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AUTOMATING REQUEST FOR QUOTATION PROCESS USING R-LANGUAGE

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Abstract

RFQ is an estimated quoted budget. A customer requests the company for an estimated quoted amount for the final product, the company sends that request to the supplier, and the supplier generates an estimated price based on the customer's requirements by looking into prices of raw material of previous projects. Based on all the prices, an estimated price is generated and sent back to the company which it provides to the customer. This whole process takes weeks to complete. The research aims to reduce time by automating the RFQ process. A multiple regression model is employed by analyzing the dataset. R programming language is used for data analysis. A model is applied according to the variables of the dataset. Test cases are generated to further prove the efficiency of the model. User requirements are put on the regression equation to provide an estimated quoted value.

1 Introduction

RFQ is a business procedure in which a company or a customer asks a seller for a quote on the purchase of goods or services. Request for Quotation (RFQ) and Invitation for Bid (IFB) are two terms that refer to the same matter [1]. An RFQ typically involves quite the worth per item (i.e. the price of each raw material and its different types), information like payment terms, quality level per item, or contract length could also during the bidding process you will submit. To collect accurate quotations, RFQ's often contain product or service requirements to ensure that all vendors are competing for the same product or service [2]. Logically, if the specifications are more detailed, it will produce a precise quote for the customer/company. The response of a quotation must be sent by e-mail, mail, or courier service in text form. To get the best price for the job, professional sourcing firms must compare quotes and check them out during the RFQ process (either by negotiations or an e-auction). The aim is to assess the fair market price of products or services so that the business can save money [3]. RFQs perform well for generic and commoditized products and services since this ensures that each supplier's quote is equivalent. RFQ requires various contractors to submit quotes, with the most cost-effective being chosen. When it comes to retailer-manufacturer collaboration, it's not enough to take the retailer's decision into account [4]. It also increases the likelihood of competitive bidding because vendors will be confident that they are not the only ones bidding for the goods. Figure 1 shows a glimpse of an RFQ process in a better manner for a better understanding.

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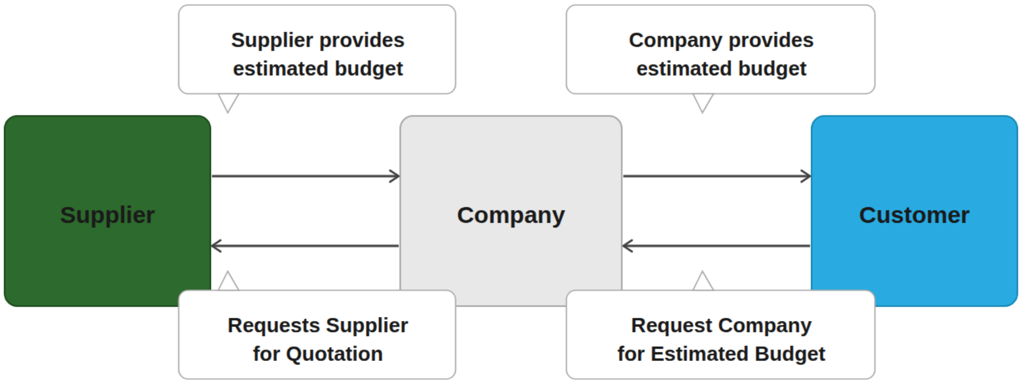

Figure 1: Request for Quotation

1.1 RFQ Automation

Costs for specific items or services are elicited via the RFQ approach. A procurement order management system, such as an automated Request For Quotation (RFQ), streamlines and standardizes the process, allowing businesses to make the most of their time and resources. Automating the RFQ approach will benefit an organization by streamlining the process and reducing response times, which is a win-win for both prospective clients and the company [5]. The World Health Organization (WHO), for example, can receive data at a far faster rate than any supplier, and WHO will create and respond to many RFQs. As clients enter their demands into intelligent software, the RFQ automation will reduce the processing time for them. This will access the company's databases obtained from suppliers and compare customers' provided inputs with database columns before gathering all the data from databases and comparing the data to arrive at the determined budget estimation. The quoted value will be sent to the customer via e-mail or another appropriate method. The processing time required for making a request to a supplier and waiting for a response from the supplier is eliminated, and the results are displayed or provided directly to clients [6]. The time spent on requesting a quotation can be reduced. Automation not only simplifies operations but also generates output from the vast amount of data gathered. Companies will learn more about consumer behavior, purchase habits, and organizational efficiencies if they use this data wisely. Strategic decisions based on genuine, real-world data can be made, and any opportunities to grow the firm can be taken advantage of as soon as they come [7].

The time spent submitting a request to a supplier and waiting for a response is eliminated, and the results are displayed or provided immediately to clients. The supplier is still involved, but the time spent sending requests for quotations to them and receiving estimates from them is reduced. Suppliers face a plethora of information and no effective way to manage it until they optimize the RFQ process. Automation not only streamlines systems but also enables the creation of new ones to collect massive volumes of data. If companies use data effectively, they can learn more about customer behavior, purchase habits, and company efficiencies. As a result, reasonable judgments based on realistic, real-world results will become a reality, as will taking any opportunity to develop the company as soon as it arises [8].

