A Framework to Predict Failures for Ground Tests on Aircrafts

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INTRODUCTION

Ground testing is an essential and expensive process for airbus defense and space (airbus ds) [1] in the manufacturing cycle of an aircraft. all parts of the aircraft, as well as the systems, must be meticulously checked in this type of test, and the testing involves a large number of company staff and resources.

To carry out the test, Airbus DS uses a test system consisting of a software application linked to a hardware system for interconnection and communication with the aircraft. It is not possible to give many details of this test system due to the confidentiality required by the Airbus DS Company. However, this is not necessary for the description of the developed framework.

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When the testing phase is carried out for an aircraft, it is common for failures to occur throughout the different tests. These failures are known in the terminology of the Airbus DS Company as "incidences." Thus, these incidences in the test process necessitate delays in the deliveries of the aircraft, as well as additional costs for the company. The delays and added costs arise because those tests that generate incidences must be repeated (totally or partially), which generates an increase in the number of hours for the workers and in the time for carrying out the test.

This work addresses the incidences that have arisen in the testing process on the A400M aircraft of the Airbus DS Company. The A400M aircraft is currently the most important and largest military aircraft as well as a flagship European collaborative procurement project. Thus, we have found recent works about this aircraft in the research literature [2]–[6], but none focused on the topic of our work. Specifically, this paper describes a framework consisting of a software application based on artificial intelligence for the prediction of incidences for ground tests on the A400M aircraft.

The framework is capable of predicting the probability that a certain test that is going to be performed on the aircraft will generate an incidence. This prediction allows the Airbus DS workers to focus on that prediction at the time of carrying out the test. In addition, and this is even more interesting for the company, the framework suggests actions to be carried out so that the incidence does not occur either in the current aircraft or in successive versions.

The framework described in this paper is framed within the project: "FSP20: Futuro Sistema de Pruebas, Visión 2020" in which our working group from the Electronic Technology Department at the University of Seville (Spain) worked for the Airbus DS Company. The FSP20 project was a collaboration project among Airbus DS and various companies and research organizations. The project was developed in Seville, since it is the city where the process of assembly and testing of the A400M is carried out.

For the development of the kernel of the framework, a data mining process was carried out from the database and the data registered for the test system that the Airbus DS Company uses in the ground tests of the A400M. If we review the research literature, we can see that although there are some research papers in incidence prediction in the context of aeronautics using data mining techniques [7]–[11], it is not possible to find published research specifically applied to ground testing on aircraft.

The developed kernel is composed of a set of models generated from this data mining process. Additionally, an application for Windows that integrates the kernel and

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provides the user with a friendly environment to show the prediction results has been developed.

In addition, the framework was applied in real cases of tests about to be carried out by the Airbus DS Company, obtaining good prediction results.

In this paper, the proposed framework is described in the following sections:

- Data mining process
- Framework environment
- Results and conclusions.

Throughout the paper, there are some figures in which certain data (such as the code for the users or the code for the tests) have been hidden due to a confidentiality agreement between Airbus DS and the University of Seville.

DATA MINING PROCESS

For the data mining process, a dump of the aircraft simulation database and extraction of the files of the folder tree of this simulation environment were used as data sources. The data relating to simulations condense all the information registered prior to the real test of the airplane. Specifically, the data used for the folder tree included both the register files of the results of the different simulated tests in the past and the source codes of the tests executed on those aircraft. The extraction of the sample was dated May 2016.

The data mining process, as well as the models generated with it, was programmed with the IBM Modeler 17 tool, which is one of the most used and powerful tools for performing a data mining process. The tool allows data miners and business analysts to perform the entire process of data mining without excessive programming task requirements.

The aim of the data mining process was to analyze the data source to generate models to predict the occurrence of the different types of incidence during the execution of the test. Specifically, Airbus DS takes into account two types of incidences:

- Abortive incidences: This type of incidence indicates the abortion of the test. They are due to serious failures during the course of the testing process. Therefore, the prediction of this type of incidence was the highest priority because it causes higher costs to the company.
- Nonabortive Incidences: This type of incidence does not imply the mandatory conclusion of the test; therefore, the operator can continue executing the test if an incidence of this type occurs. Subsequently, the operator must correct the failure that generates the incidence and executes only the section of the test that produced the failure.

The different steps carried out for the data mining process are as follows: Data preparation, data analysis and generation of prediction models.

