<u>N</u>ASA <u>I</u>nstrument <u>C</u>ost <u>M</u>odel for <u>E</u>xplorer-like Mission Instruments (NICM-E)

Hamid Habib-Agahi[1], George Fox[2], Joe Mrozinski[3]
and Gary Ball[4]
Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, 91109

NICM-E is a cost estimating relationship that supplements the traditional NICM System Level CERs for instruments flown on NASA Explorer-like missions that have the following three characteristics: 1) fly on Class C missions, 2) major development led and performed by universities or research foundations, and 3) have significant level of inheritance.

Nomenclature

C	=	instrument NICM definition of B/C/D cost (FY04$K)
M	=	instrument total mass (kilograms)
P	=	instrument maximum (peak) power demand (Watts)
R^2	=	coefficient of multiple correlation
SE	=	standard error of regression
PE	=	average prediction error of regression

I. Introduction

The NICM development team received feedback from NICM users that the NICM CERs were estimating costs much higher than grass roots estimates for many of their Explorer-like mission instrument proposals. Also, the NICM team found previously flown Explorer-like instruments to have lower actual costs compared to the actual costs of other previously flown instruments used to develop the NICM CERs. Examining these differences identified a set of criteria that these Explorer-like instruments all met which contrast with the rest of the NICM instruments: they all 1) flew on Class C missions, 2) had a university or research foundation lead and perform the majority of the instrument development (design through delivery and integration) and 3) had significant inheritance from previously developed instruments. The NICM Team created a new Cost Estimating Relationship (CER), NICM-E, which is applicable to the class of instruments which satisify the above three criteria.

II. Methodology

The first step in a data based cost modeling effort is to identify and collect the relevant data attributes. Qualitative, descriptive information on mission class, instrument inheritance and university involvement was collected from interviews of the instrument teams as well as in online and scientific journal references. Once sufficient data was collected each instrument was normalized by reviewing the data with recognized instrument experts. The next step was to develop a preliminary model estimate of parameter values in the instrument cost functional form, a scaling relationship based on technical variables. Principal Components Analysis (PCA) was used to identify the parameter values for the scaling exponents of each design variable and its resulting statistical significance. Upon testing for statistical significance, variables were eliminated and a standard bootstrap cross validation was used to calculate an average prediction error for estimating cost model predictive uncertainty. The

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[1] Manager Systems Analysis and Modeling Group, Mission Systems Concepts, 301-165, non-AIAA Member.
[2] Systems Engineer, Mission Systems Concepts, 301-165, non-AIAA Member.
[3] Systems Engineer, Mission Systems Concepts, 301-165, non-AIAA Member.
[4] Cost Engineer, Engineering Cost Estimation, 301-476, non-AIAA member.

resulting CER was then compared to the current NICM System Level CERs for each instrument to determine if this new CER is better suited for Explorer-like instrument cost estimates than the current NICM CER cost estimates.

A. Data Collection and Normalization

The technical and programmatic data for 20 instruments meeting the three criteria on missions led by Goddard Space Flight Center (GSFC), the Jet Propulsion Laboratory (JPL), and the Applied Physics Laboratory (APL) were collected (Table 1). Note that 2 of these instruments did not fly on Explorer class missions, but did have the 3 defining characteristics and thus were included. All 20 instruments are flew on heliophysics or astrophysics missions in near-earth orbits. There were no planetary mission instruments identified which met all three defining characteristics, nor were there any microwave instruments identified. Three NICM instrument types are represented in the data set: 8 instruments are Optical, 4 are Fields, and 8 are Particles. The raw cost data was expressed as a profile over years which needed to be converted to a common fiscal year cost value, which for this cost data is FY 2004, consistent with the NICM cost base year. Mission class was verified as Class C for all 20 instruments. Significant inheritance (i.e. previously flown subsystems/components, etc.) was verified by conversation with instrument developers, principal investigators, and technical experts. Similarly, university or research foundation led design and development was verified.

