International Journal of Soft Computing 1 (1) : 1-7, 2006

An Intelligent System for Machine Replacement Policies

[1]D.J. Fonseca, [2]S.Shital and [3]G.P. Moynihan
[1]Department of Industrial Engineering, [2]Department of Industrial Engineering,
[3]Department of Industrial Engineering, The University of Alabama, USA

Abstract: This study describes the formulation of a general model for the decision support needs of maintenance and production managers while deciding upon machine replacement policies. The study also focused in the applicability of genetic algorithms to solve replacement models. A genetic algorithm based Decision Support System (DSS) was successfully developed to cope with such needs. The computer system replaces the intuitive, non-quantifiable, error-prone and time-consuming calculations currently employed by managers, by a more systematic and consistent approach to decision-making.

Key words: Replacement policies, genetic algorithms, decision support systems

INTRODUCTION

Replacement decisions are no longer a tactical exercise, but rather a strategic function. Equipment availability, at any given time, exerts a major influence on a company's survival[1]. Maintenance and production managers are usually the ones responsible for making machine replacement decisions. Such decisions, along with other maintenance management related issues, are becoming of prime importance in a fast changing world[2,3].

To determine the replacement of a particular piece of equipment, alternative scenarios (e.g. repairing the machine to as-good-as-new condition, replacing it with an identical new machine, or replacing it with a more technologically advanced apparatus) should be contemplated. Therefore, in most cases, it becomes virtually impossible for maintenance practitioners to make decisions based solely on their experiences [1].

As the managers make decisions based on intuition or personal experiences, many other problems may arise. First, there is a lack of formal procedure for making replacement and maintenance decisions. This may lead to huge production losses, inefficient use of available resources and a departure from organizational goals. Maintenance schedules may not be feasible, resulting in high maintenance costs and increased production downtime. In addition, inconsistencies in equipment maintenance operations may result in reduced machine lives and thus, higher replacement turnovers and poor quality of finished parts. As the decisions made by most managers usually lack any theoretical foundation, the likelihood of excessively high maintenance and replacement costs is considerable[4].

There is an unquestionable need for the development of versatile software packages to assist maintenance and production managers in the process of developing optimal replacement policies. Since intuitive techniques, coupled with working experiences, are normally used for preventive maintenance assessments, a Decision Support System (DSS) equipped with a non-exact reasoning inference mechanism, such as a Genetic Algorithm (GA) model, represents a viable means for developing optimal equipment replacement policies.

METRIALS AND METHODS

The literature discusses the importance of a Maintenance Management Information System (MMIS) to streamline the functioning of industrial maintenance activities. Such a MMIS should be capable of performing (apart from regular chores of maintenance activities) historical data analyses, maintenance resource planning and inspection and replacement task scheduling. Part of this broad MMIS should be encompassed by the development of a decision support system for machine replacement policies. This DSS would solve problems associated with replacement decisions by generating real-time optimal policies through theoretical models. It should also consider technological changes that may come about in the near future, bringing consistency to the process of decision making[5].

Tomsovic and Baer[6] stated that the traditional approach for machine replacement is based on a vendor's recommendations and is commonly for fixed time intervals only. To correct such a situation, they have proposed a guideline for the development of intelligent systems (i.e.,

Corresponding Author: D.J. Fonseca, Department of Industrial Engineering, The University of Alabama, Box: 870288 Tuscloosa, Al 35487-0288, USA

expert systems) for reliability management analyses. Their work focused on the design of a theoretic information framework for systematically assessing equipment condition and on the incorporation of this framework into maintenance, diagnostic and operational practices. They used fuzzy logic concepts for reliability calculations and inference algorithms.

Vatn *et al.*,[7] highlighted the importance of an overall model for maintenance optimization. They emphasized the need for a closer coordination between management and maintenance personnel. Depending upon management approved performance measures, the reliability analyst forms an overall loss function, which merges the various performance measures into an overall measure for goal achievements. Well-known models on component dependability and maintenance strategies were combined to obtain a complete structured approach for optimization. The approach, followed by the authors, was based on a general decision support system for maintenance optimization for entire manufacturing plants, rather than for individual processing machines.

