A Mathematical Model to Predict Operating States of Satellites

Primavera Botelho de Souza[1] *and Mauricio Gonçalves Vieira Ferreira*[2]

National Institute for Space Research, São José dos Campos, SP, 12227-010, Brazil.

The increased on demand from orbiting satellites in operation according to the National Institute for Space Research's satellite program has motivated continuous improvement safety in the planning of routine operations in order to ensure the integrity of satellites in orbit. Therefore, we propose a mathematical model based on artificial intelligence concepts, which uses algorithms developed for machine learning in the analysis of operational data to predict future states of satellites. The application developed from this data mining predictive model is also presented as an alternative to expensive simulators to perform prediction of satellites operating conditions, reducing costs of control activities of the satellites in orbit.

I. Introduction

There is general interest in automating satellite control operations related to the task of controlling multiple satellites in INPE ´s Space Program. However, depending on the demand for satellites in orbit, would become impossible a critical analysis of flight operation plans generated to control each satellite, before the actual execution. Thus, it becomes necessary to advance in safely on the planning of satellite operations to meet this growing demand, using simulators to perform predictions of operational satellite states and assist experts in the evaluation of each plan that controls the flight operations of satellites.

However, the high cost associated with the acquisition or development of satellite simulators at INPE, has motivated the search for a solution combining efficiency and low cost. In this sense, a software tool based on mathematical analysis to make predictions of operational satellite states is being proposed. Designed to emulate a simulator in the task of generating predictions of operational states, it can be used as a tool to support decision making, helping experts in evaluating the flight plans.

The mathematical modeling of tool, based on algorithms developed in area of artificial intelligence dedicated for machine learning. The predictive model of the satellite states generated, perform the classification according levels of security defined by experts, due to the behavior of the critical power supply subsystem, directly affected by commands contained in the control activities of the satellites in orbit.

Hence, contributing to the improvement in security in the planning of operations, the proposed software tool contributes to the assurance the integrity of satellites in orbit, presenting as an alternative to the costly simulators, in the predictions of satellite operational states.

This paper presents in the following section some concepts related to the planning of the control activities for satellite in orbit. Section 3 describes the tool proposed to advance in safety on operations planning. Section 4 shows an overview of the software architecture and discusses some data mining techniques of classification for data prediction to design the tool. Section 5 presents a discussion about of performance between classifiers algorithms to determine the classification model that provides greater accuracy to predict satellite future states. Conclusions are presented in Section 6.

II. Planning of Satellite Control Operations

The planning of control operations of space missions and ground segment activities for the planning, execution and control of the satellite in orbit are included in the flight operation plan. Each flight operation plan aims to maintain the satellite in orbit, working to achieve the goals of the mission, containing all the necessary information to control the satellite, such as: procedures for flight control, procedures for recovery of contingencies, rules, plans and schedules. All activities included in a flight operation plan have as their starting point the passage of the satellite

[1] Space Science and Atmosphere (CEA) - prima@laser.inpe.br.
[2] Satellite Control and Tracking Center (CRC) - mauricio@ccs.inpe.br

over the Earth station. The amount of time that a satellite is visible to a given Earth station determines the set of flight operations that should be performed during each pass. Among the activities to control for this period is the sending of commands from the ground (telecommand), and the reception of telemetry which indicates the general state of the satellite.

The set of actions contained in a plan to be sent acts directly on data critical to maintenance of the satellite integrity such as data related to power supply subsystem. In this way, depending on the demand for satellites in orbit, a careful validation of these plans can become unviable.

To improve safety in the planning of satellites control operations, the use of satellite simulators are indicated in the literature produced by the space community, because simulators are able to represent accurately the satellite behavior. However, the development of simulators involves high cost due to the modeling construction of the one or more subsystems, considering all the rules, restrictions and also the generation of the satellite knowledge base by experts[1].

