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An Application of Machine Learning for Evaluating Geometrical Relations in the Mechanical Integration Process

Master's thesis in Product Development

Volvo Cars | CAD and Mechanical Development

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Master's Thesis 2019

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Gothenburg, Sweden 2019

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Abstract

The mechanical integration process at Volvo Cars is used for balancing geometric requirements and solutions to ensure correct packaging of all components in the vehicle. To increase efficiency in the task of validating geometrical relations, the application of machine learning is investigated.

A study of the users' behaviours is conducted through 15 interviews. Five concepts are identified as possibilities for utilizing machine learning. In addition, examination of machine learning's potential is performed by iteratively analysing data from historical integration validation. This process results in the development of a model able to predict critical geometrical relations with an accuracy of approximately 75%. The model is basis for suggestions of possible applications.

Users are found to utilize the mechanical integration process inconsistently. Hence, the data lacks certain vital pieces of information to be fully functional. Furthermore, the mechanical integration process serves as an opportunity to give the users awareness of the geometrical environment. If machine learning were to replace the human involvement the geometrical awareness will be lost.

Since this project is delimited to use historical data that is available today the results only show what is possible in the current state. The results indicate that machine learning has the potential to be applied in the mechanical integration process. However, the utility is questionable due to the needs not aligning with the current possibilities. Therefore, the recommendation is to not apply machine learning in mechanical integration process today.

If Volvo Cars is able to change the users' behaviours, mechanical integration process's interface or both, data can be collected making it possible to utilize a machine learning model better by aligning the needs and the possibilities in the future.

Keywords: Mechanical integration, machine learning, geometric relations, product development

Acknowledgement

This Master’s Thesis has been conducted in collaboration with Volvo Cars. Throughout the project’s proceeding many people have helped us. We would like to thank all people who contributed with help, knowledge and insights to this project. Also, we would like to show our gratitude to all the interviewees participating and taking their valuable time to talk to us.

We want to give special thanks to:

Our supervisor Daniel Rapo, at Volvo Cars. Thank you for your guidance and support throughout the whole process of this thesis.

Our supervisor and examiner Erik Hulthén, at Chalmers University of Technology. Thanks for your help regarding the approach to this project and guidance regarding the report.

Erica Petersson and Marcus Ronneback Thomson, November 2019

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List of Abbreviations

AGI	Artificial General Intelligence
AI	Artificial Intelligence
AI HLEG	High-level expert group on AI put together by the European Commission
CAD	Computer Aided Design
CP	Checkpoint
DE	Design Engineer
DI	Design Instance
DR	Design Representation
DPA	Digital Pre-Assembly CAD
MIE	Mechanical Integration Engineer
MIP	Mechanical Integration Process
ML	Machine Learning

1 Introduction

The introduction chapter describes the background and the underlying reasons for the issue investigated during this project. The aim of the project is presented along with the objectives which includes hypotheses that are addressed in order to complete the project. Finally, the chapter includes the project's limitations.

1.1 Background

This thesis work is carried out within the operational development team named CAD & Mechanical development, which is a part of Volvo Cars' Product Creation division. The department consists of 24 engineers responsible for CAD and Mechanical development methods at the research & development organization at Volvo Cars.

Volvo Cars is engaged in research and development of premium automobiles and solutions related thereto. To maintain their position in today's competitive industry, efficient product development is performed on a daily basis by thousands of engineers in varying areas. Standards, business rules and legislations are adopted into the development programs regularly. As the market is changing with rapid pace, new designs and ideas are continuously implemented into the design of the car. New revisions of the components are issued frequently. Since each geometry has an interface towards, at least, one surrounding geometry, a change in design rarely goes without affecting others. It is time-consuming and complex to coordinate the teams and every engineer cannot possibly inform each stakeholder about every design change.

To combat these issues, a software type called Mechanical Integration Process (MIP) is used. The system assists the engineers by continuously gather information of potentially problematic geometrical relations between components. MIP runs automatically every night to ensure that the information is up to date. The system detects and gathers mechanical geometrical relations and clashes upon pre-entered values. Subsequently, it is up to Design Engineers (DEs) and Mechanical Integration Engineers (MIEs) to validate the integration if it is OK or Not OK (NOK).

MIP points out if there is a relative distance between components that diverge from a set target value. The system also detects if there is contact or penetration between the geometries. These types of connections are called relations in MIP. In the list of relations, the engineers validate each entity with OK/NOK based on a manual examination of the geometries and its relations in a 3D environment. The validation is a time-consuming task since it requires a lot of waiting for the 3D geometries to load and a thorough visual assessment. Typically, the engineers must validate a large quantity of relations and a lot of redundant work is common.

To be more efficient in the time-consuming task of validating geometrical relations, Volvo Cars is looking for new ways to ease the workload of the engineers by applying Artificial Intelligence (AI) that can carry out decisions based on data of historical events. Large sets of data have been collected throughout several years from MIP. Thus, a task of this sort is arguably suitable for AI and more specifically Machine Learning (ML), as the algorithms improve their performance as the size of the data set increases (What Is Machine Learning?, 2019). Although, thorough investigations in the field of ML and the usage of MIP must be conducted before conclusions of the potential with such a solution can be made. Hence the reason for this thesis.

1.2 Aim

The purpose of this master's thesis is to investigate if there is any possibility to apply ML in MIP to reduce manual workload and become a pro-active solution that detects and validates potential issues early during the design development.

Therefore, the aim of this master's thesis is stated as follows:

By analysing the user behaviours and needs as well as the available historical data, verify and specify the potential for applying machine learning in the mechanical integration process at Volvo Cars.

1.3 Objectives

To fulfil the aim, three hypotheses are stated. These will act as the basis for the development and investigation during the project. The hypotheses are as follows:

1. *There is a potential for easing the work of MIP users by applying ML.*
2. *Geometrical relations can be evaluated by an ML model based on available data from MIP.*
3. *The application of ML in MIP can be executed with ethical, risk and environmental aspects taken into consideration.*

1.4 Limitations

The Master's Thesis is carried out for 20 weeks, starting the 10th of June 2019. In addition, the project follows the guidelines provided by Chalmers University of Technology regarding how a Master's Thesis should be conducted.

The two students who are conducting this Master's Thesis have limited knowledge within the field of programming. Therefore, the project's outcome is limited to a theoretical ML model. This means that no focus lays on programming a functional ML model. Instead, the programming done is used for creating a theoretical ML models for investigating the potential of ML. Furthermore, the possible application of a developed ML model is limited to MIP at Volvo Cars. Thus, only accessible data from Volvo Cars' own databases is used for the investigation. Since the application of the theoretical ML model is limited in this way, the project is only considering the application of narrow AI.

2 Workflow

This chapter aims to describe the workflow of the project. It includes an overview of how the project is planned and executed along with a short description of used methods.

