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# Using Interactive Decision Tree Models in Artillery Fuse Testing

Dariusz AMPUŁA (ampulad@witu.mil.pl)

ORCID: https://orcid.org/0000-0002-9036-9498

*Military Institute of Armament Technology*
*7 Prymasa Stefana Wyszyńskiego Str., Zielonka, Poland*

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**Abstract.** In the introduction, the concept of interactive trees is defined and the purpose of the study is presented. Then, the RGM-2 fuse is described, as are the results of its tests which served as a basis for building specific models. The types of ammunition in which this variation of an artillery fuse is used are listed. A method of building interactive classification trees, allowing the author of the model to interfere with its structure, is described as well. Models of interactive classification trees, such as C&RT, CHAID and XAID have been designed and built. For each model, a tree diagram, a predictor importance sheet, a risk assessment sheet, and a summary of the observed and predicted values are presented. The method of interacting with the constructed classification tree structures, whose task was to improve the designed models, is shown using the examples of two models. The analysis of the models built after the interaction has been performed and, based on the obtained results, the best designed model was selected.
**Keywords:** interactive classification trees, predictor, artificial intelligence, fuse, model

## 1. INTRODUCTION

Interactive trees [6] are part of a module used for building classification or regression trees, available in software [10], enabling researchers or designers to build a model that is open to intervention, meaning that the structure of the tree can be changed once the model has been built. This is very convenient for the designer, as it offers them the ability to introduce one's own divisions or delete individual elements from the tree. However, in order to make any changes to the tree structure possible, a thorough knowledge of the analyzed research problem is required, i.e. mainly knowledge of the research procedures concerning the special technical objects under consideration.

Therefore, this module uses the knowledge of an experienced analyst (researcher) who has information about a given issue. It is possible to make the individual choices "manually", i.e. interactively, while building the tree, in order to obtain the best prediction of the model being designed.

The aim of this article was to show the possibility of designing and building a model of interactive decision trees, and more specifically of interactive classification trees that process the results of tests focusing on specific elements of RGM-2 type artillery fuses. The amount of test results available for those fuses is among the highest available, meaning that the interactive classification tree models designed will be more real. The article will focus on designing three models of interactive decision trees using C&RT and CHAID modules, as well as the exhaustive CHAID module, also known as XAID, available in the Statistica software. Additionally, based on the models built, the possibility of interacting with the structure of the classification trees obtained was determined.

## 2. METHOD OF BUILDING INTERACTIVE DECISION TREES

In the software [10], interactive, classification and regression trees are built either automatically or with the use of an algorithm driven by rules and criteria specified by the user via an interactive graphical interface. The purpose of this module is to provide the user (researcher, designer) with a fully interactive environment for creating trees, so that different predictors and division criteria can be tested while enjoying an almost fully automatic tree building functionality.

The interactive trees module can be used to build trees for the purpose of predicting continuous value of a dependent variable (regression), or a categorized dependent variable (classification). The classic C&RT algorithm (Breiman, Friedman, Olshen and Stone, 1984) or the CHAID algorithm (Chi-square Automatic Interaction Detection, 1980) can be used for this purpose. A tree may also be built with the use of the XAID algorithm (Biggs and de Ville, 1991). The acronym (XAID) stands for exhaustive CHAID.

The interactive trees module available in Statistica is the most advanced in terms of classification and regression tree-based analytics [5,7]. The researcher is capable of interfering with the structure of the tree, inter alia by deleting individual branches, deleting entire levels or introducing their own node divisions. They may, obviously, rely on software suggestions and build a tree model according to the proposed parameters, but an intervention in the final form of the tree created is always possible.

To build our models of interactive decision trees, a database containing the results of diagnostic tests of RGM-2 type fuses, obtained during the first laboratory tests, was used [4,9]. In many cases, second laboratory tests were conducted as well, but the number of these cases is too small to build such a tree for the test results available.

## 3. PROCESS OF BUILDING INTERACTIVE TREES

When designing models of our interactive decision trees, it was assumed that they would be of the classification type, due to the presence of a dependent variable marked as "DEC" which, in this case, may assume six values (B5, B3, BP, BS, Z and PS). This dependent variable is a post-diagnostic decision made on the basis of the obtained results of tests focusing on individual features of the RGM-2 fuse. A detailed description of the potential decisions may be found in the test methodology [8].

