Core Retrieval Decisions Under Quality Uncertainty in Remanufacturing System

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Abstract
To ensure the flow of products with different classes in supply chains such as closed-loop supply chains, etc., managing quality uncertainty estimation is a cost-effective, profitable, and environment-friendly contribution by establishing standard recovery treatments of cores. The paper compares the quality values obtained from Bayesian analysis with deterministic levels to analyze the core retrieval strategies. The uncertainty effects due to several quality factors are demonstrated in both the inspection and disassembly stages. Such as misclassification that occurred because of overlapping of quality ranges in consideration with fuzzy evaluation during value and material recovery. Moreover, the adopted dual methodology invalidates the legitimacy of providing probability distribution to unknown variables in previously developed models. Both probabilistic and prescriptive models are moderated by the qualitative assessment of cores facilitated by realistic scenarios. With the help of the proposed mixed approaches, the current research contributes to the knowledge of core retrieval management by incorporating the quality variability in the model at the product level. The result demonstrates that quality estimates ensure precise eligibility and misclassification detection of returns of cores at the initial stages well-before exhaustive remanufacturing operations.

Keywords
Core Quality, Core Recovery, Bayesian Modeling, Prescriptive Model, Remanufacturing

1. Introduction
With a sense of responsibility to decrease the environmental impact, take-back legislation continuously pressures manufacturers, recyclers, and remanufacturers to take back the used products collectively and individually with little compensation relief like incentives, discounts, etc., to consumers. Such green initiatives instigate consumers to buy green products and the providers to manufacture green products. Quality variability and return uncertainty are significant challenges in supply chain management. Primarily returns are of four types: end-of-life returns, end-of-use returns, commercial returns, and reusable components (Fleischmann et al. 2000). The returns are uncertain and available in high volumes, various types, series, and versions (Guide 2000). Remanufacturers can reduce return volume, timing, and quality uncertainties by actively controlling the acquisition effort and methods (Wei et al. 2015).

A core is the basis of the restoration of any used product. The core consists of multiple modules component(s) of the product that retains and encapsulates the value of the product (Parkinson & Thompson 2003), that are materially recycled, reused, refurbished, or disposed of (Jayaraman 2006).
The objective of the study is to provide a solution to the problem of sorting and grading cores into different classes by establishing the quality range. In the study, the decision is made on sorting the cores using the quality index to reusable, remanufacturable, and recyclable classes. That is followed by the establishment of quality ranges for each class by determining the quality levels which grade the sorted cores. The following research questions are answered with the help of this study: (1) What are the limits of quality levels of cores eligible for different re-manufacturability statuses such as remanufacturable, recyclable, and reusable? (2) How quality estimation affects the core retrieval decisions? (3) What is the likelihood of misclassification that ensures a better quality of cores?

The questions are systematically answered in the following sections of the paper. In section 2, the models related to the quality of used products are reviewed to investigate the influence on core acquisition management. In section 3, the problem with core classification is explained. The methodology- Bayesian modeling in integration with the prescriptive formulation is implemented to assess the acquisition and reprocessing management of the remanufacturing operations. The linear programming model optimizes the solution of the estimation of the quality range for each class. In section 4, an illustrative case study is presented to demonstrate the efficiency of the proposed methods. In section 5 result is presented, and the discussion of how the decisions based on quality conditions affect the remanufacturability of cores. Finally, in section 6, concluding remarks are outlined with a few important implications.

2. Literature Review

Core retrieval is the management of uncertainties of return quantity, timing, and core quality (Wei et al. 2015). Remanufactured products possess good and better quality regarding appearance, reliability, and performance than new products (Jayaraman 2006; Parkinson & Thompson 2003; Wassenhove 2001). A quality mechanism should be devised to sort and grade the cores effectively to prevent waste of the values left within the used products and motivate value recovery processes like remanufacturing. The study is an attempt to extend the knowledge of core retrieval in choosing end-of-life strategies for cores based on their quality condition in terms of remanufacturability, reusability, and recyclability.

Quality of returns significantly influences the core acquisition and remanufacturing decisions. Due to homogeneous and heterogeneous behavior in the pattern of returning cores, the cores are sorted and graded accordingly. Researchers have classified the cores in ordinal and nominal levels to control the acquisition efforts and methods. Few studies are as follows: (Tagaras & Zikopoulos 2008) (remanufacturable, non-remanufacturable), (Aras & Aksen 2008) lowest, highest quality), (Ferguson et al. 2009) (scrap, or salvageable), (Jayaraman 2006) (nominal quality metrics), (Park & Chertow 2014) (reuse potential indicator based on technical reusability), (Zeballos et al. 2012) (Good, medium, bad) (good quality, worst/ bad quality, high or poor quality).