DATA PREPARATION

In this first phase, the processing of all available information for each test execution and the preparation of the data was carried out. Thus, a set of tables from the database of Airbus DS was used, as well as information regarding the historical files of the tests. The historical files are a set of text files generated in the course of the execution of a test that registers information relative to variable values, relevant events, and the information of the registered incidence (in the cases in which an incident occurred during that execution).

For the data mining process, we use the information relative to 6 aircraft in which all of the tests had been completed. We use the results of these aircraft tests to be considered by the Airbus DS Company as the most representative to date.

From the collected data, a stream to generate a table that condensed and registered all the useful parameters necessary for the prediction of incidences was programmed in IBM Modeler. These parameters included both input (information used to predict the incidence) and output (information about the incidence or incidences to be predicted). Thus, the set of parameters recorded in the table that would be used to generate (through training) the prediction models are shown in Table 1. Each row of the table registered the information relative to a test execution carried out in the past.

DATA ANALYSIS

In this second phase, an analysis of the data was carried out, analyzing the initial distribution of the total sample with regard to the total number of test executions carried out to date in the 6 aircraft used as well as the number of executions with an incidence of each type.

Thus, the sample set had a total of 16095 test executions. Of these executions, the sample set registered the distribution shown in Figure 1 with respect to executions with abortive incidences (or what is the same, number of records with the parameter INC_A with value 1).

The previous graph shows that 42.21% of executions had a final result of an abortive incidence. As it is possible to observe, this supposes a high percentage of executions of tests with some type of incidence.

However, if we observed the distribution in the tests with some type of nonabortion incidence or warning, or analyzed the distribution of the INC_W parameter of the generated table, we have a distribution (see Figure 2) very similar to the previous one.

Observing the distribution of tests with some type of incidence (either abortive or nonabortive), that is, seeing the distribution of the parameter INC, we observe Figure 3.

Thus, a total of 69.94% of the tests presented some type of incidence during its execution, which indicates that 7 out of 10 tests generated some type of incidence in its realization.

At this point, the importance of the different parameters on the occurrence or absence of incidences was analyzed. Thus, this process had the objective of selecting a subset of relevant features (variables as predictors) for use in model construction. Within the whole analysis that was carried out, an extract of the most relevant results is shown below.

Significant parameters in all abortive incidences

A first parameter that was important in the distribution of the incidences was the STATION where the test was executed. This can be seen in Figure 4.

Thus, we can observe in the column Proportion, which shows the executions with abortive incidences in red color and the executions without incidence in blue color, how stations SC2, SC1, and SG1 are the ones with the highest proportion of abortive incidence.

On the other hand, the parameter THEORETICALTIME was significant in the prediction of the occurrence of incidences. This importance was because the duration of a test logically affects the probability of the occurrence of an incidence throughout the test. It can be observed in Figure 5 (the parameter Percent shows the percentage of the number of tests with each THEORETICALTIME).

As it is possible to observe in the smallest values (from 0 to 5 hours of THEORETICALTIME), which is where the greatest percentage of the number of tests is centered (approximately 90% of the test executions), there is an increase in incidences with the increase of this parameter.

With regard to the number of signals for the communication necessary (VAR_AIM), it is observed (see Figure 6) as its importance was significant.

Thus, it is possible to observe how the distribution of executions with incidences (in red color) increases as the number of signals necessary increases.

Another significant parameter was the number of days elapsed since the first test of the corresponding aircraft was executed at that station (DAYS_STATION).

It is possible to observe (see Figure 7) that there is a negative correlation between the number of days elapsed and the percentage of executions with incidences. Thus, this means that the parameter provides information of relevance in the prediction model.

The parameter of the number of executions with abortive incidences of the 10 executions prior to the test to be executed (ABORT_10_PREV) can be observed in Figure 8.

As seen, there is a very clear positive correlation between increasing the probability of an abortive incidence in the execution and the increase in the number of previous executions with an abortive incidence.

GENERATION OF PREDICTION MODELS

At this point, and using the table described in "Data Preparation" section as well as the results of the study of the significant parameters, two models were generated:

- Model to predict the abortive incidences
- Model to predict nonabortive incidences

For the generation of both models, decision trees [12] were used as prediction algorithms. This type of algorithm generates diagrams of logical constructions that are translated into prediction systems based on rules. These diagrams represent and categorize a series of conditions that occur successively and that finally serve to assign a probability that something will happen. Thus, the objective of this algorithm in our case was to find a set of decision rules that explains the patterns of the different types of incidences. There were also two clear advantages in the use of these

Table 1.

