of such failures. Often, each such system is unique in the sense that there are no other identical systems for which failure data have been collected: therefore a statistical failure analysis is not possible. Furthermore, it is not only the probabilistic aspects of failure of the system which are of interest but also the initiating causes and the combination of events which can lead to a particular failure. The engineering way to tackle a problem of this nature, where many events interact to produce other events, is to relate these events using simple logical relationships (intersection, union, etc.) and to methodically build a logical structure which represents the system. In this respect, Fault tree analysis (FTA) model is the systematic, deductive technique which allows to develop the causal relations leading to a given undesired event.

Fault tree analysis (FTA) is one of the most widely used methods in the industrial sector to evaluate reliability of engineering systems. The method was developed in the early 1960s at Bell Telephone Laboratories to evaluate the reliability and safety of the minuteman Launch Control System [60]. A fault tree is a graphical representation of causal relations obtained when a system failure mode is traced backward to search for its possible causes. To complete the construction of a fault tree for a complex system, it is necessary to understand the functioning of the system. A system flow diagram (e.g. a reliability block diagram) is used for this purpose, i.e. for showing how component reliability contributes to the success or failure of a complex system. The first step in fault tree construction is the selection of the system failure event of interest. This is called the top event and every following event will be considered in relation to its effect upon it. The next step is to identify contributing events that may directly cause the top event to occur. Fault events which could cause the top event are generated and connected by logic gates such as OR and AND. The fault tree construction proceeds by generation of fault events in a successive manner until the events need not be developed any further. The analysis of fault tree is commonly done by finding minimum path sets and/or minimum cut sets of a tree. Although many symbols are used in performing FTA, the four commonly used symbols are shown in Fig. 2.1 and are described below.

- *Rectangle.* This denotes a fault event that results from the logical combination of fault events through the input of a logic gate.

- *Circle.* This represents a basic fault event or the failure of an elementary

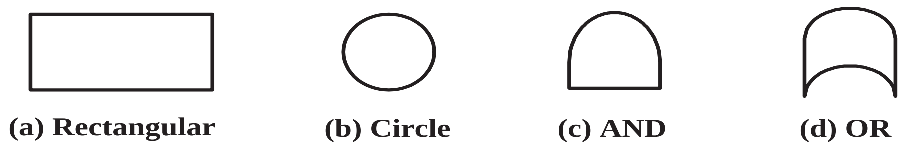


Figure 2.1: Symbols of FTA model

component. The event's probability of occurrence, failure, and repair rates are normally obtained from field failure data.

- *AND gate.* This denotes that an output fault event occurs only if all of the input fault events occur.

- *OR gate.* This denotes that an output fault event occurs if one or more of the input fault events occur.

For more details about this analysis, we refer to [60, 71].

2.3 Fuzzy set theory

Fuzzy set theory, compared to other mathematical theories, is perhaps the most easily adaptable theory to practice. The main reason is that a fuzzy set has the property of relatively, variability, and inexactness in the definitions of its elements. Instead of defining an entity in calculus by assuming that its role is exactly known, we can use fuzzy sets to define the same entity by allowing possible deviations and inexactness in its role. This representation suits well for the uncertainties encountered in practical life, which make fuzzy sets a valuable mathematical tool.

2.3.1 Crisp versus fuzzy set

In the classical set, its characteristic function also called as indicator function, assigns a value of either 1 or 0 to each individual in the universal set, thereby discriminating between members and nonmembers of the crisp set under consideration. The values assigned to the elements of the universal set fall within a specified range and indicate the membership grade of these elements in the set. The concept of fuzzy set was introduced by Zadeh [260] in 1965, which can be defined on the universe of discourse U as $\widetilde{A} = \{< x, \mu_{\widetilde{A}}(x) >| \ x \in U\}$, where $\mu_{\widetilde{A}}$ is the membership function of the fuzzy set $\widetilde{A}$ defined as $\mu_{\widetilde{A}} : U \to [0, 1]$ and $\mu_{\widetilde{A}}(x)$ indicates the degree of membership of x in $\widetilde{A}$ and its value lies between zero and one. Mathematically, fuzzy set $\widetilde{A}$ in the universe of discourse U is defined as a set of ordered pairs $(x, \mu_{\widetilde{A}}(x))$, i.e.

$$\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x)) \ \mid \ x \in U\} \tag{2.3.1}$$

where $\mu_{\widetilde{A}}(x)$ is the degree of membership of x in fuzzy set $\widetilde{A}$ and it indicates the degree that x belongs to $\widetilde{A}$. Clearly $\mu_{\widetilde{A}}(x) \in [0, 1]$. When a set is an ordinary set, its membership function can take on only two values 0 and 1, with $\chi_A(x) = 1$ or 0 according as x does or does not belong to A. $\chi_A(x)$ is referred to as the characteristic function of the set A.

2.3.2 $\alpha-$ cuts

$\alpha-$ cut of the fuzzy set $\widetilde{A}$, denoted by $A^{(\alpha)}$, is a crisp set which consists of elements of $\widetilde{A}$ having at least degree α and is defined mathematically as

$$A^{(\alpha)} = \{x \in U \ : \ \mu_{\widetilde{A}}(x) \geqslant \alpha\} \tag{2.3.2}$$

where α is the parameter in the range $0 \leq \alpha \leq 1$. Every $\alpha-$ cut of a fuzzy number is a closed interval and a family of such intervals describes completely a fuzzy number under study. Hence we have $A^{(\alpha)} = [A_L^{(\alpha)}, A_U^{(\alpha)}]$ where

$$\begin{aligned} A_L^{(\alpha)}(\alpha) &= \inf\{x \in \mathbb{R} \mid \mu_{\widetilde{A}}(x) \geqslant \alpha\} \\ A_U^{(\alpha)}(\alpha) &= \sup\{x \in \mathbb{R} \mid \mu_{\widetilde{A}}(x) \geqslant \alpha\} \end{aligned}$$

2.3.3 Extension principle

Extension principle was introduced by Zadeh in 1975 [261, 262] and is a very important tool of fuzzy set theory. This extension principle allows the generalization of crisp sets into fuzzy set framework and extends point-to-point mapping in crisp sets to mapping for fuzzy sets. This principle allows any function f, that maps an n-tuple $(x_1, x_2, \ldots, x_n)$ in a crisp set M to a point in a crisp set N, to be generalized as a set that maps n fuzzy subsets in M to a fuzzy set in N. Thus, any mathematical relationship between nonfuzzy crisp elements can be extended to deal with fuzzy entities.

Given a function $f : M \longrightarrow N$ and a fuzzy set $\widetilde{A}$ in M, where

$$\widetilde{A} = \frac{\mu_1}{x_1} + \frac{\mu_2}{x_2} + \frac{\mu_3}{x_3} + \ldots + \frac{\mu_n}{x_n} \quad \text{where} \quad \mu_i = \mu_{\widetilde{A}}(x_i)$$

the extension principle states that

$$f(\widetilde{A}) = f\left(\frac{\mu_1}{x_1} + \frac{\mu_2}{x_2} + \ldots + \frac{\mu_n}{x_n}\right) = \frac{\mu_1}{f(x_1)} + \frac{\mu_2}{f(x_2)} + \ldots + \frac{\mu_n}{f(x_n)}$$

If f maps several elements of M to the same element y in N (i.e. many-to-one mapping), then the maximum among their membership grades is taken. That is

$$\mu_{f(\widetilde{A})}(y) = \max_{\substack{x_i \in m \\ f(x_i) = y}} \mu_{\widetilde{A}}(x_i) \tag{2.3.3}$$

where x_i's are the elements mapped to same element y. The function f maps n-tuples in M to a point in N.

2.3.4 Membership function

The concept of membership function is the most important aspect in fuzzy set theory. It is a curve that defines how each point in the input space is mapped to a membership value (partial truth) between 0 and 1. They are used to represent various fuzzy sets. For a fuzzy set $\widetilde{A}$ a membership function, denoted by $\mu_{\widetilde{A}}(\cdot)$ maps U to the interval [0,1] i.e. $\mu_{\widetilde{A}} : U \to [0, 1]$, the range of the membership function is a subset of the non-negative real numbers whose supremum is finite. Many membership functions such as normal, triangular, trapezoidal can be used to represent fuzzy numbers. However, triangular membership functions (TMF) are widely used for calculating and interpreting reliability data because of their simplicity and understandability [16, 189]. The decision of selecting TMF lies in their ease to represent the membership function effectively and to incorporate the judgement distribution of multiple experts. This is not true for complex membership functions, such as trapezoidal one, and so forth. For instance, imprecise or incomplete information such as low/high failure rate that is about 4 or between 5 and 7, is well represented by TMF. Also, it not only conveys the behavior of system parameters but also reflect the dispersion of the data adequately. Based on the membership functions, the fuzzy sets can be classified as under.

Normal fuzzy set: If the membership function has at least one element in the universe whose value is equal to 1, then that set is called normal fuzzy set. Mathematically, a fuzzy set $\widetilde{A}$ in the universe U is said to be normal fuzzy set if $\mu_{\widetilde{A}}(x) = 1$ for at least one $x \in U$. Otherwise set is said to subnormal fuzzy set.

Support of fuzzy set: The support of a fuzzy set $\widetilde{A}$ is the crisp set of all $x \in X$ such that membership values are nonzero, $\mu_{\widetilde{A}}(x) > 0$.

Convex fuzzy set: A fuzzy set $\widetilde{A}$ is convex if its membership function is monotonically increasing and/or decreasing without any saddle point in the middle. Mathematically, it is expressed by the following condition

$$\mu_{\widetilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geq \min(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)) \quad \forall \quad x_1, x_2 \in U, \quad 0 \leq \lambda \leq 1$$

A fuzzy number of a fuzzy set $\widetilde{A}$ is a convex normalized fuzzy set of the real line $\mathbb{R}$ such that

(i) it exits exactly one $x_0 \in \mathbb{R}$ with $\mu_{\widetilde{A}}(x_0) = 1$

(ii) $\mu_{\widetilde{A}}$ is piecewise continuous

and its membership function is defined as

$$\mu_{\widetilde{A}}(x) = \begin{cases} f_A(x) & ; \quad a \leq x \leq b \\ 1 & ; \quad x = b \\ g_A(x) & ; \quad b \leq x \leq c \\ 0 & ; \quad \text{otherwise} \end{cases} \tag{2.3.4}$$

where $0 \leqslant \mu_{\widetilde{A}}(x) \leqslant 1$ and $a, b, c \in R$ such that $a \leqslant b \leqslant c$, and two functions $f_A, g_A : R \to [0, 1]$ are called the sides of fuzzy number. The function f_A is nondecreasing continuous functions and the function g_A is nonincreasing continuous functions. In other words, A fuzzy subset $A = \{(x, \mu_{\widetilde{A}}(x)) \mid x \in \mathbb{R}\}$ of the real line $\mathbb{R}$ is called fuzzy number if $\widetilde{A}$ is convex, normal and bounded.

A triangular fuzzy number (TFN) is defined by the ordered triplet $\widetilde{A} = (a, b, c)$ representing, respectively, the lower value, the modal value, and the upper value of a triangular fuzzy membership function. Its membership function $\mu_{\tilde{A}} : R \longrightarrow [0, 1]$, is defined as:

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a} & ; \quad a \leq x \leq b \\ 1 & ; \quad x = b \\ \dfrac{c-x}{c-b} & ; \quad b \leq x \leq c \\ 0 & ; \quad \text{otherwise} \end{cases} \tag{2.3.5}$$

The α-cuts of the triangular fuzzy set is defined in the closed interval form as below

$$A_\alpha = [a^{(\alpha)}, c^{(\alpha)}] = [(b-a)\alpha + a, -(c-b)\alpha + c] \tag{2.3.6}$$

The basic arithmetic operations, i.e., addition, subtraction, multiplication and division, of fuzzy numbers depends upon the arithmetic of the interval of confidence. The four main arithmetic operation on two triangular fuzzy sets $\widetilde{A}$ and $\widetilde{B}$ described by the $\alpha-$ cuts are given below for the following intervals:

$A^{(\alpha)} = [A_1^{(\alpha)}, A_3^{(\alpha)}]$ and $B^{(\alpha)} = [B_1^{(\alpha)}, B_3^{(\alpha)}], \quad \alpha \in [0,\ 1]$

(i) Addition : $\tilde{A}+\tilde{B}=[A_1^{(\alpha)}+B_1^{(\alpha)}, A_3^{(\alpha)}+B_3^{(\alpha)}]$

(ii) Subtraction : $\tilde{A}-\tilde{B}=[A_1^{(\alpha)}-B_3^{(\alpha)}, A_3^{(\alpha)}-B_1^{(\alpha)}]$

(iii) Multiplication : $\tilde{A}\cdot\tilde{B}=[P^{(\alpha)}, Q^{(\alpha)}]$
where $P^{(\alpha)}=\min(A_1^{(\alpha)}\cdot B_1^{(\alpha)}, A_1^{(\alpha)}\cdot B_3^{(\alpha)}, A_3^{(\alpha)}\cdot B_1^{(\alpha)}, A_3^{(\alpha)}\cdot B_3^{(\alpha)})$
and $Q^{(\alpha)}=\max(A_1^{(\alpha)}\cdot B_1^{(\alpha)}, A_1^{(\alpha)}\cdot B_3^{(\alpha)}, A_3^{(\alpha)}\cdot B_1^{(\alpha)}, A_3^{(\alpha)}\cdot B_3^{(\alpha)})$

(iv) Division : $\tilde{A}\div\tilde{B}=\tilde{A}\cdot\dfrac{1}{\tilde{B}}$, if $0\notin\tilde{B}$

It is clear that the multiplication and division of two TFNs is not again a TFN with linear sides but it is a new fuzzy number with parabolic sides.

2.3.5 Defuzzification

Aggregating two or more fuzzy output sets (or membership functions) yields a new fuzzy set (or a new membership function) in the basic fuzzy inference algorithm. In most cases, a result in the form of a fuzzy set is converted into a crisp result by the *defuzzification* process. Defuzzification is necessary for hardware applications, because conventional systems' operations are based on crisp data exchange. Among the several methods which are suggested in the literature, the most widely used methods are listed in Table 2.1. As there are two basic mechanisms: centroid and

Table 2.1: Defuzzification Methods

Centroid Methods:	Maxima Methods:
Center of Gravity	Mean of Maximums
Center of Weights	Left-Right Maxima
Center of Largest Area	Maximum Probability
Center of Mass	

maxima. The centroid methods are based on finding a balance point of property that can be the total geometric figure, the weight (area) of each fuzzy set, the area of the largest fuzzy set, or the area of highest intersection. The maximum possibility method searches for the highest peak whereas the left-right maxima method searches for the peak in a selected direction. The mean of maxima method may also be considered as one of the centroid techniques since mean and center practically refer to the same property. Out of these methods, centroid method, also known as center of mass, center of area or center of gravity method, is the most commonly used defuzzification method [195, 199]. In this method defuzzified output $\bar{x}$ is defined as

$$\bar{x} = \frac{\int x \cdot \mu_{\tilde{A}}(x)dx}{\int \mu_{\tilde{A}}(x)dx}, \tag{2.3.7}$$

where the symbol $\int$ denotes algebraic integration.

2.4 Lambda-Tau methodology

It is a traditional method in which fault tree analysis model has been used for modeling the system and the basic expressions of the system failure rate and repair time are used for evaluating their corresponding system parameters of the top event of the system. These basic expressions are summarized in Table 2.2 in which λ_i and τ_i are the failure rate and repair time of the i^{th} component of the system. But disadvantage of this methodology is that they considered the historical data as

Table 2.2: Basic Expressions of Lambda Tau Methodology

Gate	λ_{AND}	τ_{AND}	λ_{OR}	τ_{OR}
Expression	$\prod_{j=1}^{n} \lambda_j \left[\sum_{i=1}^{n} \prod_{\substack{j=1 \\ i \neq j}}^{n} \tau_j \right]$	$\frac{\prod_{i=1}^{n} \tau_i}{\sum_{j=1}^{n} \left[\prod_{\substack{i=1 \\ i \neq j}}^{n} \tau_i \right]}$	$\sum_{i=1}^{n} \lambda_i$	$\frac{\sum_{i=1}^{n} \lambda_i \tau_i}{\sum_{i=1}^{n} \lambda_i}$

such in the analysis. But the data which are collected form various resources are generally out of date or it will represent the past behavior of the data and hence contain some sort of uncertainties. Thus when the data are used as such during the analysis then lambda-tau methodology does not provide the accurate results to the system analyst. Moreover, this approach is valid only for those system whose data are precise. This idea is highlighted by Knezevic and Odoom in 2001 [138] in which uncertainties in the data are handled with the help of defining their triangular fuzzy numbers (TFNs) corresponding to each obtained crisp data. More specifically, the obtained (crisp) data are fuzzified into a triangular fuzzy number ($\tilde{\lambda}_i$ and $\tilde{\tau}_i$) with some known equal spreads (left and right sides to the middle) as suggested by system experts or decision makers (DMs) e.g. $\pm 15\%$ as depicted in Fig. 2.2. Here, $\tilde{\lambda}_i$ is fuzzy failure rate and $\tilde{\tau}_i$ is fuzzy repair time of i^{th} component in the form of triangular fuzzy number with λ_{ij} and $\tau_{ij},\ j = 1, 2, 3$, as their lower, mean (crisp) and upper limits respectively. Based on their input TFNs and the logical expressions of

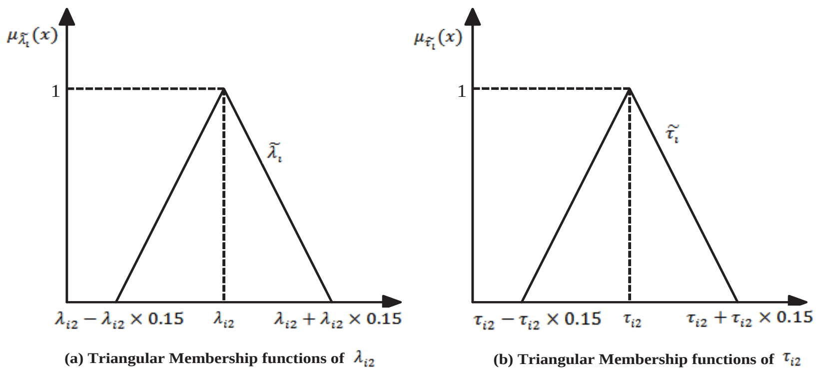


Figure 2.2: A TFN for failure rate $\widetilde{\lambda}$ and repair time $\widetilde{\tau}$

the system failure rate and repair time for the AND and OR gate, various reliability parameter of interest, which depicts the system behavior, such as failure rate, repair time, mean time between failures (MTBF) etc. (given in Table 2.3) are evaluated in the form of fuzzy membership functions with left and right spreads using various fuzzy arithmetic operations. The interval expressions for their fuzzy numbers with triangular membership function, for AND/OR transition can be obtained and are given as follows:

Expressions for AND-Transitions:

$$\lambda^{(\alpha)} = \Bigg[\prod_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\ i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}\Bigg], \qquad (2.4.1)$$
$$\prod_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\ i\neq j}}^{n}\{\tau_{i3}-\alpha(\tau_{i3}-\tau_{i2})\}\Bigg]\Bigg]$$

$$\tau^{(\alpha)} = \left[\frac{\prod_{i=1}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}}{\sum_{j=1}^{n}[\prod_{\substack{i=1\\i\neq j}}^{n}\{\tau_{i3}-\alpha(\tau_{i3}-\tau_{i2})\}]}, \frac{\prod_{i=1}^{n}\{\tau_{i3}-\alpha(\tau_{i3}-\tau_{i2})\}}{\sum_{j=1}^{n}[\prod_{\substack{i=1\\i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}]}\right] \tag{2.4.2}$$

Expressions for OR-Transitions:

$$\lambda^{(\alpha)} = \left[\sum_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}, \sum_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}\right] \tag{2.4.3}$$

$$\tau^{(\alpha)} = \left[\frac{\sum_{i=1}^{n}[\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}\cdot\{(\tau_{i2}-\tau_{i1})\alpha+\tau_{i1}\}]}{\sum_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}}, \frac{\sum_{i=1}^{n}[\{-(\lambda_{i3}-\lambda_{i2})\alpha+\lambda_{i3}\}\cdot\{\tau_{i3}-\alpha(\tau_{i3}-\tau_{i2})\}]}{\sum_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\alpha+\lambda_{i1}\}}\right] \tag{2.4.4}$$

Table 2.3: Some Reliability Parameters

Parameters	Expressions
Failure rate	$\mathrm{MTTF}_s = \frac{1}{\lambda_s}$
Repair time	$\mathrm{MTTR}_s = \frac{1}{\mu_s} = \tau_s$
Mean Time Between Failures	$\mathrm{MTBF}_s = \mathrm{MTTF}_s + \mathrm{MTTR}_s$
Reliability	$\mathrm{R}_s = e^{-\lambda_s t}$
Availability	$\mathrm{A}_s = \frac{\mu_s}{\lambda_s+\mu_s} + \frac{\lambda_s}{\lambda_s+\mu_s}e^{-(\lambda_s+\mu_s)t}$
Expected numbers of failures	$\mathrm{W}_s(0,t) = \frac{\lambda_s\mu_s t}{\lambda_s+\mu_s} + \frac{\lambda_s^2}{(\lambda_s+\mu_s)^2}[1-e^{-(\lambda_s+\mu_s)t}]$

As most of the actions taken by humans or machines are generally crisp or binary in nature. Thus the defuzzification is necessary for converting the fuzzy output to crisp output. Out of existence of various defuzzification methods, described in section 2.3.5, center of gravity method (COG) has been used because it has the advantage of being taken the whole membership function into account for this transformation.

2.4.1 Shortcomings of λ-τ methodology

The following shortcomings are observed during the analysis of the repairable industrial system/subsystems when fuzzy lambda-tau (FLT) methodology has been applied for computing their reliability parameters.

- One of the major shortcoming is observed from the study that this approach is limited for a small size structure system. In other words, when the system structure is complex or large then the computed reliability indices contain wide range of spread due to various fuzzy arithmetic operations.

- It adopted a simple strategy to compute the defuzzified values of all the reliability parameters at different levels of uncertainties and computed only defuzzified values of failure rate and repair time at a given level of uncertainties, and then used these values for obtaining the defuzzified values of other reliability parameters.

- The fuzzy arithmetic operations have been used for computing the systems' parameters and hence the method will not produce the actual trend of values of these reliability parameters as per the variations in uncertainty levels.

- There is no sensitivity analysis conducted on the system performance w.r.t. parameters variations.

2.5 Evolutionary Algorithm

This section briefly describes the evolutionary algorithms (EAs) namely Genetic algorithm, Particle swarm optimization and Artificial bee colony optimization which are used in the presented analysis.

2.5.1 Genetic Algorithm (GA)

Genetic algorithms (GAs) are a part of evolutionary algorithms, a rapidly growing area of artificial intelligence. Holland [102] is considered the father of GA. GA is a model or concept of biological evolution based on Charles Darwin's theory of natural selection. The essence of GAs involves the encoding of an optimization function as arrays of bits or character strings to represent the solutions (represented by chromosomes). Starting from possible solutions termed as the population, evolution cycle or iterations by evaluating the fitness of all the individuals in the population, creating a new population by performing crossover, and mutation etc., and replacing the old population and then iteratively again using the new population. The above process is repeated until some stopping condition is satisfied. A more detailed implementation of genetic algorithm can be found in [85, 86] etc. The pseudo code of the GA algorithm is described in Algorithm 1:

Algorithm 1 Pseudo code of Genetic algorithm (GA)

Objective function: $f(\mathbf{x})$
Define Fitness F (eg. $F \propto f(x)$ for maximization)
Initialize population
Initial probabilities of crossover (p_c) and mutation (p_m)
repeat
    Generate new solution by crossover and mutation
    if $p_c >$rand, Crossover; end if
    if $p_m >$rand, Mutate; end if
    Accept the new solution if its fitness increases.
    Select the current best for the next generation.
until requirements are met

2.5.2 Particle Swarm Optimization(PSO)

Particle Swarm Optimization (PSO) [72, 127] is a population-based optimization technique of swarm intelligence field inspired by social behavior of bird flocking or fish schooling in which each solution called "particle" flies around in a multidimensional problem search space. Unlike the genetic algorithm, PSO algorithm has no crossover and mutation operators. In this algorithm, the particle follows the piecewise paths formed by positional vectors in a quasi-stochastic manner. During movement, every particle adjusts its position according to its own experience of neighboring particles, using the best position encountered by itself and its neighbors. The former one is known as personal best (pbest, p_i) and the latter one is global best (gbest, p_g). Acceleration is weighted by random terms, with the separate random number being generated for acceleration towards pbest and gbest locations, respectively. Based on the pbest and gbest information of the each particle's, the velocity (v_i) and position of the particle (x_i) are updated according to equations (2.5.1) and (2.5.2) respectively as,

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot ud \cdot (p_i(t) - x_i(t)) + c_2 \cdot Ud \cdot (p_g(t) - x_i(t)) \quad (2.5.1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2.5.2)$$

where w is the inertia weight; $i = 1, 2, \cdots, N$ indicates the number of the particles of the population (swarm), $t = 1, 2, \cdots, t_{\max}$ indicates the iterations; Positive constant c_1& c_2 are the cognitive and social components, respectively, which are the acceleration constants responsible for varying the particle velocity towards pbest and gbest, respectively. Variables ud and Ud are two random functions in the range [0, 1]. Equation (2.5.2) represents the position update, according to its previous position and its velocity.

The essential steps of the particle swarm optimization can be summarized as the pseudo code given in Algorithm 2.

2.5.3 Artificial Bee Colony (ABC) Optimization

Artificial Bee Colony algorithm (ABC) was initially published by Karaboga in 2005 as a technical report for numerical optimization problems [116] and its co-authors for optimizing numerical problems [118, 120, 124]. Its development was motivated by simulating the intelligent foraging behaviour of honey bees in their colony and

Algorithm 2 Pseudo code of Particle swarm optimization (PSO)

1: Objective function: $f(\mathbf{x}), \quad \mathbf{x} = (x_1, x_2, \ldots, x_D)$;
2: Initialize particle position and velocity for each particle and set $t = 1$.
3: Initialize the particle's best known position to its initial position
4: **repeat**
5: Update the best known position (p_i) for each particle
6: Update the swarm's best known position (p_g)
7: Calculate particle velocity according to the velocity equation (2.5.1).
8: Update particle position according to the position equation (2.5.2).
9: **until** requirements are met.

its performance was initially measured using benchmark optimization function. As compared with other metaheuristics ABC does not employ crossover operators to produce new or candidate solutions from the present ones. It produces the candidate solution from its parent by a simple operation based on taking the difference of randomly determined parts of the parent and a randomly chosen solution from the population. Moreover, ABC employs less number of control parameters than others as it employs only population size(colony size) and maximum cycle number. Due to these features and having the advantages of memory, multi-character, local search and solution improvement mechanism, ABC is able to discover an excellent optimal solution. In recent times, however, the attention of researchers in the engineering and optimization domains have been drawn to adopt the use of ABC for a variety of decision making problems such as for constrained optimization [28, 117, 236], in engineering [7, 224], economic dispatch problems [225], neural network [104, 123, 213, 254], software engineering [58, 131, 171], multi-objective [187, 265, 269] and many others.

ABC algorithm provides solution in organized form by dividing the bee objects into different tasks such as employed bees, onlooker bees, and scout bees. These three bees/tasks determine the objects of problems by sharing information to others bees. Half of the colony consists of the employed bees, and another half consists of onlookers. The number of solutions in the swarm are equal to the employed and onlooker bees i.e. number of employed bees and onlooker bees are same as that of number of swarms positions. In these, employed bees randomly search the position of the bee in the entire swarm in the form of food sources, while on the dancing areas, they share their information with the onlooker bees which are waiting in the dance area at the hive to choose a food source. The duration of a dance is proportional to the nectar's content (fitness value) of the food source being exploited by the employed bee. When the food-source position has been visited (tested) fully, the employed bee associated with it abandons it, and may once more become a scout or onlooker bee. In the scout phase bees searching for food sources randomly. In the ABC algorithm, onlookers and employed bees perform the exploration process in the search space, while, on the other hand, scouts control the exploration process.

ABC algorithm starts with the initialization phase, in which solution or population of food sources' positions ($X_i, i = 1, 2, \cdots, SN$) are initialized randomly by the bees within the search domain and their nectar amounts (i.e. fitness function) are determined. Here, SN represents the colony size and D is the dimension size. After initialization, the population of the solutions are subjected to repeated cycle of the search processes for the employed, onlooker and scout bees. Here $cycle = 1, 2, \cdots$ MCN, where MCN represents the maximum cycle number of the search process used for the termination criterion.

In the employed bees phase, let $X_i = \{x_{i,1}, x_{i,2}, \cdots, x_{i,D}\}$ be the position of the i^{th} solution in the swarm, then the artificial employed bees search for a new food sources V_i in the neighborhood of each of its present employed bee X_i as follows:

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) \tag{2.5.3}$$

where X_k is the randomly selected candidate solution such that index k is differ from the index i i.e. $(i \neq k)$ and j is the randomly chosen dimension index from the set $\{1, 2, \cdots, D\}$ and $\phi_{i,j}$ is the random number between [-1,1]. Except for the selected parameter index j, all other parametric values of V_i are the same as that of X_i i.e. $V_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,(j-1)}, v_{i,j}, x_{i,(j+1)}, \cdots, x_{i,D})$. Based on their new candidate solution V_i, its fitness is calculated and a greedy selection process is carried out by it and its parent. If the solution is better than that of its present one then replace X_i with V_i; otherwise keep X_i unaltered.

After the employed bee phase is completed, they share their food source information with onlooker bees who are waiting in the hive by dancing on the dancing area. In this phase, based on these employed bees solutions, nectar (fitness) amount corresponding to each solution is evaluated by a fitness function and chooses a food source X_i with a probability (p_i) proportional to the nectar content as defined by Eq. (2.5.4)

$$p_i = \frac{f_i}{\sum\limits_{i=1}^{SN} f_i} \tag{2.5.4}$$

where $f_i = f(X_i)$ is the fitness of the solution represented by the food source i and SN is the number of food sources. Clearly, resulting from using Eq. (2.5.4), a good food source will attract more onlooker bees than a bad one. After all onlookers have selected their food sources, each of them determine a food source in the neighborhood of its own chosen food source and compute its fitness i.e. greedy selection process as described in Eq. (2.5.3) is performed on the onlooker bees. The best food source among all the neighboring food sources determined by the onlookers associated with a particular food source i itself, will be the new location of the food source i.

Furthermore, if the i^{th} solution of the source does not improve beyond the predetermined number called 'limit' then the employed bee associated with this solution abandons it, and becomes a scout. Assume that abandonment source is x_i and $j \in \{1, 2, \cdots, D\}$ then the scout discovers a new food source to be replaced with randomly generated food source x_i within its domain $[x_{\min}, x_{\max}]$ as follow

$$x_{i,j} = x_{\min,j} + rand \cdot (x_{\max,j} - x_{\min,j}) \tag{2.5.5}$$

where $rand$ is the random number between (0,1). So this randomly generated food source is equally assigned to this scout and changing its status from scout to employed and hence other iteration/cycle of the algorithm begins until the termination condition, maximum cycle number (MCN) or relative error, is not satisfied.

The general algorithm structure of the ABC optimization approach is given in Algorithm 3 as follows:

Algorithm 3 Pseudo code of the ABC algorithm

1: Objective function: $f(\mathbf{X}), \quad \mathbf{X} = (x_1, x_2, \ldots, x_D)$;

2: Generate an initial bee population (solution) X_i where $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$ and number of employed bees are equal to onlooker bees;

3: Evaluate fitness value

4: Initialize cycle=1

5: For *each employed bee*

  (a) Produce new food source position $v_{i,j}$ in the neighborhood of $x_{i,j}$ by Eq. (2.5.3)

  (b) Evaluate the fitness value at new source $v_{i,j}$

  (c) If new position is better than previous position then memorizes the new position.

6: End For.

7: Calculate the probability values $p_i = \dfrac{f_i}{\sum\limits_{i=1}^{SN} f_i}$ for the solution.

8: For *each onlooker bee*

  (a) Chooses a food source depending on p_i for the solutions X_i

  (b) Produce new food source positions V_i from the populations X_i depending upon p_i and evaluate their fitness.

  (c) If new position is better than previous position, then memorizes the new position.

9: End For

10: If there is any abandoned solution i.e. if employed bee becomes scout then replace its position with a new random source positions

11: Memorize the best solution achieved so far

12: cycle = cycle + 1

13: If termination criterion is satisfied then stop otherwise go to step 5

2.6 Merits of ABC over other algorithms

The following are the main features of the ABC which completely shows the justification of using ABC algorithm rather than other meta-heuristic algorithms like GA, DE, PSO etc.

1. While GA and DE employ crossover operators to produce new or candidate solutions from the present ones, ABC algorithm does not. ABC algorithm produces the candidate solution from its parent by a simple operation based on taking the difference of randomly determined parts of the parent and a randomly chosen solution from the population. This process increases the convergence speed of search into a local minimum.

2. In GA, DE and PSO the best solution found so far is always kept in the population and it can be used for producing new solutions in the case of DE and GA, new velocities in the case of PSO. However, in ABC, the best solution discovered so far is not always held in the population since it might be replaced with a randomly produced solution by a scout. Therefore, it might not contribute to the production of trial solutions.

3. Apart from the maximum evaluation number and population size, a standard GA has three more control parameters (crossover rate, mutation rate, generation gap), a standard DE has at least two control parameters (crossover rate, scaling factor) and a basic PSO has three control parameters (cognitive and social factors, inertia weight) whereas ABC algorithm has only one control parameter limit. In the present work, an expression for determining the value of "limit" depending on population (colony size) and dimension of problem has been used i.e. $limit = SN \times D$. Therefore, ABC has only two common control parameters: maximum cycle number (MCN) and colony size (SN). Consequently, ABC is as simple and flexible as DE and PSO; and also employs less control parameters.

4. In GA or DE, mutation process creates a modification on a randomly selected part of a solution to provide required diversity in the population. In ABC, rather than changing a part of a solution, a whole solution in the population is removed and then a new one produced randomly is inserted into the population by a scout. This mechanism provides the ABC algorithm a global search ability and prevents the search from premature convergence problem. Hence, there is a good balance between the local search process carried out by artificial onlooker and employed bees and the global search process managed by artificial scouts.

2.7 Parameter Setting

While using GA, PSO and ABC algorithm, the values of the common parameters used in each algorithm such as population size and total evaluation number are chosen to be the same, and are randomly as $20 \times D$ and 1000 respectively where D is the dimension of the problem. The method has been implemented in Matlab and the program has been run on a T6400 @ 2GHz Intel Core(TM) 2 Duo processor with 2GB of Random Access Memory. In order to eliminate stochastic discrepancy, 30 independent runs have been made that involves 30 different initial trial solutions. The termination criterion has been set either limited to a maximum number of generations or to the order of relative error equal to 10^{-6}, whichever is achieved first. The other specific parameters of algorithms are given below:

GA Settings: In all experiments, we employed a real coded GA having evaluation, fitness scaling, crossover, mutation units. Roulette wheel selection criterion is employed to choose better fitted chromosomes. One-point crossover with the rate of 0.85 are employed and random point mutation with rate 0.01 are used in the present analysis for the reproduction of new solution.

PSO setting: In the experiment, cognitive and social components, c_1 and c_2, in eq. (2.5.1) are both set to be 1.49 while Inertia weight (w) was defined as the linearly decreases from initial weight w_1 to final weight w_2 with the relation $w = w_2 + (w_1 - w_2)(iter_{\max} - iter)/iter_{\max}$. Here $iter_{\max}$ represents the maximum generation number and '$iter$' is used a generation number as recommended in [51, 219]

ABC Settings: There is only one control parameter except for the common parameters which is called 'limit'. The limit value is defined by using the dimension (D) of the problem and the colony size (SN) as $limit = SN \times D$ [118].

2.8 Constraints handling

The main task while solving the constrained optimization problem is to handle the constraints. In the constrained optimization problem, it is not easy to find the feasible solution of the problem due to the presence of both type of constraints in the form of equalities and inequalities. When GA or PSO algorithms are used for constrained optimization problem then penalty function, which penalize the unfeasible function, is used to handle the constraints. Despite the popularity of penalty functions, they have several drawbacks out of which the main one is that of having two many parameters to be adjusted and finding the right combination of the same may not be easy. Also during that the search is very slow and there is no guarantee that the optima will be attained. To overcome this limitation, Deb [59] modified these algorithms by proposing a parameter free penalty function given in Eq. (2.8.1) in which the fitness of an infeasible solution not only depends on the amount of the constraint violation, but also on the population of solutions at hand. Thus the modified function is

$$F(x) = \begin{cases} f_w + \sum_i g_i(x) & ;\text{if } x \notin S \\ f(x) & ;\text{if } x \in S \end{cases} \tag{2.8.1}$$

where f_w is the objective function value of the worst feasible solution currently available in the population and S is the search space. If there are no feasible solutions in the population, then f_w is set to be zero.

Chapter 3

Cost minimization of butter-oil processing plant using artificial bee colony technique

This chapter deals with the performance evaluation of butter-oil processing plant. The Reliability Block Diagram (RBD) of the system are drawn and based on it, availability-cost optimization model of the system is constructed by considering availability function, manufacturing cost and repair cost, and optimal values of MTBF and MTTR are obtained by using ABC algorithm.

3.1 Introduction

With advances in technology and increasing demand of reliable components for a longer interval of time, the study of reliability and availability optimization becomes plays a dominant role for a series-parallel system architecture. To maintain the reliability or availability of the system to a higher level, the system structural design or system components of higher reliability or both are required simultaneously. However, with the design of the highly reliable system there is correspondingly increase in their weight, cost etc. Therefore, optimization methods are necessary to obtain allowable costs at the same time as high availability levels.

The reliability of a series-parallel system has drawn continuous attention in both problem characteristics and solution methodologies. For the framework of series-parallel system, it is very difficult to find out an optimal solution under multiple constraint conditions [48]. Under an increasingly complex and diversified system environment, Yuen and Katafygiotis [259] have used simulation methods to evaluate the reliability or availability of a complex system, as common estimation methods are subjected to strict assumptions. Under repairable series-parallel system framework, there are many methods in the literature such as dynamic programming, integer programming, nonlinear integer programming and heuristic or meta-heuristic algorithms [156, 231] for determining the optimal parameters of components. Wang [243] suggested two methods for the estimation of availability. The first method is applicable when the allocation of MTBF and MTTR is subjected to exponential distribution, while the second one is to estimate the interval of availability when none of them is subjected to exponential distribution. These two methods were examined and compared by the Monte Carlo simulation. Li et al. [159] proposed a new efficient exact method for solving both pure and mixed-integer nonlinear programming problems arising from reliability optimization in complex systems using a convexification scheme. Caserta and Nodar [38] proposed a Cross Entropy-based algorithm for reliability optimization of complex systems, where one wants to maximize the reliability of a system through optimal allocation of redundant components while respecting a set of budget constraints. Apart from that a lot of researchers have investigated the problems of availability modeling by using evolutionary algorithms [37, 53, 75, 79, 85, 88, 115, 155, 158, 174, 245] and their corresponding references.

ABC is one of the most recently defined algorithms by Dervis Karaboga in 2005 [116], motivated by the intelligent behavior of honey bees and further developed by Karaboga and others [8, 24, 118, 121, 124]. As compared with other meta-heuristics ABC does not employ crossover operators to produce new or candidate solutions from the present ones. It produces the candidate solution from its parent by a simple operation based on taking the difference of randomly determined parts of the parent and a randomly chosen solution from the population. Moreover, ABC employs less number of control parameters than others as it employs only population size(colony size) and maximum cycle number. Due to these features and have the advantages of memory, multi-character, local search and solution improvement mechanism, ABC is able to discover an excellent optimal solution. Yeh and Hsieh [253] showed that the solution of series-parallel problem found by ABC is better than the other meta-heuristic techniques in reliability optimization problems. The same has also been established by Hsieh and Yeh [105]. Motivated by this, the present chapter considers the availability-cost optimization problem of a industrial system in which an optimization model has been formulated by considering the total cost (manufacturing and repairing cost) of the system as an objective retaining the preassigned system availability. The preassigned availability which may be the optimized availability of the system as obtained by some other technique acts as a constraint and the problem is solved with ABC technique. The approach has been applied on the butter-oil processing plant to find their optimal design parameters.

3.2 Problem formulation & mathematical model

3.2.1 Expression of the System Availability

Reliability or availability analysis of a series-parallel system becomes increasingly tedious as the system structure becomes complex and complex. In these cases, it is difficult, if not impossible, to construct the accurate and precise mathematical model for estimating the optimal design parameters for increasing its performance and productivity. Moreover, the information extracted from the past record/history are much dependent on the system configuration. Thus in order to obtain the optimal design parameter- MTBF and MTTR- of the system/component which make the maximum profit to the system analyst or DM, the approximate expression of the system availability index has been formulated on the basis of its reliability block diagram (RBD) under the following assumptions.

(a) the components of the system are operated independently, i.e. the failure and repair characteristics of components are statistically independent,

(b) the failure rate (λ_i) and repair rate (μ_i) of i^{th} component are constants for each component,

(c) There are no simultaneous failures among the subsystems.

(d) $\lambda_i < \mu_i$, and

(e) separate maintenance facility is available for each component. The repair process begins soon after a unit fails.

(f) The repaired unit or system is as good as new.

The basic parameters for series and parallel system are shown in Table 3.1 [25] where λ_s and μ_s represent respectively the failure and repair rates of the system. Then the

Table 3.1: Basic Parameters of Availability for Series-Parallel Systems

Type of System	Expression
Series Configuration	$\mathrm{Av}_s = \mathrm{Av}_1 \cdot \mathrm{Av}_2 \cdots \mathrm{Av}_n \approx 1 - (\frac{\lambda_1}{\mu_1} + \frac{\lambda_2}{\mu_2} + \cdots + \frac{\lambda_n}{\mu_n})$ $\lambda_s \approx \lambda_1 + \lambda_2 + \cdots + \lambda_n$; $\mu_s \approx \frac{\lambda_1+\lambda_2+\cdots+\lambda_n}{\frac{\lambda_1}{\mu_1}+\frac{\lambda_2}{\mu_2}+\cdots+\frac{\lambda_n}{\mu_n}}$
Parallel Configuration	$\mathrm{Av}_s \approx 1 - \frac{\lambda_1 \cdot \lambda_2 \cdots \lambda_n}{\mu_1 \cdot \mu_2 \cdots \mu_n}$ $\lambda_s \approx \frac{\lambda_1 \cdot \lambda_2 \cdots \lambda_n (\mu_1+\mu_2 \cdots \mu_n)}{\mu_1 \cdot \mu_2 \cdots \mu_n}$; $\mu_s \approx \mu_1 + \mu_2 + \cdots + \mu_n$

approximate expression of the availability Av_s parameter for the series and parallel system can be written as:

$$\mathrm{Av}_s = f(\mathrm{MTBF}_1, \cdots \mathrm{MTBF}_n, \mathrm{MTTR}_1, \cdots \mathrm{MTTR}_n) \tag{3.2.1}$$

3.2.2 Expression for total system cost:

A design engineer has several options to improve the reliability of a system with a given basic design. But an optimal reliability design is one in which all possible means available to a designer have been explored to enhance the reliability or availability of the system with limited available system cost. According to Aggarwal and Gupta [4] the cost of reliability is monotonically increasing function of reliability and hence on its mean time between failures. Also its cost versus reliability is an equivalent feature to the cost versus maintainability functions. As the system designer will always like to repair the fault component as soon as possible for saving money, manpower and time, the total cost of the system or component will depend upon its manufacturing as well as on its repairing. For this, manufacturing cost will depend on the product specification in which cost of the component is likely to be higher when its failure rate will be lower or equivalently MTBF is longer which lead to sharp increase in the manufacturing cost [162]. Therefore, MTBF of a component and manufacturing cost are related to each other as shown in Fig. 3.1(a), with the relation defined mathematically as [115, 231]

$$\mathrm{CMTBF}_i = \alpha_i \cdot (\mathrm{MTBF}_i)^{\beta_i} + \gamma_i \tag{3.2.2}$$

where, CMTBF_i and MTBF_i, respectively, represent the manufacturing cost and MTBF of the i^{th} component, while, α_i, β_i and γ_i are constants, representing the physical property of the i^{th} component and β_i is greater than one.

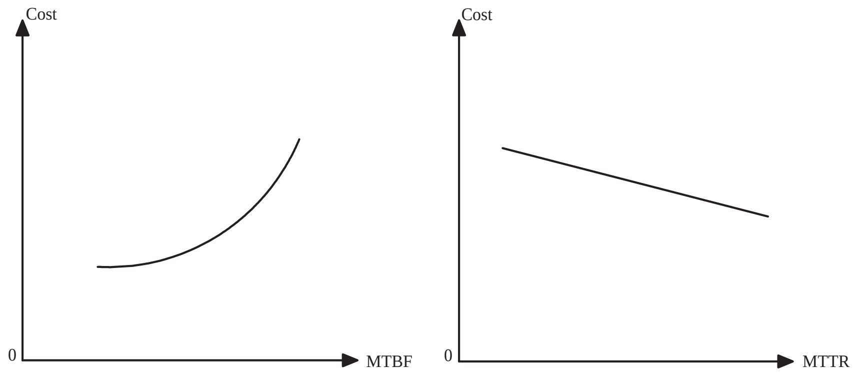
On the other hand, the failure of any component will reduce the output or even impair the efficiency of the complete system. So it is necessary to repair the faulty components of the system as soon as possible for avoiding such occurrences and to facilitate the repair within a reasonable time for saving the money, manpower and time. For this, a linear relationship between the MTTR_i and its corresponding repairing cost CMTTR_i as shown graphically in Fig. 3.1(b), are expressed mathematically as [115]:

$$\mathrm{CMTTR}_i = a_i - b_i \cdot \mathrm{MTTR}_i \tag{3.2.3}$$

while, a_i and b_i are constants depending upon the i^{th} component.

Based on equations (3.2.2) and (3.2.3), the total cost can be written as:

$$\mathrm{Tc} = \sum_{i=1}^{n} (\alpha_i \cdot (\mathrm{MTBF}_i)^{\beta_i} + \gamma_i) + \sum_{i=1}^{n} (a_i - b_i \cdot \mathrm{MTTR}_i) \tag{3.2.4}$$



(a) MTBF and Cost (b) MTTR and Cost

Figure 3.1: Relation Between (a) MTBF and the Associated Cost, (b) MTTR and the Associated Cost

3.2.3 Optimization model

Using availability (3.2.1) and the achieved cost (3.2.4) of the system, the optimization model is formulated as

$$\begin{aligned} &\text{Minimize} && \mathrm{Tc} \\ &\text{subject to} && \mathrm{Av}_s \geqslant A_{min} \\ &&& \mathrm{LbMTBF}_i \leqslant \mathrm{MTBF}_i \leqslant \mathrm{UbMTBF}_i \\ &&& \mathrm{LbMTTR}_i \leqslant \mathrm{MTTR}_i \leqslant \mathrm{UbMTTR}_i \\ &&& i = 1, 2 \cdots n \quad \text{All variables} \geqslant 0 \end{aligned} \tag{3.2.5}$$

where $\mathrm{LbMTBF}_i, \mathrm{UbMTBF}_i, \mathrm{LbMTTR}_i, \mathrm{LbMTTR}_i$ are respectively the lower and upper bound of MTBF and MTTR for i^{th} component of the system. The optimization model (3.2.5) thus obtained is solved by the evolutionary techniques.

3.3 System description

To illustrate the proposed approach the butter-oil manufacturing plant is discussed here [94, 143]. The given system consists of six sub-systems. A brief outline of the system is described as below:

1. **Sub-system A (Separator):** This part of the plant works on the principle of centrifugal force. Chilled milk from chiller is taken to the cream separator, where fats are separated from the milk in the form of cream containing 40-50 per cent fat and the remaining skimmed milk is stored in milk silos for preparing milk powder. It consists of three components in series, namely, motor, bearings and high-speed gearbox.

2. **Sub-system B (Pasteurizer):** Cream from separator is pasteurized in this sub-system. Pasteurization refers to the process of heating every particle of cream to not less than 71^0C. In practice it is heated up to 80^0C to 82^0C for no holding time. Its purpose is to destroy pathogenic and undesirable organisms, to inactivate the enzymes present and to make possible removal of volatile flavors. This sub-system is also used to remove the tanning substances present in the cream. The pasteurized cream is stored in double-jacketed cream storage tank for further processing. When the pasteurized milk goes out of this sub-system, some particles (or residues) get stuck around the outlet and the flow gets affected. This effect gradually increases with the passage of time and sludge is formed at the out let. This sludge gradually increases in size and blocks the flow of milk, thus resulting in the failure of the sub-system. This sub-system consists of a motor and bearings in series.

3. **Sub-system C (Continuous butter making):** Cream from the cream storage tank is pumped into the continuous butter making machine (CBM). The cream is churned in this machine in order to get butter granules. The buttermilk produced in this process is pumped back to raw milk silos and the butter

granules are further processed in the machine so as to get homogeneous mass of butter. The homogeneous butter is taken out from machine into butter trolleys and shifted to melting vats. The CBM consists of gearbox, motor and bearings in series.

4. **Sub-system D (Melting vats):** This sub-system consists of a double-jacketed storage tank. Butter is melted in this section at about 107^0C very gently so that the water evaporates from the melting butter. The melted butter is then allowed to remain undisturbed for about half an hour. This sub-system consists of monoblock pumps, motors and bearings in series.

5. **Sub-system E (Butter-oil clarifier):** Butter-oil from melting vats is taken out into butter-oil settling tanks where it is allowed to settle for a few hours. After this the fine particles of butter-oil residue are removed from the butter-oil and then butter-oil is stored in storage tanks. Now, it is cooled to a temperature of 28^0C to 30^0C suitable for storage of butter-oil. This sub-system consists of motor and gearbox in series.

6. **Sub-system F (Packaging):** In this sub-system the packets of processed butter-oil are created using a pouch-filling machine. It is a fill, flow and seal automatic machine. This sub-system consists of printed circuit board and pneumatic cylinder in series.

3.3.1 Mathematical Model of the System

The interaction among the various subsystem of the plant are shown by Reliability Block Diagram (RBD) in Fig. 3.2. Based on its RBD and the expression given in

Table 3.1, the optimization model of the considered plant is given as

$$
\begin{aligned}
\text{Minimize} \quad \text{Tc} &= \sum_{i=1}^{6} (\alpha_i \cdot (\text{MTBF}_i)^{\beta_i} + \gamma_i) + \sum_{i=1}^{6} (a_i - b_i \cdot \text{MTTR}_i) \\
\text{subject to} \quad & \text{Av}_s \geqslant A_{min} \qquad (3.3.1) \\
& \text{LbMTBF}_i \leqslant \text{MTBF}_i \leqslant \text{UbMTBF}_i \\
& \text{LbMTTR}_i \leqslant \text{MTTR}_i \leqslant \text{UbMTTR}_i \\
& i = 1, 2 \ldots 6 \quad \text{All variables} \geqslant 0 \\
\text{where} \quad \text{Av}_s &= 1 - \left[5 \cdot \frac{\text{MTTR}_1}{\text{MTBF}_1} + 4 \cdot \frac{\text{MTTR}_2}{\text{MTBF}_2} + 3 \cdot \frac{\text{MTTR}_3}{\text{MTBF}_3} + \sum_{i=4}^{6} \frac{\text{MTTR}_i}{\text{MTBF}_i} \right] \\
A_{\min} &= 0.96
\end{aligned}
$$

where MTBF_i and MTTR_i are the mean time between failures and mean time to repair of the i^{th} component of the system and Av_s and Tc are respectively availability and cost of the system. The lower and upper bounds of MTBF and MTTR are tabulated in Table 3.2 while the respective values of α, β and γ are taken to be 0.92, 1.94 and 1250, whereas a and b are assumed to be 18150 and 50, respectively, from the literature [143].

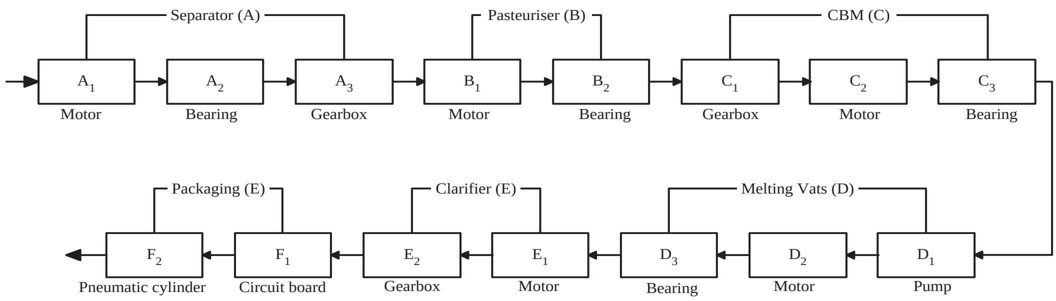


Figure 3.2: Reliability Block Diagram of Butter-Oil Processing Plant

3.4 Results and Discussions

In this section results obtained by the optimization technique are described and analyzed.

Table 3.2: Variance Range of MTBF and MTTR for each Component of the Butter-Oil Processing Plant

Component	MTBF (hrs)		MTTR (hrs)	
	LbMTBF	UbMTBF	LbMTTR	UbMTTR
Motors	4025	4125	4.0	5.0
Bearings	4100	4200	2.0	3.0
Gear Box	4075	4175	4.5	5.5
Pumps	4150	4250	2.5	3.5
Circuit Box	4070	4170	2.0	3.0
Cylinder	4115	4215	2.5	3.5

3.4.1 Computational results

By using the parameters setting as given in section 2.7, the optimal design parameters for the system cost are obtained by solving the optimization problem (3.3.1) with the three algorithms namely GA, PSO and ABC and their corresponding results are tabulated in Table 3.3. Each of the experiments in this section was repeated 30 times with different random seeds and the best values produced by the algorithms have been recorded. By using these optimal designs – MTBF and MTTR – result, the system analyst/decision maker may plan suitable maintenance strategies to improve system performance and to reduce operation and maintenance costs. The best, mean, worst, median and standard deviation (SD) values of the objective functions are summarized in Table 3.4.