Instrument Name	Lead Center	Instrument Type	B/C/D Cost ($K FY04)	Mass (kg)	Maximum Power (W)	University
CHIPS	GSFC	Optical	$5,014	23.67	30.00	Berkeley
CIPS	GSFC	Optical	$10,483	24.00	39.00	U. Colorado
EFI_THEMIS	GSFC	Fields	$2,904	16.01	13.73	Berkeley
EFPE	GSFC	Fields	$7,161	28.45	15.90	Berkeley
ESA_FAST	GSFC	Particles	$6,100	23.97	13.10	Berkeley
ESA_THEMIS	GSFC	Particles	$1,480	3.85	1.77	Berkeley
GALEX	JPL	Optical	$23,662	135.10	191.00	Berkeley, Caltech
GUVI	APL	Particles	$8,355	19.07	26.69	Johns Hopkins
IRIS	GSFC	Optical	$28,917	97.30	96.30	Stanford
LEICA	GSFC	Particles	$3,030	9.76	9.32	U. Maryland
MAG-FAST	GSFC	Fields	$2,100	7.03	2.10	Berkeley
MAST/PET	GSFC	Particles	$3,470	11.27	8.01	Caltech
NuStar	JPL	Optical	$42,275	179.00	200.00	Caltech
RHESSI	GSFC	Optical	$30,669	127.00	175.20	Berkeley
SOFIE	GSFC	Optical	$9,996	38.00	52.00	Utah State
SST	GSFC	Fields	$1,566	1.74	1.38	Berkeley
TEAMS	GSFC	Particles	$3,100	10.31	4.50	Berkeley
TIDI	APL	Particles	$16,081	40.57	53.00	U. Michigan
TRACE	GSFC	Optical	$23,895	59.13	69.00	Harvard, MSU, Stanford
ULEIS	APL	Particles	$7,512	18.40	21.20	Caltech, U.Maryland, Aerospace, Germany

Table 1: Lead Center, Instrument Type, Actual B/C/D Costs, Instrument Mass, Maximum Power and University Involvement Information by Instrument Name.

B. Model Development

The NICM System Level CERs provided the starting point for developing the NICM-E CER. The Optical, Particles, and Fields NICM CERs for B/C/D cost rely on inputs of total mass, maximum power, and design life to calculate the B/C/D Cost. Principal components analysis on the B/C/D cost and the three design variables was used to develop the new CER and its statistical properties. During the analysis it was determined that there was insufficient variability in the design life values as all but 4 of the 20 instruments had values of 24 or 25 months. There was thus no statistical justification for including design life due to this insufficient variability.

C. The Model and Its Statistical Properties

A principal components analysis determined the B/C/D cost to be a function of instrument total mass and maximum power demand as follows:

$$C\ (\$K\ FY2004) = 661\ M^{0.43}\ P^{0.34}$$

$$R^2 = 93\%,\ SE = 29\%,\ PE = 30\%$$

The coefficient of multiple correlation, R^2, of 93% is high, i.e. the CER explains 93% of the original variation in cost. A standard error of 29% is the standard deviation of the residual fitting errors of the log-log model, i.e. the actual log(B/C/D Cost) minus the log of the model estimated cost. The NICM-E standard error is comparable to current NICM System Level cost standard errors. The prediction error, which estimates cost prediction uncertainty, takes into account the errors in estimated parameters as well as the standard error from residuals. The prediction error is estimated from 10,000 bootstrap cross validation samples as 30%. The calculated 70% confidence, one-sided prediction interval has an upper bound value only 16% greater than the CER calculated cost, i.e. the median (=50%) cost.

