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Artificial Intelligence Application in Performance of Engine WIN GD XDF-72

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***Abstract*— The purpose of this paper is to create a prediction model for good or fault operation of vessels main engine Win GD XDF-72, based on mechanical learning with classification using the Exhaustive CHAID, algorithms and neural networks. The research is asked to answer the following research questions: "Is there a possibility of creating a prediction model for good or fault operation of vessels main engine Win GD XDF-72 through supervised mechanical learning?" And "is it feasible a certain parameter/measurement to be predicted through the operation of the above engine?". Training data was drawn from 301 samples of performance data of diesel (Diesel mode) and 318 samples of performance data of natural gas (Gas mode) of the subject engine. The results of the research through SPSS program and more specifically using Exhaustive CHAID with split-validation, Exhaustive CHAID with Cross validation and MLP with neural network have shown that it is possible to create such a prediction model in which the tc_ rpm and fuel parameters are the determining factors for the good or fault operation of the subject engine.**

Keywords—component; formatting; style; styling; insert (key words)

I. Introduction (*Heading 1*)

The discovery of the Diesel engine was important for the development of shipping, enhancing both the efficiency and the evolution of machine technology. In order for a main two-stroke engine to operate on a ship, specific procedures must be followed during its start-up, operation and maintenance. For this reason, it is important to develop a predictive model of good or fault operation. This identifies the parameters that are most likely to cause the machine to malfunction and thus malfunction, leading to multiple problems (intermittent operation, high probability of components failure, loss of efficiency). The subject research aims to develop a predictive model of good or fault operation of Win GD XDF-72 main engine based on machine learning by sorting using Exhaustive CHAID algorithms and using neural networks.

The research questions are the following:

- Is there a possibility of creating a prediction model for good or fault operation of vessels main engine Win GD XDF-72 through supervised mechanical learning?

In order to better approach the research question, the following research sub-question is answered below:

- Is it feasible a certain parameter/measurement to be predicted through the operation of the above engine?

II. Performance of Engine WIN GD XDF-72 and Artificial Intelligence

Artificial Intelligence is the field of computer science, which deals with the design of intelligent computing systems, i.e. systems that exhibit characteristics related to intelligence in human behavior (Barr and Feigenbaum, 1981).

Mechanical Learning is defined as 'the creation of models or patterns from a data set, from a computational system' (Vlahava et al.). Witten & Frank (2000) define it as "something he learns when he changes his behavior in such a way as to perform better in the future".

The types of mechanical learning are as follows:

- Supervised learning
- Unsupervised learning
- Reinforcement Learning

A. *Artificial Neural Networks*

Artificial Neural Networks (ANN) are technological approaches to biological counterparts, on which the superior functions of beings are based, so they vary in application. They grow on the basis of organic networks and improve as the sample of input and output data with which they are 'trained' increases. The networks' learn' and their operating mechanisms essentially incorporate the experience that is offered through these data (Anderson and Rosenfeld, 1988).

ANN process information and respond dynamically to external stimuli (inputs). Each artificial neuron consists of multiple inputs xi and a single y output.

Each input xi "weighs" with a weight wi and the results are summed through the summation function F:

$$F = \sum_{i}^{n} x_i w_i$$

The artificial neuron outputs through the transfer function only when the weighted sum of the inputs is greater than a certain threshold value θ, i.e. when:

$$\sum_{i}^{n} x_i w_i - \theta > 0$$

An artificial neuron is a simplified model of the natural neuron in that interconnecting weights form the electrical characteristics of the junction contact and the threshold value simulates the saturation behavior of the natural neuron.

B. DECISION TREES

Decision Trees (DT) is the most well-known Induced Learning algorithm and has been successfully applied in many areas where classification is required: for example, in the identification of faces in images, in medicine for incident diagnosis, in predictions necessary for advertising, products and, more generally, for knowledge mining. The DT algorithm leads to the creation of a tree-like form whose sheets are classes. This tree form can be read as a set of rules called classification rules and gives a convincing answer to the question: "How can a machine create general rules from specific observations and how credible are these rules in action? ".

III. METHODOLOGY

The training data was derived from a sample of actual operating measurements of the Win GD XDF-72 two-stroke machine. The number of the study sample collected is 301 for diesel fuel and 318 for gas. These snapshots, each of which is a state of the main engine, have attributes associated with its proper functioning, and are in particular the following:

speed	fuel	LI	power	t/c_rpm	temp_bef_T	temp_aft_T	comp	comb

The speed of the shaft in rpm.

