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System Reliability Design: A Survay

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Abstract- In System reliability design, it is essential to know the effectiveness of different design options in improving system reliability. Various Reliability models techniques have been created to evaluate these parameters by applying both analytic and simulation techniques, and this paper reviews those related primarily to reliability optimization design problems. The purpose, type of models used, type of systems modeled, heuristic and metaheauristic techniques will be discussed and serviceability parameters are surveyed. Examples of some of the key modeling issues such as RAP, UMGF and MSS , similarities and differences between various models and tools and can be help to aid in selecting models and tools for a particular tools for a particular application or designing needs for future needs.

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SYSTEMRELIABILITYDESIGNASURVAY

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I. Background Issues

System reliability can be defined as the probability that a system will perform its intended function for a specified period of time under stated conditions [1]. Many modern systems, both hardware and software, are characterized by a high degree of complexity. To enhance the reliability of such systems, it is vital to define techniques and models aimed at optimizing the design of the system itself. Estimating system reliability is an important and challenging problem for system engineers. [2]. It is also challenging since current estimation techniques require a high level of background in system reliability analysis, and thus familiarity with the system. Traditionally, engineers estimate reliability by understanding how the different components in a system interact to guarantee system success. Typically, based on this understanding, a graphical model (usually in the form of a fault tree, a reliability block diagram or a system graph) is used to represent how component interaction affects system functioning. Once the graphical model is obtained, different analysis methods [3–5] (minimal cut sets, minimal path sets, Boolean truth tables, etc.) can be used to quantitatively represent system reliability. Finally, the reliability characteristics of the components in the system are introduced into the mathematical representation in order to obtain a system-level reliability estimate. This traditional perspective aims to provide accurate predictions about the system reliability using historical or test data. This approach is valid whenever the system success or failure behavior is well understood. In their paper, Yinong Chen, Zhongshi He, Yufang Tian [6]. They classified system reliability in to two categories: topological and flow reliability.

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In topological reliability analysis, one assumes the system to be performing adequately as long as there exist any path from a specified source node (or nodes) to a specified terminal node (or nodes) [7]. Flow reliability: The flow reliability model assumes that the system components are of finite capacity. The system is considered to performing adequately only if it allows a certain a mount of flow to be transmitted from source to terminal nodes [7]. In a topological reliability Yinong, Yufang Tian assume that components are reliable while nodes may fail with certain probability, but also in literature exist components subject to failure [8]. Ideally, one would like to generate system design algorithms that take as input the characteristics of system components as well as system criteria, and produce as output an optimal system design, this is known as system synthesis [9], and it is very difficult to achieve. In the most theoretical reliability problems the two basic methods of improving the reliability of systems are improving the reliability of each component or adding redundant components [7]. Of course, the second method is more expensive than the first.

II. Basic Definishin

a) The Objective function

One of the major challenges to solving the optimal system design problem is computing the objective function. Unless a system is simple or well structured, obtaining a closed form mathematical expression for the objective function is extremely difficult specially when we deal with the complex system or non-series parallel system. In their 1965 paper, Moscowitz & Mclean [10] first formulated mathematically the optimization problem of system reliability subject to system cost. Since then, several papers have been written about optimization system reliability. Roughly speaking. These papers consider only a single Objective and applying traditional mathematical programming techniques and based on two different types of formulations for the reliability objective function as follows in equations 1 and 2 bellows:

Subject to

$$\sum_{j=1}^{N} c_{ij}(R_j) \le b_j, \qquad i-1,2,........,m$$

Or

$$\text{Minimize}\, Cs = \sum_{j=1}^{N} C_j(X_j) \qquad (2)$$

$$\textit{Maximize}\ R_s = \prod_{j=1}^{N} R_j \qquad (1)$$

Subject to

$$R_s = \prod_{j=1}^{N} R_j(X_i) \geq R_r.$$

b) Identifying System Constraints

The optimal solution should be obtained within the resource restrictions. These restrictions are also called the constraints of the optimization problem. Constraints include:

- Desired reliability
- Desired availability
- Desired MTTF or MTBF
- Allowed downtime
- Allowed unavailability
- Cost: Allowed budget for spares and/or repair resources
- Allowed weight
- Available space or volume

i. *Building Cost-Effective Systems*

In the majority of applications, the objective of system design is to minimize the overall cost associated with the system. The total cost is the sum of several cost factors [11], such as:

- System failure costs, which includes damage and inconvenience costs
- Downtime costs associated with loss of production
- Component and spare costs
- Maintenance costs, which includes repair, replacement, and inspection costs
- Maintenance personnel costs, which includes call-up costs and hourly rates
- Warranty costs
- Storage costs
- Transportation costs
- Miscellaneous costs, which includes replacing accessories

c) Fundamental system configurations

Tillman, Hwang, and Kuo [12] provide a thorough review related to optimal system reliability with redundancy. They divided optimal system reliability models with redundancy into:

- series,
- parallel,
- series-parallel,
- parallel-series,
- standby,
- complex

also in there reference book [31] add a configuration of:

- hierarchal series-parallel systems
- K- out of – n systems,
- cold standby redundancy in a single-component system,
- redundancy with imperfect switching system.
- multi-cause fauile model regardless those repairable or non repairable systems.

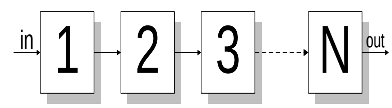

Figure 1 : Series System

$$R_s(t) = \prod_{i=1}^{k} R_i(t)$$

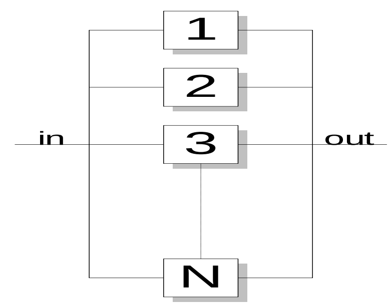

Figure 2 : Parallel Network

$$F_s(t) = \prod_{i=1}^{k} F_i(t)$$

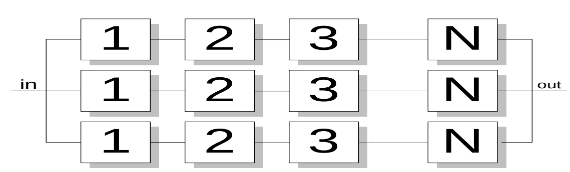

Figure 3 : Series Parallel System

$$R(t) = \left(1 - \mathop{C}_{i=-1}^{n} (1 - R_i(t))\right)^m$$

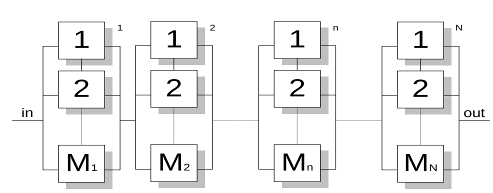

Figure 4 : Parallel-Series System

$$R(t) = 1 - \left(1 - \prod_{i=1}^{n} R_i(t)\right)^m$$

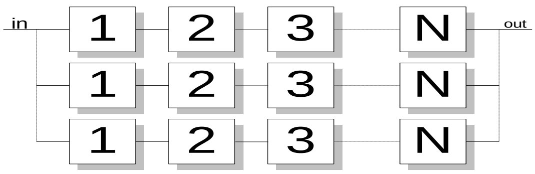

Figure 5 : Stand by System

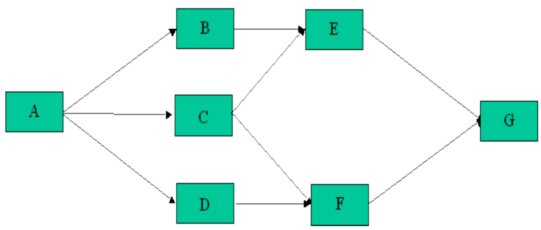

Figure 6 : Complex System

III. Classification of Reliability Optimization Techniques

Published papers which produced for techniques optimization models can be classified into two paths: and

- Heuristics methods
- Metaheuristics. methods

Heuristics methods such as

- integer programming,
- dynamic programming,
- linear programming,
- geometric programming,
- generalized Lagrangian functions, and heuristic approaches.

Metaheuristic algorisms such as

- Genetic algorithm
- The simulated annealing method
- Non equilibrium simulated annealing method.
- Tabu search method
- Ant colony optimization method ACO
- Paeticle swarm optimization method.
- Artificial immune system.
- Fuzzy system
- Artificial neural networks
- Particle swarm optimization
- Hybrid methods

a) Metaheuristic Techniques

Many classical mathematical methods have failed in handling nonconvexities and nonsmoothness in reliability– redundancy optimization problems. As an alternative to theclassical optimization approaches, the meta-heuristics have been given much attention by many researchers due to their ability to find an almost global optimal solutions.