III. Analysis

As the statistical analysis indicates, the new CER explains 93% of the historical cost variation in Explorer-like mission instruments which satisfiy the three criteria. Table 2 displays the model estimated results, the actual B/C/D Cost, and the model error for the NICM-E instrument data set. For the NICM-E instruments there was no significant cost model variation identified that depended on the instrument types of Optical, Fields or Particles. As displayed in Figure 1, a comparison between current NICM and NICM-E, points on the dashed line have actual cost equal to the estimated cost. Inspection of Figure 1 and Table 2 suggests that, when using the traditional NICM System Level CERs, all 20 instruments are estimated to have much higher costs than their actual costs. Traditional NICM assumes a new instrument development with low inheritance, minor university involvment, and mission classes A through C. Therefore, this new NICM-E CER supplements the traditional NICM by estimating development costs for instruments which will 1) fly on C Class missions, 2) have a university or research foundation lead and perform the majority of the instrument development and 3) have significant inheritance from prior instruments.

Instrument Name	Lead Center	Instrument Type	B/C/D Cost ($K FY04)	NICM-E B/C/D CER ($K FY04)	Model Error
CHIPS	GSFC	Optical	$5,014	$8,265	50.0%
CIPS	GSFC	Optical	$10,483	$9,089	-14.3%
EFI_THEMIS	GSFC	Fields	$2,904	$5,359	61.3%
EFPE	GSFC	Fields	$7,161	$7,211	0.7%
ESA_FAST	GSFC	Particles	$6,100	$6,273	2.8%
ESA_THEMIS	GSFC	Particles	$1,480	$1,450	-2.1%
GALEX	JPL	Optical	$23,662	$32,741	32.5%
GUVI	APL	Particles	$8,355	$7,239	-14.3%
IRIS	GSFC	Optical	$28,917	$22,538	-24.9%
LEICA	GSFC	Particles	$3,030	$3,800	22.6%
MAG-FAST	GSFC	Fields	$2,100	$1,990	-5.4%
MAST/PET	GSFC	Particles	$3,470	$3,839	10.1%
NuStar	JPL	Optical	$42,275	$37,531	-11.9%
RHESSI	GSFC	Optical	$30,669	$30,962	1.0%
SOFIE	GSFC	Optical	$9,996	$12,208	20.0%
SST	GSFC	Fields	$1,566	$947	-50.3%
TEAMS	GSFC	Particles	$3,100	$3,038	-2.0%
TIDI	APL	Particles	$16,081	$12,638	-24.1%
TRACE	GSFC	Optical	$23,895	$16,250	-38.6%
ULEIS	APL	Particles	$7,512	$6,593	-13.0%

Table 2: Actual B/C/D Cost and NICM-E CER Estimate with Instrument Model Error.