This Master's Thesis is conducted with a workflow combining a traditional waterfall process with an agile approach, which implies an incremental and iterative work sequences. Thereby, necessary actions taken have evolved throughout the project's proceeding. Using a partly agile working process is motivated by Volvo Cars' initiative of moving towards an agile organization. Also, since the project is within the field of ML and partly software development, an agile approach is considered appropriate (Manifesto for Agile Software Development, 2019). For planning the work and progress of the thesis, a tool called Trello is used (Trello, 2019). Trello is used to create a backlog where all tasks of the project are stored. New tasks are added to the backlog each week, for keeping it updated as the project proceeds. As soon as a task is initiated, it is moved to the ongoing log and consequently as a task is completed it is archived. Hence, the progress of the project is easy to track. The workflow throughout the project is illustrated in Figure 1.

The workflow initiates with a pre-study for gaining knowledge within the domain of MIP and the fields of AI and ML. The pre-study consists of a literature review, the participation in the course elements of AI and internal training at Volvo Cars (University of Helsinki, 2018). Consequently, the workflow is divided into two main parts; User analysis and Data Analysis & Model Enhancement. The user analysis strives for mapping the users' behaviours in MIP and determine the opportunities for applying ML in MIP. Data analysis & model enhancement is performed for investigating the possibilities of using the existing data in MIP for development of an ML model.

The two parts are performed in parallel. However, the user analysis follows a classic waterfall process while the part including data analysis & model enhancement is performed in iterations. The user analysis starts with data gathering by interviews. Then the data is interpreted and analysed for result. The part of data analysis & model enhancement is iterated five times. An iteration starts with extracting data and creating a dataset. Following, the dataset is cleaned and analysed. Finally, an ML model is created, and a resulting test of the model is done.

The two parts' results are concluded upon in separate chapters and later summarized into one converged result. Consequently, the report's ethical aspects are considered along with a risk analysis. This leads to a discussion, focusing on the thesis' converged result and the aim of the thesis. Finally, a conclusion of the findings and recommendations for the future is presented.

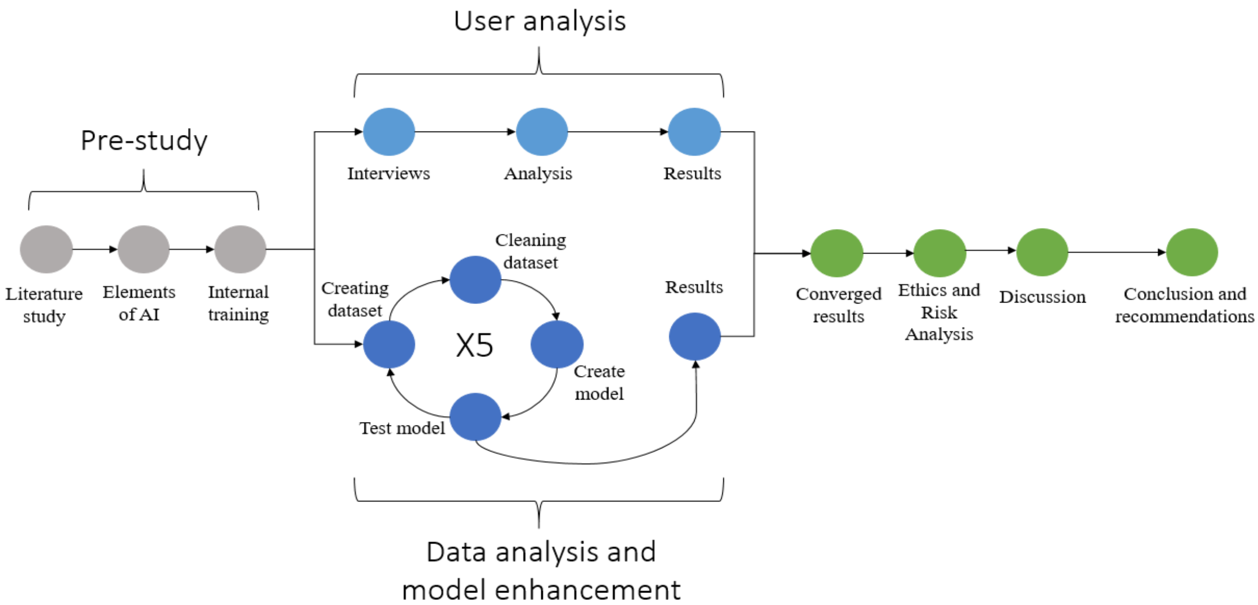

Figure 1 Workflow of the project.

3 Theoretical Framework

The theoretical framework chapter intends to introduce the topic to the reader. The basic terminology of the topic is presented along with the theoretical framework and basics of AI and ML. Also, a general description of MIP is presented. The chapter is summarized by stating opportunities and barriers for applying ML.

3.1 Artificial Intelligence

A precise definition of AI does not exist since it is constantly redefined depending on new technology. Currently, it can be defined both as an artificial life-form replicating human intelligence but also as any technology that can process data depending on whom is asked (University of Helsinki, 2018). Although, AI can be summarized into two parts, one where the function of AI is described and one where the research field of AI is described. Therefore, shortly AI is defined as intelligence ascribed to a computer-based system but also the field of science focusing on the creation of intelligent behaving computer systems (National Encyklopedin, 2019).

AI as a field of science was not established until 1956, when the Dartmouth-Conference was held. At this conference a proposal for future research about AI was presented (J. McCarthy, 1955). However, the concept of machines with the ability to think was already presented five years earlier by Alan Turing. Turing published in 1950 his ideas presenting machines with the ability to think humanlike. The most prominent in his ideas was the Imitation Game. The Imitation Game is a concept of a machine pretending to be a human. If this imitation cannot be detected by an interrogator it is said that the computer has reached human-level intelligence (Turing, 1950). Although, the ideas presented by Turing led to the philosophical question of how to define human intelligence. However, for the sake of research, this question is redundant based on the statement:

"It is unlikely to have any more effect on the practice of AI research than the philosophy of science in generally has on the practice of the science" - (McCarthy, 2006).

Since the beginning of AI as a field of science, the implementation and its applications has broadened. With a constant increase in digitization and automation, AI has been rapidly developed. The main driver for this development has been the emergence of Big Data analysis (U.S Government, 2016). Moreover, AI has become a common occurrence in the daily life of the everyday person for example through applications in smartphones. In addition, the field of AI is a highly hot topic in the automotive industry where several major car manufacturers, Volvo Cars included, have moved into research about autonomous vehicles for a safer, more sustainable and convenient mobility (Volvo Cars, 2019).