Also [13] classify them into:

See figure (7)

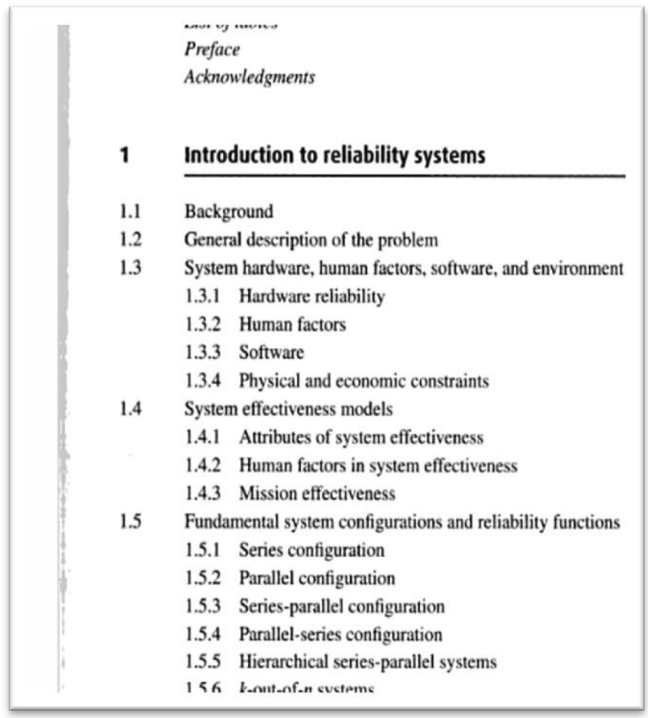

Figure 7 : Content snapshot from optimal reliability design text book

- Heuristics for redundancy allocation
- Metaheuristic algorithms for redundancy allocation.
- Exact methods for redundancy allocation
- Heauristic for reliability-redundancy allocation
- Multiple objective optimizations in reliability systems
- Optimal of interchangeable components in coherent system.

In the following section a details survey and discussion between heuristic and metaheuristic methods will be illustrated.

b) Heuristic and metaheuristics methods in literature

Many algorithms have been proposed but only a few have been demonstrated to be effective when applied to large-scale nonlinear programming problems. Also, none has proven to be generally superior. Fyffe, Hines, and Lee provide a dynamic programming algorithm for solving the system reliability allocation problem [14]. As the number of constraints in a given reliability problem increases, the computation required for solving the problem increases exponentially. In order to overcome these computational difficulties, the authors introduce the Lagrange multiplier to reduce the dimensionality of the problem. To illustrate their computational procedure, the authors use a hypothetical system reliability allocation problem, which consists of fourteen functional units connected in series. While their formulation provides a selection of components, the search space is restricted to consider only solutions where the same component type is used in parallel. Nakagawa and Miyazaki [15] show a more efficient algorithm compared to dynamic programming using the Lagrange multiplier. In their algorithm, the authors use surrogate constraints obtained by combining multiple constraints into one constraint. In order to demonstrate efficiency of the new algorithm, they also solve 33 variations of the Fyffe problem. Of the 33 problems, their N&M algorithm produces optimal solutions for 30 of them. Misra and Sharma [16] present a simple and efficient technique for solving integer programming problems such as the system reliability design problem. The algorithm is based on function evaluations and a search limited to the boundary of resources. In the nonlinear programming approach, Hwang, Tillman and Kuo [17] use the generalized Lagrangian function method and the generalized reduced gradient method to solve nonlinear optimization problems for reliability of a complex system. They first maximize complex-system reliability with a tangent cost-function and then minimize the cost with a minimum system reliability. The same authors also present a mixed integer programming approach to solve the reliability problem [18]. They maximize the system reliability as a function of component reliability level and the number of components at each stage. Using a genetic algorithm (GA) approach, Coit and Smith [19, 20, 21] provide a competitive and robust algorithm to solve the system reliability problem. The authors use a penalty guided algorithm which searches over feasible and infeasible regions to identify a final, feasible optimal, or near optimal, solution. The penalty function is adaptive and responds to the search history. The GA performs very well on two types of problems: redundancy allocation as originally proposed by Fyffe, et al., and randomly generated problems with more complex configurations. For a fixed design configuration and known incremental decreases in component failure rates and their associated costs. In table (1) a comments on some most famous approaches in heauristic methods.