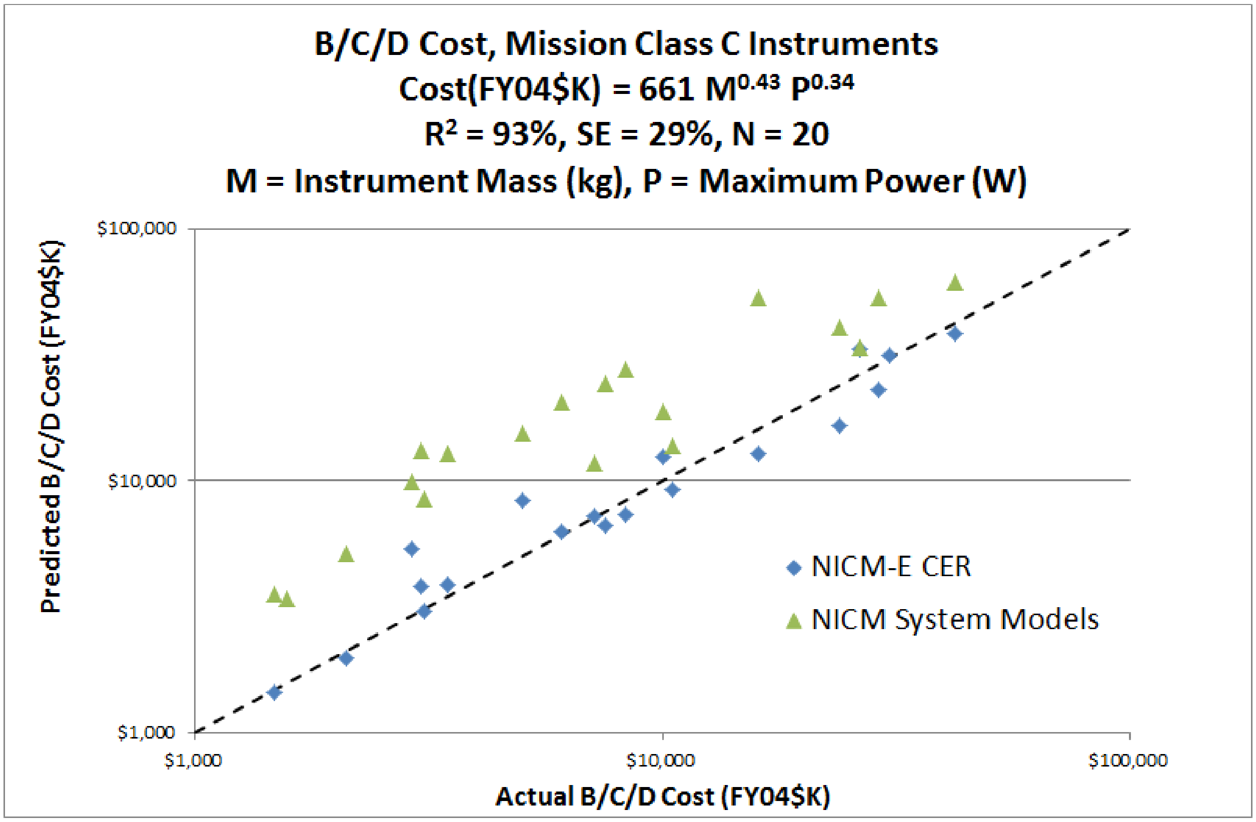

Figure 1: A Cost Comparision of the NICM-E CER Estimates with the Current NICM System CERs for the NICM-E Instruments.

IV. Conclusions

Cost estimators should use NICM-E to estimate cost for instruments that: 1) will fly on a Class C mission, 2) will have a university or research foundation perform the majority of the instrument development, and 3) will have significant inheritance derived from previously developed instruments.

If the instrument does not meet any of the above three criteria, estimators should use the current NICM System Level CERs for the given instrument type. The cost will represent a new instrument development with litte inheritance and for a mission of class A, B or C.

For instruments that meet some of the criteria but not all, users should run both NICM-E and the appropriate NICM System Level CER and interpolate based on subjective estimates of exceptions to inheritance level, significant development by universities or research foundations, or assumptions about the mission class.

Appendices

- **Principal Components Analysis**

Principal Components Analysis (PCA) is a variant of linear regression analysis that overcomes a number of regression defects when used in a data-mining context. Linear regression analysis posits a model (e.g. linear, log-linear) of how cost varies with a given set of parameters such as mass and power:

$$C_i = a_0 + a_1 * M_1 + a_2 * P_i + \varepsilon_i$$

where C_i is the cost, M_i is the mass and P_i is the power for instrument "i", and ε_i is an error term, typically assumed to be normally distributed with constant variance. In this pedagogical example cost is displayed as a linear function of mass and power. Current cost models are generally scaling relationships between cost and instrument attributes – for these models, logarithms of continuous valued variables are used when building CERs. In these applications of PCA, the data set averages of the logged variables are subtracted and divided by the data set standard deviation before estimating and validating (this is sometimes called standardization or z-score).

The cost equation (with z-score values) is traditionally solved by least squares when there is a data set $\{C_i, M_i, P_i, \ldots\}$ of attributes for the instruments of interest. The sum of the squared residuals to be minimized is:

$$\chi^2 = \sum_i \left(C_i - a_0 - a_1 * M_i - a_2 * P_i\right)^2$$

defined over parameters $\{a_0, a_1, a_2\}$. That is, χ^2 is to be minimized over all possible choices of a_0, a_1, a_2.