RGM-2 fuses are installed in fragmentation and high-explosive cartridges with full and reduced loads, as well as in smoke cartridges and in training cartridges. The RGM-2 fuse is a mechanical [3], contact-head fuse offering three different delay settings: immediate, short and long.

Due to the fact that large amounts of ammunition with RGM-2 fuses are still available, they are subject to laboratory diagnostic tests during which individual elements (features) of these fuses are tested, with a particular attention paid to the safety of their storage and use. Ammunition in long-term storage is subjected to diagnostic tests when it is moved to its warehousing location or is collected for use. This also applies to all lots of ammunition intended for disposal. Each year, the database of results obtained while testing ammunition with RGM-2 fuses continues to grow.

All the tested features of those fuses were divided, according to the test methodology, into five classes of importance: A, B, C, D and E. Depending on the inconsistencies detected during laboratory tests, a specific post-diagnostic decision was made for each of the tested fuse lots.

In the interaction tree models designed for RGM-2 fuses, all tested inconsistencies classes were taken into account during the first laboratory diagnostic tests, i.e. eight predictors were accepted in accordance with the test methodology, including the following: the number of inconsistencies in importance class A (LA), the number of inconsistencies in importance class B (LB), the number of incompatible fuses in importance class B (NB), the total number of incompatible fuses (N), the number of incompatible fuses in importance class C (NC), the number of inconsistencies in importance class C (LC), the number of inconsistencies in importance class D (LD) and the number of inconsistencies in importance class E (LE). The inconsistencies in the importance classes focus on those fuse features tested which qualify them into a specific inconsistency group. The tested features include the following: corrosion on specific components and assemblies of the fuse, decrease in the strength of mechanical protective elements, non-operation or malfunction of the igniting elements i.e. igniting and stimulating primers, retarders, self-liquidators, failure of the fuse's fire chain, physical and chemical changes in the properties of explosives and all other defects adversely impacting the safety and reliability of the fuses.

The method relied upon for analyzing the obtained qualitative parameters of the classification decision trees that have been designed and built has been presented in articles [1,2] which describe, in detail, the process of building various models of classification trees and the method of predicting the diagnostic decisions obtained for new test lots of various ammunition elements.

## 4. RESULTS OF BUILDING INTERACTIVE CLASSIFICATION TREES

Interactive tree models were designed and then built in accordance with C&RT, CHAID and XAID (exhaustive CHAID) modules available in the software [7]. Our models were of the classification variety, as "DEC" variable, denoting the accepted post-diagnostic decision, was the dependent variable.

The quantitative predictors were the results of tests focusing on the individual characteristics of RGM-2 fuses.

When designing our model of interactive C&RT trees, the costs of incorrect classifications were assumed to be "equal" and the *a priori* probabilities as "estimated". It was noted that the goodness-of-fit in our model will be determined by the Gini measure, which tells us about the heterogeneity of a given node (node inconsistency).

In order to find the best model to build, the model was forced to prune the tree, as part of the stop rule, in the event of an incorrect classification error, and also specified a minimum node size of 15 and a maximum tree depth of 10, which is the maximum number of levels. The minimum number of descendants and the maximum number of nodes indicated by the software were accepted. V-fold cross-validation with the value of the random number generator indicated by the software and the standard error rule are also marked. The use of cross-validation in the model being built prevents over-fitting of the model and allows to find estimates of the model's parameters. It also means that the best single tree will be built instead of a sequence of such trees.

After building our model, we obtained an interactive classification tree of the C&RT type, as shown in Fig. 1. This tree has seven divided nodes and eight final nodes - leaves.

