Prediction of liner erosion and life estimation of Stationary Plasma Thrusters using Machine Learning

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Abstract: Estimation of operational life time of electric propulsion thrusters has become a popular research problem and over the years many approaches have been used to predict the life-time like theoretical models, empirical methods, semi-empirical methods etc. This paper attempts to use a new approach in predicting the thruster lifetime by using Machine learning techniques. The idea is to use measurement of liner profiles for a set of hours of operation and predict the erosion for future hours of operation. Two different methods are used here to predict the life of electric thruster. One, using supervised form of learning called Artificial Neural Network (ANN) and other with Non-linear regression method using curve fitting. Both the methods show very good results for the time instants at which measured profiles are available. However, for prediction for time instants beyond the available range, the results of the two methods are compared with each other, since experimental data is not available for those time instants.

Nomenclature

ANN	=	Artificial Neural Network
SPT	=	Stationary Plasma Thruster
r	=	radial positions of the ceramic liners
z	=	axial positions of the ceramic liners
t	=	Time of profile measurement
HET	=	Hall effect thrusters
dt	=	time step
MSE	=	Mean square error
AEPS	=	All electric propulsion satellite

I. Introduction

Electric propulsion has become widely popular in recent times in the field of spacecraft propulsion due to its ability to give higher specific impulse and higher payload to propellant mass fraction when compared to that of chemical propulsion. A number of successful operations of Hall and Ion thrusters are recorded. These thrusters carry out operations like orbit raising, station keeping, etc. Hall thrusters have emerged a better choice for all-electric satellites where both orbit raising and station keeping are carried out by electric thrusters. They have better thrust to power ratio when compared to Ion thrusters, which minimizes the orbit raising duration. However, when compared to chemical propulsion, these hall thrusters deliver low thrust and hence are required to work for thousands of hours during the entire mission duration. Thus, operational lifetime of hall thruster is an important factor in deciding the life of the

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missions. Estimation of life-time of these thrusters has become a popular research problem and over the years many approaches have been used to predict the life-time. Some of the methods used are physics based theoretical models[8][4], empirical methods, semi- empirical methods[9], etc.

Hall thrusters employ radial magnetic fields to trap electrons for effectively ionizing and accelerating a neutral gas, typically xenon. Working of these thrusters can be better understood from Ref.1.

Despite multiple prediction and estimation methods, no one method can perfectly predict the life-time of the thruster, as the complex physics involved in the process is not properly understood. In principle, a thruster would require to undergo a full life time qualification test to predict the overall operational life-time of the thruster. Such a full life-time qualification test would give the most accurate lifetime prediction for flight models. However, a full-life qualification test would be highly time consuming and would incur heavy costs, owing to the large amount of propellant required and the requirement of maintaining appropriate vacuum levels for the facility. Thus, a more cost-effective and quicker approach is required for determining the operational life time of these thrusters.

II. Use of Machine Learning Technique

The primary objective of this paper is to find a cost-effective method in estimating the life time of the thruster which is quicker and does not depend upon the knowledge of the complex physics involved in the process of liner erosion. Since the aim is to derive the inference from the erosion data for first few hours of firing, data driven approach is chosen for the life estimation.

A. Artificial Neural Network (Supervised learning)

Artificial Neural network is one of the techniques used in machine learning. ANNs have become very popular in recent times and they are used in solving a variety of problems like face recognition, speech recognition, stock prediction etc. These are modeled in such a way so as to mimic the function of a human brain. Human brain consists of a network of neurons, dendrites, synapses etc. The Neurons communicate with each other with help of synapses. Similar analogy is used in the case of Artificial Neural Networks. ANN's are made up of smaller units called neurons[3]. These are the fundamental information-processing units of the network. A typical neuron can be modeled in the following manner[3].

$$y = f(\Sigma_{i=1}^{n} w_i x_i + b) \tag{1}$$

Where x_i denotes multiple inputs to the neuron, w_i refers the corresponding weights and the term b denotes the overall bias. The function $f()$ denotes the activation function and the output of this function, y is the output of the neuron. The activation functions like threshold function, sigmoid function, hyperbolic tangent functions are popular and the selection of activation function for any problem is made on the basis of suitability[3]. A typical ANN has input layers, hidden layers and output layers having multiple neurons in each of the layers.

