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Vendor's Quality Management Assurance in Automotive Electronic Products

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***Abstract* — The top factors of economic growth in the Electronic manufacturing are focusing on the "vendor-customer" relationship and identify it as a key factor for sustainable business development. In order to apply the method in practice and establish effective relationships with their customers, companies automate sales and customer service processes with the help of Customer Relationship Management systems, which favor the follow-up of the established processes and their improvement. This research paper proposes methodical tool - System for Monitoring and Assessment in Real Time Database. For facilitating the vendors' risk assessment level process, a Machine Learning Model has been developed in accordance with customized requirements of SMART Database. Random Forest Algorithms is applied for training and testing the proposed Machine Learning Model and a high level of model accuracy has been achieved – to 97% in predicting the three risk levels for vendors – high, medium and low. All the study experiments in this research are made with data, derived from worldwide electronic producer company for automotive industry.**

***Keywords*—Automotive Vendors, Electronic Products, Machine Learning, Risk Assessment, Random Forest Algorithm**

I. Introduction

In recent years, there is a change in the overall business model and business process of organizations in the Electronics field. Manufacturers of electronic components or electro-mechanical products provide a valuable competitive advantage for sustainable development, but standing in front of world material crisis. In order to apply the method in practice and establish effective relationships with their customers, companies automate sales and customer service processes with the help of Customer Relationship Management (CRM) systems, which favor the follow-up of the established processes and their improvement. This leads to optimization of resources and increase of efficiency.

CRM solutions allow management to track the activities of the sales department, to provide better customer service, to manage marketing campaigns, contracts, pricing policies, discounts and more.

The top factors of economic growth in the Electronic manufacturing are focusing on the "vendor-customer" relationship and identify it as a key factor for sustainable business development. Customer-oriented organizations in the Electronic field need a flexible "vendor-customer" relationship management system. That should allow the storage and analysis of various traceability, information, tracking all stages of profitability, quality or delivery performance for the region and market. To ensure a smooth supply and rhythm of production, no less important aspect of the activity is to build long-term stable relationships with suppliers of raw materials. In electronics manufacturing, the required quality level of produced electronic modules as electronic devices and microchips are validated through qualification testing based on standards and user-defined requirements. The challenge for the global electronics industry is that product validation is time-consuming and costly. On other hand the increasing demand and the current lack of materials for mass production in electronics lead to stock shortages, delayed deliveries, and following difficulties to achieve the targets, required for a high level of competitiveness and reliability in Automotive Industry. This paper proposes a methodical tool for overcoming the milestone of the vendor's evaluation procedure in worldwide electronics manufacturing company for automotive and household industry, called in this paper "ComEX". The proposed tool is called SMART database - System for Monitoring and Assessment in Real Time. Machine learning model for solving classification task is developed and applied in the process of vendors' risk assessment level.

II. Vendors' evaluation procedure and SMART database

Automotive industry, especially the electronic components producers are highly dependently of their vendors. In Quality Management Assessment System, the vendors' evaluation and selection is a crucial milestone which overcoming will race the manufacturer into leading automotive positions. All automotive companies work in accordance with IATF 16949:2016 [1] Automotive QMS Standard which replaces ISO/TS 16949 standard. It applies to the design/development, production and, when relevant, installation and servicing of automotive-related products [2]. Nevertheless, each automotive company has the right to implement its own procedure in compliance with the standard for vendors' selection and evaluation.

A. Vendors' evaluation procedure

The process of selection and evaluation of suppliers varies depending on the product on offer. There are several steps to be passed in preliminary checking before their inclusion in the vendors' approved list. The preliminary selection contains *phase of research* and *phase of pre – selection.* Define abbreviations and acronyms the first time they are used in the text, even after they have already been defined in the abstract

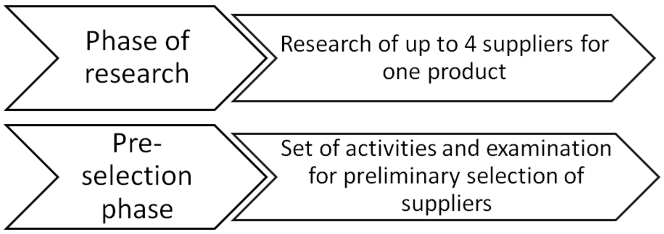

Figure 1. Preliminary Vendors' selection phases of ComEX

The pre – selection phase is applied to all the researched suppliers in the 1st phase. The activities and examinations in this phase vary based on the product and service they are providing. This set includes:
1) Verification of the proposed products and services for their compliance with company's requirements;
2) Purchase of product's sample quantity for verification through operational process;
3) Filling out questioners;
4) In house vendor's audit in order to establish the actual state of the processes and its ability to fulfil the requests;
5) Financial assessment for vendors' reliability and sustainability

In order to assure a sustainable quality delivers of electronic products or services is necessary a periodic reassessment of suppliers to be applied. The criteria for periodic revaluation should be related to the quality of the delivered products, compliance with delivery deadlines, flexible payment schemes, etc. and concern the validity of the cooperation agreement. The reassessment of suppliers implies to the same list of approved vendors, each of which shall be assigned the appropriate assessment according to the specified criteria. This re-evaluation process requires a management system implemented for every category of company's vendors. This Category Management cycle is composed of 5 process steps presented in figure 2.