Linear least squares regression analysis does not generally make a good data mining tool. It over-emphasizes data outliers when fitting models and produces poor model fits when residual errors are not from the same distribution (the case of *heteroscedasticity*). Instrument technical and programmatic variables like cost, mass and power are the outputs of a complicated instrument design and development process. As such the parameters are determined jointly, with no obvious causal model structure to guide a proper causal analysis. In addition, even if such a model existed, the necessary historical data to statistically support it is lacking. Principal components analysis avoids these problems by treating the model residuals of these parameters as equally important. Using the prior formulation, the model equations are re-written.

$$C_i = a_{i1} * c_1 + a_{i2} * c_2 + a_{i3} * c_3$$

$$M_i = a_{i1} * m_1 + a_{i2} * m_2 + a_{i3} * m_3$$

$$P_i = a_{i1} * p_1 + a_{i2} * p_2 + a_{i3} * p_3$$

Here all the data is on the left hand side of the equation and the parameters to be determined on the right side. Additional parameters representing idealized values of the instrument attributes are added in addition to the usual scale parameters in the traditional models. Re-written in a more compact notation, the equations to be solved are:

$$X_{ik} = \sum_q U_{iq} D_q V_{kq} + \varepsilon_{ik} \text{ for all i and k}$$

where X_{ik} is the parameter *k* z-score data value for instrument *i* and ε_{ik} is the error term. The right-hand side is an expression of the matrix **X** in terms of the **U**, **V** and **D** matrices, called the singular value decomposition. Here **U**, **V** and **D** are matrices to be determined from the following least squares procedure. The sum of the squared residuals

$$\chi^2 = \sum_{ik}\left(X_{ik} - \sum_{q} U_{iq} D_q V_{kq} \right)^2$$

is minimized over the set of possible values for the matrices **U**, **V** and **D**: $\{U_{iq}, D_q, V_{kq} \mid \text{for all q, i \& k}\}$ where **U** & **V** are column orthogonal. This yields a set of equations for the matrices **U**, **V** and **D** derived from the first order conditions for minimal χ^2**,**

$$U_{iq} D_q = \sum_{k}\left(X_{ik} V_{kq} \right) \text{ for } q = 1, ..., \mathrm{Min}(K, N)$$

$$V_{kq} D_q = \sum_{i}\left(X_{ik} U_{iq} \right) \text{ for } q = 1, ..., \mathrm{Min}(K, N)$$

where K is the number of parameters and N the number of instruments. Due to the inherent noise in the data, the selection of a statistically significant number of principal components Q (q=1,…, Q < min(K, N)) is determined by two independent methods: the scree chart and bootstrap cross-validation. The scree chart is a plot of the number of included principal components Q by the total reduction in model variance provided by the principal components from 1 to Q. This plot is called a scree chart because it looks like a steep mountain with scree (debris) piled up at the bottom; there is a kink in the curve where the noise in the data takes over and the curve flattens for high Q. In determining the point of the kink in the chart PCA is applied to random model data of the same dimension as the original data (N by K). This provides a comparison set of points based just on noise. The "peak of the mountain" from the real data stands out in comparison to the noisy data "peak". This comparison gets us in the vicinity of the right number of principal components; by variation in the selection of model parameters and the number of principal components, bootstrap cross-validation provides confirmation of the statistically significant parameters and appropriate group of instruments based on the predictive ability of the identified model. The results of the principal components analysis with the Cost Estimating Relationship (CER) it implies are linked up. A CER expresses the cost of an instrument as a function of the other parameters describing the instrument. The PCA identifies the primary relationship that determines the value of each significant identified parameter. To derive the CER the first order conditions that define the **U** matrix into the equation for the Cost attribute (indexed by *c*) is substituted.

$$X_{ic} = \sum_{q}^{Q} U_{iq} D_q V_{cq} + \varepsilon_{ic}^{Q} = \sum_{q}^{Q}\left(\sum_{k} X_{ik} V_{kq} \right) V_{cq} + \varepsilon_{ic}^{Q}$$

The sums over *q* and *k* are now interchanged (Q is the number of principal components that are kept). Notice that the sum over *k* contains a term in *c,* which was moved to the left side of the equation. Dividing by the coefficient of cost from the left side the equation becomes

$$X_{ic} = \sum_{k}^{'} X_{ik} \left[\frac{\sum_{q}^{Q} \left(V_{kq} V_{cq} \right)}{1 - \sum_{q}^{Q} \left(V_{cq} V_{cq} \right)} \right] + \frac{\varepsilon_{ic}^{Q}}{1 - \sum_{q}^{Q} \left(V_{cq} V_{cq} \right)}$$

where the prime on the sum over k is to denote that c is not included The term in brackets is the usual regression coefficient from linear least squares in a regression of cost against the other variables.

