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Bayesian Modeling for the Remanufacturing and Reuse of Components for the Reduction of Costs in a Line of Printing Products

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ABSTRACT

One of the options to recover or create value for products that have already fulfilled a useful life cycle is remanufacturing. Remanufacturing is the process of returning a used product to a functional state again.Remanufacturingprocessesface uncertaintyinthe quality of theproductsreturnedby customers,thissignificant variabilitycomplicates the controlof inventories. We consider necessary differentiatethe repair processwith the remanufacturing process. The firstis dedicatedonlytorepair the damageor defect,on the other hand, remanufacturingprovidesanalyzeall components of theproductwhether or notdefectiveand its main objectiveis to returnto normaloperating conditions, meeting quality standardsand in addition toaid decision-making in the elimination offewer componentsthus helpingtoreduce costs. These efforts usually involve the operation of joint manufacturing and remanufacturing systems. One of the main challenges of such hybrid systems is the stochastic nature of product returns. This document uses Bayesian Analysis to construct a Cost Model that includes the construction of subsequent distributions that decrease the effect of uncertainty and help reduce remanufacturing costs.

Keywords:*A priori distribution, Bayesian inference, linear regression model, posteriori distribution, remanufacturing, R Software.*

I.INTRODUCTION

In the remanufacturing process, a low percentage of the products is not reusable, this does not generate big problem since it is always possible to complete the deficient quantity (missing or low quality) with new elements or materials purchased from suppliers to meet the demand in a determinate period. Figure 1 shows the operating scheme of a remanufacturing process.Lund (1984) defines remanufacturing as the restoration of used products to perfect conditions, providing them with performance characteristics and durability as the original product.

The management of a process for product recovery focuses on the collection of used and discarded products and looking for opportunities to remanufacture products, reuse components or recycle materials (Aksoy, 2010). The inputs of a remanufacturing process are unpredictable, it is almost impossible to determine the quality, quantity, test times, disassembly times and remanufacture of the returned materials. The percentages of usable or non-usable products are an uncertainty for the remanufacturing process. To cope with the uncertainty of the recovery rate of the products used in the remanufacturing system, it is advisable to use Bayesian analysis. In the Bayesian analysis the new information is combined with the previous information available. At this point the previous information (previous distribution) corresponds to the historical data or the subjective thought of the decision making about the random parameter of the process involved. The consequential decision or inferential declaration (subsequent distribution) gathers all available information about the uncertain parameter of interest.

II.THE PROBLEM

Currently, the disassembly plant receives the materials that will be used in the assembly plant to be remanufactured. The assembly plant receives and makes its programming of the production according to a forecast with historical data (3 months) and on the basis of this, it requests the materials to disassembly plant before these receive the materials which are returned to the plant through the different collection centers, the collection centers have two different ways of returning the material to the disassembly plant, by bulk or in individual boxes; When the material is returned by bulk it arrives preselected but only by part number, and when it is returned in individual boxes it does not have any type of selection, so it is difficult to determine which materials are going to return or the conditions in which these are receive. When the materials arrive, it is not possible to know what percentage of the total amount received can be used in the remanufacturing plant. There is no method of supplier selection and categorization of materials thus increasing the costs of acquisition, quality, disposition, testing, dismantling and remanufacturing.

In general, we have not found a model that allows to know the impact of the variables in the processes of remanufacturing, so the cost model of the equation is posed (1), which is presented below:

$$E(CTotal\,|r_i) = c_c E(PR) + \; c_d E(D) + \; c_{pr} E(P) + c_{des} E(Des) + +c_r E(R) + \; c_{np} E(NP) \qquad (1)$$

For this it will be necessary to define the following variables and costs that by the nature of the remanufacturing process it is not possible to determine them, and by means of the application of the Bayes theorem it is sought to estimate them.

The variables considered in the model will be:

$E\ (PR)$: expected number of products returned per unit of time.
$E\ (D)$: expected number of units arranged per unit of time.

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$E\ (P)$: expected number of units tested per unit of time.

$E\ (Des)$: expected number of units disassembled per unit of time.

$E\ (Inv)$: Expected value of the inventory level available per time unit.

$E\ (R)$: expected number of units remanufactured per unit of time.

