

## Development of Multiple Parameter-based Cost Model for Small Earth Observation Satellite

Jin S. Kang  
 U.S. Naval Academy  
 121 Blake Rd., Annapolis, MD 21402; 215-200-9162  
 sukjinkang@gmail.com

Hongrae Kim, Young-Keun Chang  
 Korea Aerospace University  
 412-791 100, Hanggondai-Gil, Goyang-City, Gyeonggi-Do; +82-2-300-0286  
 ykchang@kau.ac.kr

### ABSTRACT

The satellite cost models developed based on total mass has been more widely used in the past, but many limitations often make them difficult to apply or achieve desired accuracy. In addition, the compounded errors of such models are further increased by the variety of the missions that these systems are designed to perform. For the new cost model presented in this paper, the scope of the proposed cost model has been limited to earth-observation satellites. These systems are further divided into EO (electro-optical) and SAR (synthetic-aperture radar) satellites. The proposed model can be applied to satellites with masses ranging from 100 to 1000 kg for EO satellites, and less than 5000 kg for SAR satellites. In order to overcome the limitations of the mass-based prediction models, the performance parameter was selected as the variable in a form of System Complexity Index (SCI). Cost Correction Relationship (CCR) is also applied to the cost model to increase the accuracy of the model. The resulting Cost Estimation Relationship (CER) shows that the proposed cost model provides much more accurate results in predicting the development cost of these satellites. The paper describes how the parameters were chosen and applied, discusses details of the proposed cost model, and shows application and results of the model as applied to other conceptual design cases.

### INTRODUCTION

Being able to estimate the development cost of a satellite is critical for the success of the development program. Error in initial estimation can result in cost overruns, or worse, cancellation of the project even before the project can get started. The estimation tool can also be used throughout the development process for design verification and project management. For these reasons, there has been much work performed in developing the cost estimation models. Two widely used models for cost estimation are SSCM and USCM. These models are used often, but cannot be used reliably due to large error margins (case study shown in the later section of the paper). The goal of this study is to develop a novel cost model that results in higher accuracy estimations when applied to earth-observation satellites.

This paper introduces the development process of a cost model geared towards earth-observation satellites in low-earth orbit (LEO). In order to achieve this, a database has been established containing information of satellites that are either in development or have been developed since 1999. Among these satellites, the

database focuses on satellites in the mass range of 100 to 1000 kg for electro-optical payload satellites, and those that are less than 5000 kg for SAR satellites. As the next step, the target satellites and variables were selected for deriving Cost Estimation Relationships (CERs). Based on the key variables, System Complexity Index (SCI) has been calculated and the CER has been derived using this index as an independent variable. In addition, Cost Correction Relationship (CCR) was established in order to relate the satellite cost and reliability. This enables the cost estimate to factor in the project target reliability.

### DEVELOPMENT PROCEDURE

STEP 1: Define Main Parameters for Cost Estimation and Collect Satellite Data – Cost, programmatic, and technical data from previously flown LEO observation satellites were collected.

STEP 2: Evaluate and Normalize Satellite Data – The collected instrument data were normalized to scale uniformity, ensure completeness of costs, and correct for known bias and inconsistencies.

STEP 3: Develop and Validate Cost Estimation Relationship – Statistical techniques were applied to the normalized data to drive System Complexity Index and establish Cost Estimating Relationships.

These three steps were repeated as new data were collected throughout the KEOSCM (Korea Aerospace University Earth Observation Satellite Cost Model) development cycle. This iteration process is shown in Figure 1.