III. Tool to Advance in Safety on Operations Planning

To advance in safety on operations planning, a software tool called Architecture of Generation Diagnostic was designed as an alternative to use of simulators for predicting satellites operational states[2]. Based on mathematical analysis, the tool has ability to analyze large amounts of satellite telemetry data in orbit. The Fig. 1 shows as the tool acts in operations planning.

Prognosis of states is provided by the tool, indicating the level of operational safety and also as the general state of the satellite must evolve, providing support to operations planners in the planning of routine operations (Fig. 1). It is designed on the basis of appropriate assurance techniques for space systems[3].

The mathematical model of prediction, classifies operational states, from the comparison between the telemetry values coming from satellite with telemetry values and respective operating states classified and stored in a database previously supervised by experts, according to the model that describes the power supply subsystem.

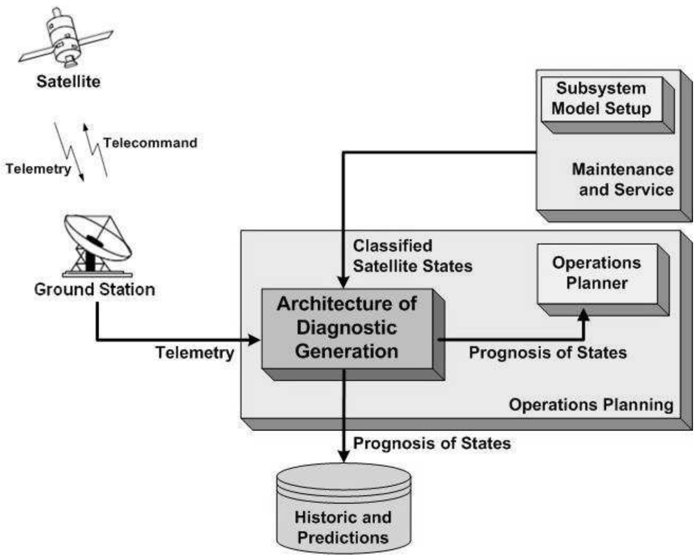

Figure 1. Diagnostic Generation tool: situation in the operations planning.

IV. Construction of Mathematical Model for Prediction

Prediction is one of the basic inference tasks in time models, in which the posterior distribution on the future state is calculated, given all the evidence to date. Predictive models have been widely used for building tools to support decision making.

Data mining is a method, in which the ultimate goal is prediction, and represents a process developed to examine routinely large amounts of data collected in search of consistent patterns and/or systematic relationships between variables. Techniques for finding and describing structural patterns in data have developed within a field known as machine learning, where different styles of learning appear, depending on the data mining application. Those applications where the predictive model requires a judgment needed to inform future decisions, a classification learning scheme takes a set of classified examples (training data) from which it is expected to learn a way of classifying unseen examples (test data)[4].

A classification technique (or classifier) is a systematic approach to building classification models from an input data set. Each technique employs a learning algorithm to identify a model that best fits the relationship between the attribute set (*input*) and class label (*output*) of the input data. The model generated by a learning algorithm should both fit the input data well and correctly predict the class labels of records it has never seen before. Therefore, a key objective of the learning algorithm is to build models with good generalization capability; i.e., models that accurately predict the class labels of previously unknown records[5].

To construct the prediction model most suitable for classification of the satellites operational states, it is necessary to perform a process of knowledge discovery in supervised databases of satellites. Thus, an architecture formed by software components and the sequence between them, which compose the process steps for the diagnostic generation was designed. The architecture of the tool is shown in Fig. 2 and the process steps are described in the following sections.