$E\ (NP)$: expected number of new products per unit of time.

c_c: Purchase cost of returned products (cost/piece).

c_d: Cost of disposition per product (cost/piece).

c_{pr}: Test cost per returned product (cost/piece).

c_{des}: Disassembly cost per returned product (Cost/Piece)

c_r: Remanufacturing cost (cost/piece)

c_{np}: Cost of new products (cost/part).

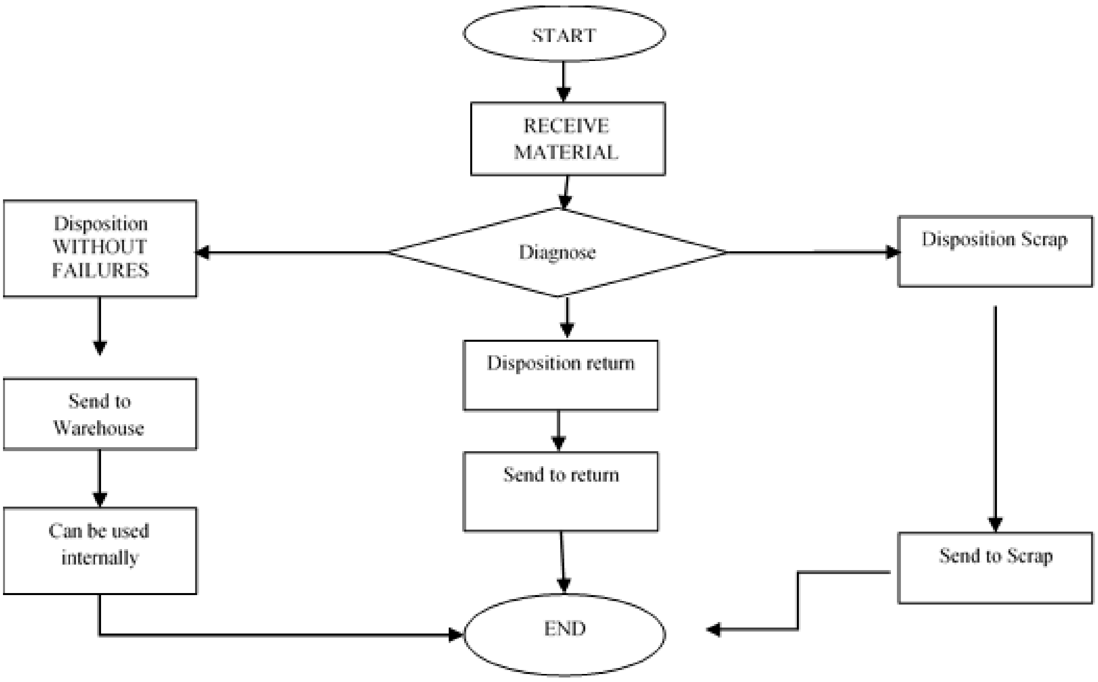

Fig 1. Operation of a Remanufacturing Process

III.METHODOLOGY

A. Bayesian Inference

Bayesian inference is based on the subjective point of view of probability (Lee, 2004). Gutierrez and Zhang (2009) mention that in recent decades Bayesian analysis has been one of the most developed aspects in the field

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of statistics. Advances in computational sciences, such as Markov chain algorithms based on Monte Carlo simulations (MCMC), have made the use of Bayesian methods increasingly common to the investigator. To perform a Bayesian analysis with respect to an unknown parameter, θ, it is necessary to model the opinion a priori that one has on the parameter by a function of probability density. However, the case in which the initial information can be expressed in terms of a specific probability distribution is not easy, mainly because this information is often diffuse.

The Bayes Theorem can be expressed as follows:

$$P(\theta|y) = \frac{P(y|\theta)P(\theta)}{P(y)} \quad (2)$$

where $P(\theta|y)$ is the aposteriori distribution, $P(y|\theta)$ is the likelihood function and $P(\theta)$ is the a priori function of the parameters, in this case, $(\mu,\ \sigma^2)$ of the normal distribution. The product of the functions $P(\theta|y) * P(\theta)$ is the joint distribution, while the denominator $P(y)$ is the marginal distribution

The components in the Bayes model will be substantiated, that is, the a priori distributions for the parameters, the likelihood function, the marginal distribution and the posteriori distribution, with which the estimation mentioned before will be developed. The calculations will be made using the R language for statistical calculations. Following are the fundamental concepts for obtaining the posteriori distribution.

