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Identification of optimal preventive maintenance decisions for composite components

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Abstract

This research proposes a decision support tool which identifies cost-optimal maintenance decisions for a given planning period. Simultaneously, the reliability state of the component is kept at or below a given reliability threshold: a failure limit policy applies. The tool is developed to support repair-or-replacement decision making for composite components likely to suffer impact damage. As a core part of the tool, a cost minimization problem is defined and solved using a search tree algorithm with heuristic constraints. Application to a case study which utilizes historical damage data and subsequent simulation shows the potential of the tool to identify cost-minimal maintenance decisions. The decision support tool is capable of incorporating a wide range of parameters to study preventive maintenance decision making in depth.

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Keywords: Aircraft maintenance; composites; decision support; preventive maintenance optimization

1. Introduction

The latest generation of wide-body transport aircraft shows a significant increase in composite structures, as evidenced in the Boeing B787 and the Airbus A350 XWB. The B787 is the first commercial aircraft to use Carbon Fiber Reinforced Plastic (CFRP) for the entire pressurized fuselage (Dhanisetty et al., 2016). Besides the fuselage, B787 uses composites for the windows, wings, tails and stabilizers, resulting in approximately 50 % share of the total weight (Zhao et al., 2014). The introduction of composites into primary structures brings the advantage of

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weight savings and therefore potential for generating fuel savings for airlines. However, compared to the decades-long experience with aluminum structures, there is a relative lack of experience of using and maintaining composites in these primary aircraft structures. In particular, the frequency, severity and rectification of impact damage are difficult to forecast, as limited historical data is available. This poses a challenge with respect to ensuring aircraft airworthiness over longer periods of time. Consequently, conservative approaches are adopted to ensure safe aircraft operations. In addition, regulatory requirements on maintenance stipulate the implementation of reliability programs to monitor and improve aircraft reliability over time.

Within the research domain of reliability engineering, significant amounts of research have been performed under the assumption of non-repairable systems, as noted by previous authors (Crow, 1990; Love and Guo, 1993; Weckman et al., 2001). However, this assumption is not valid for composite systems, which can be characterized as being repairable. When considering existing research on repairable systems (Chen and Feldman, 1997; Doostparast et al., 2014; Jayabalan and Chaudhuri, 1992a; Jayabalan and Chaudhuri, 1992b; Lie and Chun, 1986; Love and Guo, 1996; Nguyen and Murthy, 1981), it can be generally noted that strong assumptions are made when connecting reliability output with maintenance planning and control. Costs are sometimes treated as a continuous function rather than a discrete time event, which does for instance not match with composite impact damage events. Frequently, repairs are assumed to bring the component back to an 'as-good-as-new' state, which may not be true for particular composite impact damage failure modes. Furthermore, maintenance planning solutions are often obtained using optimization techniques which only estimate the solution area (as shown in (Doostparast et al., 2014; Jayabalan and Chaudhuri, 1992a; Jayabalan and Chaudhuri, 1992b)). Combinatorial, precise calculations are avoided due to the extensive computational effort involved in such an approach. Taking into account the mismatch between the aforementioned strong assumptions and real-life maintenance applications as well as the use of imprecise solution methods, a lack of application of existing optimization models for preventive maintenance can be distinguished in practice (Dekker, 1996).

Given these factors, this research aims to develop a practical decision supporting tool, which identifies cost-optimal maintenance decisions for a given planning period. Simultaneously, the reliability state of the component is kept at or below a given reliability threshold. The tool applies to composite components likely to suffer impact damage.

In Section 2, existing techniques to perform reliability analysis for composite components are investigated, together with uptake in preventive maintenance decision making. Subsequently, Section 3 describes how failure of repairable components is modelled using a Generalized Renewal Process (GRP). Furthermore, modelling of maintenance cost as discrete time events is described, which allows to realistically represent practical conditions. Reliability and cost serve as inputs towards optimization of long-term planning problems, where application of a Search Tree algorithm allows to find a precise combinatorial solution. In order to reduce the computational effort and solve long term planning problems, realistic heuristic constraints are identified and applied. The reliability, cost and optimization models are implemented in a decision support tool. In Section 4, a numerical case study has been devised on the basis of simulated damages generated by a Monte Carlo approach. Results are presented and analyzed. Sensitivity analysis is employed to present the impact of selected parameters on the resulting maintenance costs. Finally, conclusions and recommendations for future research are given.