Figure 2. Re-assessment category management cycle.

The category management perspective of improvement is one of the steps during the vendors' evaluation process in the ComEX company. Together with the development of proposed SMART database system

B. SMART Database

The implementation of developing SMART database is a tool for prediction using already validated key performance indicators for evaluation as the data constructed them is mined in real time process of testing the electronic products. The most common type of testing in the electronics industry—sequentially run electrical multi-parameter tests on the Device-under-Test (DUT). Data mining framework can identify the tests that have strong correlation to pending failure of the device in the qualification (tests sensitive to pending failure) as well as to evaluate the similarity in test measurements, thus generating knowledge on potentially redundant tests. SMART database aims to identify top worst vs. top best vendor's category of the Category Management Cycle. It is the linkage between the following aspects as a part of *Monitoring & Assessment of the Supplier performance:*
1) Supplier appraisal when the incumbent supplier is competing for the renewal of an existing contract.
2) Management of approved supplier lists.
3) Quality management & Evaluation.
4) Scrap & Cost of Non-Quality Reduction .
5) Turn-around incident treatment time management.
6) Risk assessment and live overview.

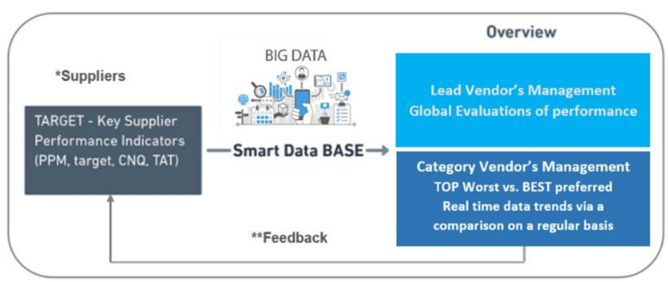

Figure 3. Re-assessment category management cycle
*For the purposes of this practice database the term 'Suppliers' includes contractors for EMS raw material's distributors and manufacturers.
**Feedback for 'performance monitoring' aims measuring, analyzing and managing Key Performance Indicators (KSPIs) as a supplier's ability to comply with, and preferably exceed, their contractual obligations, in accordance with the SQA Manual.

There are six basic steps for implementation of SMART database. Some of them need to be taken in cooperation with other departments (IT and SQA) of the company before put in use, other need to be required as additional information from the vendors. These are the following:

- ✓ Access – online via intranet
- ✓ Interface – home page with menu box
- ✓ Reporting - export a statistic data in excel
- ✓ Criteria and targets – based on the overall performance for last evaluated period
- ✓ Results – options for various visualizations by diagrams
- ✓ Feedback – regular email notification requesting:
  - Corrective actions
  - Continues improvement plan

On the figure 4 the referent architecture of the SMART Database System is presented. It is still a prototype one, but used as a referent one for the Machine Learning Model development.

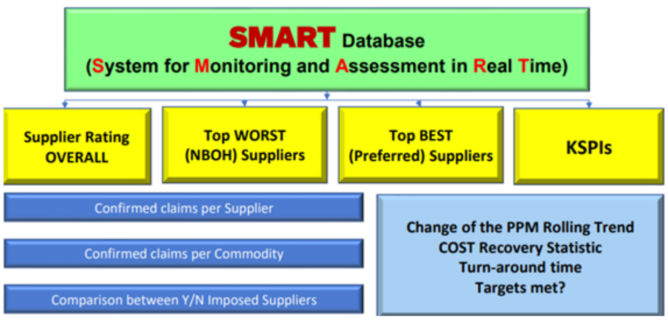

Figure 3. Referent Architecture of SMART Database System

This system represents an intelligent tool for quality assurance management. The idea is to extract data from real-time testing and combining with predefined indicators to perform vendors' overall rating, top worst and top best suppliers and most important KPIs.

As a part of classifying the top worst and top best vendors a machine learning method has been applied by using Random Forest algorithm for classification.

III. RANDOM FOREST ALGORITHM FOR CLASSIFICATION OF ELECTRONIC PRODUCTS VENDORS

As the main goal of implementation SMART database is to enhance the vendors' evaluation procedure by integrating intelligent tool for prediction of new vendor and classified between the rate of three levels – Top Risk, Medium and Low Risk, vendors. For the purpose of prediction model development, a classification task has been solved by using machine learning algorithm Random Forest.