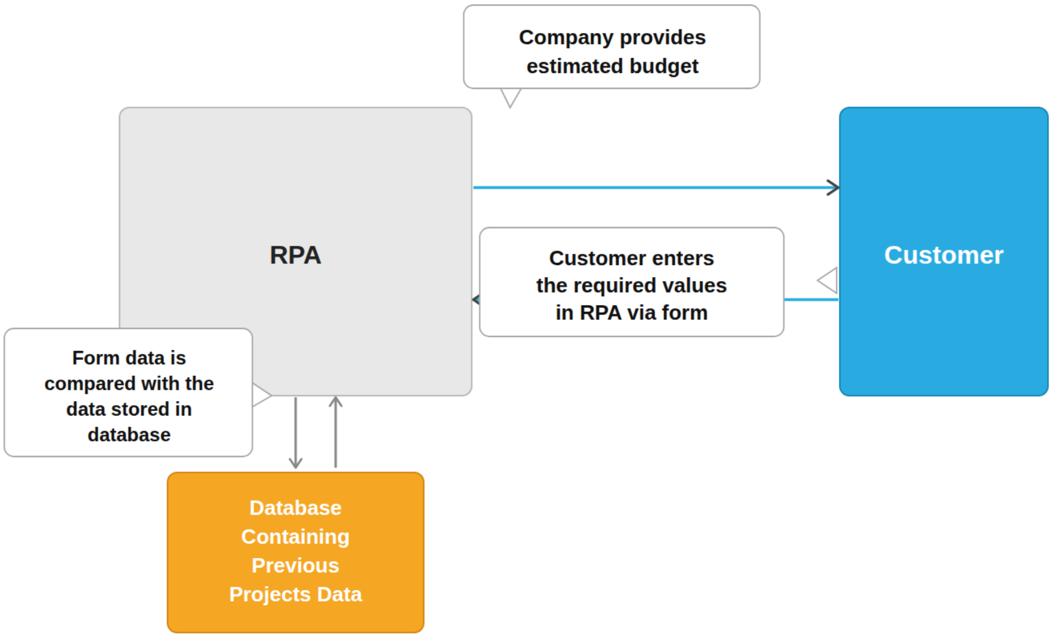

Figure 2: Request for Quotation

1.2 Use of RFQ Automation to Increase Efficiency

In the supplier-client relationship, the RFQ mechanism is crucial. It enables a customer to ensure that they are having the best prices, and therefore the best supplier, for required goods, by determining which suppliers have the best opportunity to sell the most important products at the best price, taking into account material, value, and regional considerations. The RFQ approach is known for delivering accurate information through realistic and geographic silos, increasing stakeholder interest, saving time and resources, and eliminating errors when used correctly. However, several organizations, especially in the electronics manufacturing industry, continue to use inefficient manual RFQ processes. Wholesalers, suppliers, and distributors spend hundreds of thousands of dollars and tens of thousands of hours struggling with orders and requests that are the result of obsolete, unreliable systems. With the use of intelligent and strategic RFQ control methods, these pressure points can be eliminated. Any phase of the procurement cycle can be simplified by automating the RFQ process, delivering speed, reliability, and accountability to all parties in the process [9].

RFQ automation gives businesses a competitive edge by allowing them to be leaner, more communicative, and more coordinated across teams. An accurate, straightforward, and informative quote is required when buying and selling electronic components. The data clarification that RFQ automation offers is critical to a company's success, but it can also be disruptive. Calculating win/loss ratios, deciding price elasticity, and determining which products are the most profitable (both where and when they sell better) become much simpler. Remove time-consuming activities like manual reviewing and checking thousands of lines in Excel and discovering the immediate advantages of automating the whole RFQ intake procedure. Part suppliers and distributors should determine the communication needs of their current business processes before introducing RFQ automation. Material Requirements Planning (MRP) or Enterprise Resource Planning (ERP) often involve several teams. Sales, manufacturing, and logistics both have a vested interest in supplying the consumer with correct and timely quotes [10].

Profit margins must be tracked regularly, and quoting activity must be studied. A lot of individuals contribute to the system, but if a uniform workflow isn't in place, it may unwittingly trigger unnecessary lag time in the procurement process. An organization will open channels of contact and eliminate needless conflict and miscommunication by aligning both stakeholders on the same RFQ execution plan. It can reduce repetitive and time-consuming tasks just like an RPA bot [11]. Where manual procedures are involved, this individualized sorting contributes to alienation and misalignment. Automation not only streamline operations but also allows for the collection of massive volumes of data. The technological and industrial impacts of automation are not limited to the development, production, recycling, and efficiency but also spur sustainability and economic efficiency through its application [12]. Organizations can learn more about customer behavior, purchasing habits, and corporate efficiencies by using this data intelligently. As a result, strategic decisions based on true, real-world results can be made, and all possibilities to expand the company can be taken advantage of as soon as they emerge [13].

2 Materials and Methods

The strategy is to perform data analysis, and RFQ automation for minimizing the time taken in the request for quotation process (RFQ). In this process the customer requests the company for a budget estimation for the product, the company approaches the supplier to give them the estimated budget by going through requirements of the customer and send it to the company, and then the company gives that estimated budget to the customer. However, this process takes a lot of time. To reduce this processing time, data of the products from the supplier was gathered by storing it into a dataset that contains all the previous data used in the manufacturing of that product. Regression analysis is then performed on that dataset using R-Language. The result of this regression analysis produces a regression line that provides certain R-Square, Adjusted R-Square, Standard Error, and P-Value, which indicates whether the data is suitable to work with.

A dynamic form is developed using Google Forms, and a spreadsheet is attached to it to store customer requirements. In this form, the customer enters data or inputs according to demands, and the input values are put in a regression line that provides the total estimated budget as output. The estimation can vary depending on Raw Material, Production Technology, End-Product, Inner Diameter in millimeters, Outer Diameter in millimeters (with a condition that Outer Diameter should be greater than Inner Diameter), Width in millimeters, Brutto Weight in kilograms, Netto Weight in kilograms, and Incoterms either FOB or DDU.

