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Cost Estimation Process of Remote Sensing Satellites

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Abstract*: Forecasting cost of satellites is not a recent development in space agencies, they were in practice from the beginning using traditional methods. The attempt to make it simpler, quicker and accurate; established the path to build a model by incorporating statistics, technology and technical knowledge. Building relationships between satellite cost and the technical parameters affecting them directly or indirectly became the basis of the model. The building of the cost model is more vexing than it looks. It requires data to perform regression analysis, which can be linear or nonlinear along with transformations. This paper also specifies the significance of the uncertainty impacting the cost associated with the technical parameters and the method of estimation. The overall model is mapped into three parts; the manpower and facility cost model being the deterministic bottom-up model and the combination of probabilistic and deterministic model for satellite cost.

***Keywords*: Costing, Work Breakdown Structure, Technical Cost Relationship, Uncertainty, Monte Carlo Simulation.**

I. INTRODUCTION

In the present budget environment, there is a strong need to dramatically forecast and predict the costs of satellites. This especially includes the estimation of production costs as they indicate the success of the project. A cost estimate is the organization's approximations of what a project is likely going to cost. The purpose of cost estimation is to foretell the quantity, cost and price of the materials required to finish a task within the project's scope. Cost estimates are also used to gain approvals from clients, to aid the budget planning process and procurement activities. Estimates are done in the early phases of new projects to get an original estimate and review the project futures with the same. Cost estimating models need to be frequently updated and reviewed as new information and data is available. We can observe the shift from traditional satellites to smaller effective satellites due to faster, better and cost-effective productions. The wide use of satellites due to their application in communications, earth observations and navigations has led to higher demand and gave rise to the need to build more user-based satellites for private companies. To meet the demands and to be market ready, there is a need for a cost model which is ready to quote. Parametric weight-based cost models have been devised for traditional large satellites, but these do not accurately predict the costs of other satellites due to differences in the design process. Some satellites have highly focused missions and they have a streamlined development process and shorter design lifetime. Thus, a need for a model that could estimate the costs of satellites existed.

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II. RESEARCH

The space organizational study was carried out in order to understand the overall concept of the building of satellites and those technical parameters that affect the cost of the satellite. The work breakdown structure (WBS) was under research to grip on the basic technical drivers. The cost drivers could be categorical or quantitative, for example the propellent type in the reaction control system could be mono or bi-propellent which is categorical. On the other hand, the capacity of the propellant could be the quantitative cost driver that affects. To build a cost estimate by parametric cost estimation methods, the data of the cost and technical parameters has to be known prior. Data collection for the analysis of the estimate is one the most important and lengthy process due to confidentiality and no records on websites. The data collection requires the knowledge of organizational WBS, and the technical description. The specification of the subsystem, the cost data, manpower and the facility related data were required to cover the scope of the project. The parameters need not directly affect but can also indirectly account to the cost of that subsystem [1]. The data collected were mainly concentrated on satellites weighing from 100 to 2000 Kgs. The overall data collected approximated to 49 satellites contributing to 3000 data from various web-portals and satellite dictionaries.

III. APPROACH TO BUILD TECHNICAL COST RELATIONSHIP (TCR)

The collected data were subjected to normalization to support the model. From the collected data of specifications, it had to be refined to a good number of predictor variables before analysis. The parameters themselves may be collinear and have some relationship between them. The condition of multicollinearity has to be avoided before performing parametric estimation.

The correlation matrix is plotted to define the correlation between the technical parameters themselves and those with high values are kept as less considerate.

The parameters with high correlation with the cost are considered for further steps.

The Technical Cost Relationship (TCR) is a series of mathematical relationships that relate satellite cost to physical, technical and performance parameters [2]. The regression equations were built; where the independent variables are the technical parameters of the subsystem, and the dependent variable is the cost.

The TCRs determine the cost of the required input technical parameter, for example the cost of the structure subsystem is predicted by the TCR with the input parameter volume of that subsystem. The TCRs give the deterministic value of the cost [3], [4]. The TCRs can be linear or nonlinear regression equations. The first attempt is to check if the data follows the linear regression, and they opt for other regression methods if required. The estimates were built with the prior assumption that data fits linearly with the cost function [5], [6], [7].

The data collected after normalization are evaluated for correlation with each other parameters along with the cost. The correlation measures the relationship between exploratory and predictor variables using MINITAB. The correlation between the cost and the technical parameter has to be strong to accept them.