A. Feature Extraction

The features selected for the development of ML model are taken from the vendor's evaluation criteria and could be divided into two groups – quantitative and qualitative features. The table below gives detailed information about the evaluation criteria and the methods how the features are compound and selected.

Table. 1 Evaluation Criteria and scoring methods of the features +customer (in the second row)

	EVALUATION CRITERIA	CRITERIA ON SCORING			
Quantitative Features	Delivered quantity	The total quantity delivered by the vendor for the accounted period			
	Quantity of rejection	The amount of rejected quantity for particular vendor as a sum of rejected by incoming inspection and during production process			
	Peace Per Million PPM (Maximum of 25 point) PPM Value = (Number of confirmed NOK parts for the evaluation period) / (Number of delivered quantities for the evaluation period) X1000000	0 DPPM			25
		1-50 DPPM			20
		51-100 DPPM			15
		101-200 DPPM			10
		201-300 DPPM			8
		301-500 DPPM			5
		>500 DPPM			0
	Number & Type of complaints (Maximum of 25 points) Decreasing of points in case of confirmed supplier claims. The given score is calculated by specific formula as a weighted fraction of numbers of different types of complains. NOTE: No negative score is allowed	C1 (customer complaint)			10
		C2 (ComEX production line)			2
		C3 (incoming inspection)			1
	Cost of Non-Quality (Maximum 15 points)	100% CNQ Recovery			15
		< 100% CNQ recovery			0
	Response Time (Maximum of 20points)	<10 working days to submit 8D report			20
		10< X <15 working days to submit 8D report			15
		16< X <20 working days to submit 8D report			5
		>21 working days to submit 8D report			0
Qualitative Features	Accuracy of documentation/communication (max 15 points)	The score is based on the vendor's analysis report quality.			
	Availability of Product or Service	Risk Level			
		High	Medium	Low	
		5	3	1	
	Supplier Performance Rating	Risk Level			
		High	Medium	Low	
		5	3	1	
	Strategic Partnership	Risk Level			
		High	Medium	Low	
		5	3	1	

The quantitative features consist of a) delivered by the vendor quantity for the accounted period; b) rejected from delivery quantity both from incoming inspection and production lines process; c) PPM (piece per million) – the fraction of total scrapped quantity and total delivered quantity as a million parts; d) number of complains scored by specific know-how company's formula based on three different types of complains; e) cost of non-quality; and f) response time. There are four qualitative indicators used as features for classification dataset, which scoring criteria could be considered as a subjective factor at first sight, but also is calculated very precisely via confidential know-how formula. These features are: a) accuracy of documentation / communication; b) availability of product and service; c) supplier performance rating and d) strategic partnership.

The categorization of the vendors in three levels of risk (high, medium and low) is calculated again using a complicated method that is under company's confidentiality. For the purpose of our study and the needs of this paper it was kindly provided information of full list vendors' classification for the first six months of 2021.

B. Machine learning model methodology

The development of Machine Learning model has passed through four consequence steps, shown on the fig. 4.

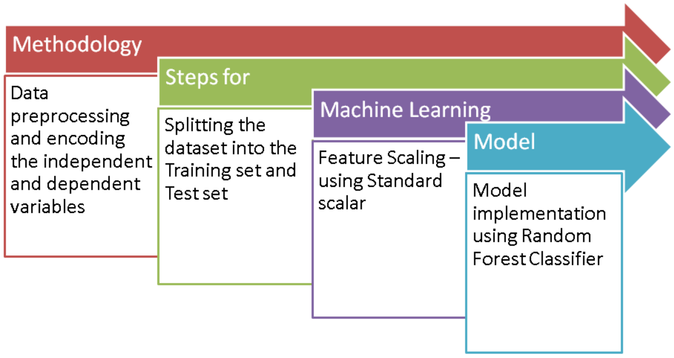

Figure 4. Methodology for ML model implementation

The dataset of preprocessing module is constructed of 10 features (independent variables) described in the previous section, one label feature (dependent variable) which represents our class – high, medium and low level risks and 311 examples of vendors of all categorical electronic products for the first semester of 2021.

Figure 5. Classification Dataset

The ML model is trained with 80% of the dataset and test with the rest 20 %. After the splitting process a feature scaling is applied to the data features, using the method of standardization:

$$\mathrm{Fe}_{\mathrm{stand}} = \frac{Fe - mean(Fe)}{Standard\ Deviation\ (Fe)}$$

where Fe is the value of the every feature.