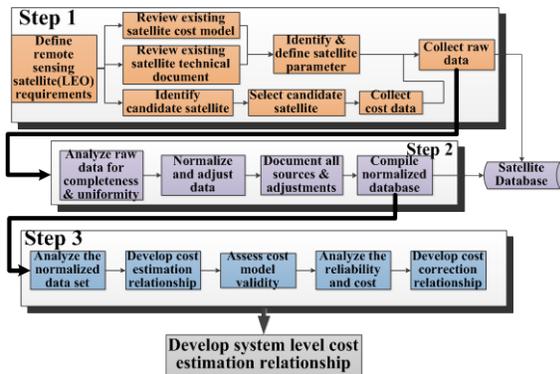


Figure 1 Development Process Flow Diagram

## DEFINITION OF MAIN PARAMETERS FOR COST ESTIMATION AND COLLECTION OF SATELLITE DATA

### Study of Previous Cost Model

As a first step, an analysis was done to identify the key parameters for cost estimation based on the previous cost models. This was done in order to develop a cost model that is more reliable by understanding the problems and identify improvements from other cost models.

However, this type of approach where the mass is used as the main parameter has the disadvantage of under-representing other parameters that affect the development cost, or in some cases, completely leaves out these parameters all together. Furthermore, the accuracy can be reduced even further when considering the fact that from the technical perspective, it actually costs more to reduce the overall mass of the system [1]. As an example, in case of the earth-observation satellites, the key elements in the payload such as mirror and lenses account for a large portion of the overall mass, and it results in a large cost increase if the mass were to be reduced while maintaining performance because new technology would have to be applied to make it possible. This kind of process results in a large increase in the development cost due to the high demand on the technology level of the components.

The most commonly used satellite development cost models are USCM, SSCM, QuickCost, Price-H, SEER-H, etc. These models are mass-based estimators, and incorporate separate performance- or program-related parameters in order to increase accuracy. As can be seen in Figure 2, mass and development cost show a very high correlation, and thus are used as the main parameter in cost estimation.

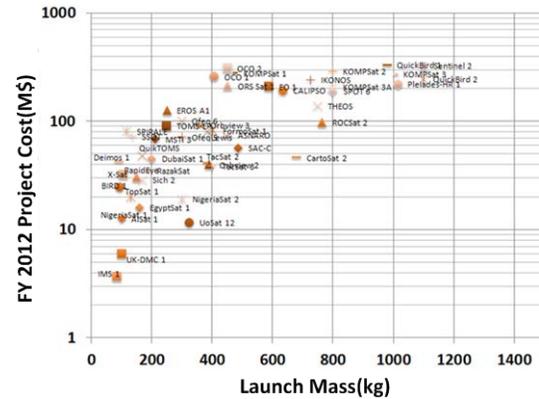


Figure 2 Satellite Development Cost(\$M) vs. Launch Mass (kg)

Effects of various parameters were considered in order to investigate ways to overcome the inherent shortcoming of the mass-based cost estimators. In case of the work by Bearden [2], complexity parameters were incorporated for researching into low-cost exploration options for deep space exploration systems. NASA developed a cost model specific for the observation satellite payloads to account for the current trend of utilizing standardized modular satellite bus [3].

In this paper, a cost model was developed that can be applied to the satellite systems with earth-observation payloads. Both Bearden's [2] work on cost estimation and Mettas' [4] research in cost estimation using reliability were considered in this development.

### Complexity Index

Complexity Index was proposed by Bearden [2] for overcoming the limitations of the cost estimation based on mass, and indicates technical and programmatic difficulty. In essence, Complexity Index represents the characteristics of the satellite and its performance, and the program. This makes it possible to apply technical complexity of the development that was not expressed in the mass-based cost models. Accordingly, the cost estimation model presented here also incorporates this index as a main parameter.

Complexity Index is calculated using a statistical method called *Percentrank* that is included in Microsoft Excel software. This method first ranks the data, then

expresses them as percentages. The values between the data points are calculated by linear interpolation. For calculating the System Complexity Index (SCI), the parameters to be used are first selected, then the Complexity Index for each of the parameter is calculated. The parameters that show a high correlation to cost are applied to calculate the average Complexity Index. This is expressed in the following Equation (1).

$$F_C = \sum w_i f_i \quad (1)$$

where  $F_C$  is the System Complexity Index,  $i$  is the number of parameters,  $f_i$  is the complexity index each factor, and  $w_i$  is the weighting factor that can be determined by users.