The correlation between the parameters itself has to be less to avoid the error due to multicollinearity. It is the occurrence of high intercorrelations among two or more independent variables. It leads to a confidence interval which results in high chances of error. This decreases the confidence of the estimator. The parameters with high correlation with cost are selected.

The correlations between the selected parameters are considered and are segregated from those which have less association. This process was done by the best subset in the MINITAB, where the high correlation parameters with the cost are automatically evaluated for the error and the correlation of determination.

The possible combinations were considered and performed for linear regression. The errors for the trained estimate were checked, if the error percentage was less than 20% and the coefficient of determination greater than 75%, the null hypothesis is accepted, that the linear regression is the best model for the data. The residual analysis was performed for each TCRs which are built several times. The assumptions are to be accepted by residuals to finalize them [8].

If the linear regression does not give an appropriate model, then the next step was to go forward with non-linear regression or transformation of the data. The right distribution had to be selected to get the error less with high confidence.

The acceptability of the TCRs for each subsystem in our project is to have correlation coefficient greater than 75%, the standard error of estimate (SEE) adding up to 30% or less and average error less than 20%. The cost estimates finalized for each subsystem followed a different relationship with its cost [9], [10].

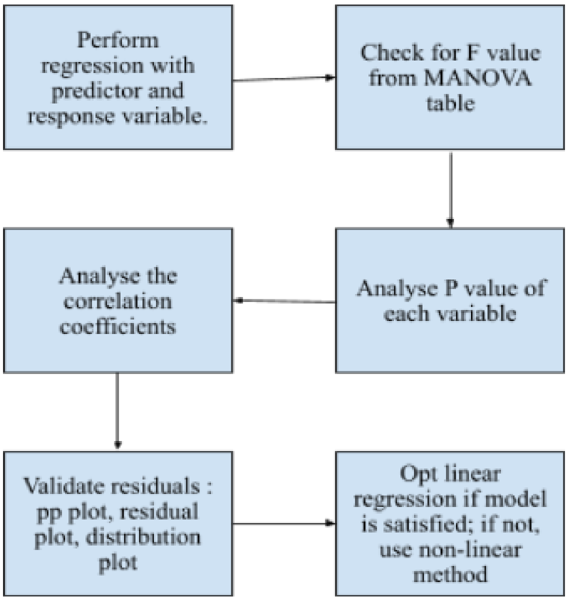

Fig.1 Approach to build TCR

IV. RESIDUAL ANALYSIS

There are analyses performed to finalize the TCRs based on the correlation coefficients, standard error of estimates, error percentage, residual analysis. The residual analysis is performed to check if the TCRs satisfies the assumption of residuals, namely;

A. The Normality Assumption

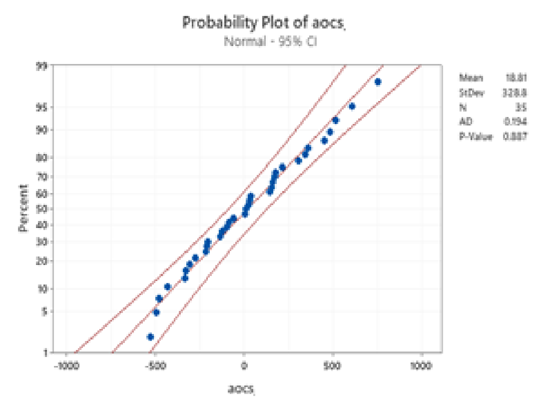

Fig.2 Normality Probability Plot

The assumption of normality is analysed by the graphical technique, if the residual data follows normal distribution or not. The residuals when take departure from the straight line it states; its departures from the normality as well. If the normal probability plot is normally distributed having one outlier, the relationship is approximately linear with the exception of the one data point. Then it proceeds with the assumption that the error terms are normally distributed upon removing the outlier from the data set. The histogram for the residuals determines if there are any outliers or if they are skewed. If the residual histogram has a long tail in one direction, they are skewed or if they are far away it has an outlier.