- **Bootstrap Cross Validation**

Bootstrap cross validation combines two simple techniques to validate regression models. Statistical model validation is the process whereby an additional random sample is drawn from the applicable population of objects ("out-of-sample") and compared with the results of the model predictions which are based on the original training sample. A useful measure of performance is the *error variance*, the sum of the squared differences of the predicted minus the actual cost values from the additional sampled population.

Cross-validation is a variation on the above out-of-sample validation, used when it is difficult and/or costly to create additional random samples. In standard cross-validation a portion of the entire dataset (typically half) is selected to estimate the model (called the training set). The remaining data is used to test the model (the test set). Multiple random selections of training data and testing data add robustness to the process.

The *bootstrap* is a modern technique for calculating statistical properties of model distributions without assuming any particular form for the distributions. For example, in classical statistics the Gaussian distribution is assumed when calculating test statistics in regression analysis. The bootstrap technique samples from the empirical distribution of the data when calculating statistical properties like sample means, standard model errors, prediction errors, confidence intervals, etc. Simulation tests on real data sets have demonstrated the usefulness and superiority of the bootstrap compared to classical methods. A good way to think about the bootstrap is that the original sample data set is treated as if it were the entire population – multiple samples of the same size with replacement are then drawn and statistics are calculated to characterize the statistical properties of the model.

Bootstrap cross-validation relaxes the usual cross-validation assumption of a fixed-training set size. N random samples (with replacement) of instruments from the original data set (of size N) are selected to be the training set. As some instruments will be duplicated, there will remain a set of instruments that have not been included in the training-data set; these are the testing set. In our application a PCA model is fitted to the training set data and the data is tested on the unselected instruments. This random-sampling process is repeated 10,000 times and the average cross validation error variance is calculated as an average over instruments of the average individual error variances when each instrument is used in a testing set

$$VAR_{bs} = \sum_{i}^{N} \left[\frac{\sum_{m}^{|M(i)|} \left(EC_{im} - C_i \right)^2}{|M(i)|} \right] * \frac{1}{N}$$

where M(i) is the set of models (out of the 10,000 model training/testing data splits) where *i* is in the testing set. EC_{im} is the predicted cost of instrument *i* in model *m*. C_i is the actual cost of instrument *i*. Each time a training/testing data split is selected, the squared errors of each model prediction of cost versus the true cost for all instruments not used to estimate the model is accumulated. After all training/testing data splits are selected each instrument's accumulated squared errors (i.e. variance) are divided by the number of times it was used in testing. Then all instruments are averaged to get the bootstrap cross-validation error variance. The ".632 cross-validation error variance," is the weighted average of the above error and the apparent error (i.e. the error of the model where all instruments are in the training set). This "*.632* error" in simulation studies has been found to be the most accurate estimate of the true model prediction error. When selecting the appropriate PCA model the number of principal components to include in the final model is varied and potential outliers in the original set of instruments are identified. Here the better models are those whose prediction errors are smaller than those of alternative models.

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References

[1]Hamid Habib-Agahi, et.al., "NASA Instrument Cost Model (NICM) Version V," JPL 982-0000 Rev. 5, May 2012.

[2]A. C. Davison & D. V. Hinkley, *Bootstrap Methods and their Application*,

[3]B. Efron & R. J. Tibshirani, *An Introduction to the Bootstrap*,

[4]J. Johnston, Econometric Methods, 2nd Edition, McGraw-Hill Book Company, 1972. Chapter 11.