### Cost Correction Relationship

In this paper, Cost Correction Factor was derived utilizing the ideas presented in Mettas' [4] work in including reliability factors, as well as the cost estimation method outlined by TANSOCOST [5]. The cost estimation method proposed by Covert [6] was also considered in the derivation. Cost Correction Factor (CCF) has been incorporated in order to compensate for the discrepancies between the actual cost and calculated cost when the Complexity Index is used in the cost estimation. CCR is derived as described by Figure 3, 4.

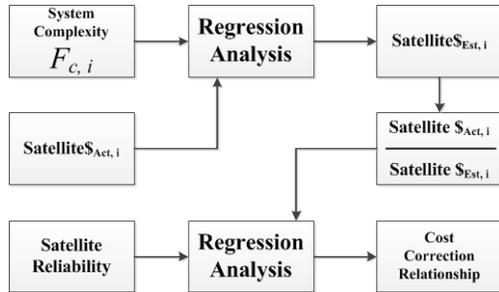


Figure 3 Procedure for derivation of cost

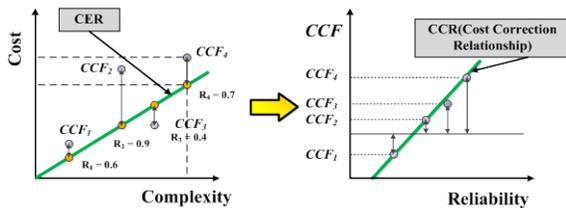


Figure 4 Derivation methodology for Cost Correction Relationship

The final version of CER is calculated by deriving CCRs, as shown in Figure 3, then multiplying with the CER. The final CER is further modified by adding in the variables representing reliability and Complexity Index.

$$CER = f_{CER}(F_C) \quad (2)$$

$$CCR = f_{CCF}(R) \quad (3)$$

$$Final\ CER = f_{CER}(F_C)f_{CCF}(R) \quad (4)$$

The reliability requirements were used as the system reliability in this paper. Because reliability describes the system reliability at the end of life, this value needs to be normalized. For this reason, the Reliability Factor was standardized to represent the system reliability after 5 years of service in space. In order to generalize the reliability model, an exponential function was applied to obtain reliability probability spread.

CCF was not applied to SAR satellites due to the scarcity of applicable data.

## EVALUATION AND NORMALIZATION OF SATELLITE DATA

### Evaluation of Satellite Data

The cost model introduced in this paper focuses on satellites that weigh 100 to 1000 kg in case of the electro-optical payload satellites, and less than 5000 kg for SAR satellites. In case of the electro-optical satellites, the ones selected have panchromatic multispectral cameras. Satellites with hyperspectral camera and particle detector were excluded. In case of SAR satellites, ones with passive SAR antenna were excluded and the selected satellites have active SAR antennas. Satellites that have been launched, or have been developed and awaiting launch were used in the pool. The satellite data selection and analysis were performed using the satellites in this pool. The outlying satellites, in terms of purpose and target performance parameters, have been excluded.

### Normalization of Cost Data

The satellite cost data carries a different monetary value depending on the point in time of the satellite cost evaluation. As an example, if the cost of a satellite is evaluated in the far past, the cost value at a later time will be higher, and the inflation must be taken into consideration. In addition, the different values of the international monetary units must be taken into consideration in normalizing the cost data. Accordingly, the cost data was normalized to FY2012 values using NASA New Inflation [7], and in case of international development, the exchange rate at that time is factored in for conversion to USD.