The normal distribution is given by

$$f(y|\mu,\sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(y-\mu)^2\right] \quad (3)$$

and according to Box &Tiao (1973), considering that $\bar{y}$ is said to be a sufficient statistic for μ, and assuming according to Box & Tiao (1973), Albert (2009), in addition to Gelman (2002), the standard a priori not informative is given by:

$$g(\mu,\sigma^2|y) \propto \frac{1}{\sigma^2} \quad (4)$$

and the likelihood function can be written as:

$$l(\mu,\sigma|y) \propto \sigma^{-n} \exp\left\{-\frac{1}{\sigma^2}[(n-1)s^2] + n(\bar{y}-\mu)^2\right\} \quad (5)$$

where the product of (4) and (5) form the joint distribution, is giving by:

$$l(\mu,\sigma|y)\cdot g(\mu,\sigma^2|y) \propto \sigma^{-(n+2)} \exp\left\{-\frac{1}{\sigma^2}[(n-1)s^2]+n(\bar{y}-\mu)^2\right\} \tag{6}$$

Equation (6) will shape the posteriori distribution in Bayes' Theorem, that is, $P\ (\theta\ |\ y)$.

IV.THE LINEAR REGRESSION MODEL

Albert (2009) mentions that, generally, when constructing a regression model, we are interested in describing the variation of the response variable and in terms of k predictor variables. The average value of y_i can be described, the response for the i-th individual, as

$$E(y_i\,|\beta,X) = \beta_1 x_{i1} + \cdots + \beta_k x_{ik}, i = 1, \ldots, n \tag{7}$$

Where $x_{i1}, \ldots x_{ik}$ are the predictor values for the i-th individual and $\beta_1, \ldots, \beta_k$ are regression parametersunknown. The model can also be represented by a row vector of regression variables and a column vector of regression coefficients as

$$E(y_i\,|\beta,X) = x_i\beta \tag{8}$$

where the $\{y_i\}$ are considered conditionally independent given the values of the parameters and the predictor variables. An important assumption in the adjustment of the regression model $\theta = (\beta_1, \ldots, \beta_k, \sigma^2)$ is that of equal variances, that is, $var\ (y_i\,|\theta,X) = \sigma^2$. Then we make that $\theta = (\beta_1, \ldots, \beta_k, \sigma^2)$ represent the vector of unknown parameters and assume that the errors $\varepsilon_i = y_i\ - E(y_i\,|\beta,X)$ are independent and normally distributed with zero mean and variance σ^2. The formulation of the model is completed assuming that (β,σ^2) has the typical non-informative prior

$$g(\beta,\sigma^2) \propto \frac{1}{\sigma^2} \tag{9}$$

The joint density function of (β,σ^2) it is represented as the product

$$g(\beta,\sigma^2|y) = g(\beta|y,\sigma^2)g(\sigma^2|y) \tag{10}$$

The posterior distributionof the regression vector β conditional on the variance of the error σ^2, $g(\beta|y,\sigma^2)$, it is normal multivariate with average $\hat{\beta}$ and matrix of variances and covariances V_β, where

$$\hat{\beta} = (X'X)^{-1}X'y, \qquad V_\beta = (X'X)^{-1} \tag{11}$$

V.APPLICATION

A. Information Processing

Table 1 shows the information obtained in the company for the variables considered for the analysis and construction of the model.

TABLEI.

12-Week Data from the Ink Cartridge Remanufacturing Plant

NP	PR	TEST	DISAS.	DISP.	REMAN
3875	55822	48541	21951	26590	22601
4032	58768	51103	324233	16870	14339
2816	44379	38590	23885	14705	12499
6488	31063	27011	18545	8466	7196
2592	45411	39488	28757	10731	9121
5760	41009	35660	24053	11607	9865
3475	30457	26484	15083	10681	9078
2592	36444	31690	22668	9022	7668
3127	37604	32699	22843	9856	8377
2470	40856	35292	25085	10207	8675
4560	36887	32076	26348	5728	4868
1728	38096	33831	27050	6781	5763