Parameters Used for the Incidence Prediction	
Parameter	**Meaning**
TI	Code that unequivocally identifies each test
MSN	Code of the A400M aircraft on which the test was executed
ATA	Standard code of the type of test for the corresponding TI
AREA	Code of the technological area (MTISA, MTISC, MTISN, MTISY) of the test
THEORETICAL_TIME	Parameter estimated by the designer of the test that registers an estimated time in hours for the test execution
VAR_AIM	Number of signals (input and output) for the communication with the aircraft defined for the test
VAR_AIMW	Number of output signals for the communication with the aircraft
TOOLS	Number of instrumentation tools necessary for the operator in the test execution
SECTIONS	Number of sections or fragments which are possible for dividing the test
TESTCODE	Code that identifies the execution of a test on a certain plane
STARTP	Date and time of the start of the test execution
FINISHP	Date and time of the completion of the test execution
DURATION	Duration time in hours of the execution of the test
STATION	Station of the Airbus DS factory in which the test was carried out
WORKSTATION	Computer of the Airbus DS on which the test system was executed
SHIFT	Parameter that identifies whether the execution was carried out in the morning (from 7:00 a.m. to 3:00 p.m., value ‘M’), afternoon (3:00 p.m. to 11:00 p.m., value ‘T’) or night shift (23:00 to 7:00, value ‘N’)
DAYS_STATION	Days that have elapsed since the first test for that aircraft was executed on the station
DAY_SAT	Flag that identifies whether the execution of the test has taken place on Saturday (1) or not (0)
TIME_SHIFT	Number of hours remaining until the end of the shift at the moment when the execution of the test began
CONCURRENCE	Number of executions of other tests that were executed in parallel with the test
ABORT_10_ PREV	Number of executions with abortive incidence of the 10 executions previous to the test in the corresponding station
ABORT_PREV	Number of previous executions with abortive incidence for that same aircraft and same test
MSNS_ABORT	Number of aircrafts in which the test generated abortive incidences in the past
OPERATORS	Number of operators necessary for the execution of the test
USER	Code of the main user that carried out the execution of the test
INC_A	Flag that registers if in the test had an abortive incidence (1) or not (0)
INC_W	Flag that registers if the test had some non-abortive incidence
INC	Flag that registers if the test had an incidence of any type (1) or not (0). Thus, this flag identifies if the test had an abortive incidence or a non-abortive incidence

Table 1.	
(Continued)	
Parameter	**Meaning**
INCIDENCE_TYPE	The type of abortive incidence (if there is one registered in the corresponding test).
DESCRIPTION	The description of the abortive incidence (if there is one registered in the corresponding test)

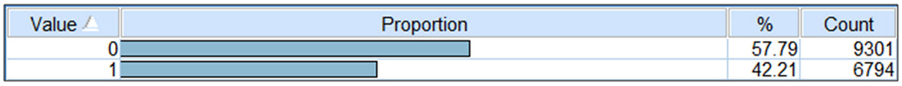


Figure 1.
Distribution of test executions with respect to abortive incidence (simulated data).

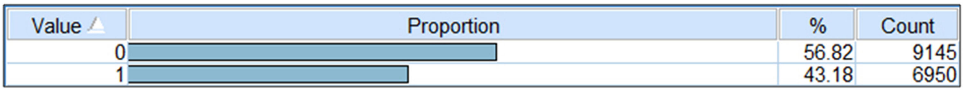


Figure 2.
Distribution of test executions with respect to the nonabortive incidence (simulated data).

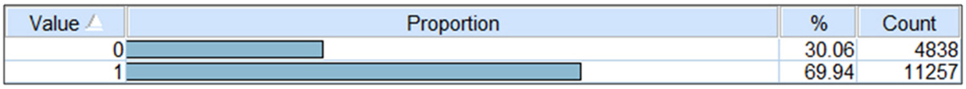


Figure 3.
Distribution of test executions with respect to any type of incidence (simulated data).

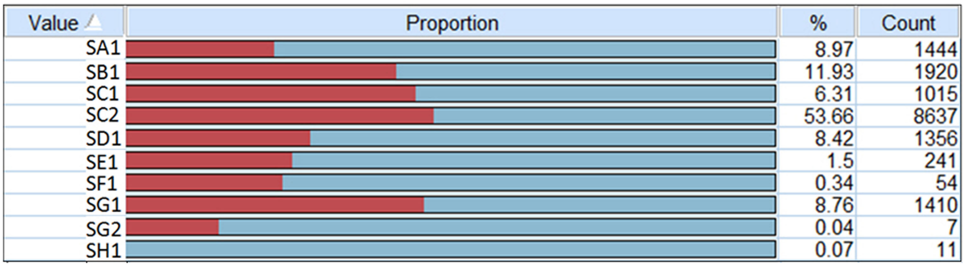


Figure 4.
Importance of the STATION parameter on the incidences (simulated data).

types of algorithms (as opposed to, for example, artificial neural networks) for our objective:

- An explanatory component was added to the data of the probability. Since the model is translated into a set of rules, and these rules carry implicit an additional explanation.
- Allocated a probability to each of the records in the database. The set of rules allowed us to have a probability value for each pattern of the test execution found in the database. This probability is obtained from the proportion of target occurrences in each leaf of the tree.