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B. The Randomness Assumption and Constant Variance

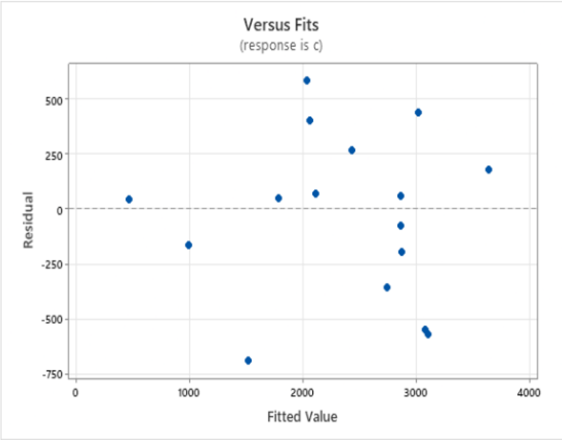

Fig.3 Residual versus Observed values plot

The assumption of randomness and constant variance is that the variability in the response does not change the value of the predictor in any direction and randomness of the residuals helps to conclude there is no heteroscedasticity in the data. The assumption is validated when residuals are plotted along the observed are distributed randomly across the horizontal plane without any. If the plots fanning or has uneven spread of residuals, it has non-constant variance. If the residuals follow a curvilinear pattern, it suggests that the residuals miss higher order terms. There may be an outlier, a point that is recognized which is far away from the zero and an influential point, a point is recognized which is far away from the other residual points in the x-direction. The solution for non-constant variance is box-cox transformation, for residuals with outliers are verified that the observation is not a data entry error or by considering the analysis performed with that one dataset and examine how it affects the result.

C. The Independence Assumption

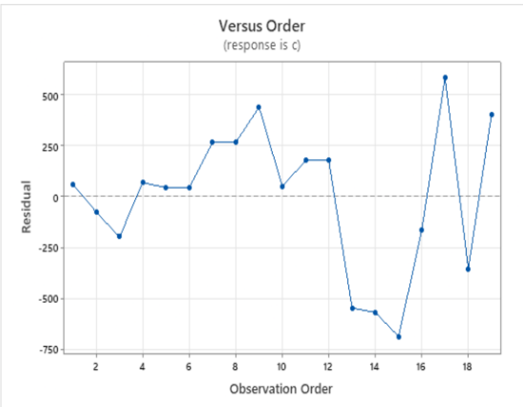

Fig.4 Residual versus Observation order plot

The assumption of independence among the residuals are verified with the plot of residuals against the observation order. The residuals should not influence the other, and this has to be validated. The independent residuals do not show trends or patterns when plotted. The pattern detects that the residuals are dependent on each other. They are also the sense of correlated residuals when plotted in time order. To accept the assumption, the residuals should ideally fall randomly around the horizontal plane.

V. UNCERTAINTY

Uncertainty is referred to situations which involve unknown or imperfect information. This uncertainty can be applied to physical measurements, to forecasts and future predictions or to the unknown uncertainty in stochastic environments. [11] Historically, all model estimates as well as independent estimations have given importance to a single cost estimate rather than range estimations.

Advances in computational capability in recent years has helped to develop uncertainty and cost risk analyses which can provide vital insights to estimating models and analysts. A typical cost estimate model is developed by calculating the cost estimates of different WBS elements and then summing them to derive a total estimate. Considering each WBS cost estimate to have approximately the best model, the whole model is assumed to be the best estimate.

This has been practiced for years which may account for cost risk and uncertainty. Assuming the estimates for each WBS element forecast the mean/average cost of that component, the only positive outcome would be the most likely cost from the point estimate out of an infinite number of possible costs. Moreover, the point estimate from the models represents the 50th percentile cost.

The interpretation of this would be that the total cost from the point estimate has a 50% chance that the cost can be lower than the estimate; similarly, there is a 50% chance that the cost can be higher than the cost estimate. Thus, this estimate does not convey anything about the possible cost ranges of the project.[12] To overcome this, uncertainty can be quantified by using a probabilistic model.

Uncertainty reflects the confidence of a point estimate from a deterministic model. Cost estimation uncertainties are due to the inaccuracies present in the methodologies used for estimating the cost. Consider an example, one component of the model uses TCRs which are built using the available data that is accurate only within a + or - percentage. Thus, uncertainty in the estimate can be incorporated by providing a range in which the true costs are likely to fall. There also might be a better TCR for each WBS element which went unnoticed and better parameters which could derive accurate TCRs. These factors also could lead to inaccuracies in the model.[13]

A known and systematic way to model for uncertainty analysis is proposed by

- Performing a regression analysis to obtain relationships with costs
- Monte Carlo simulations performed as an error propagation method.