AI is a subdiscipline of computer science. Consequently, there are more subdisciplines within AI, such as ML and deep learning. The relations between the subdisciplines are illustrated in Figure 2. A prerequisite for AI and its subdisciplines is the access to data. Data in this case refers to images, texts, numbers and sounds. The data is subsequently used to teach the underlaying algorithms to find patterns, plan, draw conclusions, solve problems and gather new knowledge. Furthermore, AI is divided into Artificial General Intelligence (AGI) or narrow AI. AGI refers to fully human behaviour, meaning that the machine can perform any intellectual task, whilst narrow AI refers to AI that only performs one task. Narrow AI is currently the one where the development has come the furthest and has main applications such as detect, monitor, predict and interpret. (University of Helsinki, 2018)

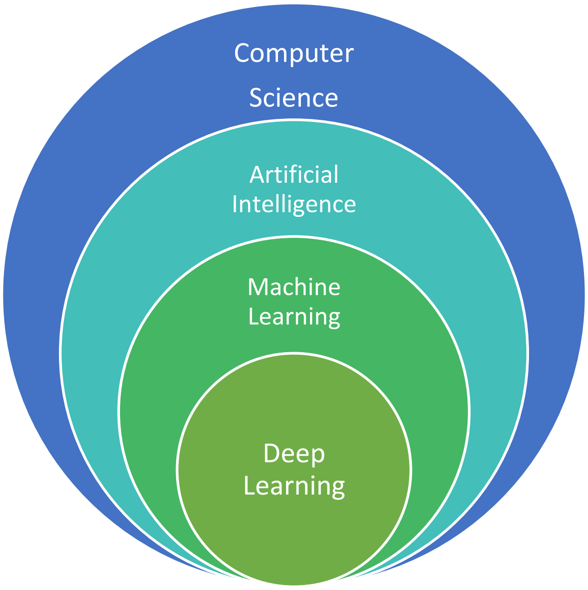

Figure 2 The related fields of AI.

3.2 Machine Learning

ML, which is a subdiscipline of AI, refers to a data analytics technique that includes teaching computers how to learn from experience. ML models can learn directly by accessing data and are improving their performance as the amount of data increases. Furthermore, ML models have no need of predetermined equations instructing the operations since it has the ability to learn from experience (What Is Machine Learning?, 2019). Instead a learning algorithm is used so that the ML model progressively improves its performance. ML is based on statistics and commonly used methods within ML are using regression algorithms as a basis, but a various number of methods are applicable within ML depending on the problem at hand. Therefore, ML can be broken down into different areas including different methods.

Firstly, whether the ML is within the area of supervised or unsupervised is declared. A supervised ML model includes a known set of input data and known responses to the data, which makes up the outcome. The ML model is then trained with this data in order to be able to predict the correct outcome when encountering a new dataset. Supervised ML is often used when the problem is to determine the classification or label the outcome, which is the case in image recognition for example. In the cases of supervised ML, methods such as classification and regression are used (University of Helsinki, 2018). Regarding unsupervised ML, the ML model is used for exploring data and to find hidden patterns or groupings that are not obvious for a human being. The unsupervised ML uses data inputs without any known response, in contrary to supervised learning. The unsupervised ML then creates a model for predicting an outcome. The method used within unsupervised learning is clustering. Consequently, unsupervised ML groups and interprets data using only input data whilst supervised ML develops a predictive model based on both input and output data (What Is Machine Learning?, 2019).

In order to perform each of the methods mentioned: regression, classification and clustering, several algorithms can be used depending partly on the accessible data and partly on the problem. The breakdown of ML and the hierarchy of areas and methods are illustrated in Figure 3. This project is focusing on the area of supervised learning.

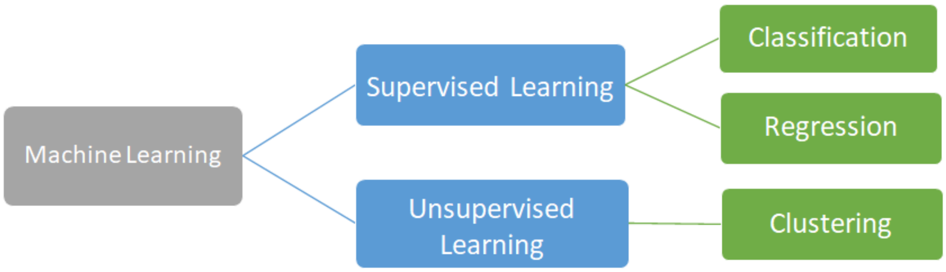

Figure 3 The breakdown and hierarchy of ML.

For creating a supervised ML model certain steps must be taken. Firstly, training data must be prepared and organized into a dataset in order to be functional. For an ML model to work, the dataset must include predictors and a response. The number of predictors can vary but each row of different predictors must be represented by one response. Furthermore, in the case of using a regression model, the response must be a numeric vector. Whilst for classification the response can be either a numerical vector, characters or a logical vector (Supervised Learning workflow Algorithms, 2019). Then, an algorithm is chosen among, for example classification trees, regression trees or nearest neighbour classification. Although, the choice of algorithm is not obvious, and many different algorithms can be applicable to the same problem. Thus, there is a need for evaluation.

The algorithm is consequently trained into a model with the training data. After the training, the model is tested with a new dataset called testing data for validating the performance. The testing data is data the model have not encountered before. This is done in order to assess the performance in terms of accuracy of the model. The testing results in predictions made by the model. Based on these results the model is either ready to make predictions upon live data or must be re-developed. A reason for re-development can be the instance of over-fitting. Over-fitting means that the model works very well on the training data but do not perform as well on the testing data. (Workflow of a Mchine Learning Project, 2019) The described steps for creating an ML model are illustrated in Figure 4.

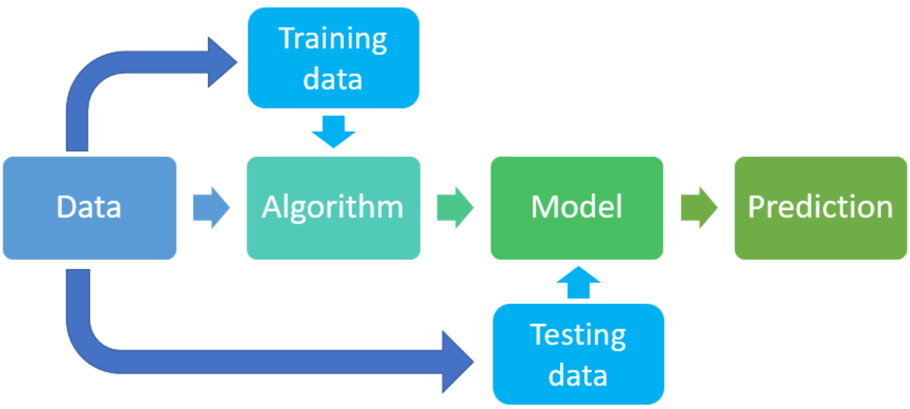

Figure 4 The steps for creating an ML model.

3.2.1 Tree Algorithms

A commonly used algorithm within ML is the tree algorithm. Consequently, the tree algorithm will be of main use within this thesis. The algorithm is based on a decision tree where decisions are hierarchy ordered leading to one outcome. Furthermore, the algorithm is used within supervised learning. Hence, the outcome is either a classification or regression prediction (Gupta, 2017).

The building of the algorithm includes two steps. Firstly, the so-called induction is made. During this step, the tree is built. Thus, all decisions and their hierarchy levels are determined. This is all based on the available dataset. The predictors act as inputs at each decision point in the tree. And the response will be the predicted outcome, either as a numerical vector if regression is used or as a class if classification is used. At each decision point, a split is made, meaning that the algorithm decides to proceed depending on the input predictor. Thus, it is of importance to design the tree in an effective way so splits only occur when the algorithm's decision is accurate. The consequence of an ill designed tree is over-fitting. The second step included in the building of a tree algorithm is pruning. This step implies the removal of unnecessary splits in the tree. The goal is to make the tree as compact as possible while keeping the prediction accuracy. The reason for pruning is the tendency of over-fitting when using tree algorithms (Pingel, 2019).

