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Bi-objective optimization of the reliability-redundancy allocation problem for series-parallel system

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ABSTRACT

The main objective of this paper is to solve the bi-objective reliability redundancy allocation problem for series-parallel system where reliability of the system and the corresponding designing cost are considered as two different objectives. In their formulation, reliability of each component is considered as a triangular fuzzy number. In order to solve the problem, developed fuzzy model is converted to a crisp model by using expected values of fuzzy numbers and taking into account the preference of decision maker regarding cost and reliability goals. Finally the obtained crisp optimization problem has been solved with particle swarm optimization (PSO) and compared their results with genetic algorithm (GA). Examples are shown to illustrate the method. Finally statistical simulation has been performed for supremacy the approach.

1. Introduction

The system reliability optimization has its importance in a 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 component reliabilities or both. The utilization of redundancy is assumed to be one of the main attributes to meet high level reliability. Several researchers since the 1960s have solved reliability optimization problems with a single objective in which reliabilities of the system components are assumed to be known at fixed positive levels which lie between zero and one [1–7]. 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 the environment. Due to the non-availability of their distribution function of 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. Such problem of maximizing system reliability through redundancy and component reliability choices is called reliability-redundancy allocation problem (RRAP) [5]. However, a fundamental trade-off problem between reliability enhanced and resources consumed has to be encountered while a high reliability system is to be designed.

Often, reliability of the component is not specific. This is due to that the reliability of a component/system depends on operational and environmental conditions. Therefore, it is not possible to determine a fixed number that lies, between zero and one, which shows reliability of a component in all conditions. Moreover, in the early design phase reliability of a system may be taken into account and hence it is difficult to determine the reliability specifically. Further, the causes may be age, adverse operating conditions and the vagaries of manufacturing processes which affect each part/unit of the system differently, and thus the issue is subject to uncertainty. To this effect, both probabilistic and non-probabilistic methods are used to treat the element of uncertainty in reliability analysis. Conventional reliability theory is based on the probabilistic and binary state assumptions. Although the probability approach has been applied successfully for many real world engineering reliability problems but still there are some limitations to the probabilistic method. For instance, probabilistic methods are based on mass collection of data, which is random in nature, to achieve the requisite confidence level. But in large scale the complicated system has the massive fuzzy uncertainty due to which it is difficult to get the exact probability of the events. Thus results based on probability theory do not always provide useful information to the practitioners due to the limitation of being able to handle only quantitative information. Moreover, in real world applications, sometimes there

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is insufficient data to accurately handle the statistics of parameters [8,9]. This is particularly true at the tail of the distributions, where reliability is very high and therefore failure observations are extremely rare. Also, at early stages of new product development, the available data (numbers of testing samples, recorded failures on test) is limited, so the required confidence level may not be met if probability methods are used. The subjective information is also not captured during reliability analysis by probabilistic methods. Due to these limitations, the results based on probability theory do not always provide useful information to the practitioners and hence probabilistic approach to the conventional reliability analysis is inadequate to account for such built-in uncertainties in the data. To overcome these difficulties, methodologies based on fuzzy set theory [10] are being used in the risk analysis for propagating the basic event uncertainty. The probabilistic approaches deal with uncertainty, which is random in nature, while the fuzzy approach deals with the uncertainty, which is due to imprecision associated with the complexity of the system as well as vagueness of human judgement.

In that direction, Bellman and Zadeh [11] developed the fuzzy optimization model by providing the aggregation operators, which combine the fuzzy goals and fuzzy decision space. Park [12] used fuzzy set theory in the reliability apportionment problem for a two-component series system subject to single constraints and solved it by fuzzy nonlinear programming technique. Sakawa [13] used the surrogate worth trade off method to a multi-objective formulation of a reliability allocation problem to maximize the system reliability and minimize the system cost. Ravi et al. [14,15] implemented simulated annealing algorithm for several reliability optimization problems. Huang [16] presented a fuzzy multi-objective optimization decision making method of reliability of the series system. Mahapatra and Roy [17] proposed a new fuzzy multi-objective optimization method to solve reliability optimization problem having several conflicting objectives. Garg and Sharma [18] presented a methodology for solving multi-objective reliability redundancy allocation problem using PSO. Recently, Garg [19] solved the fuzzy multi-objective reliability optimization problem of an industrial system using PSO and compared their results with GAs.