To perform data analysis on the dataset, the second step is to do a multiple regression analysis to know whether the data is workable or not, i.e., whether it is possible to carry out the research or not. The third step is to generate a multiple regression equation and prove the efficiency of the model by working on multiple cases. Once the efficiency is proved, the customer enters its requirement, and a quoted value is provided against those inputs. Figure 3 explains the research steps in a graphical format.

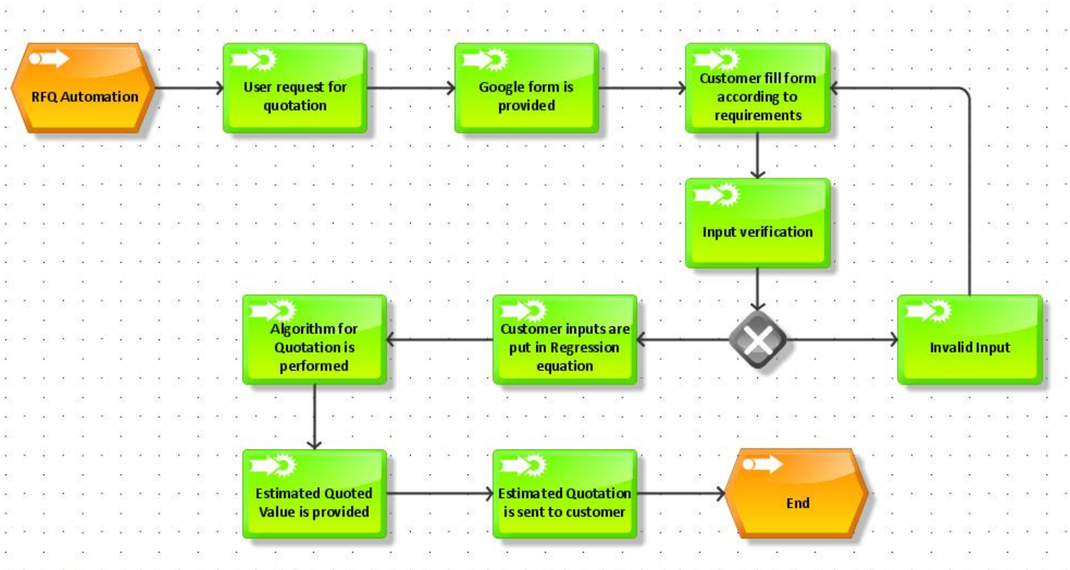

Figure 3: EPC diagram of the process involved in this project

2.1 Data Gathering and Analysis

The dataset is the most important aspect of this project as the whole RFQ automation process depends on previous data of projects the company has completed. So the first step is to perform compact research for suitable data according to research work and what goal is to be achieved. In this case, the data should be from a company that is working on manufacturing or developing a certain product.

The data analysis of the dataset is performed using R-Language. The first step is to load a CSV file into R-Studio. After loading the dataset to R-Studio, the next step is to analyze the data. The following commands are used:

```
Data_ <- read.csv("~/Data_.csv")  # Load dataset into RStudio
library(tidyverse)  # Enable data cleaning
View(Data_)  # Show the dataset in a new tab
summary(Data_)  # Show data summary
```

To perform data analysis a dataset is required. The dataset contains the following variables:

- Raw material specification: There are three types of raw materials that the company uses.
- Production Technology: Two types of production technologies are being used, either tube or forging.
- Endproduct bearing Type: Multiple bearing types are used such as DGBB, compensating element, Chaises, TRB, SRB, Needle, CRB, etc.
- Material base price: It is the base price of the material in RMB per ton.
- Annual Budget quantity: It is the annual assigned based on the quantity they are making.
- Outer Diameter: It is the outer diameter of the bearing in millimeters.
- Inner Diameter: It is the inner diameter of the bearing in millimeters and the outer diameter should be greater than the inner diameter.

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Raw.material	Production.technology	Endproduct	Materialprice	annual.quantity	Outer.Diameter.mm.	Inner.Diameter.mm.
Raw material1	PT1	EP1	5300	45,026	19.74	15.13
Raw material1	PT2	EP2	5300	22,513	16.25	11.53
Raw material1	PT2	EP2	5300	22,513	16.25	11.45
Raw material1	PT2	EP2	5300	8,755,000	17.15	11.45
Raw material1	PT2	EP2	5300	22,513	17.25	11.53
Raw material1	PT2	EP2	5300	12,657,342	18.15	11.45
Raw material1	PT2	EP2	5300	12,657,342	18.15	11.45
Raw material1	PT2	EP2	5300	8,600,000	18.20	11.50
Raw material1	PT2	EP2	5300	14,445,000	18.20	11.50
Raw material1	PT2	EP2	5300	22,513	18.20	11.53
Raw material1	PT2	EP1	5300	3,096,829	20.30	14.80
Raw material1	PT2	EP1	5300	2,329,828	23.50	16.75
Raw material1	PT2	EP1	5300	10,005	23.50	16.75
Raw material1	PT2	EP1	5300	690,460	23.50	16.75

Figure 4: Dataset Visualization

The data contains the following additional columns:

- Width: This column represents the width of the bearing in millimeters.
- Brutto weight: Brutto weight is the gross rate including packaging etc. It is in kilograms.
- Netto Weight: Netto weight is the weight of the actual product excluding packaging. Netto weight should be less than brutto weight and it is also in kilograms.
- Quoted Currency: It is the currency of the quote which is RMB.

- Endproduct Price: This column represents the price of the final product, depending on the customer's demand.
- Incoterms: Incoterms are internationally recognized rules which are globally accepted and determine the duties of seller and buyer. They are either FOB (Free on Board) or DDU (Delivered Duty Unpaid).