Table 3.3: Optimal Design Parameters for Butter-Oil Processing Plant

	GA		PSO		ABC	
Components	MTBF	MTTR	MTBF	MTTR	MTBF	MTTR
Motors	4118.9952212	4.2843858	4029.4362431	4.6938213	4029.8243580	4.3041114
Bearing	4148.3659480	2.6036587	4104.7069313	2.5729568	4107.3792059	2.5036840
Gear Box	4143.9751348	5.4818490	4083.0290973	4.8907689	4075.7680236	5.1518057
Pumps	4231.5483428	2.7229241	4159.3619740	2.5067517	4177.4317633	2.8491466
Circuit Box	4173.5656629	2.6617569	4126.7575943	2.6305498	4082.9188943	2.6350220
Cylinder	4180.8910331	3.1493177	4117.3618028	2.8729487	4116.2605990	3.4395527
System Cost	1.4427458873×10^8		1.3987850183×10^8		1.3971990799×10^8	
System Availability	0.9862856		0.9861368		0.9862664	

To test whether the mean of ABC results is statistically better than that of GA and PSO results, analysis has been done by using t-test. Since t-test assumes the

Table 3.4: Statistics Analysis for the Optimization Problem

Methods	Mean ($\times 10^8$)	Best ($\times 10^8$)	Worst ($\times 10^8$)	Median ($\times 10^8$)	SD ($\times 10^5$)
GA	1.44689425	1.44274588	1.45117503	1.44675304	1.94195049
PSO	1.40151211	1.39878501	1.40434081	1.40130492	1.57322023
ABC	1.39919068	1.39719907	1.40257548	1.39917395	1.86459902

equality of variances and hence for this one tail F–test has been performed with significant level of α=0.05. The calculated values of F-statistics (=1.08468940 and 1.40472677 respectively for GA and PSO when paired with ABC) is less than the F-critical value (=1.860811) at (29, 29) degree of freedom. Hence null hypothesis of equal variances, i.e. of equal variances may be accepted. Now a single-tail t-test with equal variances was performed with null hypothesis that their mean difference is zero for the case of ABC results with GA and PSO results at 5% level of significance. The results of the t-test for the minimum cost of the system are shown in Table 3.5

Table 3.5: t-test: Two-Sample Assuming Equal Variances for Cost of the System

	Cost of the system		
	GA	PSO	ABC
Mean ($\times 10^8$)	1.44689425	1.40151211	1.39919068
Variance ($\times 10^{10}$)	3.77117170	2.47502191	3.47672954
Std ($\times 10^5$)	1.94195049	1.57322023	1.86459903
Observations	30	30	30
Pooled variance ($\times 10^{10}$)	3.74891443	3.07849212	
Hypothesized mean difference	0	0	
degree of freedom	58	58	
t stat	95.420952	5.124272	
P(T$\leq$ t) one tail	0	1.78810753×10^{-6}	
T critical one-tail	1.671552	1.671552	

and it is indicated from the table that values of t-stat are much greater than the t-critical values. Also the probability value (p-value) obtained from the test is less than the significant level α. Thus it is highly significant and null hypothesis i.e. means of two algorithm are identical is rejected. Hence the two types of means differ significantly. Further, since mean of cost of system with ABC is less than the mean of cost of system with GA and PSO, we conclude that ABC is definitely better than GA and PSO results and this difference is statistically significant.

3.4.2 Sensitivity analysis

To analyze the impact of change in values of α_i, β_i and a_i, b_i on to the system's cost, behavioral plots have been plotted for different combinations of these parameters and are shown in Figs. 3.3 and 3.4 respectively for the first component of the system (i.e. motors). Throughout the combinations, ranges of MTBF and MTTR are fixed and have been varied, along the x and y-axes respectively, while their effects on the total cost of system are represented along z-axis. For instance, in the first three plots of Fig. 3.3, the value of β_i has been fixed to 1.93 while the α_i change from 0.91 to 0.92 and further to 0.93. Similar plots have been observed for a_i and b_i in Fig. 3.4. From these, it is clear that a_i and b_i produce a little effect on cost as compared to α_i, β_i. The computed range of system cost for all the combinations are tabulated

Table 3.6: Change in Tc for Various Combinations of (α_i,β_i) and (a_i,b_i)

S.No.	[α_i, β_i]	Tc ($\times 10^6$)	[a_i, b_i]	Tc ($\times 10^6$)
1.	[0.91, 1.93]	Min: 8.265078 Max: 8.665088	[17150, 40]	Min: 9.076228 Max: 9.517949
2.	[0.92, 1.93]	Min: 8.355693 Max: 8.760098	[18150, 40]	Min: 9.077228 Max: 9.518949
3.	[0.93, 1.93]	Min: 8.446307 Max: 8.855108	[19150, 40]	Min: 9.078228 Max: 9.519949
4.	[0.91, 1.94]	Min: 8.978721 Max: 9.415651	[17150, 50]	Min: 9.076178 Max: 9.517909
5.	[0.92, 1.94]	Min: 9.077178 Max: 9.518909	[18150, 50]	Min: 9.077178 Max: 9.518909
6.	[0.93, 1.94]	Min: 9.175635 Max: 9.622167	[19150, 50]	Min: 9.078178 Max: 9.519909
7.	[0.91, 1.95]	Min: 9.754126 Max: 10.23137	[17150, 60]	Min: 9.076128 Max: 9.517869
8.	[0.92, 1.95]	Min: 9.861103 Max: 10.34359	[18150, 60]	Min: 9.076128 Max: 9.518869
9.	[0.93, 1.95]	Min: 9.968081 Max: 10.45581	[19150, 60]	Min: 9.076128 Max: 9.519869

in Table 3.6. Based on these behavioral plots, the system manager can analyze the critical behavior of the system-cost for fixed MTBF and fixed MTTR and hence can plan for suitable maintenance and higher goals.

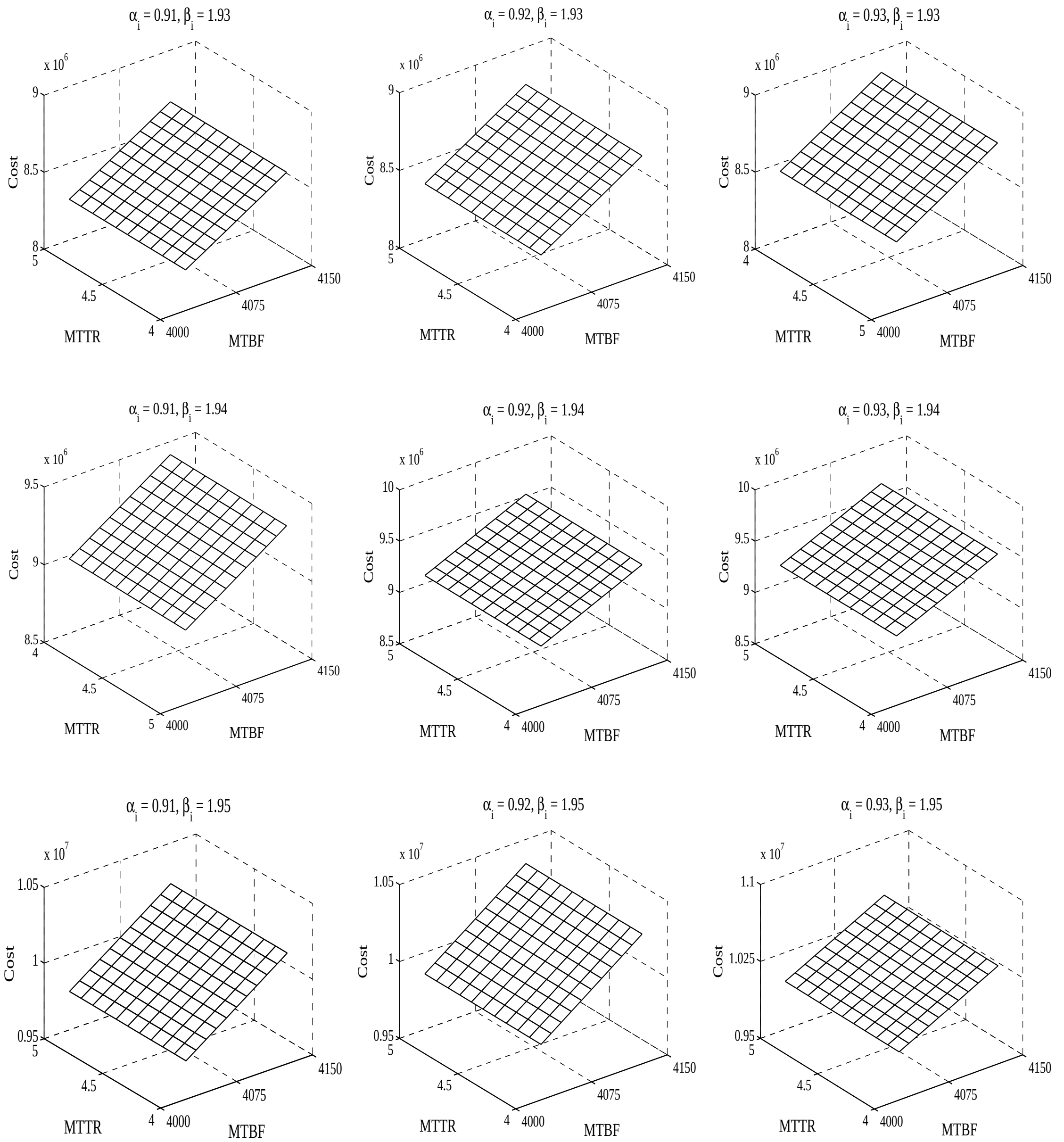


Figure 3.3: Behavior Analysis plot for different combination of α_i and β_i

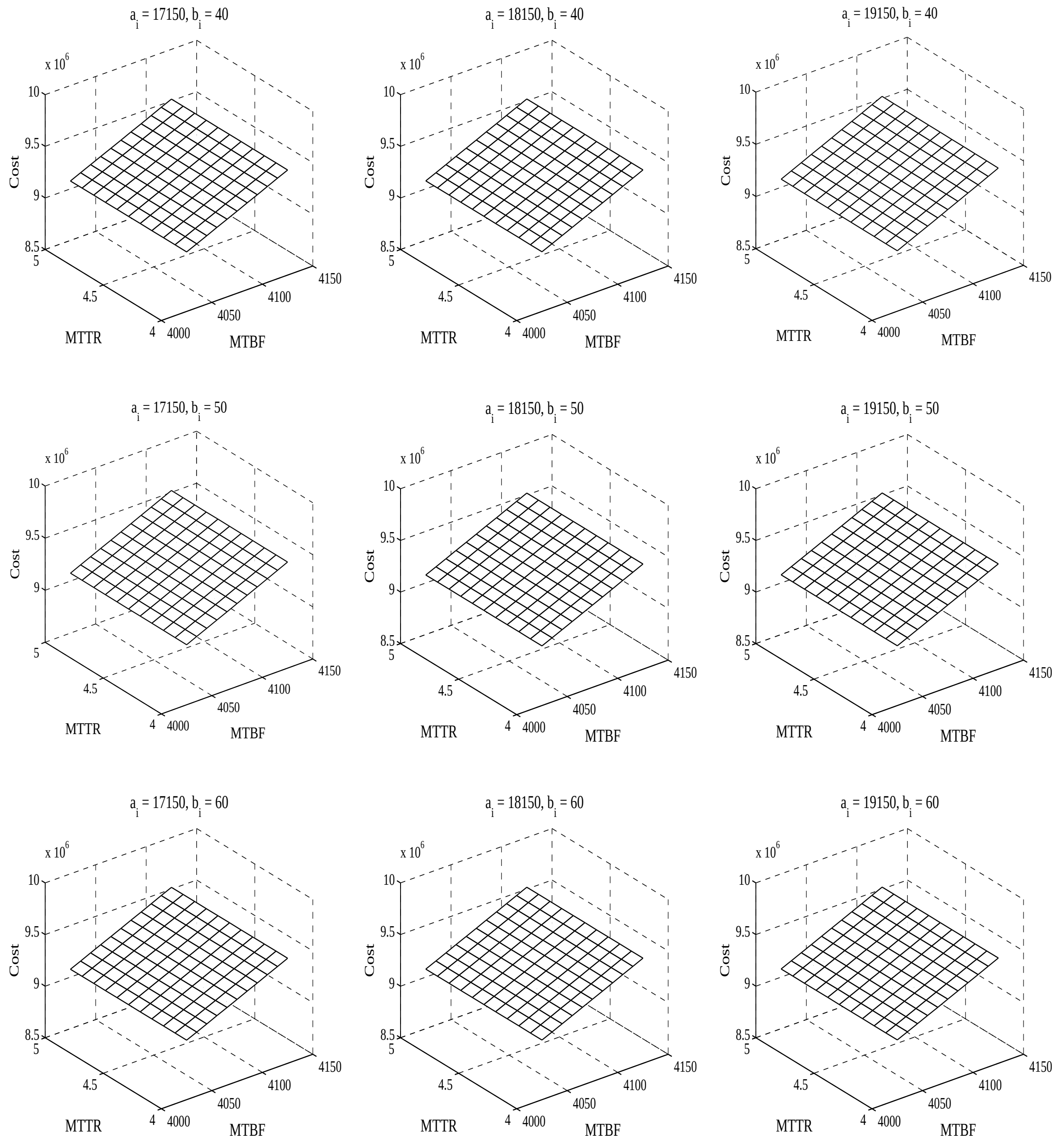


Figure 3.4: Behavior Analysis plot for different combination of a_i and b_i

3.5 Conclusion

An efficient ABC algorithm has been proposed to determine minimum cost configuration of complex repairable series-parallel system (butter oil processing plant industrial system) subject to given constraints on availability. The structural design of repairable series-parallel system is inefficient if one relies merely on empirical methods, as the industrial systems are profit oriented. It may tend to cause increasing design cost due to the difficulty of inheriting design experience. The soft computing technique has been used to analyze and optimize the design parameters of repairable series-parallel system and it appears to be very helpful as it facilitates the system analyst to choose the best repair policy according to the optimal design information. An optimization model with system availability and design constraints has been developed here and the optimal design parameters (MTBF & MTTR) are obtained by utilizing ABC technique. The search towards an optimal solution is directed from both the sides of the region i.e feasible and infeasible regions and, is much superior to the strategy of allowing only feasible solutions. The infeasibility of the solutions is handled by a penalty function, which helps the search to proceed efficiently for final optimal /near optimal solution. The obtained result by ABC algorithm is shown to be statistically significant as compared to GA and PSO in terms of means of pooled t- test. The optimal design parameters help the decision maker basically in the following two ways

(i) in deciding the related characteristics of each component

(ii) in formulating optimal design policies and repair policies for the entire system to ensure highly reliable and efficient system.

The optimization procedure may easily be applied to a wide variety of real-life structure optimization problems and with the help of the optimal results the plant maintenance personnel will decide his/her future strategy to gain optimum performance of the system.

Chapter 4

Reliability analysis of Butter-Oil Processing Plant with ABC and fuzzy methodology

The main aim of this chapter is to present the novel technique named as Artificial bee colony based Lambda-Tau (ABCBLT) technique for analyzing and predicting the behavior of a complex repairable industrial system by utilizing uncertain data. For this, butter-oil processing plant has been taken to demonstrate the approach by using their computed parameters as obtained in Chapter 3. To study the failure behavior of the system, crisp and defuzzified values are obtained at $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$ spreads. The results obtained will be useful to the system manager/analyst to plan and execute the future course of action in the industry.

4.1 Introduction

Over the last couple of decades, globalization and other factors have significantly changed the business environment. Although, the concept of failure analysis is nearly an unavoidable phenomenon for all repairable industrial systems. The cause of failure may be deteriorating and/or human error which leads to the job of reliability/system analysts more challenging. Therefore, it is very difficult to construct an accurate and complete mathematical model of an industrial system which may be very close to the real situation. In reliability and maintainability studies a small number of researchers have addressed the issue of handling uncertainties particularly related to failure data. The concept of fuzzy set theory and fuzzy arithmetic has been used in the evaluation of the reliability of the system by the various researchers [34, 42, 44, 47, 138, 180, 222]. But their approaches are limited for a small size structured system as it contains a wide range of uncertainties in the computed results. Therefore it is necessary that to develop a technique which are suitable for a large complex structured system and the uncertainties existing in the analysis are reduced up to a desired degree of accuracy.

Motivated by this and the merits of ABC algorithms over others, as mentioned in section 2.6, the main emphasis of the present chapter is to present a novel technique named as an Artificial Bee Colony based Lambda-Tau (ABCBLT) technique for analyzing the behavior of the complex repairable industrial system up to a desired degree of accuracy by utilizing uncertain and limited data. With this technique, expression of the various reliability parameters is obtained from Lambda-Tau technique and their corresponding membership functions are obtained after solving a nonlinear programming problem. An ordinary arithmetic operation has been used in the analysis instead of fuzzy arithmetic operations. The technique has been demonstrated through a case study of butter-oil processing plant and their results are compared with the existing fuzzy lambda-tau (FLT) and genetic algorithm based lambda-tau (GABLT) techniques. Sensitivity as well as performance analysis on the system availability has also been addressed. The obtained results may help the system analyst for reallocating the resources to achieve the targeted goal of higher profit.

4.2 ABCBLT technique

In the present study, a technique named as artificial bee colony based Lambda-Tau (ABCBLT) technique for analyzing the behavior of the industrial systems up to a desired degree of level has been presented. By this technique the behavior of an industrial system is depicted by using an uncertain data, collected from the various resources, Lambda-Tau methodology as well as ABC algorithm. Fuzzy set theory has been used for handling the uncertainties in the data. The analysis has been done in the form of fuzzy membership functions. Various reliability parameters reflecting the system behavior are calculated.

The expressions involved in them are obtained by Lambda-Tau methodology (with the basic expressions given in Table 2.2) and ABC has been used for computing their membership functions. The details of the technique have been discussed below under the assumptions:

(i) Component failures (λ_i) and repair rates (μ_i) are obey exponent distributions.

(ii) $\lambda_i << \mu_i$

(iii) Separate maintenance facility is available for each component and

(iv) After repairs, the repaired component is considered as good as new.

The flow chart of the presented technique is given in Fig. 4.1.

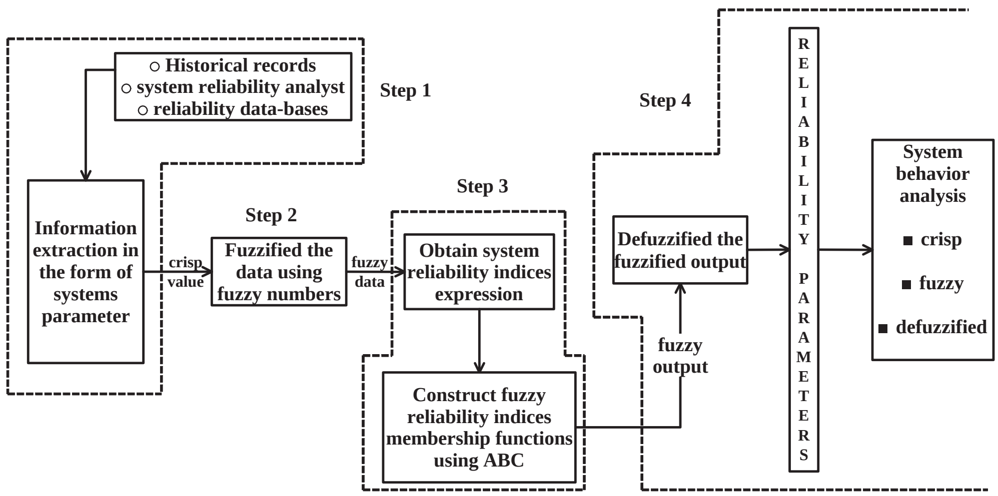


Figure 4.1: Flow chart of the ABCBLT technique

Step 1: The presented technique starts with the information extraction phase in which data/information is extracted from various sources such as historical records, reliability databases, system reliability expert opinion, etc. in the form of system's components' failure rates (λ's) and repair times (τ's).

Step 2: Since collected data are generally imprecise, vague or limited in nature, so to account the uncertainties in the analysis, the obtained data are fuzzified into fuzzy numbers. More specifically, crisp numbers in the extracted data are converted into triangular fuzzy numbers (TFN's) having known spread (support) suggested by decision makers/design maintenance expert/system reliability analyst. For instance, an input data for the i^{th} component of a system in the form of TFNs with equal spread $\pm 15\%$ in both the directions (left and right to the middle) with corresponding α-cuts is shown in Fig. 2.2. As soon as, the input fuzzy triangular numbers for failure rates and repair times for each of the components are known, the corresponding fuzzy value of the crisp failure rate (λ_s) and repair time (τ_s) can be obtained, using the extension principle coupled with $\alpha-$ cuts.

Step 3: In this step, minimal-cut set of the system are obtained from its block diagram and based on that expressions of their various reliability parameters, which depict the behavior of the system, are obtained which are generally highly nonlinear and complex due to large structured system. As a result, if FLT approach as given by Knezevic and Odoom [138] is used for analyzing their resultant system failure rate and repair time then it contains a high range of uncertainties due to various arithmetic operations used in the analysis. To overcome this problem, a nonlinear optimization problem has been constructed by taking ordinary arithmetic operations instead of fuzzy arithmetic operations for computing the membership functions of various reliability parameters. In the formulation, the quantified input data at cut level α, in the form of bounded intervals, is substituted in the expression of each obtained reliability index. The finally computed reliability index at cut level α has a wide range of solutions and it becomes smaller and smaller as the analysis progresses further i.e cut level α increases from 0 to 1. So to decrease the uncertainty level at each cut level α, a nonlinear programming problem of computing the membership functions of reliability indices is formulated as below.

Maximize/Minimize:

$$\widetilde{H}(\lambda_1, \cdots, \lambda_n, \tau_1, \cdots, \tau_m) \ \text{ or } \ \widetilde{G}(t/\lambda_1, \cdots, \lambda_n, \tau_1, \cdots, \tau_m) \tag{4.2.1}$$

$$\begin{aligned} \textit{subject to}: \ & \mu_{\lambda_i}(\mathrm{x}) \geq \alpha \\ & \mu_{\tau_j}(\mathrm{x}) \geq \alpha, \\ & 0 \leq \alpha \leq 1 \\ & i = 1, 2, \ldots, n \quad j = 1, 2, \ldots, m \end{aligned}$$

where $\widetilde{H}(\lambda_1, \lambda_2, \cdots, \lambda_n, \tau_1, \tau_2, \cdots, \tau_m)$ or $\widetilde{G}(t/\lambda_1, \lambda_2, \cdots, \lambda_n, \tau_1, \tau_2, \cdots, \tau_m)$ are time independent (failure rate, repair time, MTBF) and time dependent (reliability, availability, ENOF) fuzzy reliability indices as given in Table 2.3. The lower and upper boundary values of each reliability index are computed at each cut level α and are given as

$$\mu_{\widetilde{H}}(\widetilde{H}_{\min}) = \mu_{\widetilde{H}}(\widetilde{H}_{\max}) = \alpha \tag{4.2.2}$$

where $\widetilde{H}_{\min}$ and $\widetilde{H}_{\max}$ respectively denote the minimum and maximum value of $\widetilde{H}$.

In order to solve this problem, ABC algorithm is used as a tool to solve the optimization problem (4.2.1) in the process of determining the fuzzy membership function of each reliability index which has optimized spread. The objective function for maximization problem and the reciprocal of the objective function for minimization problem is taken as the fitness function. To stop the optimization process maximum number of generations and change in population fitness value are used as termination criteria.

Step 4: Finally, in order to make the decision more reliable by human or machines which are binary in nature so it is necessary to convert the fuzzified output into crisp output. The process of converting the fuzzy output to a crisp value is said to be defuzzification. The center of gravity (COG) method [199] has been used for this purpose as it gives the results equivalent to the mean of the data.

4.3 Butter-Oil Processing Plant

The above mentioned technique has been demonstrated by analyzing the behavior of the Butter-Oil processing plant which has already been described in Chapter 3. Under the information extraction phase, the data related to main components of the system, in the form of failure rate (λ_i's) and repair time (τ_i's), are obtained by using the computed parameters in Chapter 3 in Table 3.3. The interaction among the various subsystems of the plant are shown by RBD in Fig. 3.2. Based on that, the minimal cut sets of the system obtained are $\{A\}_{i=1,2,3}$, $\{B\}_{i=1,2}$, $\{C_i\}_{i=1,2,3}$, $\{D_i\}_{i=1,2,3}$, $\{E_i\}_{i=1,2}$ and $\{F_i\}_{i=1,2}$. Based on these cut sets and the collected data, a behavior analysis of the system has been done by using ABCBLT technique and compared their results with FLT and GABLT technique results as follow.

4.3.1 Behavior analysis

In order to taken the account of uncertainties during the computational analysis, firstly the obtained data are converted into a triangular fuzzy number with ±15% spread (also at ±25%, ±50%). After that based on their minimal cut sets and by following the basic steps (Step1 to Step 4) of the proposed technique, expressions of their various reliability parameters in the form of membership functions are calculated and depicted graphically in Fig. 4.2 for a mission time t = 10 hrs along with their crisp, FLT and GABLT techniques' results with an increment of 0.1 confidence level. From the Fig. 4.2, it has been concluded that the values of all reliability indices obtained by using traditional method (crisp) are independent of the degree of confidence level α which means that it does not consider the uncertainties in the data. On the other hand, result computed by FLT methodology contains a wide spread of uncertainties in the computed reliability parameters due to various fuzzy arithmetic operations involved during the analysis whereas ABCBLT results have reduced region and small spread in comparison of existing results. The reason behind is that ABC gives near to the optimal solution. In order to analyze the decrease in spread (in %) of the reliability parameters by ABCBLT technique in comparison to the FLT and GABLT techniques, an analysis has been done which computes the support of the parameters from the plotted Fig. 4.2 and are shown in tabulated form in Table 4.1. From the analysis, it has been concluded that the largest and the smallest decrease in spread occurs corresponding to the repair time and failure rate respectively from FLT while the largest and the smallest decrease in spread occur corresponding to availability and ENOF respectively from GABLT results when ABCBLT technique has been applied. This suggests that DMs have smaller and more sensitive region to make more sound and effective decision in lesser time.

Table 4.1: Data related to Spread of Reliability Indices

	Computed spread for reliability indices					
Technique	Failure rate	Repair time	ENOF	MTBF	Reliability	Availability
I	0.0011043	3.464054	0.011916	86.833172	0.010644	0.013811
II	0.0008469	0.926911	0.008091	54.947230	0.008269	0.003835
III	0.0002356	0.244670	0.001985	17.377297	0.002077	0.001235
	Decrease in spread (in %) from					
I to II	23.308883	73.242016	32.099697	36.720922	22.313040	72.232278
I to III	78.665217	92.936888	83.341725	79.987721	80.486659	91.057852
II to III	72.180895	73.603722	75.466567	68.374571	74.882089	67.796610

I: FLT II: GABLT III: ABCBLT

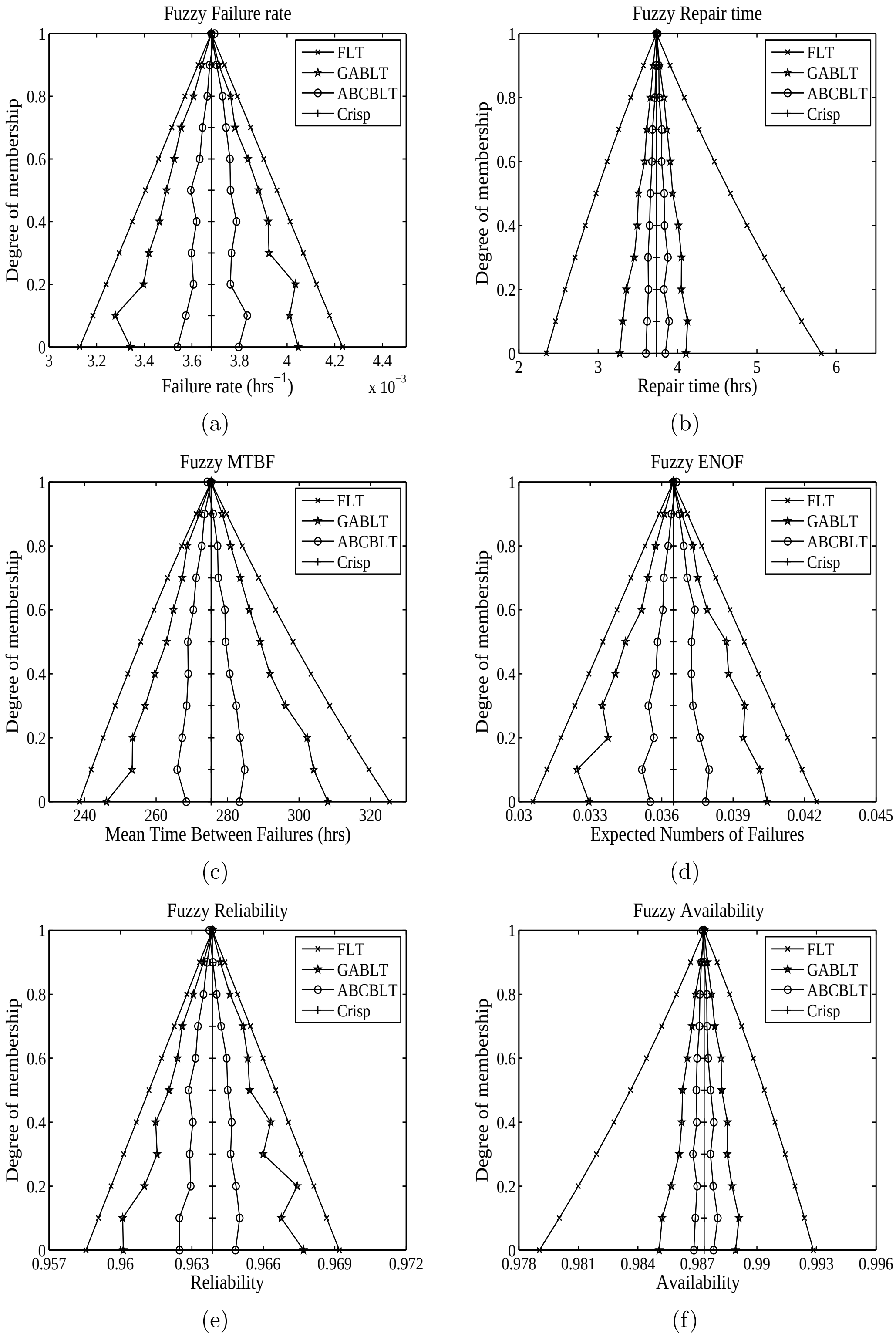


Figure 4.2: Fuzzy Reliability Analysis Plot of the System at ±15% spread

The crisp and defuzzified values of all reliability parameters at different spreads $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$ are computed in Table 4.2 by using COG method and are compared with FLT and GABLT results. It has been clearly seen that the crisp value does not change with the change of spreads while defuzzified values change with the change of spread. It has also been noticed that with the increase in uncertainty level in the form of spread from $\pm 15\%$ to $\pm 25\%$ and further to $\pm 50\%$, the variation in defuzzified values for almost all the reliability indices are not that significant for ABCBLT results as that for FLT and GABLT techniques. When the uncertainty level is optimized, plant personnel may have changed their targeted goals rather goal comes from traditional analysis. For example, if plant personnel want to optimize reliability of the system using ABCBLT results then the new target of system reliability should be greater than 0.96380879 rather 0.96386389 and 0.96386743 that comes from Lambda-Tau and GABLT when uncertainty level is taken as $\pm 15\%$. Similarly, for other reliability indices new targets will be set. The result shown by ABCBLT technique follows the same trend (increase or decrease) as that of FLT and GABLT techniques. Due to this and their reduced region of prediction, the values obtained through ABCBLT technique are conservative in nature which may be beneficial for a system expert / analyst for future course of action i.e. now the maintenance will be based on the defuzzified values rather than crisp values.

Table 4.2: Defuzzified Values of the Reliability Parameters

Spread	Technique	Failure rate	Repair time	MTBF	ENOF	Reliability	Availability
±0%	Crisp	0.00368128	3.73434034	275.378718	0.03648534	0.96385652	0.98733735
		Defuzzified values for reliability indices					
±15%	FLT	0.00368832	3.90641535	278.67612957	0.03651720	0.96386389	0.98664310
	GABLT	0.00368837	3.74332841	277.32980107	0.03649392	0.96386743	0.98728116
	ABCBLT	0.00368444	3.74210013	275.31074783	0.03654426	0.96380879	0.98729288
±25%	FLT	0.00368878	4.23049593	284.86621232	0.03658171	0.96387700	0.98528472
	GABLT	0.00367261	3.73819865	280.24523758	0.03637431	0.96365488	0.98727673
	ABCBLT	0.00368875	3.74619668	274.98202985	0.03659464	0.96364712	0.98730306
±50%	FLT	0.00369317	6.15254254	321.16324960	0.03705108	0.96393843	0.97637077
	GABLT	0.00365819	3.76773428	293.84428687	0.03647868	0.96401885	0.98715129
	ABCBLT	0.00370863	3.74375968	276.05839796	0.03683116	0.96339521	0.98735221

4.3.2 Sensitivity analysis

Sensitivity analysis has also been conducted for various combinations of reliability, failure rate and availability on the system MTBF and the corresponding results have been depicted graphically as shown in Fig. 4.3 for all the three techniques. In

Table 4.3: Variation of the MTBF Parameter for all Techniques by Changing Other Reliability Parameters

S.No.	[Reliability, Failure rate, Availability]	Mean time between Failures		
		FLT	GABLT	ABCBLT
1	[0.9528, 3.4583×10^{-3}, 0.9868]	Min: 329.6245	344.8674	370.6349
		Max: 459.5221	430.9115	395.8302
2	[0.9528, 3.6812×10^{-3}, 0.9868]	Min: 309.7096	324.0496	348.2688
		Max: 431.8494	404.9222	371.9492
3	[0.9528, 3.8025×10^{-3}, 0.9868]	Min: 299.8531	313.7462	337.1991
		Max: 418.1534	392.0594	360.1298
4	[0.9638, 3.4583×10^{-3}, 0.9872]	Min: 251.5196	263.2123	282.9034
		Max: 350.9467	328.9610	302.1537
5	[0.9638, 3.6812×10^{-3}, 0.9872]	Min: 236.3326	247.3368	265.8473
		Max: 329.8437	309.1419	283.9423
6	[0.9638, 3.8025×10^{-3}, 0.9872]	Min: 228.8161	239.4795	257.4056
		Max: 319.3992	299.3328	274.9289
7	[0.9698, 3.4583×10^{-3}, 0.9900]	Min: 209.1492	218.8576	235.2247
		Max: 291.7541	273.5085	251.2262
8	[0.9698, 3.6812×10^{-3}, 0.9900]	Min: 196.5184	205.6542	221.0394
		Max: 274.2031	257.0253	236.0801
9	[0.9698, 3.8025×10^{-3}, 0.9900]	Min: 190.2671	199.1194	214.0186
		Max: 265.5166	248.8672	228.5838

this analysis, for all different combinations, ranges of repair time have been fixed as shown in Fig. 4.2(b) at $\alpha = 0$ while for ENOF ranges have been taken as in Fig. 4.2(d) at $\alpha = 0$ corresponding to FLT, GABLT and ABCBLT techniques respectively. The corresponding ranges of MTBF by all the techniques are computed and arranged in tabulated form in Table 4.3 for different combinations of reliability parameters. For the first combination of Table 4.3, the selected values of reliability, failure rate and availability are 0.9528, 0.0034583 and 0.9868 respectively. In this combination, the computed ranges of MTBF are 329.6245 to 459.5221, 344.8674 to 430.9115 and 370.6349 to 395.8302 for FLT, GABLT and ABCBLT respectively. For this combination, it has been analyzed that the predicted range of the MTBF has been reduced up to 80.6037% from FLT and 73.4909% from GABLT, when ABCBLT is applied. This observation infers that if system analysts use ABCBLT results for the system, then they may have less range of prediction which finally leads to more sound decisions. Similar kind of reductions has been noticed for other combinations too. The plots show that as the failure rate of the system increases then for the prescribed ranges and values of the other indices, the MTBF of the system decreases exponentially.

4.3.3 Performance analysis

As the performance of the system directly depends on each of the constituent components. So to increase the performance of the system, more attention should be given to their corresponding subsystem for the effectiveness of the maintenance program. In order to find the most critical component, as per preferential order, of the system, an investigation has been done on system availability by varying their failure rate and repair time individually. The effects of failure rate and repair time on system availability has been shown graphically in Fig. 4.4 corresponding to each component of the system. This figure contains six subplots corresponding to six main components of the system. Each subplot contains two subplots against variations in failure rate and repair time respectively of the corresponding component without increase in other component's parameters. The corresponding maximum and minimum values obtained for each component of the system are given in Table 4.4.

But in a real-life modeling, the parameters of failure and repair times affect simultaneously on the system performance. For this, the effect of these parameters on system performance has been investigated for each of the components of the system with varying simultaneously their failure rate and repair time parameters and fixing the parameters of other components' at the same time. The results thus

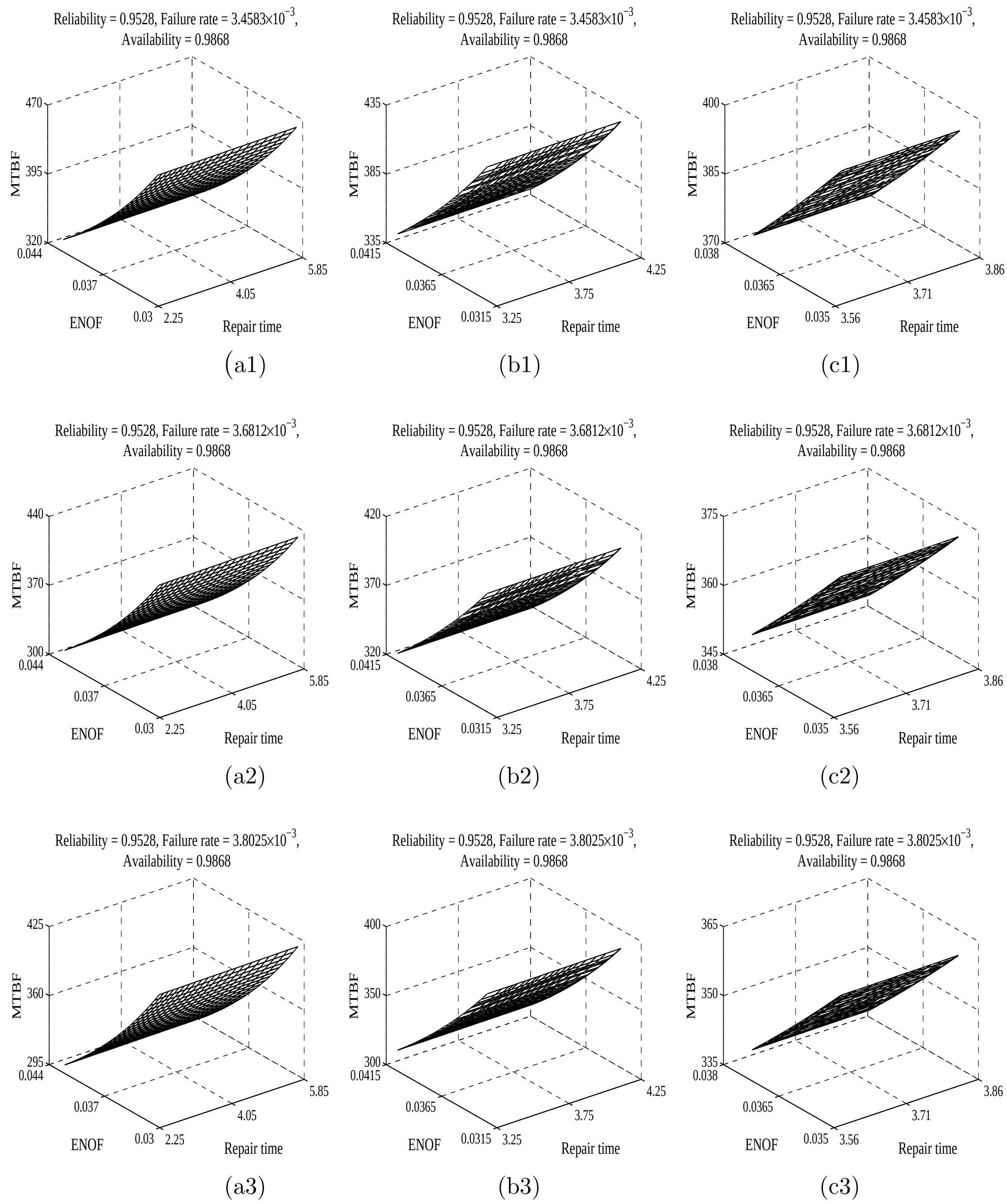


Figure 4.3: Butteroil processing unit Behavior Analysis: (a) FLT (b) GABLT (c) ABCBLT

obtained are shown graphically in Fig. 4.5 which contains six subplots corresponding to six main components of the system. It has been observed from Fig. 4.5(a)

Table 4.4: Effect of Individual Component Failure rate and Repair time on System Performance

Component	Range of failure rate(hrs^{-1}) $\lambda \times 10^{-4}$	System availability	Range of repair time (hrs)	System availability
Motors	2.111528 - 2.856773	Min: 0.98662623 Max: 0.98804971	3.658494 - 4.949728	Min: 0.98676034 Max: 0.98793717
Bearing	2.070708 - 2.801546	Min: 0.98697272 Max: 0.98770336	2.128131 - 2.879236	Min: 0.98707122 Max: 0.98760822
Gear Box	2.088135 - 2.825125	Min: 0.98684689 Max: 0.98782904	4.379034 - 5.924576	Min: 0.98692523 Max: 0.98776098
Pumps	2.036131 - 2.754766	Min: 0.98723846 Max: 0.98743628	2.421774 - 3.276518	Min: 0.98726242 Max: 0.98741264
Circuit Box	2.083188 - 2.818431	Min: 0.98724196 Max: 0.98743280	2.239768 - 3.030275	Min: 0.98726644 Max: 0.98740858
Cylinder	2.066707 - 2.796134	Min: 0.98722117 Max: 0.98745355	2.923619 - 3.955485	Min: 0.98724559 Max: 0.98742966

that the simultaneous increase in the failure and repair time of the motor component from 2.111528×10^{-4} to 2.856773×10^{-4} (hrs^{-1}) and from 3.658494 to 4.949728 (hrs) respectively shows the significant impact on the system availability. Similarly, variation in failure time from 2.088135×10^{-4} to 2.825125×10^{-4} (hrs^{-1}) and repair time from 4.379034 to 5.924576 (hrs) of the gear box components, shown in Fig. 4.5(c), will change the system availability by 0.71%. Similar effect on the system availability by the variation of the other component's failure rates and repair times are analyzed from the Fig. 4.5. The magnitude of the effect of variation in failure rates and repair times of various subsystems of the system on its performance is summarized in Table 4.5. From the results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; gear box, motors, cylinder, pumps, circuit box and bearing. Thus the system manager can analyze the critical behavior of the system and hence can plan for suitable maintenance strategy for achieving the highest goals. The maintenance engineer may therefore determine the repair policy according to the optimal design by considerations and the company strategies.

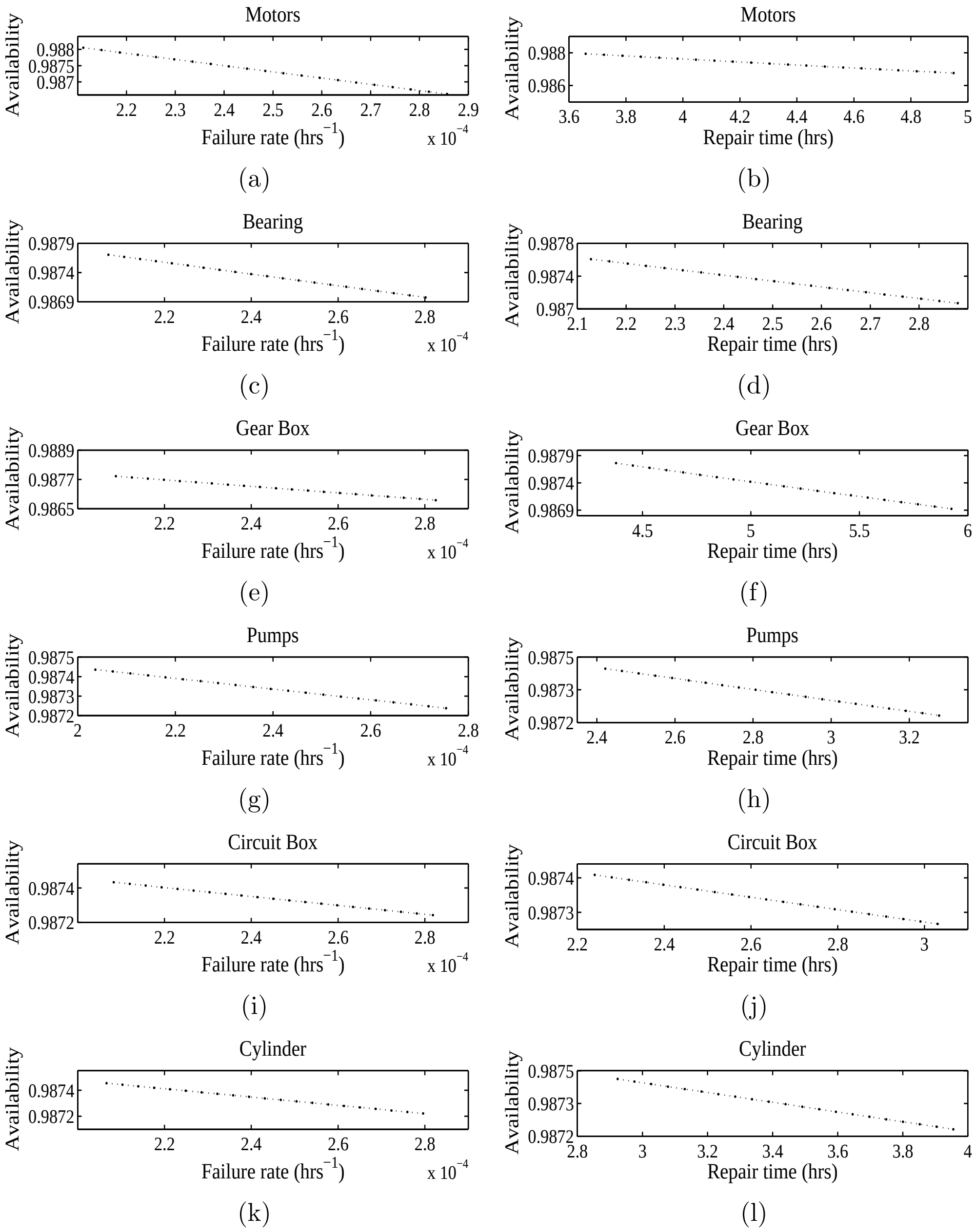


Figure 4.4: Effect of Individual Component Failure rate and Repair time on Availability Index when other Parameters are Fixed

Table 4.5: Simultaneously Effect of Failure rate and Repair time on System Performance

Component	Range of failure rate(hrs^{-1}) $\lambda \times 10^{-4}$	Range of repair time (hrs)	System availability
Motors	2.111528 - 2.856773	3.658494 - 4.949728	Min: 0.98342466 Max: 0.98926656
Bearing	2.070708 - 2.801546	2.128131 - 2.879236	Min: 0.98919964 Max: 0.99349126
Gear Box	2.088135 - 2.825125	4.379034 - 5.924576	Min: 0.98088527 Max: 0.98780600
Pumps	2.036131 - 2.754766	2.421774 - 3.276518	Min: 0.98746689 Max: 0.99277235
Circuit Box	2.083188 - 2.818431	2.239768 - 3.030275	Min: 0.98800820 Max: 0.99312737
Cylinder	2.066707 - 2.796134	2.923619 - 3.955485	Min: 0.98518834 Max: 0.99130274

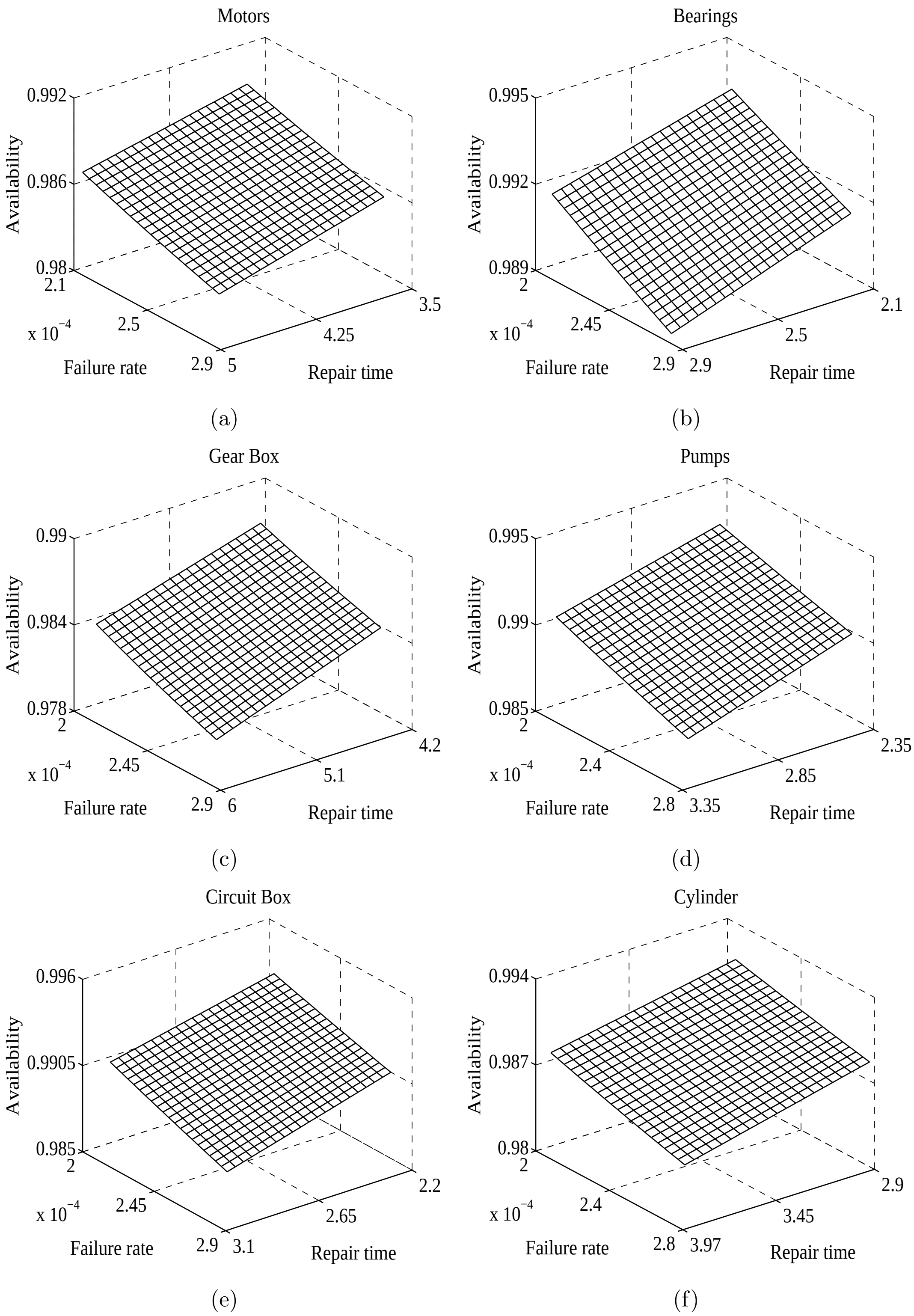


Figure 4.5: Simultaneously Effect of Components Failure rate and Repair time on the System Availability

4.4 Conclusion

In this chapter a hybridized technique named as ABCBLT for analyzing the reliability indices of an industrial system has been discussed. The technique has been demonstrated through a case study of butter-oil processing plant. In the analysis, an attempt has been made to deal with imprecise, uncertain dependent information related to system performance. Fuzzy set theory has been used for handling the uncertainties in the data and nonlinear programming problem has been formulated for constructing their membership functions. To strengthen the analysis, various reliability indices such as system failure rate, repair rate, MTBF, ENOF, availability and reliability have been computed in the form of fuzzy membership functions. The technique optimizes the spread of computing reliability indices which may be useful for the plant manager to take more relevant decisions. The defuzzified values of reliability indices for different levels of uncertainties are calculated and summarized in tabular form along with FLT, GABLT results. In order to analyze their behavior effect on system performance, a sensitivity analysis as well as performance analysis has been conducted for various combinations of reliability parameters. Based on that the system manager may analyze the critical behavior of the system and plan for suitable maintenance for improving system's performance and thereby reduce operational and maintenance costs. From the results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; gear box, motors, cylinder, pumps, circuit box and bearing. Thus, system reliability engineers/analysts may use these results to set the future targets of their interest and will help to model and predict the behavior of industrial systems in more consistent and realistic manner as they often make use of subjective judgments and uncertain data.

