

Modeling the Uncertainty of the Remanufacturing Process for Consideration of Extended Producer Responsibility (EPR)

Michael R. Johnson and Ian P. McCarthy

Abstract—There is a growing body of evidence to support the proposition of product take back for remanufacturing particularly within the context of Extended Producer Responsibility (EPR). Remanufacturing however presents challenges unlike that of traditional manufacturing environments due to its high levels of uncertainty which may further distract organizations from considering its potential benefits. This paper presents a novel modeling approach for evaluating the uncertainty of part failures within the remanufacturing process and its impact on economic and environmental performance measures. This paper presents both the theoretical modeling approach and an example of its use in application.

Keywords—Remanufacturing, Demanufacturing, Extended Producer Responsibility, Sustainability, Uncertainty.

I. INTRODUCTION

UNDERSTANDING the “greening” of supply chain management and reverse logistics has become a necessary management practice as companies today clearly recognize the impact of environmental innovation on corporate competition. Moreover in recent years, various factors such as complex environmental regulations, evolving financial and competitive pressures, and increasingly demanding customers, have escalated the importance of sustainable supply chain management and reverse logistics [1].

Literature today clearly demonstrates that sustainability through remanufacturing, recycling and reverse logistics is an important and needed area of current and future research [2]. Product remanufacturing occurs where a retired product is returned (or collected through takeback schemes such as leasing or deposits), followed by a process of product disassembly, cleaning and rebuilding the product to specifications of the original manufactured product [3]. Product demanufacturing focuses on evaluating the economic and environmental implications of material recycling, part reuse, part remanufacturing, shredding and landfill options. The central question of demanufacturing is the amount of disassembly efforts that should be invested in order to derive

“value” from the retired product [4, 5].

Remanufacturing today is a multi-billion dollar industry [6, 7] and has grown in importance over the past two decades. One reason for this growth is due to the growing body of legislation and policies associated with “Extended Producer Responsibility”(EPR). The primary aim of EPR is to increase the amount and degree of product recovery and minimize the environmental impact of waste materials. For example, the EU directive on Waste Electronics and Electrical Equipment (WEEE) has explicitly made recoverability improvements as an objective for the national regulations of member states by setting specific recovery rate targets for different product categories [8]. In the past two decades, policies on EPR continue to expand and have been implemented worldwide for a wide range of products.

Despite the potential environmental and economic rewards associated with remanufacturing, there is still limited quantitative models to allow OEMs or third parties the ability to understand and evaluate the take-back strategy of remanufacturing [9]. OEMs and third party organizations have few analytic tools to evaluate performance measures such as transitions costs, economic gains or environmental benefits when trying to incorporate remanufacturing into their current business processes. Furthermore, remanufacturing presents challenges unlike that of traditional manufacturing environments due to its high levels of uncertainty which may further distract organizations from considering its potential benefits.

The purpose of this paper is to demonstrate an approach to evaluate the uncertainty associated with the possibility of parts failing during the remanufacturing process and the impact of the quality of returned cores on the economic and environmental outcomes within an EPR environment. Using the developed model, an OEM (or third party remanufacturer) may assess the feasibility of remanufacturing taking into account such uncertainties and the possible increased cost associated with poor core quality or part failures in remanufacturing. This methodology provides a medium for improved decision making on product remanufacturing within the context of mandated or voluntary takeback systems.

II. LITERATURE REVIEW

Remanufacturing presents a number of special problems compared to a traditional manufacturing system due to high levels of uncertainty. Specific problems include uncertainty

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with material recovery (i.e., the return flow of cores), probabilistic routings within the remanufacturing process, the quality of returned items, and the required process times of remanufacturing [10, 11].

The uncertainty of remanufacturing makes it comparatively more complex to manufacturing causing challenges in the way that the supply of returned products is unpredictable in timing and quantities; the quality and composition of returned products varies; and the process routings of remanufacturing are not necessarily fixed [12, 13]. Tang (2012) [13] provides a review and classifies the breadth of remanufacturing research on uncertainty into three categories: (1) remanufacturing with uncertain demand and returns, (2) remanufacturing with uncertain quality of returns, and (3) uncertainty in remanufacturing production, planning and scheduling. The current literature review will focus on research related to the present study on remanufacturing with uncertain quality of returns. For a review of uncertain demand and returns; and production, planning and control, the reader is directed to [13].