Jardine *et al.*,[8] made a unique effort towards the development of a DSS for equipment maintenance and replacement for a naval dockyard. The developed DSS consisted of four modules: A data collection module, a most economic age model module, an interval replacement times module and an optimal inspection interval module. The data collection module takes into account parameters such as cost per parts, manpower and usage. The most economic age decision model considers discount rates, purchase price, resale value and maintenance costs. The interval replacement times module determines the optimal replacement policy based on the equipment's failure distribution. Finally, the optimal inspection interval module computes the optimal inspection intervals for multi-component systems so that worn components may be replaced before failure.

DESIGN OF THE SYSTEM

The purpose of this research was to formulate a general model for the decision support needs of maintenance and production managers on machine replacement policies, as well as to investigate the applicability of genetic algorithms to solve replacement models. A decision support system was developed to meet these needs. The objective was to develop a prototype system to replace the intuitive and non-quantifiable methods employed by managers with a systematic and more consistent approach to decision-making. Since genetic algorithms are search algorithms based on the mechanics of natural selection, they seem to be an appropriate means for solving replacement models.

The research was limited to assisting maintenance and production managers in the decision-making process for machine replacement times. The system includes a failure distribution module to fit four types of failure distributions and an optimal replacement policy module to generate optimal policies and to carryout "what-if" analyses with the help of six replacement algorithms. The system performs the following main tasks: determination of the failure distribution for a particular machine, determination of the parameters involved in the replacement decision-making, evaluation of different replacement models using a Genetic Algorithm (GA) model and development of a replacement strategy based upon the available information.

Four failure distributions, i.e., the Exponential, Normal, Log Normal and Weibull, were analyzed and their parameters estimated via Maximum Likelihood Estimators (MLE). A maximum likelihood estimator maximizes the probability that a given event becomes the most likely to have occurred for a given probability density function. The systems permits the decision-maker choose any of the above distributions to carry out "What-If" analyses.

Well-established replacement models were considered during the development of the DSS. The broad categories are replacement polices under minimization of Cost (C), minimization of downtime (DT) and combined effects. The replacement models considered under each broad category were the Constant Interval Replacement Policy (CIRP) and the Replacement at Predetermined Age (RPA) models.

The DSS considers a time horizon of up to 100,000 units of time or cycles. The optimal/near optimal replacement time, computed by the GA, is based on the time horizon selected by the user. By determining the upper limit on the search space, the GA investigates potential feasible optimal solutions with time frame boundaries. This can be used by the decision maker to make decisions for the time horizon considered as he/she may have reason to believe that the machine will be no longer in use after that time.

The system computes the optimal/near optimal replacement times for each machine rather than for a group of machines, i.e. no opportunity-based replacement is considered as the algorithm selected considers only single machine replacement decisions. The time for replacement, where the actual machine is taken out for repair, is not considered in the case of the cost-based replacement as the objective is to minimize the cost. Downtime does not affect this decision process, although it is considered for the downtime-based replacement.