Chapter 5

Behavior of the industrial systems using soft computing based technique

In this chapter already presented ABCBLT hybridized technique in chapter 4 for analyzing the behavior of an industrial system is used for time varying failure rate instead of constant failure rate and constant repair rate model. The repair rate is taken as constant here also. The technique has been illustrated by analyzing the behavior of all the subsystems/units of a paper mill, a complex repairable industrial system, individually.

5.1 Introduction

Today with growing complexity of the repairable industrial systems along with advances in technology, it is difficult, if not impossible, for the system analyst to predict and analyze the behavior of the industrial system in a more realistic and a proper manner. Thus, system reliability analysis is an important issue for academic research and practice. Realising of this, various researchers [79, 93, 109, 138, 142, 144, 149, 169, 196, 203, 216, 246] have paid more attentions to the system-behavior by using traditional and non-traditional techniques with the target that system operates for a long time for maximizing its profit as well its production. For evaluating their behavior, the data related to system parameters are generally estimated from the existing databases/sheets or historical records, which are usually imprecise in nature. Thus, if data are used as such in the analysis then the computed results contain a high amount of uncertainties and hence the results are deviated from their original behavior results. Moreover, in addition to reliability parameter other parameters like failure rate, repair time etc., are also responsible for their system's behavior failure. For considering all these factors, Knezevic and Odoom [138] highlighted this idea and extended an approach from crisp results to fuzzy results by quantifying the data in terms of fuzzy numbers. A constant failure rate model has been taken during the analysis. Also it is an established fact that preventive maintenance is not useful when the failure rate is constant. So the components having shape factor sufficiently larger than one must have been taken for the analysis, i.e. which have more deterministic deteriorating characteristics. Therefore, there is a need for developing such type of methodology which will reduce the uncertainties, for each reliability index, up to a desired degree of accuracy so that plant personnel may use these indices to analyze the system behavior more closely and take more sound decisions to improve the performance of the plant.

Thus the objective of the present chapter is to analyze the behavior of a repairable industrial system by considering the time varying failure rate and a constant repair time i.e. failure rate of the components follows the Weibull distribution and repair time follows the exponential distribution. For analyzing the behavior of these systems, ABCBLT technique is used here. Triangular membership functions have been used for representing the data. The technique has been illustrated by analyzing the behavior of all the subsystems/units of a paper mill.

5.2 Fuzzy Reliability with Weibull distribution

We assume that the object (element or system) under investigation is either in a failure free or in a failure state. The failure-free state time is a random variable X, which assumes values $t \in [0, \infty)$. Reliability or survival function is the probability that a unit perform its satisfactory operation beyond time 't'. Let the random variable X denote the lifetime of a system components then reliability function at time t is defined as

$$R(t) = P(X \geq t) = 1 - F(t) \tag{5.2.1}$$

where $F(t)$ is the failure distribution function of X, and $F(t) = 0, \forall\, t \in (-\infty, 0]$ and the unreliability function Q(t) is the probability of failure or probability of an item failing in the time interval [0, t] and is defined as

$$Q(t) = P(X \leq t) = F(t) \quad , \quad t > 0 \tag{5.2.2}$$

The fuzzy probability model of reliability presumes that the time of such a transition is a fuzzy random variable which describes the vagueness of the transition time t and the uncertainty of the probability distribution[125]. Thus the fuzzy reliability by means of the fuzzy distribution function of fuzzy random variable X is defined as $\widetilde{R}(t) = \widetilde{P}(X \geq t) = 1 - \widetilde{F}(t)$, $\forall\, t \in [0, \infty)$, where $\widetilde{P}$ is the fuzzy probability whose distribution function is $\widetilde{F}(x) = \widetilde{P}(X < x)$ and X is the random variable on $\mathbb{R}$. In order to obtain a fuzzy reliability model, we assume that the values of a fuzzy random variable X are the fuzzy numbers $\widetilde{t} = ([0, \infty), \mu_{\widetilde{t}})$ and $\widetilde{t} = \widetilde{k}t$ where t is the observed value of a crisp random number variable X representing the failure - free state time and $\widetilde{k}$ is *vagueness coefficient*. The vagueness coefficient $\widetilde{k}$ is a real triangular fuzzy number $\widetilde{k} = ([0, \infty), \mu_{\widetilde{k}})$ with the crisp value $k = 1$ and the membership function

$$\mu_{\tilde{k}}(x) = \begin{cases} \dfrac{x - k_L}{1 - k_L}, & \text{if } k_L \leq x \leq 1 \\ 1, & \text{if } x = 1 \\ \dfrac{x - k_U}{1 - k_U}, & \text{if } 1 \leq x \leq k_U \\ 0, & \text{otherwise} \end{cases} \tag{5.2.3}$$

where $0 < k_L \leq 1 \leq k_U$, and the boundary values k_L, k_U are specified by expert's estimates. Fig. 5.1 represent the graph of $\mu_{\tilde{k}}(x)$.

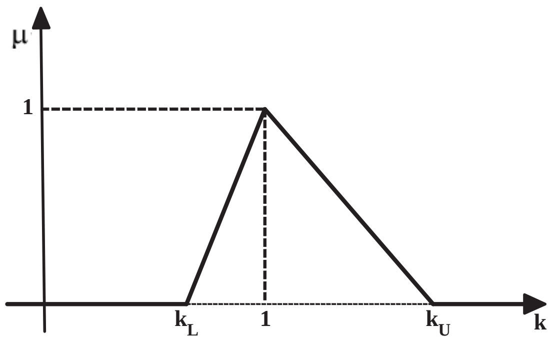


Figure 5.1: Triangular Fuzzy Number of the vagueness coefficient

It is well known that the two-parameter Weibull probability distribution $W(\theta, \beta)$ for $\beta > 0$ as its shape parameter and $\theta > 0$ as its scale parameter and $t \in [0, \infty)$ has the following functional and numerical characteristics for the crisp random number T [71].

(a) Hazard function $\lambda(t) = \dfrac{\beta}{\theta}\left(\dfrac{t}{\theta}\right)^{\beta-1}$

(b) Mean time to failure (MTTF) = expected value $E(T) = \theta\Gamma\left(1 + \dfrac{1}{\beta}\right)$ where Gamma function $\Gamma(n) = \int_0^\infty x^{n-1}e^{-x}dx$.

(c) Failure distribution function $\mathrm{F}(t) = 1 - \exp\left[-\left(\dfrac{t}{\theta}\right)^{\beta}\right]$

(d) Reliability function $\mathrm{R}(t) = 1 - \mathrm{F}(t) = \exp\left[-\left(\dfrac{t}{\theta}\right)^{\beta}\right]$

(e) Availability function $\mathrm{A}(t) = e^{-(\frac{t}{\theta})^{\beta} - \frac{t}{\tau}}\left(1 + \frac{1}{\tau}\int_0^t \exp((\frac{t}{\theta})^{\beta} + \frac{t}{\tau})dt\right)$

(f) Maintainability function $\mathrm{M}(t) = 1 - \exp(-\frac{t}{\tau})$

(g) Mean time to Repair (MTTR) $= \dfrac{1}{\mu} = \tau$; where μ is repair rate of the system.

(h) Mean time between Failure, MTBF = MTTF + MTTR

Using the above concepts, it can be seen that the Weibull fuzzy probability distribution $\widetilde{W}(\beta,\theta)$ for the fuzzy random variable that corresponds to the crisp Weibull distribution for the random variable has the following fuzzy characteristics.

(a) The fuzzy failure rate function $\widetilde{\lambda}(t) = \dfrac{\beta t^{\beta-1}}{(\widetilde{k}\ \theta)^{\beta}}, \quad \forall\, t \in [0,\infty)$, so that $\forall\, \alpha \in [0,1]$, the $\alpha-$cuts of fuzzy failure rate function

$$\begin{aligned}\widetilde{\lambda}_{\alpha}(t) &= [\widetilde{\lambda}_{L\alpha}(t),\ \widetilde{\lambda}_{U\alpha}(t)]\\ &= \left[\frac{\beta t^{\beta-1}}{(\{k_L+\alpha(1-k_L)\}\theta)^{\beta}}, \frac{\beta t^{\beta-1}}{(\{k_U+\alpha(1-k_U)\}\theta)^{\beta}}\right]\end{aligned} \tag{5.2.4}$$

(b) The fuzzy mean of fuzzy random variable $\widetilde{T}$ is triangular fuzzy number $\widetilde{E}(\widetilde{T}) = \widetilde{k}\ \theta \cdot \Gamma\left(1+\dfrac{1}{\beta}\right)$ where

$$\mu_{\tilde{E}(\tilde{T})}(t) = \begin{cases} \dfrac{t-k_L\theta\Gamma(1+\frac{1}{\beta})}{(1-k_L)\theta\Gamma(1+\frac{1}{\beta})} & \text{if } k_L\theta\Gamma(1+\frac{1}{\beta}) \le t \le \theta\Gamma(1+\frac{1}{\beta})\\ 1 & \text{if } t = \theta\Gamma(1+\frac{1}{\beta})\\ \dfrac{t-k_U\theta\Gamma(1+\frac{1}{\beta})}{(1-k_U)\theta\Gamma(1+\frac{1}{\beta})} & \text{if } \theta\Gamma(1+\frac{1}{\beta}) \le t \le k_U\theta\Gamma(1+\frac{1}{\beta}) \end{cases} \tag{5.2.5}$$

(c) The fuzzy failure distribution function $\widetilde{F}(t) = 1-\exp\left[-\left(\dfrac{t}{\widetilde{k}\ \theta}\right)^{\beta}\right] \quad \forall\, t \in [0,\infty)$, so that $\forall\, \alpha \in [0,1]$, the $\alpha-$cuts of fuzzy failure distribution function are:

$$\begin{aligned}\widetilde{F}_{\alpha}(t) &= [\widetilde{F}_{L\alpha}(t),\ \widetilde{F}_{U\alpha}(t)]\\ &= \left[1-\exp\left\{-\left(\frac{t}{\{k_U+\alpha(1-k_U)\}\theta}\right)^{\beta}\right\},\right.\\ &\qquad \left. 1-\exp\left\{-\left(\frac{t}{\{k_L+\alpha(1-k_L)\}\theta}\right)^{\beta}\right\}\right]\end{aligned} \tag{5.2.6}$$

(d) The fuzzy reliability function $\widetilde{R}(t) = \exp\left[-\left(\dfrac{t}{\widetilde{k}\theta}\right)^{\beta}\right] \quad \forall\ t \in [0,\infty)$, so that

$\forall\ \alpha \in [0,1]$, the $\alpha-$cuts of fuzzy reliability function are:

$$\begin{aligned}
\widetilde{R}_{\alpha}(t) &= [\widetilde{R}_{L\alpha}(t),\ \widetilde{R}_{U\alpha}(t)] \\
&= \Bigg[\exp\Bigg\{-\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\theta}\Bigg)^{\beta}\Bigg\}, \qquad (5.2.7) \\
&\quad \exp\Bigg\{-\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\theta}\Bigg)^{\beta}\Bigg\}\Bigg]
\end{aligned}$$

(e) The fuzzy availability function $\widetilde{A}(t) = e^{-(\frac{t}{\widetilde{k}\theta})^{\beta}-\frac{t}{\widetilde{k}\tau}}\Bigg(1+\frac{1}{\widetilde{k}\tau}\int_0^t \exp\{(\frac{t}{\widetilde{k}\theta})^{\beta}+\frac{t}{\widetilde{k}\tau}\}dt\Bigg)$ $\forall\ t \in [0,\infty)$, so that $\forall\ \alpha \in [0,1]$, the $\alpha-$cuts of fuzzy availability function are:

$$\begin{aligned}
\widetilde{A}_{\alpha}(t) &= [\widetilde{A}_{L\alpha}(t),\ \widetilde{A}_{U\alpha}(t)] \\
&= \Bigg[\exp\Bigg\{-\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\theta}\Bigg)^{\beta}-\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\tau}\Bigg)\Bigg\}\cdot \\
&\quad \Bigg\{1+\frac{1}{\{k_U+\alpha(1-k_U)\tau\}}\times \qquad (5.2.8) \\
&\quad \int_0^t \exp\Bigg\{\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\theta}\Bigg)^{\beta}+\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\tau}\Bigg)\Bigg\}dt\Bigg\}\ , \\
&\quad \exp\Bigg\{-\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\theta}\Bigg)^{\beta}-\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\tau}\Bigg)\Bigg\}\cdot \\
&\quad \Bigg\{1+\frac{1}{\{k_L+\alpha(1-k_L)\tau\}}\times \\
&\quad \int_0^t \exp\Bigg\{\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\theta}\Bigg)^{\beta}+\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\tau}\Bigg)\Bigg\}dt\Bigg\}\Bigg]
\end{aligned}$$

(f) The fuzzy maintainability function $\widetilde{M}(t) = 1-\exp\Bigg(-\frac{t}{\widetilde{k}\ \tau}\Bigg)$ $\forall\ t \in [0,\infty)$, so that $\forall\ \alpha \in [0,1]$, the $\alpha-$cuts of fuzzy maintainability function are:

$$\begin{aligned}
\widetilde{M}_{\alpha}(t) &= [\widetilde{M}_{L\alpha}(t),\ \widetilde{M}_{U\alpha}(t)] \\
&= \Bigg[1-\exp\Bigg\{-\Bigg(\frac{t}{\{k_U+\alpha(1-k_U)\}\tau}\Bigg)\Bigg\}, \qquad (5.2.9) \\
&\quad 1-\exp\Bigg\{-\Bigg(\frac{t}{\{k_L+\alpha(1-k_L)\}\tau}\Bigg)\Bigg\}\Bigg]
\end{aligned}$$

(g) The fuzzy mean time to repair $\widetilde{MTTR} = \widetilde{k}\ \tau$, $\forall\ t \in [0, \infty)$, so that $\forall\ \alpha \in [0, 1]$, the $\alpha-$cuts of fuzzy mean time to repair function are:

$$\begin{aligned}\widetilde{MTTR}_\alpha &= [\widetilde{MTTR}_{L\alpha}, \widetilde{MTTR}_{U\alpha}] \\ &= [\{k_L + \alpha(1 - k_L)\}\tau, \{k_U + \alpha(1 - k_U)\}\tau] \qquad (5.2.10)\end{aligned}$$

In the present analysis, instead of computing the membership functions of above stated reliability parameters by using their arithmetic functions, a nonlinear programming problem (5.2.11) has been constructed by utilizing the quantified fuzzy θ's and τ's. Here expressions of various reliability parameters are obtained coupled with the α-cut and ordinary arithmetic unlike of fuzzy arithmetic operations. Then, the boundary values of reliability indices are computed at cut level α by solving the optimization problems (5.2.11).

$Minimize/Maximize:$

$$\tilde{H}(\theta_1, \theta_2, \ldots, \theta_n, \tau_1, \tau_2, \ldots, \tau_m) \ \ or \ \ \tilde{H}(t/\theta_1, \theta_2, \ldots, \theta_n, \tau_1, \tau_2, \ldots, \tau_m) \qquad (5.2.11)$$

$$\begin{aligned}Subject\ \ to:\ &\mu_{\theta_i}(x) \geq \alpha, \\ &\mu_{\tau_j}(x) \geq \alpha, \\ &0 \leq \alpha \leq 1, \\ &i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m.\end{aligned}$$

where $\tilde{H}(\theta_1, \theta_2, \ldots, \theta_n, \tau_1, \tau_2, \ldots, \tau_m)$ and $\tilde{H}(t/\theta_1, \theta_2, \ldots, \theta_n, \tau_1, \tau_2, \ldots, \tau_m)$ are time independent and dependent fuzzy reliability indices. The obtained minimum and maximum values of $\tilde{H}$ are denoted by $H_{\min}$ and $H_{\max}$ respectively.

The membership function values of $\tilde{H}$ at $H_{\max}$ and $H_{\min}$ are both α that is:

$$\mu_{\tilde{H}}(H_{\max}) = \mu_{\tilde{H}}(H_{\min}) = \alpha$$

Since the problem is nonlinear in nature so it requires an efficient technique for its solution. Out of the existing techniques, ABC optimization technique is used as a tool to find out the optimal solution of the above optimization problems and compare their results with fuzzy and GA results. In order to defuzzify the fuzzy output results the center of gravity method as described in section 2.3.5 is used here.

5.3 System Description: Paper Mill

This section is devoted to the description of various subsystems/units of the system i.e. a paper mill situated in the northern part of India and producing approximately 200 tons of paper per day [140, 143, 145, 214]. The paper mills are large capital oriented engineering systems, comprising of units/subsystems namely, feeding, pulping, washing, screening, bleaching, forming, dryer and press, arranged in predefined configuration. A schematic diagram of the various interconnecting processes of a paper mill is shown in Fig. 5.2.

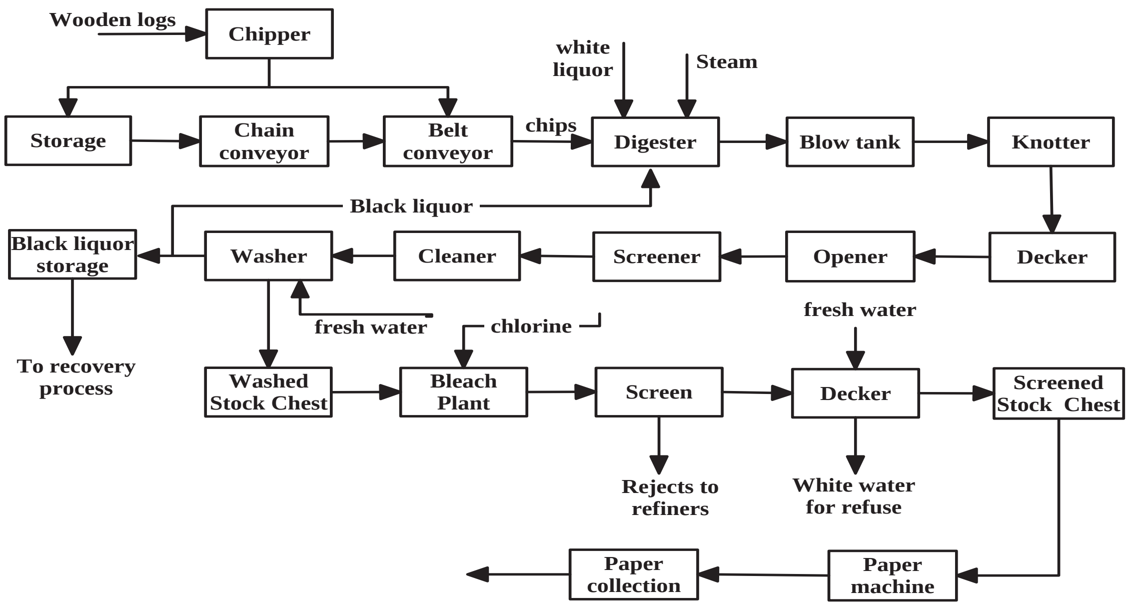


Figure 5.2: Systematic Flow Diagram of the Paper Mill

For the production of paper, the raw material (softwood, hardwood and bamboo etc.) is chopped into small pieces of approximately uniform size and transported for temporarily storage through compressed air. Conveyor in the feeding system carry the chips from the store to the digesters, whenever required. These chips are cooked in the digester by using white liquor ($NaOH+Na_2S$) with steam at pressure of 8.5 Kg/Cm^2 (around 180^0C temperature). The chips when cooked are referred to as 'pulp'. The pulp is then transported to the storage tanks and stirred continuously. After that it is further processed through fiberlizer and refiner. The pulp is then filtered and washed (in stages) with water to remove knots and chemicals. The final washed pulp is stored in a surge tank. The next stages of processing are bleaching and screening. For the production of white paper, pulp is bleached by passing chlorine gas through the pulp stored in the tank. For the production of brown pulp, used for packaging purpose, pulp is screened directly. The white pulp so obtained is passed through screeners to separate odd and oversized particles. The pulp is then made to pass through cleaners which separate heavy material from the pulp. Then, pulp is fed to the head box of the paper machine comprising of three sections viz. forming, press and dryer. In the forming section of the paper machine, the suction box (having six pumps) de-waters the pulp by vacuum action. The paper in the form of sheets produced by rolling presses is sent to press and dryer section to reduce the moisture content by means of heat and vapor transfer and to smooth out any irregularities. Finally, the rolled-dried sheet of the paper (in the form of rolls) is sent for packaging. The paper industry/production system consists of six subsystems - (a) feeding (b) pulping (c) washing (d) bleaching (e) screening (f) paper formation/production which are briefly described as follows.

(a) **Feeding system** - It consists of a chain conveyor for carrying chips from store to digesters and blower with blowing units for pneumatic conveying of chips to the digesters.

(b) **Pulping system** - It consists of digesters for cooking the pulp using NaOH, Na_2S and stem, knotter (fiberizer) to remove the knots from the cooked pulp, decker for removing the black liquor from the cooked pulp and refiner (opener) to open the knots.

(c) **Washing system** - It consists of the screening unit for separating the unwanted foreign material from the pulp, cleaner for removing heavy material from the pulp and washer for removing chemicals through washing.

(d) **Bleaching system** - It consists of filter for filtering the unbleached pulp and opener to open the fibers.

(e) **Screening system** - It is composed of four subsystems; filter to remove black liquor, screen for removing the knots and other undesirable material, cleaner and mixer for cleaning the fibers and mixing of fresh water with the pulp and washer to wash the pulp for brightness.

(f) **Paper Formation system** - It consists of fiber decomposition and water suction unit, pressing unit for ironing and smoothening the paper sheets and dryers for removing the moisture content from the paper sheets.

The six systems introduced above in the paper mill are considered to analyze the behavior for obtaining the overall capability of the paper industry. For this following analysis has been done for each of its subsystems.

(i) **Collecting the data:** Each subsystem of the paper mill namely feeding, pulping, washing, bleaching, screening, forming, press and dryer are modeled with the help of FTA as shown in Figs. 5.3(b), 5.5(b), 5.7(b), 5.9(b), 5.11(b), 5.13, 5.15 and 5.17 respectively in each of which the basic event represents the main component of the system. On the other hand, the data related to their corresponding systems are extracted from the historical records and are integrated with the plant personnel and are tabulated in Tables 5.1, 5.5, 5.9, 5.13, 5.17, 5.21, 5.25 and 5.29 respectively in the form of failure rates and repair times of the main components of the system. As mostly the collected data represent the past behavior and are collected under different conditions and hence the data generally contain some sort of uncertainty. Thus to handle these uncertainties and vagueness in the data, the collected (crisp) data are fuzzified into triangular fuzzy numbers with some support, say $\pm 15\%$ on both sides of the data. Based on these input triangular fuzzy numbers, the system expressions of the failure rate and repair time are evaluated from its cut sets.

(ii) **Analyzing the behavior:** Based on their cut sets, the fuzzy membership functions of various reliability parameters are computed at mission time $t =$ 10(hrs) after solving the nonlinear optimization problem (5.2.11) with left and right $\pm 15\%$ spreads. These computed results are depicted graphically in their respective figures along with the results by FLT and GABLT techniques.

(iii) **Defuzzified values at different spreads:** To make these results useful for the system analyst it is necessary that the obtained fuzzified output should be converted into crisp number or a single number so that the decision makers may utilize it for improving the performance of the system. For this the crisp and defuzzified values of these reliability parameters for different spreads, $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$, are computed and tabulated in Tables along with their FLT and GABLT results corresponding to each subsystem of the paper mill. It is clearly seen from their respective tables that when uncertainties' level, in the form of spread, increases then the computed results of ABCBLT technique are quite less in variation than other techniques' result.

(iv) **Change in defuzzified values:** The results computed from their defuzzified table shows that the crisp values are independent of their spreads while defuzzified values change with change of spreads. The change in their defuzzified values, for showing the sustainability of the computed results, corresponding to each reliability index by all the technique are computed and tabulated in their respective Tables. From these tables it has been concluded that variation in ABCBLT technique is smaller than existing techniques. This observation infers that if system analysts use ABCBLT results, then they may have less range of prediction which finally leads to more sound decisions. Thus, based on the behavioral analysis plots and corresponding tables, the system manager can analyze the critical behavior of the system and plan for suitable maintenance.

5.3.1 Feeding System

The main function of the feeding system [140, 143, 145, 214] is to continuously feed the wooden chips from store to the digester. It comprises of various subsystems, defined as:

- **Blower (A)**: It is used to push the chips through the pipe by compressed air whose failure will cause complete failure of the feeding system.

- **Conveyor Subsystem:** It consists of three operating units in series, namely **Chain conveyor (B)**, **Belt conveyor (C)** and **Bucket conveyor (D)**. Failure in any of the three will switch to the standby unit E, which feeds the digester slowly, causing a delay in the digestion process and hence delay in further processing.

- **Feeder (E):** A standby unit for carrying the chips by compressed air from the store to the digester (low capacity process). This unit works either when there is an extra demand for chips or there is a sudden failure in conveyor subsystem.

The systematic diagram of the feeding system and its equivalent FTA model are shown in Fig. 5.3(a) and Fig. 5.3(b) respectively [140], where FSF represents the failure top event of the feeding system. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.1. The minimal-cut sets, $\{A\}$, $\{B, E\}$, $\{C, E\}$ and $\{D, E\}$ of the system are obtained from the FTA model. Based on these cut-sets, the expressions of the failure rate and repair time for this system are given as below

$$\begin{aligned}\lambda_s &= \lambda_1 + \lambda_2\lambda_5(\tau_2 + \tau_5) + \lambda_3\lambda_5(\tau_3 + \tau_5) + \lambda_4\lambda_5(\tau_4 + \tau_5) \\ \tau_s &= \frac{\lambda_1\tau_1 + \lambda_2\lambda_5\tau_2\tau_5 + \lambda_3\lambda_5\tau_3\tau_5 + \lambda_4\lambda_5\tau_4\tau_5}{\lambda_s}\end{aligned}$$

Using these expressions of λ_s and τ_s, various reliability parameters are depicted graphically in Fig. 5.4 along with the results by FLT and GABLT techniques. From this analysis, it has been concluded that the results computed by the traditional FLT methodology are not so much useful for the system analyst or plant personnel for giving the correct idea about the behavior of the system because it contains a wide range of spread in all the computed parameters. On the other hand, the results computed by using soft computing techniques have a less range of prediction region which enables the decision maker or system analyst to take a more sensitive and effective decision in a lesser time. Moreover, it can be seen from the plots that the proposed methodology have compressed range of uncertainties as compared to other existing methodologies at any $\alpha-$ cut level of satisfaction. These computed results may lead to more sound and effective decision for future course of actions in lesser time, consequently benefitting the system analyst for analyzing the behavior of the system. For predicting the decrease in spread (or support in %) by the proposed technique over the existing techniques, an analysis has been done in which we compute the support of the reliability indices based on their behavior analysis plots and are shown in tabular form in Table 5.2. It has been seen from the table that the largest and the smallest decrease in spread occur corresponding to the availability and reliability respectively from FLT while MTBF and repair time respectively from GABLT results when ABCBLT technique has been applied. On the other hand, the largest and smallest spreads occur corresponding to repair time and availability respectively from FLT when GABLT technique has been applied, which means a prediction range of reliability parameters is decreased. This suggests that DMs have smaller and more sensitive region to make more sound and effective decision in lesser time.

The defuzzified values of these reliability parameters at different spreads are tabulated in Table 5.3. Based on these values, plant personnel may change their target goals from their traditional results. For instance, if plant personnel want to optimize the system reliability as a target then the corresponding new target should be greater than 0.87721835 rather than 0.87676541 or 0.87598915 at ±15% level of uncertainties. Similarly for other parameters new targets may be set. From Table 5.4, it is evident that defuzzified values change with change of spread. For instance, failure rate of the system increases by 3.093493%, 1.601105% and 0.119220% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 14.195106%, 3.025358% and 0.246051%, when spread changes from ±25% to ±50%. On the other hand, reliability of the system decreases firstly by 0.335381%, 0.079621% and 0.058392% and further 1.534878%, 0.315696% and 0.102252% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and from ±25% to ±50%.

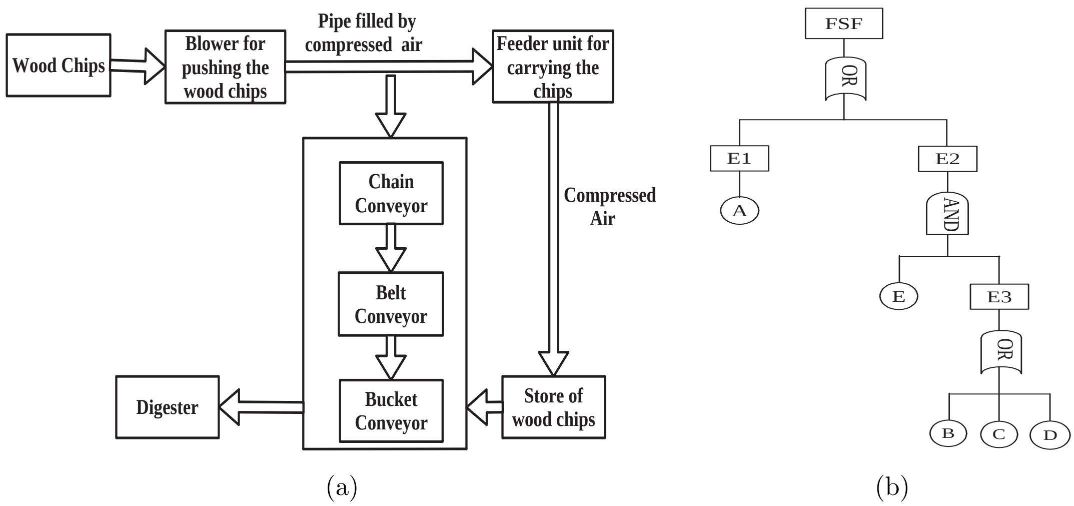


Figure 5.3: (a) Systematic diagram and (b) FTA model of the Feeding System

Table 5.1: Input Data for Feeding System

Components	Failure rate (hrs^{-1})	Repair time (hrs)
Blower	6.25×10^{-3}	10
Chain Conveyor	4.00×10^{-2}	2.5
Belt Conveyor	1.00×10^{-2}	2.0
Bucket Conveyor	8.30×10^{-2}	5.0
Feeder	1.33×10^{-2}	6.0

Table 5.2: Data related to Spread of Reliability Indices for Feeding System

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00804116	8.12678606	56.46956864	0.07026931	0.10697685	0.37166651
II	0.00521241	2.42905058	28.69243288	0.04378932	0.02500545	0.13656064
III	0.00152224	0.70904056	10.58957288	0.01347028	0.00826647	0.04185284
	Decrease in spread (in %) from					
I to II	35.17838222	70.11056324	49.18956604	37.68357765	76.62536333	63.25721141
I to III	81.06939794	91.27526484	81.24729277	80.83049342	92.27265525	88.73914144
II to III	70.79585067	70.80997135	63.09280246	69.23843531	66.94132679	69.35219401

I: FLT II: GABLT III: ABCBLT

Table 5.3: Defuzzified Values of Reliability Indices for Feeding System

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.01305029	5.77670688	82.40335655	0.87765395	0.94079291	0.82290874
		Defuzzified values for reliability indices					
±15%	FLT	0.01328078	6.40158520	85.32518355	0.87598915	0.93069158	0.80119740
	GABLT	0.01316840	5.86234357	82.87279918	0.87676541	0.94072528	0.82077631
	ABCBLT	0.01311860	5.77603147	82.27128602	0.87721835	0.94080904	0.82248426
±25%	FLT	0.01369162	7.62783469	90.85228292	0.87305125	0.91077801	0.76870473
	GABLT	0.01337924	5.93632318	85.21872527	0.87746350	0.94012728	0.81518173
	ABCBLT	0.01310296	5.78139194	82.94668964	0.87773058	0.94061041	0.82481891
±50%	FLT	0.01563516	15.8876264	123.9047285	0.85965097	0.81080251	0.68068748
	GABLT	0.01378401	6.22481066	96.86479919	0.87469338	0.93767974	0.80375018
	ABCBLT	0.01313520	5.74223319	83.48733841	0.87683308	0.94198132	0.82792347

Table 5.4: Change in Defuzzified Values of Reliability Indices for Feeding System

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	1.76616764	10.8172066	3.54576211	0.18968751	1.07370388	2.63836546
to	GABLT	0.90503735	1.48244824	0.56968872	0.10124035	0.00718861	0.25913323
±15%	ABCBLT	0.52343664	0.01169195	0.16027324	0.04963231	0.00171451	0.05158287
±15%	FLT	3.09349300	19.1554037	6.47768822	0.33538086	2.13965296	4.05551365
to	GABLT	1.60110567	1.26194599	2.83075522	0.07962106	0.06356797	0.68162055
±25%	ABCBLT	0.11922003	0.09280541	0.82094695	0.05839253	0.02111267	0.28385345
±25%	FLT	14.1951062	108.28488	36.3804238	1.53487896	10.9769338	11.45007264
to	GABLT	3.02535869	4.8596997	13.6660973	0.31569632	0.26034134	1.40233147
±50%	ABCBLT	0.24605127	0.6773239	0.65180271	0.10225233	0.14574684	0.37639292

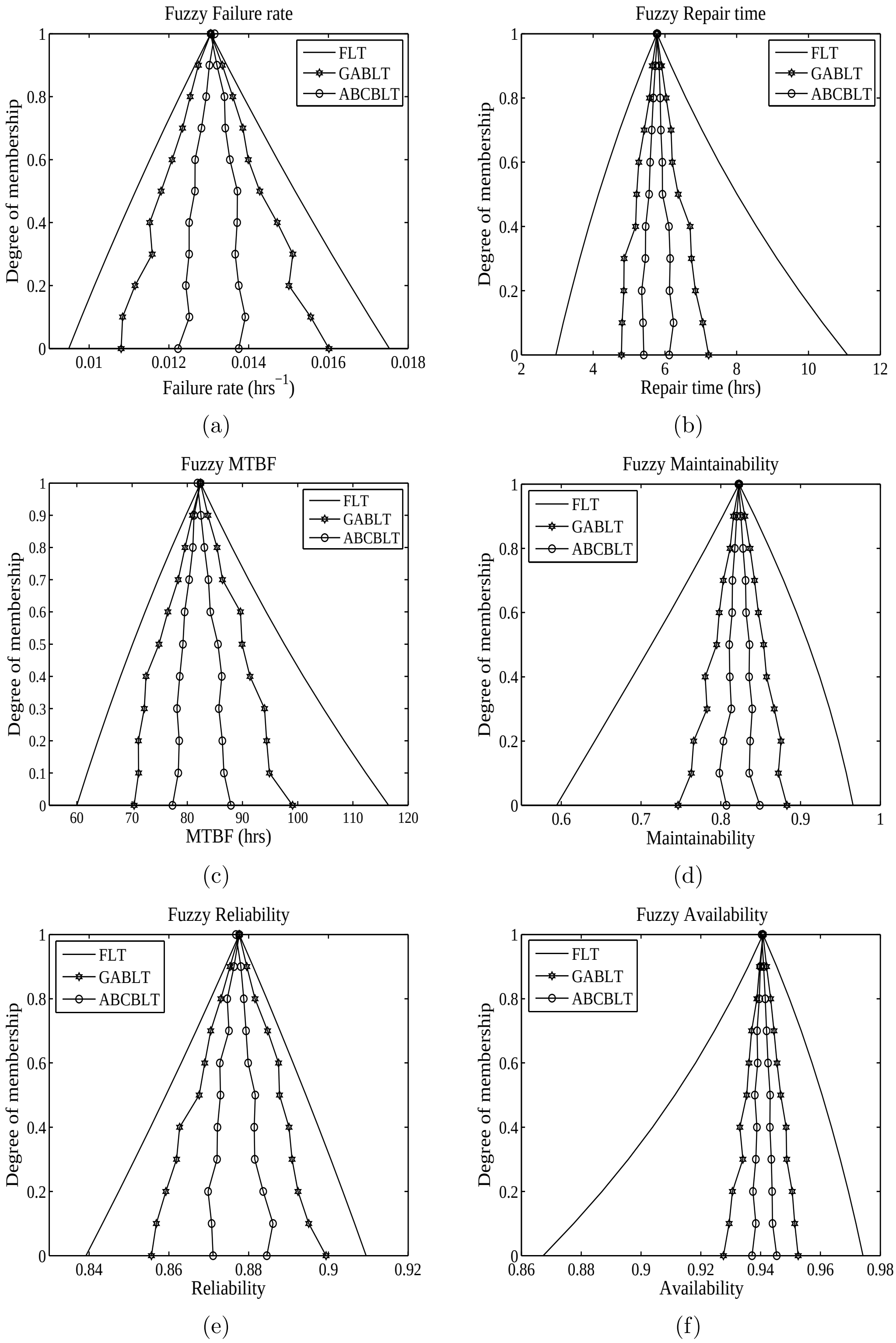


Figure 5.4: Fuzzy Reliability Indices Plot for Feeding System at ±15% spread

5.3.2 Pulping System

The four major actions carried out in the system are, (i) cooking of chips, (ii) separation of knots, (iii) washing of pulp, and (iv) opening of fibers. The pulping system [140, 143, 145, 214] consists of four subsystems, namely:

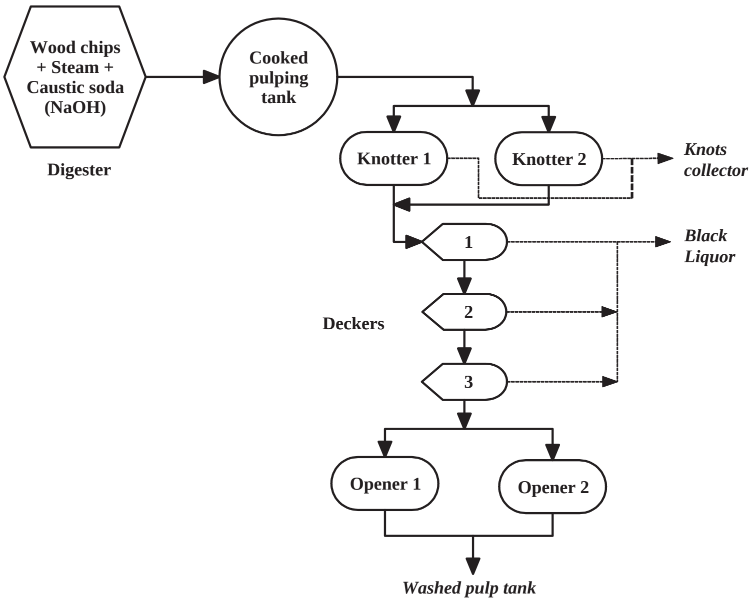
- **Digester (A):** It consists of single unit, used for cooking the chips.Here a mixture of wooden chips and NaOH + Na_2S (1:3.5 ratio) is heated by steam at 175^oC. Failure of digester stops the cooking process and hence leads to system failure.
- **Knotter (B):** It consists of two units, one working and other standby, used to remove the knots from the cooked chips because the knots preclude the production of paper. Knotter subsystem's complete failure occurs only if both of its units fail.
- **Decker (C):** It has three units, arranged in series configuration and are used to remove black liquor from the cooked chips. Failure of any one causes the complete failure of the pulping system. Although production is possible even with two or single decker, but it will reduce the quality of paper, which is less requirement and consequently lead to lesser profit.
- **Opener (D):** This subsystem possesses two units, one working and other standby and are used to break the walls of the fibers into ribbons ensuring the availability of large surface area for bonding. Complete failure of this subsystem occurs when both the units fail.

The equivalent systematic diagram of the system and their corresponding fault tree model has been given in Fig. 5.5(a) and 5.5(b) respectively [140], where PSF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.5. The minimal-cut sets, $\{A\}$, $\{B_1B_2\}$, $\{C_1\}$, $\{C_2\}$, $\{C_3\}$ and $\{D_1D_2\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.6 along with FLT and GABLT technique results. Based on these figures, the decrease in the spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.6. It has been concluded from the table that the results computed by proposed approach are more crucial as compared to other technique results because there is a significant decrease in their parametric values when compared with the other techniques results.

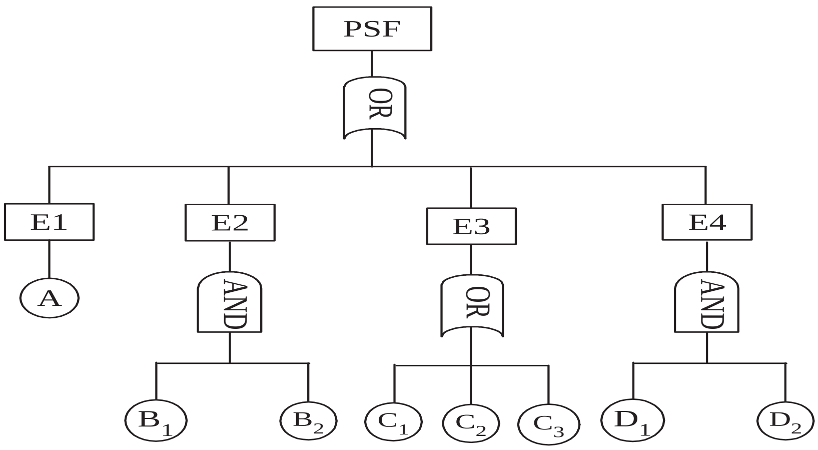
The crisp and defuzzified values for various reliability parameters at ±15%, ±25% and ±50% spreads for all the three techniques are calculated and depicted in Table 5.7. It is observed from the table that the variations in their defuzzified values by ABCBLT technique are quite less as compared to other techniques' results values. For instance, failure rate of the system increases by 6.83531028%, 5.03894116% and 2.15368555% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 46.0739272%, 26.1282019% and 16.8262806% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.8.

Table 5.5: Input data for the Pulping system

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Digester (i=1)	511	1.37	15
Knotters (i=2,3)	111	1.31	5.0
Deckers (i=4,5,6)	252	1.76	2.5
Openers (i=7,8)	151	1.19	5.0



(a)



(b)

Figure 5.5: (a) Systematic diagram and (b) FTA model of the Pulping System

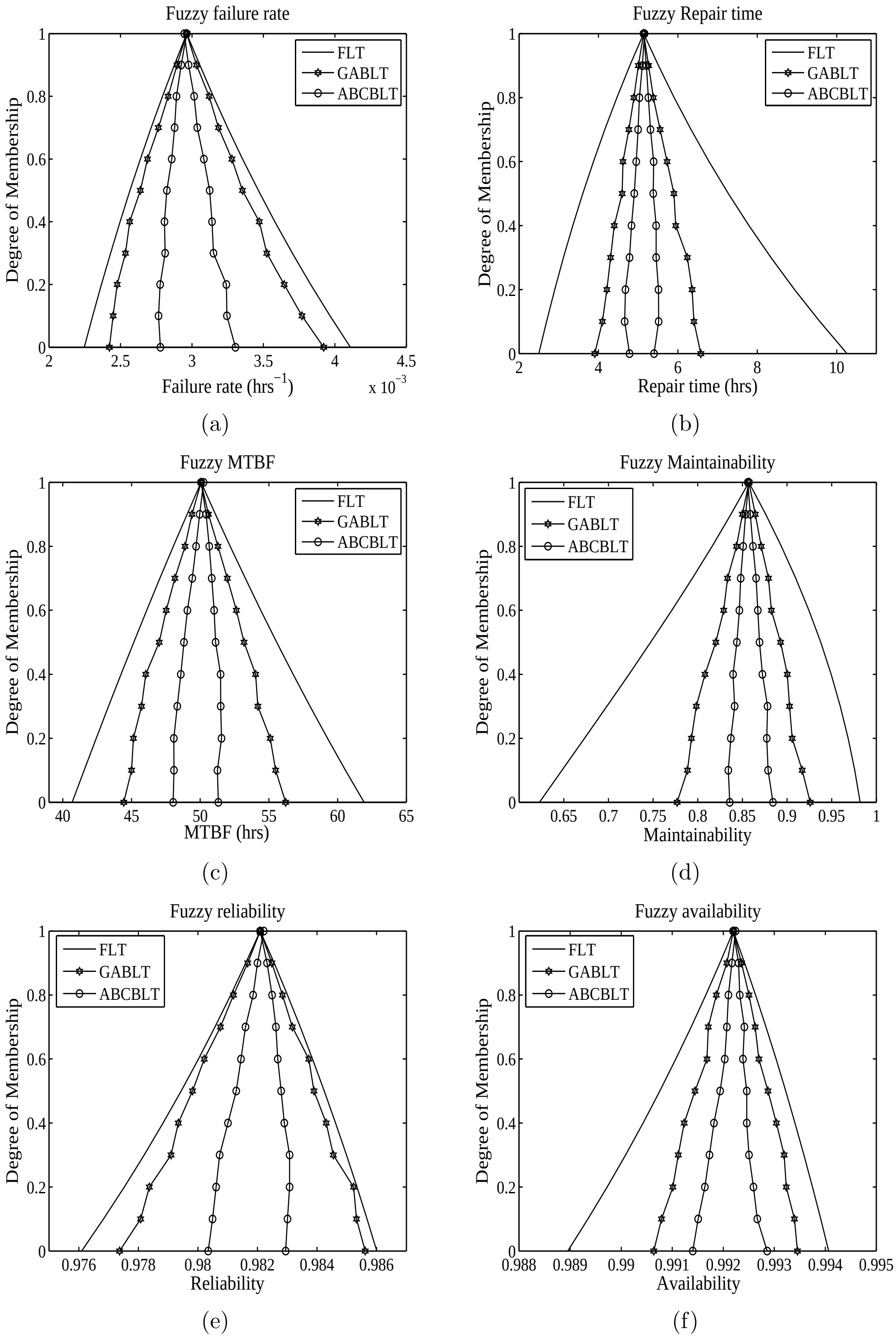


Figure 5.6: Fuzzy Reliability Indices Plot for Pulping unit at ±15% spread

Table 5.6: Data related to Spread of Reliability Indices for Pulping System

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00186220	7.76140447	21.23992825	0.00991466	0.00511243	0.35903877
II	0.00139353	2.67002602	11.77486269	0.00824847	0.00282767	0.14899611
III	0.00051635	0.61697203	3.29221745	0.00260169	0.00145857	0.04841293
	Decrease in spread (in %) from					
I to II	25.16754376	65.59867443	44.56260609	16.80531657	44.69029404	58.50138691
I to III	72.27204381	92.05076822	84.49986548	73.75916067	71.47012281	86.51596037
II to III	62.94661758	76.89265852	72.04029009	68.45851412	48.41795541	67.50725237

I: FLT II: GABLT III: ABCBLT

Table 5.7: Defuzzified Values of Reliability Indices for Pulping System

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00296371	5.13789617	50.06630877	0.98209417	0.99219734	0.85720167
		Defuzzified values for reliability indices					
	FLT	0.00307038	5.75858883	50.68198455	0.98157347	0.99182699	0.82911642
±15%	GABLT	0.00303278	5.22921543	50.11618832	0.98180298	0.99200431	0.85302591
	ABCBLT	0.00298883	5.12234622	49.92873112	0.98192776	0.99212027	0.85729468
	FLT	0.00328025	7.00582173	51.89308947	0.98056359	0.99123568	0.78867198
±25%	GABLT	0.00318560	5.37793627	50.07465495	0.98089567	0.99187728	0.84418492
	ABCBLT	0.00305320	5.13453531	49.44027938	0.98156038	0.99195566	0.85815036
	FLT	0.00479159	16.5899120	60.60456345	0.97376311	0.98746361	0.68483374
±50%	GABLT	0.00401794	6.11551231	49.83710622	0.97612388	0.99082414	0.81446331
	ABCBLT	0.00356694	4.96641027	47.47805087	0.97857934	0.99108188	0.86525583

Table 5.8: Change in Defuzzified Values of Reliability Indices for Pulping System

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	3.59920505	12.0806773	1.22972073	0.05301935	0.03732624	3.27638769
to	GABLT	2.33052491	1.77736678	0.09962697	0.02964990	0.01945479	0.48713857
±15%	ABCBLT	0.84758630	0.30265208	0.27479087	0.01694440	0.00776760	0.01085042
±15%	FLT	6.83531028	21.6586552	2.38961621	0.10288379	0.05961826	4.87801701
to	GABLT	5.03894116	2.84403735	0.08287415	0.09241263	0.01280538	1.03642690
±25%	ABCBLT	2.15368555	0.23795912	0.97829792	0.03741415	0.01659173	0.09981165
±25%	FLT	46.0739272	136.8018005	16.7873488	0.69352768	0.38054219	13.16621391
to	GABLT	26.1282019	13.71485274	0.47438915	0.48647273	0.10617644	3.52074637
±50%	ABCBLT	16.82628062	3.27439641	3.96888637	0.30370418	0.08808659	0.82799825

5.3.3 Washing System

The Washing of prepared pulp is done in three to four stages, to get it free from blackness and to prepare the fine fibers of the pulp. The washing system [140, 143, 145, 214] consists of four main subsystems, defined as:

- **Filter (A):** It consists of single unit which is used to drain black liqueur from the cooked pulp.
- **Cleaners (B):** In this subsystem three units of cleaners are arranged in parallel configuration. Each unit may be used to clean the pulp by centrifugal action. Failure of anyone will reduce the efficiency of the system as well as quality of paper.
- **Screeners (C):** Herein two units of screeners are arranged in series. These are used to remove oversized, uncooked and odd shaped fibers from pulp through straining action. Failure of any one will cause the complete failure of the system.
- **Deckers (D):** Two units of deckers are arranged in parallel configuration. The function of deckers is to reduce the blackness of pulp. Complete failure of decker occurs when both the components will fail.

The equivalent systematic diagram of the system and their corresponding fault tree model has been given in Fig. 5.7(a) and 5.7(b) respectively [140], where WSF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.9. The minimal-cut sets, $\{A\}$, $\{B_1B_2\}$, $\{C_1\}$, $\{C_2\}$ and $\{D_1D_2\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.8, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.10. The crisp and defuzzified values for various reliability parameters at ±15%, ±25% and ±50% spreads for all the three techniques are calculated and depicted in Table 5.11. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 3.63121246%, 3.47212792% and 1.68028108% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 21.94528407%, 18.81291298% and 8.475554653% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.12.