Probabilistic routings occur because remanufacturing operations are only performed as necessary (e.g., the part needs the operation to be returned to a usable condition) and there is also the possibility of part failure during the remanufacturing process itself. Remanufactured parts may be scrapped due to a part being worn beyond practical or economic repair in an effort to meet defined remanufacturing specifications [10, 14].

The majority of recent papers in this area focus on evaluating the impact of quality uncertainty on remanufacturing decisions for an existing remanufacturer in operation. For example, [15] conducted a numerical study of the impact of uncertainties on remanufacturing behaviours. This author developed a stochastic remanufacturing model to provide insights into the structure of an optimal coordination of production, remanufacturing and disposal decisions in a stochastic multi-period setting. Azadivar and Ordoobadi (2010) [9] developed a quantitative approach for making decisions on whether to recycle the good parts recovered from returned products into remanufactured products that could be sold at after-market prices. The authors also demonstrated how a simulation model can be used to estimate very complicated parameters that affect justification of remanufacturing policies.

Many consider along the same lines of analysis and consider both single and multiperiod time horizons of remanufacturing decisions [16, 17, 18 and 19]. Few papers however recognize that making a transition from a manufacturer to a combined manufacturer-remanufacturer operation requires an earlier viewpoint of remanufacturing analysis. That is, given a product that has market potential (i.e., demand) how can one produce an earlier assessment of the product's economic and environmental benefits given the uncertainty of quality in returned cores? No past research efforts have been found to account for such variability within an initial assessment of evaluating remanufacturing versus demanufacturing alternatives for EOL products. This topic would seem to be timely given the growing state of EPR

legislation worldwide and the challenges that such policies present to manufacturing companies or entrepreneurial companies considering product takeback schemes.

III. PROPOSED MODELING APPROACH

Uncertainty can be dealt with in several ways; by employing Bayesian statistics, by introducing stochastic variables, however the most general and versatile way of dealing with uncertainties is to introduce the theory of fuzzy sets. The theory of fuzzy sets allows one to model the uncertainties in any desired way (using either discrete or continuous distributions). After modeling the uncertainty, a Monte Carlo simulation technique can be employed to simulate the behavior of some chosen response variables (forecast cells) numerically when the source variables (assumptions cells) are varying throughout a large number of trials according to the modeled uncertainty associated with each assumption cell. This approach allows one to study a spectrum of outcomes - from worst case to best case - for each forecast cell. In this paper, this technique is used to predict the variability of forecasted economic and environmental variables of product remanufacturing.

This research paper presents an approach to take into account two forms of typical remanufacturing uncertainties: (1) the quality of returned cores, and (2) the probability of part failure within the remanufacturing process. As previously discussed, not every part that is destined for remanufacturing actually gets remanufactured because of the possibility of a component being damaged beyond reparation [10, 14]. Likewise, the quality of returned cores will influence the likelihood of the product being successfully remanufactured or not. Upon initial screening of the quality of a returned core, the product is either sent to be remanufactured or demanufactured. Both forms of remanufacturing uncertainty will influence the following outcomes:

- the quantity and mass of components remanufactured and demanufactured.
- the economics of remanufacturing: revenue and costs will fluctuate depending on parts being remanufactured versus demanufactured.
- the quantity and costs associated with new replacement parts.
- the actual amount of recycling and disposal: if the product is initially sent to be demanufactured instead of remanufactured due to poor core quality, the mass destinations of recycling, remanufacturing and disposal will vary.

Furthermore, if a product is sent to be remanufactured but a part fails within the remanufacturing process, the part is demanufactured which further varies the degree of recycling and disposal determined.

A. Remanufacturing Plans versus Remanufacturing Events

Certain definitions are necessary to gain further understanding of the uncertainty involved. In this research, we define an "optimal remanufacturing plan (ORP)" as a strategy or plan that consists of a "parts list" for

remanufacturing and a "part list" for demanufacturing (generated based on economic decision making). Note however that parts that are to be remanufactured within an ORP may actually fail during the remanufacturing process. Therefore, for any given remanufacturing plan (i.e., a defined list of parts to be remanufactured), it is possible to have more than one "remanufacturing event" or outcomes associated with the remanufacturing process (i.e., parts failing or passing). There is 2^n number of remanufacturing events for any given remanufacturing plan where n is equal to the number of parts designated for remanufacturing. For example, if a product had 15 parts to be remanufactured, there are 32,768 possible remanufacturing events meaning that there are 32,768 possible outcomes of "parts passing" and "parts failing" the remanufacturing process.