- Specific fuel consumption in gr / kWh (fuel).
- Load Indicator.
- Power of the machine.
- Turbocharger counting its revolutions per minute.
- Temperature before the charger at (C).
- Temperature after supercharger at (C).
- Compression pressure in Bar.
- Combustion pressure in the chamber in Bar

The "black box" model was used to study the learning model and export the results. Types of mechanical learning have been chosen as supervised learning.

In this case, the system has to "learn", i.e. to construct a new model in the form of a predictor function, which will represent given inputs to known, desired outputs, with the ultimate goal of generalizing this function and for inputs with an unknown exit. For the forecasting function, the following apply:

Each input, whether given or not, which the function can accept is characterized as an instance, thus creating a set of instances. Inputs are described based on the attributes they possess and have been characterized as significant since the beginning of the study of the problem that the system is called to solve. The given inputs are compiled by observations and form the so-called training set, which is a subset of the set of instances. The rest of the set of instances is the test set to be used during the certification phase. The function depicting an input from the training set to its known output is called a goal function. The value returned by the target function for an instance of the set of instances is given to a variable called goal variable. In supervised learning, the behavior of the target function is improved through learning processes with the help of the error function that detects the difference of the target variable from the desired output.

For each data set of the main engine with its attribute values it was decided to categorize it into a machine with good function and machine with fault function. The label therefore called operation is the discrete categorization of the above main engine. The selection criterion to classify a main engine is to change its load by 20%. Therefore, a good-performing main engine must have an average of values of features less than 20% of its rated value, whereas otherwise an average of more than 20% results in a malfunctioning main engine.

For the implementation of the mechanical forecasting model was chosen:

1) Classification by decision tree. The SPSS statistical program was used to make the decision tree finding analysis using the CHAID method and the MATLAB mathematical program using the ID3 algorithm.

2) Learning neural networks using the SPSS statistical program by doing MLP (Multilayer Perceptron)

The criterion of comparing these methods is the best possible creation of a decision tree with the greatest information gain and hence the smaller entropy.

IV. EXPERIMENTAL RESULTS

Instances classification: Using the IBM SPSS (v.24) statistical program, from IBM, we defined snapshot attributes with speed, fuel, LI, power, tc_rpm, temp_bef_T, temp_aft_T, comp, comb as Numeric input data while variable operation predictor.

A. Chi-squared Automatic Interaction Detection method

For the development and creation of the decision tree, in order to sort the instances, the CHAID method was used. OPERATION was defined as a dependent variable and the other traits as independent variables (predictors). At each step, the method selects the predictor that has the greatest effect on the dependent variable. Categories of each independent variable are merged if they do not have a significant difference with respect to the dependent variable. The Exhaustive CHAID method examines all possible separations of each independent variable. The validation process allows us to evaluate how well the structure of the trees generates for a large number of data. There are two ways to validate data:

1) Exhaustive CHAID method with split-validation for diesel fuel

In this case the tree model is created using training data and control data. Selected from 301 snapshots 50% as training data (151) and 50% as control data (150).

The below figure 1, shows the formats of the classification trees for training sample and test sample, respectively, for both categories of dependent variable operation (blue fault, good green).

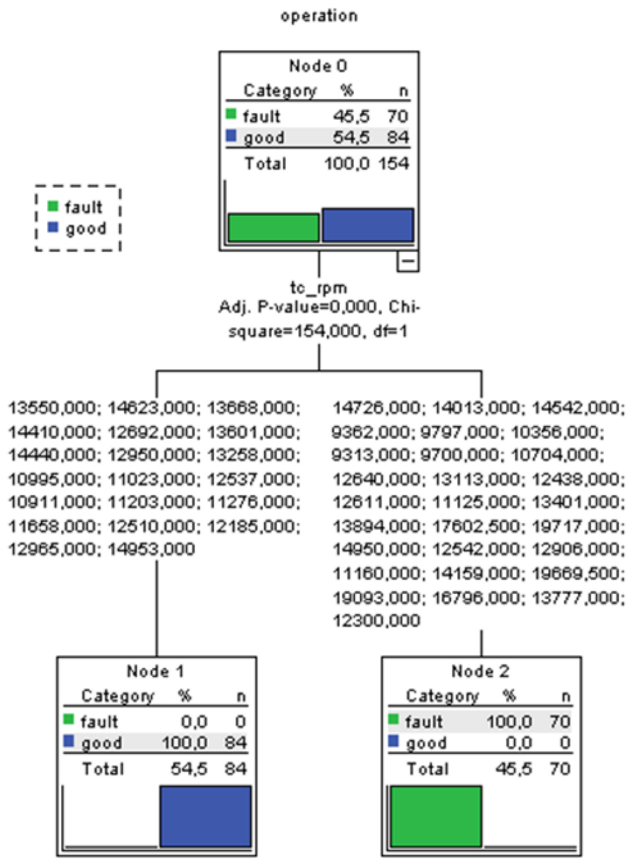

Fig. 1. *Data training structure tree*

Table I shows risk analysis of this methodology which is a measure of the accuracy of the tree's prediction. For training data, the error rate is 0% and for control data 3.8%.