Backpropagation algorithm is used for training the network. This corrects the weight and biases of the network, during the training course, in order to achieve the targeted output. The weights of the network are corrected using the weight update rule[3][5]:

$$w_{ji}^{l}(t+1) = w_{ji}^{l}(t) - \eta \frac{\partial E}{\partial W} \tag{2}$$

where w_{ji}^{l} is the weight for jth neuron in layer l for ith input. η is the learning rate and E is error between the obtained output and the targeted output. During the training phase of the data, the aim is to reduce the error E.

Fig.1 denotes a typical artificial neural network with input layer, hidden layers and output layer stacked with multiple neurons. In the network

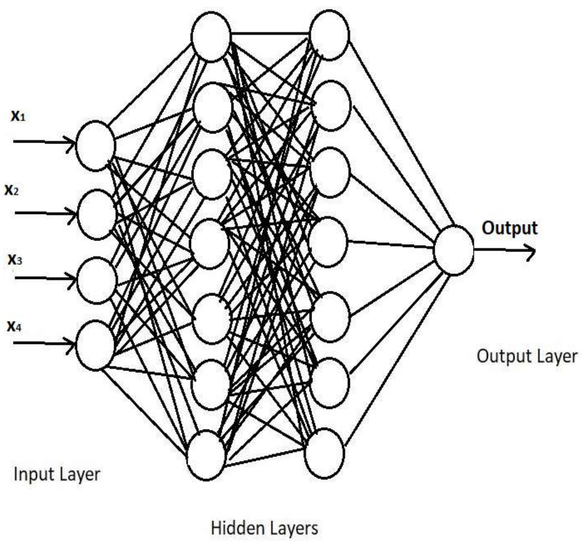

Figure 1. A typical Artificial Neural Network with Input Layers, Hidden layers and Output Layers.

designed for this problem, four inputs are used, namely time of profile measurement with respect to number of hours of thruster firing (t), Initial radial position before thruster firing ($r_{initial}$), axial position (z) and rate of change of radial profile. The required outputs are radial positions for input time instants

B. Non-linear Regression.

The second approach is Non-linear regression model using curve-fitting method. With the help of existing data, it is attempted to fit the experimental data to an equation. The choice of equation was based on observations from the normalized radial rates for the NASA-400M and T-220, studies from the life test of the SPT-100 and the normalized volumetric wear rates of the NASA-400M, NASA-120M, T-220 and the SPT-100 [6]. The radial wear decreased exponentially over time in these cases. On studying the same parameter in this test case, a similar behavior of exponentially decreasing radial wear rate is observed. Hence exponential equation $y = a\, e^{b\,x}$ is considered as the objective function for curve-fitting, where x is the input and y is the output and a and b are constants. Equations were calculated for all the axial positions(z). The number of equations was equal to the number of axial positions(z) in the dataset. The rate of decrease is higher towards farther axial position(z) and lesser on the inside. Once the equations were fit, the radial positions were calculated for future time instants at all the axial position.

III. Test Case

The study considers a 300W thruster which is tested for nearly 1000hours. Figure 2 and 3 show the erosion patterns measured at different intervals upto nearly 1000 hours for both inner and outer liner.