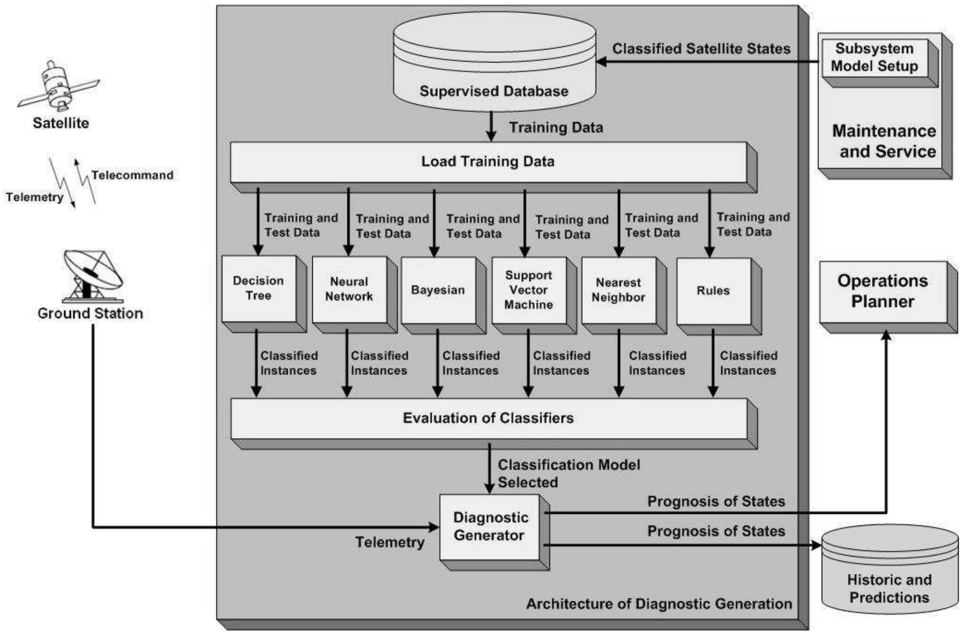

Figure 2. Architecture for diagnostic generating of the satellite states.

A. Construction of Supervised Database

A dataset with 214 records (instances) of classified examples is partially shown in Table 6. These input data used as study case, consists on attribute set of telemetries, parameters and operational limits of a simplified model of a Power Supply Subsystem (PSS) of a virtual satellite XSAT[6]. Each telemetry data record is associated with classification of satellite security levels SAFE2 and SAFE3 (STATE class label).