Monte Carlo Simulations are algorithms that depend on repeated random sampling to get numeric results. The underlying idea is to use randomness to solve problems that can be deterministic in principle. Monte Carlo simulations are widely used in modelling the probability of different possible outcomes in a process which cannot be easily predicted by single estimates due to the introduction of random variables.

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This simulation is a technique used to understand the influence of risk and uncertainty in forecasting and prediction models. Monte Carlo simulations can also be used to handle a range of problems in almost every field such as supply chain, engineering, finance and science. Monte Carlo simulations are also known as multiple probability simulations.

The takeaways from Monte Carlo simulations:

- Model used to predict the probability of different outcomes with the influence of random variables.
- Model simulations can help in explaining the impact of uncertainty and risk in predictions.
- The basis of these simulations involves assigning a number of multiple values to an uncertain variable and thus achieving multiple results and then averaging the results to obtain estimates.[14]

When confronted with huge uncertainty during the process of making an estimate or forecast, rather than simply replacing the uncertainty variable with an average number, a Monte Carlo simulation will prove a better result by using multiple values. Finance and business are highly affected by factors which are uncontrollable, Monte Carlo simulations have a huge array of expected applications in these fields. They can be utilized to estimate the likelihood of cost overruns in large projects and the probability that an asset cost will move in a certain way. Monte Carlo Simulations also have innumerable applications outside the finance and business sectors like meteorology, particle physics and astronomy.[15]

The basics of a Monte Carlo simulation is that the likelihood of varying outcomes cannot be determined because of random variable interferences. Thus, a Monte Carlo simulation centres around constantly rehashing random samples to achieve certain outcomes. A Monte Carlo simulation takes the variability that has the most uncertainty and assigns it a random value. This model is then run and an outcome is obtained. This cycle is rehashed multiple times while allocating the variable with different values. When the simulation is completed, the outcomes are averaged together to provide an estimate.

Depending on the number of parameters involved, simulations can be simple to very complex models. But all models follow the basic four levels of modelling.

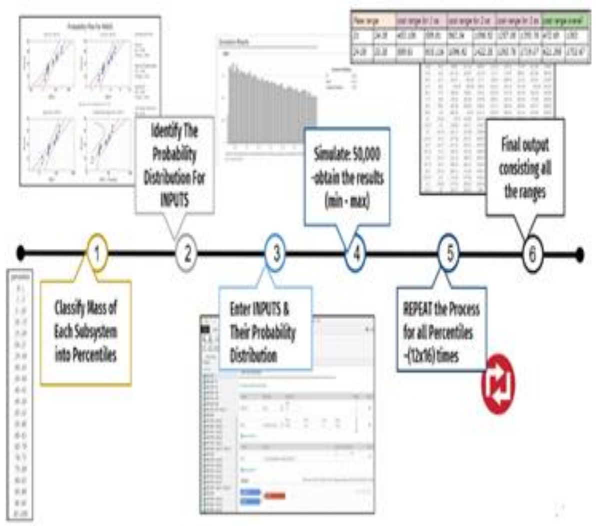

Fig.5 Step-by-step process to obtain cost range

A. Recognize the transfer equations

To create a Monte Carlo simulation, there was a need for a quantitative model for the project. The mathematical expression in the model is called Transfer Equation. This equation can be a known business or engineering formula, or it can be based on a deterministic model created by design of experiments or regression analysis. Minitab has the ability to create such complex equations, even those with multiple response variables that may be dependent on each other.

B. Define the input parameters

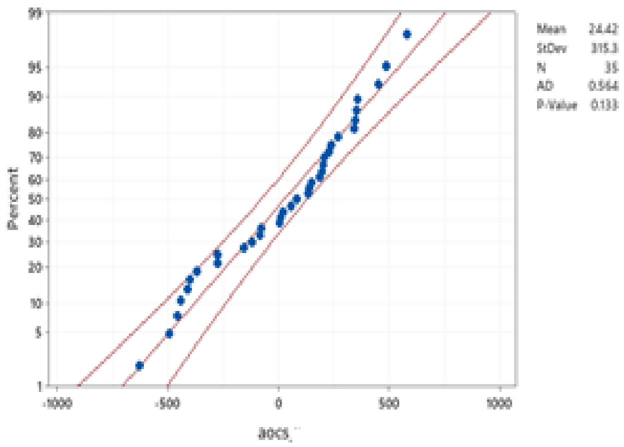

Fig.6 Input parameter distribution of AOCS subsystem

For each parameter or variable in the transfer equation, the probability distribution of its data is determined. Some inputs follow the normal distribution, while others follow a triangular or uniform distribution. Thus, depending on the data, a probability distribution for the inputs is specified. The probability distribution characteristics like mean and standard deviation for an input parameter are observed.