Albert (2009) includes an analysis of normal data with both unknown parameters, and includes the previous non-informative$g(\mu,\sigma^2) \propto {}^{1}/_{\sigma^2}$, and mentions that the posterior density of the mean and the variance is given by:

$$g(\mu,\sigma^2|y) \propto \frac{1}{(\sigma^2)^{\frac{n}{2}+1}} \exp\left(-\frac{1}{2\sigma^2}(S+n(\mu-\bar{y})^2)\right) \qquad (12)$$

where n is the sample size $(n = 12)$, and $\bar{y}$is the mean of the sample and $S = \sum_{i=1}^{n}(y_i - \bar{y})^2$. The joint posterior density has the shape of the chi-square normal / inverse distribution where

- The posterior distribution of conditionalμoverσ^2it's distributed as$N(\bar{y}, \sigma/\sqrt{n})$
- The posterior marginal density$\sigma^2$is distributed as$S\chi_{n-1}^{-2}$, whereχ_{v}^{-2}represents an inverse distribution of an inverse chi-square with $v$degrees of freedom.

Based on these concepts, the reuse rate was first analyzed, simulating by means of theconstruction of a posterior distribution, the behavior of the mean and the variance of this rate. Figure 2 shows the behavior of the reuse rate with the variance as a function of the mean. Figure 3 shows the histograms of the behavior of the parameters of thereuse rate.

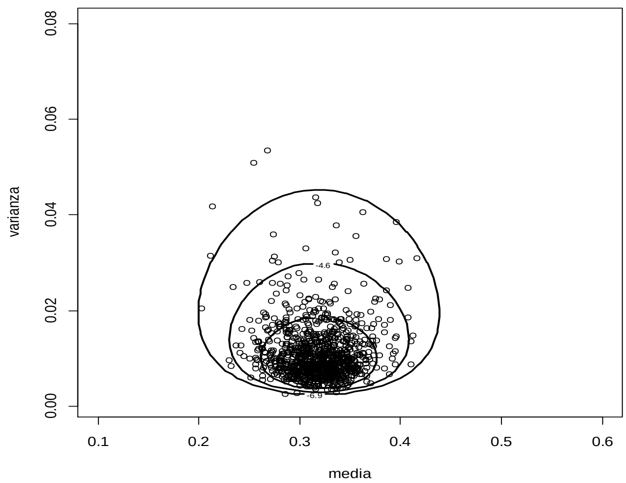


Fig 2. Behavior of the Reuse Rate Based on its Mean and Variance

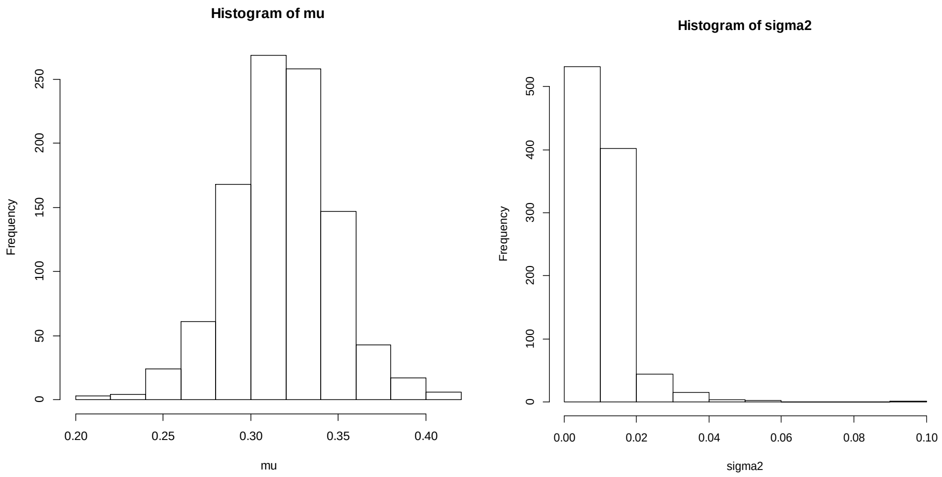
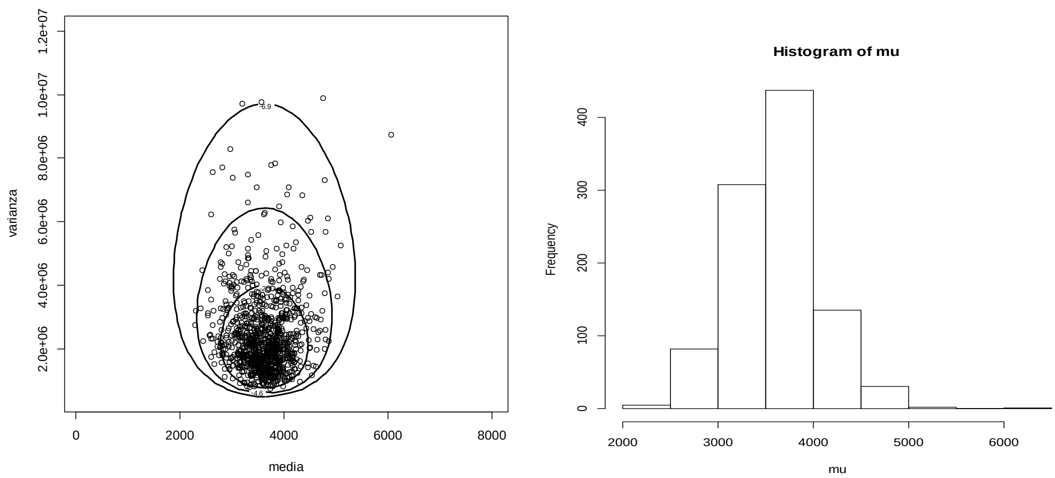