Width..mm.	Bruttoweight	Nettoweight	Enproduct.price	Incoterms	ID..AD	AD..width
34.70	0.104	0.043	2.32	FOB	0.77	0.44
8.15	0.014	0.006	0.41	DDU	0.71	1.99
10.15	0.015	0.008	0.45	DDU	0.70	1.60
9.15	0.015	0.009	0.40	DDU	0.67	1.87
8.65	0.014	0.008	0.44	DDU	0.67	1.99
8.15	0.018	0.009	0.51	DDU	0.63	2.23
8.15	0.016	0.010	0.50	DDU	0.63	2.23
8.15	0.018	0.009	0.51	DDU	0.63	2.23
8.15	0.016	0.010	0.50	DDU	0.63	2.23
10.15	0.019	0.012	0.46	DDU	0.63	1.79
9.20	0.035	0.010	0.64	DDU	0.73	2.21
14.12	0.044	0.019	0.67	DDU	0.71	1.66
14.12	0.039	0.019	0.74	DDU	0.71	1.66
14.12	0.044	0.021	0.64	FOB	0.71	1.66

Figure 5: Dataset Visualization

2.2 Summarizing the Dataset

In this phase, analysis and summarization of the dataset are performed. For summarizing the dataset, the values of columns in the dataset, which represent multiple attributes of data, are not all numerical; some of them are of character type as well. For this purpose, the first step is to deal with numerical values using the following code:

```
Data_$Materialprice.base.Rmb.t <- as.numeric(impute(Data_$Materialprice, mean))
Data_$annual.Budget.quantity <- as.numeric(impute(Data_$annual.Budget, mean))
Data_$Outer.Diameter..mm. <- as.numeric(impute(Data_$Outer.Diameter..mm., mean))
Data_$Inner.Diameter.mm. <- as.numeric(impute(Data_$Inner.Diameter.mm., mean))
Data_$Width..mm. <- as.numeric(impute(Data_$Width..mm., mean))
Data_$weight..kg..Brutto <- as.numeric(impute(Data_$Bruttoweight, mean))
Data_$weight.Netto..kg. <- as.numeric(impute(Data_$Nettoweight, mean))
Data_$Enproduct.price <- as.numeric(impute(Data_$Enproduct.price, mean))
summary(Data_)
```

Table 1. Summary of the Dataset

Variable	Summary Statistics
Raw Material Specification	Length: 1065, Class: Character
Production Technology (EP1/EP2)	Length: 1065, Class: Character
Material Base Price (Rmb/t)	Min: 3000, Median: 5300, Mean: 5502, Max: 33160
Annual Budget Quantity	Min: 11, Median: 1000, Mean: 894.2, Max: 1000
Inner Diameter (mm)	Min: 9.81, Median: 48.06, Mean: 64.06, Max: 653.60
Outer Diameter (mm)	Min: 14.63, Median: 64.00, Mean: 82.60, Max: 681.70
Width (mm)	Min: 6.95, Median: 21.72, Mean: 26.84, Max: 138.25
Brutto Weight (kg)	Min: 0.014, Median: 0.330, Mean: 1.771, Max: 49.607
Netto Weight (kg)	Min: 0.005, Median: 0.157, Mean: 0.8724, Max: 33.400
Incoterms (FOB/DDP)	Length: 1065, Class: Character

2.3 Creation of Dummy Variables

In this phase, the process of creating dummy variables is carried out. As analyzed from Table 1, numeric values are represented in a better perspective while those columns which are of character type are not clear, raising a question about their use in a multiple regression model. For this purpose, assigning certain values to these character-type columns is necessary. By creating dummy variables for each column, these character type values get a certain number which is only a type of representation.

There are multiple bearing types so the binary number allocated to each type will be around eight digits. For example, 00000000 represents one type of endproduct bearing type, 00000001 represents another bearing type.

```
print("======Dummy variable for End Product ======")
res3 <- model.matrix(~Endproduct ,Data_)
head(res3[,+0])
```

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Filter

Intercept	EndpointGDP2	EndpointGDP3	EndpointGDP4	EndpointGDP5	EndpointGDP6	EndpointGDP7	EndpointGDP8
1	0	0	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	1	1	0	0	0	0	
1	0	1	0	0	0	0	
1	0	1	0	0	0	0	
1	0	1	0	0	0	0	

Figure 6: Dummy variables for End-Product

2.4 Selection of Regression Model and Data Analysis

In this phase, the process of selecting a regression model and its implementation takes place. The first step is to select a regression model and, in this case, based on the data and the type of problem that needs to be solved, a multiple regression model is indicated. To implement the multiple regression model, the first step is to select the variables on which the multiple regression will be implemented.

```
auto.sel <- subset(Data_, select = c(Enproduct.price, Raw.material, Production.technology, Endproduct.type, Materialprice, Outer.Diameter..mm., Inner.Diameter.mm., Width..mm., weight, Brutto, weight.Netto..kg., Incoterms.FOB.DDP))
```