The collected cost data usually refers to the total project cost, and thus can be different depending on the developing institution. For this discrepancy, the satellite

development cost data have been normalized to the value obtained by adding the cost of the theoretical first unit (TFU) production cost and design, development, test and evaluation (DDT&E) cost based on the small observation satellite standard work-breakdown structure (WBS), excluding the launch cost and the ground station & operation cost. In case of the launch cost, either the published cost from the satellite database was used, or if not provided, estimated by factoring in the generic launch cost of the launch vehicle used.

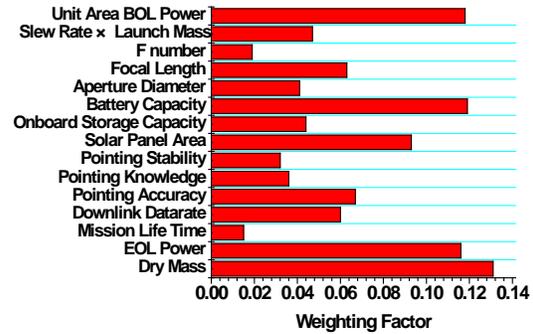
**Selection of Parameter for deriving complexity**

Parameters to be used when considering electro-optical and SAR satellites costs were selected through technical and statistical analysis. Fifteen and ten parameters were selected for electro-optical and SAR satellites, respectively. The complexity index is calculated for each parameter, and combined to derive the System Complexity Index. Because SCI is expressed as linear combinations, the complexity index of each parameter must display high linearity. Accordingly, the parameters showing high correlation, as per the correlation analysis discussed above, are assigned higher weighting factors. Correlation parameter is used as the weighting factors in this paper. The weighting factor calculated from correlation factors for the electro-optical satellites is shown in Figure 5, and the same for SAR satellites is shown in Figure 6.

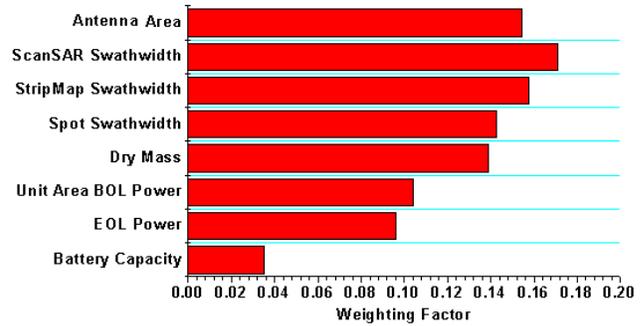
As can be seen in Figure 5, in case of electro-optical satellites, dry mass showed the highest correlation, followed by beginning-of-life (BOL) power, unit area BOL power, battery capacity, and solar panel area. In case of SAR satellites, as can be seen in Figure 6, strip mode resolution and ScanSAR swath width showed the highest correlation.

The reason why the parameter that showed the highest correlation in EO satellite is missing in SAR satellites is due to the limited amounts of SAR satellite data available. This resulted in the data that did not make much logical sense, and thus was excluded from the key parameters list.

The percent rank for each complexity index is determined by assigning the ranking according to the largest parameter. However, parameters such as pointing accuracy, knowledge, and stability have a negative correlation where the improvement in performance (decreasing value) results in increase in cost, resulting in an opposite change in percent rank. For these negatively affected parameters, the values were adjusted by mirroring the values about the y-axis, then offsetting horizontally by a value of 1.



**Figure 5 Comparison of weighting factor for each parameters(electro optic system)**



**Figure 6 Comparison of weighting factor for each parameters (synthetic aperture radar system)**

The percent rank for each complexity index is determined by assigning the ranking according to the largest parameter. However, parameters such as pointing accuracy, knowledge, and stability have a negative correlation where the improvement in performance (decreasing value) results in increase in cost, resulting in an opposite change in percent rank. For these negatively affected parameters, the values were adjusted by mirroring the values about the y-axis, then offsetting horizontally by a value of 1.