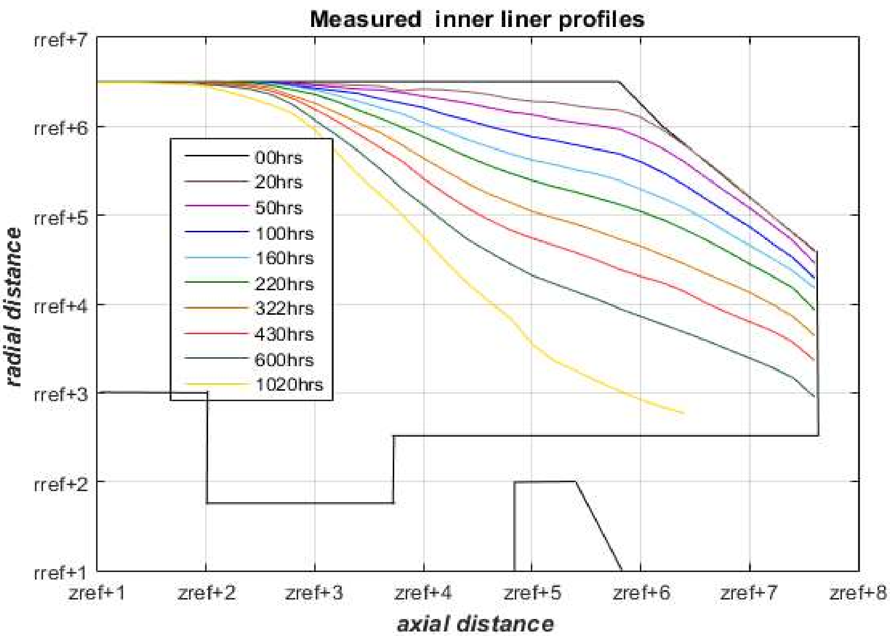

Figure 2: The measured liner profiles for inner liner for time instants 00hrs, 20hrs, 50hrs, 160hrs, 220hrs, 322hrs, 430hrs, 600hrs and 1020hrs. The profile at 00hrs is marked in black and it is the boundary of the inner liner.

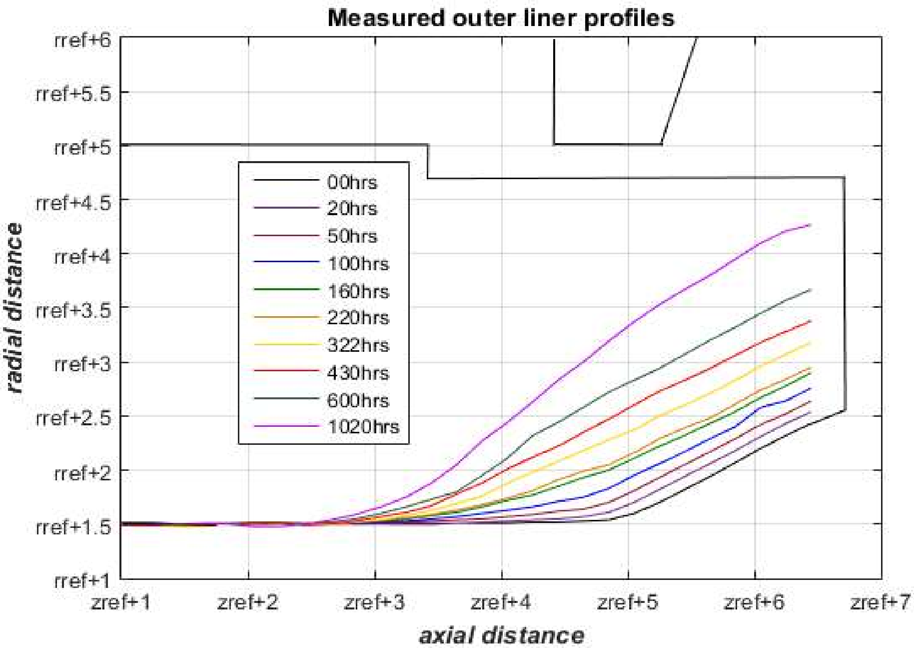

Figure 3: The measured liner profiles for outer liner for time instants 00hrs, 20hrs, 50hrs, 160hrs, 220hrs, 322hrs, 430hrs, 600hrs and 1020hrs. The profile at 00hrs is the boundary of the outer liner.