2.1 Quality Distribution Schemes

2.1.1 Based on the number of returns and recovery rate

The spread of the returns facilitates the estimation of quality levels. Some of the studies assumed a variety of distribution schemes to predict the return volumes. Such probability distributions help determine the classification errors (misclassification) in sorting and grading processes (Liao et al. 2018). Researchers have used several distributions according to the suitability of the problem context, and some are worth mentioning here. (Radhi & Zhang 2016)(exponential, and uniform in different scenarios for retreading industry), (Pokharel & Liang, 2012)(normal), (Yang et al. 2016), (Chouinard et al. 2008)(Weibull), (Chouinard et al. 2008; Wei et al. 2015) (gamma), (Ferguson et al. 2009; Van Wassenhove & Zikopoulos 2010)(beta when misclassification in the grading of returns due to overestimation etc.), (Jeihoonian et al. 2017) (Bernoulli for random quality states, availability of returns in reverse BOM), (Das 2012; Van Wassenhove & Zikopoulos 2010; Zeballos et al. 2012) (amount of returns & fraction), (Ketzenberg et al. 2006; Panagiotidou et al. 2013) (number of remanufacturables, binomial), (Aras et al. 2006) (poisson distribution), (Zikopoulos & Tagaras 2008) (uniform and, beta), (Guo & Ya 2015)(recycling rate), (Chen et al. 2015) (Recovery rate, Triangular).

2.1.2 Based on Costs and Price

In the literature on quality with remanufacturing, research scholars have different beliefs on the costs and quality of manufactured (original) and remanufactured products, perhaps due to the difference in the customer valuations of such products (Ahiska & Kurtul 2014; Teunter et al. 2006). The quality of such items significantly influences the acquisition price, remanufacturing costs, recycling rate, and other factors in derived functional relationships. Like, variation in core quality also leads to different remanufacturing costs and buyback prices (Wei et al., 2015). Further, functional relationships with quality are observed by (Guo & Y 2015)(buyback costs, recycling rate, remanufacturing costs), (Karakayali et al. 2007; Radhi & Zhang 2016)(acquisition price), (Bhattacharya & Kau 2015; Galbreth & Blackburn 2010)(remanufacturing cost). Table 1 mentions the functional and distributional relationships used to formulate returns of cores based on quality conditions in selected literature.

Table 1. Quality-based relationships determining returns

Sr. No.	Parameters	Relationship	Authors
1	Acquisition price	$\alpha + \beta * f$	Karakayali et al. (2007)
		$\alpha + \beta * q_i$	Radhi and Zhang (2016)
2	Nominal quality level	1, 2,3,4,5,6	Jayaraman (2006)
3	Quality level	sorting (Good, medium, bad)	Zeballos et al. (2012)
4	Amount of returns	Fraction	Zeballos et al. (2012)
5	Recovered quantities	Uniform distribution	Das and Chowdhury (2012)
6	Quality level of returns	Beta distribution [0,1]	Hein et al. (2012), Ferguson et al. (2009)
7	Quality level of used products	Normal distribution	Pokharel and Liang (2012)
8	Quality of returns	Weibull and Gamma distributions	Chouinard et al. (2008)
9	Quality score	Range 0 to 100	Radhi and Zhang (2016)
10	Type of core	Multinomial distribution	Teunter and Flapper (2011)
11	Remanufacturing cost of particular quality grade i	$\rho - \psi *$ (acquisition cost)	Bhattacharya and Kaur (2015)
12	Remanufacturing cost	$a + b * \lambda_i$	Galbreth and Blackburn (2010)
		$a - b * q_i$	Radhi and Zhang (2016)
		Uniform distribution, normal distribution $\int_{q_i}^{q_i^{ac}} K_i(q_i q_i^{ac}) g(q) dq$	Wei et al. (2015)
		Normal distribution	Robotis et al. (2005)
14	Expected number of remanufactured products	$yi = xi * Gi(toi)$	Yang et al. (2016)
15	Quality of core type i	Gamma distribution	Yang et al. (2016)
		Uniform, Weibull, Exponential distribution	Yang et al. (2015)
	Remanufacturing processing time	Gamma distribution	Yang et al. (2016)

16	Number of remanufacturables (returns yield)	Binomial distribution	Ketzenberg et al. (2006), Panagiotidou et al. (2013)
		Poisson distribution	Aras et al. (2006)
		Uniform distribution, Beta distribution	Zikopoulos and Tagaras (2008)
17	Fraction of returned units	Beta distribution	VanWassenhoveand Zikopoulos(2010)
18	Recovery rate	Triangular distribution	Chen et al. (2015)

Where a: fixed remanufacturing cost., b: slope of remanufacturing cost vs. quality linear relationship, λ: used items conditions- uniform distribution., ρ: maximum remanufacturing cost., ψ: slope of the remanufacturing function., α: acquisition price assigned for worst possible remanufacturing return., β: slope of acquisition price vs. quality linear relationship., q_i: actual quality of the returned item to facility i., q_i^{ac}: higher quality level., y_i: quantity of remanufactured product of core type i, x_i: given acquisition quantity, $G_i(t_{oi})$: expected remanufacturing rate, t_{oi}: remanufacturing cost threshold, $K_i(q_i q_i^{ac})$.