B. Modeling Remanufacturing Events

Monte Carlo simulation provides a modeling approach to learn from the presence of uncertainty in remanufacturing. The following steps can be used to forecast the variability of the economic or environmental outcomes of remanufacturing uncertainty:

1. For all parts remanufactured in the ORP, "probabilities of part failure" are estimated from either historical data or sampling techniques.
2. For each part, the forecasted economic (or environmental) variable is calculated based on both events: (1) the part failing during the remanufacturing process, and (2) the part passing the remanufacturing process.
3. All remanufacturing events are then generated from ORP. There are 2^n remanufacturing events for any given remanufacturing plan where n is equal to the number of parts to be remanufactured. Thus, 2^n number of joint probabilities must be calculated using:

$$\text{Joint Probability}(Jpr_i) = \prod_i P_{frm}(1 - P_{frm}) \quad (1)$$

where P_{frm} represents the probability of no part failure in remanufacturing whereby any given part either fails during remanufacturing or passes.

4. For each remanufacturing event, the forecasted economic variable is calculated based on the sequence of remanufacturing events. Each remanufacturing event has a unique combination of parts "passing" and "failing" and requires a calculation of the forecasted economic variable for each unique sequence of events. At this point a probability distribution of all remanufacturing events and their respective forecast outcomes can be generated.

For example, let us consider the uncertainty of part quality on remanufacturing costs. Not every part that is destined for remanufacturing actually gets remanufactured because of the possibility of a component being damaged beyond repair. That is, there is a probability that the part will fail remanufacturing and a new part will be needed in its place. Thus, when a part fails in the remanufacturing process, the following costs should be accounted for:

- (1) the partial costs of remanufacturing the component prior to its failure, and
- (2) the cost to replace the failed part with a new part and the cost to demanufacture the retired component.

The following equation represents the mathematical expectation of remanufacturing costs (i.e., $E(CRM_i)$) from a long term perspective:

$$E(CRM_i) = \sum_i [CRM_i + CA_i + CD_i](P_{frm}) + \sum_i [CRMT_i + CNP_i + CA_i + CD_i + MaxMRO_i](1 - P_{frm}) \quad (2)$$

where P_{frm} represents the probability of no part failure in remanufacturing (i.e., the part is remanufactured); CRM_i represents the cost of remanufacturing the i^{th} part with no part failure; $CRMT_i$ represents the cost of the i^{th} part failure during remanufacture including labour and material investments; CNP_i represents the cost of purchasing the i^{th} new component for replacement of the failed part; $MaxMRO_i$ represents the maximum Material Recovery Opportunity (MRO) for the i^{th} component; and CA_i and CD_i represent the respective assembly and disassembly costs.

Equation 2 depicts two events that results in the remanufacturing process: (1) successful remanufacturing of subassemblies or parts, and (2) failure of parts or subassemblies in remanufacturing and the need for new replacement parts and the necessary demanufacturing of failed components.

5. Using Monte Carlo simulation, generate random numbers between 0 and 1 to reflect the probability of any given part passing remanufacturing. Based on the random number generated, calculate the forecasted economic variable. Continue generating random numbers and forecasted economic outcomes over 500 to 1000 simulations. At this point, a distribution of the forecasted variable and descriptive statistics can be used to gain a further understanding of the true economical or environmental metrics of remanufacturing the identified parts in the ORP.

Steps 3, 4, and 5 can be successfully formulated using either a spreadsheet, Crystal Ball (an add-in program for Microsoft Excel) or another modeling software that supports Monte Carlo simulations. The output of this technique will include the following analysis:

- i. Variability of the Total Rebuild Costs.
- ii. Variability of the Predicted Reuse and Remanufacturing Mass.
- iii. Variability of the Demanufacturing Masses (Landfill, Shred, and Recycle)
- iv. Variability of the Estimated Energy Savings of Remanufacturing and Demanufacturing.

It is contended that using descriptive statistics generated from Monte Carlo simulations of the above four forecasted variables would provide an OEM with a more accurate representation of the economic and environmental metrics involved in product remanufacturing.

IV. APPLICATION: CONSUMER TELEPHONE

A. Input Parameters

In this research, the necessary remanufacturing and demanufacturing data was collected through both collaboration with industry partners (Nortel Networks) and using online research tools. The key economic and environmental parameters of a consumer telephone are modeled in an effort to develop and enhance the usefulness of the simulation model presented.