TABLE I. RISK ANALYSIS

Risk		
Sample	Estimate	Std. Error
Training	,000	,000
Test	,038	,015
Growing Method: EXHAUSTIVE CHAID Dependent Variable: operation		

Table II shows the results of the classification. This table shows the number of cases correctly and incorrectly classified for each dependent variable category with a total prediction rate of 100 % for training data and 96.2 % for test data.

TABLE II. CLASSIFICATION WITH SPLIT-VALIDATION

Classification				
		Predicted		
Sample	Observed	fault	good	Percent Correct
Training	fault	74	0	100,0%
	good	0	68	100,0%
	Overall Percentage	52,1%	47,9%	100,0%
Test	fault	75	6	92,6%
	good	0	78	100,0%
	Overall Percentage	47,2%	52,8%	96,2%
Growing Method: EXHAUSTIVE CHAID Dependent Variable: operation				

2) Exhaustive CHAID method with Cross validation for diesel fuel

In this case, the sample is divided into a number of patterns or folds. Tree models are then produced, excluding data from each pattern in turn. The first tree is based on all cases except those of the first sample, the second tree is based on all cases except those of the second sample and so on. For each tree, the risk of incorrect classification is calculated by applying the tree to the pattern that is excluded for its creation. The number of slices of the sample was set to the maximum of 25. Cross-validation produces a single final tree model. The risk assessment with this method for the final tree is calculated as the average risk for all trees.

The below figure 2 shows the sorting tree for all data for both classes of dependent variable operation (fault in green, good blue in color).

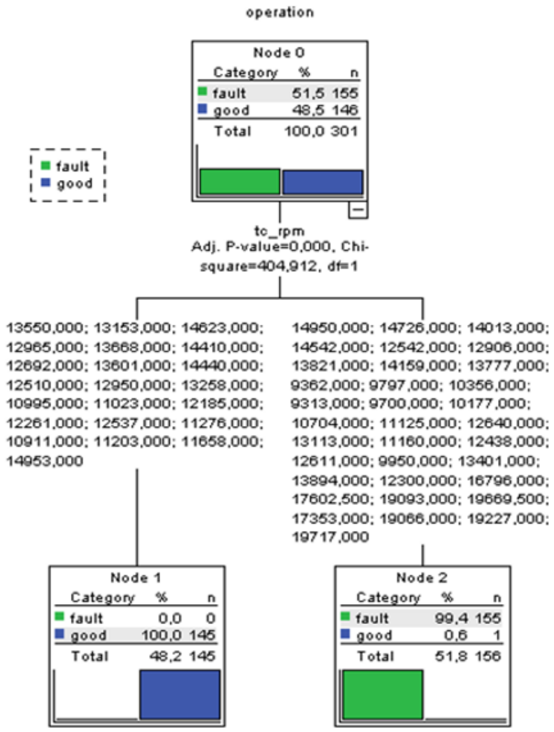

Fig. 2. *Cross Validation Classification Tree*

Table III shows the results of the classification. The overall correct prediction rate of all data is 99.7% and therefore 0.03% error rate.

TABLE III. CLASSIFICATION WITH CROSSVALIDATION

Classification			
	Predicted		
Observed	fault	good	Percent Correct
fault	155	0	100,0%
good	1	145	99,3%
Overall Percentage	51,8%	48,2%	99,7%
Growing Method: EXHAUSTIVE CHAID Dependent Variable: operation			

B. *MLP method with neural network*

Using IBM's SPSS (v.24) statistical program, the neural network MLP was selected to sort the data. The Perceptron (MLP) multilayer process produces a prediction model for one or more dependent (predictor) variables based on predictive variable values (independent variables). As a dependent variable, the main engine's operation was defined and the variables speed, fuel, LI, power, tc_rpm, temp_bef_T, temp_aft_T, comp and comb were defined as factors. The neural network architecture was set to two (2) hidden levels whereas the functions that connect the hidden layers and their units to each other are the sum of the weights of the inputs to the dependent variable. The function in hidden levels is excessive of the form γ (c) = tanh (c) while the function at the output level of the form γ (c) = c. Of the total 301 data, 200 samples (66.7%) were taken as training data and 100 (33.3%) as randomized control data as shown in Table IV.