Table 1. Input data from the virtual satellite XSAT

DATE/TIME	SAG	PSAG	PPL1	PPL2	PAV	BAT	VBAT	QBAT	CBAT	IBAT	DOD	STATE
19/4/2010 12:30:10	SUN	1600	100	5	715	FULL	50	60	1,2	0	0	SAFE3
19/4/2010 12:30:40	SUN	1600	100	5	715	FULL	50	60	1,2	0	0	SAFE3
19/4/2010 12:31:10	SUN	1600	100	5	715	FULL	50	60	1,2	0	0	SAFE3
19/4/2010 12:31:40	SUN	1600	100	5	715	FULL	50	60	1,2	0	0	SAFE3
19/4/2010 12:32:10	SUN	1600	100	5	715	FULL	50	60	1,2	0	0	SAFE3
19/4/2010 12:32:40	ECL	0	100	5	-885	DIS	50	59,84	1,2	-19,47	0	SAFE3
19/4/2010 12:33:10	ECL	0	100	5	-885	DIS	49,86	59,68	1,2	-19,52	0,01	SAFE3
19/4/2010 12:33:40	ECL	0	100	5	-885	DIS	49,73	59,51	1,2	-19,58	0,01	SAFE3
19/4/2010 12:34:10	ECL	0	100	5	-885	DIS	49,59	59,35	1,2	-19,63	0,01	SAFE3
19/4/2010 12:34:40	ECL	0	100	5	-885	DIS	49,46	59,18	1,2	-19,68	0,01	SAFE3
19/4/2010 12:35:10	ECL	0	100	5	-885	DIS	49,32	59,02	1,2	-19,74	0,02	SAFE3
19/4/2010 12:35:40	SUN	1600	100	5	715	CHG	49,18	59,14	1,2	14,54	0,01	SAFE3
19/4/2010 12:36:10	SUN	1600	100	5	715	CHG	49,28	59,26	1,2	14,51	0,01	SAFE3
19/4/2010 12:36:40	SUN	1600	100	5	715	CHG	49,38	59,38	1,2	14,48	0,01	SAFE3
19/4/2010 12:37:10	SUN	1600	100	5	715	CHG	49,49	59,5	1,2	14,45	0,01	SAFE3
19/4/2010 12:37:40	SUN	1600	100	5	715	CHG	49,59	59,62	1,2	14,42	0,01	SAFE3
19/4/2010 12:38:10	SUN	1600	100	5	715	CHG	49,69	59,74	1,2	14,39	0	SAFE3
19/4/2010 12:50:10	SUN	1600	100	5	715	CHG	49,25	59,23	1,2	14,52	0,01	SAFE3
19/4/2010 12:50:40	ECL	0	800	5	-1585	DIS	49,35	58,93	1,2	-35,33	0,02	SAFE3
19/4/2010 12:51:10	ECL	0	100	5	-885	DIS	49,11	58,77	1,2	-19,82	0,02	SAFE3
19/4/2010 12:51:40	ECL	0	100	5	-885	DIS	48,97	58,6	1,2	-19,88	0,02	SAFE3
19/4/2010 12:52:10	ECL	0	100	5	-885	DIS	48,83	58,43	1,2	-19,93	0,03	SAFE3
19/4/2010 12:52:40	ECL	0	100	5	-885	DIS	48,7	58,27	1,2	-19,99	0,03	SAFE3
19/4/2010 12:53:10	ECL	0	100	5	-885	DIS	48,56	58,1	1,2	-20,05	0,03	SAFE3
19/4/2010 12:53:40	SUN	1600	100	5	715	CHG	48,42	58,22	1,2	14,77	0,03	SAFE3
19/4/2010 12:54:10	SUN	1600	100	5	715	CHG	48,52	58,35	1,2	14,74	0,03	SAFE3
19/4/2010 12:54:40	SUN	1600	100	5	715	CHG	48,62	58,47	1,2	14,71	0,03	SAFE3
19/4/2010 12:55:10	SUN	1600	100	5	715	CHG	48,72	58,59	1,2	14,67	0,02	SAFE3
19/4/2010 12:55:40	SUN	1600	100	5	715	CHG	48,83	58,71	1,2	14,64	0,02	SAFE3
19/4/2010 12:56:10	SUN	1600	100	5	715	CHG	48,93	58,84	1,2	14,61	0,02	SAFE3
19/4/2010 13:44:40	ECL	0	800	15	-1595	DIS	47,25	56,39	1,2	-37,13	0,06	SAFE2
19/4/2010 13:45:10	ECL	0	100	5	-885	DIS	47	56,22	1,2	-20,71	0,06	SAFE2
...	...	...	...	...	...	...	...	...	...	...	...	...

B. Processing datasets using the machine learning algorithms

The supervised dataset shown on the Table 1 was used as set of input data for learning algorithms. A method to random subsampling called cross-validation.was used to handle the input set for all classifiers algorithm[7]. Due to the proven effectiveness was selected the 10-fold cross-validation method, which the data was segmented into 10 equal-sized partitions. During each run, one of the partitions is chosen for testing, while the rest of them are used for training. This procedure is repeated 10 times so that each partition is used for test exactly once.

Each one of the six classifiers algorithms (Fig. 2), suitable for binary classification, represents a different classification learning scheme (Table 2), generating its own classification model. The classifiers algorithms used are an integral part of the Waikato Environment for Knowledge Analysis (WEKA), a suite of machine learning software written in Java, containing the same evaluation module used to evaluate the performance of the classifier[4].

Table 2. Classification model and classifier corresponding

Classification Model	Classifier Algorithm
Decision Tree	J48
Neural Network	LVQ2_1
Bayesian	NaiveBayes
Support Vector Machine	SMO
Nearest Neighbor	KStar
Rules	JRip

The Figure 3 below shows the output of J48 one of the classifier used to prognosis of the satellite state, which to begin with the decision tree model, number of rules founded and size of the tree. Also, performance statistics measures are included as correctly and incorrectly classified instances, error functions.