Table 1 : Comments on some heuristic approaches:

Approaches	Comments
Sharma-Venkatswaran approach [5]	The algorithm is simple and can be applied easily to all problems. However, the solutions are not always the optimal ones, they may be suboptimal ones.
Misra‟s approach [3]	It is for linear constraints problems only. As the number of constraints increases the computational time becomes large.,
Aggarwal et al.‟s approach [1,2]	Widely applicable to many redundancy allocation problems for both linear and nonlinear constraints, but fail to solve Problem3. An effective method for linear constraints problems.
Nakagawa-Nakashima‟s approach [4]	Very through discussion on the balance between the objective function and constraints but can not solve complex system problem.
Tillman et al.‟s approach [8]	Combination of Hooke and Jeeve pattern search and a heuristic method of mixed integer programming problems.
Extended Nakagawa - Nakashima‟s	An algorithm for redundancy optimization of a general system. The balancing coefficient is there.
Uskakov‟s approach [9]	It is the only algorithm to solve the cost minimization problem for multifunction system.

In recent studies, redundancy allocation problems (RAP) are mainly considered, because it is more difficult to improve the component reliability. Which can be improved by [22] (Wang, 1992):

- Use more reliable components;
- increase redundant components in parallel;
- utilize both #1 and #2; and
- enable repeatedly

As one of the latest studies on the reliability allocation problem, Yalaoui et al. [23] used dynamic programming to determine the reliability of the components in order to minimize the consumption of a system resource under a reliability constraint in a series-parallel system. The RAP is to select the optimal combination of components and redundancy degree to meet resource constraints while maximizing the system reliability. A wide variety of these problems have been formulated and a large number of solution techniques have been proposed for various system structures such as series, network, k-out-of-n, etc. Aggarwal and Gupta [24] and Ramirez-Marquez et al. [25] proposed heuristic algorithms. Hsieh [26] used the linear approximation method and Ha and Kuo [27] adopted integer programming for the problem. We refer the readers to a review paper by Kuo and Prasad [28] and a book on the topic by Kuo et al. [29].

The meta-heuristic methods have been using to find the optimal solution of combinatorial optimization problems since Chern [30] proved the RAP is a NP-hard problem. Coit et al. [31, 32] and Yokota et al. [33] used the genetic algorithm (GA), and Liang and Smith [34] and Nahas and Nourelfath [35] proposed an ant system for solving RAP. Levitin [36, 37] and Wu and Chan [38] considered a multistate system using meta-heuristic methods. However, Boland and EL-Neweihi [39] showed that it is not true in the case of redundancy in series system with non-identical spare parts. In the real system, the multi-level redundancy in which system, module, and component levels are simultaneously considered as the objects of redundancy can be applied to the RAP. In other words, exact algorithms for finding the optimal solution are not appropriate when the numbers of subsystems and component types are large. Hence, some search techniques involving heuristics or meta-heuristics have been proposed for solving MSPS redundancy allocation problem, such as Genetic Algorithm (GA) approaches [40, 41, 42], and Ant Colony Optimization (ACO) approach [43, 44]. These approaches are utilizing the so-called universal generating function [45] to estimate the system reliability and have been demonstrated to yield very good solutions. These meta-heuristics have main advantages in solving MSPS redundancy allocation problem: only few constraints for the solution representation required and no extra information from the objective function needed. Before employing any meta-heuristic on a NP-hard problem such as MSPS, it is important to understand the essential of the problem under investigation. Hence, some problem-specific issues have to be studied in advance to perform a so-called intelligent search to avoid unnecessary computational burden. These issues are based on the influence of solution representation, neighborhood structure and solution initialization on the designing of algorithm. Note that stochastic population-based search approaches, such as GA and ACO, enjoy the advantage of global search. However, no matter what kind of solution coding they adopt for solving MSPS, the (randomized) initial population may contain a certain amount of infeasible or undesirable (much higher cost or reliability than system‟s requirement) solutions. For each specified MSPS problem, the solution representations for the above approaches have to be defined and coded according to the universal generating function. Moreover, the genetic operations in GA or solution/pheromone updating in ACO may result in dramatically changes in solutions (infeasible or undesirable). These search techniques also lack the capability of doing in-depth local search could need a considerable amount of generations to perform some necessary neighborhood moves to approach an optimal solution. Furthermore, either a solution repairing procedure (using local search) or penalization on objective is required for these search approaches to ensure feasibility because the properties of MSPS solutions are not considered. Tabu Search (TS), proposed by Glover, is another popular and promising meta-heuristic optimization technique [46, 47]. Most TS approaches can be characterized by two important features: (1) executing local search, and (2) prohibiting moves that have been selected previously. Hence, TS has the ability to escape the trap of local optimum, and unlike GA and ACO, TS can execute in-depth local search and use memory performing an intelligent search. TS has been employed to solve some reliability problems, such as structural design problems with reliability constraints [48, 49], and optimal configuration problems depending on the reliability of components [50]. TS also demonstrated its efficiency in finding the optimal solution for the redundancy allocation problem for k-out-of-n system [51]. Most of the researches restricted the MSPS redundancy allocation problem under the so-called "without component mixing" condition [52, 53, 54, 55], which means that once a component type is selected in a subsystem, only the same type of component can be used redundantly to provide the required function. a tabu search without the need of the universal generating function is proposed for optimizing MSPS redundancy allocation problem, and it can be implemented to handle "with or without component mixing" restriction. In order to limit the chance of moving from a feasible solution to infeasible or undesirable one, a tailored neighborhood structure and corresponding moves are proposed to perform an intelligent search by considering the properties of MSPS solutions. Genetic Algorithm (GA) is a probabilistic search method stimulated by genetic evolution [56](Holland, 1975). It was initiated from the 1970s and widely applied to many fields since 1980s. GA can efficiently solve the availability optimization problem of series-parallel, as it is suitable to the domain of feasible solution with non-linearity or discontinuity. [57] (Goldberg (1989) made a systematic study on GA mechanism, and identified three basic operators: reproduction, crossover and mutation. When the solution space to be searched is relatively large, noisy, non-linear and complicated, the GA has higher opportunity for obtaining near-optimal solutions. The GA solely takes fitness function as its evaluation criterion. It is also a parallel processing mechanism, which searches for different areas by multiple starting points.