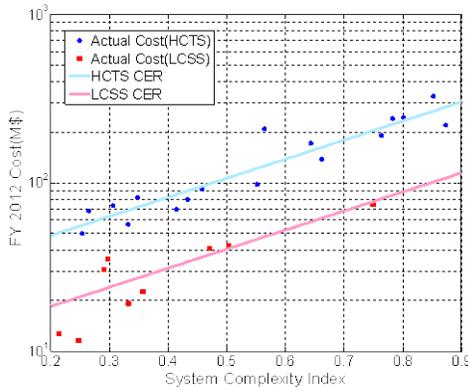
**DEVELOPMENT OF COST MODEL**

System complexity of each satellite is calculated using Complexity Index and weighting factors for each parameter as shown in Equation 1. Figure 7 shows the system Complexity Index and cost for each EO satellite, and Figure 8 shows the same for SAR satellites.

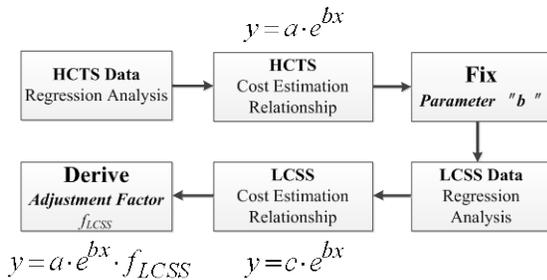
CERs are derived using the system Complexity Index for each satellite. CER is performed using regression analysis. The regression analysis results were expressed by values such as adjusted  $R^2$ , SE (Standard Error), F value, and p-value, in order to statistically validate CERs.

### EO Satellite CER Derivation

In general, the satellite cost increases with increasing System Complexity Index for both EO and SAR satellites. However, two types of trends are formed for EO satellites according to the development concept. More specifically, satellites developed using the concept of Low Cost Small Satellite (LCSS) shows lower development cost than the ones developed using High Cost Traditional Satellite (HCTS) concept. Therefore, EO CER derivation is divided into two types according to the development concept in this paper. In order to be able to express the CER with a single equation for both cases,  $f_{LCSS}$  parameter has been adopted. The process for expressing the CER using a single equation is shown in Figure 9.

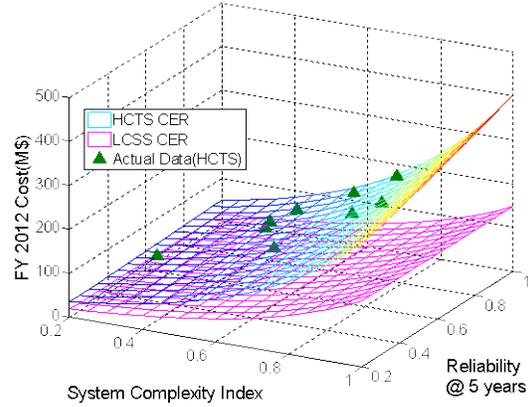


**Figure 7 Development cost vs. System Complexity Index (EO Satellite)**



**Figure 8 Procedure for derivation of adjustment factor**

CER obtained from regression analysis for HCTS can be expressed by Equation (6). The corrected factor in this case was 0.881. Considering the SE value of 20%, F of 119.376, p-value of 0.000, it can be claimed that the CER is a valid relationship.



**Figure 9 Procedure for derivation of adjustment factor**

$$f_{CER_{HCTS}}(F_C) = 28.986 \times e^{2.606 \times F_C} \quad (6)$$

CER derived for LCSS based on this analysis is as described by Equation (7). The result of analysis showed determination factor value of 0.699, SE of 33%, F value of 19.543, p-value of 0.003, indicating that this is a valid relationship.

$$f_{CER_{LCSS}}(F_C) = 11 \times e^{2.606 \times F_C} \quad (7)$$

Equation (7) shows the incorporation of  $f_{LCSS}$  and it can be expressed by Equation (8).  $f_{LCSS}$  is calculated by dividing Equation (7) by Equation (6), and the value of  $f_{LCSS}$  is 0.379. For HCTS calculations, the value of  $f_{LCSS}$  is simply set to 1.