In addition, the use of these types of algorithms as predictors is well extended and validated in the research literature [13]–[16].

Specifically, among the different decision tree algorithms, such as C4.5, CHAID, and C&RT, we decided to use C&RT (classification and regression trees) which obtained the best results in the tests carried out. Some advantages of the C&RT algorithm are as follows:

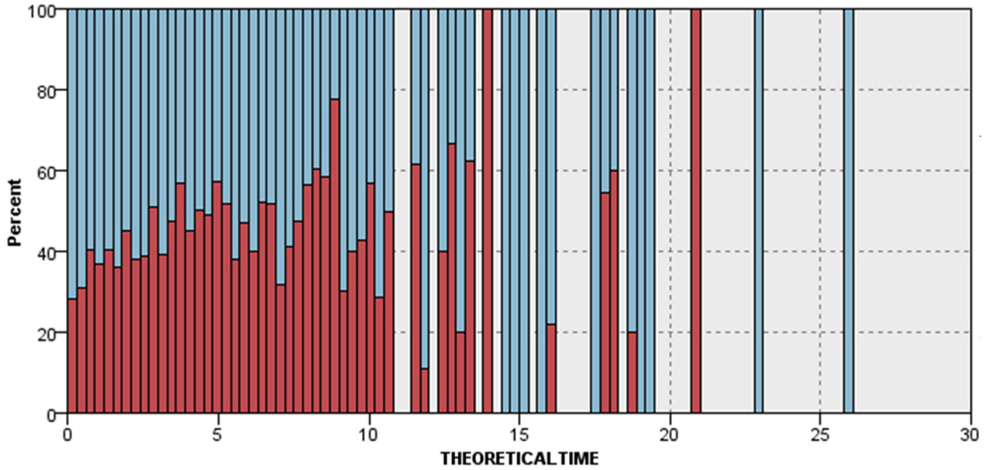


Figure 5.
Importance of the THEORETICAL_TIME parameter on the incidences (simulated data).

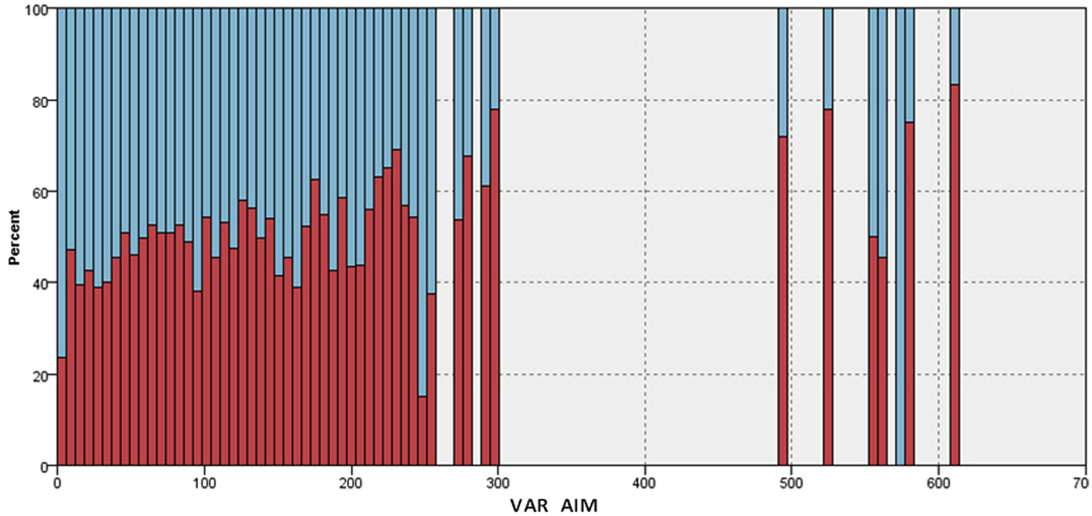


Figure 6.
Importance of the VAR_AIM parameter on the incidences (simulated data).