[5]S-Plus 7 Guide to Statistics, Volume 2, Insightful Corporation. Chapter 20 Principal Components Analysis.

[6]Takeshi Amemiya, *Advanced Econometrics*, Harvard University Press, 1985. pps.58-60.

[7]NASA Procedural Requirements – NPR 8705.4, "Subject: Risk Classification for NASA Payloads (Revalidated July 9, 2008)

[8]T. D. Tarbell, M. Bruner, B. Jurcevich, J.Lemen, K. Strong, A. Title, J. Wolfson, L. Golub, R. Fisher, "THE TRANSITION REGION AND CORONAL EXPLORER (TRACE)," Proc. Of the Third SOHO Workshop – Solar Dynamic Phenomena and Solar Wind Consequences, held at Estes Park, Colorado, USA. 26 – 29 September 1994 (ESA SP-373. December 1994).

[9]Timothy L. Killeen, Wilbert R. Skinner,Roberta M. Johnson, Charles J. Edmonson, Qian Wu, Rick J. Niciejewski, Heinz J. Grassl, David A. Gell, Peter E. Hansen, Jon D. Harvey, and Julie F. Kafkalidis, TIMED Doppler Interferometer (TIDI), Space Physics Research Laboratory, Department of Atmospheric, Oceanic, and Space Sciences, The University of Michigan, Ann Arbor, Mi. 48109-2143.

[10]D. M. Klumpar, E.Möbius, L. M. Kistler, M. Popecki, E. Hertzberg, K. Crocker, M. Granoff, Li Tang, C. W. Carlson, J. Mcfadden, B. Klecker, F. Eberl, E. Künneth, H. Kästle, M. Ertl, W. K. Peterson, E. G. Shelly And D. Hovestadt, THE TIME-OF-FLIGHT ENERGY, ANGLE, MASS SPECTROGRAPH (TEAMS) EXPERIMENT FOR FAST, Space Science Reviews 98: 197–219, 2001.

[11]Davin Larson, Thomas Moreau, Robert Lee, Ron Canario,Vassilis Angelopoulos, Robert Lin, THEMIS PRE-LAUNCH TEAM MEETING - SST, THEMIS Pre-Launch Team Meeting for the Solid State Telescope (SST), UCB, February 12, 2007.

[12]Larry L.Gordley, Mark E. Hervig, Chad Fish, James M. Russel III, Scott Bailey, James Cook, Scott Hansen, Andrew Shumway, Greg Paxton, Lance Deaver, Tom Marshall, John Burton, Brian Magill, Chris Brown, Earl Thompson, John Kemp, The solar occultation for ice experiment, Journal of Atmospheric and Solar-Terrestrial Physics 71(2009) 300–315.

[13]R. P. Lin, B. R. Dennis, G. J. Hurford, D. M. Smith, A. Zehnder, P. R. Harvey, D. W. Curtis, D. Pankow, P. Turin, M. Bester, A. Csillaghy, M. Lewis, N. Madden, H. F. Van Beek, M. Appleby, T. Raudorf, J. Mctiernan, R. Ramaty, E. Schmahl, R. Schwartz, S. Krucker, R. Abiad, T. Quinn, P. Berg, M. Hashii, R. Sterling, R. Jackson, R. Pratt, R. D. Campbell, D. Malone, D. Landis, C. P. Barrington-Leigh, S. Slassi-Sennou, C. Cork, D. Clark, D. Amato, L. Orwig, R. Boyle, I. S. Banks, K. Shirey, A. K. Tolbert, D. Zarro, F. Snow, K. Thomsen, R. Henneck, A. Mchedlishvili, P. Ming, M. Fivian, John Jordan, Richard Wanner, Jerry Crubb, J. Preble, M. Matranga, A. Benz, H. Hudson, R. C. Canfield, G. D. Holman, C. Crannell, T. Kosugi, A. G. Emslie, N. Vilmer, J. C. Brown, C. Johns-Krull, M. Aschwanden, T. Metcalf And A. Conway, THE REUVEN RAMATY HIGH-ENERGY SOLAR SPECTROSCOPIC IMAGER (RHESSI), Solar Physics 210: 3–32, 2002.