IV.Results

A. Using ANN

Both Artificial Neural Network and curve-fitting approaches mentioned above are applied for estimating the erosion pattern and thus, predicting the thruster life. The first approach i.e., Artificial Neural Networks, uses the profile measurements for initial hours of firing as the training dataset. The network formed is a feed forward neural network. The inputs for the network are time instants of profile measurement, liner profile boundary before firing and the rate of change of radial profile of the liner and the targeted outputs are radial liner profile corresponding to the time instants and axial position. The backpropagation algorithm is used for training. Due to the limited amount of data available,

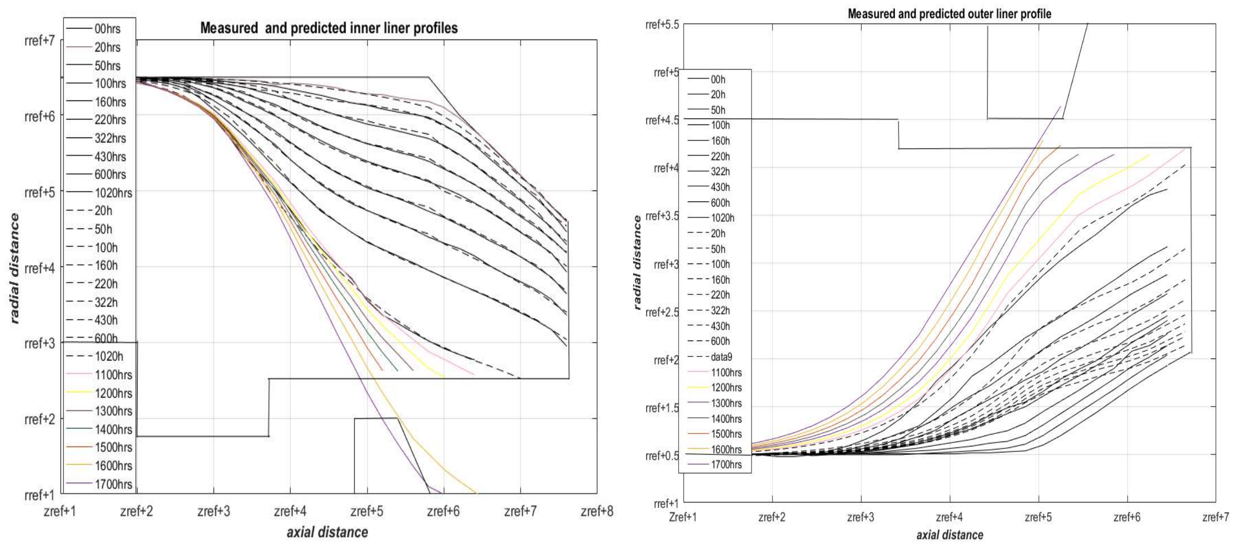

Figure 4. Predicted and measured profiles of inner and outer liner respectively using ANN.

the data fed into the network is in pointwise form rather than sets of profiles for a given time instant. Input data is four-field matrix covering the ranges of axial distance and the time instants of profile measurement. The radial position for the particular four-field input is the corresponding targeted output. The data is divided into training set, validation set and testing test in the ratio 0.7,0.15 and 0.15 respectively. This division is randomly selected and the selection changes for every epoch. The performance measure used is the mean square error between the actual outputs and the outputs.

By using two hidden layers, the network is suitably trained. The liner profiles for different time instants are plotted in Fig. 4. The life of the thruster is considered here as the time at which the profile grazes the magnetic pole piece. In the case of inner liner, the profile touches the magnetic pole piece at 1600 hours. And for outer liner it touches at 1700hours. Since the life of the thruster is decided by the minimum of these two, 1600hours is the estimated life.