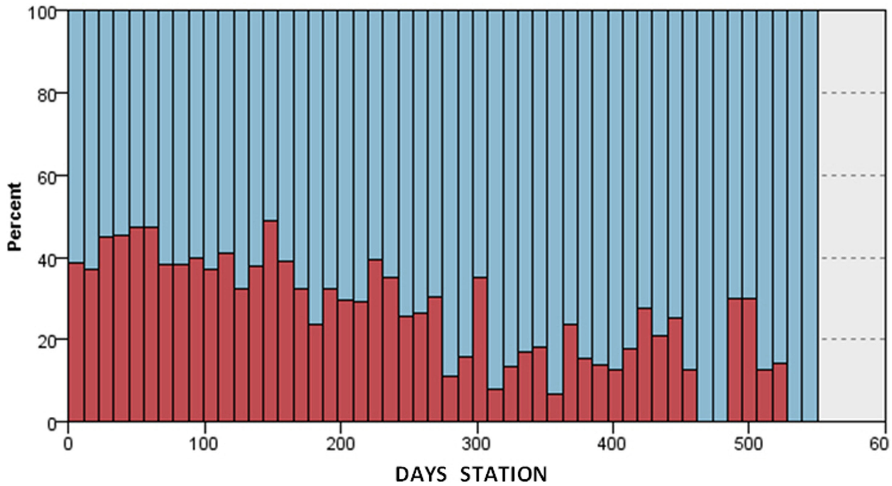


Figure 7.
Importance of the DAYS_STATION parameter on the incidences (simulated data).

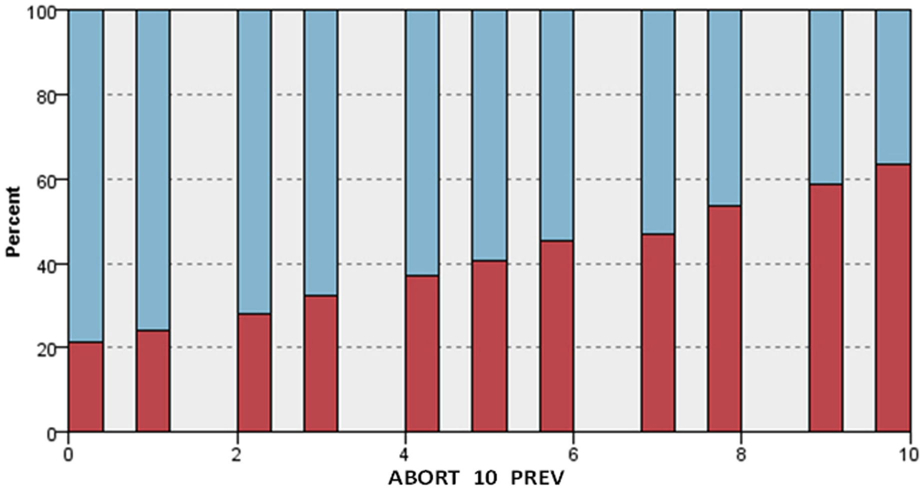


Figure 8.
Importance of the ABORT_10_PREV parameter on the incidences (simulated data).

- This algorithm does not make assumptions about the distribution of any type (either of the variables for prediction or of the criterion variable).
- The input and output variables can be of different types either continuous or discrete.
- The algorithm is not affected by extreme values. Thus, outliers can be isolated in a node and have no effect on division.

Model to predict abortive incidences

The first model developed was the one to predict abortive incidences. The objective of this model was to obtain an output with a probability that a pattern test generates an incidence.

The C&RT algorithm allows carrying out a first split based on a selected parameter. This initial split is verified in the related literature [12] that it can improve the results. This first partition generates a different tree for each of the values of the selected parameter. The partition must be carried out with a parameter that makes it possible to differentiate the sample into several homogeneous subsets.

Specifically, after carrying out various tests with various parameters, the partition was made based on the technological area parameter (AREA). This parameter allowed a first partition among tests of different natures (for being of different technological areas). Airbus has four technological areas that perform different types of ground tests on the airplanes:

- MTISY: Ground Systems Tests (Flight Controls, Hydraulics, and Doors).
- MTISC: Electrical, Data Communication & Cargo GST Engineering.
- MTISA: Avionics, Communications & Mission Systems.
- MTISN: Fuel, PwP, and Pneumatic GST Engineering.

Thus, the number of trees generated was a total of four.