Reason for decision trees being a popular algorithm to use within ML is that little data preparation is needed in comparison to many other algorithms. However, even in the case of using tree algorithms, predictors are always in needed to be tweaked for fitting the algorithm (Seif, 2018).

3.3 Mechanical Integration Process

MIP is an integration tool used by DEs and MIEs at Volvo Cars. It is used to analyse relations between components of the vehicle. In MIP, the users can see the relations of their component and detect the geometrical limitation of their component. MIP is an expansion and update of the older system called DPA[0]. The main difference between the systems is that MIP works at a higher level in the product structure. DPA[0] compares relations of components while MIP compares relations at assembly level, which leads to a better overview for the users. MIP also accommodates a modern and graphically improved user interface in comparison to DPA[0].

Before data enters MIP, it is first created, computed and extracted. It starts with the creation of a 3D component in CAD. Components created with the CAD-standard structure at Volvo Cars is called Design Instance (DI). The DIs are containing the Design Representation (DR) which refers to the geometrical representations of a component. Moreover, the DR comprises the bodies of the DI, therefore a DI can consist of multiple DRs. Furthermore, each DI is connected to a project through the software Teamcenter. Also, the DIs are classified into an ART, declaring to which system of the car it belongs to. The total number of ARTs within a vehicle is approximately 50.

Every night, a software from Siemens called Integrated Clearance Management (ICM) runs, which calculates the relations between components by measuring the distance between DRs of different DIs. ICM is detecting whether there is a penetration, contact or distance between the DRs. The relations are shown in Figure 5.

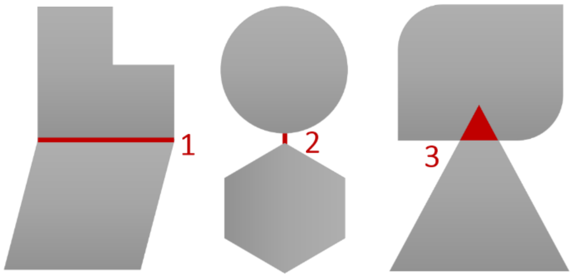

Figure 5 The three types of geometrical relations in MIP. (1) Contact (2) Distance (3) Penetration

Due to the time-consuming process of calculating all relations between DRs, a matrix called the distance target matrix is used for limiting the number of calculations. Predefined values are included in the matrix declaring a target distance between ARTs. Thus, if two DRs having a distance less than the target distance, the relation is included in ICM's calculations. On the other hand, if the value exceeds the target distance, the relation is neglected. For example, if two DRs of different ARTs has a distance between each other of 4 mm and the target distance is 5 mm, the relation is included in the calculations. Furthermore, the target distances are set in such a way that ARTs located far from each other in the vehicle are having a greater target distance than ARTs located close to each other. Due to confidential reasons the distance target matrix and the ARTs cannot be shown as whole. Although, a schematic version is shown in Figure 6, displaying the principles of the distance target matrix.

	Electronics	Lightning	Interior	Powertrain	Exterior Roof	Exterior Floor	Exterior Sides	Exterior Front	Exterior Back
Electronics	10								
Lightning	5	5							
Interior	5	5	5						
Powertrain	10	20	25	5					
Exterior Roof	10	10	25	25	5				
Exterior Floor	5	15	20	10	25	10			
Exterior Sides	10	10	15	25	15	15	10		
Exterior Front	15	5	25	5	25	10	10	5	
Exterior Back	15	5	25	25	15	15	10	30	5

Figure 6 Schematic distance target matrix. Values in mm.

After ICM finishes the calculations, the detected relations are transferred and stored into the Clearance Calculation Data Base (CCDB). Finally, the data stored in CCDB is translated into business values such as checkpoints (CPs), relations and sub relations though Extract Transform Load (ETL) and extracted into MIP. However, the data exposed in MIP is supplemented by the Graphical User Interface (GUI). Since the user of MIP are evaluating the CPs the GUI adds data which updates each CP within MIP. The whole data transformation from CAD to MIP is shown in Figure 7.

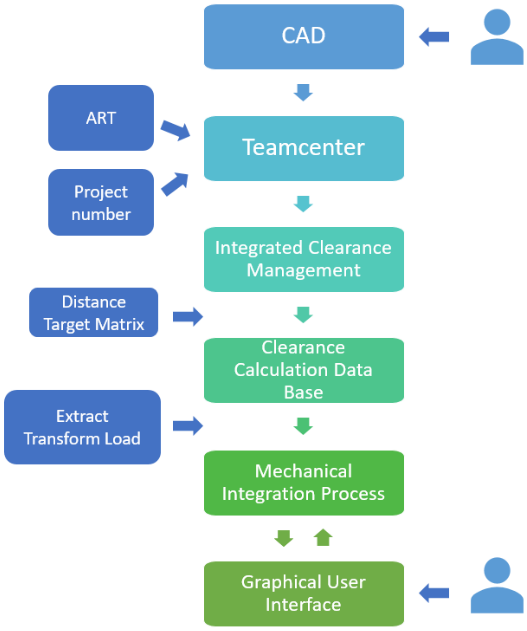

Figure 7 Description of how data is transformed from CAD to MIP.

Since ICM is running every night, MIP is also updated every night. Thus, new CPs are created when DIs are added but also when a DI is visually changed in a project. The CPs and its underlaying relations are needed to be validated to ensure the correct integration of DIs in the vehicle. It is up to MIEs to validate the geometrical relation on CP level whilst it is the DEs responsibility to validate at a relation level. The structure of a CP is illustrated in Figure 8. If a CP or relation cannot be validated, actions must be taken. In MIP the function of creating issues are included for emphasising that validation is not possible. With this function, MIEs can classify a CP as an issue and give it a rank of urgency. Furthermore, DEs can create an issue on relation level indicating that the DI or the DR must be changed.

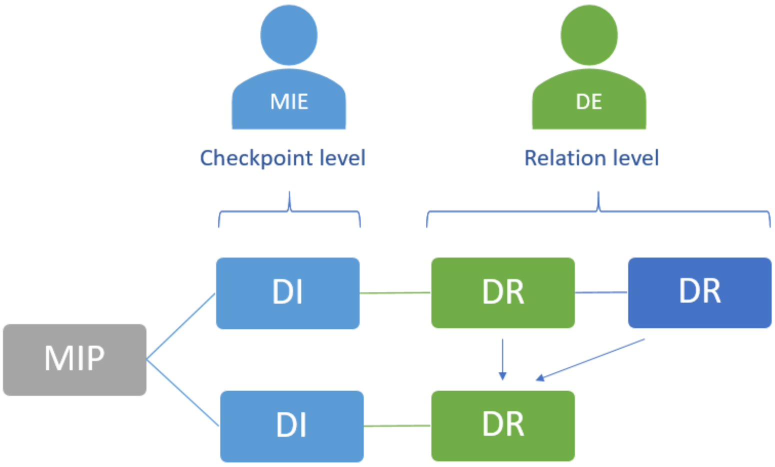

Figure 8 The checkpoint structure in MIP.