B. Non-linear regression using curve-fit

In addition to using ANN, a second approach is employed using curve-fitting. Using the existing data, the curve fitting equations are obtained and from them, the values for radial positions for future time instants are calculated. The radial rate varied at different axial positions. Hence the radial positions were calculated individually for different axial positions. The liner profiles for time instants beyond 1020 hours were plotted. From Fig 5, it can be observed that the profile for 1600hours grazes the magnetic pole piece in case of inner liner and at 2000 hours for outer liner. The minimum of these two, i.e., 1600 hours can be considered as the life of the thruster.

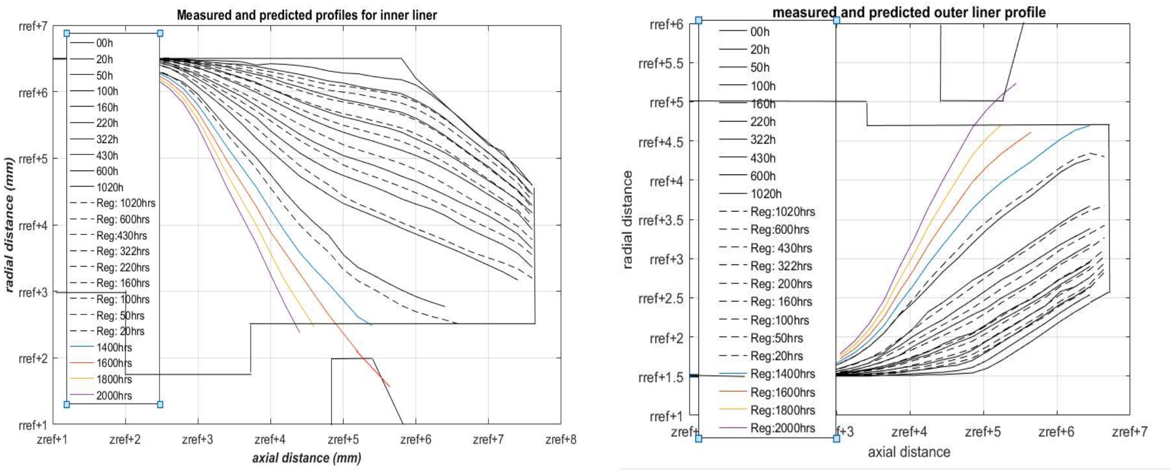

Figure 5. Predicted and measured profiles of inner and outer liner respectively by curve fitting.

Thus, the liner profiles for inner and outer liners are predicted using two data driven methods. The comparison between these two approaches in terms of performance is discussed in the section below.

V. Comparison between the two approaches

The performance for both the methods was measured using Mean squared error (MSE). However, for the approach using ANN, the performance was measured for the input points and not the total profile. Hence to compare both the approaches using a common parameter, MSE is measured for the profile at a particular time instant as shown in the table 1. The obtained output for a particular time instant was compared with the experimental profile measurements. The calculated performance measures for both the methods are showing very good performance for time instants for which measured profile is available. However, to verify the performance beyond 1020hrs, profiles for those time instants will have to be measured.

Time (hrs)	20	50	100	160	220	322	430	600	1020
Inner: ANN (mm)	0.0633	0.0551	0.0536	0.0528	0.0556	0.0587	0.0548	0.0591	0.0867
Inner: Curve-fit (mm)	0.8232	0.6052	0.0169	0.1305	0.2385	0.4642	0.3677	0.2856	0.4268
Outer: ANN (mm)	1.0356	1.0109	0.9232	0.9151	0.7135	0.7128	0.6165	0.8168	0.7202
Outer: Curve-fit(mm)	0.7124	0.7064	0.1025	0.0953	0.0025	0.1068	0.5113	0.4088	0.6114

Table 1: Comparison between the performance measures of Artificial Neural Network and Curve-fitting approach for both inner and outer liners.