Enproduct.price	Raw.material.specification	Production.technology..Tube..Forging	Endproduct.bearing.type	Materialprice.base.Simb.1	Outer.Diameter.mm.	Inner.Diameter.mm.	Width..mm.	weight..Kg..Brutto	weight..Netto..Kg	Incoterms.FOB.DDP
1.15	100C6	Forging	D285	5300	47.25	25.00	15.00	0.1700000	2.347	FOB Shanghai
1.15	100C6	Forging	D285	5300	47.25	25.00	15.00	0.1700000	2.347	FOB Shanghai
1.15	100C6	Forging	D285	5300	47.25	37.00	12.00	0.1700000	2.347	FOB Shanghai
4.02	100C6	Forging	Concentrating Tanker	5300	47.62	34.00	23.75	0.3200000	3.127	DDU
1.15	100C6	Forging	D285	4500	47.62	38.10	17.46	0.2200000	3.049	FOB Shanghai
1.15	100C6	Forging	D285	5300	47.62	38.10	17.46	0.2200000	3.049	FOB Shanghai
1.42	100C6	Tube	n/a	5300	48.25	39.75	17.10	0.1500000	2.976	FOB Shanghai
2.75	100C6	Forging	D288	5300	48.27	36.75	16.78	0.1600000	3.013	FOB Shanghai
1.15	100C6	Forging	D288	6300	48.40	38.99	17.00	0.2100000	3.096	FOB Shanghai
2.60	100C6	Forging	D285	6522	49.48	34.73	17.00	0.2100000	3.063	FOB Shanghai
2.60	100C6	Forging	D285	6522	49.48	34.73	21.24	0.2700000	3.063	FOB Shanghai
2.45	100C6	Forging	D285	6522	49.52	34.99	16.75	0.2100000	3.087	FOB Shanghai
2.45	050Cr4-4	Tube	n/a	5750	48.54	40.84	16.75	0.1400000	2.960	DDU
2.27	100C6	Forging	D285	6522	50.00	32.00	14.00	0.1800000	3.044	FOB Shanghai
2.30	100C6	Forging	D285	6522	50.00	34.00	15.50	0.2000000	3.088	FOB Shanghai

Figure 7: Variables of the model

The variables in the regression model are:

- Dependent Variable: End-product price is the dependent variable.
- Independent Variables: Raw material specification, production technology, bearing type, material base price, outer diameter, inner diameter, width, brutto weight, netto weight, and incoterms.

2.5 Analysis of Variables

The data's variables are analyzed, and multiple problems are resolved:

- Data is clear and well-defined.
- Every numerical variable is explained in terms of its mean, mode, and median as analyzed in the summary phase in Table 1.
- Dummy variables are created for non-numeric data type variables.
- The independent and dependent variable is clear (i.e., End-product price).

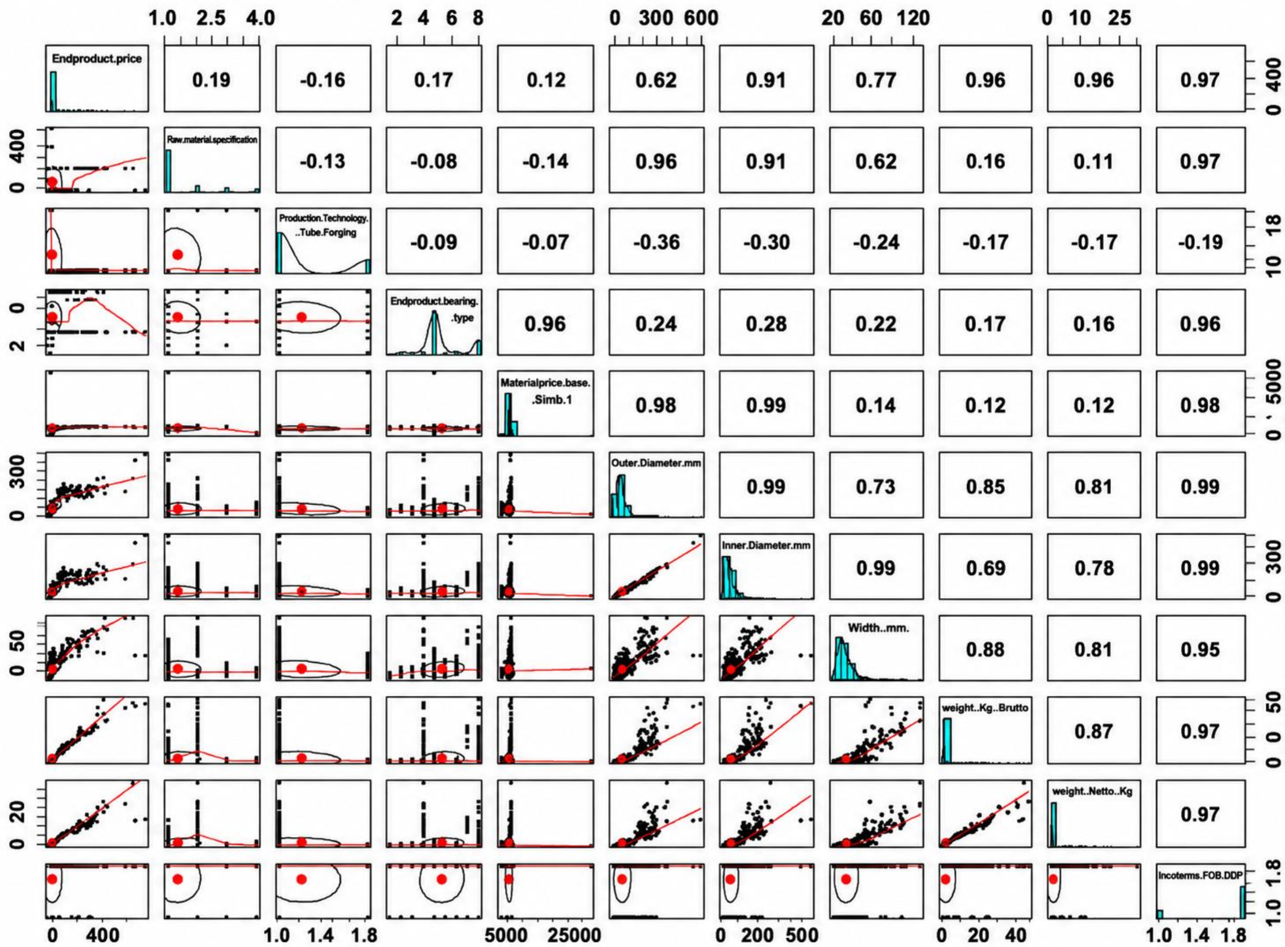

Figure 8: Visualization of the Variable Analysis (Pairs Panels showing scatter plots, histograms, and Pearson correlation)