Fig. 3 Histograms of the Behavior of the μ and σ Parameters of the Reuse Rate.



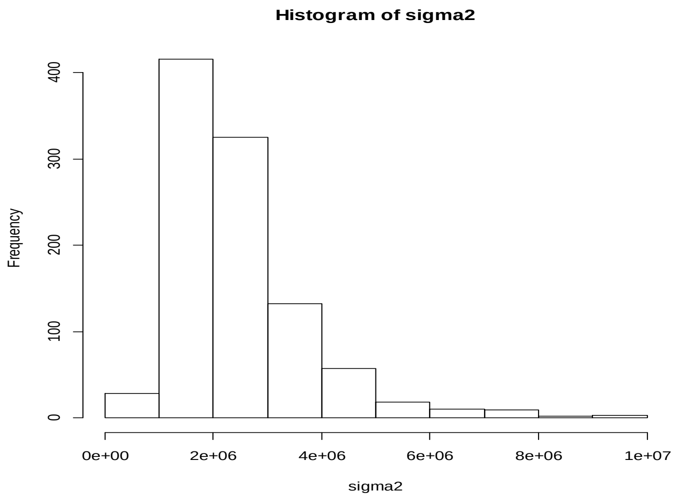


Fig. 4 Contour plot, Mean Histogram and Variance Histogram of New Products

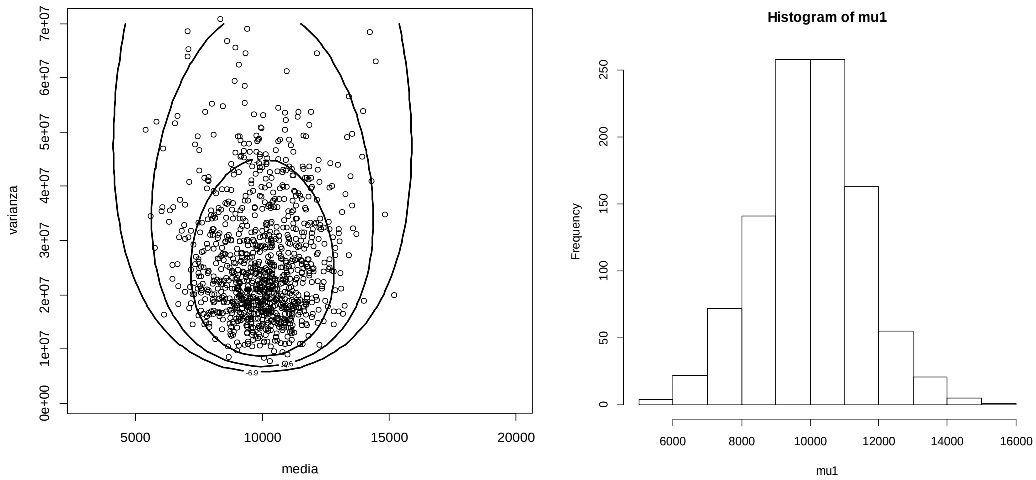


Fig.5. Behavior of the Remanufacted Variable

Table 2 summarizes the information of the parameters of each of the variables for 1000 simulated values of each of the variables by a function of normal likelihood and a non-informative prior to mean and variance unknown.