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In [25]:print(sc.transform(X_test[:,2:]))
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Figure 6. Test data values after standardization process

C. Random Forest implementation and results

Random Forest (RF) is a popular and powerful ensemble supervised classification method [3]. Ensemble algorithms have achieved success in machine learning by combining multiple weak learners to form one strong learner [4].

Due to its superior accuracy and robustness, and some ability to offer insights by ranking of its features, RF has effectively been applied to various machine learning applications, including many in bioinformatics and medical imaging [5]. Random forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model [6]. The reason why this algorithm has been chosen for the building the proposed model is avoiding the model over fitting and no need of hyper parameters' optimization. Random Forest hyper parameters work perfectly both for increasing the predictive power and festers the model.

For building ML model with Random Forest algorithm initially it has been used 10 trees and activation function "entropy" for model quality measurement. These two parameters are very important for the general model evaluation performance. The entropy criterion computes the Shannon entropy of the possible classes. It takes the class frequencies of the training data points that reached a given leaf m as their probability. Using the Shannon entropy as tree node splitting criterion is equivalent to minimizing the log loss (also known as cross-entropy and multinomial deviance) between the true labels yi and the probalistic predictions $T_k(x_i)$ of the tree model T for class k.[7] On the figures 7 and 8 are shown a single tree of the applied RF algorithm (fig.7) and the first 5 trees (fig. 8) of the same algorithm with <<n_estimators =10, criterion = 'entropy'>>.

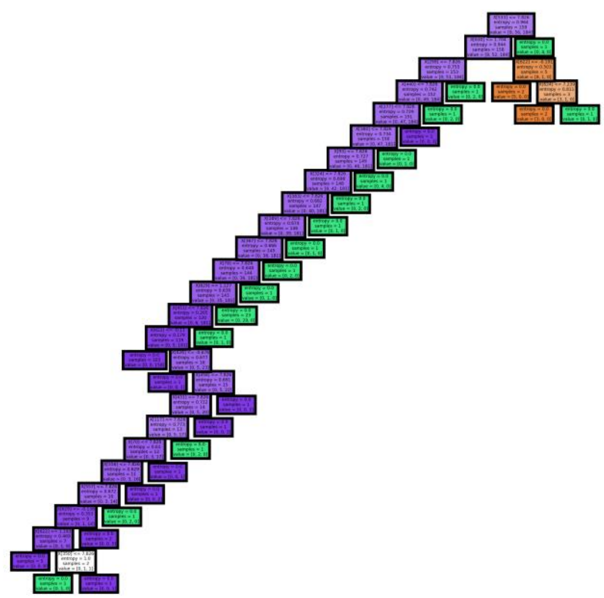

Figure 7. Individual tree of the created ML model with RF algorithm

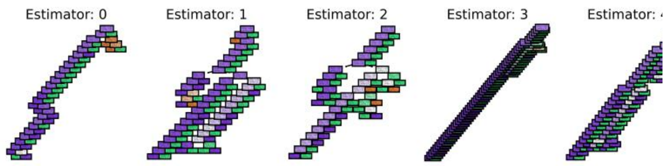

Figure 8. The first five trees of the created ML model with RF algorithm

The best accuracy has been achieved with 100 trees. The initially created model with 10 trees and activation function "entropy" achieved evaluation performance accuracy of 92%. In table 2 are presented the RF model accuracies with different numbers of trees with the one and the same activation function "entropy":

Table 2 ML model accuracy achieved by different numbers of decision trees in the RF algorithm

No of Trees	Accuracy %
10	92
50	94
100	97
250	95
500	94

As there is no rule of the thumb regarding the optimal number of the trees in the Random Forest algorithm, in general the more trees are used the better results, but from the statistics which resulted in table 2 is visible that for every specific case the tuning of the hyper parameters in algorithm is individual. In the fig. 9 are shown the first 10 correctly predicted examples of the model.

Figure 9. Model's correctly predicted examples

Conclusion and Future Work

This research work proposes a System for Monitoring and Assessment in Real Time – SMART Database for evaluation the vendors' quality performance in the automotive industry. It will help both Vendor's Quality Management Assurance and Customer Relationship Management CRM systems. Its implementation in automotive electronic producers' attempts to increase the customer satisfaction and company's performance coefficient by real-time analysis, predicting, preventing shortages, target's follow up, investment planning data overview with its negative and positive trends. Although its implementation carries a lot of technological and economic challenges with the standard adoption and big amount of investments for the companies, the benefits for all the involved parties are uncountable. A Machine Learning model has been developed especially for the customized requirements of the SMART Database by applying a Random Forest algorithm. As the system attempts to grow in time and the amount of data will be continuously pouring out the algorithm need to be enhanced which is a discussion for future work. Proposed in this paper Random Forest machine learning model is going to sophisticated and two more algorithms – ANN and Deep Learning will be implemented and tested in the ML model of SMART Database.

Acknowledgment

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