The major focus of recent work on the redundancy allocation problems is on the development of heuristic/meta-heuristic algorithms for solving the redundancy allocation problems [3,20,22–24,21,25,26,18,28,27]. In the single objective optimization, one attempts to obtain the global solution/decision, but in multiple objective it is difficult or rarely possible to find one optimal solution which is best (global minimum or maximum) with respect to all the objectives. Today most of the real-world decision-making problems in economic, technical and environmental ones are multidimensional and multi-objective. In multi-objective optimization, there exists a set of solutions which are superior to the rest of the solution in the search space when all the objectives are considered, but are inferior to other solutions in the space in one or more objectives (not all). For handling such types of situations, one usually tries to search for a solution which is as close to the decision makers (DMs) expectations as possible. For this, the problem is solved interactive manner in which DM is initially asked to specify his or her preferences towards the objectives. Based on these preferences, the problem is solved and the DM is provided with a possible solution. If the DM is satisfied with this solution the problem ends there, otherwise he or she is asked to modify his or her preferences in the light of the earlier obtained results. This iterative procedure is continued till a satisfactory solution is achieved which is closed to DM's expectations.

As in the early stages, due to the non-availability of their distribution function of the product design, the reliability of component is treated as a positive number between zero and one. But the reliability of a component/system depends on operational and environmental conditions. Therefore, in order to handle the inaccurate parameter specified to the reliability, we have considered the reliability of each component as a triangular fuzzy number (TFN). For this, uncertainty parameter I is consider, as specified by the DM/system analyst towards the reliability of each component of the system, and based on that component reliability is measured in the form of TFN. The motivation of the work presented here is to give a method for solving bi-objective reliability-redundancy allocation problems of a series-parallel system, under fuzzy set environment, in which the decision variables may have real or integer values. The major contribution of the present work is with regards to reliability as a triangular fuzzy number and hence the considered problem is treated as a fuzzy reliability optimization model. The developed fuzzy model is converted to a crisp model by using the expected value of fuzzy numbers. A conflicting nature between the objectives is resolved with the help of defining their linear as well as non-linear membership functions. Also, the intention is to use an aggregate operator for aggregation of the different fuzzy goals and a robust global optimization technique for the solution of the resultant single objective optimization problem formulated with the DM/system expert's priority amongst the objectives. Finally, the so obtained crisp single objective optimization problem is solved with the help of PSO and compares their results with GA. The approach has been illustrated through an example of complex bridge and overspeed protection gas turbine systems.

The rest of the manuscript is organized as follows: the assumptions and notations which are used throughout the manuscript are given in Section 2. The basic definitions related to fuzzy set theory and their fuzzy number are presented in Section 3. Section 4 describes the general formulation of multi-objective nonlinear RRAP while the methodology for solving the fuzzy optimization problem has been presented in Section 5. An illustrative examples have been taken in Section 6 and their results are presented in Section 7. Finally, some concrete conclusions have been presented in Section 8.

2. Assumptions and notations

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

2.1. Assumptions

(i) The supply of components is unlimited.
(ii) The components' weight and volume are known and deterministic.
(iii) All the redundant components for individual subsystem are identical.
(iv) Failed components do not damage the system, and are not repaired.
(v) All redundancies are active: hazard function is the same whether it is in use or not.
(vi) Failures of individual components are independent.

2.2. Notations

Considering m-subsystems in the system, following notations have been used for the ith subsystems ($i = 1, 2, \ldots, m$).

n_i	the number of components in ith subsystem.
M	number of constraints.
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 ith subsystem.
r	$=(r_1, r_2, \ldots, r_m)$, the vector of component reliabilities for the system.