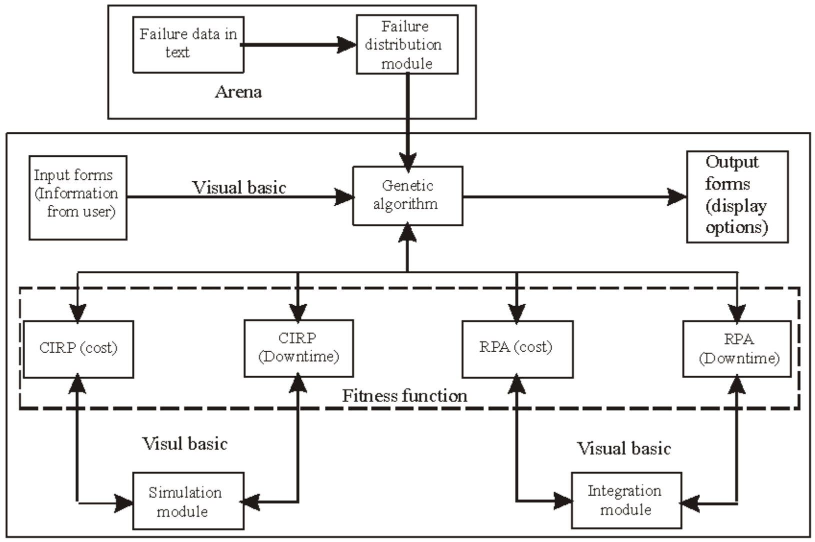

Fig. 1: DSS system architecture

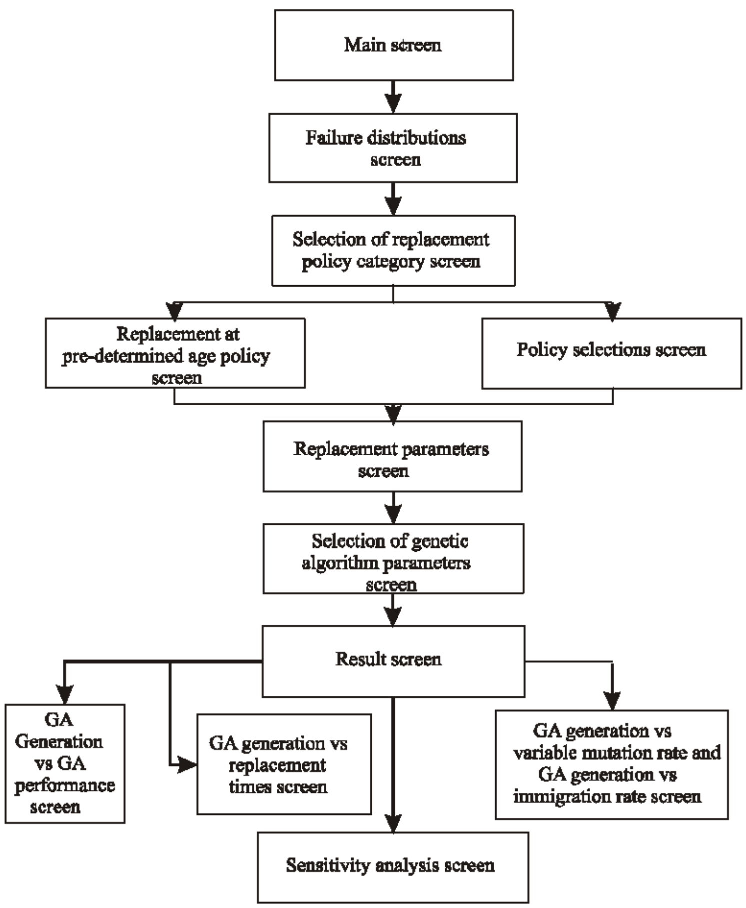

Fig. 2: System screen flowchart

Intermediate failure of machines is allowed during replacement periods as a part of the algorithm formulation, thus making it unsuitable for sensitive industries such as airlines. The decision-maker has the choice of either replacing or overhauling the machine to an "as good as new" state as both actions reduce the failure rate.

DESCRIPTION OF THE SYSTEM

The DSS was developed to cater to the needs of maintenance and production managers while deciding upon machine and equipment replacement times. There are well-established replacement models available in the literature. However, they are prone to calculation errors, variability of model selection from person to person and there may not be sufficient time for the decision-maker to formulate the policy and execute the models[1,2,9,10,]. Thus, a DSS freed from the of above limitations was needed. For this study, four replacement policy models were selected i.e. Constant Interval Replacement Policy (CIRP) under cost minimization as well as downtime minimization and the Replacement at Predetermined Age (RPA) under cost minimization as well as downtime minimization. The DSS uses the statistical capabilities of the Input Analyzer module of ARENA (a simulation software package) to estimate failure distribution parameters. Theoretical calculation of the expected number of failures is time consuming and requires an enumerative type approach. To overcome such a difficulty, the DSS uses a GA search mechanism to achieve better solutions. It also employs simulation and integration approaches to support the GA in exploring better solutions. Simulation and integration modules provide a supportive role for the objective or fitness function of the GA. The GA's search mechanism was further enhanced by using varying mutation rates, varying immigration rates and scaling of objective values.