C. Evaluation of classifiers

As algorithms classifiers used are based on different methods of predictive classification (Table 2), the classification of the satellite states for the same set of training data and test (Table 1) presented differences in performance between the six classifiers. The performance measurements are obtained from a defined set of statistical functions to evaluate a classifier[8]. Therefore, the inductors used include the same routine containing these functions, as shown in Fig. 3 to the classifier J48. The statistical functions defined to evaluate classifiers are:

- Confusion matrix;
- Accuracy and Error rate;
- Kappa statistic;
- Other functions error statistics for evaluation of classifiers.

```
=== Run information ===
Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     PSS
Instances:    214
Attributes:   12
SAG    PSAG   PPL1   PPL2   PAV    BAT    VBAT   QBAT   CBAT   IBAT   DOD    STATE
Test mode:    10-fold cross-validation

=== Classifier model (full training set) === J48 pruned tree

VBAT <= 47.72: SAFE2 (109.0/3.0)
VBAT > 47.72: SAFE3 (105.0/3.0)

Number of Leaves  :   2

Size of the tree :    3

Time taken to build model: 0.05 seconds

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances         202   94.3925 %
Incorrectly Classified Instances        12    5.6075 %
Kappa statistic                          0.8879
Mean absolute error                      0.0792
Root mean squared error                  0.2317
Relative absolute error                 15.8356 %
Root relative squared error             46.3509 %
Total Number of Instances              214

=== Confusion Matrix ===
   a   b   <-- classified as
 101   4 |   a = SAFE3
   8 101 |   b = SAFE2
```

Figure 3. Output from J48 classifier algorithm.

Hence, it became necessary to include in the tool architecture (Fig. 2) a procedure for comparing the classifiers performance, in order to select the predictive model with better perform in the classification of the satellite states to unknown instances (data test).

Performance evaluation of a classifier is based on the counts of test records correctly and incorrectly predicted by the model. These counts are tabulated in a table know as confusion matrix. The Table 3 shows the confusion matrix of the six classifiers (Table 2), used to classify XSAT satellite states.

Each entry e_{ij} in the Table 3 denotes the number of records from class SAFE3 predicted to be class SAFE2. For instance, e_{ji} is the number of records from class SAFE2 predicted incorrectly predicted as SAFE3. Thus, based on the entries in the confusion matrix, the total number of correct predictions and total number of incorrect predictions of each model was calculated[4]. From these matrix elements is possible also get the performance metrics such as accuracy for each model and the error rate values, shown in Table 4.

Most classification algorithms seek models that attain the highest accuracy, or equivalently, the lowest error rate. Then, evaluating in terms of percentages, the accuracy and error rate values for each classifier, we can say that the classifier NaiveBayes shows the better accuracy value (96,2%) and minor error rate (3,7%) followed of the SMO classifier (95,7%) and (4,2%). The worse accuracy and error rate associated was the J48 classifier (94,4%) and (5,6%).

Table 3. Confusion matrix for all classifiers

J48	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 101	e_{ij} = 4	105
Class = SAFE2	e_{ji} = 8	e_{jj} = 101	109
Total	109	105	214
LVQ2_1	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 99	e_{ij} = 6	105
Class = SAFE2	e_{ji} = 5	e_{jj} = 104	109
Total	104	110	214
NaiveBayes	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 99	e_{ij} = 6	105
Class = SAFE2	e_{ji} = 2	e_{jj} = 107	109
Total	101	113	214
SMO	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 100	e_{ij} = 5	105
Class = SAFE2	e_{ji} = 4	e_{jj} = 105	109
Total	104	110	214
KStar	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 100	e_{ij} = 5	105
Class = SAFE2	e_{ji} = 5	e_{jj} = 104	109
Total	105	109	214
JRip	**Class = SAFE3**	**Class = SAFE2**	**Total**
Class = SAFE3	e_{ii} = 100	e_{ij} = 5	105
Class = SAFE2	e_{ji} = 5	e_{jj} = 104	109
Total	105	109	214