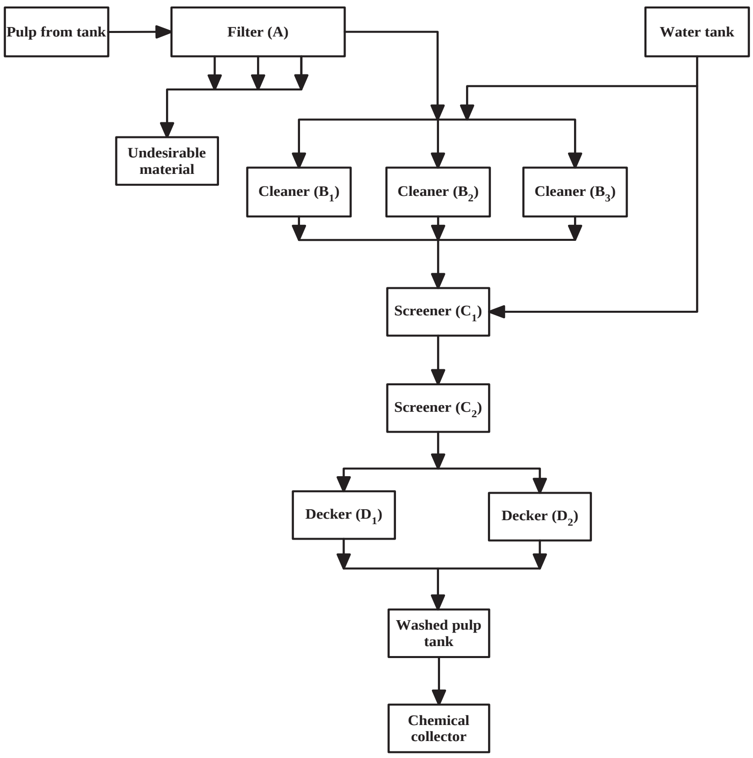
Table 5.9: Input Data for the Washing System

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Filter (i=1)	337	1.33	3.5
Cleaners (i=2,3,4)	170	1.88	2.0
Screeners (i=5,6)	426	1.46	4.0
Deckers (i=7,8)	252	1.76	2.5

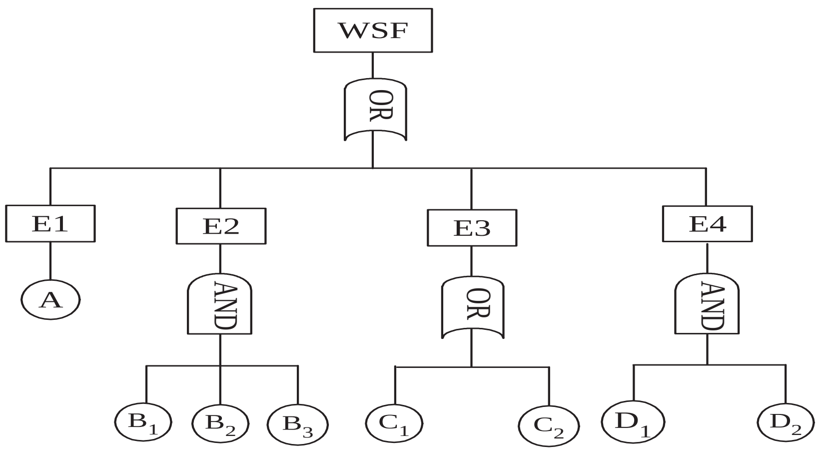
Table 5.10: Data related to Spread of Reliability Indices for Washing System

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00106276	4.48841061	24.19241643	0.00747565	0.00462835	0.21022394
II	0.00101359	1.06030015	16.69617207	0.00697279	0.00266581	0.05308428
III	0.00019810	0.23675094	4.60344901	0.00112911	0.00089560	0.01256076
	Decrease in spread (in %) from					
I to II	4.62663254	76.37693513	30.98592644	6.72663915	42.40258407	74.74869893
I to III	81.35985547	94.72528338	80.97152046	84.89616287	80.64969157	94.02505727
II to III	80.45560828	77.67132825	72.42811711	83.80691229	66.40420735	76.33807974

I: FLT II: GABLT III: ABCBLT



(a)



(b)

Figure 5.7: (a) Systematic diagram and (b) FTA model of the Washing System

Table 5.11: Defuzzified Values of Reliability Indices for Washing System

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00245830	3.74652200	69.42654140	0.98249050	0.99277595	0.93068835
		Defuzzified values for reliability indices					
±15%	FLT	0.00250605	4.03899283	69.71699758	0.98215885	0.99258197	0.90796267
	GABLT	0.00250394	3.74391932	69.51780162	0.98220870	0.99267327	0.92967769
	ABCBLT	0.00247042	3.75361555	69.31634847	0.98240450	0.99277380	0.93028859
±25%	FLT	0.00259705	4.60599201	70.26950357	0.98152808	0.99221235	0.87320168
	GABLT	0.00259088	3.75671173	69.29305777	0.98159663	0.99235548	0.92869121
	ABCBLT	0.00251193	3.75704513	68.82121168	0.98215572	0.99263145	0.92962589
±50%	FLT	0.00316698	8.37595488	73.69205035	0.97761985	0.98990460	0.76597076
	GABLT	0.00307830	3.77792750	68.69727268	0.97825935	0.99165891	0.92174277
	ABCBLT	0.00272483	3.76369840	65.62112887	0.98068754	0.99229121	0.92868797

Table 5.12: Change in Defuzzified values of Reliability Indices for Washing System

spread	%age change in defuzzified values(in magnitude) from						
	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	1.94239921	7.80646236	0.41836475	0.03375605	0.01953915	2.44181416
to	GABLT	1.85656754	0.06946923	0.13144860	0.02868221	0.01034271	0.10859274
±15%	ABCBLT	0.49302363	0.18933693	0.15871873	0.00875326	0.00021656	0.04295315
±15%	FLT	3.63121246	14.03813286	0.79249825	0.06422280	0.03723823	3.82846026
to	GABLT	3.47212792	0.341684980	0.32328963	0.06231567	0.03201355	0.10610989
±25%	ABCBLT	1.68028108	0.091367375	0.71431458	0.02532358	0.01433861	0.07123595
±25%	FLT	21.94528407	81.84909704	4.87060048	0.39817811	0.23258630	12.28020083
to	GABLT	18.81291298	0.564743092	0.85980487	0.33998486	0.07019359	0.748197024
±50%	ABCBLT	8.475554653	0.177087838	4.64984956	0.14948546	0.03427656	0.100892198

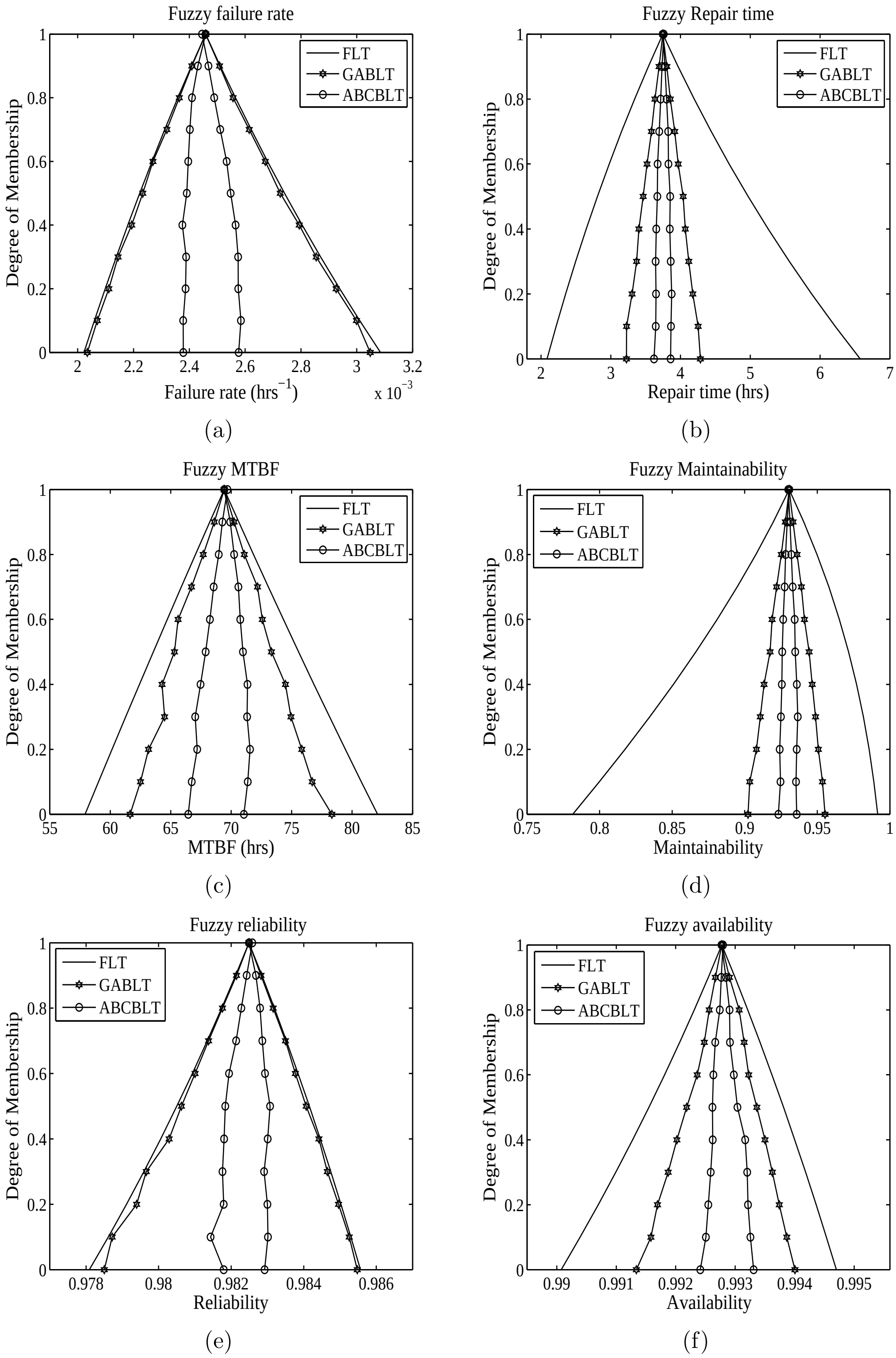


Figure 5.8: Fuzzy Reliability Indices Plot for Washing System at ±15% spread

5.3.4 Bleaching System

The bleaching system [140, 143, 145, 214] is used to bleach the pulp and to obtain bright pulp for the production of white paper. It consists of bleaching tank along with two subsystems arranged in series which are defined below.

- **Bleaching Tank (A):** It is a tank with a stirrer where the washed pulp from the washing system is stored and the chlorine is passed here into the pulp for brightening it. Failure in this unit will cause the complete failure of bleaching system.

- **Filter (B):** The primary action of a filter is to remove chlorine and unbleached mass from the pulp received from the washing system. This subsystem consists of two units in parallel, and is said to be failed when both the units have failed.

- **Washer (C):** Their primary action is to wash the fibers and to remove chlorine from the pulp. It consists of two units in parallel, and is said to be failed when both the units have failed.

The equivalent systematic diagram of the system and their corresponding fault tree model has been given in Fig. 5.9(a) and 5.9(b) respectively [140], where BSF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.13. The minimal-cut sets, $\{A\}$, $\{B_1B_2\}$ and $\{C_1C_2\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.10, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.14. The crisp and defuzzified values for various reliability parameters at $\pm15\%$, $\pm25\%$ and $\pm50\%$ spreads for all the three techniques are calculated and depicted in Table 5.15. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 4.74800088%, 4.47261738% and 0.28214064% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 29.83989578%, 27.88525307% and 3.278367887% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.16.

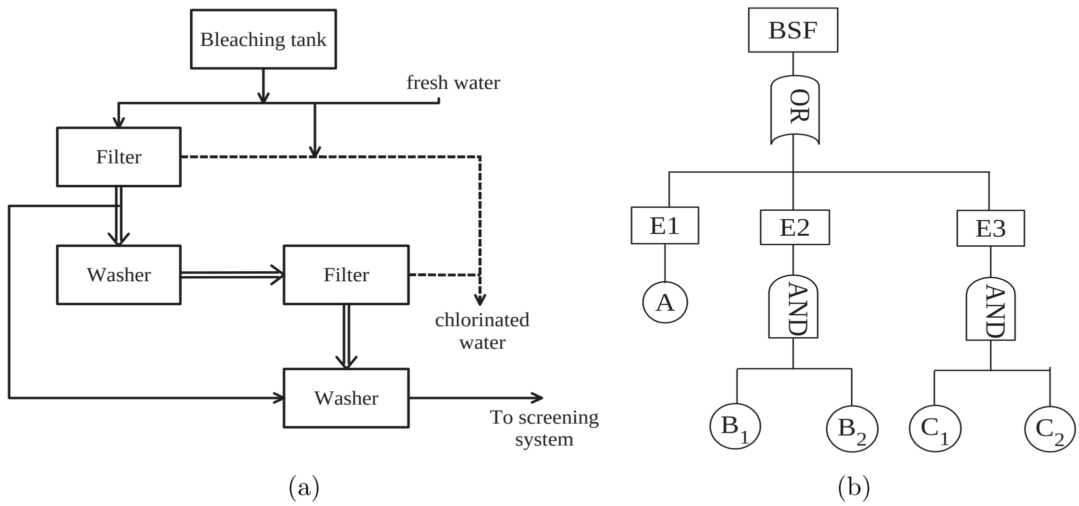


Figure 5.9: (a) Systematic diagram and (b) FTA model of the Bleaching System

Table 5.13: Input Data for the Bleaching System

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Bleaching Tank (i=1)	311	1.60	2.5
Filters (i=2,3)	337	1.33	2.0
Washers (i=4,5)	426	1.46	3.0

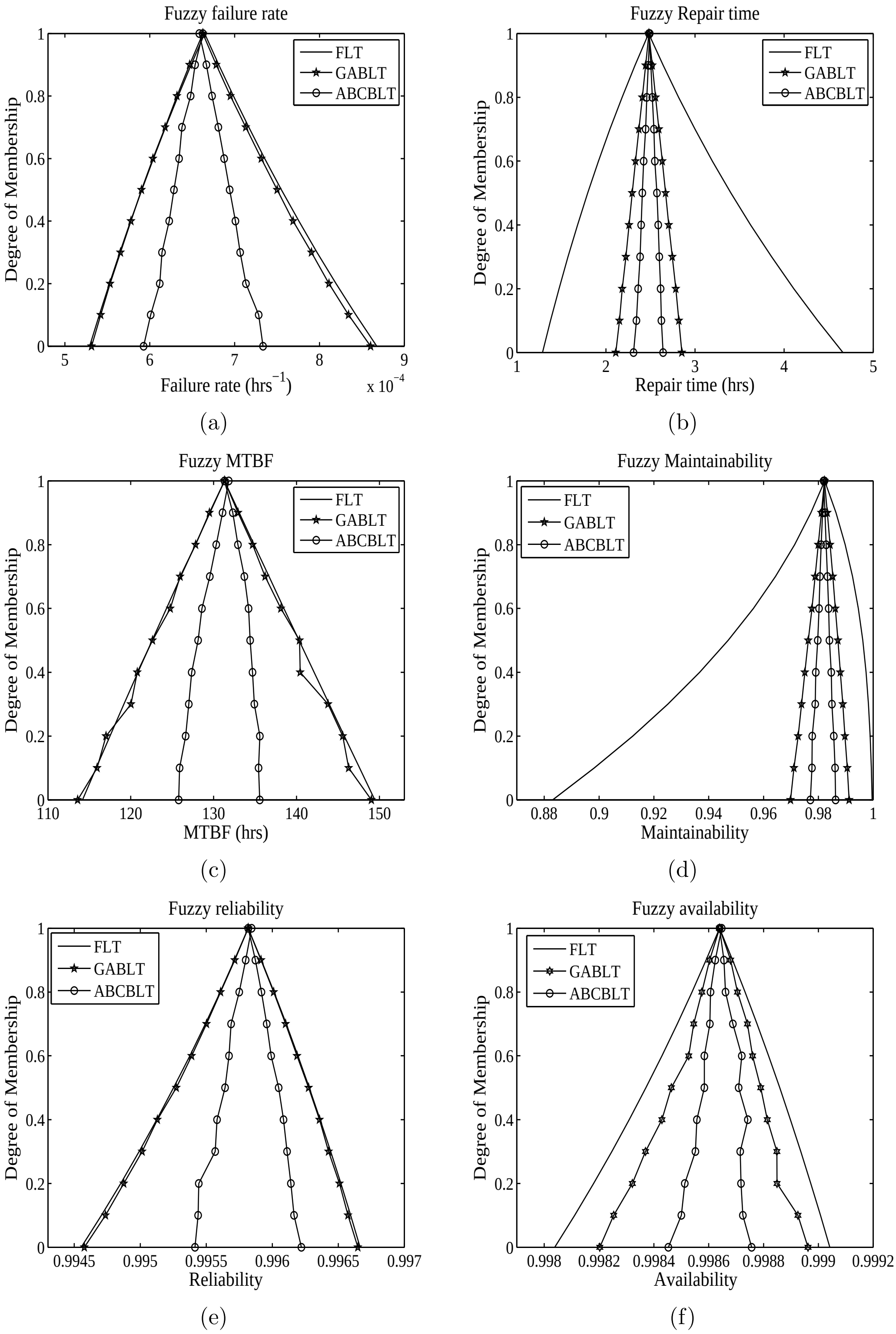


Figure 5.10: Fuzzy Reliability Indices Plot for Bleaching System at ±15% spread

Table 5.14: Data related to Spread of Reliability Indices for Bleaching System

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00033834	3.37131717	35.27890412	0.00211302	0.00100331	0.11652513
II	0.00032675	0.74811544	36.24033395	0.00206287	0.00075968	0.02126761
III	0.00013461	0.31573520	11.20475275	0.00082881	0.00030397	0.00908812
	Decrease in spread (in %) from					
I to II	3.42554826	77.80940201	2.72522589	2.37338028	24.28262451	81.74847777
I to III	60.2145770	90.63466342	68.2395101	60.7760456	69.70328213	92.20072099
II to III	58.8033664	57.79592518	69.0820929	59.8224803	59.98709983	57.26778890

I: FLT II: GABLT III: ABCBLT

Table 5.15: Defuzzified Values of Reliability Indices for Bleaching System

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00066254	2.48278847	131.31685950	0.99581710	0.99863981	0.98218526
		Defuzzified values for reliability indices					
±15%	FLT	0.00068155	2.72707261	131.55826373	0.99571315	0.99858954	0.96054987
	GABLT	0.00067835	2.48296828	131.43108974	0.99572024	0.99861384	0.98136810
	ABCBLT	0.00066279	2.48925318	131.07142124	0.99582455	0.99864537	0.98182177
±25%	FLT	0.00071391	3.21630347	132.02623486	0.99551313	0.99849433	0.92358028
	GABLT	0.00070869	2.48253921	131.60714590	0.99552483	0.99851350	0.97996486
	ABCBLT	0.00066466	2.48825118	130.05489665	0.99578500	0.99866371	0.98150158
±50%	FLT	0.00092694	6.72112800	134.94771911	0.99420776	0.99787436	0.79407091
	GABLT	0.00090631	2.48507852	131.04073964	0.99429806	0.99807127	0.97364493
	ABCBLT	0.00068645	2.51157171	124.15001724	0.99569629	0.99862809	0.97990675

Table 5.16: Change in Defuzzified Values of Reliability Indices for Bleaching System

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0% to ±15%	FLT	2.86926072	9.83910401	0.18383338	0.01043866	0.00503384	2.20278097
	GABLT	2.38627101	0.00724226	0.08698825	0.00972668	0.00260053	0.08319815
	ABCBLT	0.03773357	0.26038102	0.18690536	0.00074812	0.00055675	0.03700829
±15% to ±25%	FLT	4.74800088	17.93978122	0.35571397	0.02008811	0.00953444	3.84879444
	GABLT	4.47261738	0.017280526	0.13395320	0.01962499	0.01004792	0.14298814
	ABCBLT	0.28214064	0.040253036	0.77555013	0.00397158	0.00183648	0.03261182
±25% to ±50%	FLT	29.83989578	108.9705795	2.21280585	0.13112534	0.06209048	14.02253521
	GABLT	27.88525307	0.102286803	0.43037652	0.12322846	0.04428883	0.644913941
	ABCBLT	3.278367887	0.937225718	4.54029764	0.00890854	0.00356676	0.162488785

5.3.5 Screening System

The screening system [140, 143, 145, 214] is used to screen the pulp available from bleaching and/or pulping and to make it free from impurities. It consists of four main subsystems, defined as:

- **Filter (A):** A single unit of filter is employed for removal of black liquor from the pulp. its failure causes failure of the system.
- **Screener (B):** Screener has one unit which is used to remove oversized, uncooked and odd shaped fibers from pulp through straining action. Its failure will cause system to fail.
- **Cleaners (C):** This subsystem has three units in parallel. Here water is mixed with pulp to cleanse it by centrifugal action. Failure of any one will reduce the efficiency of the system, and hence, reduces the quality of paper with respect to cleanliness.
- **Decker (D):** A single unit of decker is used to wash and remove the impurities from the pulp before delivering it to the head box of the paper machine.

The equivalent systematic diagram of the system and their corresponding fault tree model has been given in Fig. 5.11(a) and 5.11(b) respectively [140], where SSF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.17. The minimal-cut sets, $\{A\}$, $\{B\}$, $\{C_1C_2C_3\}$ and $\{D\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.12, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.18. The crisp and defuzzified values for various reliability parameters at $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$ spreads for all the three techniques are calculated and depicted in Table 5.19. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 4.06283693%, 3.40957694% and 1.84339009% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 24.90227688%, 18.63179663% and 11.54419922% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.20.

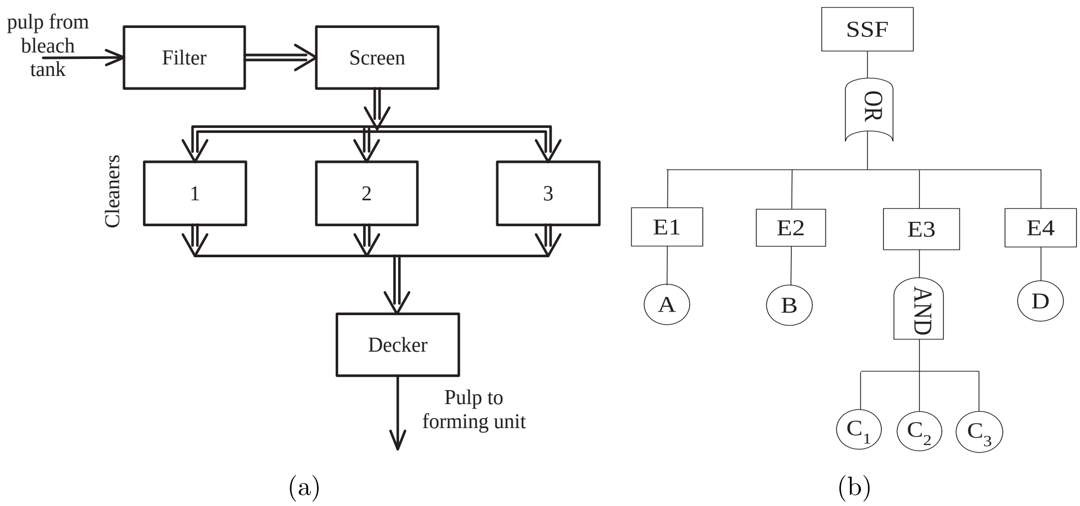


Figure 5.11: (a) Systematic diagram and (b) FTA model of the Screening System

Table 5.17: Input Data for the Screening System

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Filter (i=1)	337	1.33	2.0
Screeners (i=2)	315	1.54	4.0
Cleaners (i=3,4,5)	470	1.88	2.0
Deckers (i=6)	252	1.76	5.0

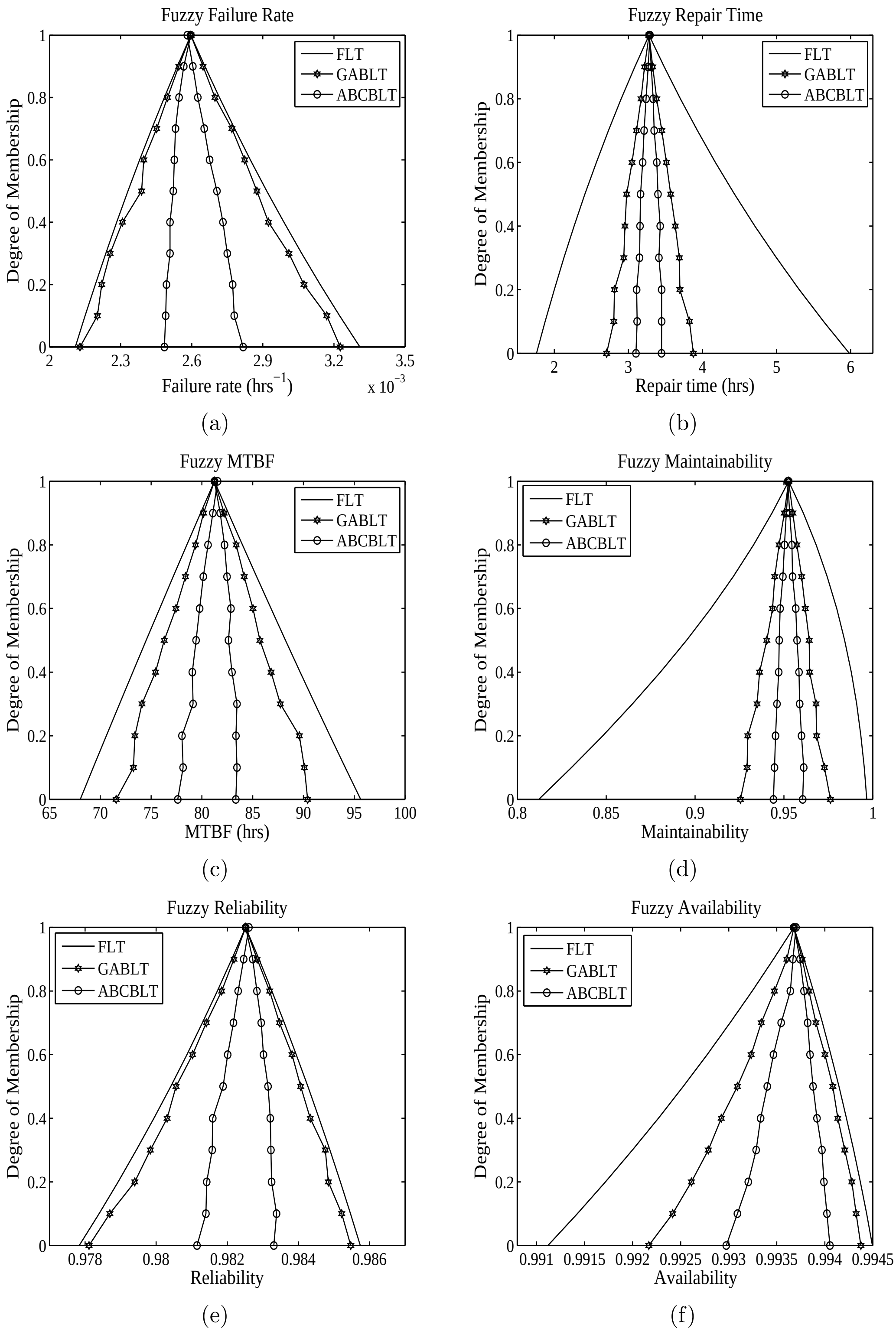


Figure 5.12: Fuzzy Reliability Indices Plot for Screening System at ±15% spread

Table 5.18: Data related to Spread of Reliability Indices for Screening System

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00120092	4.22311337	27.60903436	0.00790404	0.00337698	0.18456749
II	0.00109760	1.17198062	18.83765407	0.00736161	0.00220702	0.05071374
III	0.00033229	0.34472321	5.71329338	0.00216078	0.00107863	0.01639967
	Decrease in spread (in %) from					
I to II	8.60340405	72.24842154	31.76996404	6.86269301	34.64515632	72.52292914
I to III	72.33038004	91.83722576	79.30643533	72.66233470	68.05933111	91.11454026
II to III	69.72576530	70.58627044	69.67088705	70.64799683	51.12731194	67.66227456

I: FLT II: GABLT III: ABCBLT

Table 5.19: Defuzzified Values of Reliability Indices for Screening System

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00259627	3.27925706	81.23232702	0.98251623	0.99367855	0.95261603
		Defuzzified values for reliability indices					
±15%	FLT	0.00265258	3.57551107	81.52610962	0.98215219	0.99315659	0.92744100
	GABLT	0.00264197	3.28789856	81.25766926	0.98219078	0.99342732	0.95107977
	ABCBLT	0.00261963	3.28320212	81.03557825	0.98242826	0.99364004	0.95250914
±25%	FLT	0.00276035	4.15696018	80.34480159	0.98145753	0.99256723	0.88879311
	GABLT	0.00273205	3.33022187	81.19098639	0.98168133	0.99354363	0.94822880
	ABCBLT	0.00266792	3.29850564	80.34480159	0.98203008	0.99358383	0.95174317
±50%	FLT	0.00344774	8.21918073	85.70664633	0.97708415	0.98953749	0.76937920
	GABLT	0.00324108	3.38059898	81.58548505	0.97861175	0.99302807	0.93392026
	ABCBLT	0.00297591	3.31960956	76.83199291	0.98008021	0.99304296	0.95162085

Table 5.20: Change in Defuzzified Values of Reliability Indices for Screening System

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0% to ±15%	FLT	2.16888074	9.03418074	0.36165724	0.03705180	0.05252805	2.64272584
	GABLT	1.76021754	0.26352005	0.03119723	0.03312413	0.02528282	0.16126749
	ABCBLT	0.89975233	0.12030346	0.24220501	0.00895354	0.00387549	0.01122068
±15% to ±25%	FLT	4.06283693	16.2619860	1.44899350	0.07072834	0.05934210	4.16715349
	GABLT	3.40957694	1.28724500	0.08206347	0.05186874	0.01170795	0.29976139
	ABCBLT	1.84339009	0.46611568	0.85243626	0.04053018	0.00565697	0.08041602
±25% to ±50%	FLT	24.90227688	97.7209396	6.67354282	0.44560053	0.30524279	13.4355125
	GABLT	18.63179663	1.51272533	0.48588972	0.31268599	0.05189102	1.50897547
	ABCBLT	11.54419922	0.63980245	4.37216672	0.19855501	0.05443627	0.01285220

5.3.6 Forming Unit

The function of the forming unit [140, 143, 145, 214] is to carry metered quantity of the pulp for further processing. It consists of head box, wire mat, suction box and a number of rollers. Cooked pulp after processing through number of stages is fed to head box of paper machine from where pulp is made to run on the wire mat, supported by number of rollers. The head box delivers stock (pulp + water) in controlled quantity to moving wire mat, supported by series of tables and wire rolls. The suction box (having six pumps) de-waters the pulp through vacuum action. Four pumps out of six should keep on working to keep the system working. The chances of failure of head box are negligibly small.

- **Head box (A):** It consists of a single unit only. Its failure causes complete failure of the system.
- **Wire mat (B):** It consists of a single unit of wire mat. Its failure causes complete failure of the system.
- **Suction box (C):** Six pumps are arranged in complex configuration and is considered as a single system. Failure of more than two pumps at a time causes failure of the system.
- **Rollers (D,E,F):** This subsystem consist of roller bearing, roller bending and roller rubber wear.

The interaction among the working components of the system are shown in Fig. 5.13 [140], where FUF represents the system top failure event of the forming unit. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.21. The minimal-cut sets, $\{A\}$, $\{B\}$, $\{C\}$, $\{D\}$, $\{E\}$ and $\{F\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.14, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from

FLT and GABLT technique and their corresponding values are tabulated in Table 5.22. The crisp and defuzzified values for various reliability parameters at ±15%, ±25% and ±50% spreads for all the three techniques are calculated and depicted in Table 5.23. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 3.16343271%, 1.59023512% and 1.46965625% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 18.88864406%, 10.56909685% and 8.454456966% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.24.

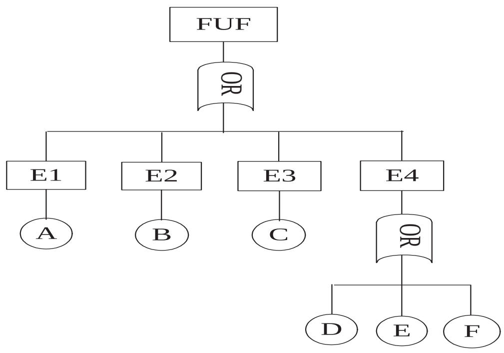


Figure 5.13: FTA model of the Forming Unit

Table 5.21: Input Data for the Forming Unit

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Head Box	415	1.60	10
Wire Mat	342	1.80	12
Suction Box	960	1.22	2.5
Roller Bearing	523	1.17	2.0
Roller Bending	424	1.21	4.0
Roller Rubber Wear	313	1.24	3.0

Table 5.22: Data related to Spread of Reliability Indices for Forming Unit

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00211420	4.67327578	24.61603726	0.01584372	0.00858562	0.22547575
II	0.00145098	1.14974776	16.51028825	0.01221376	0.00381519	0.06188913
III	0.00045447	0.39769248	4.74455827	0.00357712	0.00184429	0.02043862
	Decrease in spread (in %) from					
I to II	31.36978526	75.39739116	32.92873229	22.91103351	55.56302282	72.55175778
I to III	78.50392583	91.49007037	80.72574305	77.42247401	78.51884895	90.93533561
II to III	68.67841045	65.41045837	71.26301977	70.71237686	51.65928826	66.97542847

I: FLT II: GABLT III: ABCBLT

Table 5.23: Defuzzified Values of Reliability Indices for Forming Unit

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00536426	4.04733997	70.52321155	0.95829314	0.98484149	0.91547928
		Defuzzified values for reliability indices					
±15%	FLT	0.00545515	4.34356997	70.81748232	0.95763420	0.98423790	0.89435564
	GABLT	0.00543253	4.08334430	70.30825894	0.95782415	0.98478052	0.91397452
	ABCBLT	0.00539650	4.06192449	70.34123193	0.95804598	0.98472096	0.91460789
±25%	FLT	0.00562772	4.91756397	71.37733246	0.95638865	0.98336874	0.86174266
	GABLT	0.00551892	4.08478788	70.41299876	0.95718573	0.98468339	0.91044414
	ABCBLT	0.00547581	4.06321641	69.88420866	0.95753611	0.98456588	0.91371524
±50%	FLT	0.00669072	8.73843164	74.85338400	0.94887855	0.97850278	0.75973975
	GABLT	0.00610222	4.26226956	70.06419996	0.95209849	0.98344317	0.89892753
	ABCBLT	0.00593876	4.10464963	66.75943508	0.95385152	0.98824364	0.91119569

Table 5.24: Change in Defuzzified Values of Reliability Indices for Forming Unit

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	1.69436231	7.31912817	0.41726796	0.06876184	0.06128803	2.30738591
to	GABLT	1.27268253	0.88958007	0.30479696	0.04894013	0.00619084	0.16436854
±15%	ABCBLT	0.60101486	0.36034828	0.25804216	0.02579169	0.01223851	0.09518402
±15%	FLT	3.16343271	13.2147980	0.79055357	0.13006532	0.08830791	3.64653372
to	GABLT	1.59023512	0.03535288	0.14897228	0.06665315	0.00986311	0.38626678
±25%	ABCBLT	1.46965625	0.03180561	0.64972315	0.05321978	0.01574862	0.09759920
±25%	FLT	18.88864406	77.6983826	4.86996560	0.78525607	0.49482557	11.8368179
to	GABLT	10.56909685	4.34494238	0.49536137	0.53147888	0.12595114	1.26494416
±50%	ABCBLT	8.454456966	1.01971482	4.47135860	0.38479906	0.37354128	0.27574783

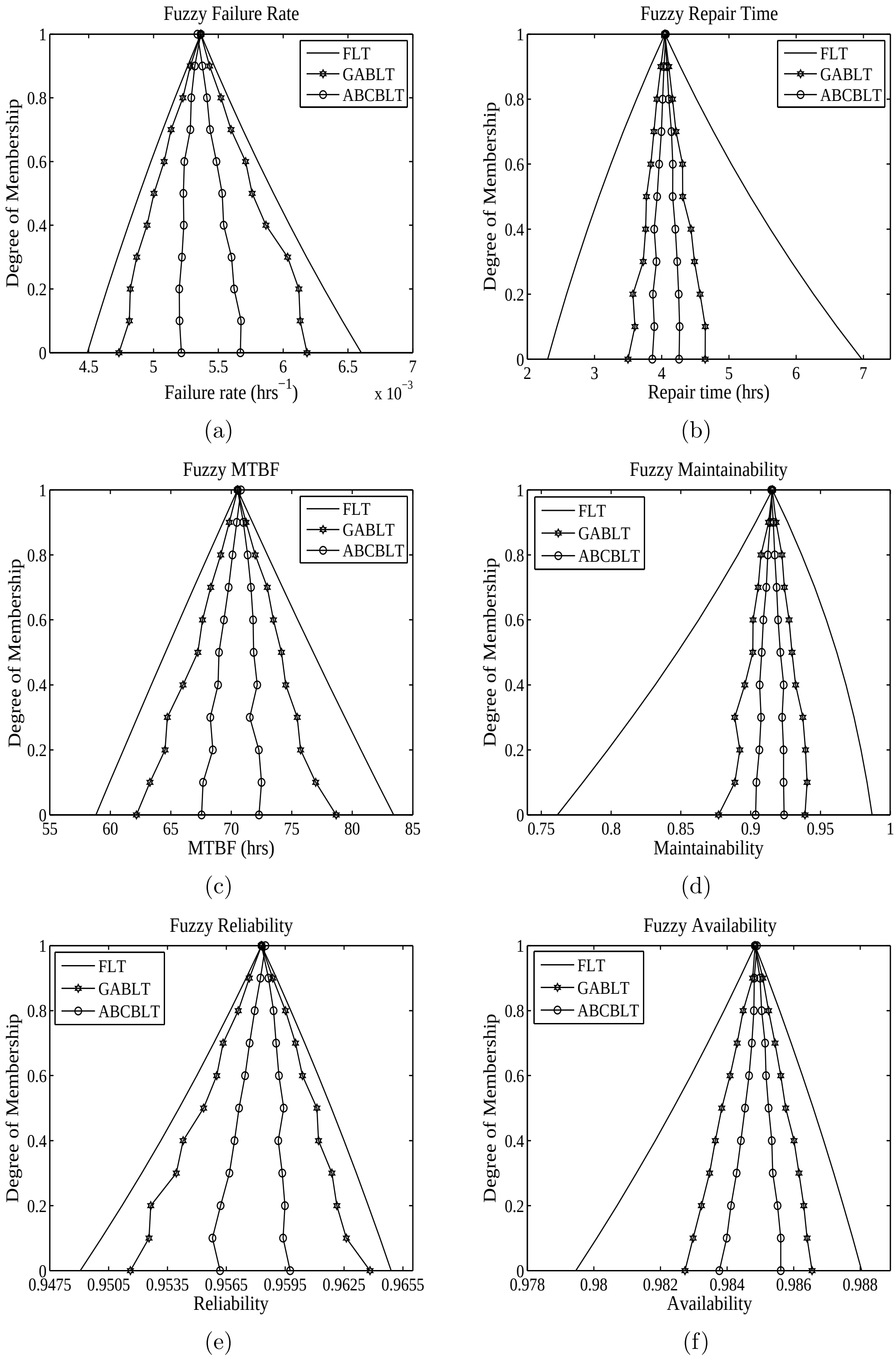


Figure 5.14: Fuzzy Reliability Indices Plot for Forming Unit at ±15% spread

5.3.7 Press Unit

The main function of the press unit [140, 143, 145, 214] is to reduce the moisture content of the paper by pressing the pulp under the rolls received from forming unit of machine. The system consists of synthetic belt (felt), upper and bottom rollers as main components. The unit receives wet paper sheet from forming unit on to the synthetic belt, which is further, carried through press rolls thereby reducing the moisture content to almost 50-60%. The system consists of the following subsystems defined as:

- **Synthetic Belt(A):** It consists of a single belt only. Its failure causes the complete failure of the system.

- **Upper Rollers(B,C,D):** This subsystem consist of bearing, bending and rubber wear arranged in series configuration.

- **Lower Rollers(E,F,G):** It also has bearing, bending and rubber wear arranged in series configuration.

The interaction among the working components of the system are modeled with their fault tree which has been given in Fig. 5.15 [140], where PUF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.25. The minimal-cut sets, $\{A\}$, $\{B\}$, $\{C\}$, $\{D\}$, $\{E\}$, $\{F\}$ and $\{G\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.16, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.26. The crisp and defuzzified values for various reliability parameters at ±15%, ±25% and ±50% spreads for all the three techniques are calculated and depicted in Table 5.27. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 2.88208121%, 2.22605915% and 1.22303368% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 16.9629697%, 10.8618221% and 7.56578244% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.28.

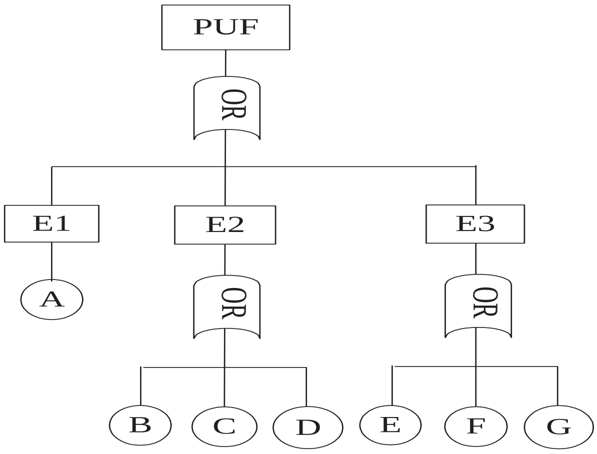


Figure 5.15: FTA model of the Press Unit

Table 5.25: Input Data for the Press Unit

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Felt (i=1)	1045	2.40	5.0
Roller bearing (i=2,5)	523	1.17	2.0
Roller bending (i=3,6)	434	1.21	3.5
Roller rubber wear (i=4,7)	313	1.24	4.0

Table 5.26: Data related to Spread of Reliability Indices for Press Unit

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00309302	3.53428329	16.3707788	0.02378282	0.01254591	0.15518350
II	0.00218671	0.95715940	18.0028037	0.02048058	0.00547232	0.04391716
III	0.00074202	0.31623352	5.12545109	0.00617058	0.00148575	0.01364099
	Decrease in spread (in %) from					
I to II	29.30178272	72.91786420	9.96913415	13.88498083	56.38164150	71.69985211
I to III	76.00985444	91.05240032	68.6914645	74.05446452	88.15749515	91.20976779
II to III	66.06683099	66.96124804	71.5297062	69.87106810	72.84972370	68.93927111

I: FLT II: GABLT III: ABCBLT

Table 5.27: Defuzzified Values of Reliability Indices for Press Unit

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00828005	3.29634520	69.64655236	0.93391670	0.97690247	0.95186101
		Defuzzified values for reliability indices					
	FLT	0.00840816	3.50214818	69.85066521	0.93296867	0.97592786	0.93370339
±15%	GABLT	0.00835737	3.30691464	69.60651464	0.93319642	0.97641768	0.95075604
	PSOBLT	0.00832520	3.29851908	69.44763593	0.93350628	0.97673760	0.95151731
	FLT	0.00865049	3.89560133	70.23181031	0.93118494	0.97467663	0.90472467
±25%	GABLT	0.00854341	3.30447480	69.67961557	0.93185341	0.97653744	0.94930196
	PSOBLT	0.00842702	3.29904959	68.85239394	0.93279659	0.97636286	0.95150865
	FLT	0.01011787	6.37215311	72.39361302	0.92065257	0.96815424	0.80552919
±50%	GABLT	0.00947138	3.36924022	69.19201356	0.92397784	0.97361727	0.93970612
	PSOBLT	0.00906459	3.30569446	65.88485400	0.92765158	0.97697570	0.95115385

Table 5.28: Change in Defuzzified Values of Reliability Indices for Press Unit

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	1.54721287	6.24336856	0.29306956	0.10151119	0.09976533	1.90759152
to	GABLT	0.93381078	0.32064117	0.05748701	0.07712465	0.04962522	0.11608522
±15%	PSOBLT	0.54528656	0.06594819	0.28560843	0.04394610	0.01687681	0.03610821
±15%	FLT	2.88208121	11.2346231	0.54565707	0.19118862	0.12820927	3.10363230
to	GABLT	2.22605915	0.07377995	0.10502024	0.14391503	0.01226524	0.15293933
±25%	PSOBLT	1.22303368	0.01608327	0.85710907	0.07602412	0.03836649	0.00091012
±25%	FLT	16.9629697	63.5730294	3.07809623	1.13107177	0.66918501	10.9641621
to	GABLT	10.8618221	1.95993081	0.69977712	0.84515117	0.29903308	1.01083115
±50%	PSOBLT	7.56578244	0.20141770	4.31000255	0.55156826	0.06276764	0.03728815

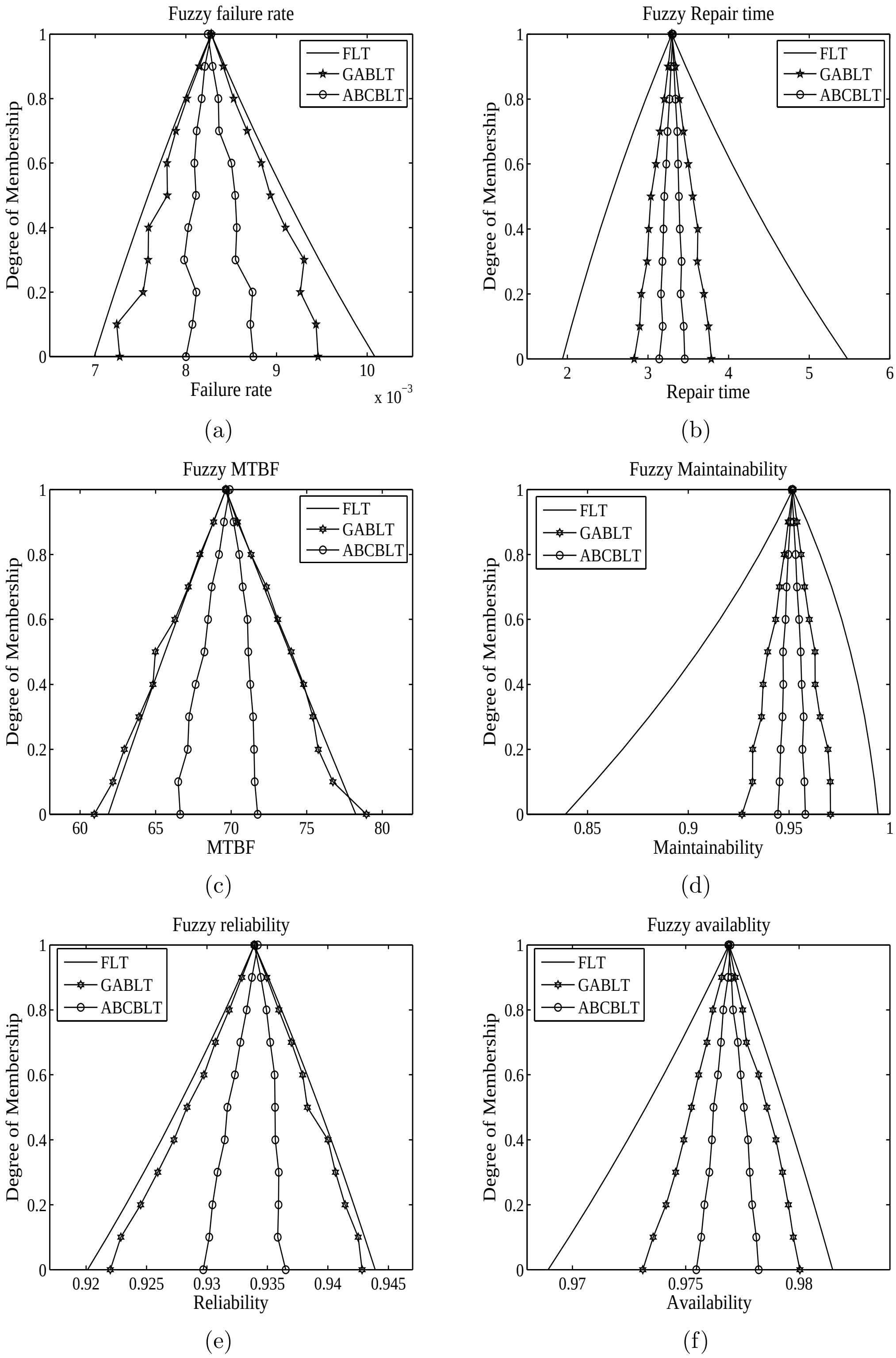


Figure 5.16: Fuzzy Reliability Indices Plot for Press Unit at ±15% spread

5.3.8 Dryer Unit

In the dryer unit [140, 143, 145, 214], the pulp is further dried by heating and thus vaporizing the moisture content to zero level. The system consists of steam-heated rolls (dryers), in stages, and the steam is supplied from steam handling systems. The rolls are heated with superheated steam and remove the moisture content of the paper rolled over them completely. The system consists of the following subsystems defined as:

- **Belt (A):** It consists of a single belt only. Its failure will cause the complete failure of the system.
- **Upper Rollers (B,C):** There are two rollers each of them consists of bearing and bending.
- **Bottom Rollers (D,E):** It also have two rollers and each of them consists of bearing and bending.

The interaction among the working components of the system are modeled with their fault tree which has been given in Fig. 5.17 [140], where DUF represents the system top failure event. The input data related to failure rate and repair time parameters of the main components of the system are given in Table 5.29. The minimal-cut sets, $\{A\}$, $\{B\}$, $\{C\}$, $\{D\}$ and $\{E\}$ of the system are obtained from their FTA model. Based on these cut sets various reliability parameters are depicted graphically in Fig. 5.18, along with FLT and GABLT technique results. Based on these figures, the decrease in spread in the form of uncertainties are calculated by ABCBLT technique from FLT and GABLT technique and their corresponding values are tabulated in Table 5.30. The crisp and defuzzified values for various reliability parameters at $\pm15\%$, $\pm25\%$ and $\pm50\%$ spreads for all the three techniques are calculated and depicted in Table 5.31. It is observed from the table that the variation in their defuzzified values by ABCBLT technique ar quite less as compared to other techniques results values. For instance, failure rate of the system increases by 2.90442074%, 2.65330367% and 1.04311581% for FLT, GABLT and ABCBLT respectively, when spread changes from ±15% to ±25%, and it further increases by 17.1109324%, 15.4289801% and 5.48240159% when spread changes from ±25% to ±50%. The complete analysis of the decrease or increase in their defuzzified values, when spread changes from ±15% to ±25% and further from ±25% to ±50% are summarized in Table 5.32.

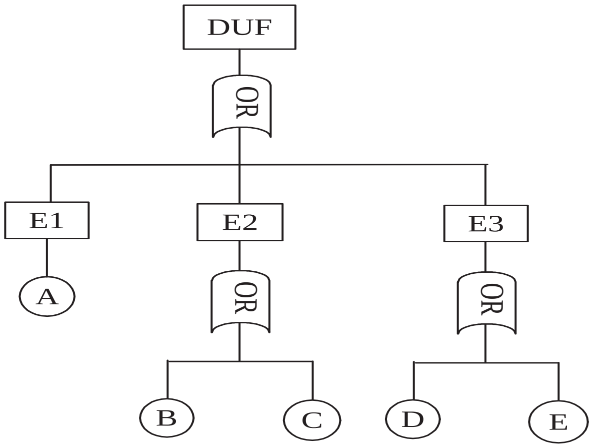


Figure 5.17: FTA model of the Dryer Unit

Table 5.29: Input Data for the Dryer Unit

Components	Failure data		Repair time
	Webiull distribution		
	scale (θ)(hrs)	shape(β)	τ (hrs)
Felt (i=1)	1045	2.40	10
Roller bearing (i=2,4)	523	1.17	2.0
Roller bending (i=3,5)	324	1.25	4.0

Table 5.30: Data related to Spread of Reliability Indices for Dryer Unit

	Computed spread for reliability indices					
	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
I	0.00207215	3.42535887	25.14556939	0.01623914	0.00767241	0.14634740
II	0.00193976	1.08320235	21.94243950	0.01521692	0.00405819	0.04466586
III	0.00054109	0.41230365	7.08183191	0.00409405	0.00165526	0.01720821
	Decrease in spread (in %) from					
I to II	6.38901623	68.37696746	12.73834702	6.29479147	47.10671092	69.47956711
I to III	73.88750814	87.96319843	71.83666116	74.78899744	78.42581405	88.24153350
II to III	72.10531199	61.93659938	67.72541216	73.09540958	59.21186538	61.47346093

I: FLT II: GABLT III: ABCBLT

Table 5.31: Defuzzified Values of Reliability Indices for Dryer Unit

Spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	Crisp	0.00552089	3.17655936	98.41298694	0.95561227	0.98517284	0.95706467
		Defuzzified values for reliability indices					
	FLT	0.00560697	3.37733617	98.61219926	0.95495494	0.98437007	0.93902792
±15%	GABLT	0.00559755	3.18780318	98.41359082	0.95500723	0.98502619	0.95556664
	ABCBLT	0.00557081	3.17592457	98.08817270	0.95530016	0.98498296	0.95690310
	FLT	0.00576982	3.76153168	98.98503169	0.95371576	0.98344696	0.91006439
±25%	GABLT	0.00574607	3.19421402	98.56709785	0.95395732	0.98480731	0.95306835
	ABCBLT	0.00562892	3.18016744	97.35544411	0.95480405	0.98501110	0.95686136
	FLT	0.00675709	6.18905215	101.12610411	0.94633121	0.97887225	0.80968882
±50%	GABLT	0.00663263	3.26174703	98.19366622	0.94750523	0.98303253	0.94013029
	ABCBLT	0.00593752	3.18915406	94.05682695	0.95222728	0.98433350	0.95527553

Table 5.32: Change in Defuzzified Values of Reliability Indices for Dryer Unit

	%age change in defuzzified values(in magnitude) from						
spread	Technique	Failure rate	Repair time	MTBF	Reliability	Availability	Maintainability
±0%	FLT	1.55916890	6.32057478	0.20242482	0.06878626	0.08148519	1.88459051
to	GABLT	1.38854423	0.35396221	0.00061361	0.06331438	0.01488571	0.15652338
±15%	ABCBLT	0.90420203	0.01998357	0.33005221	0.03266073	0.01927377	0.01688182
±15%	FLT	2.90442074	11.3756964	0.37807941	0.12976319	0.09377672	3.08441627
to	GABLT	2.65330367	0.20110526	0.15598153	0.10993738	0.02222072	0.26144592
±25%	ABCBLT	1.04311581	0.13359479	0.74701013	0.05193236	0.00285690	0.00436198
±25%	FLT	17.1109324	64.5354253	2.16302645	0.77429254	0.46517099	11.0295019
to	GABLT	15.4289801	2.11422934	0.37886032	0.67634996	0.18021596	1.35751648
±50%	ABCBLT	5.48240159	0.28258323	3.38822054	0.26987422	0.06879110	0.16573247

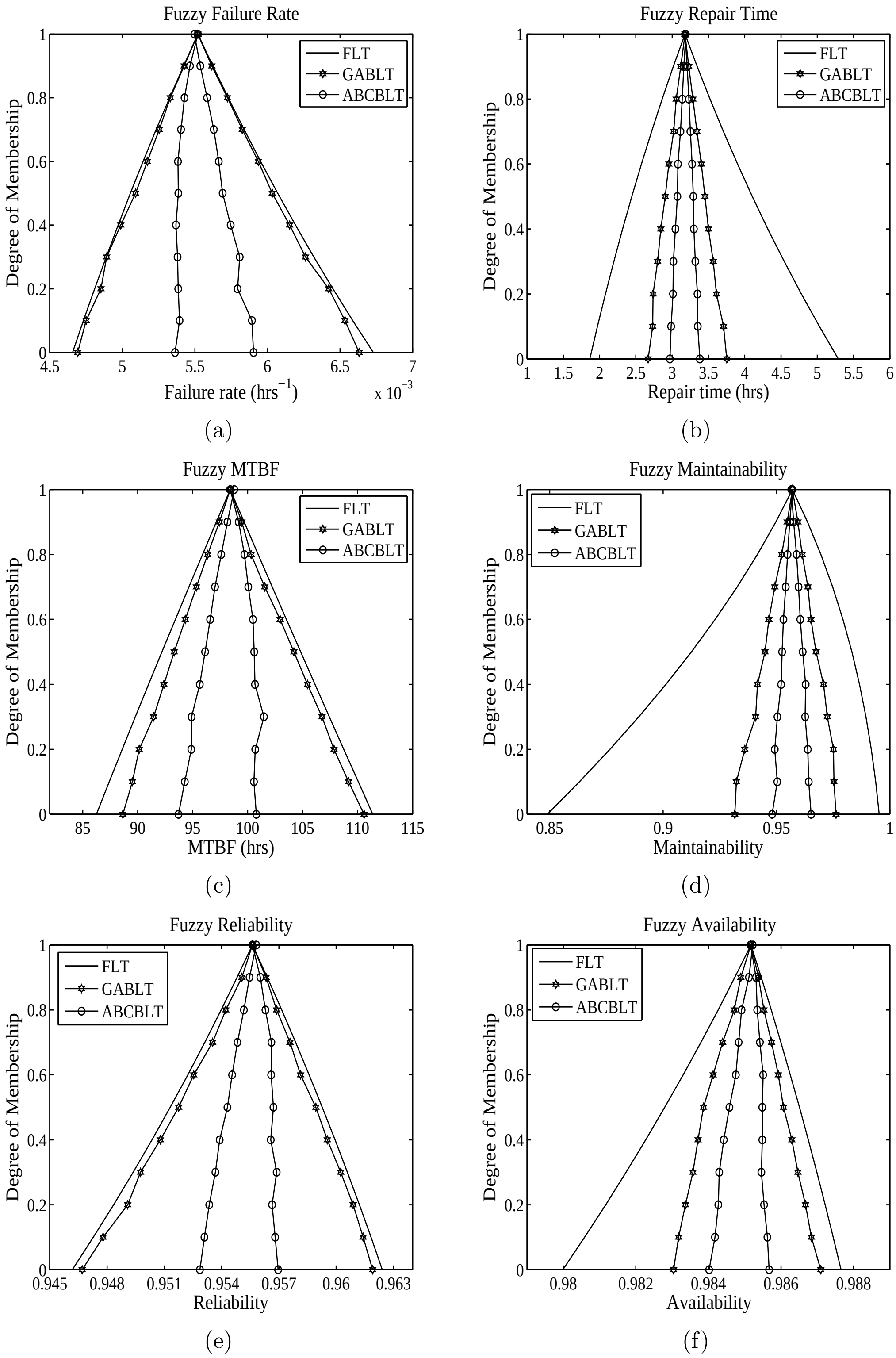


Figure 5.18: Fuzzy Reliability Indices Plot for Dryer Unit at ±15% spread

5.4 Conclusion

The main objective of this chapter has been to analyze the behavior of the paper mill, a repairable industrial system more closely by utilizing uncertain, vague and imprecise data. For this, data related to time varying failure rate and a constant repair time model has been used during the analysis. The uncertainties which are present in the data are handled with the help of triangular fuzzy numbers which will greatly increase the relevance of the reliability study. FTA model has been used for modeling the system and hence on that minimal cut set of the system are obtained. In order to analyze the behavior of the system, six well known reliability indices which depicts the behavior of the system are calculated in the form of fuzzy membership functions. For constructing these membership functions, a novel technique namely artificial bee colony based lambda-tau (ABCBLT) has been proposed in which a nonlinear optimization problem has been formulated by utilizing the quantified failure and repair rate data. The computation of the various reliability parameters at different degree of membership values will help the system analyst or maintenance managers to understand the behavior of the system. Based on their analysis, the system analyst may predict the behavior of the system and also take necessary steps to build the reliability into the system. The corresponding defuzzified as well as crisp values will helps the plant personnel to implement the corresponding results on their system. The computed results by the proposed approach are finally compared with the traditional (crisp) and FLT and GABLT techniques results in the tabular and in figure form. The major advantages for the system analyst from the view of proposed technique results is that it gives compressed range of region for each reliability index which gives higher sensitive zone and thus may have useful for the reliability engineers/experts to make more sound decisions. Moreover, the variation of the their defuzzified values are quite less as compared to other technique results. Thus, it will facilitate the management in reallocating the resources, making maintenance decision and enhancing the overall production as well productivity of the paper industry and thereby reduce operational and maintenance costs.