3. Methodology

3.1. Problem description

The problem is to sort and grade the core into different quality classes to control the quality and quantity of the returns for different stages of remanufacturing. We propose the grading tool based on both probabilistic and prescriptive analysis of the cores. The study incorporates factors based on the quality condition of cores at the inspection and disassembly stages. Returns of uncertain quality are inspected and sorted according to their physical and functional aspects. The proposed tool devises an indicator system that determines a range to a particular class of recovery to which core belongs. The novel core retrieval tool enables, with the help of quality ranges, precise sorting of cores to reuse, remanufacturing, and recycling processes with acceptable grades. We use data from our previous research work (Mishra et al. 2021) on the quality-based classification of cores. Returns of uncertain quality are inspected and sorted according to their physical and functional aspects.

3.2. The Probabilistic Bayesian approach

The problem description has utilized the arguments proposed in the following studies. First is the work of (Merrick et al. 2005), which quantifies the effects of multiple factors on the probability of an event. And second, (Van Wassenhove & Zikopoulos 2010) relies on and advocates the use of Bayesian modelling in data scarcity scenarios in the estimation quality for the classification of cores. In addition to this, authors promote Bayesian modeling because it captures different characteristics of cores even in critical situations such as suppliers' unavailability, the need for information updates on core supplies, and the credibility of new and old suppliers when no historical data is available.

The Bayesian approach is the inclusion of uncertainties with the evaluation of the probability of getting cores and probability of getting specific quality of cores with quantification of experts' knowledge, and experiences. Hyperparameter measures the effects of both qualitative and quantitative factors on the probability of getting the specific quality of cores with an effective confidence level in data scarcity conditions. Figure 1 demonstrates the classification problem and steps undertaken in the proposed ML framework oriented with the Bayesian approach.

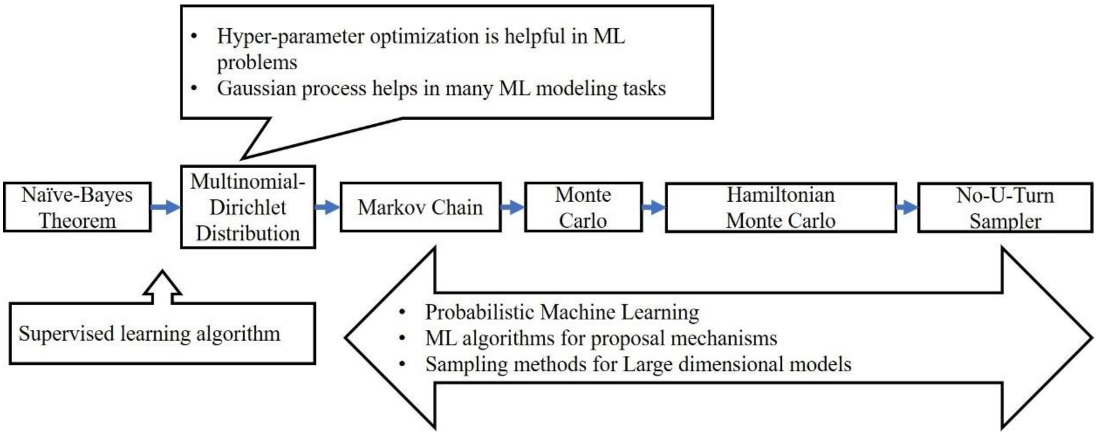

Figure 1. Outline of steps for proposed Bayesian approach to probabilistic ML framework

3.2.1 Bayesian Model

Consider each feature of a returning core is represented by a vector X. The vector consists of features that are independent of each other. Each core is an output class $k \in$ Remanufacturable, Reusable, Recyclable denoted by Y . With N observations, each observation has Q features, and we denote the i^{th} feature of the j^{th} observation as x_{ji}. In supervised learning, our focus is to specify Y, which represents the discrete number of possible classes for each input X. Let $X = (x_1, x_2, x_3, \dots, x_q)^T$ denote the q factors or features on which classification of discrete values is made. The multinomial distribution is used to find probabilities in N repeated trials where there are more than two possible outcomes to each. Suppose that each trial results in one of k possible outcomes with probabilities $\theta_1, \dots, \theta_k$ to set a random variates $X_1, X_2, X_3, \dots, X_k$ such that probability that X_1 occurs x_1 times,..., X_n occurs x_n times, then $P(Y|X)$ is the conditional probability of Y given X represents the predictive distribution function $X \sim Multinomial_k(n,\theta)$.

$$P(X_1 = x_1, \dots, X_k = x_k | n, \theta_1, \dots, \theta_k) = \frac{n!}{\prod_{i=1}^{k} x_i!} \prod_{i=1}^{k} \theta_i^{x_i} \quad (1)$$