Based on continuous evolution of generations and efficient search using the information of parent generation, it is possible to increase the speed of finding an optimal solution [58]((Lin, Zhang, & Wang, 1995). The mutation mechanism provides more opportunities to overcome the spatial limitations of local optimum, and allows for convergence towards global optimum. GA was applied to a wide variety of fields in recent decades [59], [60] (((Lapa, Pereira, & De Barros, 2006; Lin, Wang, & Zhang, 1997). It was also successfully used to solve the reliability optimization problem of a series-parallel system. [61] (Painton and Campbell (1995) solved the reliability optimization problem related to personal computer design. They regarded a personal computer as a series-parallel system of twelve components, each of which has three optional packages. [62](Yokota, Gen, and Ida (1995) utilized GA to solve successfully the reliability optimization problem of series-parallel system with parallel components and several failure modes.[63](Azaron et al. (2005a) developed a new approach to evaluate the reliability function of a class of dissimilar-unit redundant systems with exponentially distributed lifetimes. There are few researches toward the reliability optimization of non repairable systems with cold-standby redundancy scheme. [64] (Gnedenko and Ushakov (1995) presented algorithms to maximize the median time to failure. [65] (Nakashima and Yamato (1977) solved an analogous problem to maximize the time period where system reliability remains above a preselected value. Their algorithm assumes that components have exponential lifetimes, but that the distribution parameters are the decision variables to be determined in addition to the redundancy levels. The problem of reliability optimization of nonrepairable cold-standby redundant systems has received less attention. [66] (Albright and Soni (1984) have solved a reliability optimization problem for nonrepairable systems with standby redundancy. They assumed exponential lifetime and one component choice per subsystem. [67] Robinson and (Neuts (1989) studied system design for nonrepairable systems with cold-standby redundancy. They considered systems with components that have phase-type lifetime distributions. [68] (Coit (2001) has determined optimal design configurations for nonrepairable series–parallel systems with cold-standby redundancy. His problem formulation considers nonconstant component hazard functions and imperfect switching. [69] (Prasad et al. (1999) considered the problem of allocating multifunctional redundant components for deterministic and stochastic mission times. In their formulation, there is a limit on the total number of redundant components, which can be used. There are also a few papers that consider the multi-objective reliability optimization for either time-independent case see [70] (Sakawa 1978) or active redundant systems [71] ((Sakawa 1980; [72] (Dhingra 1992) and optimize system reliability, cost, weight, and volume for a given mission time. [73] (Azaron et al. (2005b) used the surrogate worth trade-off method to find the optimal distribution parameters (continuous decision variables like [74] (Nakagawa and Miyazaki 1981) in a cold-standby system.