The developed DSS has the ability to analyze different arising scenarios due to the combination of failure distributions, replacement polices and cost/downtime effects for replacement, i.e. to carry out "What-If" type analyses. What-if analysis has been widely implemented as a key feature in computer-based decision aids and Decision Support Systems (DSS). This DSS feature is needed for investigating various alternatives arising in the decision-making process and providing the decision-maker with the possible effects of various alternatives.

The user is given full control of guiding the GA search mechanism through the selection of various parameters used by the GA. Finally, the user is provided with a comprehensive analysis of the performance of the GA, i.e. the optimal/near optimal replacement times achieved under the specified conditions. This DSS has also the capability of carrying out sensitivity analyses to obtain the ten best solutions found in the search, so that the user can decide either to prolong or shorten the replacement times.

SYSTEM ARCHITECTURE

The DSS processing architecture consists of four main components. Failure distribution parameters are estimated through the Input Analyzer, which originates from ARENA. Once the failure parameters are defined, the GA Module starts the search for optimal solutions for the selected replacement policies. To further buttress the objective function of the GA mechanism, a Simulation Module and Integration Module, both developed in Visual Basic, are included in the system's design. Fig. 1 depicts the DSS system architecture, while Fig. 2 shows the hierarchy of the system's screens as they are normally navigated during a session.

GA search mechanism: GA's are search algorithms based on the mechanics of natural genetics and are a class of computer programs that use simulated evolution to solve problems. Genetic algorithms were inspired by Darwin's theory[11]. A genetic algorithm is initiated with a set of solutions (represented by chromosomes) called the population. Solutions from one population are taken and used to form a new population. This is motivated by a hope that the new population will be better than the old one. Solutions which form new solutions (offspring) are selected according to their fitness - the more suitable they are, the more chances they will have to reproduce. This is repeated until some condition (for example, the number of populations or improvement of the best solution) is satisfied[12].

The important decisions to be made for the GA formulation are the coding scheme (i.e. how will the chromosome be represented – binary or decimal), the objective function/fitness function formulation, the type of crossover, mutation and finally, the selection of good solutions for mating[13]. These decisions are made depending upon the problem at hand.

The replacement models considered by the DSS involve two factors: Replacement times and downtime/maintenance costs. The selected coding scheme consisted of a set of numbers (integers, from 0 to 9) which represents unique replacement times. Each bit position may take a value between 0 and 9. The user determines the length of the number of bits, thus providing an upper bound for the search space. Each set of n numbers forms a solution (i.e. replacement periods)

Table 1: Predictive validation case 1

Test Input/Output parameters	Input data	
Machine selection	M1001	
First parameter	2110	
Second parameter	1.21	
Replacement policy category	CIRP(Cost)	
Failure distribution	Weibull distribution	
Constant interval replacement policies	No	
Replacement at pre-determined age policies	Yes	
Cost of overhauling/ replacement	50	
Cost of breakdown replacement	100	
Time to perform overhauling/ replacement	-	
Time to Perform breakdown replacement	-	
Simulation replication	-	
Number of GA runs	50	
Population size	50	
Cross over rate	0.9	
Chromosome size	5	
Mutation rate	0.1	
Type of optimization	1	
Tournament selection	4	
Max value: First bit position	9	
Min value: First bit position	0	
	Expected outputs	DSS outputs
GA objective value	-	1.10679 E-7
Replacement times	8277	8277
Involved actual costs	6.7438E-06	3.3268E-4
Variation	-	0%
Top ten solutions	-	Ok

Table 2: Predictive Validation Case 2

Test Input/Ouput parameters	Input data	
Machine selection	M1001	
First parameter	1000000	
Second parameter	100000	
Replacement policy category	CIRP(Cost)	
Failure distribution	Normal distribution	
Constant Interval replacement policies	Yes	
Replacement at pre-determined age policies	No	
Cost of overhauling/ replacement	50	
Cost of Breakdown replacement	100	
Time to perform overhauling/ replacement	-	
Time to Perform breakdown replacement	-	
Simulation replication	10	
Number of GA runs	50	
Population size	50	
Cross over rate	0.9	
Chromosome size	8	
Mutation rate	0.1	
Type of optimization	1	
Tournament selection	4	
Max value: First bit position	9	
Min value: First bit position	0	
	Expected outputs	DSS outputs
GA objective value	-	2.148
Replacement times	800000-900000	1073688
Actual cost	0.000063	0.0000465
Variation	-	19%
Top ten solutions	-	Ok

by converting it into a complete number. For example, the set {5, 3, 8} represents a replacement period of 538 units. A unique feature of this type of coding scheme is that the individual bit positions are retained for carrying out crossover and mutation operations, while the converted complete number is used for calculation of the objective function. The replacement time search space range is from zero units to the upper limit of the search space, which ensures that the solutions generated are feasible ones.