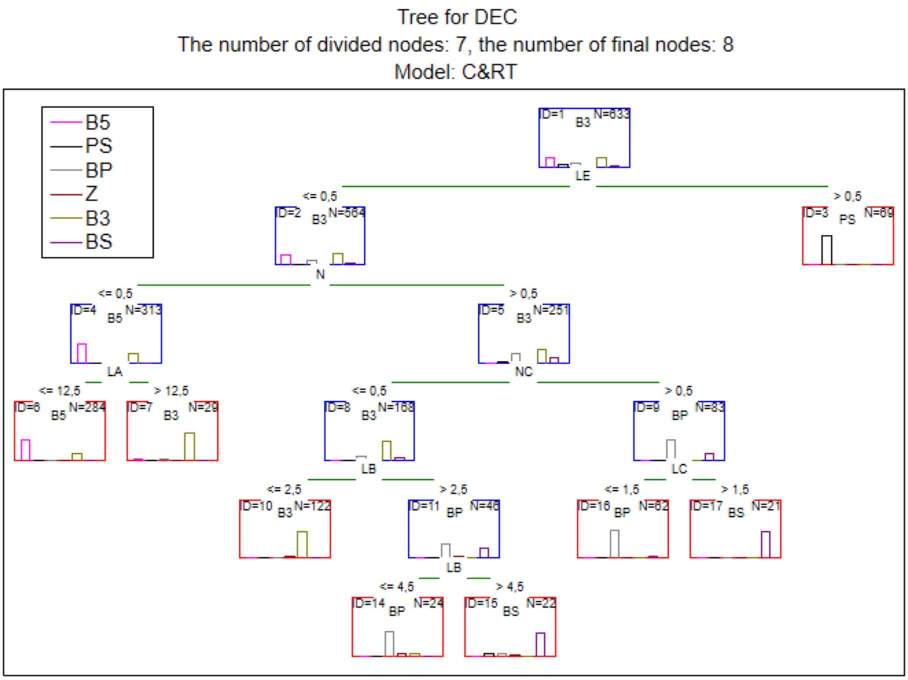


Fig. 1. Diagram of a tree for the C&RT model – software screenshot

The quality of the model created is determined by the risk evaluation, as presented in Fig. 2. We obtained risk evaluation score for a learning sample equal to 0.170616 and for the standard error value of 0.014952.

| | Risk evaluation (RGM-2) Dependent variable: DEC Model: C&RT | |
|---|---|---|
| | **Risk Evaluation** | Standard error |
| **Laerning** | 0.170616 | 0.014952 |

Fig. 2. Risk evaluation sheet for the C&RT model – software screenshot

The next stage in the interpretation of the model consists in comparing the predictor importance ranking, as presented in Table 1. The predictor that has the greatest impact on the dependent variable is the "N" predictor, while the one that has the leas influence is the "LD" predictor.

Table 1. Predictor importance table for the C&RT model

| | Importance of predictors (RGM-2) Dependent variable: DEC Model: C&RT | |
|---|---|---|
| | **variable rank** | Importance |
| **N** | 100 | 1.000000 |
| LB | 83 | 0.826480 |
| NB | 82 | 0.822064 |
| NC | 63 | 0.626020 |
| LC | 63 | 0.634693 |
| LA | 16 | 0.163634 |
| LE | 12 | 0.117152 |
| LD | 5 | 0.048236 |

The quality of the built model can also be checked by comparing the observed values (actual post-diagnostic decisions) with the predicted values (decisions predicted according to our model). A fragment of the predicted values sheet is shown in Table 2. It can be seen that some decisions undertaken by our model (marked red) are different from those undertaken by the person assessing the test results. It is therefore advisable to re-analyze these test results.

Table 2. Sample of predicted values (in individual classes) for the C&RT model

| | Prediction (RGM-2) Dependent variable: DEC Model: C&RT; Attempt: Analisys | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Observed value | Predicted value | Probability B5 | Probability PS | Probability BP | Probability Z | Probability B3 | **Probability BS** | Final nodes |
| 50 | B3 | B3 | 0.034483 | 0.000000 | 0.034483 | 0.000000 | 0.931034 | 0.000000 | 7 |
| 51 | BS | BP | 0.000000 | 0.016129 | 0.935484 | 0.000000 | 0.000000 | 0.048387 | 16 |
| 52 | BP | BP | 0.000000 | 0.000000 | 0.833333 | 0.083333 | 0.083333 | 0.000000 | 14 |
| 53 | BS | BS | 0.000000 | 0.047619 | 0.000000 | 0.047619 | 0.000000 | 0.904762 | 17 |
| 54 | BP | BS | 0.000000 | 0.090909 | 0.090909 | 0.045455 | 0.000000 | 0.772727 | 15 |
| 55 | B5 | B5 | 0.718310 | 0.007042 | 0.010563 | 0.010563 | 0.253521 | 0.000000 | 6 |
| 56 | BS | BS | 0.000000 | 0.047619 | 0.000000 | 0.047619 | 0.000000 | 0.904762 | 17 |
| 57 | BS | BS | 0.000000 | 0.047619 | 0.000000 | 0.047619 | 0.000000 | 0.904762 | 17 |
| 58 | B5 | B5 | 0.718310 | 0.007042 | 0.010563 | 0.010563 | 0.253521 | 0.000000 | 6 |
| 59 | B5 | B5 | 0.718310 | 0.007042 | 0.010563 | 0.010563 | 0.253521 | 0.000000 | 6 |
| 60 | B5 | B5 | 0.718310 | 0.007042 | 0.010563 | 0.010563 | 0.253521 | 0.000000 | 6 |