2. Theoretical context

Preventive maintenance (PM) is a scheduled maintenance event, which triggers a planned maintenance task. It is often assumed that a component is replaced at a PM maintenance event. However, for repairable components, such as composites, both types of maintenance action (repair or replacement) can be feasible. The aim of the preventive maintenance is to improve the reliability state of the component. Several subpolicies can be identified as part of preventive maintenance; in this paper, the focus is on a failure limit policy (Pham and Wang, 1996), where the reliability of a given component must not drop below a given threshold.

To apply a failure limit policy towards maintenance planning, it is imperative to estimate component reliability. Many research efforts have focused on non-repairable systems (Crow, 1990; Love and Guo, 1993; Weckman et al., 2001). The general approach when analyzing the reliability state of a non-repairable system is to use renewal theory, which reduces the considered system to a single component [4] with only two states: operating and failed. Such a system neglects the influence of imperfect maintenance by assuming that the state of the component after maintenance is as good as new. This assumption is not necessarily valid for systems consisting of composites, which are 1) repairable in nature and 2) may not be subject to maintenance which brings the condition back to an as-good-as-new state. As such, reliability models for repairables which are able to incorporate repair efficiency should be considered to model composite components. Examples are Generalized Renewal Processes, with Kijima Type-1 and Type-2 models seeing considerable uptake in scientific literature (Kijima, 2016; Yañez et al., 2002).

In order to develop a maintenance schedule for preventive maintenance, traditional approaches rely on algorithms with the ultimate goal to decide whenever a component should be replaced or be repaired. In Nguyen and Murthy (1981), a study is presented which solves the problem of optimal preventive maintenance (PM) under the assumption of an infinite time horizon. The author assumes that the failure rate increases with the number of carried out repairs. It is shown that depending on the initial assumptions, the developed schedule results into two unique solutions (replacement only policy and repair only policy). In Jayabalan and Chaudhuri (1992b), an algorithm is presented which creates a preventive maintenance policy for the case of imperfect maintenance under the assumption of a constant improvement factor (i.e., repair efficiency). The improvement factor describes the quality of performed maintenance. The maintenance actions are carried out whenever the system reaches the predefined maximum failure rate. The cost estimation is based on constant cost factors for replacement and repair which both are influenced by the interest rate over time. The same authors made an extension (Jayabalan and Chaudhuri, 1992a) by presenting a branching algorithm with effective dominance rule to reduce the computational time. In Chen and Feldman (1997), an optimal replacement model using three states (operating, replacement and repair) is introduced. The assumption of minimal repairs is made. It means after the component is repaired the reliability of the component is as good as shortly before failure (as good as old). The states are changing at time of failure (corrective maintenance). In Love and Guo (1996), the repair limit analysis is extended by including the changing force of mortality with the age of the unit. In Lie and Chun (1986), the improvement factor as a function of repair cost and age of the unit is proposed. It presents an algorithm with two states of a system (operating or failed). The cost estimation is done based on an average cost-rate between cycles. Finally in Doostparast et al. (2014), the problem of reliability-based periodic preventive maintenance planning for systems with deteriorating components is studied. The model shows three states (simple service, preventive repair and preventive replacement). The infinite planning horizon is divided into equal intervals. For any interval, a decision between those states must be made.

Generally, a lack in implementation of developed models and policies was recognized in Dekker (1996). It is caused by made unrealistic assumptions, leaving a gap between theory and practice (Dekker, 1996). A common assumption is the estimation of maintenance cost as a continuous function (Chen and Feldman, 1997; Jayabalan and Chaudhuri, 1992a; Jayabalan and Chaudhuri, 1992b; Love and Guo, 1996). This assumption does not always reflect reality since maintenance costs can be related to discrete events such as impact damage, where the actual costs are strongly dependent on the occurred damage. Furthermore, an assumption of a constant improvement factor missing any connection to the reliability analysis was noticed (e.g. in (Chen and Feldman, 1997; Jayabalan and Chaudhuri, 1992a; Jayabalan and Chaudhuri, 1992b)). In Love and Guo (1996), a fuzzy graphical solution method for determination of the improvement factors is presented. This method neglects any direct reliability data dependence showing a dependence on maintenance cost and system age. In Chen and Feldman (1997), the improvement factor is neglected completely by providing only one type of repair (minimal repair).

Furthermore, maintenance planning solutions are often obtained using optimization techniques which only estimate the solution area (as shown in Jayabalan and Chaudhuri (1992b), Jayabalan and Chaudhuri (1992a), Doostparast et al. (2014)). Combinatorial, precise calculations are avoided due to the extensive computational effort involved in such an approach.