In nutshell, the important managerial implications drawn by using the discussed technique are to

- model and predict the behavior of industrial systems in a more consistent manner;
- carry out design modifications, if any, required to achieve minimum failures,
- help in maintenance (repair and replacement) decision making,
- analyze failure behavior of industrial systems in more realistic manner as they often make use of imprecise data;
- analyze the behavior of the system in higher sensitivity zone;

Chapter 6

RAM analysis of an industrial systems by utilizing uncertain data

In this chapter analysis RAM parameters of an industrial system are analysed by utilizing uncertain, imprecise data. A composite measure of RAM parameters, namely RAM-Index has been given for performance analysis of the system. ABCBLT technique has been used here for analysis of this index. The technique has been applied on the paper mill.

6.1 Introduction

Today industrial systems are becoming more complex and getting more complicated due to modern technology and higher reliability requirements. So utilisation of multi-level redundant, bridge design structures have been seen immensely increasing in many practical systems like communication system, network design etc., which allow a system to achieve high reliability at the expense of system complexity. In addition to complexity of the system, most of the real-world industrial systems are repairable in nature and hence when the system/components are failed then they get repaired based on different distributions and with additional constraints such as spare parts availability, repair crew response time, etc. The effectiveness of production processes and the equipment that are part of them are generally measured according to the results of reliability and availability indicators, as well as through the economic analysis of its life cycle. The behavior of such systems can be studied in terms of their reliability, availability and maintainability (RAM). RAM encompasses the essential features of reliability in general. These features are interrelated in such a way that it is necessary to have both a high reliability and a good maintainability in order to achieve a high availability.

For the last four decades, there are several investigations with the objective to identify the principal factors that directly affect the maximization of economic benefit, and that converge at empirical consideration of RAM indicators [142, 145, 196, 216]. Moreover, a company cannot adopt a rapid response strategy if its systems are unavailable and unreliable. So it is expected that a production system should remain operative for maximum possible duration to achieve the desired goals of production. For the correct estimation of a RAM analysis, it is necessary that a logical sequence of procedures for ensuring the correct assessment of the process has been followed. Further, it is necessary to require precise knowledge of numerical probabilities and system's components' functional dependencies which may be difficult to obtain in any large-scale system. Thus in such situation, it is difficult, if not impossible, to analyze the RAM parameters and consequently their behavior. Therefore, it is very difficult to construct a precise and comprehensive mathematical model for an industrial system which may be close to real conditions. Thus in order to minimize the deleterious effects of system/ subsystem failures, different improvement opportunities can be identified and recommendations be made for the most appropriate actions needed to be developed through the use of a maintenance management support tool.

In the framework of reliability, availability and maintainability analysis, some researcher have paid attention on that issue in which they analyzed the performance of the system by considering reliability, availability or maintainability as an objective function. In their analysis they utilized the historical data for analysis without quantifying the uncertainty. Thus the computed results did not follow actual trend of the system because historical data/reords can only represent the past behavior of the system but unable to predict the future behavior. Thus it is necessary that the collected data should be quantified in order to handle the uncertainties in the data. For this, fuzzy set theory [260] has been used for representing the collected data in terms of fuzzy numbers. In analysis of the RAM of an industrial system, researchers have paid more attention on the components whose failure follows the exponential distribution. But in real-life modeling, as we know, the most popular reliability distributions for the failure rate are Weibull distributions. Therefore, it seems that there is a need for a more generalized methodology that can be applied for variable failure rates. In this light, the main objective of this chapter is to investigate the effect of failure and repair rates parameters on the composite measure of the RAM for an industrial system by using limited, imprecise and vague data. A time varying failure rate and constant repair rate model have been for an industrial system for analysis. The approach has been applied for all the important functioning units of a paper mill and help the system analyzer to analyze the system performance on the basis of past failure and repair data.

6.2 Mathematical Aspects of RAM parameters

System reliability, maintainability and availability have assumed great significance in recent years due to a competitive environment and overall operating and production costs. Performance of equipment depends on the reliability and availability of the equipment used, operating environment, maintenance efficiency, operation process and technical expertise of operators, etc. When the reliability and availability of systems are low, efforts are needed to improve them by reducing the failure rate or increasing the repair rate for each component or subsystem. Thus, reliability, availability and maintainability are the important key features for keeping the production and productivity of the system high. For maintaining this, a composite measure of RAM parameters named as the RAM-Index has been analyzed by the researchers

[142, 196, 216] for increasing the performance of the system. But the disadvantages of Sharma and Kumar [216] approach are that they applied Markovian approach by utilizing historical crisp data without quantification of involved uncertainties. On the other hand, Rajpal et al. [196] developed an artificial neural network (ANN) model for assessing the effect of input parameters on system performance at specified times i.e. its value does not change with time. But in real life situations, industrial system behavior changes with time. Thus it does not provide the actual trend of the system behavior. Also it is unable to access and analyze the sensitive component of the system. Komal et al. [142] extended this idea by quantifying the uncertainty in the analysis. But their approach is limited to a system whose components follow the constant failure rate model i.e. following the exponential distribution. Thus there is a need of a generalized index for a time varying component parameter for measuring the performance of the system such that system analyst may find the component on which more attention should be given to save money, manpower and time. Therefore, the proposed RAM-Index is valid for a time varying failure rate model instead of constant failure rate model (exponential distribution) and is given as below

$$RAM(t) = w_1 \times R(t) + w_2 \times A(t) + w_3 \times M(t) \tag{6.2.1}$$

where w_i's are the weights associated with the reliability parameters such that $\sum_{i=1}^{3} w_i = 1$. Here $W = [0.36, 0.30, 0.34]$ are the values of weights used during the analysis corresponding to reliability, availability and maintainability respectively. The equation (6.2.1) can be rewritten in more elaborative form as

$$\begin{aligned} \mathrm{RAM}(t) \quad &= \quad w_1 \times \exp\left[-\left(\frac{t}{\theta}\right)^{\beta}\right] + w_3 \times \left\{1 - \exp\left(\frac{-t}{\tau}\right)\right\} \\ &\quad + w_2 \times \exp\left\{-\left(\frac{t}{\theta}\right)^{\beta} - \frac{t}{\tau}\right\}\left[1 + \frac{1}{\tau}\int_0^t \exp\left\{\left(\frac{t}{\theta}\right)^{\beta} + \frac{t}{\tau}\right\} dt\right] \end{aligned} \tag{6.2.2}$$

The major benefit/advantages of this index is that by varying individually the components' parameters the corresponding combined effects on the system performance have been analyzed which effect the plant personnel/DMs/system analyst for predicting the impact of components' parameters on its performance. Moreover, this index has simultaneously considered the reliability parameters which affect the system performance directly. For analyzing the performance of the system through this index, a large amount of data are required which are difficult to obtain from the maintenance personnel due to lack of human error etc. Also, if somehow they are collected then they have a large range of uncertainties as they represent only the past behavior and unable to predict the future behavior of the system. Thus the collected data are usually incomplete, imprecise, conflicting, and lead to inadequate knowledge of system behavior. Therefore fuzzy methodology has been used for handling such uncertainties and hence triangular fuzzy numbers corresponding to the collected data are developed for increasing the relevance of the study. Therefore by using quantified input data, RAM parameters and consequently their RAM-Index becomes a triangular fuzzy membership function which can be expressed as

$$\widetilde{RAM}(t) = (RAM_L(t), RAM_M(t), RAM_U(t)) \tag{6.2.3}$$

Since each reliability parameter at any time 't' belongs to (0, 1) and RAM-Index is a linear combination of these parameters and hence it is clear that $RAM(t) \in (0, 1)$.

6.3 RAM analysis of various subsystems of a Paper mill

The behavior of all the system of the paper mill is already described in Chapter 5 in which various reliability parameters are addressed in the form of fuzzy membership functions by using ABCBLT technique. As it can been seen from the analysis that the initial condition of the equipment or system should be changed in order to increase the performance of the system. For this necessary maintenance action or special attention should be given to the equipments/components as per the preferential order. But it is difficult for the system analyst as to how to find the component on which more attention should be given for improving the performance and to save the money, manpower and time. Also there are so many inherent factors that affect the system performance internally. Thus it is very difficult, if not impossible, to find the components as per their behavior so that decision makers/system analysts may increase the production and productivity of the system by adopting the necessary actions. This problem can be resolved by RAM analysis using the proposed RAM-Index which may be very helpful for the system analyst/plant personnel for finding out the components on which more attention should be given to improve the performance of the system. For analysis the below given schedule is followed:

(i) As the system performance depends on the performance of its subsystems and their components which in turn again depends on their components' parameters. Moreover, failure of a component will reduce the efficiency of the system and hence the performance. Handling the uncertainties also plays an important role during the analysis. Thus it is necessary that the uncertainties during the analysis must be reduced first, up to a desired level. In view of this, the behavior of the system RAM-index has been analyzed first at $t = 10$(hrs) in the form of fuzzy membership functions by ABCBLT technique, and then with different level of uncertainties ranging from 0 to 100% for all the subsystems of a paper mill. This has been depicted through plots. These two plots are shown for all the subsystems in their respective analysis. This analysis suggests that for achieving higher performance of the system, involved uncertainties should be minimized.

(ii) At different $\alpha-$ cuts (0, 0.5, 1), the long-run period behavior of the RAM and their corresponding RAM-index has been analyzed and shown in their respective figures which shows that RAM-Index of the system increases within a fixed time interval and attains a maximum at a certain time and after that system performance reduces exponentially.

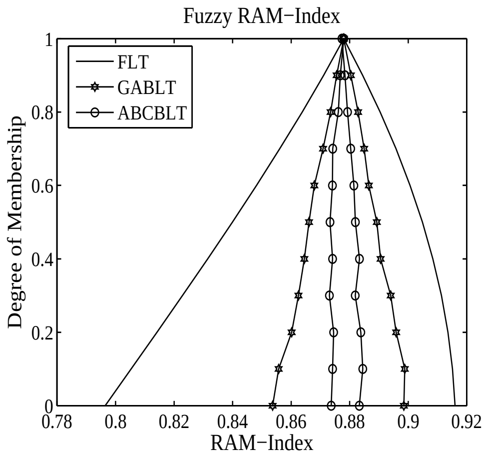
(iii) Effect on the subsystems' RAM - Index consequently on its performance has been examined by varying each component's parameters individually and simultaneously and at the same time by keeping both the parameters of other components fixed. Based on their performance analysis results, recommendations have been given to the plant personnel or system analyst for maintaining the performance of the system as per the obtained preferential order.

Thus in this section, RAM analysis of a various subsystems of a paper mill has been done by using RAM-Index.

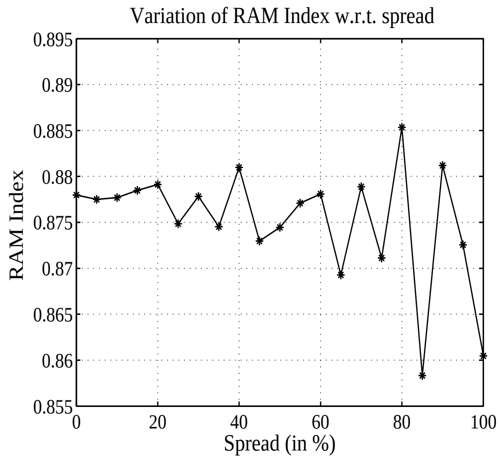
6.3.1 Analysis of Feeding system

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM-index and the spread from 0 to 100(in %) have been shown for the feeding system in Fig. 6.1(a) and 6.1(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.2 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 17 (hrs) and then attains its maximum value in the interval range 0.880037245 - 0.909273575 at t = 17 (hrs) and after that system performance reduces exponentially. Thus it is found that current condition of the system or equipments should be changed after t = 17 (hrs). In order to find the component, at this time, on which more attention should be given for saving money, time etc., an investigation has been done on RAM-Index from the view-point of system's performance by varying each component's parameters individually. The effect of each component parameters, failure parameter λ for failure rate and τ for repair time, on system RAM-Index has been analyzed and shown graphically in Fig. 6.3 which contains five subplots corresponding to the five main components of the system. Each subplot contains two subplots corresponding to the variation of the failure rate and repair time parameters. The ranges of their corresponding parametric values are summarized in Table 6.1. This analysis will suggest the system analyst that how the components' failure and repair rates significantly affect its performance.

But in real-life situation, components failure and repair rates simultaneously affect the system performance. Hence it is necessary to analyze the simultaneous impact of components parameters on its RAM-Index. For this, by varying the components' parameters, λ and τ, of each component simultaneously then the corresponding effect on the system performance has been analyzed and shown through their surface plot in Fig. 6.4 which contains five subplots corresponding to each component of the system. It may be observed from the Fig. 6.4(a) that the variations in the failure rate and repair time of the blower components show the significant impact on the performance of the system i.e. an increase in their failure rate from 0.0053125 to 0.0071875 hrs^{-1} and repair time from 8.500 to 11.500 hrs reduce the system index by 4.803%. Similar effects on system RAM-Index by the variations in the other components' failure rate and repair times are also observed from the Fig. 6.4. The magnitude of effect of variation in failure rate and repair times of various subsystems of the system on its performance is summarized in Table 6.2. On the basis of these tabulated results, it has been analyzed that for improving/increasing the performance and productivity of the system, more attention should be given to the components by the plant personnel as per preferential order; chain conveyor, blower, feeder, bucket conveyor and belt conveyor.



(a)



(b)

Figure 6.1: RAM-Index variation for Feeding System

Table 6.1: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Feeding System

Component	Range of failure rate $\lambda(\text{hrs}^{-1})$	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Blower	0.0053125 - 0.0071875	Min: 0.86819680 Max: 0.88870809	8.500 - 11.500	Min: 0.86400908 Max: 0.89254844
Chain Conveyor	0.03400 - 0.04600	Min: 0.87668248 Max: 0.87895755	2.125 - 2.875	Min: 0.87702666 Max: 0.87894140
Belt Conveyor	0.00850 - 0.01150	Min: 0.87764213 Max: 0.87830340	1.700 - 2.300	Min: 0.87779086 Max: 0.87817381
Bucket Conveyor	0.007055 - 0.009545	Min: 0.87793712 Max: 0.87800929	4.250 - 5.750	Min: 0.87758526 Max: 0.87837987
Feeder	0.011305 - 0.015295	Min: 0.87610521 Max: 0.87914560	5.100 - 6.900	Min: 0.87775234 Max: 0.87799854

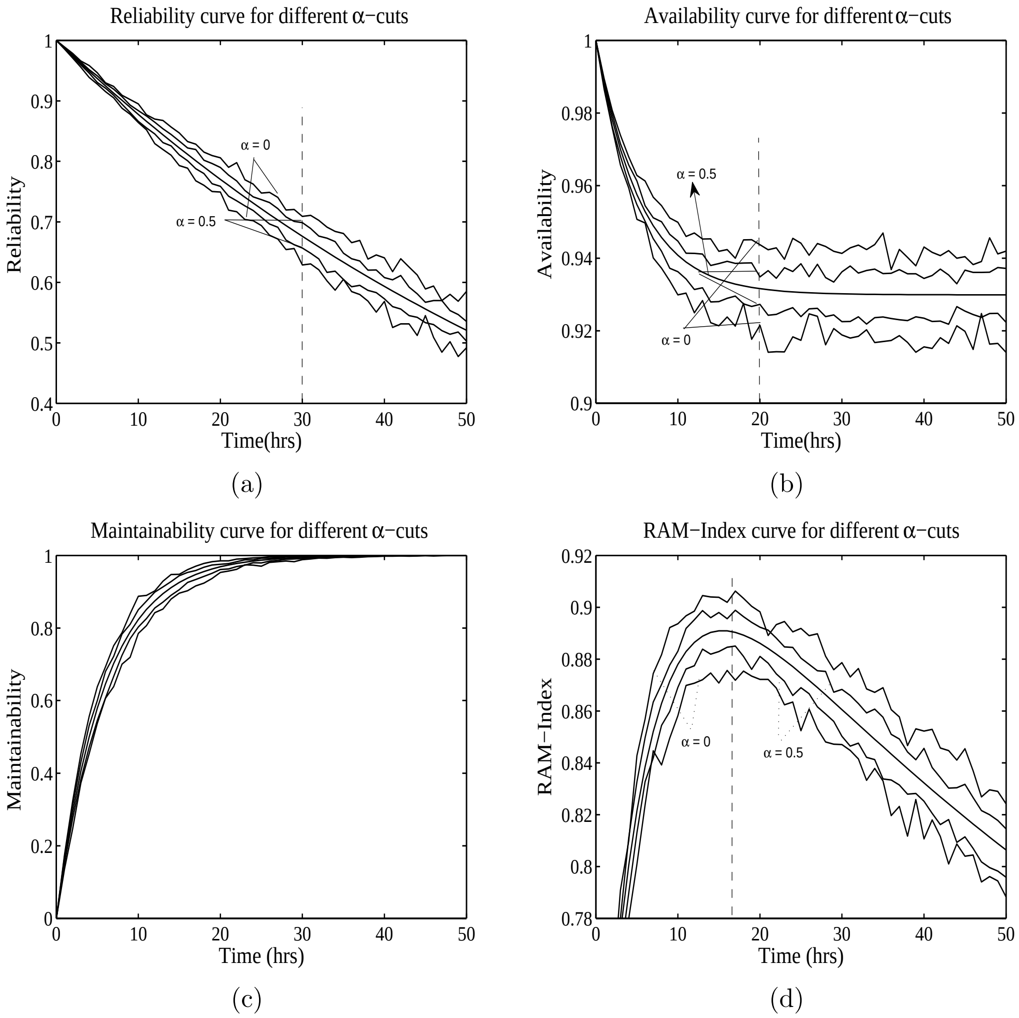


Figure 6.2: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Feeding System

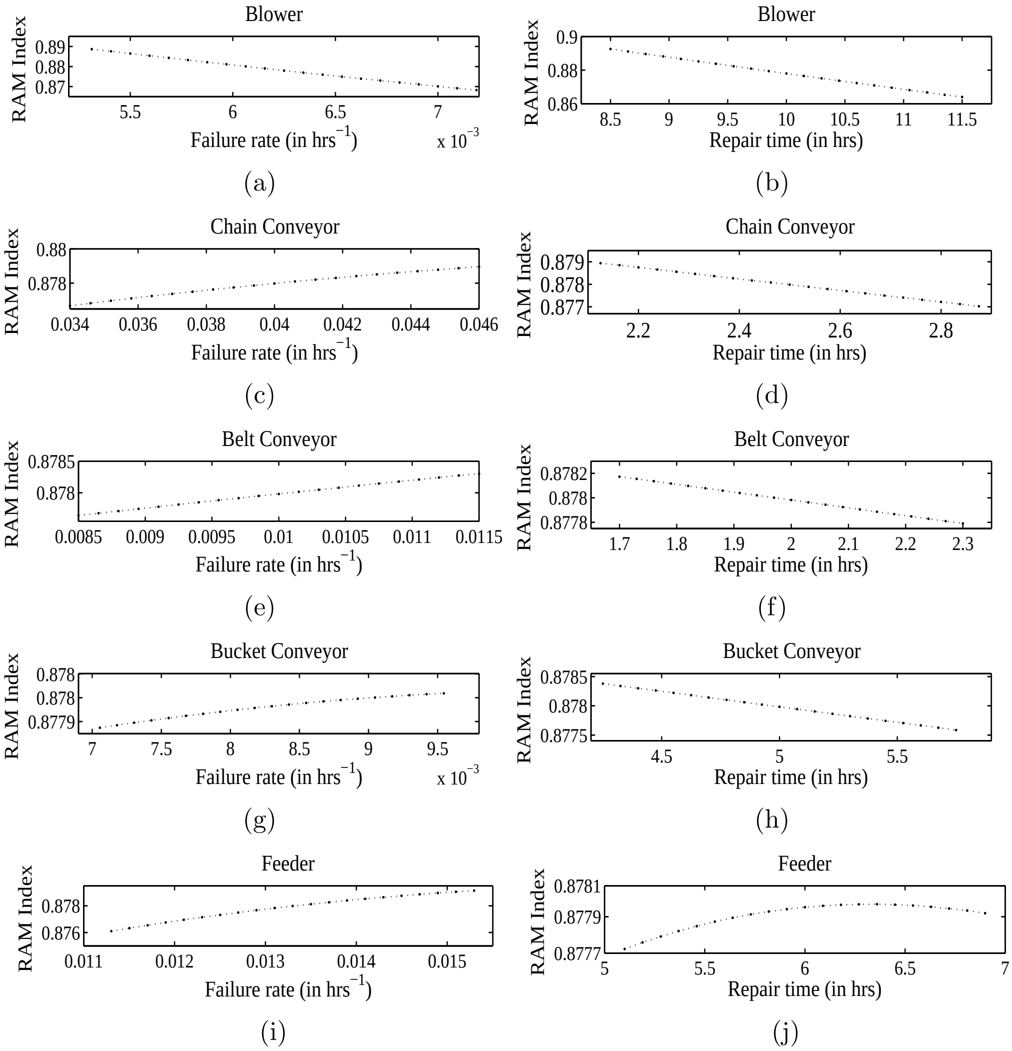


Figure 6.3: Effect of Varying Individual Components' Parameters on RAM-Index for Feeding System

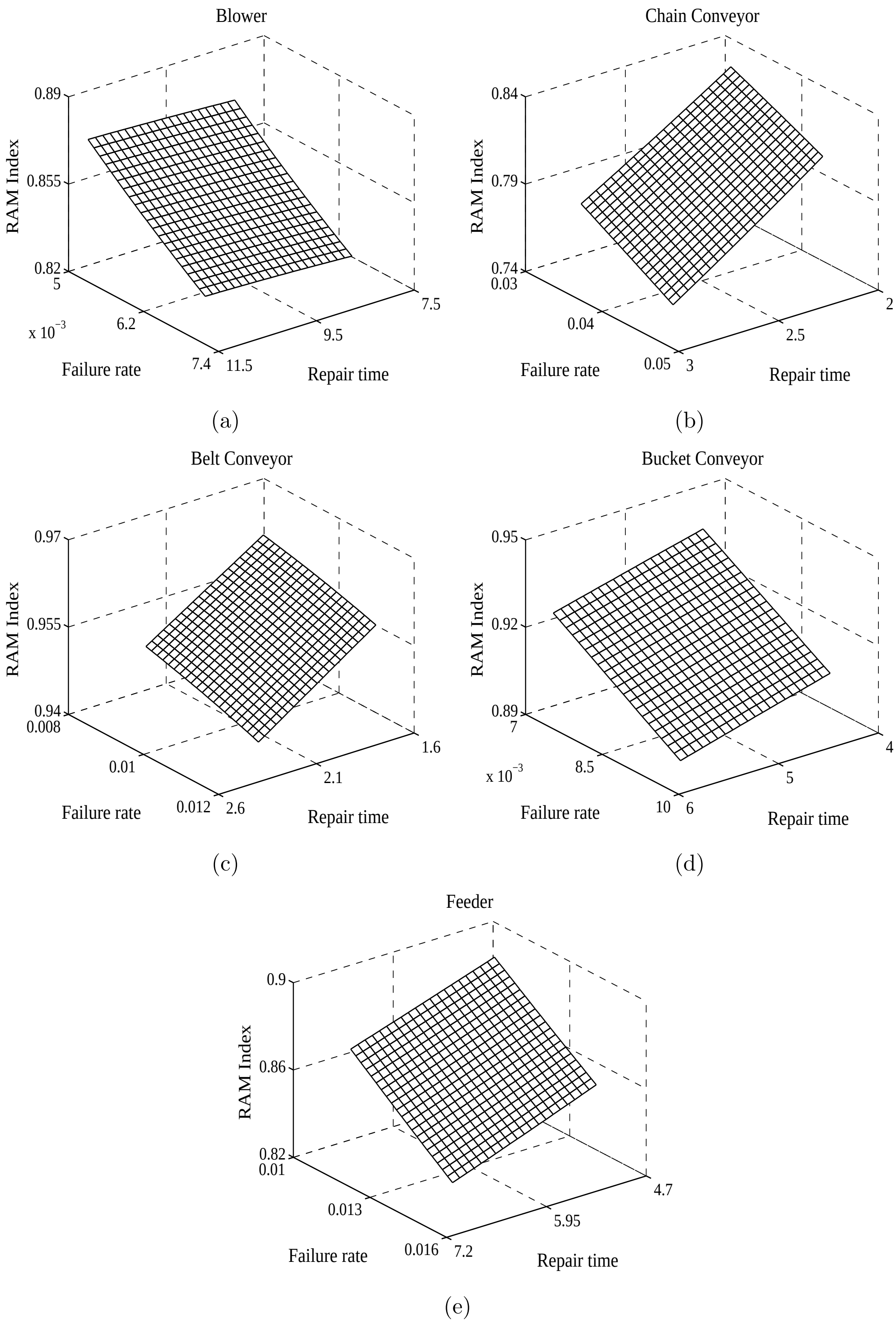


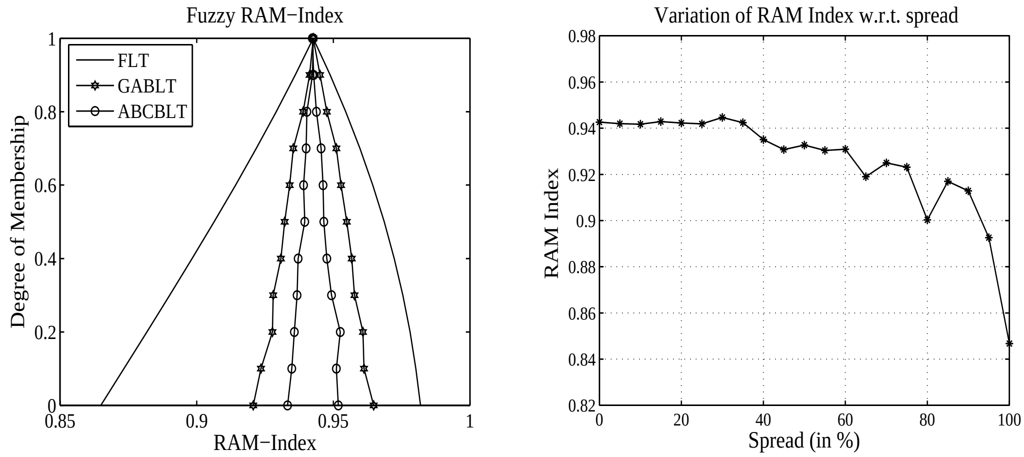
Figure 6.4: Effect of Simultaneously Varying the Components' Parameters on RAM-Index for Feeding System

Table 6.2: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Feeding System

Component	Range of failure rate $\lambda(\text{hrs}^{-1})$	Range of Repair Time MTTR(hrs)	RAM-Index
Blower	0.0053125 - 0.0071875	8.500 - 11.500	Min: 0.83690744 Max: 0.87711190
Chain Conveyor	0.03400 - 0.04600	2.125 - 2.875	Min: 0.75314666 Max: 0.83560871
Belt Conveyor	0.00850 - 0.01150	1.700 - 2.300	Min: 0.94410519 Max: 0.96304723
Bucket Conveyor	0.007055 - 0.009545	4.250 - 5.750	Min: 0.89477042 Max: 0.93581206
Feeder	0.011305 - 0.015295	5.100 - 6.900	Min: 0.83732381 Max: 0.89606563

6.3.2 Analysis of Pulping system

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM-Index and the spread from 0 to 100(in %) have been shown for the pulping system in Fig. 6.5(a) and 6.5(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.6 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 19hrs and attains its maximum value at t = 19 hrs in the interval 0.960801250 - 0.96506191 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=19hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.7 and Fig. 6.8 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.3 and Table 6.4 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; digester, knotters, openers and deckers.



(a) (b)

Figure 6.5: RAM-Index variation for Pulping System

Table 6.3: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Pulping System

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Digester	434.350 - 587.650	Min: 0.93297831 Max: 0.95005046	12.750 - 17.250	Min: 0.93393685 Max: 0.95143491
Knotters	94.350 - 127.6500	Min: 0.94126214 Max: 0.94485643	4.250 - 5.750	Min: 0.94253238 Max: 0.94266240
Deckers	214.200 - 289.800	Min: 0.93629069 Max: 0.94924583	2.1250 - 2.8750	Min: 0.93835874 Max: 0.94698597
Openers	128.350 - 173.650	Min: 0.94179008 Max: 0.94402525	4.2500 - 5.7500	Min: 0.94257357 Max: 0.94266190

Table 6.4: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Pulping System

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Digester	434.350 - 587.650	12.750 - 17.250	Min: 0.80673255 Max: 0.84184266
Knotters	94.350 - 127.6500	4.250 - 5.750	Min: 0.88890019 Max: 0.93671713
Deckers	214.200 - 289.800	2.1250 - 2.8750	Min: 0.97622526 Max: 0.98638181
Openers	128.350 - 173.650	4.2500 - 5.7500	Min: 0.90912831 Max: 0.94905336

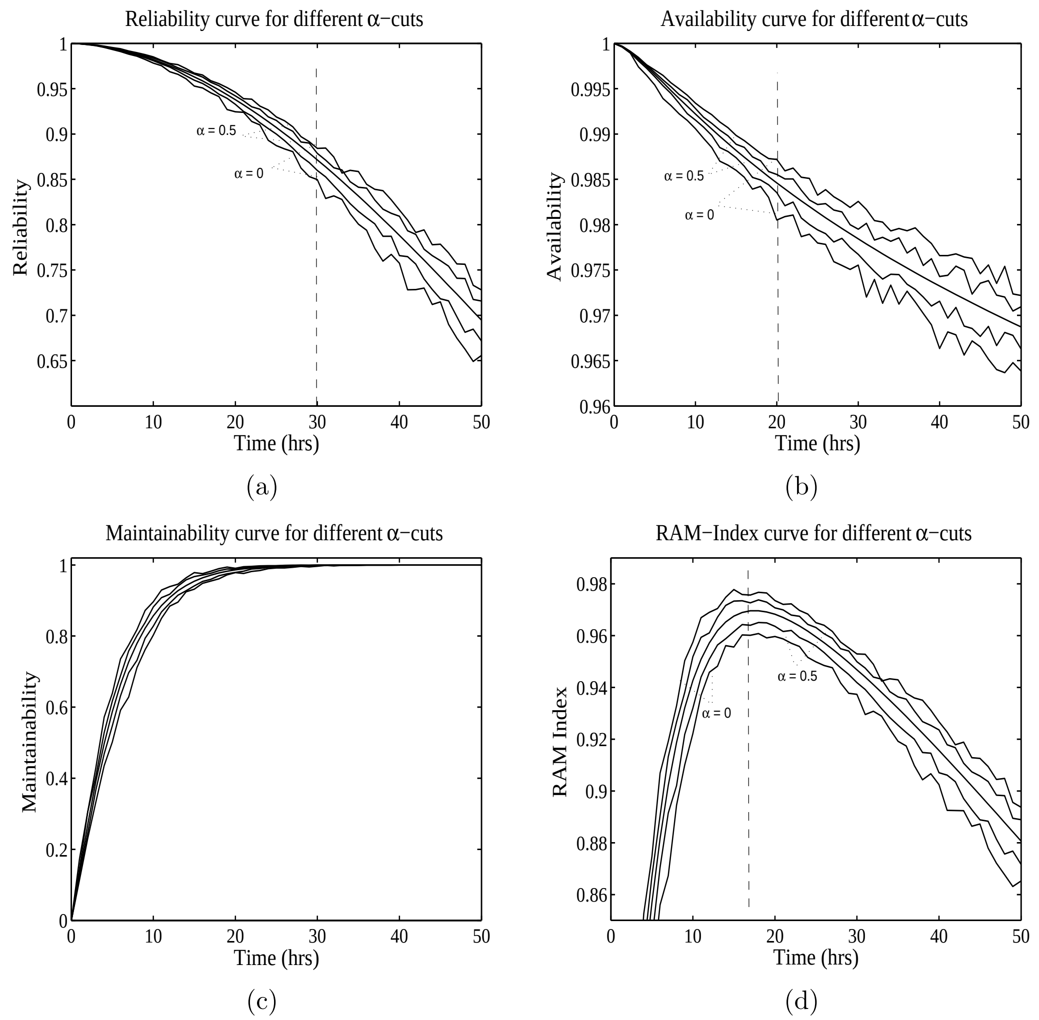


Figure 6.6: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Pulping System

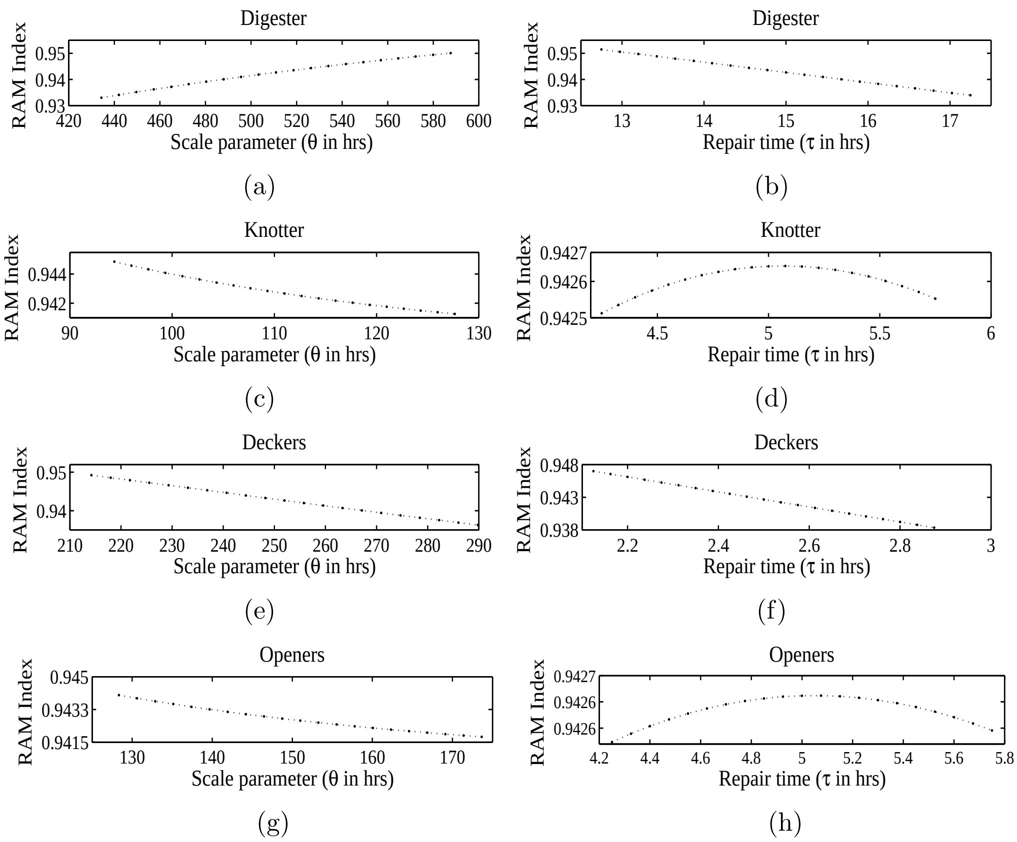


Figure 6.7: Variation of RAM-Index by varying components' failure and repair rate parameters for Pulping System

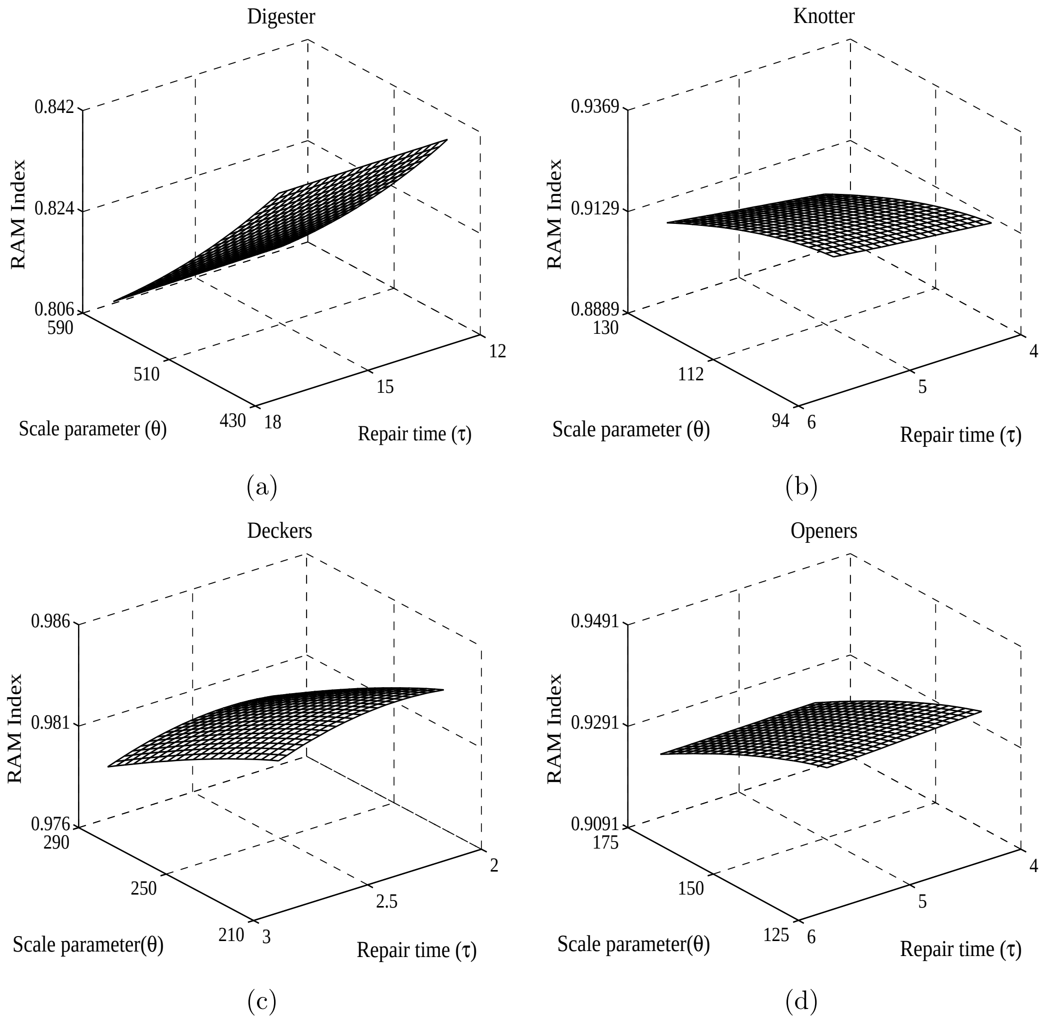


Figure 6.8: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Pulping System

6.3.3 Analysis of Washing system

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM-Index and the spread from 0 to 100(in %) have been shown for the washing system in Fig. 6.9(a) and 6.9(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.10 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 17hrs and attains its maximum value at t = 17 hrs in the interval 0.97637403 - 0.97875121 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=17hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.11 and Fig. 6.12 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.5 and Table 6.6 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; screener, filter, cleaner and decker.

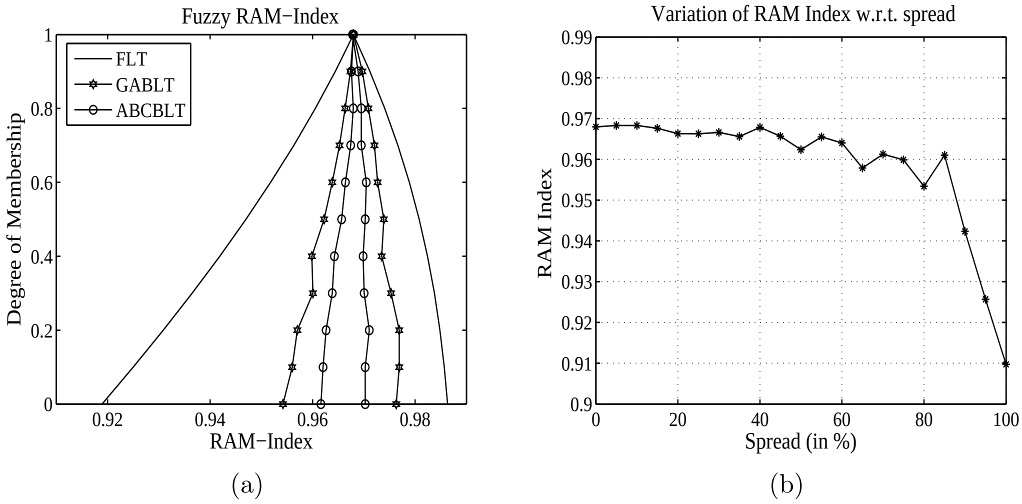


Figure 6.9: RAM-Index variation for Washing System

Table 6.5: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Washing System

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Filter	286.45 – 387.55	Min: 0.9673619 Max: 0.9683148	2.975 – 4.025	Min: 0.9633272 Max: 0.9724028
Cleaner	144.50 – 195.50	Min: 0.9679633 Max: 0.9679636	1.700 – 2.300	Min: 0.9679633 Max: 0.9679634
Screener	362.10 – 489.90	Min: 0.9663787 Max: 0.9691401	3.400 – 4.600	Min: 0.9627452 Max: 0.9729289
Decker	214.20 – 289.80	Min: 0.9679531 Max: 0.9679836	2.125 – 2.875	Min: 0.9679608 Max: 0.9679652

Table 6.6: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Washing System

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Filter	286.45 – 387.55	2.975 – 4.025	Min: 0.95884551 Max: 0.97848162
Cleaner	144.50 – 195.50	1.700 – 2.300	Min: 0.96566412 Max: 0.98015829
Screener	362.10 – 489.90	3.400 – 4.600	Min: 0.95186796 Max: 0.97436143
Decker	214.20 – 289.80	2.125 – 2.875	Min: 0.97142664 Max: 0.98559936

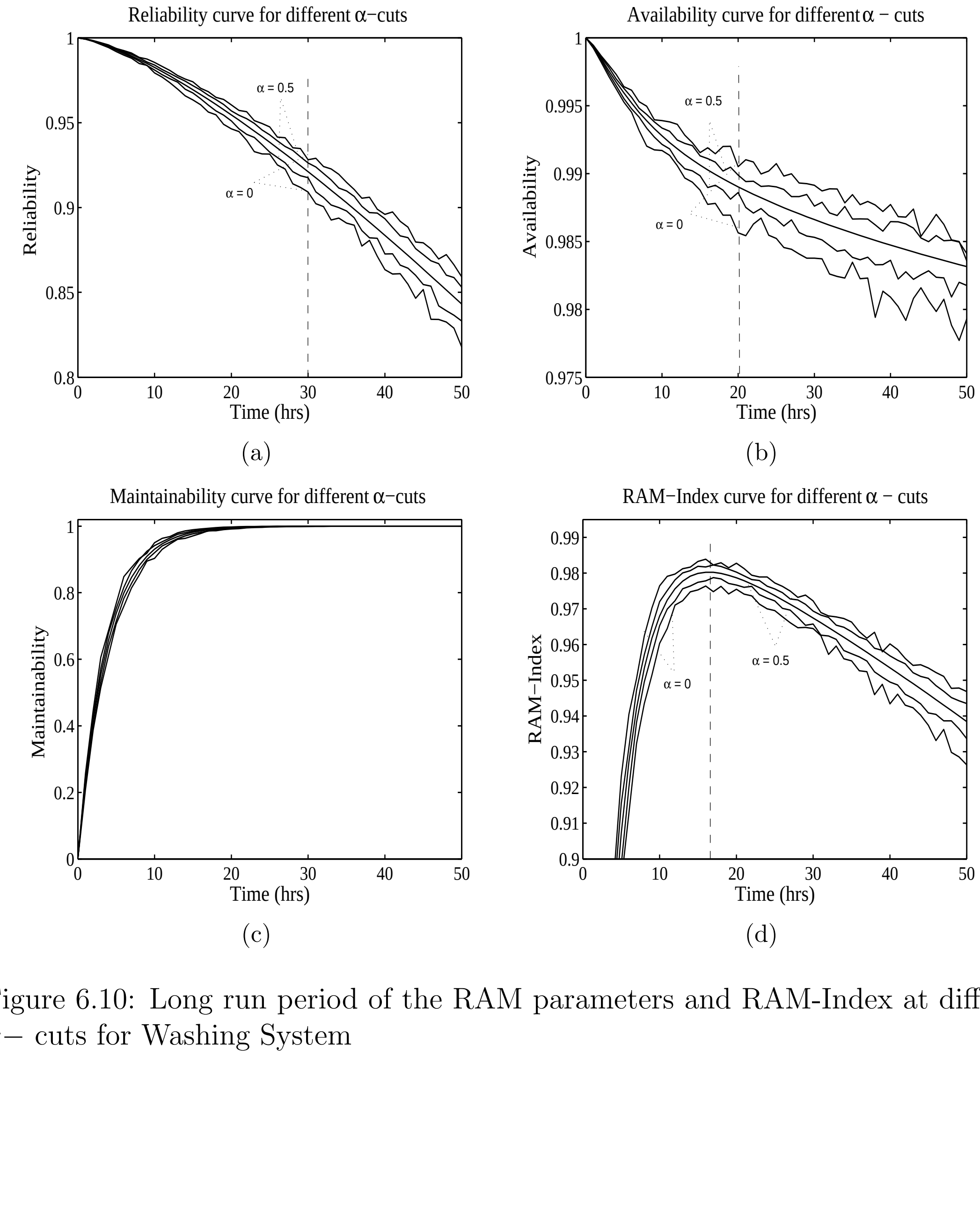


Figure 6.10: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Washing System

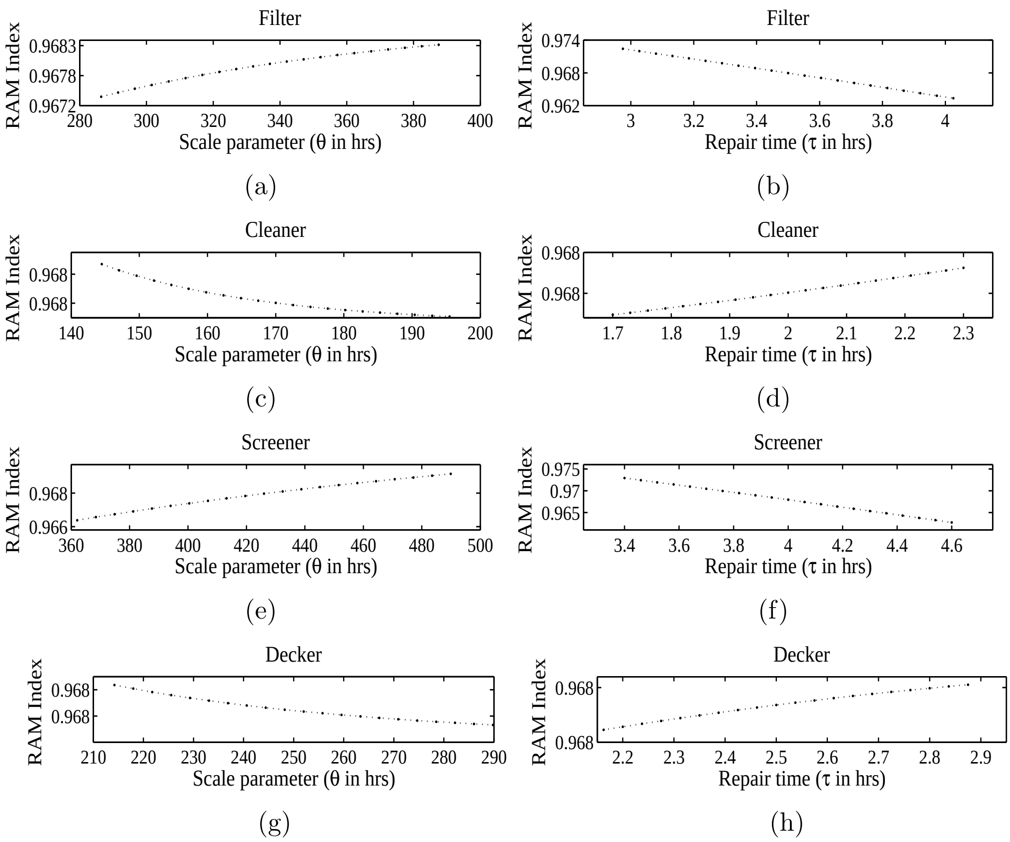


Figure 6.11: Variation of RAM-Index by varying components' failure and repair rate parameters for Washing System

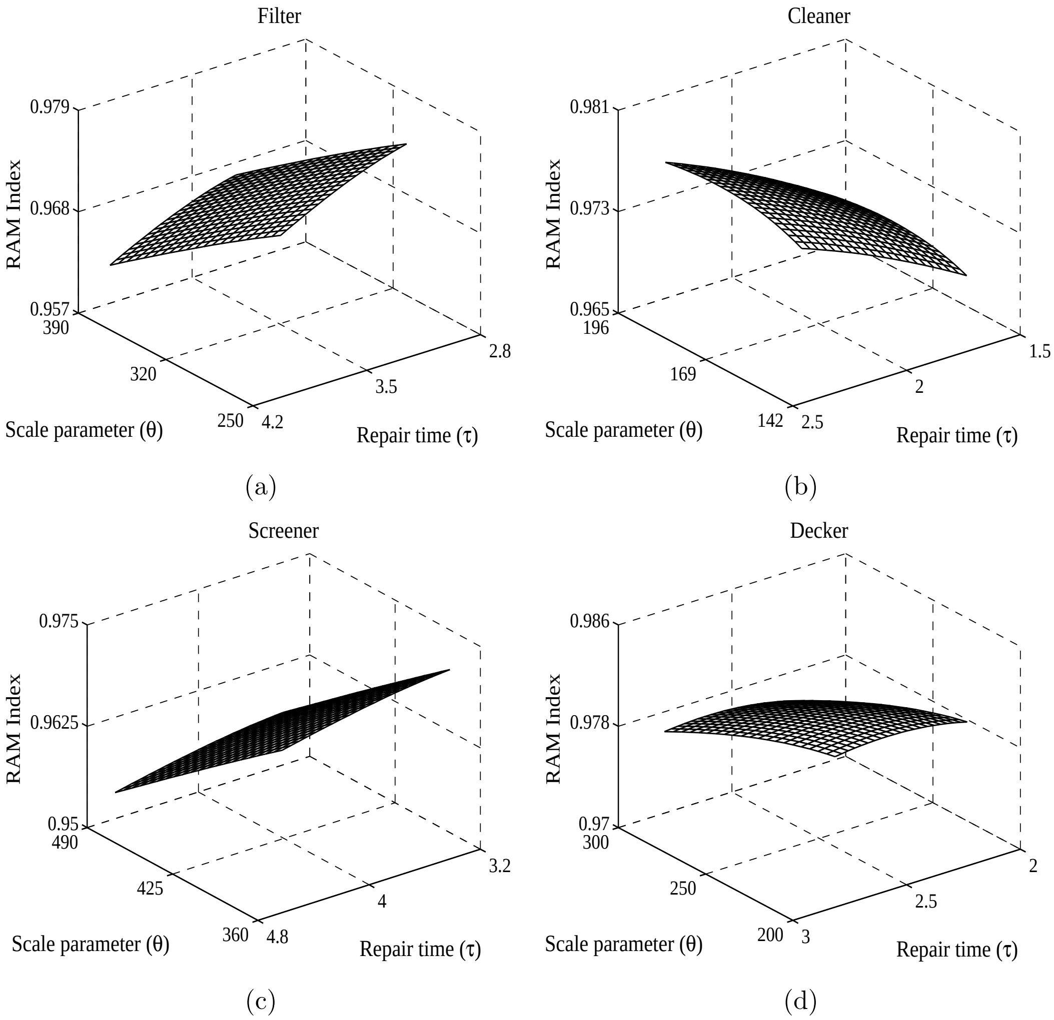


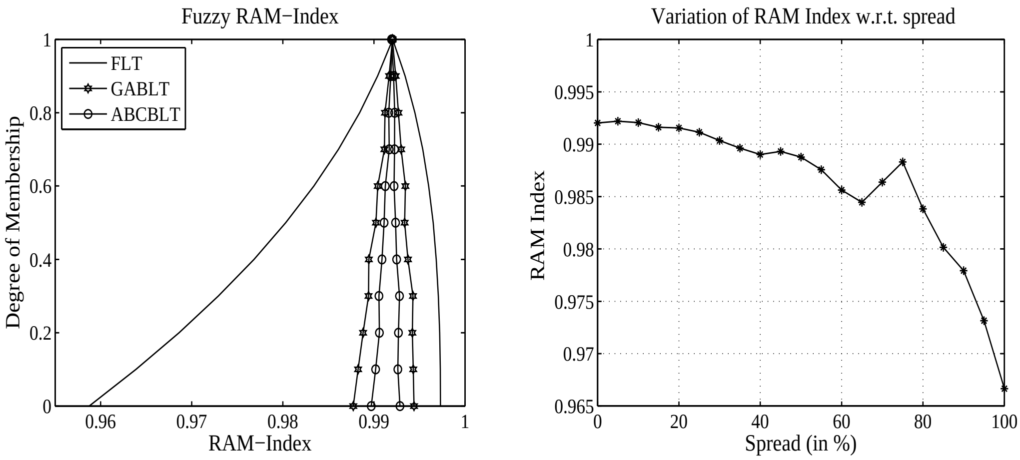
Figure 6.12: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Washing System

6.3.4 Analysis of Bleaching system

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM-index and the spread from 0 to 100(in %) have been shown for the bleaching system in Fig. 6.13(a) and 6.13(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.14 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 18hrs and attains its maximum value at t = 18 hrs in the interval 0.99406699 - 0.99491802 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=18hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.15 and Fig. 6.16 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.7 and Table 6.8 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; washer, bleaching tank and filter.