[14]Fiona A. Harrison, Steven Boggs, Finn Christensen, William Craig, Charles Hailey, Daniel Stern, William Zhang, Lorella Angelini, HongJun An, Varun Bhalereo, Nicolai Brejnholt, Lynn Cominsky, W. Rick Cook, Melania Doll, Paolo Giommii, Brian Grefenstette, Allan Hornstrup, Victoria M. Kaspi, Yunjin Kim, Takao Kitaguchi, Jason Koglin, Carl Christian Liebe, Greg Madejski, Kristin Kruse Madsen, Peter Mao, David Meier, Hiromasa Miyasaka, Kaya Mori, Matteo Perri, Michael Pivovaro, Simonetta Puccettii, Vikram Rana, Andreas Zoglauer, The Nuclear Spectroscopic Telescope Array (NuSTAR), The Nuclear Spectroscopic Telescope Array (NuStar) Science Paper, 2010.

[15]R. C. Elphic, J. D. Means, R. C. Snare, R. J. Strangeway, L. Kepko, R. E. Ergun, MAGNETIC FIELD INSTRUMENTS FOR THE FAST AURORAL SNAPSHOT EXPLORER, Space Science Reviews 98: 151–168, 2001.

[16]Bart De Pontieu, IRIS Mission and Instrument Overview, November 30, 2011, Lockheed Martin Solar & Astrophysics Laboratory Presentation.

[17]Andrew B. Christensen, R. L. Walterscheid, and M. N. Ross, C. -I. Meng, L. J. Paxton, D. E. Anderson, G. Crowley, S. Avery, J. D. Craven, R. R. Meier, D. J. Strickland, The Global Ultraviolet Imager (GUVI) for the NASA TIMED mission, SPIE Vol. 2266/451.

[18]C. W. Carlson, J. P. Mcfadden, P. Turin, D. W. Curtis, A. Magoncelli, THE ELECTRON AND ION PLASMA EXPERIMENT FOR FAST, Space Science Reviews 98: 33–66, 2001.

[19]J.P. McFadden, C.W. Carlson, D. Larson, M. Ludlam, R. Abiad, B. Elliott, P. Turin, M. Marckwordt, V. Angelopoulos, The THEMIS ESA Plasma Instrument and In-flight Calibration, Space Sci Rev (2008) 141: 277–302.

[20]R. E. Ergun, C. W. Carlson, F. S. Mozer, G. T. Delory, M. Temerin, J. P. Mcfadden, D. Pankow, R. Abiad, P. Harvey, R. Wilkes, H. Primbsch, R. Elphic, R. Strangeway, R. Pfaff, C. A. Cattell, THE FAST SATELLITE FIELDS INSTRUMENT, Space Science Reviews 98: 67–91, 2001.

[21]J. W. Bonnell, F. S. Mozer, G. T. Delory, A. J. Hull, R. E. Ergun, C. M. Cully, V. Angelopoulos, P. R. Harvey, The Electric Field Instrument (EFI) for THEMIS, thm_efi_instrument_paper_revE.doc

[22]W.E. McClintock, D.W. Rusch, G.E. Thomas, A.W. Merkel, M.R. Lankton, V.A. Drake, S.M. Bailey, J.M. Russell III, The cloud imaging and particle size experiment on the Aeronomy of Ice in the mesosphere mission: Instrument concept, design, calibration, and on-orbit performance, Journal of Atmospheric and Solar-Terrestrial Physics 71(2009)340–355.

[23]M. Sholl, W. Donakowski, M.M. Sirk, T. Clauss, M. Lampton, J. Edelstein, M. Hurwitz, Opto-mechanical Design of the Cosmic Hot Interstellar Plasma Spectrometer (CHIPS), sholl@ssl.berkeley.edu; tel. (USA) 510-643-2098; Space Sciences Laboratory, University of California, Berkeley, CA 94720 USA.