Table 4. Accuracy and Error rate performance metrics

Classifiers	**Accuracy (%)**	**Error rate (%)**
J48	94.3925 %	5.6075 %
LVQ2_1	94.8598 %	5.1402 %
NaiveBayes	96.2617 %	3.7383 %
SMO	95.7944 %	4.2056 %
KStar	95.3271 %	4.6729 %
JRip	95.3271 %	4.6729 %

Other key measure for evaluating classifiers is Kappa statistics or Kappa coefficient. A measure of agreement used in nominal scale, that gives us an idea of how much the observations deviate from those expected due to chance, giving us so how legitimate interpretations are**.** This observer disagreement is indicated by how observers classify individual subjects into the same category on the measurement scale. During in run, each classifier assigned items to one of two classes SAFE3 and SAFE2, but the number of individuals assigned to each class by classifier are disagree (see Table 3).

The values of Kappa are interpreted as the maximum of 1 when agreement is perfect, 0 when agreement is no better than chance and negative values when agreement is worse than chance. Other values can be roughly interpreted as[9]:

- Poor agreement = Less than 0.20
- Fair agreement = 0.21 to 0.40
- Moderate agreement = 0.41 to 0.60
- Good agreement = 0.61 to 0.80
- Very good agreement = 0.81 to 1.00

Kappa measures the percentage of data values in the main diagonal of the confusion matrix (Table 3) and then adjusts these values for the amount of agreement that could be expected due to chance alone. In Table 5, the kappa coefficient values of each classifier are reported and interpreted.

Table 5. Kappa coefficient values provided by the classifiers

Classifiers	**Kappa**	**Agreement**
J48	0.8879	Very good
LVQ2_1	0.8971	Very good
NaiveBayes	0.9252	Very good
SMO	0.9158	Very good
KStar	0.9065	Very good
JRip	0.9065	Very good

When the results of accuracy, error rate or kappa among classifiers show very similar or even identical, as observed in KStar and JRip, becomes necessary to use other statistics functions for additional measures to evaluate classifiers[8]. They are: Mean Absolute Error, Root Mean Squared Error, Relative Absolute Error and Root Relative Squared Error. The values obtained for each measurement are presented in Table 6 below:

V. Discussion

The results of the performance metrics presented in Table 4 show that all classifiers had accuracy in the classification of states around 95% and an error rate around 5%.

The kappa values were within the range (0.81 to 1), whose interpretation of the agreement defines the number of correct answers very close to the maximum value of 1 (Table 5), i.e. an excellent concordance in comparison to the existing classification in the training set. All metrics used to compare the classifiers performance are presented in Figure 4 below:

The results indicate that all the classification models used showed reliability around 95% in the prediction. However, for this case study, the stochastic classifier algorithm NaiveBayes presented better results, indicating the Bayesian method as the best classification model generated to predict future satellite states with a confidence degree higher than 96%.

However, the modifications in telemetry and parameters describing the power supply for each satellite, become necessary to perform again the processing machine learning data sets using the algorithms and evaluate of classifiers for determining the classification model with the highest accuracy, explaining the sequence of components in Figure 2.

Table 6. Other statistical functions to evaluate each classifier quality

Classifier	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error
J48	0.0792	0.2317	15.8356 %	46.3509 %
LVQ2_1	0.0514	0.2267	10.2828 %	45.3468 %
Naive Bayes	0.0427	0.1662	8.5375 %	33.249 %
SMO	0.0421	0.2051	8.4132 %	41.0177 %
KStar	0.0601	0.1948	12.0209 %	38.9689 %
JRip	0.0732	0.2132	14.634 %	42.643 %