MIP is used in all projects regarding the vehicle and powertrain at Volvo Cars. Although, for easing the mechanical integration and dividing the responsibility of CPs, the vehicle is divided into seven blocks. Thereby, MIEs are only working on the integration of DIs within their block. The division of blocks are illustrated in Figure 9. Furthermore, DEs are only working with CPs with DIs that belongs to their ART. Thus, the CPs within MIP can be filtered both by seven blocks and approximately 50 ARTs. However, the number of CPs and relations are vast and means a lot of work for both DEs and MIEs.

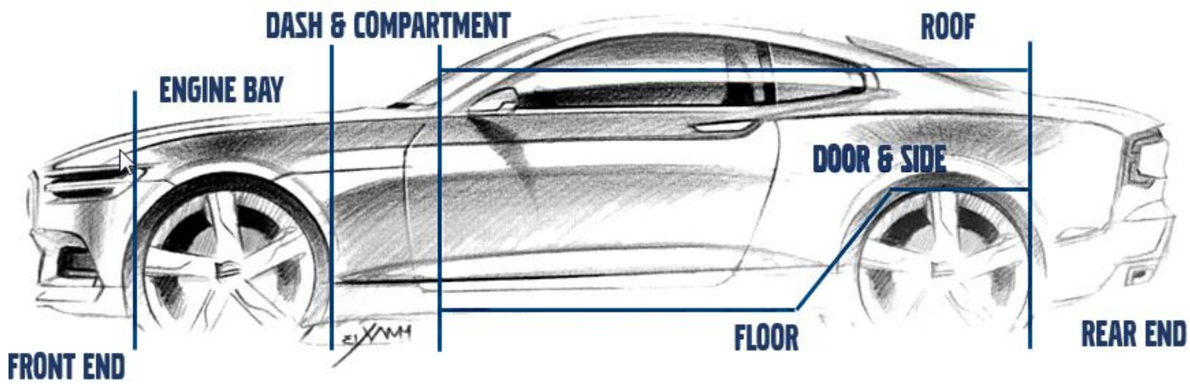

Figure 9 The seven blocks of a Volvo Vehicle.

3.3.1 Opportunities for Machine Learning in MIP

With the increasing digitalisation, great amounts of data are automatically generated. The constantly swelling amount of data paves the way for applying AI in many ways. The usage of AI in the case of MIP at Volvo Cars may be an opportunity to take advantage of data regarding previously taken decisions of geometrical relations. A successful implementation of ML implies time reductions since it can take decisions based on historical data of decisions and eliminating a lot of manual work. Furthermore, DEs and MIEs would not have to validate a large number of CPs. Since the validation of CPs is based on several parameters such as the block, ART, distance between DRs, material and the type of DI; it paves the way for using an ML model to predict a validation class. Consequently, CPs that are considered redundant can be filtered and evaluated without the intervention of DEs nor MIEs.

In addition, the data in MIP is constantly growing. This implies that the dataset is increasing every day, meaning that an ML model can constantly improve its performance by learning from more data. Furthermore, there are possible opportunities of including risk analysis of problematic areas in MIP. Meaning that an ML model possible can detect geometrical relation problems in beforehand. This opportunity implies not only benefits for the DEs and MIEs working with MIP but also a more time-efficient project flow since problems can be proactively prevented.

3.3.2 Barriers for Machine Learning in MIP

Challenges with applying an ML model in MIP includes the question of responsibility. In the current situation, the validation of the geometrical relations is the DE's responsibility. Any decisions leading to errors can be traced back to the person responsible. However, if the decision is made by an ML model, the question of who to held responsible for a faulty decision arises. Consequently, there is a challenge with assigning the responsibility for a faulty decision made by an ML model.

Furthermore, barriers include ensuring that the ML model learns the right things in order to take the right decisions. This implies challenges with the data and that the data should not be biased. In addition, factors such as legalisations, safety and ethics must be considered by the ML model to be used as a sustainable tool. Furthermore, the parameters that acts as basis for the human decision whether a geometrical relation is classified as OK or NOK must be determined and included in the data in order for the ML model to make rightful decisions. Thus, the behaviour of DEs and MIEs must be tracked and determined in order to find the right parameters.

A prerequisite for an ML model is the access to adequate data. Historical data of the procedures in MIP must be gathered and extracted. In addition, the data must be applicable to an ML model meaning that the data includes both predictors and response. Therefore, the quality and performance of an ML model are directly correlating with the quality of the data at hand. The data must also be split into two entities, one for training the model and one for testing the model. Moreover, the risk of overfitting an ML model may occur.

4 User Analysis

In the user analysis chapter, an analysis of how MIP is used by DEs and MIEs is performed. The purpose is to track the users' working path, habits and thoughts when using MIP. Thus, finding the opportunities for applying ML. Data is gathered through interviews and the data is summarised with the KJ-method. An analysis of the data is performed, and is divided in two main parts, one for MIEs and one for DEs. Consequently, an evaluation of the possibilities to applying ML in MIP for easing the work of DEs and MIEs is presented.

4.1 Data Gathering and Analysis Method

In order to understand the users' behaviours and their needs, in-depth interviews with a duration of approximately one hour are used. A semi-structured interview method is used, meaning that predefined questions with possible follow up questions are asked. The questions asked can be found in Appendix A. The interviews are held face to face and the format is formal but leaves room for probing and enabling the interviewee to form one's thoughts and statements. Furthermore, a computer with the MIP application is used as a mediation tool. With this mediation tool discussions can evolve, and the interviewee can fill out their answer with practically showing their way of work.

Since both MIEs and DEs are users of MIP, people from both categories are represented in the selection of interviewees. In total, 15 interviews are conducted. The distribution of interviewees is 10 DEs and 5 MIEs. The reason for interviewing more DEs than MIEs is simply because the number of DEs at Volvo Cars is significantly greater than the number of MIEs. This, since each block have only approximately four to six MIEs. The interviews are complemented with attendance and observation of a mechanical integration meeting where MIEs and DEs meet up to discuss integration problems.

For summarizing the interviews, the KJ-Method is used. Therefore, each interview is reviewed and statements from each of the interviews are extracted. Subsequently, the statements are sorted into categories enabling a visualisation of the answers. This leads to a better overview where the main aspects easily can be pointed out (Spool, 2004). The analysis of the gathered data is presented in the following chapter and the result of the KJ-method are found in Appendix B.

4.2 Mechanical Integration Engineers

Within MIP, the MIEs main responsibilities are to balance geometric requirements and solutions during the development. It is also to integrate the geometric system and make sure of correct fit of all components throughout all variants of the vehicles. The task includes informing and coordinating the DEs when they design components which is placed in close proximity to or overlapping another component. The risk of overlapping geometries is especially high when there are multiple variants or when large changes are made in the design of the car. Also, requirements from safety, legislations, repairability etc. are included in their assessment of the mechanical integration.

The MIEs work within the limits of its block in the cars. If a geometry stretches over one or more blocks limits, it is typically divided between MIEs in the respective blocks. Every block has typically four to six MIEs. In some rare cases a geometry is located precisely in between the blocks of the car. Such components lack block belonging in MIP and thus do not appear in any list when the MIEs look for new components. For that reason, MIEs must actively look in the system to find components of this type.