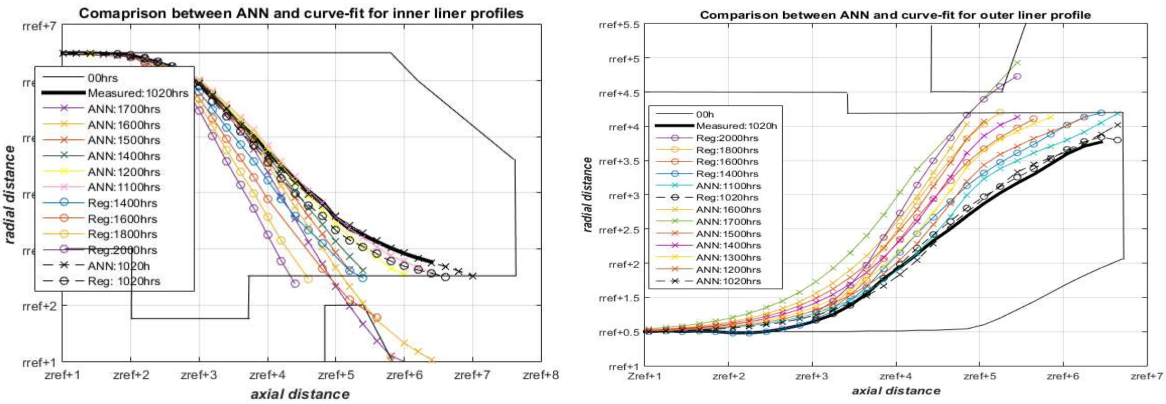

Figure 6: Comparison between the estimated liner profiles using ANN and curve-fit approaches for inner and outer liners.

As shown in fig 6, by ANN method, the inner liner erosion profile grazed the pole piece at 1600hrs whereas outer liner erosion grazed the magnetic pole piece at 1700hrs. Thus, the life-estimate is 1600hrs by ANN approach. By Non-linear regression method using curve-fitting, the inner liner profile grazes the pole piece at 1600hrs and the outer liner profile at 2000hrs. Therefore, the estimated life by this approach is 1600hrs. Since the full life-time qualification is not carried out for this thruster, the exact life of the thruster is unknown. From [2],[11] it is understood that the life of similar low power thrusters is in the range of 1000-2000 hours. However, hall thrusters have known to work beyond the point where the erosion grazes the pole piece and the life estimated in those cases, will be at a time instant which is beyond the time at which grazing occurs[13]. Hence the accurate picture of the effectiveness these methods will be known only after full-life qualification.

ANN type of approach is highly dependent on the input data fed to the network. Unlike analytical models, this method will need sufficient thruster firing data for large amount of time. The trained model for a thruster at certain operation conditions won't necessarily hold good for the same thruster at different operating conditions. This is because the profile for different operation conditions can be different and since the training depends on the liner profiles fed to the network, there will be a difference in the trained network. Thus, the trained model can be used to predict the liner profiles for future time instants, but only at the same operating conditions. In addition to this, the range of time for which the liner profile is fed to the network, plays a crucial role in predicting the profiles for future time instants. With wider time range for profiles, the learning of the network will be better, as it will be able to capture the trend from a wider range. And hence the prediction will be better. With lesser range of values, if prediction is attempted for very far time instants, the network becomes very unstable and gives unreliable outputs. Hence data for a wider range of time is necessary. This can be done either by firing the thruster for those many hours or by augmenting synthetic data.

In the second approach, equations are fit for each of the axial positions based on the radial wear of the liner over time in an exponential manner. However, all these equations have to be reduced to one, in order to find the actual relation between the radial positions, axial positions and time instant. This gap can be resolved by understanding the underlying physical process.

VI. Conclusion and Future Scope

The approaches used in this paper show very good accuracy when used to predict for time instants within the range of the experimental data (here time ≤ 1020 hours) which is used as the input. However, to verify the effectiveness for future time instants, full life qualification has to be carried out and liner profiles will have to be measured at those time instants. Only the life test will give the most accurate picture of the accuracy of these methods both in terms of profiles of the liner and the lifetime of the thruster thus assessed. Although, the life-time of the thruster is considered as the time at which the erosion grazes the magnetic pole piece, these hall thrusters have known to be operational much beyond the time after which it grazed the magnetic pole piece. Hence the definition of life-time considered here is very conservative.