In order to fully evaluate our designed C&RT model, other parameters should be analyzed as well, e.g. the incorrect classification matrix obtained, indicating the error fractions for individual predictors. However, due to space-constraints affecting this article, other parameters will be analyzed outside of its scope, as they also determine the quality of the model obtained.

The CHAID type model of interactive classification trees was the next iteration we designed and built. The model was based, obviously, on the same data, i.e. it relied on the results RGM-2 fuse tests. While building this model, the costs of incorrect classification were introduced at an "equal" level and the stop parameters were the same as those used in the C&RT model. Additionally, the "p" parameter for dividing and for combining is assumed to equal 0.05. A v-fold cross-test v = 10 and the initial value of the random number generator equal to 1 were also introduced into the model. Automatic predictor intervals for each node are also marked and a Bonferroni correction is introduced to make it difficult to consider a single test result as statistically significant when testing multiple times based on the same data.

By building our interactive classification tree model of the CHAID type, we obtained a tree presented in Fig. 3.

The tree consists of four divided nodes and eight final nodes. So, the number of nodes is lower than in the C&RT tree. This means that the number of some nodes is larger.

The risk evaluation sheet that determines the quality of the designed tree is presented in Fig. 4. The risk evaluation value for the learning sample was 0.21485 and the standard error was 0.016325. These are slightly higher than in the case of the C&RT model.

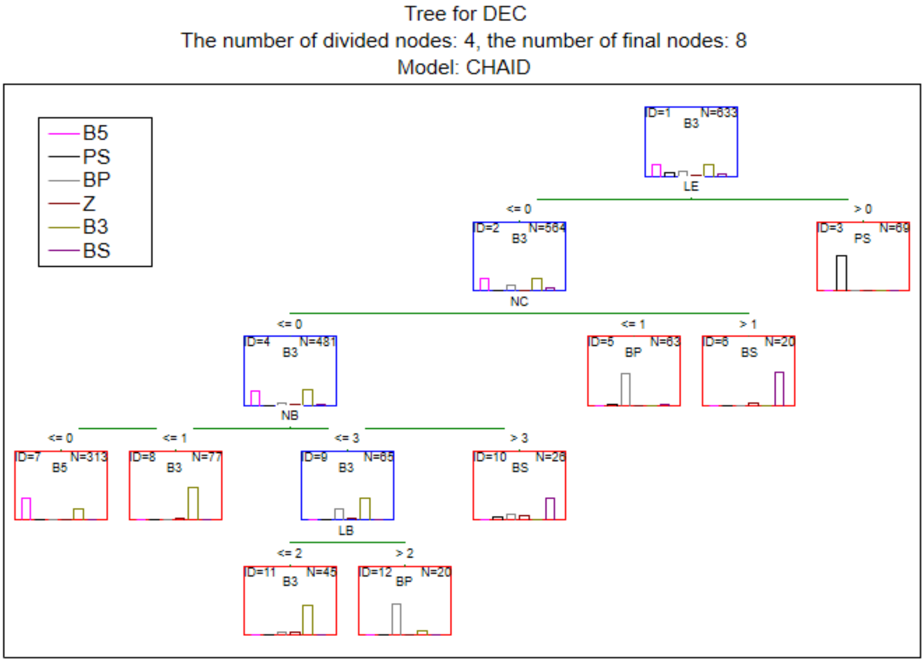


Fig. 3. Diagram of a tree for the CHAID model – software screenshot

| | Risk evaluation (RGM-2)<br>Dependent variable: DEC<br>Model: CHAID | |
|---|---|---|
| | **Risk Evaluation** | Standard error |
| **Learning** | 0.214850 | 0.016325 |
| V-fold | 0.297064 | 0.018991 |

Fig. 4. Risk evaluation sheet for the CHAID model – software screenshot

The predictor importance ranking, as presented in Table 3, is the next element taken into consideration. In this model, "LC" and "LA" are the most and the least important predictors, respectively. As once can notice, these predictors are different than for the C&RT model.