3. Decision support tool for preventive maintenance planning

On the basis of the preceding discussion, a decision support tool has been developed with the capability to incorporate the output of reliability models for repairable systems and discrete event cost modelling. Furthermore, it incorporates an optimization approach tailored towards structured exploration of the solution space. In the next subsection, the logic flow and main elements of the decision support tool are highlighted. This is followed by a more in-depth look at the related cost models and optimization approach.

3.1. Decision support tool: logic and flow

The decision supporting tool logic is presented in Fig. 1. The starting point is the availability of maintenance data, where for a given component the occurred damage, type of repair and time of failure are listed. Based on that data the reliability parameters can be obtained. Reliability analysis is performed using a repairable system approach, namely the Generalized Renewal Process (GRP), where the concept of virtual age is introduced to model system condition and associated repair effectiveness. In essence, a virtual age of 0 corresponds to a new component, with subsequent use being reflected by an increase in virtual age. Subsequent repair activities can 'turn back the clock'; with a fully effective repair, the component is repaired to an as-new state. However, repairs can also be less than 100% effective, resetting virtual age only partially. Based on historical event data (e.g. failure times or damage occurrence times), the GRP model can be used to estimate the intensity function *λ(t)* and its associated parameters, utilizing Monte Carlo simulation for parameter estimation.

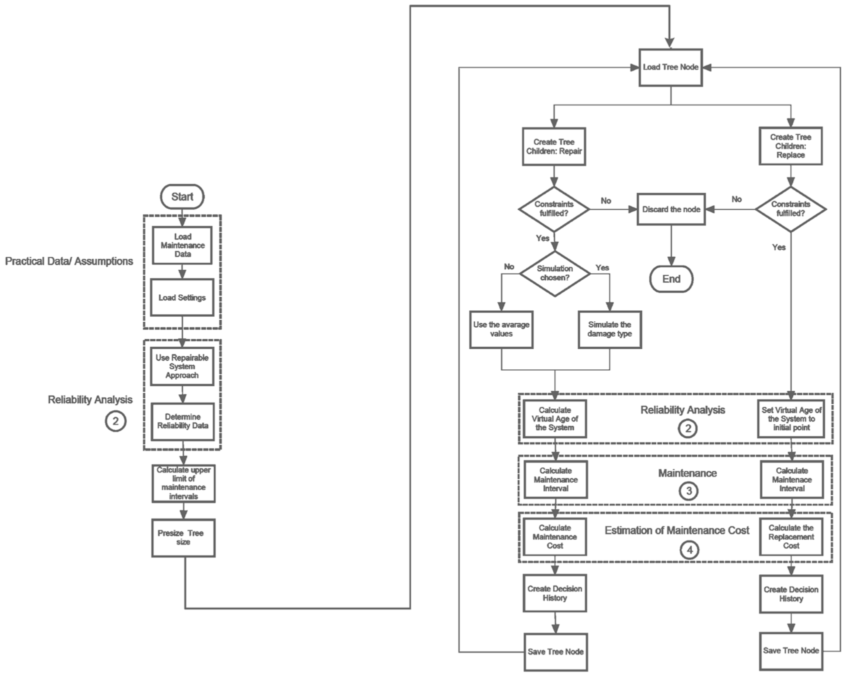

Fig. 1. Decision support tool flowchart

To make the connection between reliability analysis and subsequent planning optimization, the decision support tool is realized using three states: operating, repaired and replaced. In keeping with the failure limit policy, the switch between states is triggered by the maximal allowable value of the intensity function λ_{max}, whenever the component intensity function $\lambda(t)$ reaches λ_{max}. The policy is visualized in Fig. 2.

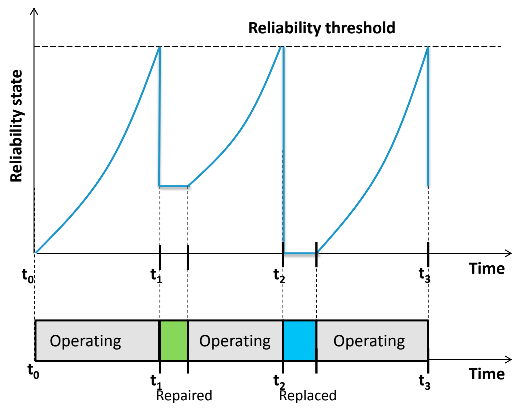

Fig. 2. Failure limit policy and repair / replacement impact

Over time, a maintenance schedule can be composed. This schedule is constituted by a sequence of states, including repair and replacement decisions. The next subsection describes the approach to model and optimize this scheduling effort.