The consumer telephone analyzed in this study has a number of important economic and environmental characteristics that are used as input into the Monte Carlo simulation. First, the product depicts the scenario of remanufacturing within the context of EPR such as WEEE. That is, the product itself falls within WEEE legislation and is recovered and furthermore demonstrates through remanufacturing analysis that it has the potential for remanufacturing at its EOL that is economically viable. This data is derived through a remanufacturing optimization study as shown in [20]. Through remanufacturing analysis (comparing the economics of demanufacturing versus remanufacturing on a part and product levels), the product demonstrates an ORP with material and economic characteristics as presented in Tables I and II. The result of the remanufacturing optimization (from [20]) that evaluates the economic tradeoff between remanufacturing versus demanufacturing is shown in the Appendix.

TABLE I
MATERIAL DESTINATIONS OF REMANUFACTURING AT EOL

I. New versus Reuse	Mass (Kg)	% of Total Mass
Total Mass of New Parts	0.50	25.13%
Total Mass of Remanufactured and Reused Parts	1.49	74.87%
Total Mass	1.99	100.00%
II. Material Destinations	Mass (Kg)	% of Total Mass
Mass Remanufactured and Reused (Kg)	1.49	74.87%
Mass Recycled (Kg)	0.15	7.54%
Mass Landfilled (Kg)	0.35	17.59%
Total Mass	1.99	100.00%

TABLE II
ECONOMICS OF REMANUFACTURING AT EOL

Economic Total	Amount
Total Rebuild Cost	-\$6.87
Total Cost of New Parts (sum of CNP)	-\$1.67
Total Remanufacturing Costs (sum of CRM)	-\$3.54
Total Demanufacturing Costs (Landfill and Recycling)	-\$0.02
Total Demanufacturing Revenue (Reuse and Recycling)	\$0.12
Total Disassembly & Assembly Costs (sum of CA and CD)	-\$1.77

B. Modeling the Uncertainty of the Remanufacturing Process and its impact Economic Outcomes and Material Destinations

Eight parts within the consumer telephone are economically viable for remanufacturing (compared to demanufacturing alternatives of recycling and new part replacement costs). Using historical data from industry, the parts were analyzed to determine the likelihood of part failure during remanufacturing (see Table III). These probabilities were

modeled into a spreadsheet (see the Appendix) along with respective remanufacturing and demanufacturing economics, should the parts pass or fail during the remanufacturing process.

TABLE III
PROBABILITY OF PART FAILURES IN REMANUFACTURING

Part #	Probability of no part failure in remanufacturing (P_{frm})
A2	0.75
A3	0.8
A5	0.5
E	0.9
F	0.6
G	1
H	1
J	0.5

Fig. 1 demonstrates the variability of remanufacturing costs taking into consideration the uncertainties of part failure during remanufacturing simulated over 1000 trials.

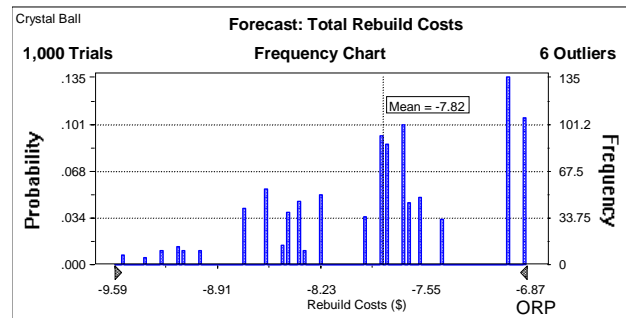


Fig. 1 Monte Carlo Simulation of Total Rebuild Costs

There are several important outcomes with respect to remanufacturing these components as shown using the Monte Carlo simulation:

1. The total rebuilds costs range from \$6.87 (the optimal value generated by the remanufacturing optimization model) to \$10.08. The distribution of total costs is left skewed and the peak of the distribution directed towards the optimal remanufacturing value of \$6.87.
2. The mean of the total rebuild costs is \$7.82 (median cost is \$7.79). Note that Crystal Ball automatically calculates all descriptive statistics of the simulation results including the occurrence of statistical outliers.

As stated, variability in the overall profitability of remanufacturing may be analyzed using the Monte Carlo simulation approach. Fig. 2 illustrates the profitability of remanufacturing the telephone assuming a 20% added cost for indirect overhead costs (relative to the total rebuild costs) and a mean price of \$15 retail (normally distributed with a standard deviation of \$1.00). The mean profit of \$6.42 estimated in section 5.2.1, lowers considerably to a mean value of \$4.80 (maximum = \$9.27, minimum = \$0.83) due to the added costs (recycling, landfill and new part costs)

associated with part failures in remanufacturing.