2.6 Creation of Multiple Regression Model

As this part is the most important phase of the project, a thorough explanation is necessary. The multiple regression model contains a dependent value which is 'End Product Price' and this dependent value depends on multiple independent variables. Following is the chunk of code that implements multiple regression modeling:

```
    model12 <- lm(Enproduct.price ~ Raw.material + Production.technology
+ Endproduct + Materialprice + Outer.Diameter..mm. + Inner.Diameter.mm. +
Width + Bruttoweight + Nettoweight + Incoterms, Data_)
```

anova(model12)

```
Analysis of Variance Table

Response: Enproduct.price
                        Df  Sum Sq Mean Sq   F value    Pr(>F)    
Raw.material             3  970809  323603 1431.3376 < 2.2e-16 ***
Production.technology    1   42697   42697  188.8530 < 2.2e-16 ***
Endproduct               7 1238896  176985  782.8283 < 2.2e-16 ***
Materialprice            1    3082    3082   13.6320 0.0002342 ***
Outer.Diameter..mm.      1 1651370 1651370 7304.2234 < 2.2e-16 ***
Inner.Diameter.mm.       1   16312   16312   72.1500 < 2.2e-16 ***
Width..mm.               1  101395  101395  448.4839 < 2.2e-16 ***
Bruttoweight             1  418161  418161 1849.5795 < 2.2e-16 ***
Nettoweight              1  315719  315719 1396.4653 < 2.2e-16 ***
Incoterms                2     380     190    0.8408 0.4316522    
Residuals             1012  228797     226                        
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
```

Figure 9: Analysis of Variance

2.7 Coefficient of the Model

The coefficient of the model when the confidence interval is 0.95 or 95 percent is shown in Figure 10.

```
> coefficient<- coefficients(model12, interval ="confidence")
> coefficient
          (Intercept) Raw.materialRaw material2 Raw.materialRaw material3 Raw.materialRaw material4  Production.technologyPT2          EndproductEP2
        -6.407462e+00             -1.350208e+00              3.302571e+00              2.145253e+00              4.527820e+00          1.251053e+00
        EndproductEP3             EndproductEP4             EndproductEP5             EndproductEP6             EndproductEP7          EndproductEP8
        -1.114613e-01             -1.538261e+00             -1.781780e+01             -3.972948e-01             -6.063158e+00         -6.676358e-01
        Materialprice       Outer.Diameter..mm.        Inner.Diameter.mm.                Width..mm.              Bruttoweight            Nettoweight
         1.904506e-04             -6.978226e-02              2.497781e-01             -2.542339e-01              5.071181e+00          1.628532e+01
         IncotermsFOB              IncotermsFOB
         1.291068e+01              1.207085e+00
>
```

Figure 10: Coefficient of Model

2.8 Histogram of the Coefficient

The histogram diagram for the coefficient of the model depicts the frequency by which the coefficients occur in the model.

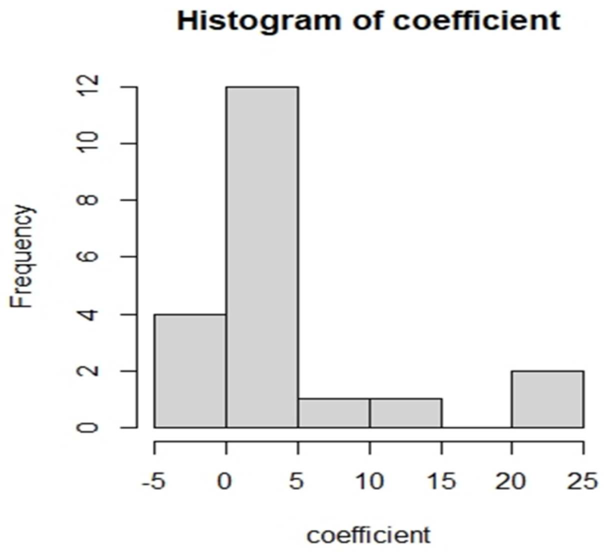

Figure 11: Histogram Coefficient of Model

2.9 Summary of Multiple Regression Model

The multiple regression formula is as follows:

Y^ = B0 + B1X1 + B2X2 + ... + BnXn

Applying this to the model:

Enproduct.price = Intercept + B1(Raw.material.specification) + B2(Production.technology) + B3(Endproduct.bearing.type) + B4(Materialprice.base.Rmb.t) + B5(Outer.Diameter..mm.) + B6(Inner.Diameter.mm.) + B7(Width..mm.) + B8(weight.kg.Brutto) + B9(weight.Netto.kg.) + B10(Incoterms.FOB.DDP)

Table 2. Multiple Regression Equation Values

Regression Equation	Values
(Intercept)	6.6487705
Raw.material 1	3.51E-01
Raw.material 2	3.73E+00
Raw.material 3	2.8038197
EP1	-3.889541
EP2	1.77E+00
EP3	3.98E+00
EP4	2.50E+01
EP5	1.20E+00
E6	1.69E+00
E7	4.10E-01
EP8	2.31E+01
EP10	1.88E-01
Outer.Diameter	-6.94E-01
Inner.Diameter	7.20E-01
Width	7.03E-02
Bruttoweight	1.34E+01
Nettoweight	-2.10E+00
Incoterms.FOB	2.68E-01
Incoterms.DDU	2.68E-01

```
Residual standard error: 15.04 on 1012 degrees of freedom
Multiple R-squared:  0.9541,    Adjusted R-squared:  0.9533
F-statistic:  1108 on 19 and 1012 DF,  p-value: < 2.2e-16
```

Figure 12: Summary of Regression Analysis

Key observations from the multiple regression analysis:

- Standard Error: The standard error provides the absolute measure of typical distance from data points to the regression line. Considering the large set of variables and realistic model, the value of standard error is quite low.
- Multiple R Squared Value: The value of multiple R squared is 97.07, indicating that 97 percent of the data is explanatory.
- Adjusted R Squared Value: The value of Adjusted R Squared is 0.9702, reflecting the significance of the newly added variables.
- F-Statistic: The F-calculated value is 1821. This tells that on 95% confidence level, the values of beta1, beta2, ..., BetaN cannot be zero. The coefficients where probability values are significant at 15 or 10 percent means those factors influence the production.