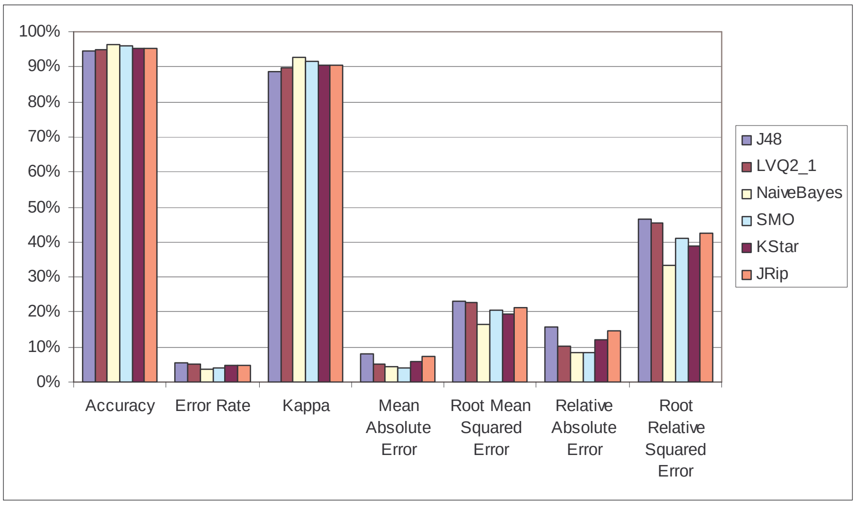

Figure 4. Graph comparing the statistics of the classifiers.

VI. Conclusion

Designed as an alternative to use of expensive simulators to predict operational states of satellites in orbit, this paper presented to build the mathematical model of a prediction tool, based on machine learning algorithms and data mining techniques in artificial intelligence, to obtain a model able to provide greater accuracy in the diagnosis of these states, to increase security in maintaining the integrity of the satellite.

Thus, it was realized a comparative study of performance between classifiers algorithms used in data prediction to determine the classification model that provides greater accuracy to predict satellite future states. The classification model consist on the design of a prediction tool, developed to performs data prediction of a critical platform subsystem, directly affected by the actions contained in each flight operation plan generated to control and track satellites. In addition, the tool assists experts in impact analysis of each plan’s action on the satellite behavior.

Other significant contribution of the Diagnosis Generator tool is related to decision support making, providing effective support to experts, and representing an advance in safety of the satellite control activities, especially considering multiple launchings planned for the near future, when a careful evaluation of these plans, before real execution would be impossible.

Acknowledgments

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References

[1]Wertz, J.and Larson, W. Space mission analysis and design. 3. ed. [S.l.]: Microcosm, Inc. and Kluwer Academic Publishers, 1999.

[2]Souza, P. B.; Ferreira, M. G. V.; Silva, J. D. S. A tool for prediction of satellite future states. Journal of Aerospace Computing, Information, and Communication**,** v.7, n. 12, p. 406-414, 2010.

[3]Blanquart, P., Fleury, S., Hernek, M., Honvault, C., Ingrand, F., Poncet, J. C., Powell, D., Strady-L_ecubin, N., and Thevenod-Fosse, P. "Software Safety Supervision On-board Autonomous Spacecraft.", *In 2nd European Congress on Embedded Real Time Software (ERTS-2)*, Toulouse, France, 11p, 2004.

[4]Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I. H. The WEKA Data Mining Software: An Update. *SIGKDD Explorations*, Volume 11, Issue 1, University Mark Hall, 1999.

[5]Tan, P-N, Steinbach, M. and Kumar, V.. Introduction to Data Mining. Addison-Wesley, 2005.

[6]Tominaga, J., Ferreira, M. G. V., Silva, J. D. S."An Implementation of a Satellite Simulator as a Fuzzy Rule-Based Inference Machine", *WORCAP 2009*, INPE, São José dos Campos, Brazil, 2009.

[7]Witten, I.H. and Frank E. Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations (The Morgan Kaufmann Series in Data Management Systems), 1st ed. Morgan Kaufmann, October, 1999.

[8]Ferreira, C.. Gene expression programming: mathematical modeling by an artificial intelligence. 2. ed. Berlin: Springer-Verlag, 2006.

[9]Sheskin, D. J. Handbook of Parametric and Nonparametric Statistical Procedures, Third Edition**,** Chapman & Hall/CRC, 2003, ISBN 1584884401.