After analyzing the importance of the parameters in an abortive execution, the following 14 parameters from Table 1 were used as input in the model:

ATA, THEORETICAL_TIME, VAR_AIM, TOOLS, SECTIONS, STATION, WORKSTATION, DAYS_STATION, TIME_SHIFT, CONCURRENCE, ABORT_10_PREV, ABORT_PREV, OPERATORS, USER.

The parameter to be predicted was INC_A.

Once the various tests for the training and generation of the model were carried out, a definitive model was obtained with a 91.93% success in the predictions (in 91.93% of the patterns, the algorithm was able to correctly predict the occurrence or not of an abortive incidence).

Figure 9 shows a distribution of the errors (8.07%) in the prediction, represented in red in the cases of the value 0 (prediction of no incidence) and in blue in the cases of the value 1 (prediction of an incidence).

The decision tree model generated a total set of 739 rules, distributed by technological area in the following way: 94 for the tree related to MTISC, 231 for MTISY, 188 for MTISA and, finally, 226 in MTISN.

An example of a rule generated (specifically for MTISY) is the following:

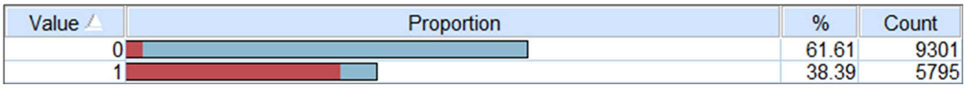
Rule 201 for 1 (Instances 46; Confidence 0.957)

if VAR_AIM $>=60$

and ABORT_10_PREV $>=6$

and ABORT_PREV $>=2$

and SECTIONS $<=15$



Value	Proportion	%	Count
0		61.61	9301
1		38.39	5795

Figure 9.
Prediction results for the model of abortive incidences (simulated data).

and TIME_SHIFT > 2.54

and TIME_SHIFT < = 2.75

then 1.

Thus, this rule generated a pattern for a total of 46 execution tests and had a 95.7% probability of success (that is, 44 of the 46 test executions that included this rule in the sample set registered an abortive incidence).

Model to predict nonabortive incidences

Once the different models for abortive incidences were generated and validated, the model relative to nonabortive incidences (located at the second level of priority with respect to the previous ones) was approached.

For the generation of the model relating to nonabortive incidences, the same configuration was used: C&RT trees (which were the best results generated) and the same 14 input parameters. In addition, the partition was made based on the technological area parameter (AREA).

Once the model was trained and generated, a prediction model with 90.69% success was obtained. The C&RT tree resulted in a total of 739 rules with the next distribution by technological area: 94 for the tree related to MTISC, 231 for MTISY, 188 for MTISA and, finally, 226 in MTISN.

An example of the rule generated for the technological area MTISA is detailed below:

Rule 127 for 1 (Instances 36; Confidence 0.917)

if Num_SECTIONS > = 8

and VAR_AIM< = 313

and ABORT_10_PREV < = 4

and DAYS_STATION > = 441

and CONCURRENCE < = 1

and STATION in ["SB1" "SC2" "SG1"]

and ATA in [34 99 23 89 90 43 31]

then 1.

The previous rule included 36 execution tests with a 95.7% probability of success (33 of the 36 test executions included in this rule registered a nonabortive incidence).

FRAMEWORK ENVIRONMENT

For the use of the prediction models by the Airbus DS Company, we developed an application to be executed on Microsoft Windows. This application was developed in the C++ language.

ENVIRONMENT

Thus, once the application is executed, the user is shown in the main window. This window is shown in the following captured image (see Figure 10).

The window of the application has the following sections, with their corresponding controls with which the user can interact.

In the upper left part (FILTERS), there is a set of filters that make it possible to select one or more tests from the historical executions whose pattern needs to be analyzed. Specifically, it contains three filters: ATA, MSN, and TI. These filters were recommended by Airbus DS to facilitate the selection of the tests.

The data table shown at the bottom of the previous filters, as indicated by its name (HISTORICAL EXECUTIONS), contains the list of test executions carried out in the past in the test system, filtered by the three fields described above.

Once the filter has been applied, the user must select a row in the table for the selection of a certain execution test. Once done, the parameters of the selected row are copied to the list of parameters shown below (PATTERN ANALYZED). In this part, only those parameters used for prediction are copied. Thus, these parameters make up an execution pattern, and the corresponding prediction will be made using these parameters. In addition, the user can manually modify any of these parameters in the environment to see how that change affects the probability of an incidence in the test.