The future scope of this work would be to assess the life-time of the thruster of AEPS, wherein hall thrusters will be operated at different operating points. Hence predicting the liner profiles will require additional inputs like operational voltage, flow rate etc. The further versions of this model will incorporate all the operating points.

References

[1]. Dan M. Goebel, Ira Katz- "Fundamentals of electric propulsion Ion and Hall thrusters"-Published by John Wiley & Sons, Inc., Hoboken, New Jersey

[2] Ryan W. Conversano, Dan M.Goebel, Richard R. Hofer, Taylor S. Matlock and Richar E. Wirz " Development and Initial testing of a magnetically shielded miniature hall thruster"-0093-3813,2014 IEEE transactions on plasma science

[3]Simon Haykin ," Neural Networks and Learning machines", Third edition, Adaptation from US edition , published by Pearson Education Inc.

[4]Hu Yanlin, Chen Jian, Mao Wei, Shen Yan, Chen Jun, "Lifetime assessment of Hall Thruster", IEPC-2013-172, 33rd International Electric Propulsion Conference, The George Washington University, Washington D.C, Oct 6-10, 2013.

[5]Hirotaka Fuchigami, Yusuke Egawa, Taichi Morita and Naoji Yamamoto" Prediction of the Thruster Performance in Hall Thrusters Using Neural Network", IEPC-2017-453, Presented at the 35th International Electric Propulsion Conference Georgia Institute of Technology Atlanta, Georgia, USA

[6] Peter Y. Peterson , David T. Jacobson, David H. Manzella, Jeremy W. John "The Performance and Wear Characterization of a High Power High-Isp NASA Hall Thruster", AIAA 2005-4243, 41st AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit 10 - 13 July 2005, Tucson, Arizona.

[7]George Cristian Potrivitu , Constantin Rotaru- "Hall Effect Thruster Erosion Mechanism and the Thruster Lifetime"- 12th International Conference on Applied and Theoretical Electricity.

[8]Shannon Yun,Ming Cheng- "Modeling of Hall thruster lifetime and erosion mechanisms", PhD Thesis in Space Propulsion, Massachusetts Institute of Technology June 2007.

[9]. Richard R. Hofer, Ioannis G. Mikellides, Ira Katz, and Dan M. Goebel -"BPT-4000 Hall Thruster Discharge Chamber Erosion Model Comparison with Qualification Life Test Data "IEPC-2007-267,Presented at the 30th International Electric Propulsion Conference, Florence, Italy September 17-20, 2007.

[10]. W. Ethan Eagle, Iain D. Boyd,Samuel G. Trepp and Raymond J. Sedwick "The Erosion Prediction Impact on Current Hall Thruster Model Development". 44th AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit 21 - 23 July 2008, Hartford, CT

[11]. David Manzella ,Steve Oleson NYMA, John Sankovic , Tom Haag , Alexander Semenkin , Vladimir Kim , 32nd Joint Propulsion Conference cosponsored by AIAA, ASME, SAE, and ASEE Lake Buena Vista, Florida, July 1-3, 1996.

[12]. O.A. Gorshkov, M.B. Belikov, V.A. Muravlev, A.A. Shagayda, K.M. Shanbhogue, S. Premkumar, V. Nandalan, M. Jayaraman "The GEOSAT electrical propulsion subsystem based on the KM-45 HET", Acta Astronautica 63 (2008) 367–378, doi:10.1016/j.actaastro.2007.12.051

[13]. B. Arkhipov, A. Bober, R. Gnizdor, K.Kozubsky, A. Koryakin, N.Maslennikov, S.Pridannikov"The results of 7000hour SPT100 Life testing", 24th IEPC,CP039, Moscow, 1995.