The major limitations in the reliability evaluation and optimization approaches for dissimilar-unit cold-standby systems, thus far, are:

- Most available algorithms assume that each unit is composed of a single component, but they also cannot get the results in closed form [75] ((Goel and Gupta 1983).
- Available algorithms that do address dissimilar-unit multicomponent cold stand by systems assume that each unit is composed of a number of components arranged in a series configuration. Although this is a start, there are many more complicated system configurations that should be examined. The problem lies in the difficulty of presenting more complicated structures.
- Existing system reliability optimization algorithms are most often available for active redundancy. The logarithm of system reliability for an active standby redundant system is a separable function; dynamic programming or integer programming can be used to determine optimal solutions to the problem.
- Available algorithms that do address cold-standby optimization generally assume similar redundant units and exponential lifetimes.
- Most available optimization algorithms consider continuous decision variables. In this case, it is difficult in practice to select a component to match a specific distribution parameter.
- Only one criterion for time-dependent reliability, like maximizing mean time to failure (MTTF) or maximizing the system reliability at a given mission time is considered in the model. In the reliability optimization problem, one often wishes to lower the risk that systems with short system lifetime are produced, but only maximizing MTTF is not always fit for the requirement, especially A multi-objective discrete reliability optimization problem when the optimally designed system has a large variance of time to failure (VTTF). The system reliability at the mission time is another important criterion, which should be considered in the model. As is addresses in recent review of the literature for example in [76], [77]. Generally, the methods of MSS reliability assessment are based on four different approaches:

i. The structure function approach.
ii. The stochastic process (mainly Markov) approach.
iii. The Monte-Carlo simulation technique.
iv. The universal moment generating function (UMGF)

approach. In reference [76], a comparison between these four approaches highlights that the UMGF approach is fast enough to be used in the optimization problems where the search space is sizeable. The reliability optimization problem ROP is studied in many different forms as summarized in [78], and more recently in [79]. The ROP for the multi-state reliability was introduced in [80]. In [81] and 82], genetic algorithms were used to find the optimal or nearly optimal transformation system structure. This work uses an ant colony optimization approach to solve the ROP for multi-state plastic recycling system. The idea of employing a colony of cooperating agents to solve combinatorial optimization problems was recently proposed in [83]. The ant colony approach has been successfully applied to the classical traveling salesman problem in [84], and to the quadratic assignment problem in [85]. Ant colony shows very good results in each applied area. It has been recently adapted for the reliability design of binary state systems in [86]. The ant colony has also been adapted with success to other combinatorial optimization. The ant colony method has not yet been used for the redundancy optimization of multi-state systems.

In the table 2 we will mention a set of well-known lates published paper s in the last years with its main approach and concepts.

Table 2 : Latest Paper Published In System Reliability

Published paper	**Contributions**
Mettas‟s approach [87]	There are some limitations to simulation methods for estimating the reliability of non-repairable systems effectiveness. For example, if the number of simulations performed is not large enough, simulation offers a small range of calculation results when compared to analytical methods. A software tool has been developed that calculates the exact analytical solution for the reliability of a system. In addition, optimization and reliability allocation techniques can be utilized to aid engineers in their design improvement efforts. Finally, the time-consuming calculations and the non repeatability issue of the simulation methodology are eliminated.
Wang‟s approach[88]	Through the use of reliability block diagrams (RBD), is often used to obtain numerical system reliability characteristics. Traditional use of simulation results provides no easy way to compute reliability importance indices. To bridge this gap, several new reliability importance indices are proposed and defined in this paper. These indices can be directly calculated from the simulation results and their limiting values are traditional reliability importance indices. Examples are provided to illustrate the application of the proposed importance indices.
Larry‟s approch [89]	International Standards, ANSI National Standards, and various industry handbooks and standards. These documents have many typical reliability management and analysis tasks in common such as prediction, allocation, worst case analyses, part selection, Failure Mode Effects and Criticality Analysis (FMECA), Failure Reporting and Corrective Action System (FRACAS), etc. DoD studies have shown that even when the basic reliability tasks are implemented the resulting system reliability is often lower than expected and often insufficient. This problem was addressed by the Panel on Statistical Methods for Testing and Evaluating Defense Systems, National Research Council (NRC) in 1998 (Ref. 2 Significant to the NRC‟s recommendations to DoD and the rewrite of the Primer is the question: Just how effective are reliability tasks in identifying design flaws and correcting reliability deficiencies early in system development? Clearly the effectiveness will vary from system to system but are there data or studies that will give insight into this issue? This paper provided a framework and data for addressing these questions, beside this paper mentioned a practical metric to measure the effectiveness of the reliability tasks that take place before reliability growth or other prototype testing. In addition this paper provided a number of proven methods for increasing the effectiveness of several reliability tasks.
Huairui‟s approuch[90]	Most of the existing degradation analysis methods assume that the degradation process can be regularly inspected In this paper, a design of experiment (DOE) method of using the degradation process together with the observed failure data to improve reliability is proposed. Unlike other degradation analysis methods, the proposed method does not require regular degradation measurements. In the use of DOE, all the factors that affect the degradation process are classified into two types. The Type I factor is called the amplification factor. Its effect on degradations is well known based on the engineering knowledge of the physical process of the degradation. The Type II factors are called control factors. Their