In Bayesian statistics, $Dir(\alpha)$ is used as a conjugate prior to the multinomial distribution. That is if $(X|\theta) \sim Multinomial_k(n,\theta)$ and $Dir(\theta|\alpha)$, then $Dir(\alpha + x)$ serves as a conjugate prior for the probability parameter θ of the multinomial. α is a concentration parameter that parametrizes the prior distribution and is also known as a hyper-parameter. $\alpha_i > 0$ determines the shape of the distribution such that the higher the value of α, the more even is the distribution and for lower values, the more sparse is the distribution (Frigyik et al., 2010). As a result, posterior of Multinomial and Dirichlet distribution $P(\theta|X)$ is Dirichlet with parameters $x + \alpha$ *(figure 2)*

.

$$\begin{aligned} P(\theta|X,\alpha) &\propto \left(\prod_{i=1}^{k} \theta_i^{x_i}\right)\left(\prod_{i}^{k} \theta_i^{\alpha_i - 1}\right) \\ &= \frac{\Gamma(n + \sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i + x_i)} \prod_{i=1}^{k} \theta_i^{x_i + \alpha_i - 1} \\ P(\theta|X,\alpha) &= Dir(x_i + \alpha_i) \end{aligned} \quad (2)$$

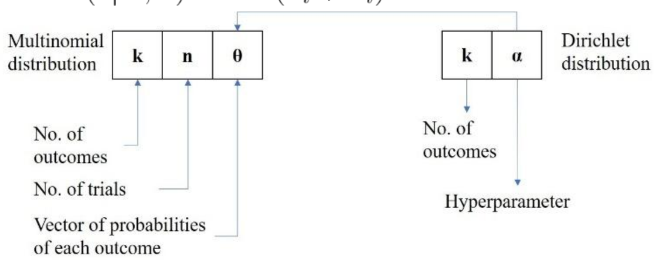

Figure 2. Conjugate priors Multinomial-Dirichlet distribution

To generate samples sequentially from the posterior distribution of higher dimensional, MCMC is used (Monnahan et al., 2017). Because MCMC measures uncertainty gets a range of estimates by fair sampling from the posterior from limited actual data to approximate the posterior. Since the sampling is done sequentially, the distribution of the sampled draws depends on the last value drawn; hence, the draws form a Markov chain (Gelman et al., 2013). The sequence of the Markov chain is satisfied by the Markov property, which states (say s) that only the most recent state in the particular set of values (say X_t) affects what happens next. It means that X_{t+1} depends upon the X_t, but it does not depend upon $X_{t-1}, X_{t-2}, \ldots, X_1, X_0, \forall t = 1,2,3,\ldots; s = s_0, s_1, s_2, \ldots, s_t$.

$$P(X_{t+1} = s | X_t = s_t, \ldots, X_0 = s_0) = P(X_{t+1} = s | X_t = s_t) \tag{3}$$

NUTS, a variant of MCMC, is used for sampling from the target distribution. MCMC algorithms designs proposal mechanisms to generate candidates' hypotheses within the computational power of the ML framework (Figure 3), providing solutions to open problems in easier and less time have strengthened mutual support in recent years (Andrieu et al. 2003).

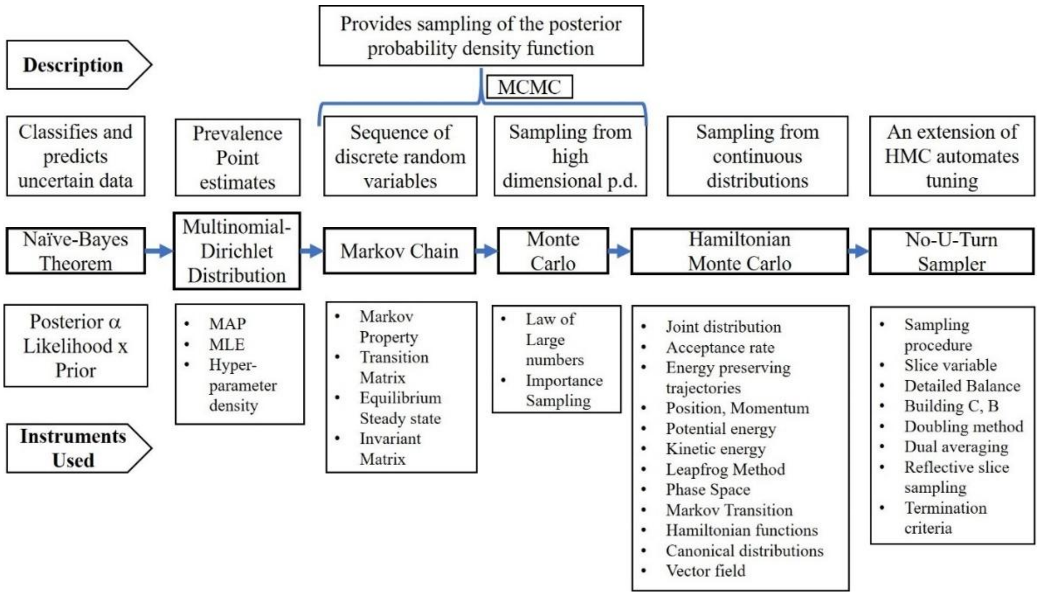

Figure 3. Instruments used in different steps of the proposed Bayesian approach with the description of purposes