The comparison of the observed and predicted values is presented in Table 4. In this comparison, we see much more discrepancies (marked red) between these values than in the previous model.

Table 3. Predictor importance table for the CHAID model

| | Importance of predictors (RGM-2) Dependent variable: DEC Model: CHAID | |
|---|---|---|
| | variable rank | Importance |
| LC | 100 | 1.000000 |
| N | 95 | 0.954787 |
| NC | 95 | 0.948332 |
| LE | 94 | 0.942405 |
| NB | 87 | 0.870477 |
| LB | 86 | 0.855138 |
| LD | 20 | 0.197307 |
| LA | 13 | 0.125352 |

Table 4. Sample of predicted values (in individual classes) for the CHAID model

| | Prediction (RGM-2) Dependent variable: DEC Model: CHAID; Attempt: Analisys | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Observed value | Predicted value | Probability B5 | Probability PS | Probability BP | Probability Z | Probability B3 | Probability BS | Final nodes |
| 1 | BS | BS | 0.000000 | 0.000000 | 0.000000 | 0.050000 | 0.000000 | 0.950000 | 6 |
| 2 | B5 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |
| 3 | B3 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |
| 4 | B5 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |
| 5 | B3 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |
| 6 | BP | BP | 0.000000 | 0.031746 | 0.920635 | 0.000000 | 0.000000 | 0.047619 | 5 |
| 7 | BP | BP | 0.000000 | 0.031746 | 0.920635 | 0.000000 | 0.000000 | 0.047619 | 5 |
| 8 | B3 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |
| 9 | BP | BP | 0.000000 | 0.031746 | 0.920635 | 0.000000 | 0.000000 | 0.047619 | 5 |
| 10 | B3 | B5 | 0.654952 | 0.006390 | 0.012780 | 0.009585 | 0.316294 | 0.000000 | 7 |

The last model designed is the CHAID exhaustive (XAID) model. While building this model, the same parameter values were introduced as in the case of the CHAID model, for comparison purposes. The obtained tree structure is shown in Fig. 5. The tree consists of five divided nodes and seven final nodes. So, it is slightly more extensive than a CHAID tree.

The values of the risk evaluation sheet are shown in Figure 6. Both the risk evaluation value of 0.21327 and the standard error value of 0.016281 are slightly lower than the same parameters for the CHAID model.

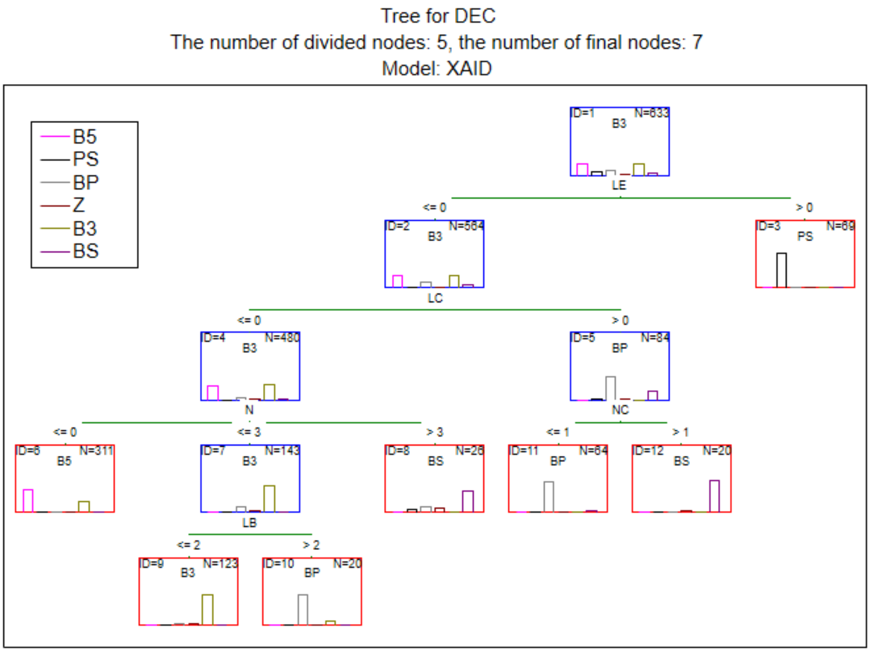


Fig. 5 Diagram of a tree for the XAID model – software screenshot

| | Risk evaluation (RGM-2) Dependent varaible: DEC Model: XAID | |
|---|---|---|
| | Risk Evaluation | Standard error |
| Learning | 0.213270 | 0.016281 |
| V-fold | 0.278066 | 0.018620 |