Table 6.7: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Bleaching system

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Bleaching Tank	264.350 - 357.650	Min: 0.99143531 Max: 0.99244581	2.125 - 2.875	Min: 0.98782547 Max: 0.99514513
Filter	286.450 - 387.550	Min: 0.99199712 Max: 0.99208389	1.700 - 2.300	Min: 0.99202085 Max: 0.99203318
Washer	362.100 - 489.900	Min: 0.99202047 Max: 0.99204461	2.550 - 3.450	Min: 0.99202524 Max: 0.99203069



(a) (b)

Figure 6.13: RAM-Index variation for Bleaching unit

Table 6.8: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Bleaching system

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Bleaching Tank	264.350 - 357.650	2.125 - 2.875	Min: 0.98721290 Max: 0.99462516
Filter	286.450 - 387.550	1.700 - 2.300	Min: 0.99362376 Max: 0.99780882
Washer	362.100 - 489.900	2.550 - 3.450	Min: 0.98033122 Max: 0.99257253

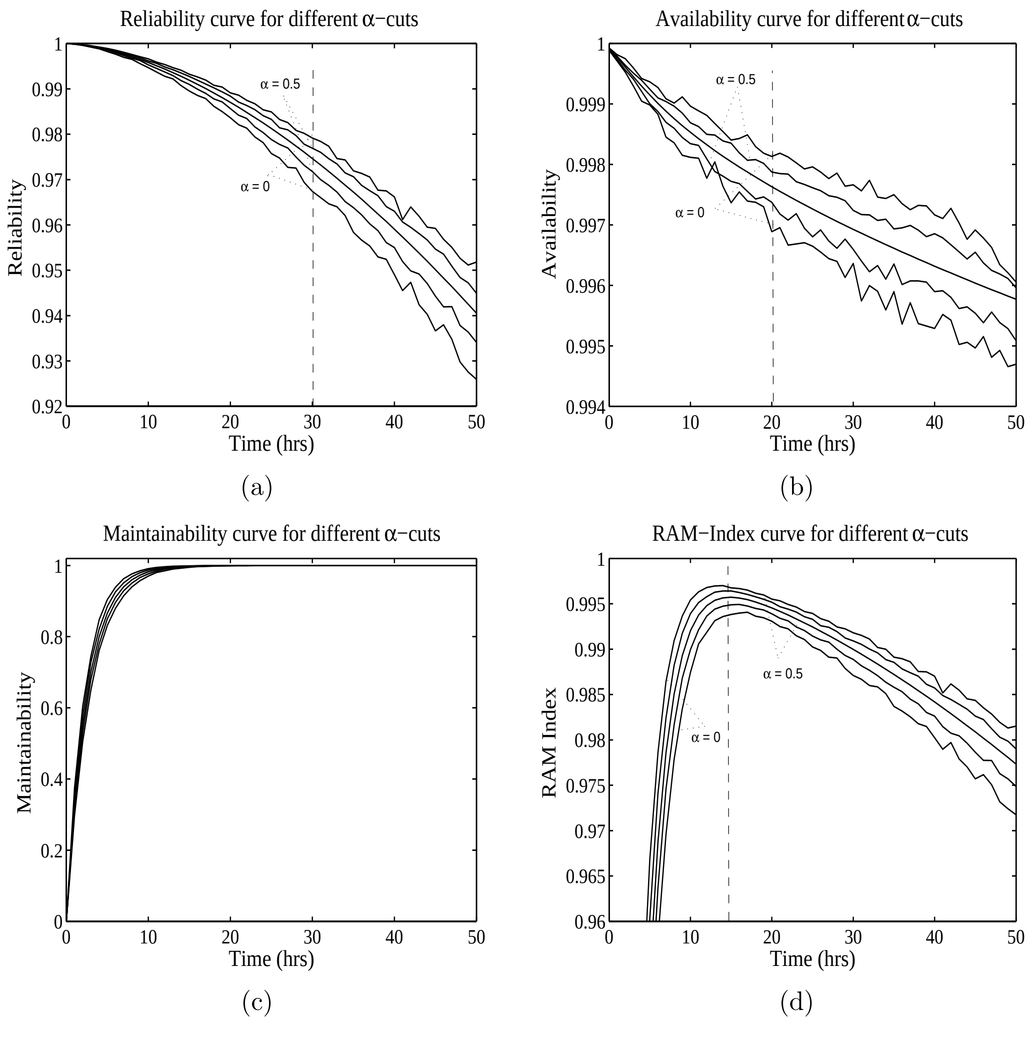


Figure 6.14: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Bleaching System

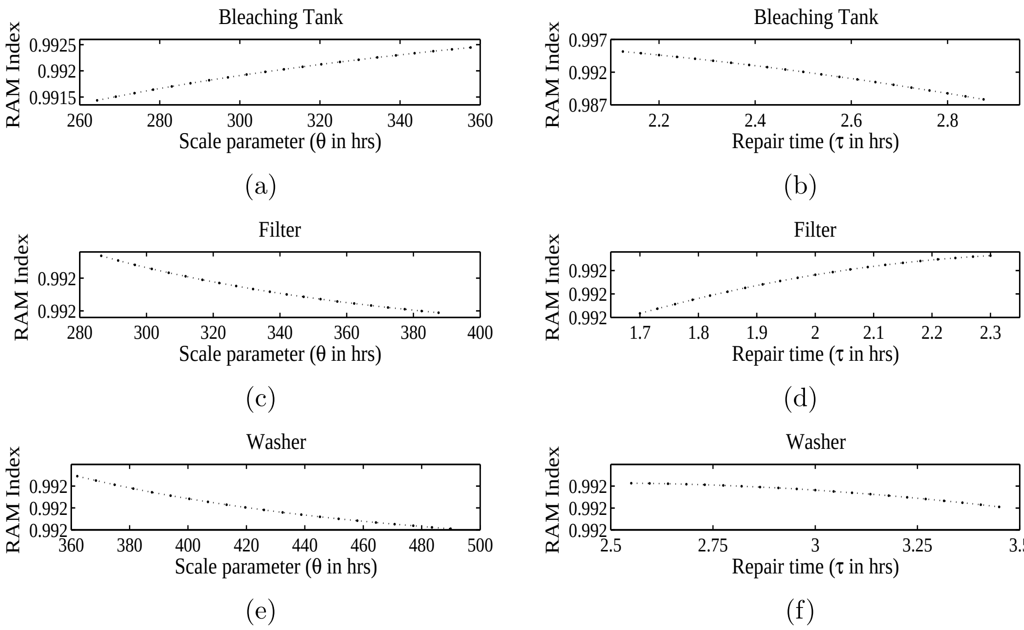


Figure 6.15: Variation of RAM-Index by varying components' failure and repair rate parameters for Bleaching system

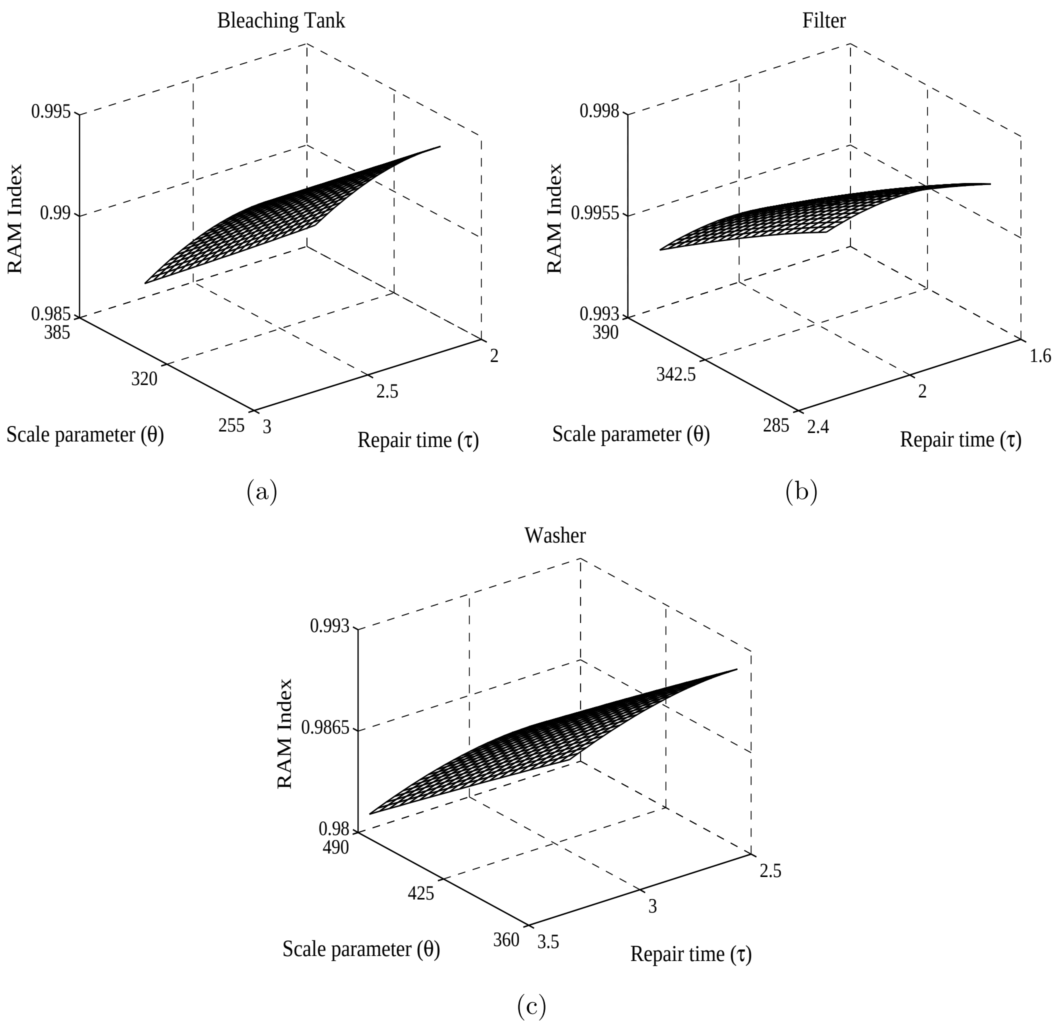
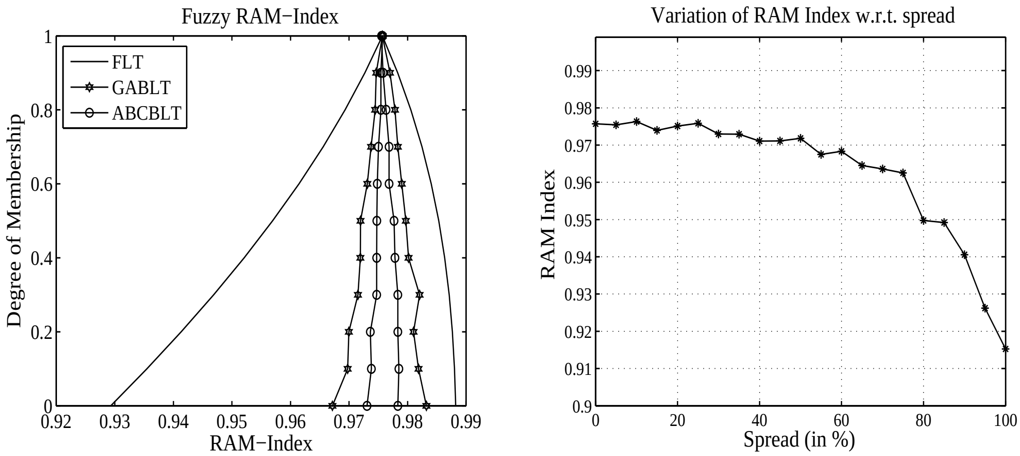


Figure 6.16: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Bleaching system

6.3.5 Analysis of Screening system

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM-index and the spread from 0 to 100(in %) have been shown for the screening system in Fig. 6.17(a) and 6.17(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.18 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 16hrs and attains its maximum value at t = 16 hrs in the interval 0.97846852 - 0.98042122 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=16hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.19 and Fig. 6.20 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.9 and Table 6.10 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; decker, screener, filter and cleaner.



(a) (b)

Figure 6.17: RAM-Index variation for Screening unit

Table 6.9: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Screening system

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Filter	286.450 - 387.550	Min: 0.97465822 Max: 0.97667539	1.700 - 2.300	Min: 0.97342489 Max: 0.97787954
Screener	267.750 - 362.250	Min: 0.97417942 Max: 0.97680809	3.400 - 4.600	Min: 0.97294317 Max: 0.97831576
Cleaner	399.500 - 540.500	Min: 0.97569885 Max: 0.97569885	1.700 - 2.300	Min: 0.97569885 Max: 0.97569885
Decker	214.200 - 289.800	Min: 0.97324561 Max: 0.97743319	4.250 - 5.750	Min: 0.97298904 Max: 0.97827127

Table 6.10: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Screening system

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Filter	286.450 - 387.550	1.700 - 2.300	Min: 0.98675020 Max: 0.99197856
Screener	267.750 - 362.250	3.400 - 4.600	Min: 0.95034946 Max: 0.97417884
Cleaner	399.500 - 540.500	1.700 - 2.300	Min: 0.99011339 Max: 0.99565120
Decker	214.200 - 289.800	4.250 - 5.750	Min: 0.92456143 Max: 0.95706339

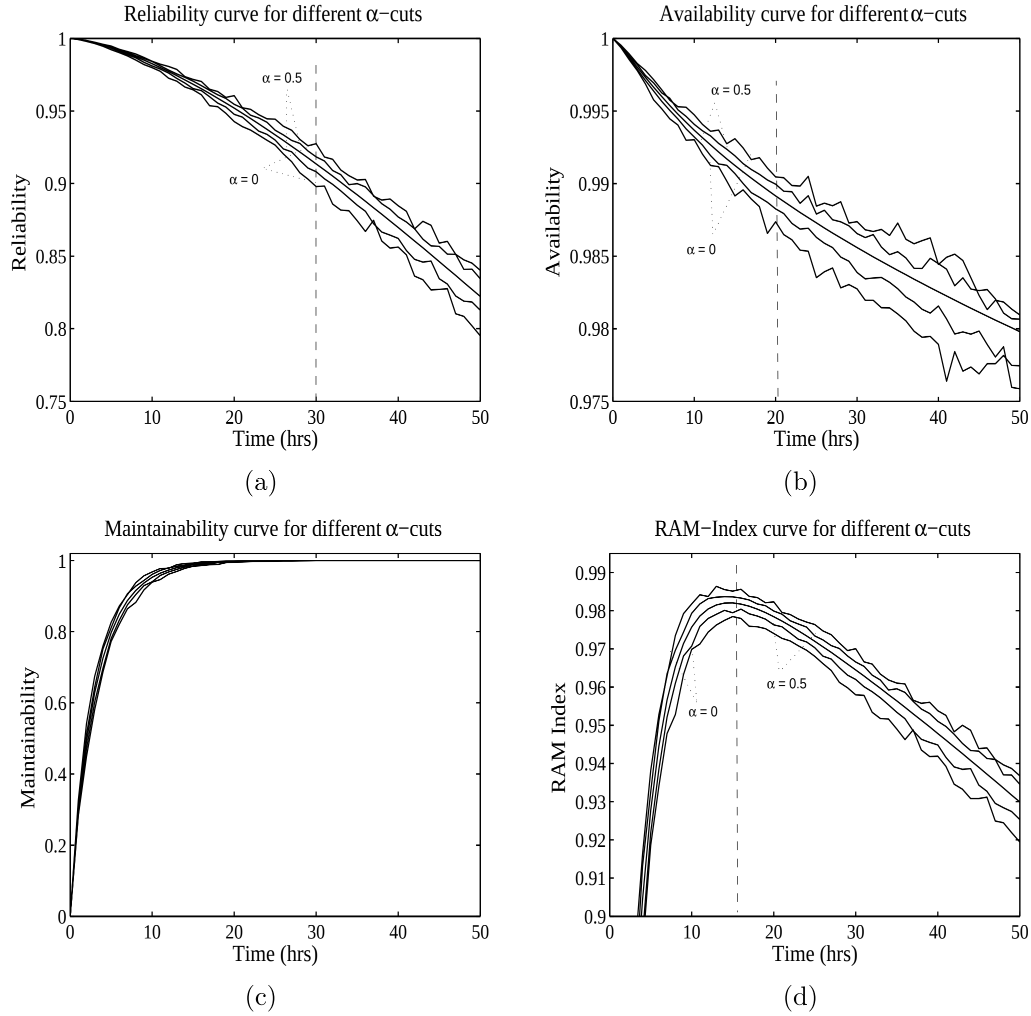


Figure 6.18: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Screening System

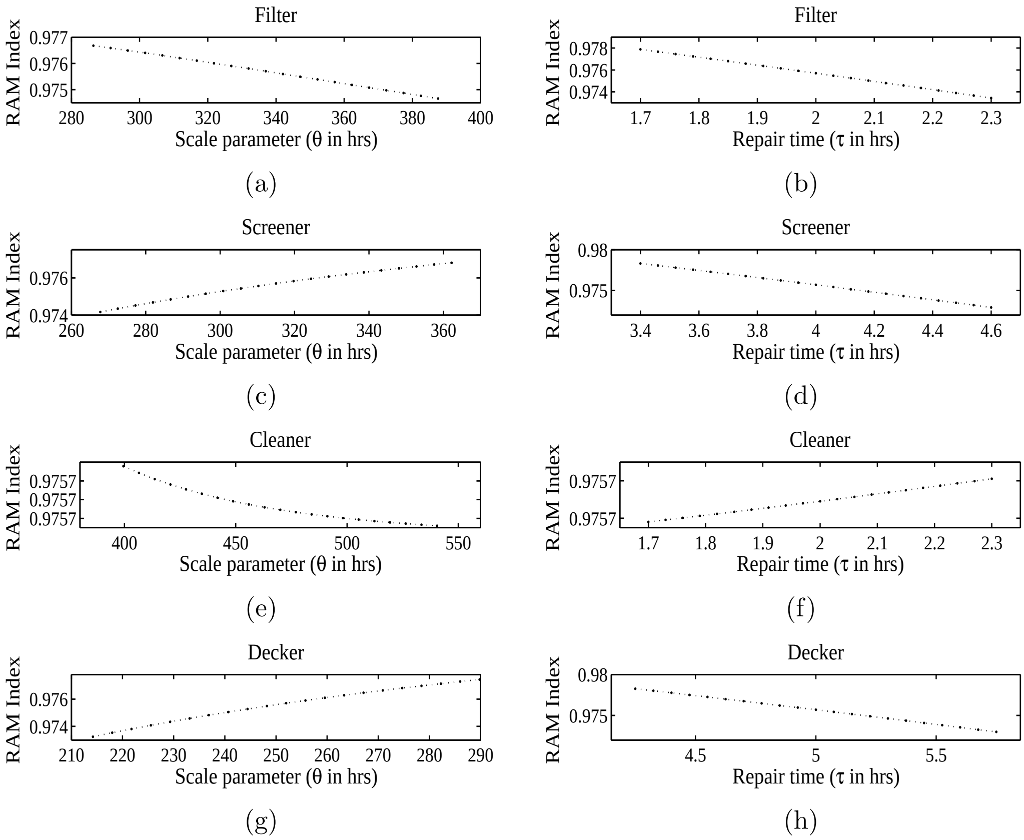


Figure 6.19: Variation of RAM-Index by varying components' failure and repair rate parameters for Screening system

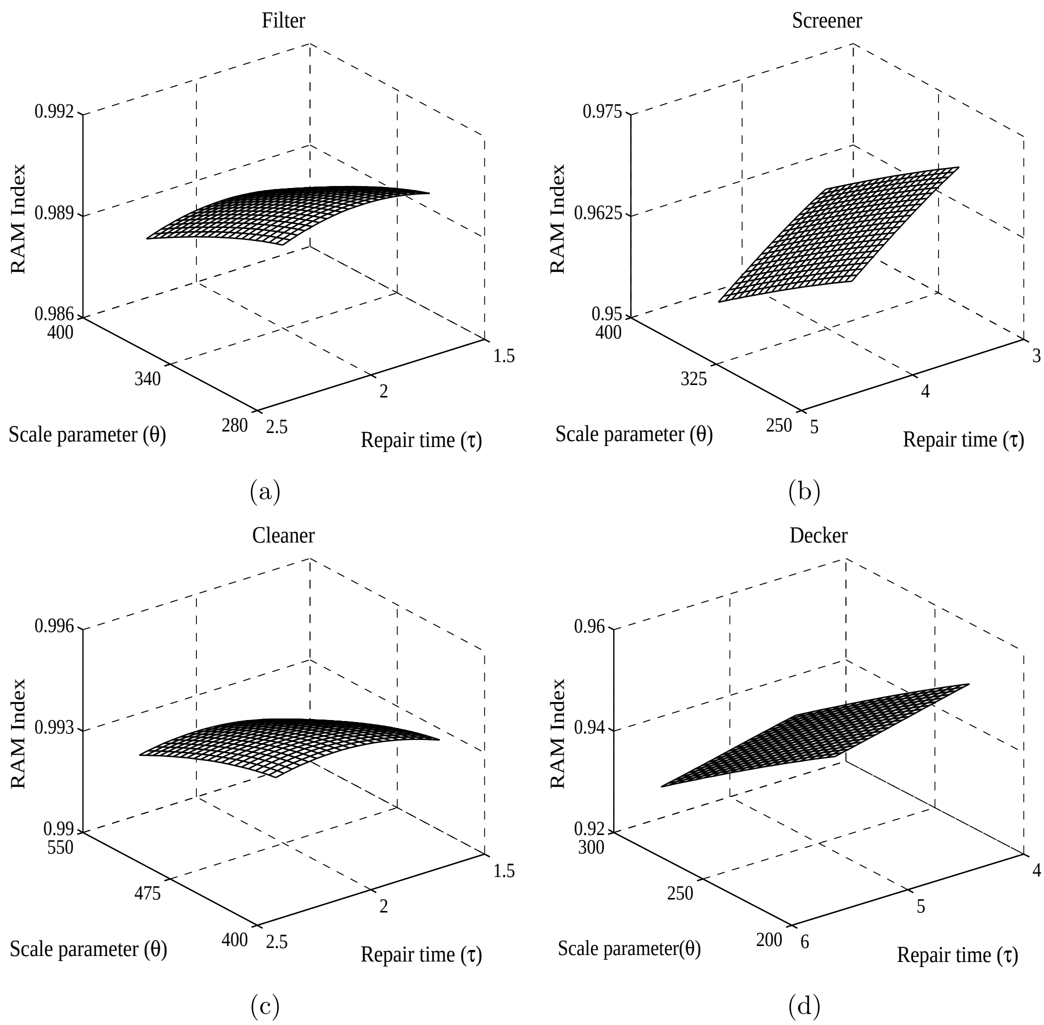
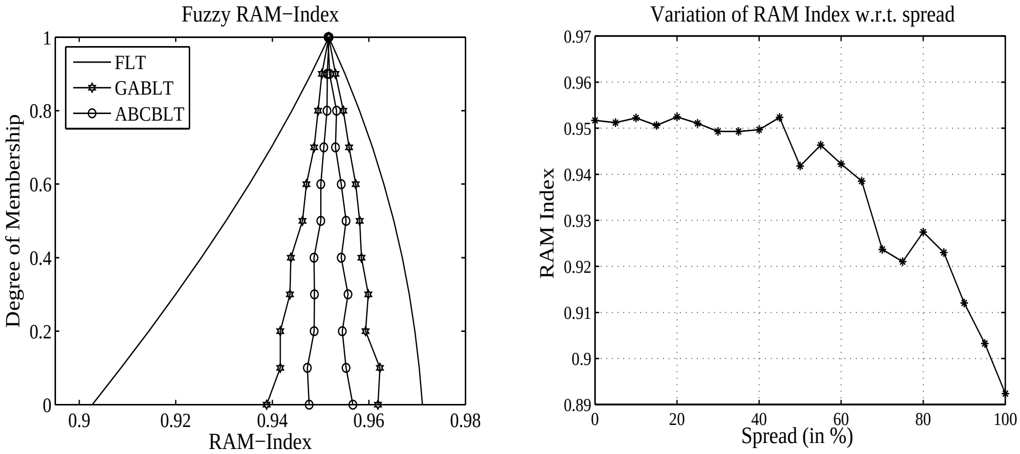


Figure 6.20: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Screening system

6.3.6 Analysis of Forming unit

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM index and the spread from 0 to 100(in %) have been shown for the forming system in Fig. 6.21(a) and 6.21(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.22 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 17hrs and attains its maximum value at t = 17 hrs in the interval 0.95344938 - 0.95617210 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=17hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.23 and Fig. 6.24 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.11 and Table 6.12 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; wire mat, head box, roller bending, roller rubber wear, roller bearing and suction box.



(a) (b)

Figure 6.21: RAM-Index variation for Forming unit

Table 6.11: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Forming unit

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Head Box	352.750 - 477.250	Min: 0.94893083 Max: 0.95361064	8.500 - 11.500	Min: 0.94964214 Max: 0.95373846
Wire Mat	290.700 - 393.300	Min: 0.94864037 Max: 0.95373651	10.200 - 13.800	Min: 0.94984082 Max: 0.95354232
Suction Box	816.000 - 1104.000	Min: 0.95158189 Max: 0.95184939	2.125-2.875	Min: 0.95108967 Max: 0.95231269
Roller Bearing	444.550 - 601.450	Min: 0.95110995 Max: 0.95238686	1.700 - 2.300	Min: 0.95049021 Max: 0.95290690
Roller Bending	360.400 - 487.600	Min: 0.95066132 Max: 0.95244384	3.400 - 4.600	Min: 0.94900352 Max: 0.95437178
Roller Rubber Wear	266.050 - 359.950	Min: 0.95155516 Max: 0.95170786	2.550 - 3.450	Min: 0.94897402 Max: 0.95439904

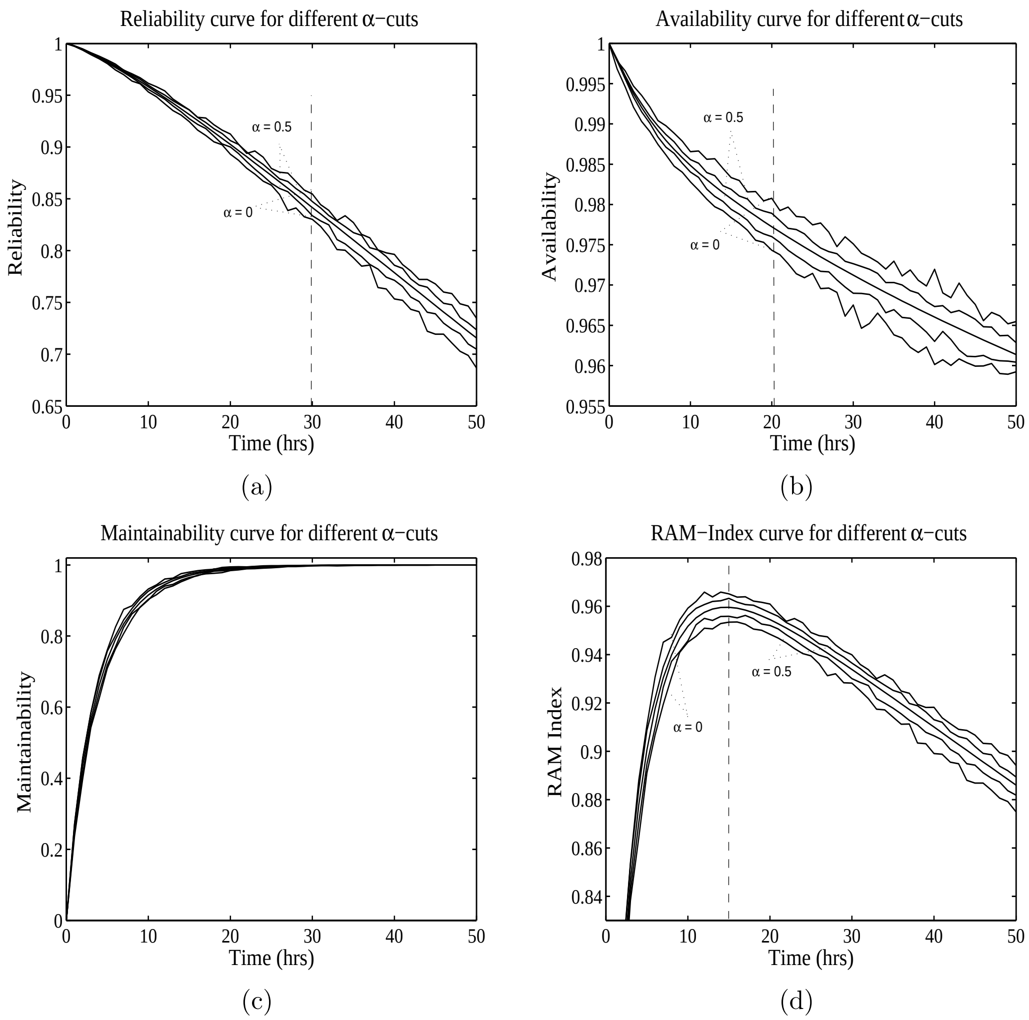


Figure 6.22: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Forming Unit

Table 6.12: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Forming unit

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Head Box	352.750 - 477.250	8.500 - 11.500	Min: 0.82485552 Max: 0.87276252
Wire Mat	290.700 - 393.300	10.200 - 13.800	Min: 0.79314723 Max: 0.84373886
Suction Box	816.000 - 1104.000	2.125-2.875	Min: 0.98012622 Max: 0.99014132
Roller Bearing	444.550 - 601.450	1.700 - 2.300	Min: 0.97659914 Max: 0.98505662
Roller Bending	360.400 - 487.600	3.400 - 4.600	Min: 0.93367518 Max: 0.96211070
Roller Rubber Wear	266.050 - 359.950	2.550 - 3.450	Min: 0.94328083 Max: 0.96601023

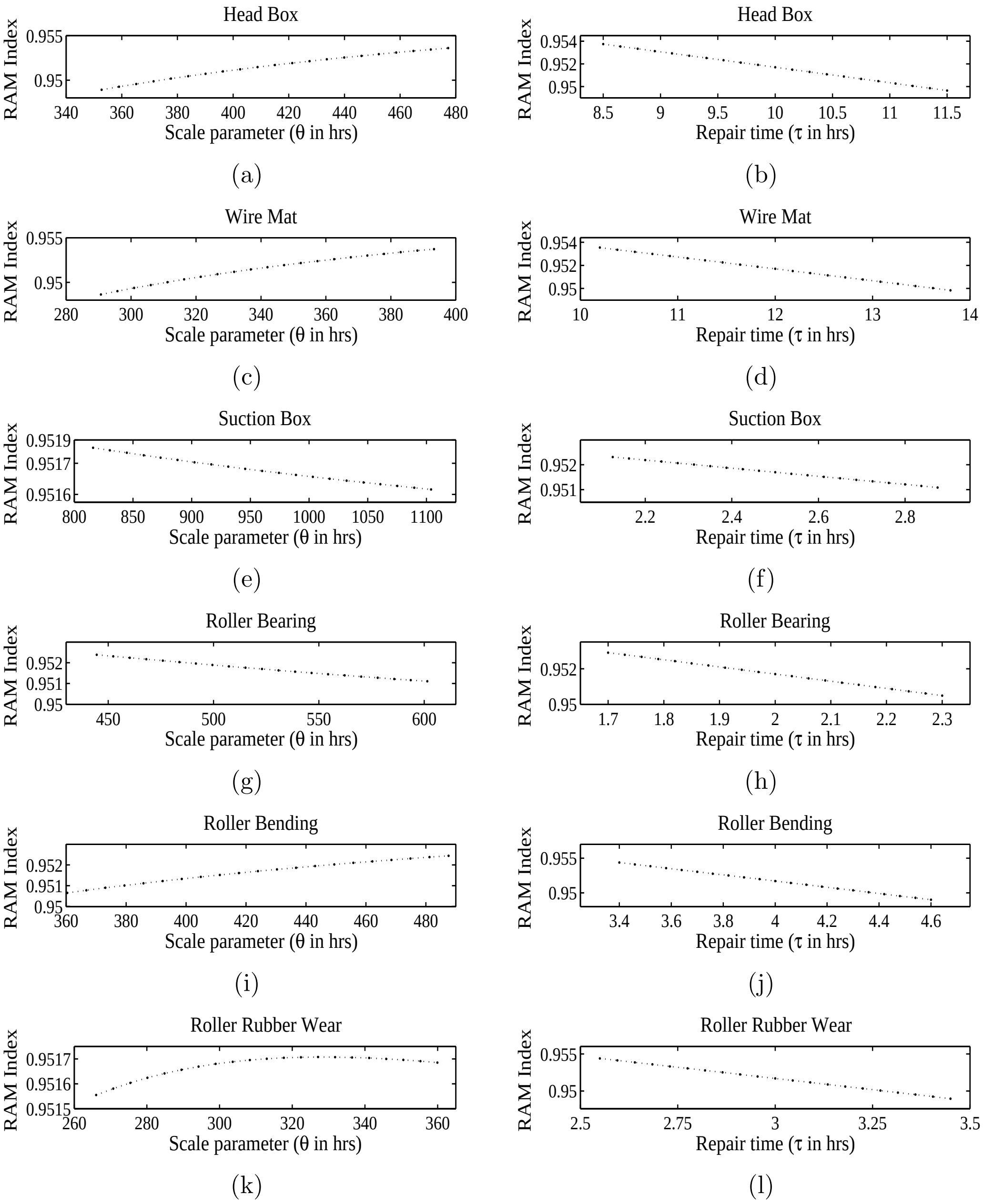


Figure 6.23: Variation of RAM-Index by varying components' failure and repair rate parameters for Forming Unit

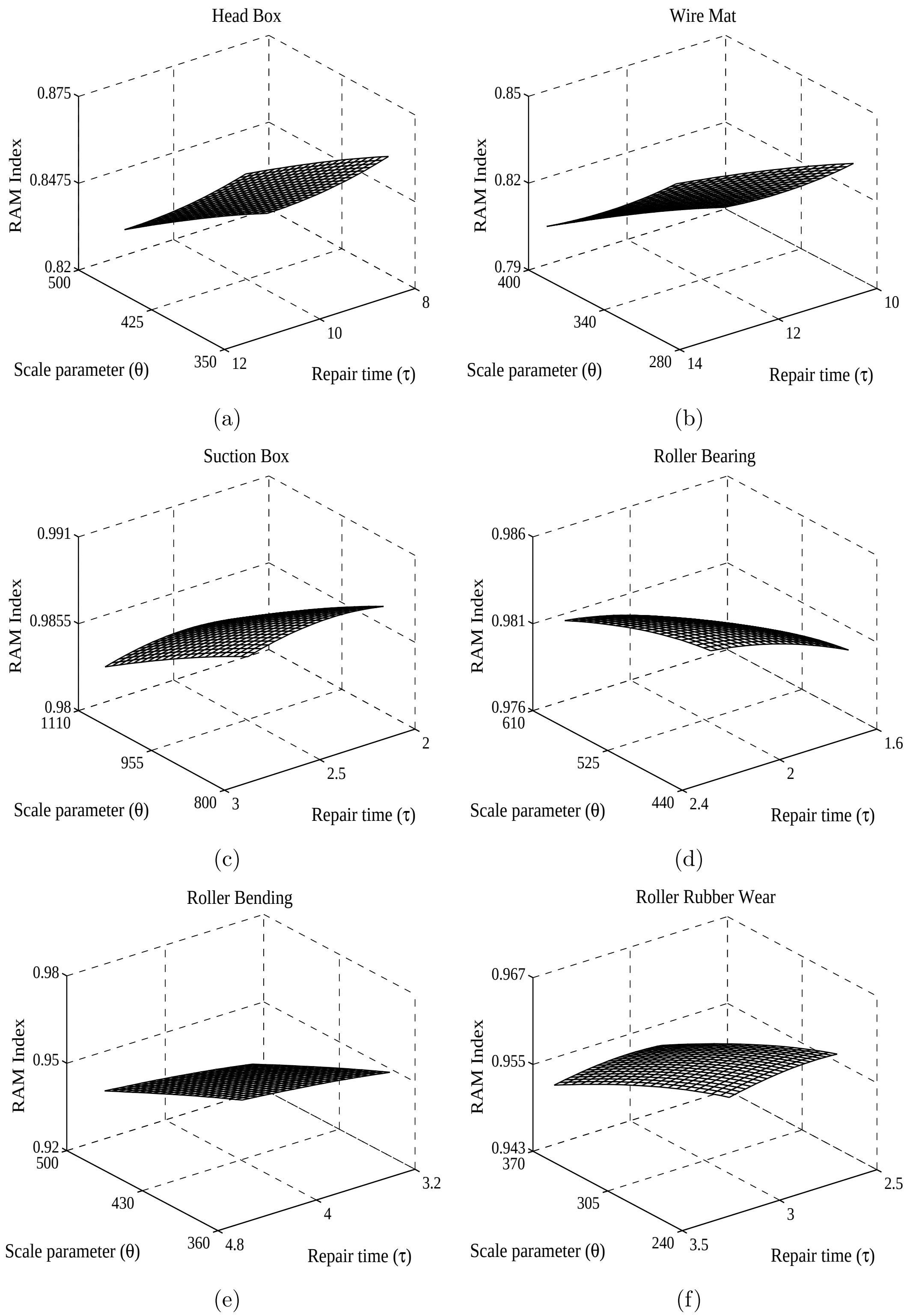


Figure 6.24: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Forming Unit

6.3.7 Analysis of Press unit

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM index and the spread from 0 to 100(in %) have been shown for the press unit in Fig. 6.25(a) and 6.25(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.26 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 13hrs and attains its maximum value at t = 13 hrs in the interval 0.94689267 - 0.94982651 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=13hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.27 and Fig. 6.28 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.13 and Table 6.14 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; roller rubber wear, felt, roller bending and roller bearing.

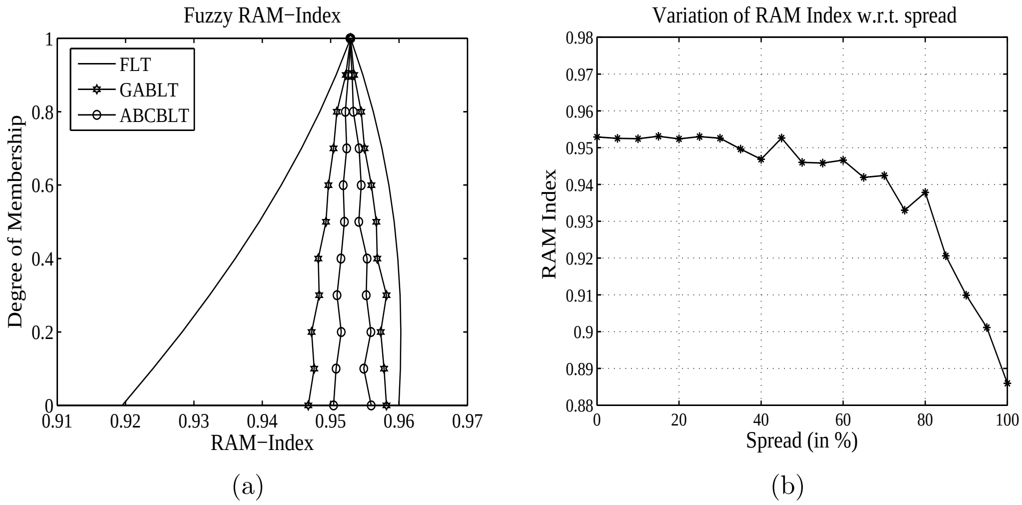


Figure 6.25: RAM-Index variation for Press unit

Table 6.13: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Press unit

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Felt	888.250 - 1201.750	Min: 0.95290494 Max: 0.95291861	4.250 - 5.750	Min: 0.95290868 Max: 0.95291834
Roller Bearing	444.550 - 601.450	Min: 0.95233001 Max: 0.95324182	1.700 - 2.300	Min: 0.95147981 Max: 0.95432199
Roller Bending	368.900 - 499.100	Min: 0.95071606 Max: 0.95450743	2.975 - 4.025	Min: 0.95020223 Max: 0.95553040
Roller Rubber Wear	266.050 - 359.950	Min: 0.94916368 Max: 0.95569419	3.400 - 4.600	Min: 0.94866045 Max: 0.95691173

Table 6.14: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Press unit

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Felt	888.250 - 1201.750	4.250 - 5.750	Min: 0.92661313 Max: 0.95862976
Roller Bearing	444.550 - 601.450	1.700 - 2.300	Min: 0.96916705 Max: 0.97851774
Roller Bending	368.900 - 499.100	2.975 - 4.025	Min: 0.93545317 Max: 0.96074888
Roller Rubber Wear	266.050 - 359.950	3.400 - 4.600	Min: 0.90718910 Max: 0.94123915

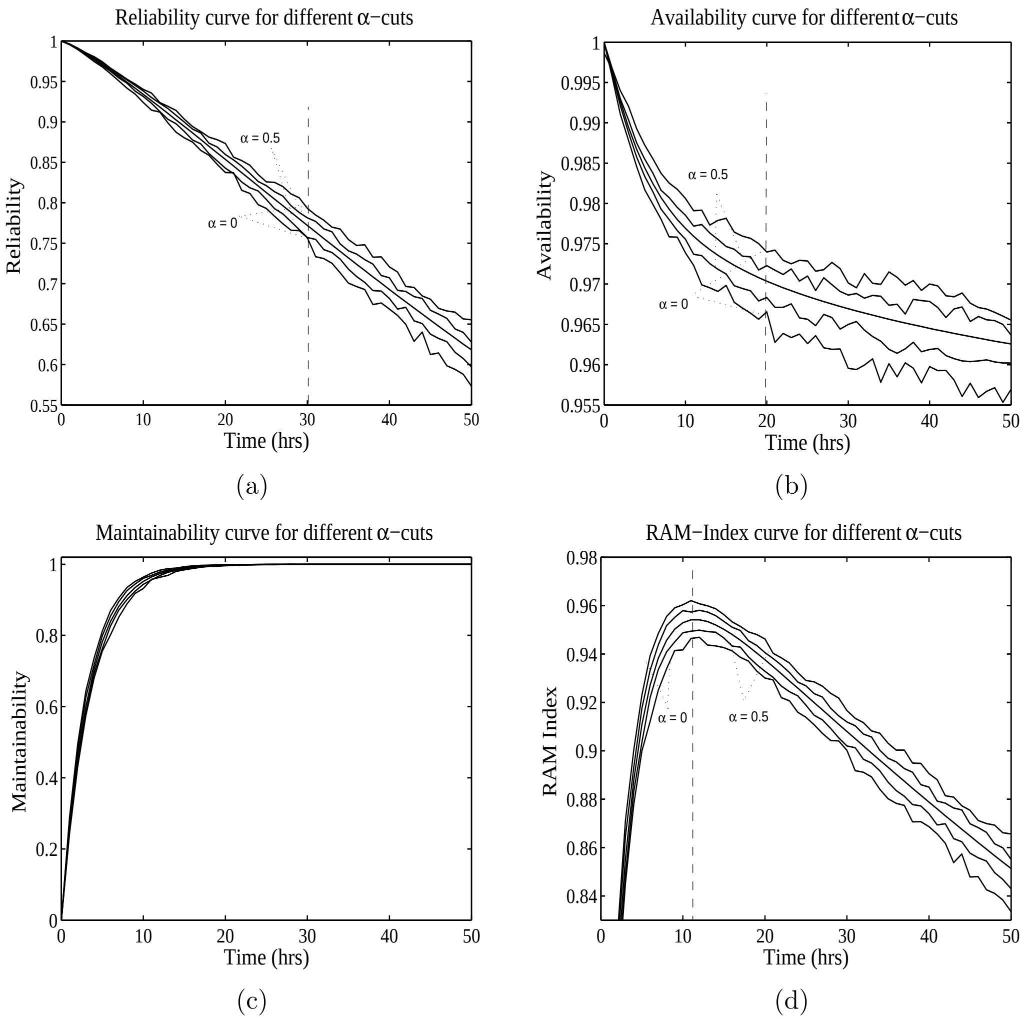


Figure 6.26: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Press Unit

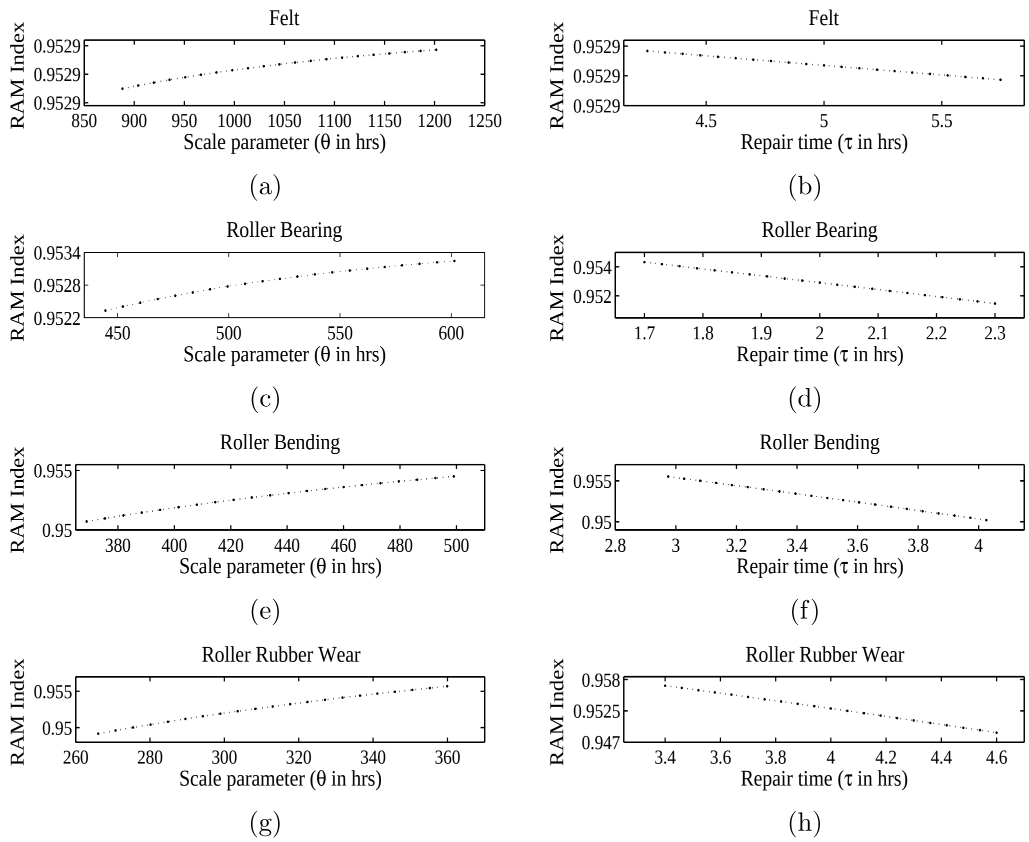


Figure 6.27: Variation of RAM-Index by varying components' failure and repair rate parameters for Press unit

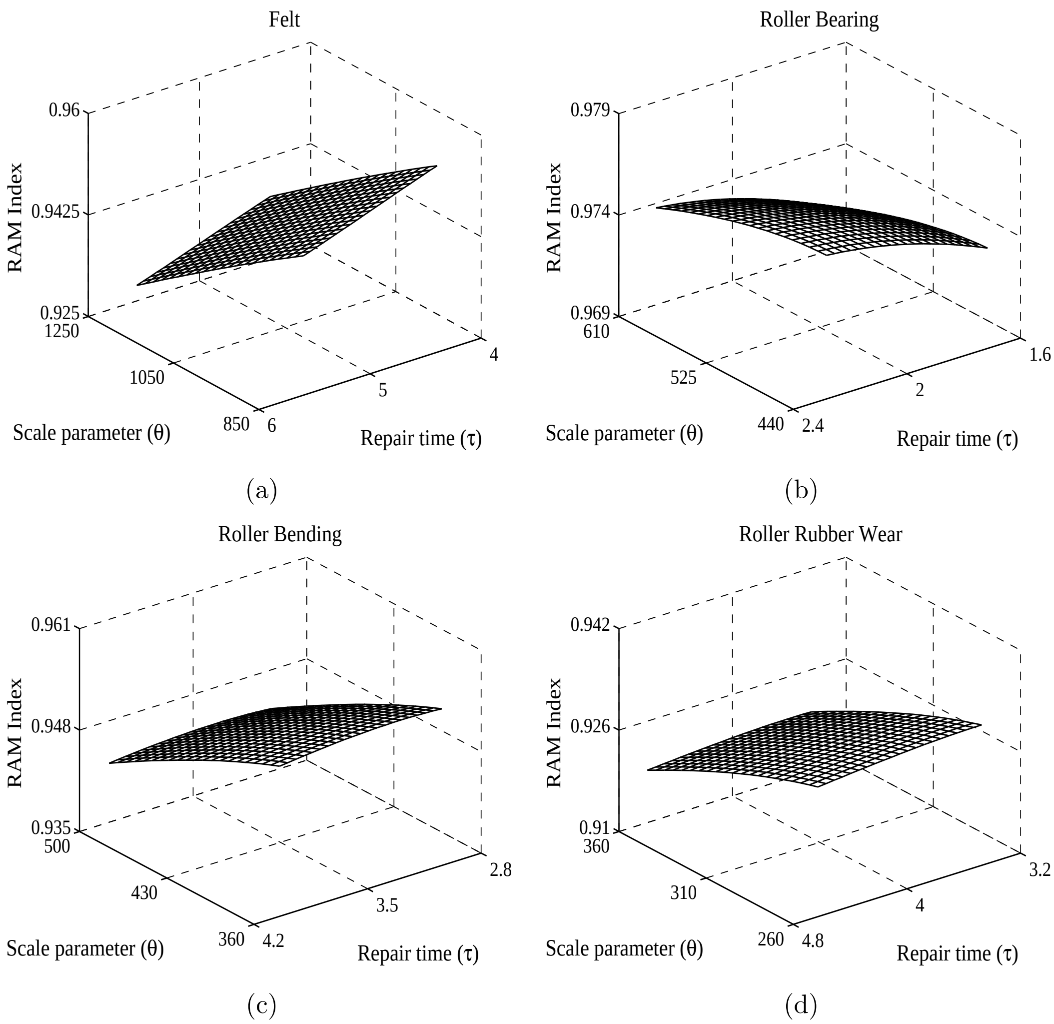


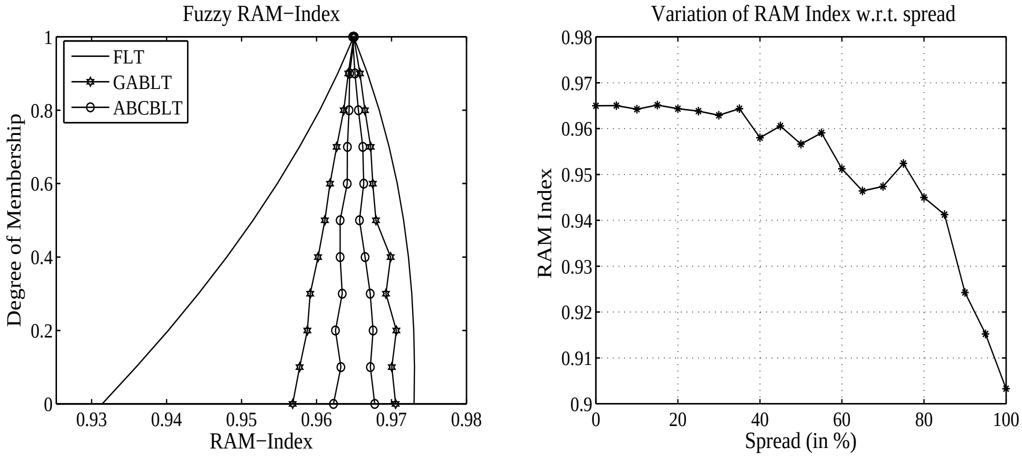
Figure 6.28: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Press unit

6.3.8 Analysis of Dryer unit

The behavior of the RAM-Index in the form of fuzzy membership function and a plot between RAM index and the spread from 0 to 100(in %) have been shown for the dryer unit in Fig. 6.29(a) and 6.29(b) respectively. On the other hand, the variation of their RAM parameter along with their index for a long-run period are shown in Fig. 6.30 which shows that the RAM-Index of the system increases within the time interval from t = 0 to 12hrs and attains its maximum value at t = 12 hrs in the interval 0.95930246 - 0.96380728 and after that system performance reduces exponentially. Thus it is found that for increasing the performance of the system, a necessary action should be taken after time t=12hrs. The sensitivity of system performance is analyzed by varying individually and simultaneously their components' failure rate (θ) and repair time (τ) as done in section 6.3.1 of this chapter. In this analysis, computation have been done for each of the components of the systems by varying the values of θ and τ individually and simultaneously and fixing failure rate and repair time parameters of other components at the same time. The results are depicted graphically by Fig. 6.31 and Fig. 6.32 respectively. The maximum and minimum values of each of the component are noticed and given in Table 6.15 and Table 6.16 respectively. On the basis of tabulated results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; felt, roller bending and roller bearing.