3.3. The Linear Programming Model

This optimization section determines the quality range by formulating the whitenisation functions into the equivalent ordinary linear programming model. The model adopts the weight responses of the experts given to the core at the time of data collection as in our previous work. For simplicity, the weights are kept constant to fix the priorities of the factors. We intend to classify the core as reusable, remanufacturable, and recyclable by establishing the range for each class. This optimization model provides both the minimum and maximum values to the response part of the factors. During the inspection, the quality range of cores is determined by optimizing using Equations 4-12.

$$w_1 \frac{(100 - x_1)}{100} + \frac{1}{5}\left(\sum_{i=2,3,12} w_i * x_i + \sum_{i}^{11} w_i * (5 - x_i) \right) \tag{4}$$

$$1 \le x_i \le 5 \; \forall i \in [2, 12] \tag{5}$$

$$1 \le x_1 \le 100 \tag{6}$$

$$w_1 \frac{(100 - x_1)}{50} + \frac{1}{2.5}\left(\sum_{i=2,3,12} w_i * (5 - x_i) + \sum_{i=4\ldots11} w_i * (5 - x_i) \right) \tag{7}$$

$$2.5 \le x_i \le 5 \; \forall \in [2, 12] \tag{8}$$

$$50 \le x_1 \le 100 \tag{9}$$

$$w_1 \frac{x_1}{100} + \frac{1}{5}\left(\sum_{i=2,3,12} w_i * (5 - x_i) + \sum_{i=2}^{11} w_i * x_i\right) \tag{10}$$
$$1 \le x_i \le 5 \; \forall \, i \in [2, 12] \tag{11}$$
$$1 \le x_1 \le 100 \tag{12}$$

All the decision variables are positive. $x_i \, \forall i \in [2,12]$ holds positive integers, while x_1 holds continuous positives. The vector of weight parameters w_1 to w_{12} is [0.155, 0.087, 0.059, 0.058, 0.112, 0.046, 0.065, 0.080, 0.064, 0.041, 0.088, 0.128]. Quality determination at the disassembly stage is modeled for the different classes using Equations 13-21.

$$\frac{1}{5}\left(\sum_{i} w_i * (5 - x_i) + w_4 * x_4\right) + \frac{1}{100}(w_2 * (100 - x_2)) \tag{13}$$
$$1 \le xi \le 5 \, \forall i \in [1,3,4] \tag{14}$$
$$1 \le x2 \le 100 \tag{15}$$
$$\frac{1}{2.5}\left(\sum_{i=1,3} w_i * x_i + w_4 * x_4\right) + \frac{1}{50}(w_2 * x_2) \tag{16}$$
$$1 \le xi \le 2.5 \, \forall i \in [1,3,4] \tag{17}$$
$$1 \le x2 \le 50 \tag{18}$$
$$\frac{1}{5}\left(\sum_{i=1,3} w_i * x_i + w_4 * (5 - x_4)\right) + \frac{1}{100}(w_2 * (100 - x_2)) \tag{19}$$
$$1 \le xi \le 5 \, \forall i \in [1,3,4] \tag{20}$$
$$0 \le x2 \le 100 \tag{21}$$

4. Results and Discussion
4.1 Probabilistic Approach
This section describes the results of the 12 factors on the quality estimation of any core come to inspection. Based on the results we can deduce the probability of a core under uncertainty (range) of quality levels. Table 2 shows the engine cores observed in the remanufacturing firm. The frequency of parameters observed in the inspection stage are as follows: X_i = {[5,2,5],[6,1,5],[6,1,5]}, and with prior values or hyper-parameters included are: α_i = {[0.1,0.1,0.1],[1,1,1],[5,5,5],[15,15,15]}, α_o=[1, 1, 1]. Expected value of quality of engine core in percentage are as follows: $\theta_{i=1=Remanufacturable}$ = 46.15%, $\theta_{2=Reusable}$ = 12.99%, $\theta_{3=Recyclable}$ = 40.86%. MAP of the D-M Distribution for α = [1,1,1]: Remanufacturable=47.22%, Reusable=11.11%, Recyclable=41.67%.