Fig. 6. Risk evaluation sheet for the XAID model – software screenshot

Looking at the ranking of the predictors shown in Table 5, one can see that "N" is the most important predictor for the dependent variable, while "LA" is the least important predictor, as it was the case in the CHAID model.

The last sheet analyzed in the article is the list of observed and predicted values. In this model, more discrepancies (marked red) are observed than in the C&RT model, but their number is slightly lower than in the CHAID model (Table 6).

Table 5. Predictor importance table for the XAID model

| | Importance of predictors (RGM-2)<br>Dependent variable: DEC<br>Model: XAID | |
|---|---|---|
| | **variable rank** | Importance |
| **N** | 100 | 1.000000 |
| NB | 82 | 0.821996 |
| LB | 81 | 0.809087 |
| NC | 77 | 0.773473 |
| LC | 77 | 0.770891 |
| LE | 64 | 0.638414 |
| LD | 14 | 0.140031 |
| LA | 9 | 0.091636 |

Table 6. Sample of predicted values (in individual classes) for the XAID model

| | Prediction (RGM-2)<br>Dependent variable: DEC<br>Model: XAID; Attempt: Analisys | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Observed vakue** | Predicted value | Probability B5 | Probability PS | Probability BP | Probability Z | Probability B3 | Probability BS | Final nodes |
| 50 | B3 | B5 | 0.659164 | 0.006431 | 0.006431 | 0.009646 | 0.318328 | 0.000000 | 6 |
| 51 | BS | BP | 0.000000 | 0.031250 | 0.921875 | 0.000000 | 0.000000 | 0.046875 | 11 |
| 52 | BP | BP | 0.000000 | 0.000000 | 0.900000 | 0.000000 | 0.100000 | 0.000000 | 10 |
| 53 | BS | BS | 0.000000 | 0.000000 | 0.000000 | 0.050000 | 0.000000 | 0.950000 | 12 |
| 54 | BP | BS | 0.000000 | 0.076923 | 0.153846 | 0.115385 | 0.000000 | 0.653846 | 8 |
| 55 | B5 | B5 | 0.659164 | 0.006431 | 0.006431 | 0.009646 | 0.318328 | 0.000000 | 6 |
| 56 | BS | BS | 0.000000 | 0.000000 | 0.000000 | 0.050000 | 0.000000 | 0.950000 | 12 |
| 57 | BS | BS | 0.000000 | 0.000000 | 0.000000 | 0.050000 | 0.000000 | 0.950000 | 12 |
| 58 | B5 | B5 | 0.659164 | 0.006431 | 0.006431 | 0.009646 | 0.318328 | 0.000000 | 6 |
| 59 | B5 | B5 | 0.649164 | 0.006431 | 0.006431 | 0.009646 | 0.318328 | 0.000000 | 6 |
| 60 | B5 | B5 | 0.659164 | 0.006431 | 0.006431 | 0.009646 | 0.318328 | 0.000000 | 6 |

In the designed models of interactive classification trees, for the purposes of further use of such built models, codes were generated that effectively determine the predicted values. Thanks to these codes (PMML /Predictive Models Markup Language/ codes were used in our case), these models can be used for new lots of RGM-2 fuses.

A precise analysis of the three interactive classification tree models that were designed and the built has resulted in the possibility of enlarging the CHAID and XAID models by adding additional nodes.

The C&RT model is a complete model and no further divisions can be made here. Node 6 (B5) still holds a large number of observations (284), including 72 B3 results. The division of this node, made by the author, unfortunately increases the evaluation errors of the tree built.

The removal of some branches or leaves from this model, in the opinion of the author of this article, is also no longer advisable.