C. Set up the simulations

For valid simulations, there must be a very large number of random data for each input parameter somewhere around 100000 data points. These random data try to simulate the values that can be seen over a larger period for each input parameter. This may seem to be a lot of work but Minitab workspace shines in this part of the simulation. Only the inputs and its characteristics are submitted, the simulation is done by Workspace.

D. Analyze the output

With all the simulated data in one place, the transfer equation is used to calculate the simulated outcomes. Running the simulation with a large quantity of parameter data through the model will give a reliable indication of the range of outputs and their probability of occurrence with the given uncertainty in the input variations.[16]

For the project, the TCRs of each subsystem are already obtained by regression methods and data for the input parameters. In table I, we can see the different parameters with their input variables and their probability distributions.

Table I: Descriptive Statistics of Parameters

Subsystem	Input Parameter	Probability Distribution	Descriptive Statistics
Structure	Subsystem Mass (M^3)	Normal	Mean = 4.34 St Dev = 12.82
Mechanism	Subsystem Mass (Kg)	Normal	Mean = 19.97 St Dev = 20.36
Thermal	Subsystem Mass (Kg)	Normal	Mean = 43.5495 St Dev = 26.3697
	Altitude (Km)	Triangular	Low = 460 Mode = 505 Upper = 865
Reaction Control System	1N Thrusters (Number)	Triangular	Low = 0 Mode = 8 Upper = 9
	Pressurant Mass (Kg)	Normal	Mean = 0.3 St Dev = 0.24
	F&D Valves (Number)	Fixed	Values =1 ,2, 3
Attitude and Orbit Control system (AOCS)	Subsystem Mass (Kg)	Normal	Mean = 118.2 St Dev = 42.62
	Start Sensors (Number)	Fixed	Values =1 ,2, 3
RF System	Subsystem mass (Kg)	Normal	Mean = 43.88857 St Dev = 20.17285
DH System	Subsystem mass (Kg)	Normal	Mean = 20.05 St Dev = 10.4
	Storage Capacity (GB)	Fixed	Values =16, 32, 64, 200, 400, 600, 2400
Power System	Subsystem mass (Kg)	Normal	Mean = 85.36238 St Dev = 53.3833

Percentile	Mass	1SS	2SS	3SS
0	21	453	960	1,257
1	24	590	1,097	1,394
5	33	915	1,422	1,719
10	45	1,205	1,713	2,009
15	56	1,428	1,936	2,232
20	67	1,609	2,116	2,413
25	78	1,761	2,268	2,565
30	89	1,891	2,398	2,695
35	99	2,005	2,513	2,809
40	110	2,107	2,614	2,911
45	121	2,199	2,706	3,003
50	131	2,282	2,789	3,086
55	141	2,358	2,865	3,162
60	152	2,428	2,935	3,232
65	162	2,492	3,000	3,296
70	172	2,553	3,060	3,357
75	182	2,609	3,116	3,413
80	192	2,662	3,169	3,465
85	201	2,711	3,218	3,515
90	211	2,758	3,265	3,562
95	221	2,802	3,309	3,606
100	230	2,844	3,351	3,648

Fig.7 Output from Monte Carlo simulation for AOCS subsystem (SS- Star Sensor)

VI. DIRECT STAFF AND FACILITY COST

An element of direct staff cost has been considered in our model; here the data related to the number of employees who contribute in the building of a satellite is considered in order to account for the total satellite cost. It is considered as a deterministic value. The direct staff has been divided into five phases namely; design phase, fabrication phase, testing phase, launch phase and post-launch phase. In order to calculate the total direct staff cost, the first step is to collect the basic information regarding the salaries of employees from the available and trusted sources on the net.