4.2.1 Mechanical Integration Engineers' use of MIP

MIEs works mainly at the CP level in MIP. Thus, the MIEs do not always check the integration at relation level, but rather the integration of DIs at CP level.

The first step in the MIEs MIP work is to assign newly created CPs to owners. Typically, the MIE is responsible for all CPs in his or her appointed projects within the block. To find newly created CPs a filtration function is used that reorganizes the CPs with new ones at the top. In that way, all CPs within a specified project and block are identified. The new CPs are marked with NEW, which indicates that it lacks ownership in MIP, typically because a new component has been added or altered in the car. When ownership is assigned, the CP will appear in the MIEs own list of CPs and should normally from that point be continually checked by the person claiming ownership until the end of the project. The status of the CP also switches from NEW to OK as well as changes colour from white to green.

MIEs visually analyses each of its CPs in turn to ensure that no problem with the integration is unnoticed. It starts with the MIE loading the CPs' geometry into a visualisation software, called TCVis, directly from MIP. When TCVis is opened, both the component and its surrounding neighbours are displayed with its current positioning in order to enable study of their relative integration. Well inside of TCVis, parts can be added to the view for a more extensive visual inspection. An important piece in the MIEs work is to ensure the packaging of components in all variants of the car. For that reason, the MIE often loads the entire geometry of all car variants into TCVis at the same time. Thus, problems with for instance rare combinations of components are detected and correct integration can be assured throughout the entire set of variants. However, some MIEs prefer to inspect the geometries directly in CATIA. This since their personal preference are that CATIA is a more convenient tool than TCVis. An important part of the MIEs work is to ensure the packaging of components in all variants of the car. For that reason, the MIE often loads the entire geometry of all car variants into TCVis at the same time. Thus, problems with for instance uncommon combinations of components are detected and completely correct integration can be assured throughout the entire set of variants. However, some MIEs prefer to inspect the geometries directly in CATIA. This since their personal preference are that CATIA is a more convenient tool than TCVis.

Using MIP brings several benefits for the MIEs. It has been stated by the MIEs that MIP entails an overview of the geometries. The system also helps with keeping track of the project status and making sure that the project has the correct speed of problem solving. It helps MIEs avoid having to remember a lot of information. MIP is also used as a scorecard that can be used to keep track of the execution of activities by the DEs and to monitor the consequences arising from these. This is archived by adding so called issues to CPs.

4.2.2 The Issue Function

If a problem with a CP is identified, the MIE creates an issue to notify the involved individuals. The issue usually contains an explanation of the problem and possibly a suggested solution. It has a follow-up date by which the issue should preferably be solved by the affected DEs. The issue is assigned a risk level of either one, three, four or five (excluding number two) that is replacing the status of the CP. The risk levels are explained in Table 1. This means that the status of a CP changes from OK to a given risk level indicating the urgency of the identified problem. The column where the risk level is seen is illustrated in Figure 10.

Table 1 Risk level explanation.

Level	Set by	Explanation
K1	DE	Issues set by DEs to make DE of counterpart and MIEs notified of an issue regarding the integration.
S1	MIE	Well-planned solution ready, only the model update is required.
S3	MIE	More difficult problem, but the direction to solve the problem is identified.
S4	MIE	No problem solutions available right now.
S5	MIE	No problem solutions available, and a serious impact on the product is predicted (Rarely used).

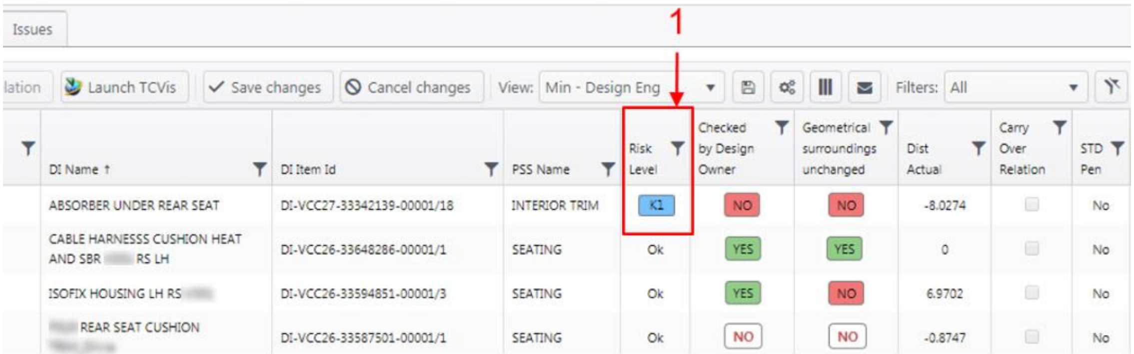

Figure 10 MIP's interface. (1) Risk level column.

The MIEs plan and lead mechanical integration meetings where issues with higher level of risk is discussed. In these meetings, DEs, MIEs and a variety of people with other positions get together to sort out problems and find solutions. The format of meeting face to face and discuss solutions with experts from the affected areas is considered the best for these kinds of issues. If someone cannot join the meeting Skype is normally used as a compliment. The MIEs brings counterparts together in this way in order to handle cases where the responsibility, actions or problem is not completely clear.

4.2.3 Mechanical Integration Engineers' Evaluation in MIP

The MIE manually inspects the relation of the geometries at CP level in TCVis. If a relation is deemed incorrect, it gets an issue. Normally this inspection requires knowledge of the block and the interplay between the components. Some experienced MIEs can even tell were issues will arise beforehand. A large number of parameters is however considered when the MIEs asses the relations. Inputs from the design department, crash test results and internal tolerance standards are some examples. Furthermore, requirements for assembly, corrosion protection and knowledge about necessary play in moving parts are vital pieces of the evaluation.

4.3 Design Engineers

DE's foremost task is to design components. The task includes drawing components that meet requirements. Therefore, DEs must take many aspects into consideration when designing, such as safety, heat transfer, manufacturability and material properties. Consequently, DEs must have a holistic view and knowledge in many different areas. However, at Volvo Cars DEs are allocated to work in ARTs. This limits the area of a vehicle that a DE is working on and enables the DEs to focus on a few components with similar constrains and requirements.

The creating and designing of DIs are done in the CAD software CATIA. Consequently, the DIs created are assigned a project number and a location within the vehicle through Teamcenter. The design process also includes the assurance of geometrical fit of the DE's component. Therefore, the DE must be aware of the nearby geometrical surrounding.

4.3.1 Design Engineers' use of MIP

MIP is mostly used as a complement for checking the surrounding geometrical environment by DEs. It is claimed that most of the geometrical evaluation is already done in CATIA. However, MIP is used as a tool to assure nothing is missed. This explains the non-frequently usage of MIP. Most DEs state that they use MIP only when the project grows closer to a release. Releases occurs every twelfth week and two weeks before that the so called geofreeze takes place. The geofreeze implies that all geometrical shapes should be defined. Therefore, most DE tend to do all the MIP work during the two weeks between the geofreeze and the release. However, exceptions in form of DEs who uses MIP continuously exists. DEs expresses that MIP enables an extra check of the geometry which ensure that the DE have designed as good as possible.