On the right side of the PATTERN ANALYZED, there are two selectable tabs: ABORTIVE and NONABORTIVE, depending on whether the user wants to carry out a prediction of the abortive incidence or nonabortive incidences. Once selected, the prediction information is shown (PREDICTION), as well as possible actions to be carried out by Airbus DS engineers to improve in terms of incidences that result from the test execution (RECOMMENDATION).

The result of the prediction includes the following information:

- PROBABILITY: The probability in the percentage that this execution pattern produces an incidence of the selected type.
- SUPPORT: The number of executions in the history of the test system with that same pattern. The higher this number is, the stronger and more supportive the prediction will be.

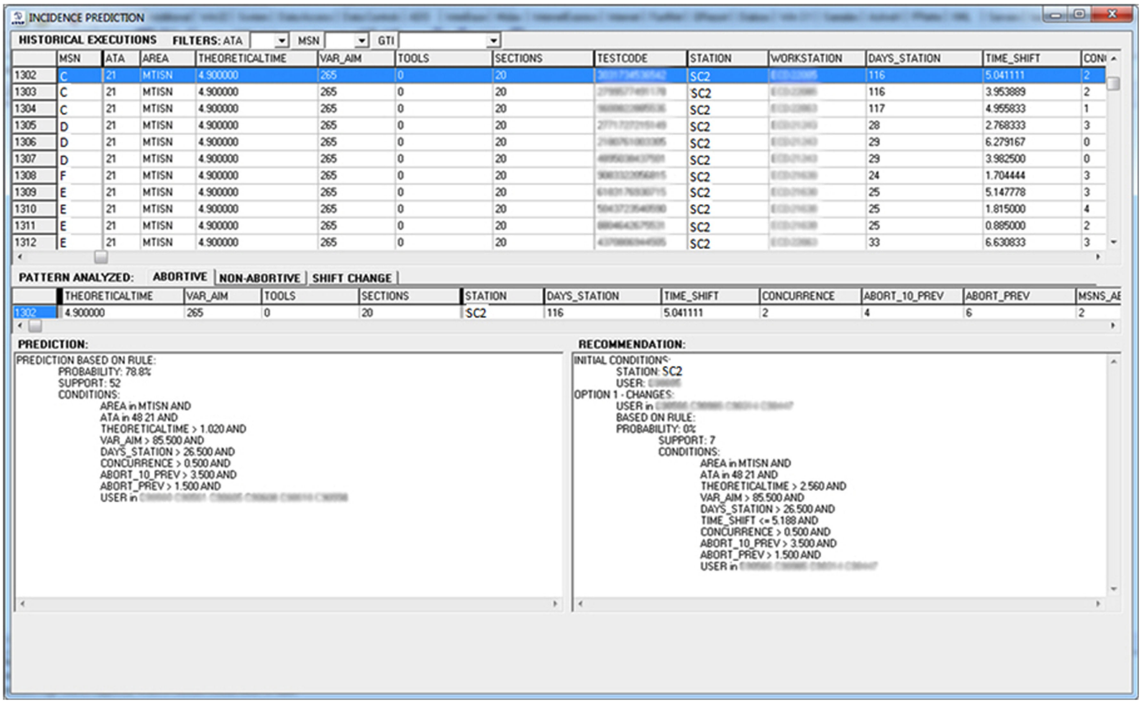


Figure 10.
Environment of the prediction framework.

- CONDITIONS: The rule applied to the set of rules of the models generated with data mining to carry out the prediction.

On the other hand, the recommendation includes the following information:

- INITIAL_CONDITIONS: The parameters of the prediction rule which can be modified by the Airbus DS engineer who schedules the test execution. It is necessary to take into account that there are parameters that cannot be modified because they are implicit to the type of test to be executed (for instance THEORETICAL_TIME or DAYS).

- OPTION n CHANGES: One or more options for changing the previous parameters (INITIAL CONDITIONS) to improve the results of the execution of the test decreasing the probability of an incidence.

- BASED ON RULE: The rule of those included in the models on which the recommendation is based.

DESIGN

For the design and programming of the environment, the following steps were carried out:

- Programming the import of the models: Once the models were generated with IBM Modeler, they were exported to text files (one per package of rules). Later, to carry out the reading of each one of these text files of rules, as well as to integrate them in the application, a parser was made for reading and interpreting the corresponding rules. To carry out this parser, the Parser Generator of Bumble-Bee Software was used, and the corresponding C ++ code was generated.

- Programming the reading of the data table: Additionally, a new parser using the Parser Generator software was made to read in the application the information relative to the input table with the list of executions, as well as its parameters in each execution.