The salary per month is then calculated by taking into account all the other factors and allowances depending on the designation. The total salary is then used to calculate the per hour cost for that particular designation using the formula,

TS - Total Salary

D - Total number of working days in a month (22 days)

H - Total number of working hours in a day (8 hrs)

$$\text{Cost/hour}=TS/(D*H) \qquad (1)$$

The next step was to design a table where the user could input the values for;

A. the number of employees in each phase

B. the total number of days taken to complete each phase

TCp - Total Cost for Each Phase

i - Designation

N - Number of employee

C - Per hour cost of employee (₹)

H - Number of hours worked per day (8 hrs)

D - Total number of days required to complete the phase

$$TCp = \sum_{i=1}^{n} (N * C * H * D) \qquad (2)$$

Similarly, the cost for the rest of the phases is calculated and summed up to obtain the final cost of staff. In order to test the satellites, there are various facilities setup which help qualify the satellite and its subcomponents before the launch. The cost of seven facilities has been accounted for in the cost estimating model. The cost of the facility is considered as a deterministic value. In order to calculate the total facility cost, understanding a few terms is essential. The total cost of ownership looks at the cost of owning an asset long-term by assessing both its purchase price and the costs of operation. In this case the complete facility setup, the machinery and all the equipment are considered as an asset.

ADE - Annual depreciation expense

CA - Cost of an Asset

SC - Salvage cost or Residual Value

L - Useful life of an Asset

$$ADE =(CA-SC)/L \qquad (3)$$

The annual depreciation expense is calculated using a straight-line equation of depreciation as the expense amount is the same every year over the useful life of the asset.

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Here since the salvage value of the asset is unknown / cannot be determined the value is considered as zero. The obtained Annual depreciation expense is then used to calculate the total cost of ownership per day using formula,

TCO - Total cost of ownership

ADE - Annual depreciation expense

D - Number of days worked in a year.

$$TCO = ADE/D \quad (4)$$

The other factors that are affecting the facility cost are maintenance cost, power consumption cost and in some cases fuel cost.

VII. OVERALL MODEL RESULT

This model is implemented in the form of a workbook on Excel, where the three main cost components are split into different sheets. These worksheets are self-explanatory and all the necessary information which is required for estimating the cost of a satellite is clearly mentioned. The workbook contains tables for the direct staff cost, direct facility cost and subsystem realisation cost, all of which is finally incorporated into a table along with the project management and administrative overhead cost, which is then summed up to give the overall cost of the satellite, after which inflation is accounted to give the final cost. Project management cost accounts to 2% of the (direct staff cost and direct facility cost) and the cost of administrative overhead accounts to 1% of the (direct staff cost and direct facility cost).

A. Subsystem Realization Cost Model

The first sheet is for the subsystem realization cost. The TCR for all the subsystems have been determined and finalized. The subsystems along with the parameters which are accounted for in the TCRs are listed. This table is called the input table II, it contains the maximum and minimum range of the specified parameters which this model is suitable for. A column is provided for the user to input the values of the satellite for which the cost is to be estimated. As the values are entered the deterministic cost and the probabilistic cost is displayed in the adjacent table called the output table.

Table II: Technical Parameter Range

Subsystems	Input Parameters	Min	Max	Input
Mechanism	Mass	1.60 Kg	41.22 Kg	XXX
AOCS	Mass	21 Kg	228 Kg	XXX
	Star Sensor	1	3	XXX
Power	Mass	16 Kg	196 Kg	XXX
Reaction Control	1n Thruster	0	9	XXX
	Pressurent Mass	0.07 Kg	1.2 Kg	XXX
	F&D Valves	1	4	XXX
Structure	Volume	$0.2016m^3$	$22\ M^3$	XXX
Thermal	Mass	9 Kg	130 Kg	XXX
	Altitude	460 Km	865 Km	XXX
Radio Frequency	Mass	14 Kg	79 Kg	XXX
Data Handling	Mass	3 Kg	47.11	XXX
	Capacity	16 Gb	2400 Gb	XXX

The output table III is embedded with the TCRs for each subsystem where it displays the deterministic value of the satellite and the probabilistic value is calculated with the help of the output table from the Monte Carlo simulation.