Whenever a DE is using MIP, they evaluate CPs on the deeper level, meaning they control the relations included in the CP. They locate the CP that is concerning their DI and consequently check each relation their DI is having with other DIs. Often the evaluation proceeds with the DE filtering the relations that is not yet checked and load them into TCVis. In TCVis, a clearance analysis is done to show the geometrical relations. The found relations in the clearance analysis is then matched with the relations found in MIP. After a relation is screened, the DE changes the column of Checked by Design Owner to YES. The three columns that is indicating whether a relation is checked or not are illustrated in Figure 11. However, column one saying Checked by Design Owner is the only one that the DE changes. The second column, Geometrical Surrounding Unchanged only states that the latest change is checked. This column is changed whenever a relation is changed more than 0.2 mm. Lastly the third column, Clearance Status, is only applicable if a relation has a distance requirement. Consequently, the column indicates whether the relation is within acceptable distance. However, it is stated that the function of distance requirement is rarely used. Thus, most relations have the clearance status None Applicable (NA).

Figure 11 MIP s interface. (1) Checked by design owner column. (2) Geometrical surroundings unchanged column. (3) Clearance status column.

It was found in the interviews that there exist two different perceptions of what the status YES means in the column called Checked by Design Owner. The two perceptions are:

- *I am aware of the relation, there might be a need for actions*
- *The relation is OK, no need for actions*

This indicates that DEs do not have a uniform perception of when a relation is OK. Some DEs further stated that the responsibility of a relation lays at the MIEs. Whilst the MIEs state the opposite. Thus, it is concluded, based on these statements, that MIP lacks a clear indicator of when a relation is OK. Furthermore, since there are three columns that indicates the status of a relation, different variances of status exist. Six different statuses are illustrated and explained in Figure 12. In addition, some DEs say that it is unnecessary to examine certain relations because they already know that the relation is correct. Therefore, some relations are left without any DE checking them. Further, it is also found that some ARTs are more geometrically flexible than other. For example, the transmission box is in such position that its geometry is nonflexible, meaning that it is rather the surrounding DIs that must be moved than the transmission. Therefore, DEs working within that ART is perceiving MIP as a less important geometrical assurance tool.

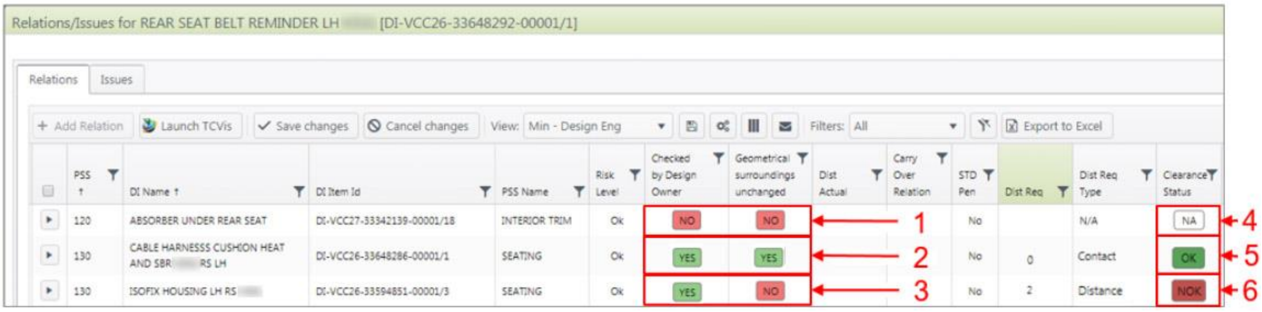

Figure 12 Explanation of the different relation statuses MIP interface. (1) The relation has not been checked. (2) The relation is checked. (3) The relation is checked but there is a change in relation context. (4) There is no requirement on clearance stated. (5) The clearance requirement is fulfilled. (6) The clearance requirement is not fulfilled.

If the DEs consider a relation being a problem, they often contact the owner of the counterpart to find a solution. This contact is usually done face to face, through email or skype. However, the DE has the possibility to, likewise MIEs, create an issue. The DE then creates a so called K1 by filling in the column of Risk Level. This returns a marking on the relation, indicating that actions are needed. Although, the function of creating a K1 is perceived as awkward and leads to more work than just sending an email to the counterpart. Furthermore, it is claimed that a K1 creates discord between DEs since it implies that the counterpart must take an action to solve the problem. It is also stated, if a DE encounter a relation considered being a problem, the DE tend to change the Checked by Design Owner to YES and then change the DI in CATIA to solve the problem. This means that the data stored in MIP has fallacies in form of some problems being marked with K1 whilst some problems are simply changed in CATIA without any documentation in MIP.

4.3.2 Design Engineers' Evaluation in MIP

DEs state that the benefit of MIP is the security it provides in the form of an extra check. Although, it is also claimed that MIP is mainly used as a scorecard for monitoring how the project proceeds. The DEs' perception of MIP's utility is diverse. In addition, when describing the evaluation of relations, the DEs are unanimous.

It is stated that evaluation of relations is foremost done visually by inspecting the model in TCVis. The DE can then take the decision regarding actions needed or not. It is said that this visual evaluation is based on experience. It is explained by the DEs possessing enough knowledge about their component and surrounding environment so that it is obvious for them if the component needs to be changed or not. However, occasionally new relations that the DE was not aware of occurs. In these cases, information externally can help the evaluation. Therefore, DEs are taking external information into account such as crash simulations etc. However, if such information is affecting the decision is not documented within MIP.

It can be concluded from the interviews that many parameters affect the evaluation of relations and that the parameters differ depending on the ART concerned. However, it is stated that carryover parts, parts that are already developed and transferred from previous projects, are creating a lot of unnecessary work for the DE. Sometimes, relations that are similar to relations in older projects occur which forces the DEs to examine already before validated relations.

4.4 Conclusions of User Analysis

It is concluded that there are two possible ways of using ML in MIP. The ML model would either be evaluating or supporting. With an evaluating approach, the ML model will be evaluating relations on its own entity. On the other hand, a supporting ML model would be used to facilitate the human actions.

An evaluating ML model has the potential to evaluate relations and CPs based on historical data. The ML model would then conclude whether the relation is OK or if modifications to the geometry are needed. However, there is no clear indication of when a relation is OK in MIP which might be problem with accessing data that can provide training for an ML model. As found in the User Analysis, there are different combinations of statuses stating YES or NO, these must be interpreted as either OK or NOK stating the classification of the CP or the relation.

Also, found in the user analysis, DEs' emphasise MIP's importance for assuring that their components do not have any geometrical issues with the surroundings. Therefore, MIP is a powerful tool that should not be neglected in DEs' work tasks. This finding makes an evaluating ML model riskful since it could erase one of the main functions of MIP; giving DEs awareness of their geometrical surroundings. In addition, by replacing human decisions with AI decisions, the question of responsibility would be introduced. The traceability of the basis for the decision would be lost, thus it would be impossible to understand why the decision was taken. In summary, the idea of having an evaluating ML model could potentially be effective but introduces several difficulties.