Figure 4, the traceplot shows that the kernel density estimate (KDE) is smoother histograms that converge faster to true density. The model contrues $\theta_{Remanufacturable} > \theta_{Recyclable} > \theta_{Reusable}$. KDE measures the posterior distribution. The first half is similar to the second half of the chain for each class of quality of engine cores and so confirms the regular densities check. Posterior uncertainties reduce more number of observations.

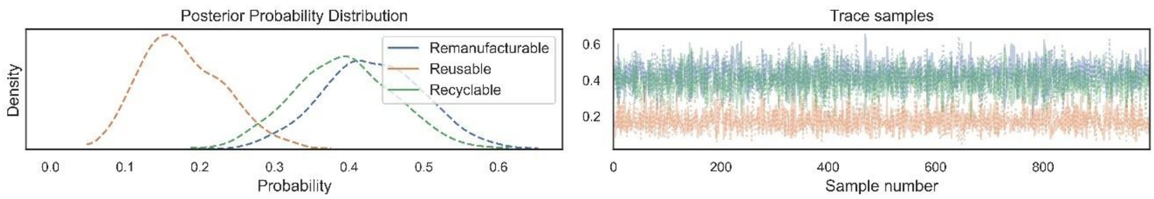

Figure 4. Posterior probability distribution of Engine cores at inspection phase

For some engines, no factors classify core in the recyclable category, which shows the significant effect of the second quality check at the remanufacturing centre (RMF). Below details are regarding the qualitative assessments done to the core. So, the number of observed cores is three under four attributes pertaining to the eligibility of core to be disassembled for further remanufacturing. Given, observed engine cores: X_j={[2,0,2],[0,0,4],[2,1,1]}, hyper-parameters: α_i={[0.1,0.1,0.1],[1,1,1],[5,5,5],[15,15,15]}, α_o=[1, 1, 1]. Expected value of the quality levels of engine cores observed while disassembling are as follows: $\theta_{k=1=Remanufacturable}$ = 33.50%, $\theta_{2=Reusable}$= 13.84%, $\theta_{3=Recyclable}$ = 52.66%. MAP of the D-M Distribution for α=[1,1,1]: Remanufacturable =33.33%, Reusable=8.33%, Recyclable=58.33%. With the collection of three observation points, we can deduce the effect of this quality check of a core at the remanufacturing facility with the help of Bayesian analysis.

Bayesian estimates are very helpful in the case studies scenarios. All three engines are observed under the case study approach with the provision of a second quality diagnostic at the remanufacturing facility. We argue that such provision ensures (1) Eligibility of incoming cores from collection centers to remanufacturing facilities (2) Detect misclassification of the cores at collection centers and subsequently at remanufacturing facilities. Since qualitative assessments regarding the disassembly under four factors are included in the inspection itself, which assures the core is analysed well enough before entering into remanufacturing, it further ensures savings in operational cost and processing time beforehand. Also, quantities of perfect categories can only be managed through supply channels.

With a uniform prior $\alpha = 1$, normal with a mean of 0.335 and standard deviation of 0.120, it is implied with a 95% confidence interval that core quality signifies core is remanufacturable. Similarly, the mean of 52.7% core quality confirms highly probability that the core is recyclable. The posterior distribution for each quality of engine core is plotted on the left of figure 5, expressing smoothed histograms of the samples of each recovery class. On the right of figure 5, the plot is the traceplot that combines chains having traces of parameter values across iterations on the x-axis, and it is observed that the NUTS sampler, a variant of MCMC, has done mixed well. The NUTS simulation in two chains draws 1000 posterior samples in sequential order with 500 discarded tuning samples from each chain. It is observed from the figure that the model has a large range of uncertainty that implies probability inequalities among different quality classes $\theta_{remanufacturable} > \theta_{recyclable} > \theta_{reusable}$.

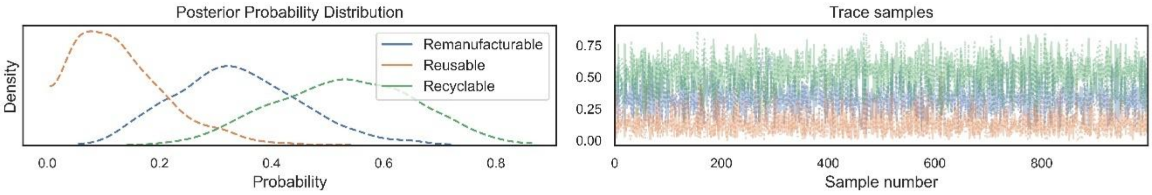

Figure 5. Posterior probability distribution of Engine cores at disassembly phase

4.2 Prescriptive Approach

In the 0-1 quality scale refer to in figure 6, the remanufacturable range is between 0.30-0.75. In inspection, it is an effective quality level for the acceptance of any engine core to get further into the remanufacturing processes. Similarly, for the recyclables, effective quality levels range between 0.06-0.30, and for the reusables, the range is 0.75-.81. The obtained quality levels signify the acceptable limit of returns. The range is between 0 to 1.0 denotes core to be treated as disposable with utmost low quality. The value of 1 means the quality level is as high as the original product.