TABLE III: Output Table for Bus Cost

Input Table		Output Cost		
Subsystems	Input Parameters	Low	Value	High
Mechanism	Mass	ZZZ	ZZZ	ZZZ
AOCS	Mass	ZZZ	ZZZ	ZZZ
	Star Sensor	ZZZ	ZZZ	ZZZ
Power	Mass	ZZZ	ZZZ	ZZZ
Reaction Control	1n Thruster	ZZZ	ZZZ	ZZZ
	Pressurant Mass	ZZZ	ZZZ	ZZZ
	F&D Valves	ZZZ	ZZZ	ZZZ
Structure	Volume	ZZZ	ZZZ	ZZZ
Thermal	Mass	ZZZ	ZZZ	ZZZ
	Altitude	ZZZ	ZZZ	ZZZ
Radio Frequency	Mass	ZZZ	ZZZ	ZZZ
Data Handling	Mass	ZZZ	ZZZ	ZZZ
	Capacity	ZZZ	ZZZ	ZZZ
Total		(ZZZ)	(ZZZ)	(ZZZ)

B. Direct Staff Cost Matrix

The next sheet is for direct staff cost, where the data regarding the number of employees who contribute in the building of the satellite is entered in order to calculate the total cost. The salary breakdown and the per hour cost for the employees of all the designations has been displayed and calculated in table IV. The goal here is to obtain the final cost of manpower by combining the total cost obtained from all the five phases. The sheet contains 3 tables where the first table contains data regarding the per hour cost of the employees, the second table is for the user to input the data and the third table displays the final cost. The input table is where the user needs to enter the number of employees and the total number of days worked for a particular phase. The total cost of each phase is then added up to obtain the final staff cost. The summary table IV is displayed below.

TABLE IV: Final Direct Staff Cost Matrix, (XXX- Input, YYY- Output)

Phase	No Of Employees	No Of Days Worked	Total Cost (Lakhs)
Design	XXX	XXX	YYY
Fabrication	XXX	XXX	YYY
Testing	XXX	XXX	YYY
Launch	XXX	XXX	YYY
Post Launch	XXX	XXX	YYY
Total	XXX	XXX	YYY

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C. Direct Facility Cost Matrix

The next sheet is for direct facility cost, where the data regarding the number of days that the satellites are tested in a particular facility is entered as the input. The model is built in such a way that as the input is entered into the cell the final facility for that particular facility is calculated from their respective sheets and is displayed into the cell that is adjacent to the input. Each facility cost is separately calculated by accounting all the factors that play a role in running that facility. The final facility cost is displayed in the table V below.

TABLE V: Final Facility Cost Matrix, (XXX- Input, YYY- Output)

Facility	No. Of Days of Testing	Final Facility Cost (Lakhs)
Thermovac Chamber	XXX	YYY
Vibration	XXX	YYY
Acoustic Test Facility	XXX	YYY
Hils Test	XXX	YYY
CG/MI Measurement	XXX	YYY
EMI/EMC Test	XXX	YYY
Cleanroom	XXX	YYY
Approx Total Cost Of Facility Tests (Lakhs)		(YYY)

VIII. CONCLUSION

The analogy and bottom-up cost estimation for very large satellites to Pico satellites has been a tradition at various space agencies. The project's scope was to facilitate the estimation of cost of these satellites in such a way to ease the process. In the venture of building a cost estimate for each bus subsystem, the team came up with parametric cost estimate relationships along with multiple uncertainty costs incorporated. The relationship between cost and technical parameters were procured by regression techniques along with transformations. They were validated by the coefficient of determination, average error percentage along with the standard error of estimate.

The uncertainty due to the estimate and the technical parameters has been accounted for with user defined probability distribution for each of the subsystems using Monte Carlo simulation.

There is always effort for improvement as the number of satellites being launched increases the confidence of the model tends to be stronger. The model scope is to validate the model with other sensitive data to build a strong confidence of the model. The model was built for the year 2020, as the data were normalized to the same year. The longevity of the model is increased by accounting inflation for the year for estimation using the formula,

I - Inflated cost

Y - Value obtained from the model

CP_1 - Consumer Price index of the present year

CP_2 - Consumer Price index for 2020

$$I = (CP1*Y)/CP2 \tag{5}$$

The next approach would be to attempt the model for other mission satellites so as to check their confidence for the same model. Since the project incorporated only the bus cost of the satellite for the mode, the future scope is to incorporate for the payload as well. The new satellite proposal's cost is to be estimated using this model after the complete validation of the model is done.

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