Table 6.15: Effect of Variations of System's Components' Failure and Repair Times on its RAM-Index for Dryer unit

Component	Range of scale parameter θ(hrs)	RAM-Index	Range of Repair Time MTTR(hrs)	RAM-Index
Felt	888.250 - 1201.750	Min: 0.96494118 Max: 0.96499400	8.500 - 11.500	Min: 0.96496069 Max: 0.96498784
Roller bearing	444.550 - 601.450	Min: 0.96463578 Max: 0.96503641	1.700 - 2.300	Min: 0.96296715 Max: 0.96690805
Roller bending	275.400 - 372.600	Min: 0.960860599 Max: 0.96812013	3.400 - 4.600	Min: 0.95928853 Max: 0.97005414



(a) (b)

Figure 6.29: RAM-Index variation for Dryer unit

Table 6.16: Effect of Simultaneous Variations of System's Components' Failure and Repair Times on its RAM-Index for Dryer unit

Component	Range of scale parameter θ(hrs)	Range of Repair Time MTTR(hrs)	RAM-Index
Felt	888.250 - 1201.750	8.500 - 11.500	Min: 0.84743224 Max: 0.88842020
Roller bearing	444.550 - 601.450	1.700 - 2.300	Min: 0.97792739 Max: 0.98438871
Roller bending	275.400 - 372.600	3.400 - 4.600	Min: 0.92627537 Max: 0.95431901

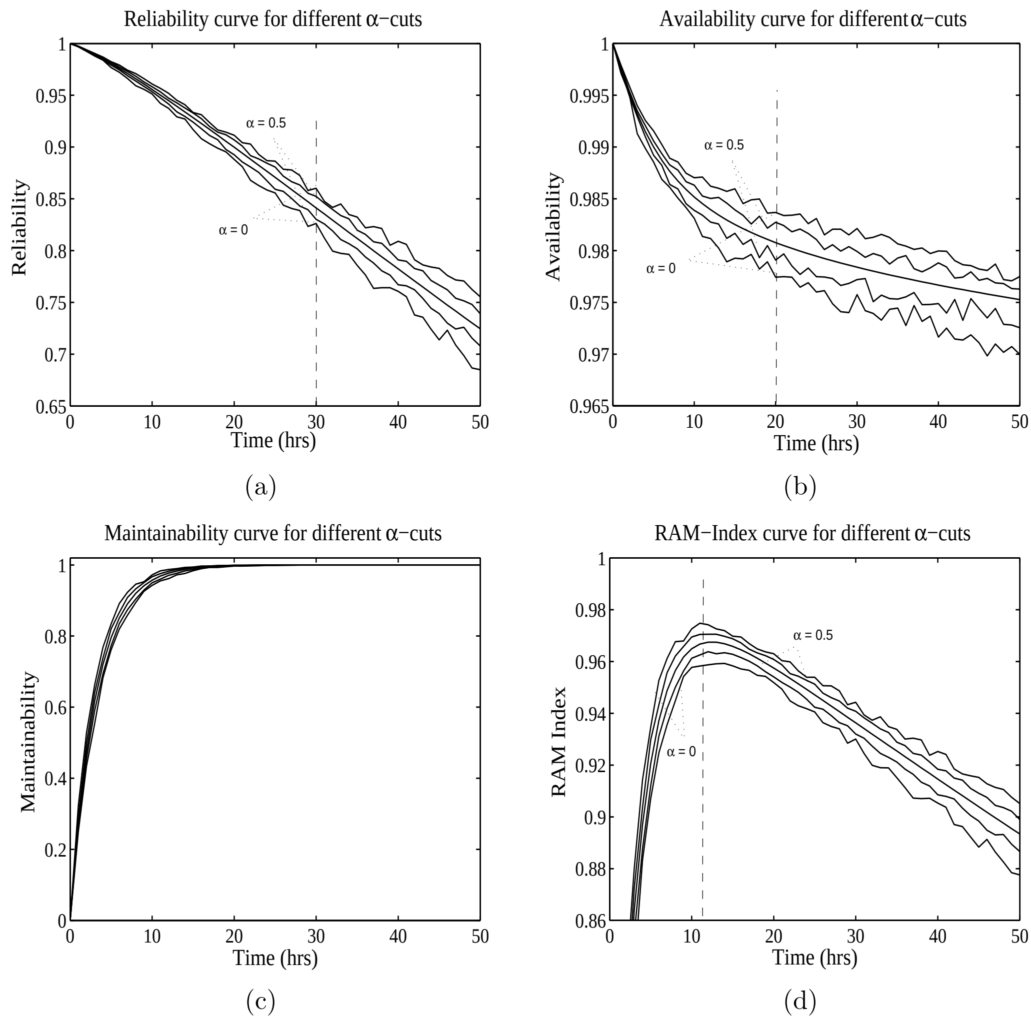


Figure 6.30: Long run period of the RAM parameters and RAM-Index at different $\alpha-$ cuts for Dryer Unit

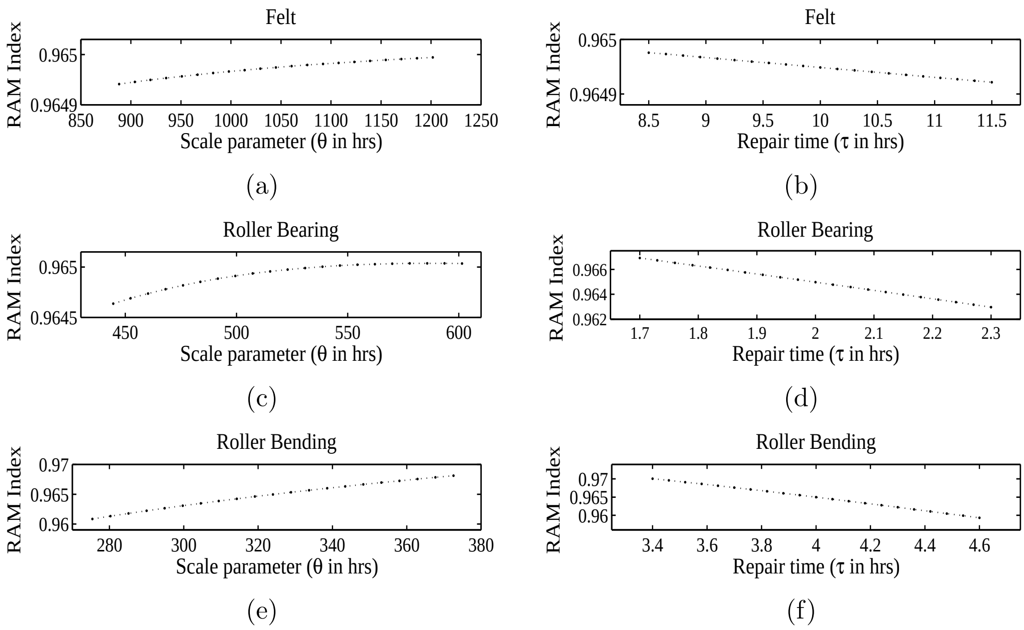


Figure 6.31: Variation of RAM-Index by varying components' failure and repair rate parameters for Dryer unit

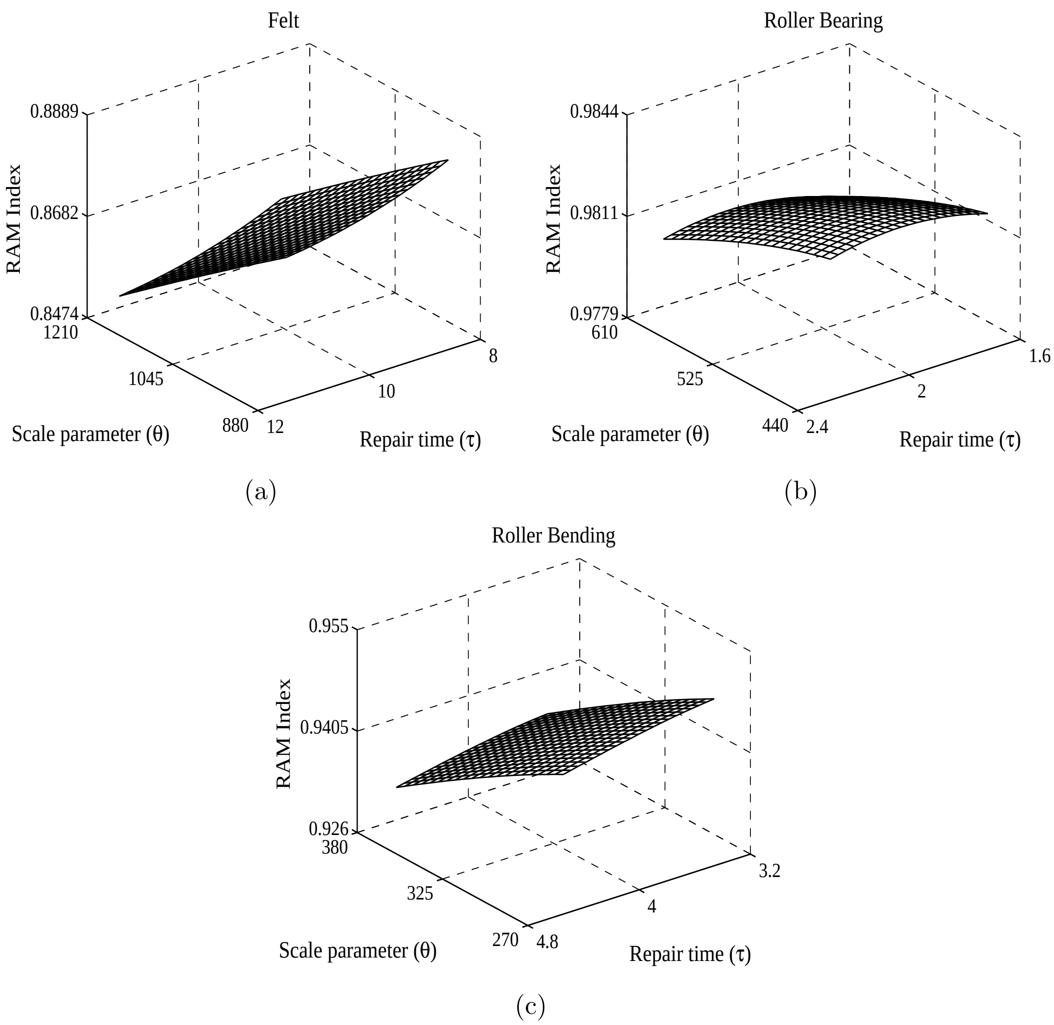


Figure 6.32: Effect of Simultaneously Varying the Components' Parameters on its RAM-Index for Dryer unit

6.4 Conclusion

In this chapter, an attempt has been made to enhance the performance of the paper industry by utilizing uncertain, vague and imprecise data. The uncertainties in the data are handled with the help of fuzzy approach in order to increase the efficiency of the system and their membership functions are computed by using ABCBLT technique. In order to find the most critical component of the system, a time varying RAM-Index has been proposed for analyzing the performance of the system by using ABCBLT technique and compared their results with FLT and GABLT techniques results and concluded that proposed results have lesser range of uncertainties and hence predictions. The major advantage of this index is that by varying the system component parameter individually the simultaneous effect on its performance has been computed and observed. Apart from that a conceptual model has been suggested through which it is illustrated, how a suitable performance analysis based maintenance can be identified. Components of each of the subsystems/units of the plant which have excessive failure rates, long repair time or high degree of uncertainty associated with these values, are identified and reported in preferential order. The critical component of each of the units has been found by studying the effects on RAM index of varying individually and simultaneously the parameters of failure and repair rates of components and also of fixing failure rate and repair time of other components at the same time. This analysis indicates the effects of taking wrong decision on to the system's behavior as well as performance. Based on these analyses, it has been concluded that for increasing the performance of the system, it is necessary that proper maintenance actions are needed for enhancing its performance. Apart from these advantages, the system performance analysis may be utilized to conduct cost-benefit analysis, operational capability studies, inventory/spare parts management, and replacement decisions.

Chapter 7

An approach for solving RRAP through ABC technique

The main objective of this chapter is to develop a two-phase approach for maximizing the reliability of the system under redundancy allocation environment. More clearly the aim is to propose a method for solving a reliability redundancy allocation problem (RRAP) by finding the reliability of components as well as the number of redundant components simultaneously that maximize the system reliability under the system's cost, weight and volume constraint. Justification of the suggested approach has been ascertained by applying it on four benchmark problems and observing the better results than the already existed results in the literature.

7.1 Introduction

The system reliability optimization is very important in the real world applications and the various kinds of systems have been studied in the literature for the decades. To design a highly reliable system there are mainly two ways of improving the system reliability. One is - adding redundant components, and the other is - increasing the component reliability. Both the ways usually increase the resources (cost, volume, weight, etc). Therefore, at the stage of designing a highly reliable system, an important problem is to get the balance between reliability and other resources [155].

Besides the above two ways, the combination of the two approaches and reassignment of interchangeable elements are another feasible ways for increasing the system reliability [100, 155]. Such problem of maximizing system reliability through redundancy and component reliability choices is called "reliability-redundancy allocation problem (RRAP)".

The general mathematical formulation of the reliability - redundancy allocation problem is

$$\begin{aligned} \text{Maximize} \quad & R_s(r_1, r_2, \ldots, r_m;\ n_1, n_2, \ldots, n_m) \\ \text{subject to} \quad & g(r_1, r_2, \ldots, r_m;\ n_1, n_2, \ldots, n_m) \leq b \\ & 0 \leq r_i \leq 1 \ \ ; \ \ i = 1, 2, \cdots, m \quad r_i \in [0, 1] \subset \mathbb{R} \\ & 1 \leq n_i \leq n_{i,max} \quad n_i \in \mathbb{Z}^+ \end{aligned}$$

where $g(\cdot)$ is the set of constraint functions usually associated with the system's weight, volume and cost; $R_s(\cdot)$ is the objective function for the overall system reliability; r_i and n_i are the reliability and the number of redundant components in the i^{th} subsystem, respectively; m is the number of subsystems in the system and b is the vector of resource limitation. This problem is an NP problem and belongs to the category of constrained nonlinear mixed-integer optimization problems because the number of redundancy n_i are the positive integer values and the component reliability r_i are the real values between 0 and 1. The goal of the problem is to determine the number of components n_i and the components' reliability r_i in each subsystem so as to maximize the overall system reliability.

During the last two decades, numerous reliability design techniques have been introduced to solve these problems. These techniques can be classified as implicit enumeration, dynamic programming, branch and bound technique, linear programming, Lagrangian multiplier method, heuristic methods and so on. To solve this type of problem, Kuo et al. [156], Tillman et al. [231] have extensively reviewed the several optimization techniques for system reliability design. Nakagawa [183] compared three heuristic methods (Nakagawa - Nakashima, Gopal - Aggarwal - Gupta, Sharma - Venkateswaran) for solving reliability optimization problems with nonlinear constraints. Their effectiveness, measured in terms of computation time, optimality rate, and relative error, is evaluated on several sets of randomly generated test problems with nonlinear constraints for series systems. After combining Lagrange multiplier and branch and bound algorithms, Kohda and Inoue [139] gave a heuristic approach in which new criterion of local optimality was presented. They showed that their method generates solutions which are optimal in 2-neighborhood for the redundancy optimization problem. Kuo et al. [154] proposed a heuristic algorithm for a series system and obtained solutions close to the optimal one via Lagrange multiplier. Misra and Sharma [177] proposed an algorithm and solved problems by integer programming, which serves as an algorithm searching for nearby boundary of the domain of feasible solution. Prasad and Kuo [192] pointed out that the algorithm given by Misra and Sharma sometimes cannot yield an optimal solution, and suggested a method for searching the upper limit of reliability objective function. Kim and Yum [133] solved the reliability optimization problem of a series-parallel system by using heuristic algorithms. The method proposed by them allows excursions over a bounded infeasible region, and hence gives global optimal solution. On the basis of computational results they proved that the approach was faster and straight-forward than any other heuristic method. Shi [218] developed a heuristic method with separable, monotonic nondecreasing constraints function following the approach of adjusting unit-increment with time.

However, the heuristic techniques require derivatives for all non-linear constraint functions, that are not derived easily because of the highly computational complexity. To overcome this difficulty metaheuristics have been selected and successfully applied to handle a number of reliability optimization problems. These heuristics include genetic algorithms (GA), simulated annealing (SA), tabu search (TS), particle swarm optimization (PSO), artificial bee colony (ABC) etc. Painton and Campbell

[188], Yokota et al. [257] and Hsieh et al. [106] applied genetic algorithms to solve these mixed-integer reliability optimization problems. Coit and Smith [56] combined GA and neural network (NN) to tackle the series-parallel redundancy problem. Chen [46] applied the immune algorithm (IA) for solving the reliability–redundancy allocation problem. Coelho [53] proposed an efficient PSO algorithm based on Gaussian distribution and chaotic sequence to solve the reliability - redundancy optimization problems. Yeh and Hsieh [253] developed a penalty guided artificial bee colony algorithm (ABC) for solving the reliability optimization problems.

In the light of the advantages of the meta-heuristics techniques, the presented chapter discusses the two phase approach for the reliability - redundancy allocation problem. In the first phase, the optimal solution of the reliability–redundancy allocation problem has been obtained with one of the meta-heuristic technique namely artificial bee colony (ABC) while in the second phase the component reliability allocation is improved after fixing the number of component redundancy as obtained during Phase I. Four benchmark problems of reliability-redundancy allocation are solved with the proposed technique and it is observed that the our results are all better than the existing results in the literature.

7.2 Problem formulation: reliability redundancy allocation problem

The following assumptions and notations for RRAP have been used in this chapter.

7.2.1 Assumptions:

- If a component of any subsystem fails to function, the entire system will not fail.
- All redundancies is active redundancy without repair.
- The components and system have only two states – operating state or failure

state.

7.2.2 Notations:

m	number of subsystems in the system.
M	number of constraints.
n_i	the number of components in the subsystem $i, 1 \leq i \leq m$.
n	$=(n_1, n_2, \ldots, n_m)$, the vector of redundancy allocation for the system.
r_i	reliability of each of the components in subsystem $i, 1 \leq i \leq m$.
r	$=(r_1, r_2, \ldots, r_m)$, the vector of component reliabilities for the system.
g_j	the j^{th} constraint function, $j = 1, 2, \ldots, M$.
w_i	the weight of each component in subsystem $i, 1 \leq i \leq m$.
c_i	the cost of the each component in subsystem $i, 1 \leq i \leq m$.
v_i	the volume of each component in subsystem $i, 1 \leq i \leq m$.
R_i	$= 1 - (1 - r_i)^{n_i}$ is the reliability of the i^{th} subsystem $1 \leq i \leq m$.
Q_i	$1 - R_i$ is the unreliability of the i^{th} subsystem.
$n_{i,max}$	maximum number of components in subsystem $i, 1 \leq i \leq m$.
R_s	the system reliability.
C, W	the upper limit of the system's cost, weight respectively.
S	feasible search space.

7.2.3 Problem Description

Out of the four benchmark problems of the reliability - redundancy allocation problem studied in this chapter, the first three problems with non-linear constraints used by Chen [46], Hikita et al. [100], Hsieh et al. [106], Xu et al. [251], Yeh and Hsieh [253] are a series system, series-parallel system and complex (bridge) system, respectively as shown in Fig. 7.1. The fourth problem, investigated by Chen [46], Coelho [53], Dhingra [62], Yeh and Hsieh [253], Yokota et al. [257] is of overspeed protection system. All these problems are to maximize the systems' reliability subject to multiple nonlinear constraints and can be stated as the mixed-integer nonlinear programming problems. For each problem both, the component reliabilities and redundancy allocations are to be decided simultaneously. The mathematical formulation of these four reliability-redundancy allocation problems is given below.

Problem 1: Series System (Fig. 7.1(a)) [46, 100, 106, 132, 253]

$$\begin{aligned}
\text{Maximize} \quad R_s(r,n) &= \prod_{i=1}^{5}[1-(1-r_i)^{n_i}] \\
\text{s.t.} \quad g_1(r,n) &= \sum_{i=1}^{5} v_i n_i^2 - V \le 0 && (7.2.1)\\
g_2(r,n) &= \sum_{i=1}^{5} \alpha_i(-1000/\ln r_i)^{\beta_i}[n_i+\exp(n_i/4)] - C \le 0 && (7.2.2)\\
g_3(r,n) &= \sum_{i=1}^{5} w_i n_i \exp(n_i/4) - W \le 0 && (7.2.3)\\
0.5 &\le r_i \le 1 \quad , r_i \in [0,1] \subset \mathbb{R}^+, \\
1 &\le n_i \le 5, \quad n_i \in \mathbb{Z}^+ \quad ; \quad i = 1,2,\cdots,5
\end{aligned}$$

Problem 2: Series-parallel system (Fig. 7.1(b)) [46, 100, 106, 132, 253]

$$\begin{aligned}
\text{Maximize} \quad R_s(r,n) &= 1-(1-R_1R_2)(1-(1-R_3)(1-R_4)R_5) \\
\text{s.t.} \quad & g_1(r,n),\ g_2(r,n),\ g_3(r,n) \\
& \text{(as specified by (7.2.1), (7.2.2), (7.2.3) respectively)} \\
& 0.5 \le r_i \le 1 \quad ; \quad r_i \in [0,1] \subset \mathbb{R}^+ \\
& 1 \le n_i \le 5 \quad ; \quad n_i \in \mathbb{Z}^+ \quad i = 1,2,\cdots,5 \\
\text{where} \quad & R_i = 1-(1-r_i)^{n_i}
\end{aligned}$$

Problem 3: Complex(bridge) system (Fig. 7.1(c)) [46, 53, 100, 106, 132, 253]

$$\begin{aligned}
\text{Maximize}\ \ R_s(r,n) &= R_5(1-Q_1Q_3)(1-Q_2Q_4)+Q_5[1-(1-R_1R_2)(1-R_3R_4)] \\
\text{s.t.} \quad & g_1(r,n),\ g_2(r,n),\ g_3(r,n) \\
& \text{(as specified by (7.2.1), (7.2.2), (7.2.3) respectively)} \\
& 0.5 \le r_i \le 1 \quad ; \quad r_i \in [0,1] \subset \mathbb{R}^+, \\
& 1 \le n_i \le 5 \quad ; \quad n_i \in \mathbb{Z}^+, \quad i = 1,2,\cdots,5 \\
\text{where} \quad & Q_i = 1 - R_i = (1-r_i)^{n_i}
\end{aligned}$$

Problem 4: Overspeed protection system (Fig. 7.1(d)) [46, 53, 62, 132, 253, 257]

The fourth problem is considered for the reliability-redundancy allocation problem of the overspeed protection system for a gas turbine. Overspeed detection is continuously provided by the electrical and mechanical systems. When an overspeed occurs, it is necessary to cut off the fuel supply. For this purpose, 4 control valves (V1-V4) must close. The control system is modeled as a 4-stage series system. The objective is to determine an optimal level of r_i and n_i at each stage i such that the system reliability is maximized. This reliability problem is formulated as follows:

$$\begin{aligned}
\text{Maximize}\ \ R_s(r,n) &= \prod_{i=1}^{4}\{1-(1-r_i)^{n_i}\} \\
\text{s.t.}\ \ g_1(r,n) &= \sum_{i=1}^{4} v_i n_i^2 - V \le 0 \\
g_2(r,n) &= \sum_{i=1}^{4} \alpha_i(-1000/\ln r_i)^{\beta_i}[n_i + \exp(n_i/4)] - C \le 0 \\
g_3(r,n) &= \sum_{i=1}^{4} w_i n_i \exp(n_i/4) - W \le 0 \\
0.5 &\le r_i \le 1 \quad ; \quad r_i \in [0,1] \subset \mathbb{R}^+, \\
1 &\le n_i \le 10 \quad ; \quad n_i \in \mathbb{Z}^+, \quad i = 1,2,\cdots,4
\end{aligned}$$

where v_i is the volume of each component at stage i, w_i is the weight of each component at the stage i, $Q_i = 1 - R_i$ is the failure probability of each component in subsystem i. The factor $\exp(n_i/4)$ accounts for the interconnecting hardware. The parameters β_i and α_i are the physical features (shaping and scaling factor) of the cost - reliability curve of each component in stage i. V is the upper limit on the volume; C is the upper limit on the cost of the system, and W is the upper limit on the weight of the system. Constraints $g_1(r,n)$ is the volume constraints, $g_2(r,n)$ is a cost constraints while $g_3(r,n)$ is a weight constraints. The values of the input parameters defining the specific instances of these problems has been taken the same as in [46, 53, 62, 100, 106, 132, 153, 251, 253, 257], and are given in Tables 7.1-7.3.

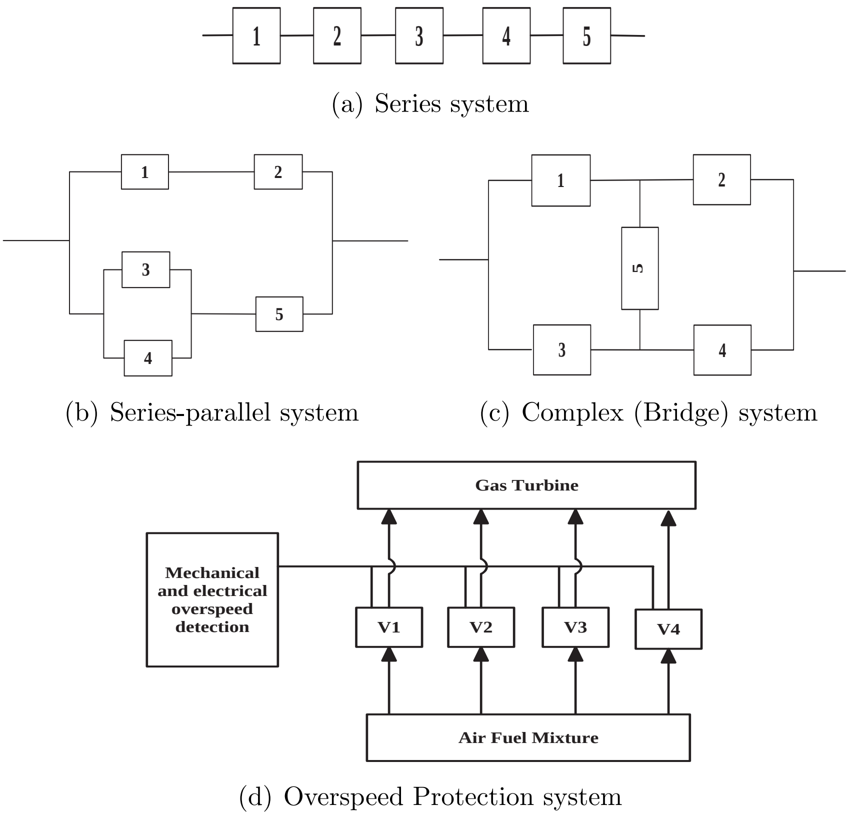


Figure 7.1: Series, Series - parallel, Bridge and Overspeed protection systems

7.3 Two Phase approach

The presented approach for solving the reliability-redundancy allocation problem is divided into two phases. In the first phase, problem is solved with the ABC

Table 7.1: Parameter used for Problems 1 and 3

i	$10^5\alpha_i$	β_i	v_i	w_i	C	V	W
1	2.330	1.5	1	7			
2	1.450	1.5	2	8			
3	0.541	1.5	3	8	175	110	200
4	8.050	1.5	4	6			
5	1.950	1.5	2	9			

Table 7.2: Parameter used for Problem 2

i	$10^5\alpha_i$	β_i	v_i	w_i	C	V	W
1	2.500	1.5	2	3.5			
2	1.450	1.5	4	4.0			
3	0.541	1.5	5	4.0	175	180	100
4	0.541	1.5	8	3.5			
5	2.100	1.5	4	3.5			

Table 7.3: Parameter used for Problem 4

i	$10^5\alpha_i$	β_i	v_i	w_i	C	V	W
1	1.0	1.5	1	6			
2	2.3	1.5	2	6	400	250	500
3	0.3	1.5	3	8			
4	2.3	1.5	2	7			

algorithm in which constraints are handled with the help of parameter-free based penalty functions. Local search process has been applied for improving the solution. On the other hand, the computed reliability allocation is improved in the second phase after fixing the number of component redundancy as obtained during the phase I. Both the phases are described as below.

7.3.1 Phase I: Obtaining the solution

During this phase, the reliability-redundancy allocation problems have been solved by using the artificial bee colony algorithm which has been described in section 2.5.3. During the evolution, the reliability and the number of redundant components are treated as continuous variables and the corresponding constraints are handled with the parameter-free penalty method as described in section 2.8.

7.3.2 Phase II: Improvement procedure

In the second phase, we fix the number of component redundancy as obtained by Phase-I and then use the following procedure to improve the component reliability allocation. The main steps of the second phase are as follows.

Step 1: Obtain the solution (n, r) and R_s by Phase I.

Step 2: In order to increase the efficiency of the system, the obtained r's is to be converted into closed interval $[r_i, r_j]$ with equal spread $\pm 0.5\%$ in both the directions (left and right) of r's i.e. $r_i = 0.995r$ and $r_j = 1.005r \leq 1$

Step 3: Find $\max \widetilde{R_s}(\widetilde{r}, n)$ where $\widetilde{r} \in [r_i, r_j]$ s.t. $r_i, r_j \in [0, 1]$ w.r.t. g_1, g_2, g_3.

Step 4: If $\widetilde{R_s} > R_s$ and $|\widetilde{R_s} - R_s| > \in$ then $R_s \longleftarrow \widetilde{R_s}$, $(r, n) \longleftarrow (\widetilde{r}, n)$ and go to next step, otherwise go to Step 3.

Step 5: Report the optimal or near optimal solution.

7.4 Computational Results

This section turns to the description and analysis of the results obtained by the optimization tests.

7.4.1 Parametric setting

The bees' particle for each problem uses the variable vectors n and r. During the evolution process, the integer variable n_i are treated as real variables, and in evaluating the objective functions, the real values are transformed to the nearest integer values. In the experiment we set $\in = 10^{-7}$. The presented algorithm is implemented in Matlab (MathWorks) and the program has been run on a T6400 @ 2GHz Intel Core(TM) 2 Duo processor with 2GB of Random Access Memory(RAM). In order to eliminate stochastic discrepancy,in each case study, 30 independent runs are made for each of the optimization methods involving 30 different initial trial solutions for each optimization method.

7.4.2 Results and Discussion

The numerical results corresponding to the four problems are shown in Tables 7.4-7.7 respectively, in which the best solutions of each problem are reported. For the series system (i.e. Problem 1), Table 7.4 shows that the best solution by the presented approach is 0.931682387672 which is better than solutions obtained by the other approaches available in the literature [46, 84, 87, 100, 101, 106, 153, 248, 251] with an improvement factor 2.75072%,1.99881%, 0.33755%, 0.00788%, 0.46532%, 0.15256%, 0.00934%, 0.00642%, 0.00349%, 0.02908%, 0.00006% respectively. It should be noticed that even very small improvements in reliability are critical and beneficial to system security and system efficiency. It is worth notifying here that solution by ABC algorithm, as given by Yeh and Hsieh [253], is infeasible solution as it violates the cost constraint. The results of the experiment for the problem 2, shown in Table 7.5, indicate that the best solution by the presented approach (R_s= 0.999976649054) is much better than the solutions given by [46, 100, 106, 107, 132]. It is worth mentioning that the solution obtained by Yeh and Hsieh [253] by using ABC algorithm is not a feasible solution as it violates the cost constraint function. From Table 7.6 it may be clearly observed that the solution to the Problem 3 as obtained by us is relatively with more significant improvement over the solutions presented by [46, 53, 100, 106, 107, 132]. It may again be pointed out that the solution by ABC algorithm, obtained by Yeh and Hsieh [253] is also infeasible, since it again violates the cost constraint function. Table 7.7 depicts that the solution of Problem 4 as obtained by the proposed approach is better than the previously known solutions by [46, 62, 107, 132, 257]. The optimal component redundancy by the proposed approach is (5,5,4,6) which is completely different from those from the other approaches. Here again we have observed through calculations that the solutions given by Yeh and Hsieh [253] and Yokota et al. [257] are not feasible solutions as both of these violate the cost constraint function. Moreover, the solutions found by the proposed approach for all the four problems dominate the solutions obtained by other methods discussed in literature. This confirms the superiority of the presented approach over the approaches available in the literature.

To evaluate the performance of proposed approach, the following maximum possible improvement (MPI) index [46] has been used to compute the relative improvement

$$\text{MPI} = \frac{R_s(\text{approach}) - R_s(\text{other})}{1 - R_s(\text{other})}$$

where $R_s(\text{approach})$ is the best-known solution obtained from proposed approach and $R_s(\text{other})$ is the best solution by other typical approaches. Numerical results are reported in Tables 7.4-7.7 which show that proposed approach when compared with other optimization approaches leads to improvement. Clearly, greater MPI implies greater improvement. Moreover, the standard deviations of system reliabilities by proposed approach are pretty low, and it further implies that the approach seems reliable to solve the reliability-redundancy allocation problems. For example, the standard deviations of system reliabilities for Problems 1 – 4 are 2.37214×10^{-8}, 3.18206×10^{-11}, 8.667×10^{-9}, 3.38683×10^{-11} respectively.

Table 7.4: Optimal solutions of the problem 1

Method	Kuo et al. [153]	Gopal et al. [87]	Hikita et al. [101]	Xu et al. [251]	Hikita et al. [100]	Hsieh et al. [106]	Gen and Yun [84]	Chen [46]	Yeh and Hsieh [253]	Wu et al. [248]	Hsieh and You [107]		Proposed approach	
											Phase I	Phase II	Phase I	Phase II
n	(3,3,2,3,2)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3,2,2,3,3)	(3, 2, 2, 3, 3)	(3, 2, 2, 3, 3)	(3,2,2,3,3)	(3,2,2,3,3)
r	0.77960	0.8	0.774887	0.77939	0.777143	0.779427	0.780874	0.779266	0.779399	0.78037307	0.780624390	0.779462304	0.778383314081	0.779403565208
	0.80065	0.8625	0.870065	0.87183	0.867514	0.869482	0.871292	0.872513	0.871837	0.87178343	0.872299194	0.871883456	0.872307790659	0.871833201410
	0.90227	0.90156	0.898549	0.90288	0.896696	0.902674	0.902316	0.902634	0.902885	0.90240890	0.904159546	0.902800879	0.902426561194	0.902886411643
	0.71044	0.7	0.716524	0.71139	0.717739	0.714038	0.711945	0.710648	0.711403	0.71147356	0.710647583	0.711350168	0.712061479297	0.711398061305
	0.85947	0.8	0.791368	0.78779	0.793889	0.786896	0.786995	0.788406	0.787800	0.78738760	0.785079956	0.787861587	0.787402330497	0.787808548579
R_s	0.92975	0.930289	0.931451	0.931677	0.931363	0.931578	0.931676	0.931678	0.931682	0.931680	0.931662515	0.931682340	0.931678415673	0.931682387672
MPI(%)	2.75072%	1.99881%	0.33755%	0.00788%	0.46532%	0.15256%	0.00934%	0.00642%	[a]	0.00349%	0.02908%	0.00006%	0.00581%	-
Slacks of	27	27	27	27	27	27	27	27	27	27	27	27	27	27
$g_1 \sim g_3$	0.00001	0.0265	0.108244	0.013773	0	0.121454	0.003352	0.001559	-0.0002184[b]	0.121454	0.00059	0.0000005284	2.12529×10^{-9}	2.258957×10^{-10}
	10.57248	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918	7.518918241	7.518918241
Mean	-	-	-	-	-	-	-	-	0.930580	-	0.9263678	0.93168222	0.92988735978	0.931682352234
Std	-	-	-	-	-	-	-	-	8.14×10^{-4}	5.2382×10^{-3}	0.0000435	1.3×10^{-14}	2.543×10^{-3}	2.37214×10^{-8}
Mean CPU	-	-	-	-	-	-	-	-	0.696	-	341.59	53.07813	2.3266	0.2911

Table 7.5: Optimal solutions of the problem 2

Method	Hikita et al. [100]	Hsieh et al. [106]	Chen [46]	Kim et al. [132]	Yeh and Hsieh [253]	Wu et al. [248]	Hsieh and You [107]		Proposed approach	
							Phase I	Phase II	Phase I	Phase II
n	(3,3,1,2,3)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)	(2,2,2,2,4)
r	0.83819295	0.785452	0.812485	0.812161	0.8197457	0.81918526	0.826843262	0.819591561	0.822437533034	0.819737753469
	0.85506525	0.842998	0.843155	0.853346	0.8450080	0.84366421	0.851425171	0.844951068	0.842382359204	0.844991099776
	0.87885933	0.885333	0.897385	0.897597	0.8954581	0.89472992	0.907211304	0.895428548	0.897571538285	0.895529543820
	0.91140223	0.917958	0.894516	0.900710	0.9009032	0.89537628	0.874832153	0.895522339	0.891862760631	0.895433687206
	0.85035522	0.870318	0.870590	0.866316	0.8684069	0.86912724	0.865188599	0.868490229	0.868597930940	0.868434824469
R_s	0.99996875	0.99997418	0.99997658	0.99997631	0.99997731	0.99997664	0.999976094	0.999976649	0.999976609441	0.999976649054
MPI (%)	25.27697%	9.56256%	0.29485%	1.43121%	[c]	0.03875%	2.32181%	0.00023%	0.16935%	-
Slacks of	53	40	40	40	40	40	40	40	40	40
$g_1 \sim g_3$	0.000011	1.194440	0.002627	0.007300	-1.469522[d]	0.000561	0.002385	0.000000	3.6006×10^{-7}	1.39152×10^{-10}
	7.110849	1.609289	1.609289	1.609289	1.609289	1.609289	1.609289	1.609289	1.609288966	1.609288966
Mean	-	-	-	-	0.99997517	-	0.999951900	0.999976649	0.9999647207	0.999976649011357
std	-	-	-	-	2.89×10^{-6}	1.3362×10^{-5}	7.6×10^{-10}	3.0×10^{-21}	1.458×10^{-5}	3.18206×10^{-11}
Mean CPU	-	-	-	-	0.936	-	135.73	410.375	1.0261	0.2236

[a] infeasible
[b] violate constraint
[c] infeasible
[d] violate constraint

Table 7.6: Optimal solutions of the problem 3

Method	Hikita et al. [100]	Hsieh et al. [106]	Chen [46]	Kim et al. [132]	Coelho [53]	Yeh and Hsieh [253]	Wu et al. [248]	Zou et al. [267]	Hsieh and You [107]		Proposed approach	
									Phase I	Phase II	Phase I	Phase II
n	(3,3,2,3,2)	(3,3,3,3,1)	(3,3,3,3,1)	(3,3,3,3,1)	(3,3,2,4,1)	(3,3,2,4,1)	(3,3,2,4,1)	(3,3,2,4,1)	(3,3,3,3,1)	(3,3,3,3,1)	(3,3,2,4,1)	(3,3,2,4,1)
r	0.814483	0.814090	0.812485	0.807263	0.826678	0.828087	0.82868361	0.82983999	0.814422607	0.816624176	0.827222999061	0.827970276262
	0.821383	0.864614	0.867661	0.868116	0.857172	0.857805	0.85802567	0.85798911	0.867172241	0.868767396	0.856301308081	0.857874758586
	0.896151	0.890291	0.861221	0.872862	0.914629	0.704163	0.91364616	0.91333926	0.859344482	0.858748781	0.914575667656	0.914186404228
	0.713091	0.701190	0.713852	0.712673	0.648918	0.648146	0.64803407	0.64674479	0.715805054	0.710279379	0.651220477286	0.648355386813
	0.814091	0.734731	0.756699	0.751034	0.715290	0.914240	0.70227595	0.70310972	0.741836548	0.753429200	0.701774721926	0.703575311047
R_s	0.99978937	0.99987916	0.99988921	0.99988764	0.99988957	0.99948407[a]	0.99988963	0.99988960	0.9998891120	0.9998893505	0.9998895964609	0.999889635809
MPI(%)	47.60281%	8.66914%	0.38433%	1.77625%	0.05958%	[b]	0.00526%	0.03243%	0.47237%	0.25784%	0.03564%	-
Slacks of	27	18	18	18	5	5	5	5	18	18	5	5
$g_1 \sim g_3$	0.000000	0.376347	0.001494	0.007300	0.000339	-25.433926[c]	0.00000359	0.00000594	0.011392	0.000000	1.874635×10^{-6}	3.74636763×10^{-4}
	10.572475	4.264770	4.264770	1.609289	1.560466	1.560466288	1.56046629	1.56046629	4.264770	4.264770	1.560466288	1.560466288
mean	-	-	-	-	0.99988594	0.99988362	-	0.99988263	0.999824	0.9998893503	0.9998865255	0.99988962347
std	-	-	-	-	0.00000069	1.026×10^{-5}	4.0163×10^{-5}	1.6×10^{-5}	5.6×10^{-9}	4.0×10^{-20}	1.186×10^{-5}	8.667×10^{-9}
Mean CPU	-	-	-	-	-	1.0956	-	-	138.8469	234.2188	2.0827	0.3837

Table 7.7: Optimal solutions of the problem 4

Method	Dhingra [62]	Yokota et al. [257]	Chen [46]	Kim et al. [132]	Coelho [53]	Yeh and Hsieh [253]	Zou et al. [268]	Wu et al. [248]	Hsieh and You [107]		Proposed approach	
									Phase I	Phase II	Phase I	Phase II
n	(6,6,3,5)	(3,6,3,5)	(5,5,5,5)	(5,5,5,5)	(5,6,4,5)	(5,6,4,5)	(5,6,4,5)	(5,6,4,5)	(5,5,4,6)	(5,5,4,6)	(5,5,4,6)	(5,5,4,6)
r	0.81604	0.965593	0.903800	0.895644	0.902231	0.901614	0.90186194	0.90163164	0.900863647	0.901588628	0.901840702077	0.901626809561
	0.80309	0.760592	0.874992	0.885878	0.856325	0.849920	0.84968407	0.84997020	0.891220093	0.888192380	0.888232944989	0.888208355883
	0.98364	0.972646	0.919898	0.912184	0.948145	0.948143	0.94842696	0.94821828	0.949249268	0.948166022	0.948285851863	0.948134377884
	0.80373	0.804660	0.890609	0.887785	0.883156	0.888223	0.88800590	0.88812885	0.843612671	0.849969792	0.849492971195	0.849942135673
R_s	0.99961	0.999468	0.999942	0.999945	0.999953	0.999955	0.99995467	0.99995467	0.999953931	0.999954674	0.999954671156	0.999954674663
MPI(%)	88.37811%	[a]	21.85286%	17.59029%	3.56311%	[d]	0.01028%	0.01028%	1.61423%	0.00146%	0.00774%	-
Slacks of	65	92	50	50	55	55	55	55	55	55	55	55
$g_1 \sim g_3$	0.064	-70.73357[b]	0.002152	0.9380	0.975465	-0.0003364[e]	0.00120356	0.000009	0.0761580	0.0001250	1.74702×10^{-9}	5.57304247×10^{-9}
	4.348	127.583189	28.803701	28.8037	24.801882	24.80188272	24.8018827	24.081883	15.3634631	15.3634631	15.3634630874	15.3634630874
mean	-	-	-	-	0.999907	0.9999487	0.99992624	-	0.9999062	0.999954673	0.99995051535	0.9999546746091
std	-	-	-	-	0.000011	9.244×10^{-6}	2.8874×10^{-5}	1.3895×10^{-5}	5.7×10^{-9}	4.14×10^{-18}	5.543×10^{-6}	3.38683×10^{-11}
Mean CPU	-	-	-	-	-	0.592	0.93	-	124.7787	66.54688	1.1309	0.2819

[a] in [253], it was reported 0.99988962
[b] infeasible
[c] violate constraint
[d] infeasible solution
[e] violate constraint

7.5 Conclusion

The goal of this chapter is to present an efficient two phase approach for solving the constrained reliability redundancy allocation problem of series, series-parallel and complex (bridge) system under different resource constraints. The objective of these problems is to maximize the system reliability subject to three nonlinear resource constraints, namely cost, weight and volume. In these optimization problems, both the redundancy and the corresponding reliability of each component in each subsystem are decided simultaneously. In the proposed approach, firstly an optimal reliability and the corresponding redundant components of each subsystem have been computed using ABC algorithm and their results are compared with other evolutionary algorithm results. While the improvement on the component reliability has been made in their second phase by preserving the redundant components corresponding to each subsystem. The resource constraints have been handled with the help of parameter-free penalty technique. The performance of proposed algorithm is evaluated through the comparison of numerical experiments with the previous study for mixed-integer reliability problems. The best solutions found by this approach are all individually better than the well-know best solutions by other heuristic methods for mixed-integer reliability problems.

Chapter 8

Reliability analysis of industrial system using vague set theory

In this chapter, vague set theory, an extension of fuzzy set theory, has been used for developing a methodology to analyze the behavior of a repairable industrial system using uncertain, limited and vague data. Finally results are compared with traditional and fuzzy methodologies.

8.1 Introduction

In fuzzy set theory, the degree of belonging of an element to the set is represented by a membership value in the real interval [0, 1] and there exists degree of non-membership which is complementary in nature. From latter point of view, it is true and acceptable that grade of membership and non-membership are complementary. But in real life situations, it is assumed that a certain object may or may not be in a set A to a certain degree, but it is possible to entertain some doubt about it. In other words, some hesitation about the degree of belongingness exists. This hesitation in the membership degree may be modeled by intuitionistic fuzzy sets (IFS) defined by Attanassov [13] and has been found to be well suited for dealing with problems concerning vagueness. The concept of IFS can be viewed as an alternative approach to define a fuzzy set in a situation where available information is not sufficient for the definition of an imprecise concept by means of a conventional fuzzy set. Gau and Buehrer [82] extended the idea of fuzzy sets by vague sets. Biswas [26] pointed out that there were situations where IFS theory is more appropriate to deal with. Bustince and Burillo [30] showed that the notion of vague sets coincides with that of IFSs. Therefore, it is expected that IFSs could be used to simulate any activities and processes requiring human expertise and knowledge, which are inevitably imprecise or not totally reliable. A lot of work has been done to develop and enrich the IFS theory given in [12, 17, 40, 45, 78, 144, 149] and their corresponding references in terms of reliability evaluation of series-parallel system.

Thus it is observed from the study that by using limited, vague and imprecise data of the system, the behavior and the performance analysis of the complex repairable industrial system in terms of their reliability parameters may be calculated. The objective of the present investigation is divided into two folds. In the first fold, behavior of the complex repairable industrial systems are analyzed in the form of the various reliability parameters by utilizing the uncertain, limited or vague data, while in second fold, the effect of failure pattern on a composite measure of reliability, availability and maintainability (RAM) of industrial system has been assessed which will help the system analyst to rank the components as per preferential order. The model will help to analyze the system's behavior on the basis of past failure and repair data. To remove the uncertainty in the available/collected data, intuitionistic fuzzy numbers are developed using fuzzy possibility theory.

8.2 Intuitionistic fuzzy/ Vague set theory

Uncertainties exist always everywhere and are a result of lack of information, in particular, inaccuracy of measurements. This idea is highlighted by Zadeh in 1965 with a concept of fuzzy logic, and is a mathematical tool for dealing with uncertainty[260]. It provides an inference structure that enables appropriate human reasoning capabilities. Among the extension of the notion of fuzzy set, the theory of intuitionistic fuzzy set (IFS) firstly proposed by Attanassov [13] by two characteristic functions that express the degree of membership and non-membership of elements in the universe. Gau and Buehrer [82] extended the idea of fuzzy sets by vague sets. Bustince and Burillo [30] showed that the notion of vague sets coincides with that of IFSs. Mathematically, let U be a universe of discourse then IFS $\widetilde{A}$ of universe of discourse U is characterized by a membership function $\mu_{\widetilde{A}} : U \to [0,1]$, and a non-membership function $\nu_{\widetilde{A}} : U \to [0,1]$ with the condition $\mu_{\widetilde{A}}(x) + \nu_{\widetilde{A}}(x) \leq 1$, $\forall x \in U$ where $\mu_{\widetilde{A}}(x)$ is considered as the lower bound for the degree of membership of x in $\widetilde{A}$ (based on evidences) and $\nu_{\widetilde{A}}(x)$ is the lower bound of the negation (derived from the evidence against of x) of the membership of x in $\widetilde{A}$. Therefore, the degree of membership of x in the vague set $\widetilde{A}$ is characterized by the interval $[\mu_{\widetilde{A}}(x), 1 - \nu_{\widetilde{A}}(x)]$. A typical illustration of a vague set $\widetilde{A}$ is shown in Fig. 8.1.

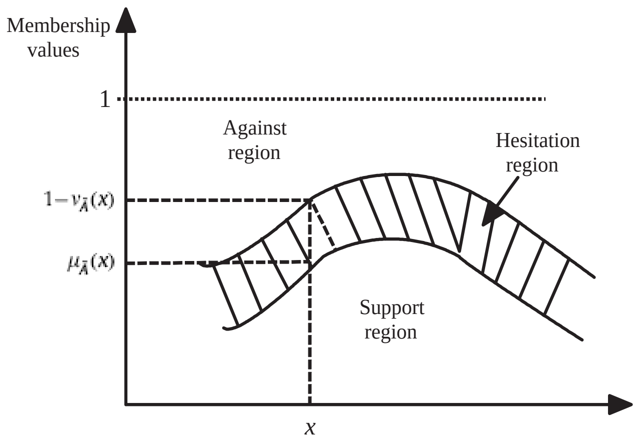


Figure 8.1: Representation of a vague set

A vague set $\widetilde{A}$ in universe U is said to be convex if and only if

(i) Membership functions of $\mu_{\widetilde{A}}(x)$ of $\widetilde{A}$ is fuzzy - convex i.e.

$$\mu_{\widetilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geq \min(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)) \quad \forall \quad x_1, x_2 \in U, \quad 0 \leq \lambda \leq 1$$

(ii) Non-membership functions of $\nu_{\widetilde{A}}(x)$ of $\widetilde{A}$ is fuzzy - concave i.e.

$$\nu_{\widetilde{A}}(\lambda x_1 + (1-\lambda)x_2) \leq \max(\nu_{\widetilde{A}}(x_1), \nu_{\widetilde{A}}(x_2)) \quad \forall \quad x_1, x_2 \in U, \quad 0 \leq \lambda \leq 1$$

On the other hand, vague set is said to be normal vague set if there exist at least two points $x_1, x_2 \in U$ such that $\mu_{\widetilde{A}}(x_1) = 1$ and $\nu_{\widetilde{A}}(x_2) = 0$. A vague subset $\widetilde{A} = \{< x, \mu_{\widetilde{A}}(x), 1 - \nu_{\widetilde{A}}(x) >| \; x \in R\}$ of the real line R is called vague number if

(i) $\widetilde{A}$ is convex and normal.

(ii) $\mu_{\widetilde{A}}$ is upper semi-continuous and $\nu_{\widetilde{A}}$ is lower semi-continuous.

α- cut of an vague set: In vague set $\widetilde{A}$, α-cut of a membership function is a crisp set which consists of elements of $\widetilde{A}$ having at least degree α. It is denoted by $A^{(\alpha)}$ and is defined mathematically as

$$A^{(\alpha)} = \{x \in U \;:\; \mu_{\widetilde{A}}(x) \geq \alpha\} \tag{8.2.1}$$

while for non-membership function, it is defined as

$$A_{(\alpha)} = \{x \in U \;:\; 1 - \nu_{\widetilde{A}}(x) \geq \alpha\} \tag{8.2.2}$$

where α is the parameter in the range $0 \leq \alpha \leq 1$.