3.2. Optimization approach

The components of the optimization problem can be captured in the following description:
"For a given time period, find a maintenance plan, which optimizes the cost of preventive maintenance, by simultaneously keeping the reliability state of the system at or below a predefined threshold".

3.2.1. Optimization model

The objective function and associated constraints are stated below:

$$Min\ C(D,t) \tag{1}$$

Where D = Maintenance Decision, with

$$t_i = \sum_{n=1}^{i}\left(1-\frac{1}{\alpha}\right)^{i-1} + t_{maintenance} \tag{2}$$

$$t_1 = f\left(\lambda(t)\right) \tag{3}$$

$$t_{maintenance} = f\ (D) \tag{4}$$

Where t_1 is the time of the first maintenance event, which depends on the intensity function obtained from reliability analysis as well as the maximum attainable value of the intensity function; t_i represents the i^{th} maintenance event where a component is restored to its virtual age, which is dependent on the improvement factor α

(also known as repair effectiveness); and $t_{maintenance}$ is time required to fulfil the maintenance event, which may be a repair or a replacement action, and is therefore dependent on the maintenance decision.

To evaluate cost, replacement cost and repair costs are considered for preventive maintenance. The costs for replacement are calculated using:

$$RC = \overline{RC}\ (1+r)^t \tag{5}$$

Where $\overline{\mathrm{RC}}$ represents the summed costs of replacement activity and component purchase price (see eq. 6), with r representing an inflation rate which is applied using operational time t.

$$\overline{RC} = RC_{purchase} + RC_{installation} \tag{6}$$

The costs for repair are calculated using:

$$MC = \overline{MC}\ (1+m)^t \tag{7}$$

Where $\overline{MC}$ represents a constant repair cost, which is subsequently inflated by a rate m.

3.2.2. Solution technique

To solve the introduced optimization problem, a Search Tree Algorithm is applied. This is a well-known technique which allows to explore the state space of a given problem by its predefined tree paths. That way it allows generating combinatorial solutions. The logic of the algorithm is presented below as a pseudo algorithm.[†]

```
Create initial node
Calculate the upper limit of maintenance events - n

for i = 1 : n
        for j = 1 : 2^i
                Create Node
                        if ((condition 1)) & ((condition 2)) &. . .& ((condition n))
                                Save Node
                        else
                                Branch Node

                        end
        end
end
```

A generic example of a binary search tree is given in Fig. 3. To maintain overview, only the return of the reward function C is shown. The reward function is also known as the objective function. It is the function which has to be optimized (e.g. cost function). The decisions are marked by the letters R (replacement) and M (repair). Using backwards iteration, the total reward can be obtained (see green route in**Error! Reference source not found.** Fig.

† The actual algorithm was programmed in Matlab R2014b

3). Backwards iteration means that starting from the end node, the total reward is calculated by following the unique path to the initial node. The nodes values are summed up to generated the total reward of the solution (see eq. 8).

$$C_{sol,1} = C_{1.1.1} + C_{1.1} + C_1 + C_0 \tag{8}$$

In order to explore the complete state space and find the optimal solution, this procedure has to be done for each path. The set of solutions C_{sol} contains each possible path, which can be used to establish the optimal solution (see eq. 9).

$$C_{sol} = \min[C_{sol,i}] \tag{9}$$

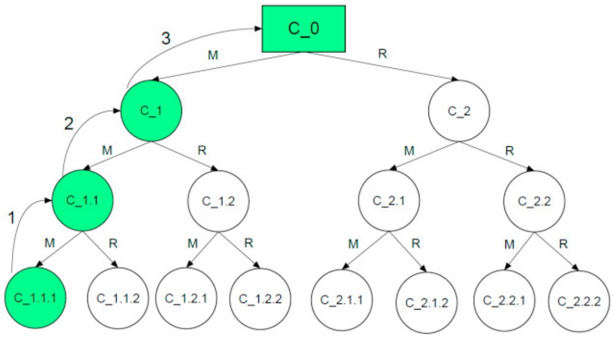

Fig. 3. Symmetric binary tree with backwards iteration

To restrict the number of possible options (and thereby the search space and associated computational time), heuristics can be used to constrain the search. Examples will be shown in the next section.