The objective values for the various CIRP replacement policies have their own theoretical formulations, which are evaluated through the Simulation Module. For the RPA policies, the partial derivatives of the theoretical modelsare equated to zero and, after a

Table 3: Predictive validation case 3

Test Input/Output parameters	Input data	
Machine selection	M1001	
First parameter	1000000	
Second parameter	100000	
Replacement policy category	CIRP(Cost)	
Failure distribution	Normal Distribution	
Constant Interval replacement policies	Yes	
Replacement at pre-determined age policies	No	
Cost of overhauling/ replacement	-	
Cost of breakdown replacement	-	
Time to perform overhauling/ replacement	25000	
Time to perform breakdown replacement	50000	
Simulation replication	10	
Number of GA runs	50	
Population size	50	
Cross over rate	0.9	
Chromosome size	8	
Mutation rate	0.1	
Type of optimization	1	
Tournament selection	4	
Max value: First bit position	9	
Min value: First bit position	0	
	Expected outputs	DSS ouputs
GA objective value	-	1.6219
Replacement times	800000-900000	888888
Actual cost	0.000064	0.0002735
Variation	-	4.5%
Top ten solutions	-	Ok

mathematical manipulation, they are used to calculate the objective function. This is done via the Integration Module. For combined policies, the objective values for the individual policies are computed and combined through a factor-weighing scale defined by the user.

Simulation module: For the CIRP policies, there is a need for calculating the expected number of failures occurring in the time period under consideration. The theoretical method for performing such calculations includes integration of the probability distribution function to assess the failure rate. This takes a considerable amount of time and effort if manually computed. It then becomes an enumerative type of approach and requires prior knowledge of the behavior of the machine as well as the probable times for component failures. The general mathematical formulation for the expected number of failures is described[2]:

$$M(T) = \sum_{i=0}^{T-1} [1 + M(T - I - 1)] \int_{i}^{i+1} f(t)dt \quad (1)$$

with : $T \geq 1$, $M(0) = 0$

To avoid the difficulties of computing such an integral, a simulation approach was followed. The failure distribution parameters, based on a random number generation, are used by the Simulation Module to compute simulated failure times. These times are then added to the simulation clock so that component failures can be counted. The GA carries out this process until the simulation clock crosses the replacement time under consideration. This approximate method needs statistical confidence, which is provided by the simulation replications. This smoothes the variations in the expected number of failures, providing consistent and reliable results.

Integration module: The replacement policies for RPA require the integration of either a reliability factor or a probability density function. Simpson's 3-point rule was used in this study for such a computation (Dodson, 2001). This algorithm is valid for integration between two known limits.

The GA model sends the replacement times to the Integration Module, which in turn carries out the required computations. This module returns a final calculated value for the policy, which is used as the objective value for the GA solutions. For the RPA cost and downtime, the GA objective functions represent their own respective theoretical formulations. For the combined policy, the formulations of each version of the policy are solved and then combined depending upon the user's provided preferences.

VALIDATION OF THE SYSTEM

Case scenarios from domain experts and the available literature were used to validate the system. Expected and achieved results from three test cases are shown in

Tables 1-3. After analyzing the results from the predictive validation tests, it is concluded that the system generates satisfactory results when compared against computed theoretical values. The test cases results were within ± 10% of the expected values.

CONCLUSIONS

The purpose of this study was to formulate a general model on the decision support needs of maintenance and production managers when deciding upon machine replacement policies, as well as to investigate the applicability of genetic algorithm to solve replacement models. A decision support system was successfully developed to address such needs. The DSS system replaces the intuitive, non-quantifiable, error-prone and time-consuming calculations currently employed by managers, by a more systematic and consistent approach to decision making.

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