TABLE 2.

Average Values and Standard Deviation Estimated for Each of the Variables

	Media	Standard Deviation
Reusable rate	0.3189393	0.09623735
Returnedproducts	41484	9243
Tested	36130	189
Disassembled	24334	5123
Disposed	11831	5973
Remanufactured	9989	5109
New Products	3617	1516

VI.CONSTRUCTION OF THE COST MODEL

Albert (2009) considers that the expressions for the posterior and predictive distributions lead us to develop efficient simulation algorithms. Thus, to simulate from the joint posterior distribution the coefficient vector of regression β and the variance of error σ^2, one should simulate a value of the error variance of its posterior marginal density $g(\sigma^2|y)$for right away, simulate a value of β of density Posterior conditional $g(\beta|\sigma^2, y)$. The algorithm in R for the simulation of values for the mean and the variance is then shown from the inverse and normal multivariate distributions of the components.

```
> fit=lm(CTOTAL~Cpr+Cnp+Cprob+Cdes+Cdisp+Crem,data=data, x=TRUE,y=TRUE)
> summary(fit)
Call:
lm(formula = CTOTAL ~ Cpr + Cnp + Cprob + Cdes + Cdisp + Crem,
   data = data, x = TRUE, y = TRUE)
Residuals:
1       2       3      4       5       6       7       8      9      10     11      12
-645.1  1088.1  489.5  -1430.1 -2571.8 -1112.4 -1795.7 505.2  2201.9 4727.2 -1616.1 -1722.0

Coefficients:
            Estimate    Std. Error  t value  Pr(>|t|)
(Intercept) -3.030e+03  1.365e+04   -0.222   0.833
Cpr         -1.016e+04  2.222e+04   -0.457   0.667
Cnp         1.250e+00   6.297e-01   1.984    0.104
Cprob       -2.230e+05  1.565e+05   -1.425   0.213
Cdes        2.967e+04   2.106e+04   1.409    0.218
Cdisp       4.097e+04   2.472e+04   1.657    0.158
```

Crem	-4.317e+03	2.505e+03	-1.723	0.145

Residual standard error: 3098 on 5 degrees of freedom
Multiple R-squared: 0.9816, Adjusted R-squared: 0.9594
F-statistic: 44.34 on 6 and 5 DF, p-value: 0.0003545.

It is observed that the significance of regression is 0.0003545 which means that the different cost variables if they are strongly related, which confirms the coefficient of determination (R-squared) with a high value, 0.9816. That is, although the P-value of the different cost values are not less than the significance value of 0.05. According to the results obtained and explained in the preceding paragraph, the regression model shall be:

$$C(Total) = -3030 - 10160c_{pr} + 1.25c_{np} - 22300c_{prob} + 29670c_{des} + 40970c_{disp} - 4317c_{rem}$$

The regression model that was obtained after the analysis of the data has negative coefficients, this is because it is a model that considers the reuse of components so that the higher the percentage of reuse the costs will be diminished in Proportion to the value of the coefficient. Note that the new parts coefficient is only 1.25 which would be the increase in cost per unit. It is also important to note that the cost of disassembly and the cost of disposition should be continuously controlled as they are the ones that contribute most to the cost function. Rodriguez Aguilar (2018)

VII.CONCLUSIONS

The previous selection of the returned products that is made in the disassembly plant and the established acceptance criteria if they significantly influence the reuse percentage and the total remanufacturing costs as shown by the results obtained.

The quality, quantity, testing times, dismantling and remanufacturing times of the returned materials influence reuse and total remanufacturing costs as shown by the results obtained.The materials of the suppliers established by the company are previously selected (before entering the disassembly process) so that they meet the quality required by the assembly plant in such a way that disposal costs are reduced. From the results of the construction of the Cost Model it can be observed that the adjustment of the regression is adequate (R^2 = 0.9816), which allows us to make estimates of the costs depending on the demand, reuse rate and the behavior of the rest of variables involved.

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