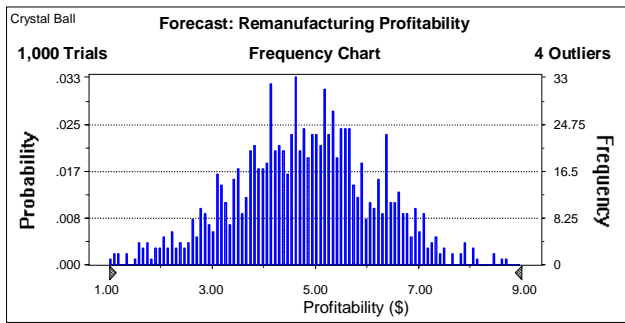


Fig. 2 Monte Carlo Simulation of Remanufacturing Profitability

An additional scenario of the variability of the remanufacturing economics was investigated using the developed technique. In an interview with Nortel, remanufacturing costs were stated to sometimes vary considerably due to substantial rework requirements of a few select telephone components. Nortel classifies such defects as "major defect costs" that require a substantial amount of labour or material investment in the rebuild of the product. To model this scenario, the main electrical subassembly is assumed to have a major defect cost for 50% of the remanufacturing cycles. Each "major defect" is assumed to cost an extra \$2.50 on top of the estimated remanufacturing costs. As shown in Fig. 3, the occurrence of a major defect cost creates a bimodal distribution of remanufacturing costs: the lower cost modal distribution demonstrates the remanufacturing costs without the major defect, and the higher cost modal distribution demonstrates the remanufacturing costs with the major defect. The mean remanufacturing costs is \$8.60 (median cost is \$7.71) and the variability extends from a minimum cost of \$6.87 (ORP) to a maximum of \$12.23.

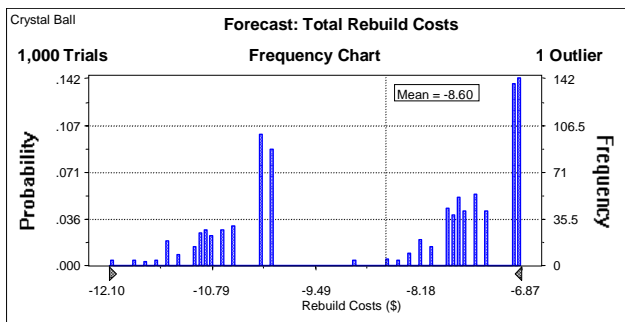


Fig. 3 Monte Carlo Simulation of Total Rebuild Costs - Major Defect Scenario

As shown in Fig. 4, the estimated profitability demonstrates that remanufacturing the consumer telephone may incur a loss in profitability when a major defect is modeled in the analysis. The mean remanufacturing profits lowers to \$3.85 (median profitability is \$4.44) and the variability extends from a minimum profit of -\$2.73 to a

maximum profit of \$8.37.

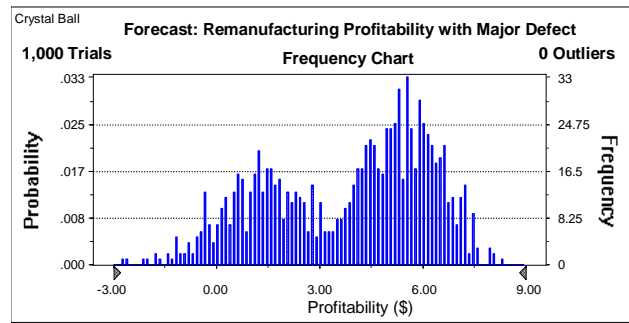


Fig. 4 Monte Carlo Simulation of Profitability - Major Defect Scenario

Other Monte Carlo simulations were generated for the prediction of actual mass of the product remanufactured and reused, recycled and landfill mass, and the predicted energy savings based on the variability of remanufacturing (all modeled without the scenario of a major defect).

Figure 5 demonstrates the variability of the total telephone mass that is remanufactured and reused. According to the original parameters of the input model, the plan generates an optimal savings of 1.49 kilograms (approximately 75% of the total telephone mass). Any variation of the 6 components not being remanufactured decreases the "reuse" mass savings and increases the mass demanufactured (i.e., through either recycling or landfilling). The variability of the remanufacturing plan brought on by the probability of part failure creates a bi-modal distribution pattern as shown in Fig. 5. The statistical output of the simulation demonstrates a mean material savings of 1.12 Kg (or 56.42% of the total telephone mass) from the original input model. The variability of material savings ranges from 0.44 Kg (or 22.11% of the total product mass) to 1.49 Kg (or 74.87% of the total product mass).