- Programming in C ++ of the prediction and recommendation functions. The prediction functions search the prediction rule from a selected test execution pattern where it is included. Then, the recommendation functions look for test execution patterns similar to the selected pattern (but changing some of its input parameters) but with better behavior in terms of the occurrence of possible incidences.

- Design and programming of the environment. The graphic environment of the application was programmed with the C ++ Builder XE (from Embarcadero RAD Studio XE).

RESULTS

The incidence predictions of the framework were tested with real cases (not simulated) of test executions

Table 2.

Prediction Results of the Tests				
TESTS	**Prediction**		**Actuality**	
Test analyzed	**Abortive incidence**	**Nonabortive incidences**	**Abortive incidence**	**Nonabortive incidences**
1	10%	3.60%	NO	NO
2	100%	14.80%	YES	NO
3	3.40%	3.10%	NO	NO
4	0%	8%	NO	NO
5	5.10%	40%	NO	NO
6	25%	100%	NO	YES
7	25%	100%	NO	NO
8	2.10%	35.60%	NO	NO
9	12.50%	0%	YES	NO
10	23.90%	0%	YES	NO
11	100%	3.80%	YES	NO
12	100%	0%	YES	NO
13	0%	8.50%	NO	NO
14	2.40%	4.20%	NO	NO
15	0%	0%	NO	YES
16	5.10%	8.50%	NO	NO
17	86.30%	2.90%	YES	NO
18	86.30%	0%	NO	NO
19	0%	91.30%	NO	YES
20	25%	14%	NO	NO
ACCURACY			86%	

carried out by the Airbus DS Company. Specifically, the results of these predictions were obtained after the realization of a battery of tests, and they are described in this section.

To achieve the results of the tests, a six-month time period was needed. Thus, the procedure followed in those six months consisted of the following steps:

- Making predictions of incidences with the framework to a set of test executions previously carried out by the Airbus DS Company. Specifically, the selected sample set had a total of 20 executions selected randomly by the company in one of the aircraft in a test. The extraction of the sample data was dated May 2016.
- After 6 months (November 2016), obtain the real results registered by the Airbus DS Company after the executions of these tests.
- Comparison and evaluation of the results to evaluate the precision of the framework.

The results of the tests after carrying out these steps are shown in Table 2. In the column Prediction, the percentages of predictions made by the framework are shown. In the column Actuality, the actual results of these tests are shown in relation to whether an incidence occurred (YES) or not (NO). Prediction rates above 50% probability were considered YES, while those below 50% were considered NO.

Thus, in the table are marked in yellow, those predictions that did not coincide with what happened after the tests by Airbus DS are shown. The rest of the predictions (in white) coincided with what actually occurred after the tests.

Once the results were quantified, it is possible to observe that a prediction accuracy of 87.5% was obtained (35 correct predictions out of 40). Thus, the results showed a high degree of accuracy in the prediction of incidences.

In addition, to avoid those incidences in the future, the Airbus DS Company studied and executed the recommendations generated by the framework.

CONCLUSION

The failures (known in the terminology of the Airbus DS Company as "incidences") in the test process of an aircraft create delays and costs for the company. Our team from the Electronic Technology Department (Spain) worked with the Airbus DS Company and developed a framework for incidence prediction from a data mining process. Specifically, the framework is designed for predicting the incidences generated in the ground testing process of the A400M aircraft.

Specifically, in the issue of using data mining for the prediction of incidences for ground tests, it is not possible to find any work in the research literature; this is an important contribution of the paper.

The framework consists of a set of prediction models and an application with a graphic environment that integrates these models. The models are based on decision tree algorithms, which achieved very good results above 90%. These algorithms have the advantage that they provide an explanatory component to the prediction, which is fundamental for this type of problem. The explanatory component is derived from the rules.

The predictions made by the framework allow Airbus DS engineers to anticipate the occurrence of incidences. This anticipation allows the company to focus on these tests, saving costs on testing and avoiding delays in the airplane test process.

The framework has been tested with real tests to obtain good accuracy results. These results allow us to conclude that the incidences are predictable in the tests and that data mining is of great help for this.

At the same time, and based on past patterns, data mining models can generate recommendations on test parameters related to their context so that these incidences do not occur again for these tests in successive aircraft. The recommendations allowed the Airbus DS Company to apply the recommendations suggested by the framework so that the incidences did not happen again in those tests.

Thus, Airbus is currently using the developed framework to predict incidences and apply recommendations in the actual testing of its aircraft.

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