The Search Tree algorithm has been implemented in the decision support tool to solve the aforementioned optimization problem. The decision support tool output consists of the minimum cost solution, which comprises a sequence of maintenance activities (repair or replacement decisions at specific points in time), with associated total costs (consisting of the summed repair and replacement decisions over the life of a component).

4. Results

4.1. Input

The decision support tool (DST) has been implemented in Matlab. On the basis of this tool, a numerical case study has been performed to test and validate the functionality. The available inputs are presented in Table 1, with Table 2 showing the inputs related to the results presented in this section. For some variables, the values can be varied across a range (e.g. the improvement factor, which varies from 1 ('bad-as-old') to 10 (highly effective repair, though not 'as-good-as-new'); time of first maintenance; cost coefficient). With respect to the latter, the cost coefficient is introduced to describe the relation of replacement cost to the cost of repair. For instance, a factor of 3 represents the case where the costs for the replacement are 3 times higher than the costs for repair. Furthermore, two entries are of particular note:

1. **Option for damage simulation:** a Monte Carlo simulation which generates damage events over time can be incorporated. The underlying distribution of the MC simulation is based on distribution fitting of historical data of damage events on secondary composite structures (e.g. flaps, slats).

2. **Probability of damage occurrence:** the MC simulation generates damage events, but these have to be translated to failure modes. Five failure modes (debond; delamination; through damage; surface damage; heat damage) are considered. Each is associated with a certain (constant) probability of occurrence, which is applied to the MC output to generate failure mode-specific events. The probabilities of occurrence are generated on the basis of historical data of impact events and associated consequences.
3. **Search heuristics:** For the heuristics, it is assumed that a composite component can be repaired five times in a row before a replacement needs to be performed. Additionally, it was assumed that the optimal solution cannot be obtained by replacing a component twice in a row. This assumption is not valid if the cost for replacement and the cost for repair are nearly the same. Both assumptions are used to branch corresponding combinations allowing to solve long term planning problems.

Table 1. DST general settings

	Description	Values	Units
General Settings	Planning Period	15/30	months
	Option for damage simulation	on/off	-
Reliability Parameters	Improvement factor	1-15	-
	Initial failure rate	10^{-5}	-
	Maximal failure rate	10^{-4}	-
Maintenance Data	Component age	0	months
	Time of the first maintenance	1-8	months
	Time to repair	0.2	months
	Time to replace	0.4	months
Probability of damage occurrence	Debond	20	%
	Delamination	25	%
	Through Damage	5	%
	Surface Damage	40	%
	Heat Damage	10	%
Cost Parameters	Cost Coefficient	1-10	-
	Initial Cost	0	man-hours
	Cost for repair	50	man-hours
	Cost for replacement	50-500	man-hours
	Inflation rate	4	%/year
Search Heuristics	Max. numb. of repairs[1]	5	-
	Max. numb. of replacements [1]	1	-

Table 2. DST case study settings

	Description	Values	Units
General Settings	Planning Period	**30**	months
	Option for damage simulation	**on**	-
Reliability Parameters	Improvement factor	**3**	-
	Initial failure rate	10^{-5}	-
	Maximal failure rate	10^{-4}	-
Maintenance Data	Component age	0	months
	Time of the first maintenance	3	months
	Time to repair	0.2	months
	Time to replace	0.4	months
Damage type probability	Debond	20	%
	Delamination	25	%
	Through Damage	5	%
	Surface Damage	40	%
	Heat Damage	10	%
Cost Parameters	Initial Cost	0	man-hours
	Inflation rate	4	%
	Cost for replacement	150	man-hours
	Cost for repair: Debond	37	man-hours
	Cost for repair: Delamination	45	man-hours
	Cost for repair: Through Damage	120	man-hours
	Cost for repair: Surface Damage	50	man-hours
	Cost for repair: Heat Damage	54	man-hours
Search Heuristics	Max. numb. of repairs[3]	5	-
	Max. numb. of replacements [3]	1	-

4.2. Results and sensitivity analysis

With the parameter settings as given in Table 2, the MC simulation for damage has been run 100 times per damage event occurrence, helping to generate an acceptable spread in damage type probabilities.