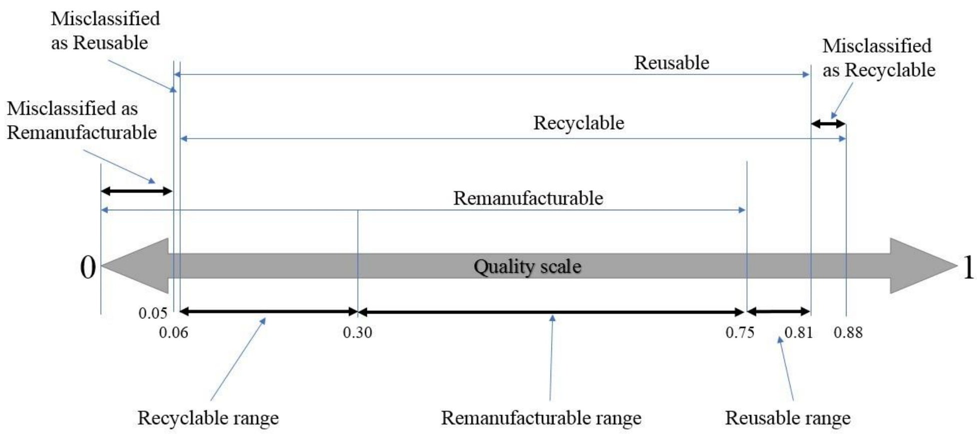

Figure 6. The quality range for different classes of Engine core for the inspection stage

The overlapping is found in certain levels of quality due to fuzzy responses from the experts. The overlapping ranges facilitate the effective valuations for remanufacturable, reusables, and recyclables based on which they should be treated in the remanufacturing processes and the supply chain operations. For example, take a range for reusables. First, identify the range obtained from the optimization of the objective function for $k = 1$, which is 0.05-0.81 since the quality of the core should be maximum if the core is to be reused. Therefore locate higher value and move to lower value until the intersection is met with remanufacturable higher value, the subsequent quality class. The effective quality level for the reusables must be between 0.75-and 0.81. Fractional overlapping of 0.05-0.06 in the lower levels suggests recyclable returns are misclassified as reusables. This is by locating the lower value of reusable limit until the intersection is met with the next lower class, i.e., recyclable. Since both the quality levels of remanufacturables overlap with the quality levels of reusables and recyclables, the range established for this class is between 0.30-0.75.

Table 2 Quality range for the different classes of engine core for the inspection stage

Classification	Quality Range
Reusable	0.75-0.81
Remanufacturable	0.30-0.75
Recyclable	0.06-0.30
Misclassified as reusable	0.05-0.06
Misclassified as remanufacturable	0-0.05
Misclassifed as recyclable	0.81-0.88

In the disassembly stage, obtained quality levels are slightly better than in the inspection stage. The reason is we get the filtered core using the quality index in the inspection stage itself. The optimal ranges for reusables, remanufacturables, and recyclables are 0.85-0.9, 0.300.85, and 0.1-0.3, respectively, by chopping off the overlapping as well as misclassification zones with min (max) technique as described in the inspection stage. The acceptable quality limits are mentioned in figure 7.

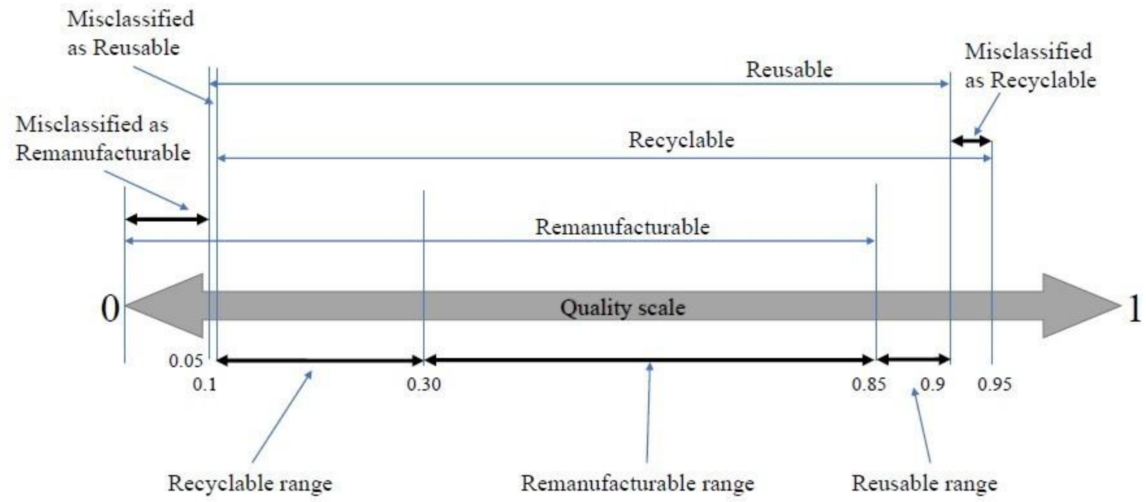

Figure 7. Disassembly stage quality range for engine core

It is evident that the quality of core is getting higher as we move towards the reusable class. The quality gets lower when the core is sorted and graded from the class remanufacturable to the recyclable. Due to this, misclassification ranges are easily identifiable and can be located, as shown in figure 7. The related ranges, when misclassified as reusable, recyclable, and remanufacturable, are 0.05-0.1, 0-0.05, and 0.9-0.95, respectively (Table 3).