2.10 Multiple Regression Line Visualization

Figure 13 shows the mapping of data on multiple regression equations/multiple regression lines.

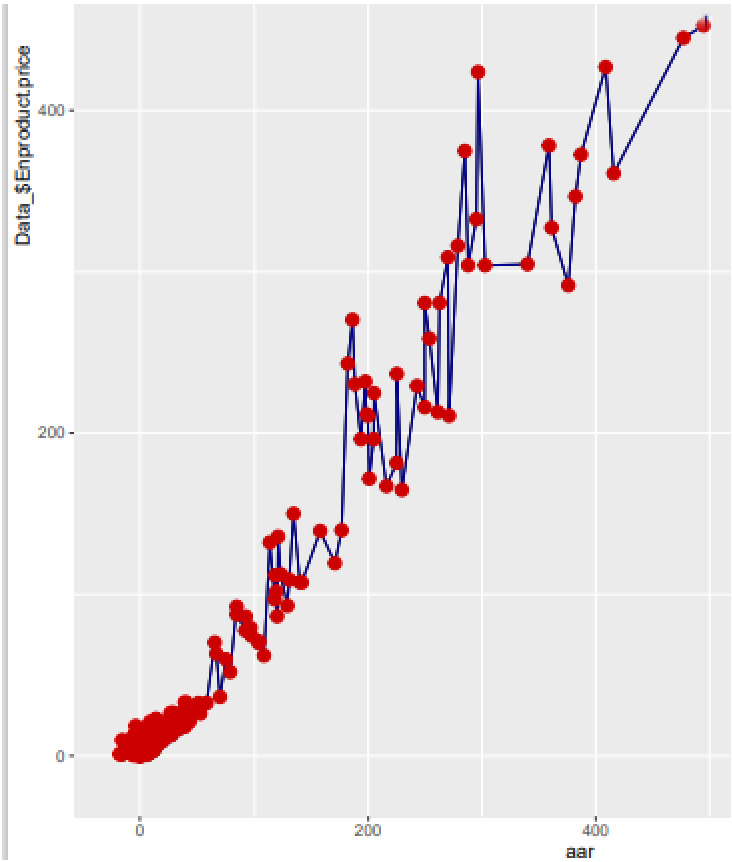

Figure 13: Multiple Regression Line Visualizations

2.11 Comparison of End-Product Price and Fit Price Value

The comparison of the end-product price and the predicted fit value predicted by the model is shown in Figures 14 and 15. The highlighted part in Figure 15 shows that the mean of both prices is the same, thus supporting the multiple-regression model and showing that the outcome of the model is the desired one as the trend-line is progressing towards the desired direction.

	A	B
1	**Fit Value**	**Enproduct price**
2	8.433225817	2.32
3	3.892619428	0.41
4	3.984772239	0.45
5	3.287950196	0.4
6	3.229724068	0.44
7	2.564021396	0.51
8	2.535136057	0.5
9	2.565317518	0.51
10	2.536432179	0.5
11	2.734537631	0.48
12	1.00338003	0.64
13	3.002195532	2.55
14	0.633975995	0.67
15	0.567024595	0.74
16	0.897506851	0.64
17	0.550717145	0.64
18	0.558977149	1
19	0.421103948	0.66
20	2.743599314	1.23

Figure 14: Comparison of the predicted fit value and end-product price

1046	113.8973911	92.98
1047	244.9530437	212.99
1048	183.6847232	139.77
1049	253.9256094	291.59
1050	115.8669607	86.52
1051	362.5560533	360.92
1052	259.4699978	258.57
1053	407.9226661	452.68
1054	294.6715057	332.56
1055	589.2091306	684.3
1056	624.5317111	756.77
1057	567.3372102	660.42
1058	522.1780918	605.95
1059	398.8262064	444.91
1060	303.5891036	304.66
1061	175.880272	171.78
1062	109.9046678	111.85
1063	33.09307061	10.67
1064	30.00323973	4.45
1065	41.48875511	21.08
1066	31.63315283	8.49
1067	20.39569014	20.39569014

predictivevalue123 | Sheet1

Figure 15: Comparison of the predicted fit value and end-product price

3 Results

The implementation of requirements was achieved by understanding business requirements, gaining an in-depth understanding of the supply chain and processes involved in RFQ Automation. After the implementation of multiple regression analysis, desired results were obtained for all relevant statistical parameters: standard error, R-square, Adjusted R-square, F-statistics, and P-values. The multiple regression equation was generated, and 40 test cases were generated to get multiple quotes based on the model.

3.1 Test-Cases Implementation

To further support the efficiency of the model, random test cases are generated from multiple random values stored in the dataset to get the end-product price. All these prices are in the Chinese Yuan (RMB). A total of 40 test cases are generated by putting random values from the dataset. These test cases are shown in the following tables.