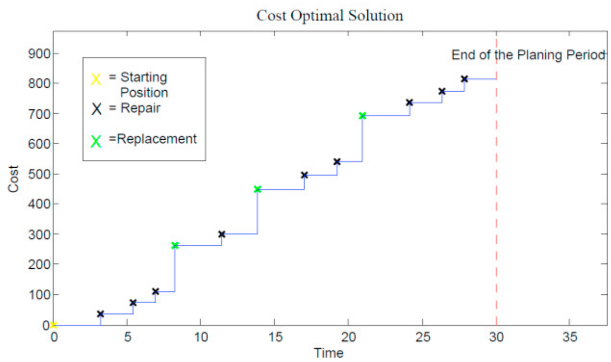

Fig. 4. Cost optimal solution

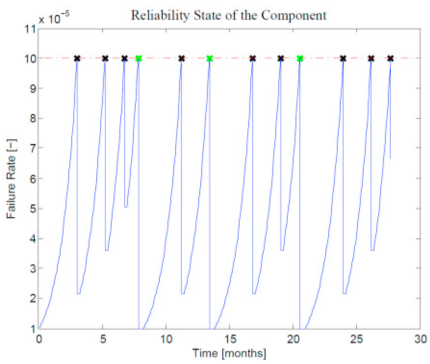

Fig. 5. Reliability behavior in optimal solution

Error! Reference source not found. Fig. 4 visualizes the cost optimal output. Here, the proposed optimal solution can be observed as a sequence of repair and replacement decisions, in the order MMMRMRMMMRMMM, with M representing a repair decision and R representing a replacement decision. The associated costs and times can be observed in the graph. Fig. 5 shows the resulting reliability behavior over time, with a clear representation of the failure limit policy, as well as the effect of repair efficiency (i.e., improvement factor) on the failure rate.

To investigate the effect of parameter settings, a systematic sensitivity analysis has been performed. The majority is omitted here, but one parameter variation is shown as a representative example. Table 3 shows the related inputs, where the improvement factor is studied across a range from 1–15. To allow for a full search, the heuristic constraints have been omitted in the analysis. The output of the sensitivity analysis is visualized in Fig. 6. An increase in improvement factor corresponds to an increased repair quality, which leads increased preference for repair decisions. Two unique solutions, being repair only and replacement only policies, can be identified at the edges of the improvement factor range.

Table 3. Sensitivity analysis settings

	Description	Values	Units
General Settings	Planning Period	15	months
	Option for damage simulation	off	-
Reliability Parameters	Improvement factor	**1-15**	-
	Initial failure rate	10^{-5}	-
	Maximal failure rate	10^{-4}	-
Maintenance Data	Component age	0	months
	Time of the first maintenance	3	months
	Time to repair	0.2	months
	Time to replace	0.4	months
Cost Parameters	Cost Coefficient	**3**	-
	Initial Cost	0	man-hours
	Cost for repair	50	man-hours
	Cost for replacement	150	man-hours
	Inflation rate	4	%/year

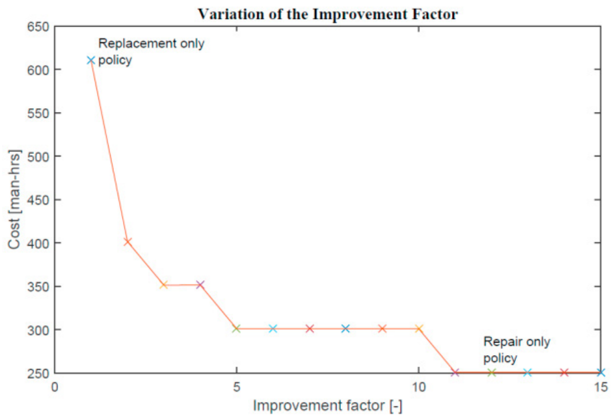

Fig. 6. Improvement factor sensitivity

5. Conclusions

A decision supporting tool has been presented which identifies cost-optimal maintenance decisions for a given planning period. It uses the failure limit policy in combination with a Generalized Renewal Process modelling approach to ensure maintenance action before a critical threshold. By incorporating a Search Tree optimization technique in combination with heuristics, the formulated cost optimization problem can be solved successfully, leading to identification of cost-minimal maintenance decisions. The decision support tool is capable of incorporating a wide range of parameters to study preventive maintenance decision making in depth.

Limitations of the proposed solution concern the use of historical data from secondary composite structures to simulate damage to primary structures. Both the frequency of failures and the failure mode distribution may vary significantly for primary structures, as the operational characteristics for these structures can be quite different. Furthermore, the used solution technique is only capable of fast generation of solutions if the number of nodes is limited, or if heuristics are used to direct the search. Alternative solution techniques will be investigated in future research.

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