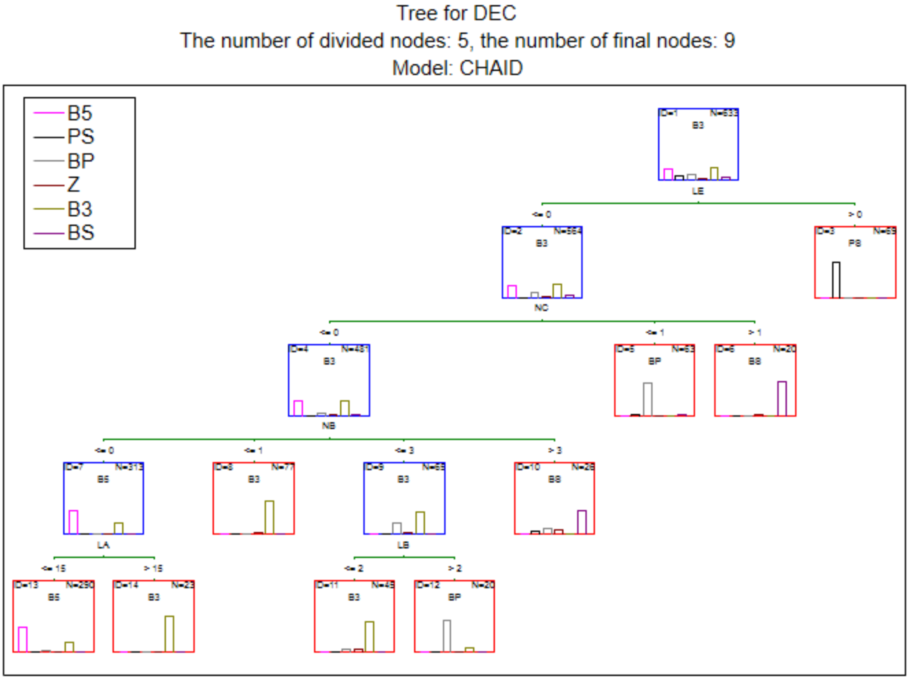


Fig. 7. Diagram of a tree for the CHAID model – software screenshot

In the case of the CHAID model, due to the large size of node 7, it was divided into two nodes. The graph of the new tree created this way is shown in Fig. 7. The tree consists of five divided nodes and nine final nodes. Two new "B5" and "B3" class nodes (13 and 14) were created. "LA" is the dividing predictor for node no. 7. Node 13 still contains a large number of case (290) but it is no longer possible to divide it according to the accepted observations contained therein.

For the XAID model, node no. 6 was divided, with "LA" being the division predictor and with "15" being the dividing value. Two new nodes (13 and 14) were created, with the former still containing a large number of cases, but without any ability of being divided. The new graph of the tree is shown in Fig. 8.

The addition of new divisions to some nodes should, in the opinion of the author of the article, make the method of classifying new test results more reliable and accurate. Hence, for nodes with large numbers, these divisions should be made, provided that they are possible, of course.

After making changes to the structures of the built models, it should be checked whether they have caused significant changes in the parameters of the designed interactive tree models.

In the case we have analyzed, the addition of more nodes to the developed CHAID and XAID models failed to bring about any significant changes for the better.