Table 3. Quality range for the different classes of engine in the disassembly stage

Classification	Quality Range
Reusable	0.85-0.90
Remanufacturable	0.30-0.85

Recyclable	0.1-0.3
Misclassified as reusable	0.05-0.1
Misclassified as remanufacturable	0-0.05
Misclassifed as recyclable	0.9-0.95

4.3 Misclassification Scenarios

During the inspection of any engine core, fuzziness in the classification process (i.e., sorting and grading) is responsible for such ranges. The possibility of error in the classification process of returns is misclassification. With effective credibility intervals, the quality of cores is estimated at the most crucial inspection and disassembly stages of remanufacturing. The posterior density plots are shown for all the quality classes w.r.t. probability on the x-axis. For both, the stages length of the quality classes are not equal to each other and do not match with equal probability intervals. Suppose a quality of a returned core falls to the recyclable category even then a quality proportion of it consists little amount of qualities of reusable and remanufacturable. This might increase remanufacturing costs, processing costs and other related recovery costs than usual due to misclassification if done. The proportion of each class having some quality of different classes might hamper the associated cost structure (Table 4).

Table 4. Result of prediction part carried out using Bayesian modeling in estimating quality uncertainty

Remanufacturing stages	Quality of returns	0.1	1	5	15
Inspection	α	0.472	0.46	0.43	0.395
	β	0.113	0.129	0.178	0.237
	γ	0.415	0.412	0.392	0.369
Disassembly	α_1	0.338	0.335	0.338	0.335
	α_2	0.094	0.137	0.22	0.281
	α_3	0.568	0.529	0.443	0.385

The misclassification is found and analyzed in overlapping ranges in the quality levels. The uncertainties found in experts' insights when asked to classify the core in both the inspection and disassembly stage during core acquisition phases. Such error incorporates unfeasible and unacceptable quality levels which misjudge the particular class of core into other classes. The following scenarios can be mentioned for unfeasible quality levels. First, it is quite infeasible to recover parts after a severe disassembly process with utmost functionality levels and no disassembling time. The value corresponding in this situation is 0.05; refer to the leftmost value in figure 4. Another similar scenario could be when the core takes maximum disassembling time with no parts recovery, without any destruction but fulfilling the highest satisfaction levels (rightmost value 0.95). In the former scenario, the core is misclassified as reusable, and later the core is misclassified as recyclable. A core is misclassified as remanufacturable when severe disassembling is done without proper invigilation and assumes the core is satisfactory with the perception of being recyclable.

The misclassification of cores can be devised by identifying and locating any recoverable's minimum and maximum quality levels. Misclassification occurred, and hence, both the highest and lowest quality cores are devoid of proper recovery treatments. But the probability of misclassification must be included when grading the returns during the inspection. If the engine core is graded in the recyclable range, then 0.06-005=0.01 margin is included. Similarly, if the core is graded in the reusable range, then 0.88-0.81=0.07 margin is included. Such inclusions incorporate the misclassification errors in the grading mechanism and extend the range of quality levels by calculated margins.

6. Conclusion and Managerial Implications

The study fills the gaps in establishing quality levels of returns by investigating two approaches, viz. probabilistic and prescriptive. The proposed grading and sorting tool provides the determination of quality range at the product level rather than assuming any popular distribution scheme. Some managerial implications are as follows: Firstly, the quality levels are better in the disassembly stage due to the attainment of filtered cores after inspection. The unfeasible scenarios should be identified and rectified by the managers in the decision making (1) When the core is fully functional and possess recoverable after severe disassembly in no time. (2) When the core is fully functional with no parts recovery when given maximum time for disassembly without any severe destruction.

Secondly, misclassification can be prevented in the classification scenario. The core is misclassified as remanufacturable when severe disassembling is done without proper invigilation and assumes the core is satisfactory with the perception of being recyclable. The corrective actions are prescribed at the operational levels by prioritising quality factors, which are mostly responsible for the core retrieval such that maximum value recovery is attained. The scope of the current research can be extended to capture the value in other stages of remanufacturing. Since the universal scale is adopted using whitenisation functions to establish the quality ranges, the study can be applied to different variety of products, from heavy electrical machinery to white goods.

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