TABLE IV. CASE PROCESSING SUMMARY MLP METHOD

Case Processing Summary			
		N	Percent
Sample	Training	200	66,7%
	Testing	100	33,3%
Valid		300	100,0%
Excluded		1	
Total		301	

The type of training that determines how the network processes the training data records was defined as a Batch. This technique only updates the summary weights after passing all the records of the training data, i.e. it uses information from all the files in the training data set, minimizing the total error directly by lamda, sigma, center interval, offset interval. Fig. 3 illustrates the structure of the neural network that classifies the data where the gray-colored lines have a positive weight, while those with a blue have a negative synaptic weight.

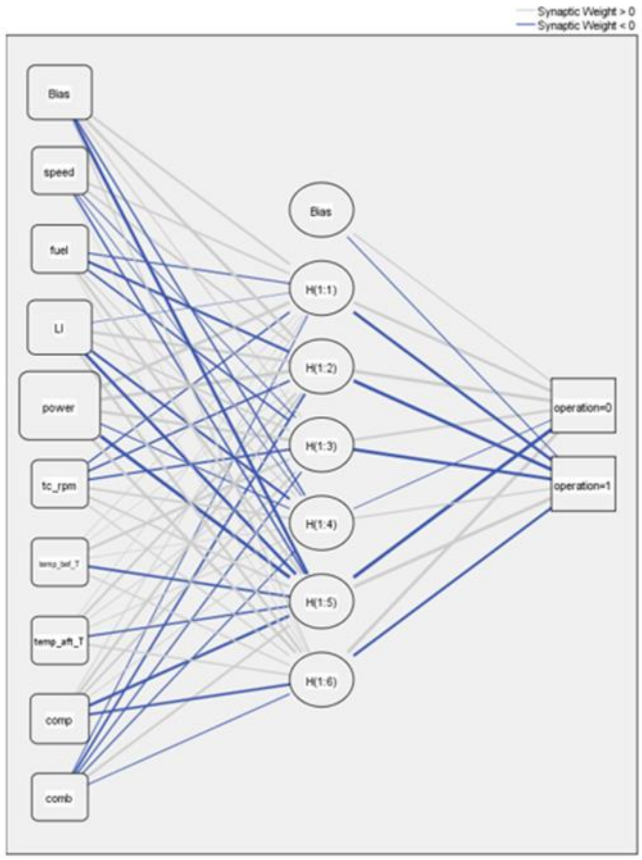

Fig. 3. *Neutral network structure*

Table V presents the results of neural network training and control data classification separately for the two categories of fault operation, good and the overall prediction rate is 100%.

TABLE V. PREDICTION PERCENTAGE FOR TRAINING AND TEST DATA

Classification					
		Predicted			
Sample	Observed	0	1	Percent Correct	
Training	0	106	0	100,0%	
	1	0	94	100,0%	
	Overall Percent	53,0%	47,0%	100,0%	
Testing	0	48	0	100,0%	
	1	0	52	100,0%	
	Overall Percent	48,0%	52,0%	100,0%	
Dependent Variable: operation					

Table VI shows the significance of the independent variables with respect to the dependent variable. The speed parameter has the highest significance with 14.4% and 100% normalization rates.

TABLE VI. EFFECT OF INDEPENDENT NEURAL NETWORK VARIABLES

Independent Variable Importance		
	Importance	Normalized Importance
tc_rpm	,119	82,4%
speed	,144	100,0%
fuel	,107	74,7%
LI	,106	73,9%
power	,123	85,9%
temp_bef_T	,101	70,1%
temp_aft_T	,104	72,2%
comp	,110	76,2%
comb	,086	59,9%

V. CONCLUSIONS

In this work, we investigate the prediction model for good or fault operation of vessels main engine Win GD XDF-72, based on mechanical learning with classification using the Exhaustive CHAID, algorithms and neural networks. In the MLP neural network method it is possible to create a machine performance prediction model with a total of 100% correct prediction for training data and 100% for control type data. Table VII shows the comparison between three methods.

TABLE VII. COMPARISON OF PREDICTION METHODS

Μέθοδος	Ποσοστό πρόβλεψης δεδομένων εκπαίδευσης	Ποσοστό πρόβλεψης δεδομένων ελέγχου
Exhaustive CHAID με split-validation	100%	96.2%
Exhaustive CHAID με Cross validation	99.7%	
MLP με νευρωνικό δίκτυο	100%	100%

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