Table 3. Test Case 1

Regression Equation	Equation Values	Test-Case 1
(Intercept)	6.6487705	1
Raw.material 1	3.51E-01	1
Raw.material 2	3.73E+00	0
Raw.material 3	2.8038197	0
EP1	-3.889541	1
EP2	1.77E+00	0
EP3	3.98E+00	0
EP4	2.50E+01	0
EP5	1.20E+00	0
E6	1.69E+00	0
E7	4.10E-01	0
EP8	2.31E+01	0
EP10	1.88E-01	1
Outer.Diameter	-6.94E-01	32.22
Inner.Diameter	7.20E-01	25.72
Width	7.03E-02	18.14
Bruttoweight	1.34E+01	0.076
Nettoweight	-2.10E+00	0.04
Incoterms.FOB	2.68E-01	1
Incoterms.DDU	2.68E-01	0
Result		160.087

Table 4. Test Case 2

Regression Equation	Equation Values	Test-Case 2
(Intercept)	6.6487705	1
Raw.material 1	3.51E-01	0
Raw.material 2	3.73E+00	0
Raw.material 3	2.8038197	1
EP1	-3.889541	0
EP2	1.77E+00	1
EP3	3.98E+00	0
EP4	2.50E+01	0
EP5	1.20E+00	0
E6	1.69E+00	0
E7	4.10E-01	0
EP8	2.31E+01	0
EP10	1.88E-01	0
Outer.Diameter	-6.94E-01	28.4
Inner.Diameter	7.20E-01	12.1
Width	7.03E-02	13.6
Bruttoweight	1.34E+01	0.094
Nettoweight	-2.10E+00	0.04
Incoterms.FOB	2.68E-01	0
Incoterms.DDU	2.68E-01	1
Result		137.1245

All these test cases are derived from the dataset by taking random values and putting the customer input values into the regression line. By putting customer input into the multiple regression line an estimated quotation is generated to provide the customer with the quoted value, where 0 and 1 are binary values that indicate the customer's selected choice.

3.2 Customer's Input into Multiple Regression Equation

The process of putting the customer's input onto a regression line is shown in Table 5, which explains the process of converting the customer's input into an estimated value.

Table 5. Customer's Input in the Estimated Quoted Value

Variable	Regression Equation	Customer's Input
(Intercept)	6.6487705	1
Raw.material.specificationC45	2.8038197	1
Raw.material.specification100CrMnSi6-4	3.51E-01	0
Raw.material.specification100CrMnSi6-4A	3.73E+00	0
Production.technology.tube	-3.889541	0
Endproduct.bearing.typeCompensating Element	3.98E+00	1
Endproduct.bearing.typeClutch release bearing	1.77E+00	0
Endproduct.bearing.typeCRB	2.50E+01	0
Endproduct.bearing.typeDGBB	1.20E+00	0
Endproduct.bearing.typen.a.	1.69E+00	0
Endproduct.bearing.typeNeedle	4.10E-01	0
Endproduct.bearing.typeSRB	2.31E+01	0
Endproduct.bearing.typeTRB	1.88E-01	0
Outer.Diameter..mm.	-6.94E-01	18.2
Inner.Diameter.mm.	7.20E-01	11.53
Width..mm.	7.03E-02	10.15
weight..kg..Brutto	1.34E+01	0.019
weight.Netto..kg.	-2.10E+00	0.012
Incoterms.FOB/DDP	2.68E-01	1
Incoterms.DDP	2.68E-01	0
Result		122.802

4 Conclusions

The study was undertaken in the field of supply chain management, primarily in RFQ automation to reduce time. As it takes a lot of time to generate a request for a quotation, when the customer requests a quotation from the company, it is sent to the supplier, and the supplier makes a quotation based on the estimated price of the raw material by considering previous projects. This whole process takes time to generate an estimated quoted price.

To reduce this time, work was performed on the previous company's dataset. The main idea is to have previous projects data available to the company and based on that data, the company generates an estimated price which is according to the user's requirement. The first step is data gathering and cleaning the dataset from invalid values and redundancies, based on which multiple regression analysis was selected. There are some non-numeric variables so for those variables dummy variables are created. By performing multiple regression analysis using R-Language, acceptable results were obtained for all relevant statistical parameters. Work on the dataset which contains data about the company's previously sold products and their budget resulted in a regression equation. Forecasting or predicted values were calculated and the variation among predicted values and real values were analyzed and there was no significant difference among the outcome. This strengthens and supports the implementation of RFQ automation.

5 Limitations of the Research

The study was conducted with brevity and succinctness in mind, leaving some open ends. The following study limitations are noted:

- This RFQ automation is limited to the dataset which is being analyzed, and all the operations are carried out for that particular dataset; thus the algorithm of the model is not generic for new datasets.
- The user must enter numeric data in the field such as Inner diameter, Outer diameter, Width, Brutto Weight, and Netto Weight.
- The outer diameter must contain a greater value than the inner diameter.
- The value of brutto weight should be higher than the netto weight.
- This RFQ automation will provide value after the implementation of user inputs and this value is in Yuan (RMB).

6 Future Research Perspective

The field of Robotic Process is making waves along with AI and introduction of new LLM models more than ever before. Companies are adopting and deploying AI and RPA tools more often as they are getting familiar with them and the advantages these tools offer is countless. As the work on AI is on its way, early signs about the prospective targets indicate that it can revolutionize the process of an organization by digitizing the whole organization. In terms of this project, the following are prospects for further research:

- Large Language Models (LLMs) integration. The next iteration of the project will focus on embedding LLM model for the interpretation of unstructured data
- Implementation of Machine Learning algorithms by using ML detection algorithms.
- It can be extended to multi agent system where instead of having one automated outcome multiple agents' architect can be deployed to handle end to end RFQ automation lifecycle using autonomous AI agents.

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