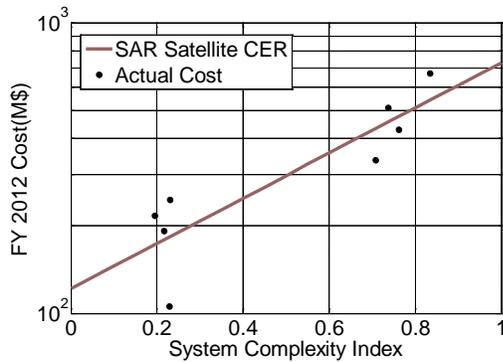
$$f_{CER}(F_C, f_{LCSS}) = 28.986 \times e^{2.606 \times F_C} \times f_{LCSS} \quad (8)$$

### Derivation of CER for SAR Satellites

The CER derivation for SAR satellites follows the same process as the EO satellite CER derivation. However, in case of SAR satellites, the limited data resulted in cases where the trend was hard to determine. For this reason, cost correction factor and adjustment factor has not been implemented for SAR satellites.

$$f_{CER}(F_C) = 121.74 \times e^{1.788 \times F_C} \quad (9)$$

For regression result of SAR satellite data, Equation (9) was derived. The regression analysis result and the data used is shown in Figure 10. The adjusted determination factor is 0.730. The equation can be considered statistically valid, with SE value of 31%, F value of 19.94, p-value of 0.0043.



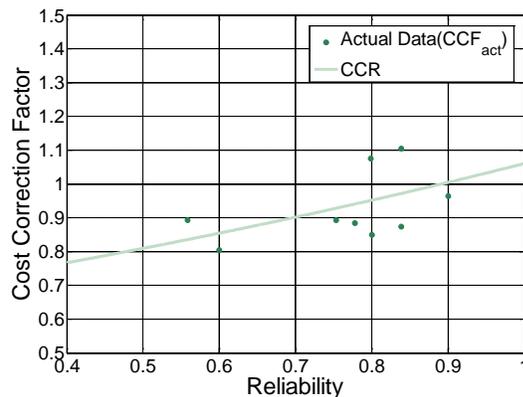
**Figure 10 Development cost vs. System Complexity**

**Derivation of Cost Correction Relationship**

CCF is applied only to EO satellites. The satellite data used for CER derivation were 6 sets out of the total of 26 data sets. These data sets are from satellites that have design reliability information. Using this data, CCR for reliability was derived by following the estimation process as shown in Figure 2. The relationship between reliability correction factor and reliability is shown in Figure 11.

$$f_{CCF}(R) = 0.618 \times e^{0.54 \times R} \quad (10)$$

Equation (10) is the result of regression analysis. Adjusted coefficient of determination is 0.206 and has the SE value of 10%, F value of 2.824, and p-value of 0.148.



**Figure 11 CCF vs. reliability**

**VERIFICATION OF COST MODEL**

**Cost Model Verification Using Actual Data**

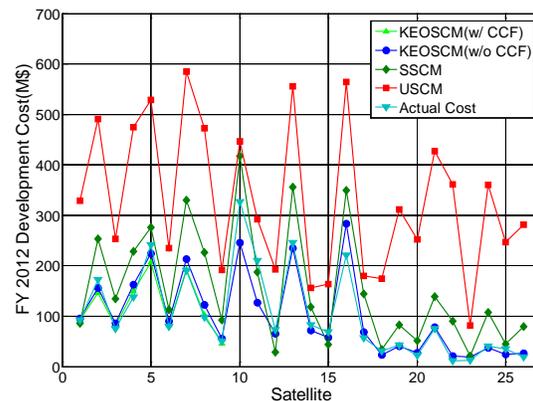
As a final step, the cost model verification was performed using the cost data that included reliability information. When using KEOSCM in estimating the development cost of EO satellite, the resulting error was 21% when CCF is not applied and 7% when it is

applied. In case of SAR satellite, the resulting error was 24%. Figures 10 and 11 show the result of satellite cost estimation per each satellite development program for EO and SAR satellites, respectively.