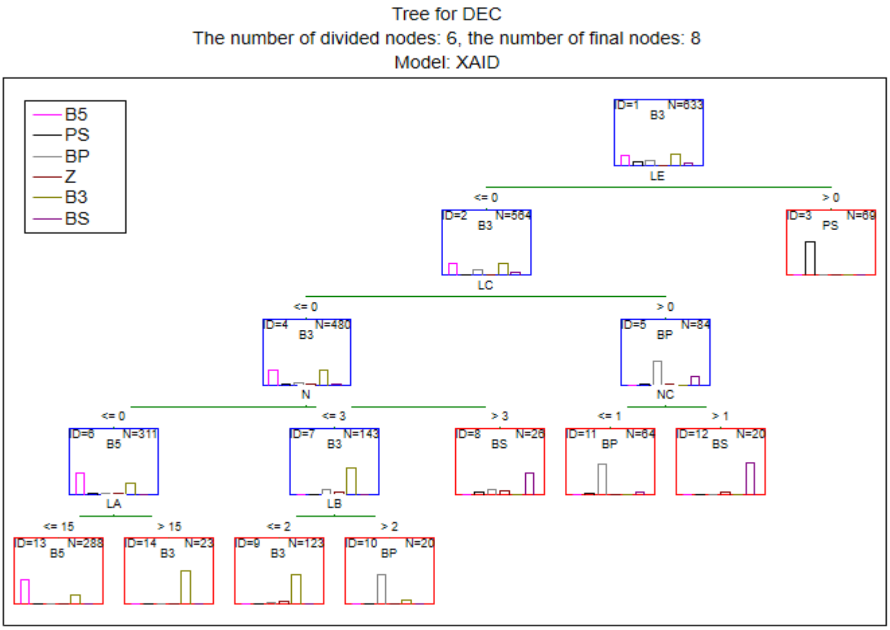


Fig. 8. Diagram of a tree for the XAID model – software screenshot

## 5. CONCLUSIONS

The article presents a method of designing and building three models of interactive classification trees that can be deployed to analyze the results of tests of RGM-2 fuses. All three models were based on the same diagnostic test results. Different model-specific parameters were obtained in C&RT, CHAID and XAID models. So, the question is: which of these models is the best?

A detailed analysis of the obtained parameters pertaining to the built trees has rendered some specific data providing a clear answer to the aforementioned question. The best risk evaluation parameters were achieved by the C&RT tree and this model is considered the best. Of course, it is also possible to make a predictive evaluation for new test results using the two remaining interactive classification tree models developed, but it should be borne in mind that they are characterized by higher evaluation error values and a correct post-diagnostic decision obtained based on such models may be burdened with these errors.

The interaction method described in the article (i.e. manual enlargement of the tree with subsequent nodes) could suggest an improvement in these extended models. However, the reality turned out to be different, as a change in the structure of the trees failed not mitigate the evaluation errors.

The interactive C&RT classification tree model proved to be complete from the beginning, as it did not offer any possibility of enlargement or reduction.

In the opinion of the author, the objective set forth at the beginning of the article has been fully achieved. Therefore, it is possible to design and build interactive classification trees based on the results of diagnostic tests of RGM-2 artillery fuses. Additionally, the article shows how to interfere with the structure of the created predictive models based on interactive decision trees.

To recapitulate: the article describes the process of designing, building and selecting an interactive C&RT classification tree model that can be used in practice for the predictive evaluation of new test results of RGM-2 fuses. The implementation of this model in practical applications is conditional upon its acceptance by the management of the research unit dealing with these tests. The formal requirement would be to create specific terminals at the test stands and connect these with the software [7] owned by the Institute, so that the designed evaluation model could be used.

Thus, interactive classification trees are another artificial intelligence tool that can be used to predict the dependent variable for new lots of artillery fuses tested. Of course, the possibility of using this tool depends primarily on the size of the results database. The more results are available, the more reliable the model of interactive decision trees will be. In some cases, with a small results database, the construction of this type of trees is simply impossible.

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# Modele interakcyjnych drzew decyzyjnych w badaniach zapalników artyleryjskich

Dariusz AMPUŁA

*Wojskowy Instytut Techniczny Uzbrojenia*
*ul. Prymasa Stefana Wyszyńskiego 7, Zielonka*

**Streszczenie.** W artykule we wstępie zdefiniowano pojęcie drzew interakcyjnych oraz określono cel artykułu. Następnie, scharakteryzowano zapalnik RGM-2, którego wyniki badań zostały przygotowane do budowy modeli oraz wskazano rodzaje amunicji w których występuje przedmiotowy zapalnik artyleryjski. Opisano metodę budowy interakcyjnych drzew klasyfikacyjnych, która umożliwia ingerencję autora modelu w jego strukturę. Zaprojektowano oraz zbudowano modele interakcyjnych drzew klasyfikacyjnych typu C&RT, CHAID oraz XAID. Dla każdego z modeli przedstawiono schemat zaprojektowanego drzewa, arkusz ważności predyktorów, arkusz oceny ryzyka oraz zestawienie wartości obserwowanych i wartości przewidywanych. Pokazano na dwóch modelach sposób interakcji w zbudowane struktury drzew klasyfikacyjnych, których zadaniem było poprawienie zaprojektowanych modeli. Dokonano analizy zbudowanych po interakcji modeli oraz na podstawie otrzymanych wyników, wskazano najlepszy zaprojektowany model.
**Słowa kluczowe:** interakcyjne drzewa klasyfikacyjne, predyktor, sztuczna inteligencja, zapalnik, model