	effects are unknown and need to be studied by experiments. By combing the engineering knowledge and the observed failures, the effects of control factors are analyzed using a linear regression method.
Huairui‟s approach [91]	In this paper, a systematic procedure of applying ccelerated life tests and simulation to analyze the reliability and availability of such dynamic systems is first proposed. Methods for solving both non-repairable and repairable systems are provided. For non-repairable systems, an analytical solution based on cumulative damage theory is discussed. Therefore, the exponential assumption, which is used in many existing methods, is not required in the proposed method. In addition to the analytical solution, a cumulative damage-based simulation solution is also provided. For repairable systems, based on different scenarios in real applications, the repairable phased-mission system is classified into three categories. Because of the complexity of the problem, only simulation results are given for repairable systems. The proposed systematic procedure of applying accelerated life tests in phased-mission system analysis provides a general guideline for dealing with real-world applications. The cumulative-damage-based analytical and simulation method provide a practical and useful approach for solving phased-mission system problems.
Dingzhou‟s approach [92]	In this paper, They proposed a reliability optimization framework based on Dynamic Bayesian Networks (DBN) and Genetic Algorithm (GA) which considers system reliability as a design parameter in design stages and can accelerate the design process of a reliable system. In this paper, they extend it to a more complicated system with dynamic behavior. In order to capture the different dynamic behaviors of a system, DBN is used to estimate the system reliability of a potential design. Two basic DBN structures "CHOICE" and "REDUNDANCY" are introduced in this study. GA is developed . Simulation results show that the integration of GA optimization capabilities with DBN provides a robust, powerful system-design tool system.
Mingxiao‟‟ as approuch. [93]	One of the important reliability activities in Design for Reliability (DFR) is system reliability allocation at the early product design stage. Complex systems consist of many subsystems, which are developed concurrently and sometimes independently. final system prototype is ready after months or years of development. From a project management point of view, the reliability for each subsystem or sub-function should be examined as early as possible. This paper propose a new approach forallocating system reliability together with confidence level to the subsystems. The proposed method can be used for complex systems with serial, parallel, and k-out-of-n configurations.

IV. Conclusion

This paper is a state-of-art review of the literature related to optimal system reliability with and without redundancy. The literature is classified as follows. Optimal system reliability models with redundancy Series Parallel Series-parallel Parallel-series Standby Complex (nonseries, nonparallel) Optimization techniques for obtaining optimal system configuration Integer programming Dynamic programming Maximum principle Linear programming Geometric programming Sequential unconstrained minimization technique (SUMT) Modified sequential simplex pattern search Lagrange multipliers and Kuhn-Tucker conditions Generalized Lagrangian function Generalized reduced gradient (GRG) Heuristic approaches Parametric approaches Pseudo-Boolean programming Miscellaneous. We present a brief survey of the current state of the art in system reliability. Most system reliability problems are, in the worst case, NP-hard and are, in a sense, more difficult than many standard combinatorial optimization problems. Nevertheless, there are, in fact, linear and polynomial time algorithms for system reliability problems of special structure. We review general methods for system reliability computation and discussed the central role played . We also point out the connection with the more general problem of computing the reliability of coherent structures. The class of coherent structures contains both directed and undirected networks as well as logic (or fault) trees without not gates. This topic is a rich area for further research.

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