**Accuracy Comparison to Other Models**

The accuracy of the proposed model was determined by comparing to the performance of other previous models. Due to the fact USCM includes CERs for optical payload satellites, it was used for EO cost estimation. SCCM was used for both EO and SAR satellites.

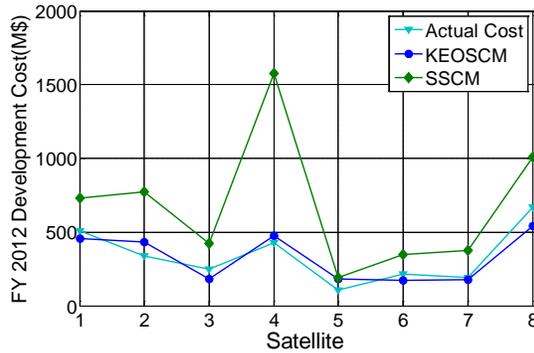
When applied to EO satellites, USMC showed average error of 460% and SCCM showed 98% error. Figure 12 shows the USCM can estimate the cost with a better accuracy than SCCM. When applied to SAR satellite, SCCM resulted in 100% error, as compared to 24% error for KEOSCM.



**Figure 12 Comparison of estimation results for each cost model(EO Satellite)**

This can be attributed to the fact that the satellite data used for cost estimation in USCM is different from that of KEOSCM's. USCM is based on satellite communication satellites as well as geostationary (GSO) earth-observation satellites and scientific research satellites developed by NASA. Military satellites generally require more intense systems engineering and integration technology, resulting in higher cost than commercial satellites. In addition, USCM CER derivation used satellites in GSO that generally have a much longer mission life, necessitating use of much more expensive components that have higher reliability rating. This results in higher development cost per unit mass when compared to satellites in lower orbits. This seems to be the reason for large discrepancies in estimating development cost of small satellites. Unlike USCM, SCCM was developed for small satellites, and also encompasses planetary exploration and scientific missions, in addition to earth-observation mission satellites. The large error can be attributed to the fact that the model

covers a wide range of satellite missions, instead of focusing on a single type of satellite.



**Figure 13 Comparison of estimation results for each cost model(SAR Satellite)**

### APPLICATION OF KEOSCM TO SATELLITE CURRENTLY UNDER DEVELOPMENT

As a case study, the proposed cost estimation model was applied to satellites that have completed conceptual design. The target altitude for an EO satellite is 650 km, has an aperture of 0.5 m, and has launch mass of 550 kg. SAR satellite has 1 m resolution and launch mass of 900 kg. The specifications of the conceptual-design stage EO and SAR satellites are given in Table 1 and 2, respectively.

When EO satellite cost is calculated using the specifications as listed in Table 1, SCI has a value of 0.765. If the satellite was developed with LCSS concept, then development cost is estimated at \$81M, and for HCTS case, the cost estimation is \$192 M.

In case of the SAR satellite, SCI was calculated to be 0.529 using the specifications as listed in Table 2. The total development cost was estimated to be \$313 M.