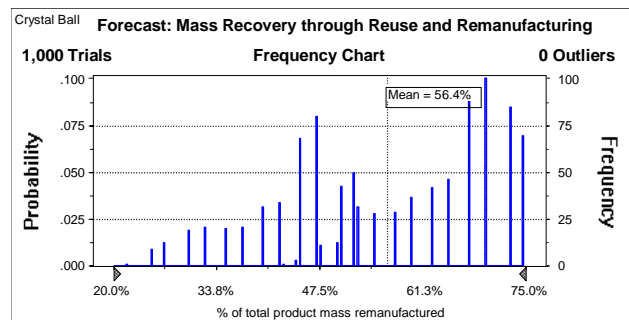


Fig. 5 Monte Carlo Simulation of Total Remanufacturing and Reuse Mass

The variability of energy savings of remanufacturing was also analyzed. Energy savings will fluctuate according to a part being remanufactured, recycled or landfilled. When successfully remanufactured, the energy embodied in a component's materials is saved. Otherwise the energy is lost

when demanufactured via recycling. The results of the simulation demonstrate that the mean energy savings is 77,067 KJ per telephone (median is 82,476 KJ). The variability of energy savings of remanufacturing varies from 42,300 KJ to 93,823 KJ per telephone. The maximum energy savings is represented by the remanufacturing event of all 6 components successfully remanufactured (93,828 KJ).

V. CONCLUSION

This paper presents an approach for assessing the impact of remanufacturing uncertainty at the early stage of product takeback considerations for strategies associated with EPR and product stewardship. The modeling approach was developed to provide a test bed for assessing two forms of remanufacturing uncertainty: (1) the quality of returned cores, and (2) the probability of part failure within the remanufacturing process. Future research will be expanded to other products that are potential candidates for remanufacturing and will also further investigate the energy

and material savings of remanufacturing uncertainty.

APPENDIX

REMANUFACTURING OPTIMIZATION

Part #	Decision Variables					Interpretation of Output
	X1	X2	X3	X4	MaxMRO	
A	0	0	0	1	0	receiver subassembly remanufactured
A1	0	0	0	1	0	reuse bolts
A2	0	1	0	0	0	remanufacture
A3	0	1	0	0	0	remanufacture
A4	0	0	1	0	RC	demanufacture via recycling
A5	0	1	0	0	0	remanufacture
B	0	0	1	0	RC	demanufacture via recycling
C	0	0	1	0	RC	demanufacture via recycling
D	0	0	0	1	0	telephone base remanufactured
E	0	1	0	0	0	remanufacture
F	0	1	0	0	0	remanufacture
G	0	1	0	0	0	remanufacture
H	0	1	0	0	0	remanufacture
I	0	0	1	0	LF	demanufacture via landfill
J	0	1	0	0	0	remanufacture
K	0	0	1	0	LF	demanufacture via landfill

MONTE CARLO SIMULATION OF REMANUFACTURING COSTS

1) Part Number	A2	A3	A5	E	F	J
Pr	0.75	0.8	0.5	0.9	0.6	0.5
2) Part Number	A2	A3	A5	E	F	J
PLMreman (if part is remanufactured)	-0.85	-0.756	-0.122	-0.844	-2.467	-0.328
2 PLMreman (if part fails in remanufacturing)	-1.13	-1.219	-0.191	-0.9	-1.187	-0.412
50% of cost	-0.425	-0.378	-0.061	-0.422	-0.4835	-0.164
subtotal	-1.555	-1.597	-0.252	-1.322	-1.6705	-0.576
3) Monte Carlo Simulation -						
Remanufacturing Events ("1" represents remanufacture, "0" represents demanufacture)	1	1	1	0	1	0
Random Number Generator	0.390361	0.755156	0.046400	0.752826	0.054872	0.786021
6) Outcome based on Remanufacturing Events	A2	A3	A5	E	F	J
	-0.85	-0.76	-0.122	-1.322	-0.967	-0.576
Legend for Above 6 Cells:	SUM of Remfg. Outcomes (A3+...+J)			Constant	Total	
1. Identify probability of part failure for each part to be remanufactured (Pr _{reman})				-4.597	-3.005	-7.602

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