Triangular vague number and interval arithmetic operations: Let $\widetilde{A}$ be vague set denoted by $\widetilde{A} =< [(a, b, c); \mu, 1 - \nu] >$, where $a, b, c \in \mathbb{R}$ then the set $\widetilde{A}$ is said to be triangular vague number if its membership function is given by

$$\mu_{\widetilde{A}}(x) = \begin{cases} \mu \times \left(\dfrac{x-a}{b-a}\right) & ; \quad a \leq x \leq b \\ \mu & ; \quad x = b \\ \mu \times \left(\dfrac{c-x}{c-b}\right) & ; \quad b \leq x \leq c \\ 0 & ; \quad \text{otherwise} \end{cases} \tag{8.2.3}$$

and

$$1 - \nu_{\widetilde{A}}(x) = \begin{cases} \nu \times \left(\dfrac{x-a}{b-a}\right) & ; \quad a \leq x \leq b \\ \nu & ; \quad x = b \\ \nu \times \left(\dfrac{c-x}{c-b}\right) & ; \quad b \leq x \leq c \\ 0 & ; \quad \text{otherwise} \end{cases} \tag{8.2.4}$$

where the parameter b gives the modal values of A i.e. $\mu_{\tilde{A}}(b) = 1$ and a, c are the lower and upper bounds of available area for the evaluation data. A triangular vague set defined by the triplet (a, b, c) with α-cuts, is defined as

$$A^{(\alpha)} = [a^{(\alpha)}, c^{(\alpha)}] = [a + \frac{\alpha}{\mu}(b-a), \quad c - \frac{\alpha}{\mu}(c-b)] \tag{8.2.5}$$

$$\text{and} \quad A_{(\alpha)} = [a_{(\alpha)}, c_{(\alpha)}] = [a + \frac{\alpha}{1-\nu}(b-a), \quad c - \frac{\alpha}{1-\nu}(c-b)] \tag{8.2.6}$$

where $a^{(\alpha)}, a_{(\alpha)}$ are the increasing functions and $c^{(\alpha)}, c_{(\alpha)}$ are decreasing functions of $0 \leq \alpha \leq 1$.

8.3 Vague Lambda-Tau Methodology

Traditionally in order to analyze the behavior of the repairable system, crisp as well as fuzzy Lambda-Tau (FLT) methodology has been used with their basic events, associated with logical AND and OR gates, for evaluating the system failure rate and repair time. Their expressions are summarized in Table 2.2. But there are some disadvantages of these methodologies. For instance, crisp methodology does not consider the uncertainties during the analysis which are in the data while FLT methodology does not consider the degree of hesitation between the membership functions. Also the highest level of confidence of domain experts is taken as 1 in their methodology. Thus the results computed by these methodologies are not so much beneficial for the system analyst for predicting the system behavior. Keeping these points in view, the technique named as Vague Lambda-Tau methodology (VLTM), has been used [78] for analyzing the behavior of the complex repairable system. The constant failure rate model is adopted in this technique because most of the technical systems exhibit constant failure and repair rates(i.e. exponentially distributed) after initial burn-in-period in bathtub curve. The uncertainties present in the data are removed with the help of vague fuzzy numbers instead of fuzzy and crisp numbers because it allow experts' opinion, linguistic variables, operating conditions, uncertainty and imprecision in reliability information to be incorporated into the system model. The detail of the methodology are described as follow:

The technique starts from the information extraction phase in which data related to main component of the system in the form of failure rates (λ_i's) and repair times (τ_i's) are extracted from the historical records/sheets or collected from the various resources. As these data are collected under the different conditions and environment and hence they will contain some sort of uncertainties. Moreover, the collected data

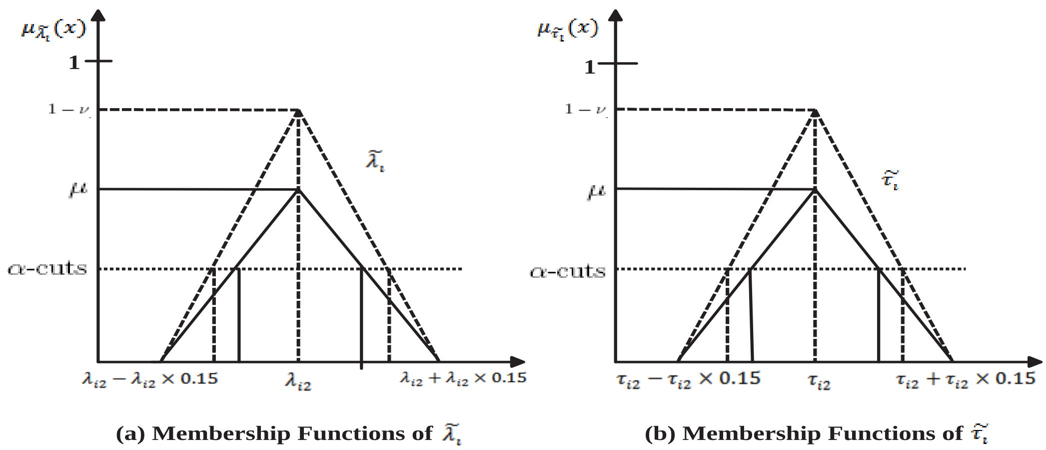


Figure 8.2: Failure rate and repair time in the form of triangular vague numbers

are represent the past behavior of the system. Thus to incorporate these data into the future behavior of the system, the uncertainties which are present in the data are needed to be quantified. For this the obtained data are fuzzified into the triangular vague numbers with some support as suggested by decision makers (DMs) on both sides of the data. For instance, membership functions for failure rate (λ_i) and repair time (τ_i) of the i^{th} component of a system in the form of triangular vague numbers with equal spread $\pm 15\%$ in both the directions (left and right to the middle) with corresponding α-cuts are shown in Fig. 8.2.

Thus based on that, an input data which represents the basic events of the system are represented in the form of fuzzy numbers then the corresponding values of their top event (system fail) can be obtained by using extension principle and interval arithmetic operations on triangular vague numbers. For this, an expression of the system failure rate $\tilde{\lambda}$ and repair time $\tilde{\tau}$ in the form of membership and non-membership functions for AND and OR transitions are used which are as follows.

For truth membership functions:

Expressions for AND-Transitions

$$\lambda^{(\alpha_\mu)} = \Bigg[\prod_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\frac{\alpha_\mu}{\mu_i}+\lambda_{i1}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\frac{\alpha_\mu}{\mu_i}+\tau_{i1}\}\Bigg], \prod_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\frac{\alpha_\mu}{\mu_i}+\lambda_{i3}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\frac{\alpha_\mu}{\mu_i}+\tau_{i3}\}\Bigg]\Bigg] \quad (8.3.1)$$

$$\tau^{(\alpha_\mu)} = \left[\frac{\prod_{i=1}^{n}\{(\tau_{i2}-\tau_{i1})\frac{\alpha_\mu}{\mu_i}+\tau_{i1}\}}{\sum_{j=1}^{n}[\prod_{\substack{i=1\\i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\frac{\alpha_\mu}{\mu_i}+\tau_{i3}\}]}, \frac{\prod_{i=1}^{n}\{-(\tau_{i3}-\tau_{i2})\frac{\alpha_\mu}{\mu_i}+\tau_{i3}\}}{\sum_{j=1}^{n}[\prod_{\substack{i=1\\i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\frac{\alpha_\mu}{\mu_i}+\tau_{i1}\}]}\right] \quad (8.3.2)$$

Expressions for OR-Transitions

$$\lambda^{(\alpha_\mu)} = \left[\sum_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\frac{\alpha_\mu}{\mu_i}+\lambda_{i1}\}, \quad \sum_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\frac{\alpha_\mu}{\mu_i}+\lambda_{i3}\}\right] \quad (8.3.3)$$

$$\tau^{(\alpha_\mu)} = \left[\frac{\sum_{i=1}^{n}[\{(\lambda_{i2}-\lambda_{i1})\frac{\alpha_\mu}{\mu_i}+\lambda_{i1}\}\cdot\{(\tau_{i2}-\tau_{i1})\frac{\alpha_\mu}{\mu_i}+\tau_{i1}\}]}{\sum_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\frac{\alpha_\mu}{\mu_i}+\lambda_{i3}\}}, \frac{\sum_{i=1}^{n}[\{-(\lambda_{i3}-\lambda_{i2})\frac{\alpha_\mu}{\mu_i}+\lambda_{i3}\}\cdot\{-(\tau_{i3}-\tau_{i2})\frac{\alpha_\mu}{\mu_i}+\tau_{i3}\}]}{\sum_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\frac{\alpha_\mu}{\mu_i}+\lambda_{i1}\}}\right] \quad (8.3.4)$$

For false membership functions (i.e. non-membership functions):

Expressions for AND-Transitions

$$\lambda^{(\alpha_{1-\nu})} = \Bigg[\prod_{i=1}^{n}\{(\lambda_{i2}-\lambda_{i1})\frac{\alpha_\nu}{1-\nu_i}+\lambda_{i1}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\i\neq j}}^{n}\{(\tau_{i2}-\tau_{i1})\frac{\alpha_\nu}{1-\nu_i}+\tau_{i1}\}\Bigg], \prod_{i=1}^{n}\{-(\lambda_{i3}-\lambda_{i2})\frac{\alpha_\nu}{1-\nu_i}+\lambda_{i3}\}\cdot\sum_{j=1}^{n}\Bigg[\prod_{\substack{i=1\\i\neq j}}^{n}\{-(\tau_{i3}-\tau_{i2})\frac{\alpha_\nu}{1-\nu_i}+\tau_{i3}\}\Bigg]\Bigg] \quad (8.3.5)$$

$$\tau^{(\alpha_{1-\nu})} = \left[\frac{\prod_{i=1}^{n} \{(\tau_{i2} - \tau_{i1})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i1}\}}{\sum_{j=1}^{n} [\prod_{\substack{i=1\\ i\neq j}}^{n} \{-(\tau_{i3} - \tau_{i2})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i3}\}]}, \quad \frac{\prod_{i=1}^{n} \{-(\tau_{i3} - \tau_{i2})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i3}\}}{\sum_{j=1}^{n} [\prod_{\substack{i=1\\ i\neq j}}^{n} \{(\tau_{i2} - \tau_{i1})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i1}\}]} \right] \quad (8.3.6)$$

Expressions for OR-Transitions

$$\lambda^{(\alpha_{1-\nu})} = \left[\sum_{i=1}^{n} \{(\lambda_{i2} - \lambda_{i1})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i1}\}, \quad \sum_{i=1}^{n} \{-(\lambda_{i3} - \lambda_{i2})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i3}\} \right] \quad (8.3.7)$$

$$\tau^{(\alpha_{1-\nu})} = \left[\frac{\sum_{i=1}^{n} [\{(\lambda_{i2} - \lambda_{i1})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i1}\} \cdot \{(\tau_{i2} - \tau_{i1})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i1}\}]}{\sum_{i=1}^{n} \{-(\lambda_{i3} - \lambda_{i2})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i3}\}}, \right.$$
$$\left. \frac{\sum_{i=1}^{n} [\{-(\lambda_{i3} - \lambda_{i2})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i3}\} \cdot \{-(\tau_{i3} - \tau_{i2})\frac{\alpha_\nu}{1-\nu_i} + \tau_{i3}\}]}{\sum_{i=1}^{n} \{(\lambda_{i2} - \lambda_{i1})\frac{\alpha_\nu}{1-\nu_i} + \lambda_{i1}\}} \right] \quad (8.3.8)$$

In order to analyze the system behavior qualitatively as well as quantitatively, various reliability indices of interest namely, failure rate, repair time, MTBF, ENOF, reliability, availability of the system, with left and right spreads, are obtained at various membership grades by using the expressions of failure rate and repair time given in equations (8.3.1-8.3.4) and (8.3.5-8.3.8) with the increment of 0.1 confidence level α in the form of truth (membership) and false (non-membership) functions. The expression of these reliability indices are summarized in Table 2.3. Finally, the obtained fuzzified output are necessary to convert into binary or crisp form in order to implement these into the system behavior. Thus defuzzification is necessary for conversion of these values into crisp values. Out of existence of various defuzzification methods, described in section 2.3.5, center of gravity method (COG) has been used because it has the advantage of having taken the whole membership function into account for this transformation.

8.4 Case Study

To illustrate the proposed approach for analyzing the system failure behavior, a case study of a pharmaceutical plant is done in the vague set [0.6, 0.8] i.e. degree of acceptance $\mu = 0.6$ and degree of rejection is $\nu = 1 - 0.8 = 0.2$.

8.4.1 System Description

The Pharmaceutical plant consists of various subunits viz. Weighing Machine, Shifter Machine, Mass Mixer, Granulator, Fluid Bed Dryer, Octagonal Blender, Rotary Compression Machine, Coating Machine, Air Compressor and Strip Packing Machine all are arranged in series [77, 81]. Initially, different raw materials are

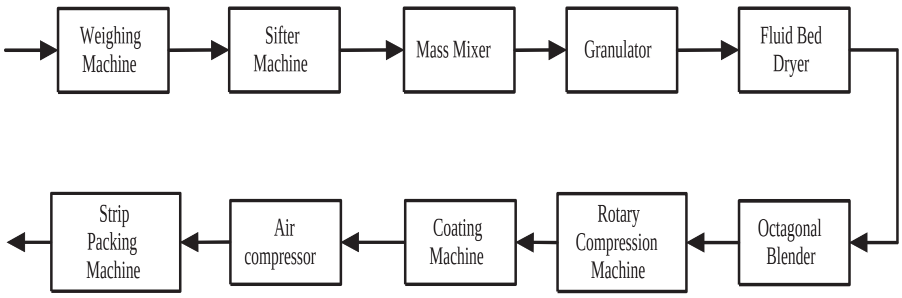


Figure 8.3: Flow diagram of the Pharmaceutical Plant

weighed according to the master formula with the help of weighing machine. Then this mixture is placed into the Shifter. Shifter is used for sieving of raw material. After sieving, raw material is transferred to Mass Mixer for proper mixing and then granulation is done with the help of granulator, then these wet granules are dried up with the help of Fluid Bed Dryer. After drying, the granules are shifted to Octagonal blender for lubrication, then lubricated granules are compressed with the help of compression machine. Then coating of compressed tablets are done with the help of coating machine and hereafter coated tablets are ready for final packing. The systematic flow diagram of the considered plant is shown in Fig. 8.3.

8.4.2 Behavior Analysis

The data related to main component of the subsystem of the plant are tabulated in Table 8.1. To handle the vagueness and uncertainties in the data, the obtained

Table 8.1: Input data in the form of failure rate and repair time for the Plant

Components $\longrightarrow$	Main Component of the Plant				
	Weighting Machine	Shifter Machine	Mass Mixer	Granulator	Fluid Bed Dryer
Failure rate (λ_i's) hrs^{-1}	5×10^{-3}	2×10^{-3}	1×10^{-3}	5×10^{-3}	1.5×10^{-3}
Repair time (τ_i's) hrs	6	3	2	5	3
	Octagonal Blender	Rotary Compression Machine	Coating Machine	Air Compressor	Strip Packing Machine
Failure rate (λ_i's) hrs^{-1}	3×10^{-3}	1×10^{-4}	2×10^{-3}	3×10^{-3}	2.5×10^{-3}
Repair time (τ_i's) hrs	10	10	2	3.5	4

crisp data, λ_i and τ_i are converted into triangular vague fuzzy numbers with $\pm15\%$ (also at $\pm25\%$ and $\pm50\%$) spreads as suggested by the decision makers/ system analyst. Based on these fuzzifier data of the basic events of the system, the system reliability expression are obtained at different $\alpha-$ cuts by using the expression given in equation (8.3.1)-(8.3.4) and (8.3.5)-(8.3.8) respectively for the membership and non-membership functions with left and right spreads with the increment of the 0.1 confidence level. The results obtained corresponding to the reliability indices are shown in Fig. 8.4 that corresponds to $\pm15\%$ spread along with the FLT and traditional(crisp) methodologies results which indicate that results obtained from VLTM are in between crisp and FLT values, i.e. VLTM technique acts as a bridge between Markov process (crisp values) and Lambda-Tau technique.

From these plots the following conclusions are drawn.

(i) The values of all reliability indices computed by using traditional methods(crisp) are independent of the degree of confidence level (α). It shows that while obtaining the results by these method, attention has not been paid to the uncertainties in the data. Thus this methodology is not practically sound as uncertainties play an important role during the analysis. Hence their results will be suitable only for a system with precise data.

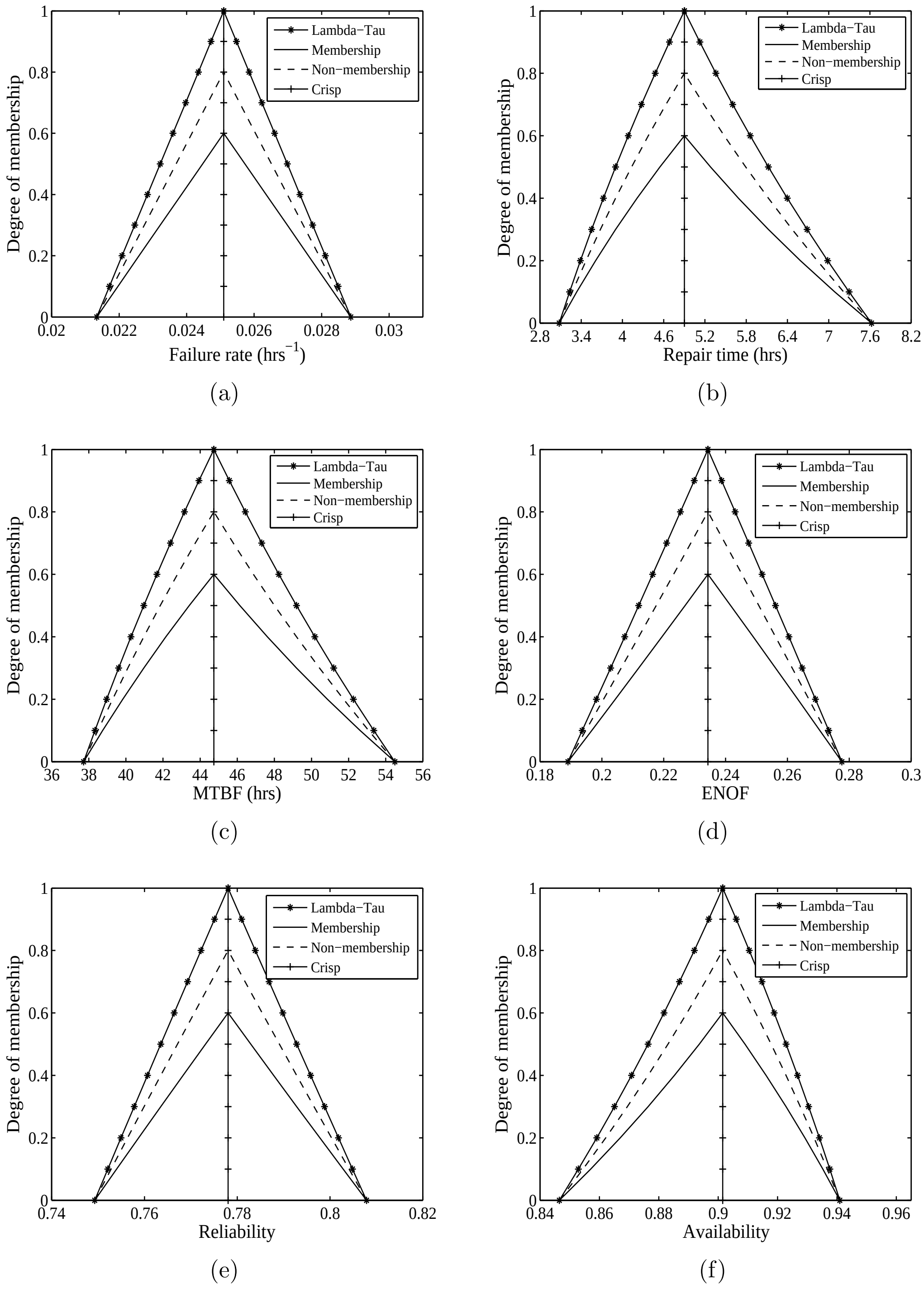


Figure 8.4: Reliability indices plot for Pharmaceutical Plant at ±15% spread

(ii) The results computed by the FLT technique are presented in figure with FLT legend. While computing the results by the usual methodology the degree of interminancy between the membership functions have not been considered. In other words, the degree of rejection of the membership function is simply one minus of the degree of acceptance so that their is zero degree of hesitation between them. Moreover the domain of confidence level is taken to be one i.e. ($\alpha = 1$). Therefore the results computed by FLT methodology are not that practical.

(iii) The proposed approach provides improvement over the above shortcoming by considering 0.2 degree of hesitation between the degree of membership and non-membership functions shown by solid and dotted lines respectively. In the proposed approach the domain of confidence level is clearly $\alpha \leq 0.8$. In this, if γ_1 is the degree of membership function for some reliability index and γ_2 be the degree for the corresponding non-membership function then there is $1 - \gamma_1 - \gamma_2$ degree of hesitation between the degree of membership functions. For instance, the degree of membership and non-membership functions corresponding to reliability value 0.763513 are 0.3 and 0.4 respectively. Therefore there is 0.3 degree of interminancy between the reliability indices for the reliability 0.763513. Thus, the proposed technique is beneficial for the system analyst for analyzing the behavior of the system in more flexible ways in lesser time.

In order to maintain the trend of the analysis the approach has been applied at different spreads say $\pm 15\%$, $\pm 25\%$ and $\pm 50\%$. To import the results into the daily life situation, it is necessary that the obtained fuzzified output should be in the form of crisp or binary in nature since most of the actions implemented by the machines or humans are binary in nature. Thus center of gravity method has been used for defuzzification and their corresponding values are listed in tabular form in Table 8.2 along with their crisp as well as FLT techniques values. From this table it is clearly seen that the crisp value does not change irrespective of the spread chosen while defuzzified value changes with the change of spread.

Table 8.2: Defuzzified Values of Reliability Parameters at different spreads of Pharmaceutical Plant

Spread	Technique	Failure rate (hrs^{-1})	Repair time (hrs)	MTBF (hrs)	ENOF	Reliability	Availability
	Crisp	0.02510000	4.90039841	44.74103586	0.23429202	0.77802237	0.90154518
		Defuzzified values for reliability indices					
±15%	I	0.02510000	5.12620431	45.42517504	0.23380002	0.77829904	0.89765461
	II	A: 0.02510000	5.12760158	45.42941239	0.23379737	0.77830067	0.89763044
		B: 0.02510000	5.12664662	45.42651635	0.23379918	0.77829956	0.89764696
±25%	I	0.02510000	5.55147994	46.71049157	0.23298795	0.77879106	0.89035970
	II	A: 0.02510000	5.55587121	46.72380401	0.23298218	0.77879560	0.89028577
		B: 0.02510000	5.55287133	46.71470920	0.23298613	0.77879249	0.89033629
±50%	I	0.02510000	8.07369090	54.26883528	0.23020329	0.78110016	0.85141817
	II	A: 0.02510000	8.10768811	54.37125153	0.23020814	0.78111838	0.85107614
		B: 0.02510000	8.08453623	54.30148454	0.23020487	0.78110592	0.85130985

I: FLT technique II: proposed approach A: membership function B: nonmembership function

It may also be observed from the Table 8.2 that when uncertainty levels in the form of spread increase, defuzzified values of reliability parameters also follow the same trend of increment or decrement with respect to the existing methodology. This means that values obtained through vague methodology are conservative in nature, which may be beneficial for plant personnel and have some idea about the system's behavior. Moreover, variation of the defuzzified values are quite less as compared to the FLT results, for instance, the repair time of the system increases by 8.296111%, 8.352240% and 8.313908% for FLT, vague membership and nonmembership respectively, when spread changes from ±15% to ±25%, and it further increases by 45.433127%, 45.930094% and 45.591996%, when spread changes from ±25% to ±50%. Similar observation is also there for all the reliability parameters. The complete change in defuzzified values for both the techniques from the crisp results is tabulated in Table 8.3 at ±15% spread and concluded that variation in VLTM technique is quite less as compared to FLT methodology. Maximum percentage of decrease (↓) and increase (↑) is noticed for availability and repair time, respectively which means that the prediction range of the system parameters decreases. Hence, the maintenance is performed using defined defuzzified values rather than crisp values.

Table 8.3: Change in Defuzzified value of Reliability Parameters of Pharmaceutical Plant

	Defuzzified values at ±15% spread					
Method	Failure rate	Repair time	MTBF	ENOF	Reliability	Availability
I	0.02510000	5.12620431	45.42517504	0.23380002	0.77829904	0.89765461
II	A: 0.02510000	5.12760158	45.42941239	0.23379737	0.77830067	0.89763044
	B: 0.02510000	5.12664662	45.42651635	0.23379918	0.77829956	0.89764696
	Change in defuzzified values from					
I to A	0	0.02725739	0.00932819	0.00113344	0.00020943	0.00269257
	–	↑	↑	↓	↑	↓
I to B	0	0.00862841	0.00295278	0.00035928	0.00006681	0.00085222
	–	↑	↑	↓	↑	↓

8.4.3 Sensitivity analysis

The effect of the various reliability parameters on the system MTBF has been addressed by varying all the other components simultaneously. The behavioral plots are obtained and shown in Fig. 8.5 in which repair time and ENOF are plotted against x-axis and y-axis, respectively in the range computed by their membership functions (Figs. 8.4(b) and 8.4(d)) at cut-levels $\alpha = 0$, whereas MTBF varies along z-axis. The change in MTBF for nine combinations of reliability, availability and failure rate are summarized in Table 8.4. For the first three combinations of the Table 8.4, the selected values of reliability and availability are 0.7715 and 0.8812 respectively while failure rate changes from 0.0215 to 0.0251 and further to 0.0343. For these combinations, computed ranges of MTBF are 44.783811 – 68.614352, 38.549610 – 59.460427 and 28.563176 – 44.796950. This suggests that slight change in system's failure rate may change its MTBF largely and consequently behavior of the system. Similar effect is observed from Fig. 8.5 for other combinations. Thus, based on the behavioral and sensitivity analysis plots and corresponding tables, the system manager can analyze the critical behavior of the system and plan suitable maintenance.

The system analyst or plant personnel is always eager to find the most critical

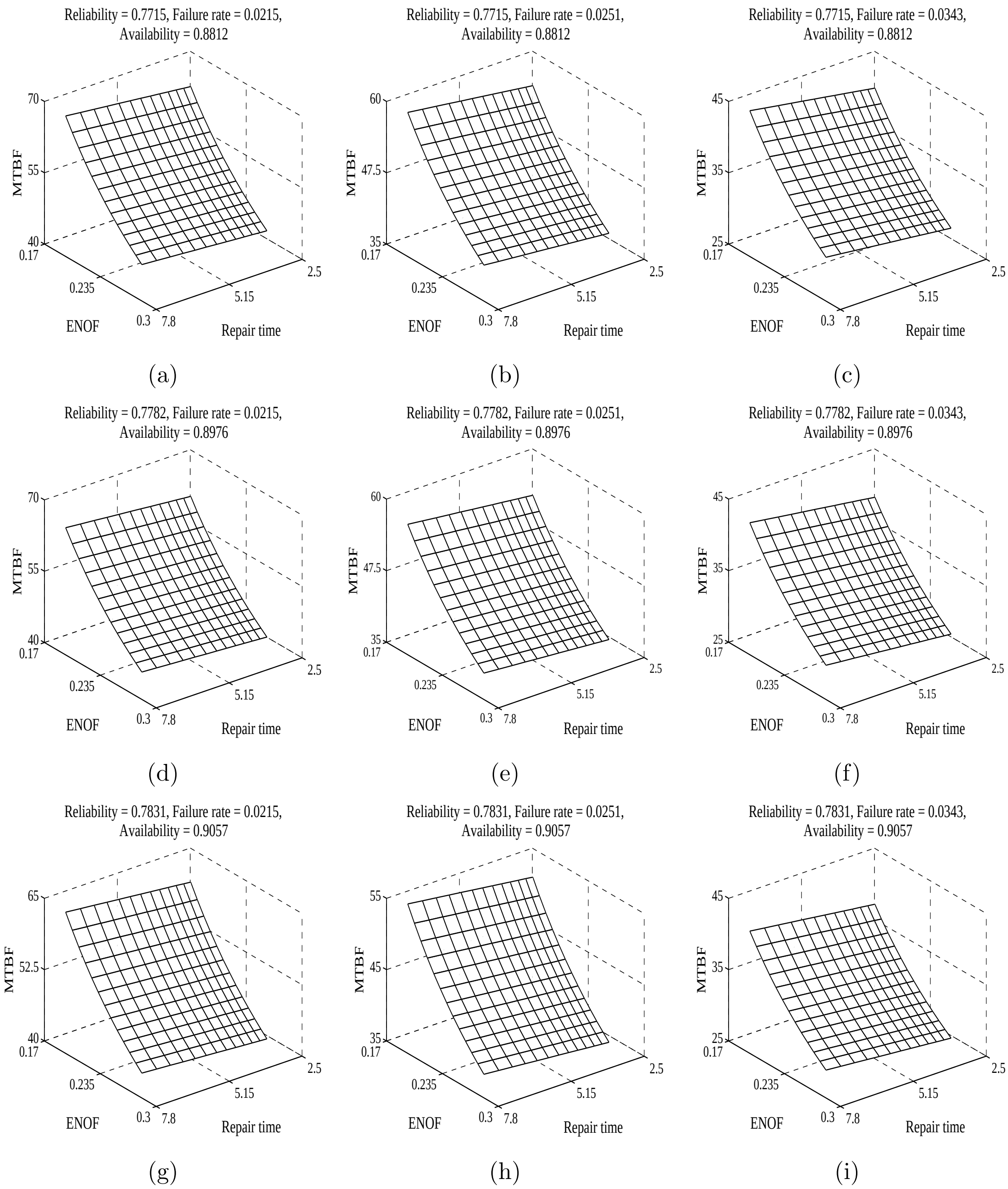


Figure 8.5: Variation of the Reliability Parameters on system MTBF

component of the system on which more attention should be given so as to maintain or save the money and time. For this suitable strategy is needed to find that

Table 8.4: Effect of Various Reliability Parameters on MTBF

Fig.	[Reliability, Failure rate, Availability]	$MTBF_{min}$	$MTBF_{max}$
8.5(a)	[0.7715, 0.0215, 0.8812]	44.783811	68.614352
8.5(b)	[0.7715, 0.0251, 0.8812]	38.549610	59.460427
8.5(c)	[0.7715, 0.0343, 0.8812]	28.563176	44.796950
8.5(d)	[0.7782, 0.0215, 0.8976]	43.153115	65.825605
8.5(e)	[0.7782, 0.0251, 0.8976]	37.126712	56.976797
8.5(f)	[0.7782, 0.0343, 0.8976]	27.473144	42.802079
8.5(g)	[0.7831, 0.0215, 0.9057]	42.011580	63.954681
8.5(h)	[0.7831, 0.0251, 0.9057]	36.136018	55.327360
8.5(i)	[0.7831, 0.0343, 0.9057]	26.724080	41.507437

component for increasing the performance and productivity of the system. The following RAM-Index analysis may help the system analyst for finding the most critical component of the system based on its performance.

8.4.4 Performance analysis: RAM-Index

It is quite understood that if the current condition of the equipment or system are not changed then the performance of the system decreases rapidly. Thus, in order to achieve higher performance of the systems, involved uncertainties should be minimized. For this, firstly the fuzzy RAM-Index has been analyzed at $\pm 15\%$ by using VLTM and results are compared with the FLT along with crisp results in Fig. 8.6(a) while behavior of the defuzzified values of vague membership functions of RAM-Index against different uncertainty (spread from 0 to 100%) levels has been plotted and shown in Fig. 8.6(b). Figure shows that as uncertainty level increases RAM index decreases i.e. to achieve higher performance of the system uncertainties should be minimize. For a long run period, Fig. 8.6(c) shows the variation of RAM-Index for a time-range of 0-100(hrs) using VLTM technique for depicting the behavior of the system. It is observed from the analysis that RAM-Index increases for 0 to 11(hrs) and then decreases gradually. The results shows that at $t = 0$, the value of RAM-Index for the system is 0.66 and then attains its maximum value 0.901447 at $t = 11$(hrs) and after that it is decreases gradually to 0.621704 at $t = 100$ (hrs). Thus it has been concluded that if current condition of system components does not change then after $t = 11$(hrs) then system performance decreases exponentially.

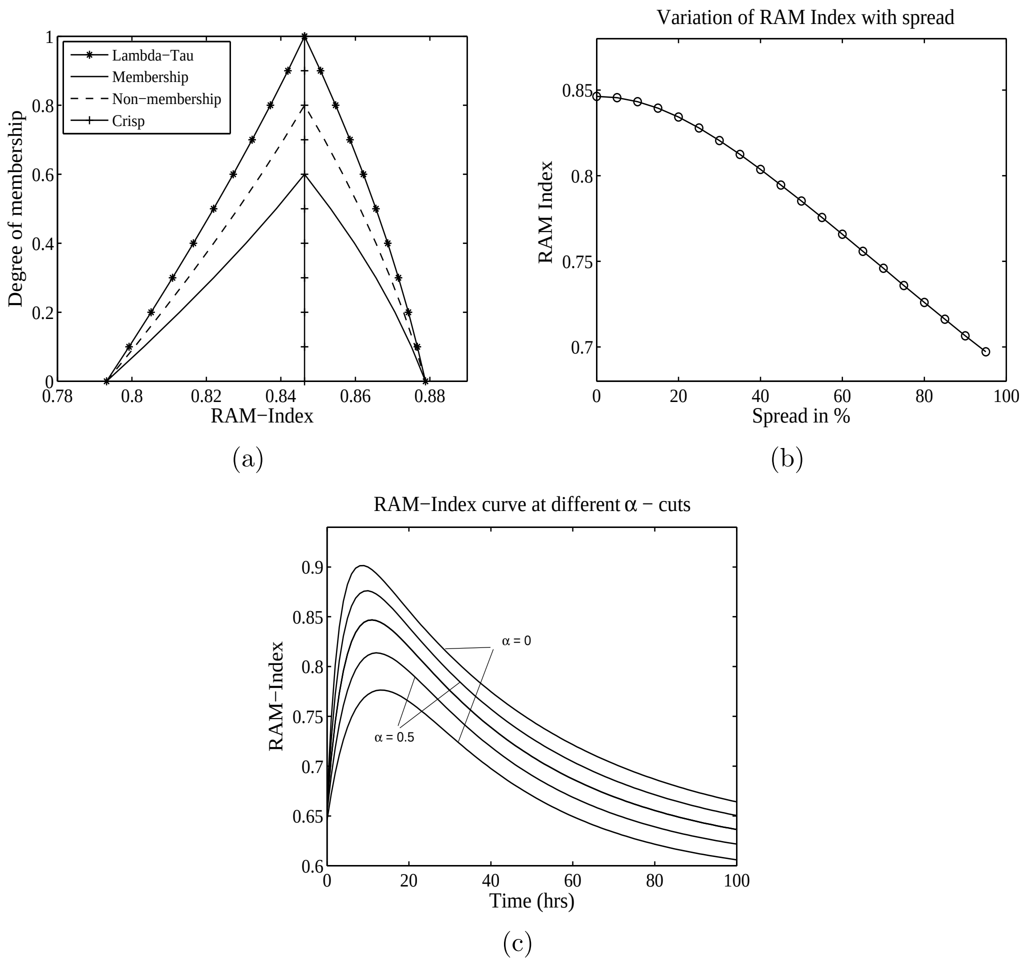


Figure 8.6: RAM-Index Analysis plot of Pharmaceutical Plant

As the performance of the system directly depends on each of the constituent subunits/components. So to analyze the effect of components' parameters on its performance, a simultaneous effect of each of its failure rate and repair time on the system performance has been investigated. In their analysis, failure rate and repair time of each of the component varies simultaneously and fixing the parameters of other components' at the same time. The corresponding results obtained are shown through surface plots in Fig. 8.7 which contains ten subplots corresponding to ten main component of the system. Based on these subplots the range of their corresponding parameters are summarized in Table 8.5 in the form of their maximum and minimum values. On the basis of results, it can be analyzed that for improving the performance of the system, more attention should be given to the components as per the preferential order; Weighing Machine, Octagonal Blender, Granulator, Air Compressor, Strip Packing Machine, Rotary Compression Machine, Shifter Machine, Coating Machine, Fluid Bed Dryer and Mass Mixer.

Table 8.5: Effect of Simultaneously Variations of System's Components' Failure and Repair Times on its RAM-Index for Pharmaceutical System

Component	Range of failure rate $\lambda(\text{hrs}^{-1})$	Range of Repair time $\tau(\text{hrs})$	RAM-Index	
			Min	Max
Weighing Machine	0.00425 - 0.00575	5.1000 - 6.9000	0.69342253	0.77897878
Shifter Machine	0.00170 - 0.00230	2.5500 - 3.4500	0.88844543	0.92472760
Mass Mixer	0.00085 - 0.00115	1.7000 - 2.3000	0.95001127	0.96545412
Granulator	0.00425 - 0.00575	4.2500 - 5.7500	0.72016770	0.79998280
Fluid Bed Dryer	0.001275 - 0.001725	2.5500 -3.4500	0.90992254	0.94088835
Octagonal Blender	0.00255 - 0.00345	8.5000 - 11.5000	0.69619037	0.77345448
Rotary Compression Machine	0.000085 - 0.000115	8.500 - 11.500	0.85125129	0.89061483
Coating Machine	0.00170 - 0.00230	1.7000 - 2.3000	0.90880883	0.93436469
Air Compressor	0.00255 - 0.00345	2.9750 - 4.0250	0.83530920	0.88659050
Strip Packing Machine	0.002125 - 0.002875	3.4000 - 4.6000	0.84212471	0.89377705

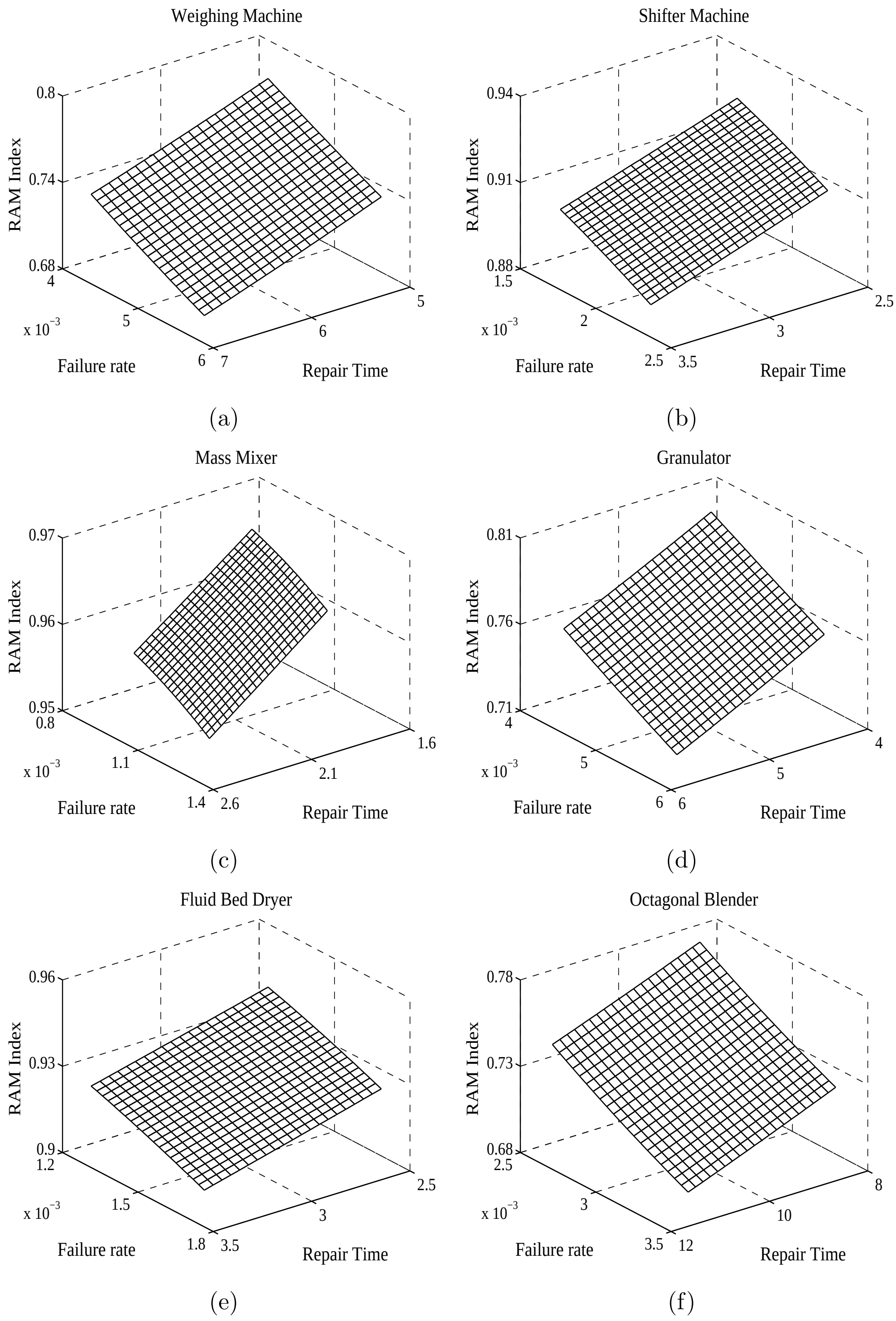


Figure 8.7: Effect of Varying Components Parameters on its Performance(Contd.)

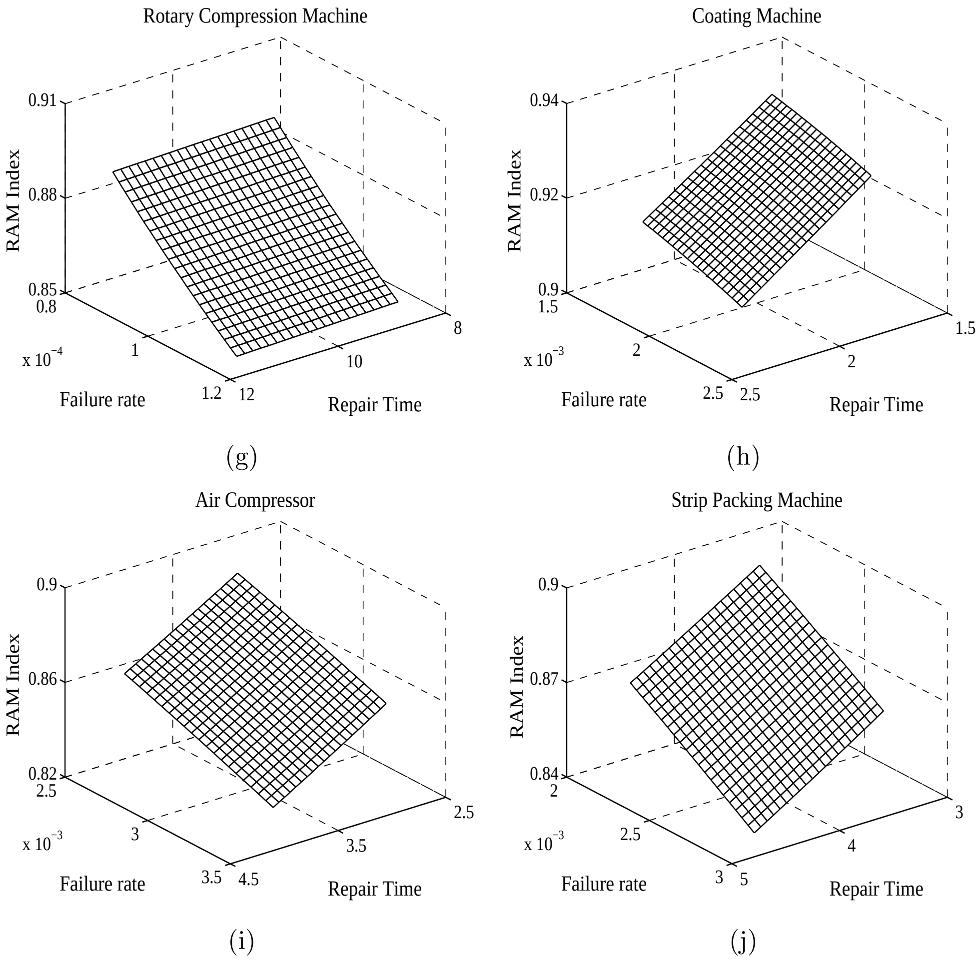


Figure 8.7: Effect of Varying Components Parameters on its Performance

8.5 Conclusion

In the present study a technique for improving the reliability and availability of a repairable system by using RAM analysis under the vague environment has been described. As the collected data obtained from the historical records are imprecise, vague or limited and thus have a some sort of uncertainties. The development of vague numbers from the available data and using vague possibility theory can greatly increase the relevance of reliability study. A vague set theory over fuzzy set theory has been used as the vague sets separates the trueness and falseness evidence for membership of an element in a set and also, in vague set, the level of confidence of domain experts lies between [0 1] instead of 1 as in fuzzy set theory. The technique has been applied for analyzing the behavior of the repairable industrial system namely a Pharmaceutical plant. To strengthen the analysis, various reliability parameters of interest which depict the system behavior closely have been computed using vague lambda-tau methodology and compared their results with fuzzy lambda-tau and crisp methodologies. From the analysis it is inferred that approach approach has overcome the shortcomings of the existing techniques by considering the interval valued membership functions instead of single one. Depending on the confidence level 'α', the system analysts may predict the behavior of the system. Sensitivity analysis on the system MTBF for various combinations of reliability parameters has also been addressed. The outcomes of sensitivity analysis will help the management to understand how the maintenance resources, policies and subsystem conditions affect the performance of the system. For ranking the critical components of the system on the basis of their performance on which more attention is to be given to save money, manpower and time, a RAM-Index analysis has been done. The major advantage of this index is that by varying individual component's failure rate and repair time, the impact on the system's performance can be analyzed effectively to plan the future course of action. Using these analysis and results tabulated in tables, it has been concluded that more attention should be given in preferential order to the components; Weighing Machine, Octagonal Blender, Granulator, Air Compressor, Strip Packing Machine, Rotary Compression Machine, Shifter Machine, Coating Machine, Fluid Bed Dryer and Mass Mixer for improving the performance of the system. Thus, it will facilitate the management in reallocating the resources, making maintenance decisions, achieving long run availability of the system, and enhancing the overall productivity of the plant.

In nutshell, the important managerial implications drawn using the discussed techniques are to:

- deal with imprecise, uncertain dependent information related to system performance by vague set methodology.
- determine reliability indices such as MTBF, MTTR which are important for planning the maintenance need of the systems;
- sensitivity analysis on system MTBF has been addressed for taking the effect of wrong combinations of reliability parameters.
- Performance analysis of the system has been done by using composite measure of the system reliability, availability and maintainability called RAM-Index.
- Ranking of the system for improving the performance of the system as per preferential order has been given.

Chapter 9

Summary and Future Scope

The chapter highlights the major research contribution and presents a comprehensive summary of the research work presented in this thesis. It also outlines the recommendations to system analysts for improving the systems' performance. Finally the scope for future work has been outlined.

9.1 Summary of the work

The research work presented in this thesis is an attempt to analyze the behavior of a repairable industrial system by using soft computing based techniques. The data available is uncertain. The detailed overview of the available literature on reliability optimization in different scerenio using conventional methods; fuzzy methodology, reliability-redundancy allocation problem, performance analysis has been given. From the reviewed literature, it is concluded that the job of the system analyst is quite challenging to maintain the performance of the system for maximum possible duration of time by using vague, imprecise and limited data. In the present thesis proper attention has been given to balance the different resources by making use of fuzzy set theory and evolutionary algorithm technique namely artificial bee colony. Fault tree analysis has been used for modeling and interacting the different components of the repairable industrial system.

Keeping these points in view, different optimization problem has been formulated for a complex repairable industrial system. Due to, the growing complexity of industrial systems it is very difficult to have a complete and accurate mathematical model of the system. Moreover, the design of a repairable series-parallel system becomes insufficient, if the analysis are based on the empirical methods. Therefore, soft computing technique, such as ABC is useful, to analyze and to optimize the design problems of repairable systems. Also the data obtained from historical records/sheets are generally out of date and hence it represents the past behavior of the system. Thus the main theme of the present work is to analyze the behavior and performance of the complex repairable industrial systems by utilizing uncertain, imprecise and vague data. An approach has been given to compute the various reliability parameters in the form of membership functions for depicting the behavior and performance of industrial systems. A structured framework may help the system analyst or plant personnel to analyze and predict the system behavior and related characteristics of each of the system-components.

For this, a novel technique named as artificial bee colony based lambda-tau (ABCBLT) has been proposed in this work. To strengthen the analysis, various reliability parameters (failure rate, repair time, MTBF, ENOF, reliability and availability) have been analyzed individually for all the subsystems of the industrial systems by using traditional FLT, GABLT and the discussed ABCBLT techniques. Sensitivity and performance analyses of the system have also been carried out for various combinations of reliability index and their effects have been shown graphically, and also summarized in terms of minimum and maximum values. Based on these analyses, system analyst/plant personnel may find the most critical component of the system, as per preferential order, and plan the suitable maintenance strategies. From the analysis it has been concluded that ABCBLT performs consistently well in comparison of GABLT and traditional FLT techniques as it gives a reduced region of predictions and hence may give results closer to real situation.

The computed results are further used to formulate and then solve the performance optimization problem for the system.

The conclusions made from the work presented in this thesis are summarized below:

(i) An availability-cost optimization model has been developed for the butter-oil processing plant by taking manufacturing and repairing cost function as an objective and solved in terms of optimal MTBF and MTTR by using ABC algorithm and compared their results with GA and PSO. A statistical t-test has been performed by ABC with other algorithms' results and shown that the results computed by the suggested approach are statistically significant.

(ii) A hybridized technique named as ABCBLT for analyzing the behavior of industrial systems by utilizing uncertain data with reduced uncertainty is proposed. Fuzzy set theory has been used in it for increasing the efficiency of handling the data as compared to probability theory. A constant failure rate model has been taken during the analysis. Sensitivity as well as performance analysis have also been carried out by varying the failure rate and repair time on its availability index. These analyses will help the system analyst for finding the most critical component of the system on which more attention should be given for saving money, manpower and time by adopting a suitable maintenance strategy.

(iii) Instead of considering the constant failure rate model, a study has been done for analyzing the behavior of industrial systems by considering time varying component model, i.e. by considering the Weibull distribution for failure rate parameters. The uncertainties which are present in their corresponding parameters are removed with the help of triangular fuzzy numbers. Various reliability parameters are addressed to strengthen the analysis in the form of fuzzy membership function by using ABCBLT technique and compared their results with the Crisp, FLT and GABLT technique results. From this analysis, it has been concluded that maintenance should be based on the defuzzified values rather than crisp values for getting a safe inspection interval between maintenance action to monitor the condition and status of the equipments constituting the system before reaches to crisp value.

(iv) A time dependent RAM-Index has been given in Chapter 6 of this thesis for analyzing the composite effect of reliability, availability and maintainability of each subsystem/units of a paper mill. The major advantage of this analysis is that by varying the individual component failure rates and repair times parameter of the component, the corresponding effect on its performance has been analyzed. Based on their analysis, the system analyst may plan the suitable maintenance strategies for improving the performance of the system and thus decreasing their operational and maintenance cost.

(v) A two-phase approach has been introduced in Chapter 7 for reliability-redundancy allocation problem of a series, series-parallel and bridge systems. In the first phase, an optimal reliability and the corresponding redundant component of each subsystem has been computed using ABC algorithm and the results have been compared with other evolutionary algorithm results. While the improvement on the component reliability has been made in the second phase by preserving the redundant components corresponding to each subsystem. Finally the computed results during both the phases are compared to show the superbly of the proposed approach with the existing techniques.

(vi) A structural framework has been developed in Chapter 8 to model, analyze and predict the failure pattern of the system behavior in both quantitative as well as qualitative manner. In their framework, degree of hesitation or indeterminacy between the membership functions have been considered in which basic events are represented in the form of vague fuzzy numbers of triangular membership functions. Vague set theory over fuzzy set theory has been used as the vague sets separate the trueness and falseness evidence for membership of an element in a set. Also, in vague set, the level of confidence of domain experts lies between [0,1] instead of 1 as in fuzzy set theory. To strengthen the analysis, various reliability parameters of interest are computed and compared their results with their crisp as well as fuzzy technique results. The most important benefit is that the crisp, vague and defuzzified values for even highly complex integrated system can be obtained all at once.

9.2 Future scope of the work

The method of analysis, design and reliability/availablity optimization aspects in the production and manufacturing system can be extended in the following directions:

(i) The present work has been investigated for a system whose functional dependency are known, so in future we are working on the development of the methodology for those systems or large complex systems whose functional dependency are not known.

(ii) The presented study can be performed equally well to evaluate the system behavior of other process industries such as sugar industry, power plant, cement industry, petroleum, food processing etc. as the considered methodology can overcome various kind of problems in the area of quality, reliability and maintainability, which strongly needs the management attention.

(iii) The presented methodology will be further extended and improved using other optimization tools/algorithm such as Ant colony optimization, Firefly algorithm etc. and artificial neural network will be used to handle the complex nature of the systems.

(iv) The study can be extended with the consideration of the degree of uncertainty between the membership functions and domain of confidence.

(v) The present research work can be extended to arbitrary repairs and failure time distribution.

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