**Table 1 Specification of example satellite (EO Satellite)**

Factors	Values
Launch Mass	537.96 kg
Dry Mass	517.84 kg
Mission Life Time	5 years
EOL Power	1203 W
Downlink Data Rate	576 Mbps
Pointing Accuracy	0.0024 deg
Pointing Knowledge	0.002 deg
Pointing Stability	0.0002 deg/s
Slew Rate	2 deg/s
Solar Panel Area	3 m <sup>2</sup>
Onboard Memory Capacity	300 Gbits
Battery Capacity	30.1 Ah
Aperture Diameter	0.87 m
Focal Length	8.8 m
F Number	10.09
Reliability	0.7 @ 5 years

**Table 2 Specification of example satellite (SAR Satellite)**

Factors	Values
Launch Mass	954 kg
Dry Mass	918 kg
Mission Life Time	5 years
EOL Power	4497 W
Downlink Data Rate	238 Mbps
Pointing Accuracy	0.024 deg
Pointing Knowledge	0.002 deg
Pointing Stability	0.0005 deg/s
Slew Rate	1 deg/s
Solar Panel Area	19.4 m <sup>2</sup>
Onboard Memory Capacity	15.7 Gbits
Battery Capacity	114 Ah
ScanSAR Swathwidth	500 km
StripMap Swathwidth	30 km
Spot Swathwidth	15 km
ScanSAR Resolution	50 m
StripMap Resolution	2 m
Spot Resolution	1 m

### CONCLUSION

Many of the satellite cost estimation models developed previously rely on the total mass of the system. In order to increase accuracy, these models employ correction factors or program-related parameters for adjustments. The cost models based on total mass has been more widely used in the past, but many limitations often make them difficult to apply or achieve desired accuracy. In addition, the compounded errors of such models are further increased by the variety of the missions that these systems are designed to perform. The proposed cost estimation model was based on the database consisting of 118 satellites. Of these, 93 satellites were EO payload satellites with development cost data available for the 49 of these satellites. Similarly, the database included 13 SAR payload satellite, 14 of which the development cost data was available. The established database was analyzed for correlations, and in case of EO satellites, a total of 15 factors were selected. A total of 8 factors were used for SAR satellites. These factors were converted into weighting factors, and were applied in deriving the final System Complexity Index. The final result was a cost estimation model consisting of two cost estimation equations. When applied to EO satellites, the model resulted in approximately 7% average error, and SAR satellites estimation resulted in approximately 24% average error. When using SSCM and USCM in estimating cost for EO satellites, the resulting error was 21% and 7% respectively. When SSCM is applied to SAR satellite, the resulting error was 24%. The result shows that the proposed cost model provides much more accurate results in predicting the development cost of these satellites. The authors intend to periodically update the cost model and plan on

developing a combined satellite conceptual design tool package is in the future.

### ***Acknowledgments***

This work was supported by Global Surveillance Research Center (GSRC) program funded by the Defense Acquisition Program Administration (DAPA) and Agency for Defense Development (ADD).

### ***References***

1. C.R. Joyner II, J. R. Laurie, D. J. H. Levack, E. Zapata, Pros, Cons, and Alternatives to Weight Based Cost Estimating, 47<sup>th</sup> AIAA/ASME/SAE/ASEE Joint Propulsion Conference, San Diego, 31 July –3 Aug 2011.
2. D.A. Bearden, A complexity-based risk assessment of low-cost planetary missions: when is a mission too fast and too cheap?, *Acta Astronautica*, Vol. 52, Issue. 2-6, 2003, pp.371–379.
3. H.Habib-Agahi, J. Mrozinski, G. Fox, NASA Instrument Cost/Schedule Model, Aerospace Conference Proceedings, 2011 IEEE, 5-12 March 2011.
4. A. Mettas, Reliability Allocation and Optimization for Complex Systems, Reliability and Maintainability Symposium 2000 Proceedings, 24 – 27 Jan 2000, pp.216 – 221
5. E.Koelle, Handbook of Cost Engineering for Space Transportation Systems (Rev.3) with TRANSCOST 8”, Ottobrunn, Germany, 2010.
6. R. P. Covert, T. P. Anderson, Regression of Cost Dependent CERs, The Aerospace Corporation, 2012.
7. NASA Inflation Calculator, <http://cost.jsc.nasa.gov/inflation/nasa/inflatenasa.html>