The possibilities with a supporting ML model imply easing the process of assuring mechanical integration at the same time keep the human involvement. A supporting ML model would mean a proactive solution that could complement the decisions of humans. Thus, meeting the desires of the MIP users by making the mechanical integration easier.

It is concluded that there is greater potential for easing the work of DEs in MIP rather than the MIEs' work. DEs are evaluating geometrical relations on a more extensive level, namely the relation level, whilst MIEs evaluate on CP level. This means that DEs' work includes more repetitive tasks since the number of relations to be evaluated is greater than the number of CPs. In addition, DEs are not using MIP as frequently which leads to a stacking of relations needed to be evaluated. Hence, a large number of relations needs to be evaluated in a short time. Furthermore, DEs uses MIP as a supporting tool for designing whilst MIEs uses it as a scorecard for ensuring the total integration of components. To automate parts of the tasks in MIP with an ML model would simplify the task for DEs but potentially interfere with the main objective of the MIEs. The MIEs role is naturally more overreaching and thus not easily replaceable by ML. However, the possibility to ease the MIEs work with supporting functions is still considered feasible.

The following section explains the different opportunities to use ML for supporting the mechanical integration process.

4.4.1 Identified Opportunities

In this section, identified opportunities to use ML in MIP are presented in the form of concepts. Consequently, the opportunities are described, and the applicable concept explained. Also, the chapter concludes on which concept to proceed with.

Concept 1 | OK/NOK recognition

An ML model will be trained to classify relations as OK or NOK. An ML model could hypothetically make completely perfect evaluations of the relations, thus, eliminate the need for checking every relation. Only the relations in need of actions would be displayed for the user. A system like this would be timesaving since no non-productive relation assessment would be needed. Furthermore, excluding the relations without need for actions, and in that way reduce the number of instances, increases the focus, leading to better quality and overview in the problem assessment (Pillay, 17). This concept is the only one with an evaluating character.

Concept 2 | CPs' risk tendency

A supporting ML model can classify and highlight CPs that tend to become an issue in projects. Stated in the interviews, MIEs expresses that there is a pattern in where issues usually emerge. Since each CP today is evaluated by being classified as OK or given a risk level, there is a possibility to use ML to find the pattern of when a CP has risk tendency. This supporting ML model's function would be used as a tool for early risk detection by giving the CP a status from the risk level list. By this kind of supporting ML model, the users of MIP keep the geometrical overview, but their focus can be prioritized to high risk CPs. Thus, dealing with the most urgent problems first. This in turn leads to a more time efficient process since the CPs with a risk are found easily. Further, benefits include mitigating the risk of missing an important problem. However, there is a risk based on the human factor that non prioritized CPs would be overlooked. Although, this supporting ML model can make users' working process more organized by giving them a clear staring point.

Concept 3 | Relations' risk tendency

This concept of supporting ML model works at relation level. Although, since there is no clear indication whether a relation is OK or NOK it complicates the usage of ML. As mentioned before, at relation level, the DE is only marking if the relation has been checked. However, the issue function is adapted to work at relation level. Therefore, a supporting ML model can be used to evaluate the relations and determine if a risk or not exists. Likewise, such a supporting ML model would lead to a more time efficient working process by prioritizing relations with possible risks. Potentially, this kind of ML model would ease the usage of MIP for DEs, enabling them to use it continuously and not only close to releases and geofreeze. Furthermore, such a concept allows the user to keep the awareness of the surrounding geometrical environment,

Concept 4 | High-risk notification

Likewise, the previous concepts, a supporting ML model can indicate when a high-risk CP or relation is detected. However, in this case, the supporting ML model would not have the right to classify the CP or relation by assign a risk level. Instead, the supporting ML model would only indicate that the CP or relation most likely includes an issue. But it is still up to the human to classify it. Whenever, a relation or CP would need human evaluation, the owner of the CP or relation would be notified. The notification system is inspired by ideas from the interviewees. It is likely that MIP users would use the system more continuously rather than just close to geofreeze if they were notified when their evaluation is needed.

Concept 5 | TCVis view

Found in the interviews are the need of an improved interface between MIP and TCVis. It is desired by users that finding the concerned relation in a graphic environment would be easier. A supporting ML model in this case could include snapshots of the concerned relation. Alternatively, open TCVis with the desired view, exposing the relation. This would lead to great timesaving in form of eliminating frustrating work of examine the whole model to find the concerned relation. Furthermore, the process of evaluating a relation would be faster, meaning that more focus can be put on more relevant geometrical relations.

Concept 6 | Decision verification

The final concept includes a supporting ML that verifies the decision of a relation or CP. Since it is expressed in the interviews that most DEs sometimes feel insecure or even guesses when evaluating a relation, there is an opportunity to use ML. Such a concept would include an ML model that when an evaluation is not unitary with the predicted response, the DE will be notified. In this case, the DE can once more evaluate the relation making sure that their judgement is correct. Benefits with such ML would be that DEs still control the surrounding environment but can relax and speed up the evaluation process when screening all relations.

4.4.2 Concept Elimination

The six proposed concepts are evaluated and screened for only proceeding with feasible concepts. For this, an elimination matrix is used. The result of the elimination matrix is presented in Table 2 Elimination matrix for concepts..

As mentioned in the theoretical framework, for using ML a response is needed. In the proposed concepts there are clearly two kinds of responses: risk level and OK/NOK classification. Consequently, the OK/NOK recognition and Decision verification is based the same response namely the OK/NOK classification. On the other hand, CPs' risk tendency, Relations' risk tendency and High-risk notification is based on the same response in form of risk level. This means that all five concepts are modifications build upon only two different ML models with respective response. Thus, it is concluded that the proceeding project will investigate two different models of ML. Namely one model with risk level as response and one model with OK/NOK classification as response.

Concept 5 TCVis View is outside the scope of this thesis since it would involve developing an ML model that is not based on historical data in MIP.

Table 2 Elimination matrix for concepts.

		Response	**Proceed with Concept?**
Concept 1	OK/NOK recognition	OK/NOK	Yes
Concept 2	CPs' risk tendency	Risk Level	Yes
Concept 3	Relations' risk tendency	Risk Level	Yes
Concept 4	High-risk notification	Risk Level	Yes
Concept 5	TCVis View	No Data	No
Concept 6	Decision verification	OK/NOK	Yes

5 Data Analysis & Model Enhancement

For testing the possible concepts, several iterations are sequentially performed. The iterations include analysis and enhancements of data followed by creation of an ML model. The result of respective model's performance in training and testing is presented. Consequently, each iteration is concluded upon, resulting in actions taken for improving next iteration.

5.1 Methodology for Data Analysis & Model Enhancement

A typical structure of an ML project is an iterative approach with five main steps. The structure is illustrated in Figure 13. The first step is to collect data in order to create a dataset. This dataset needs to be adapted for fitting an ML model, hence cleaning the dataset is necessary. Also, the data is split into a training and testing set during this step. Consequently, the model is trained with the training data. As soon as the model is trained, it can be tested with the test data. When the model is declared ready, the model is deployed for usage. This step is followed by a monitoring step. The monitoring is necessary to ensure the model working appropriate in a live environment. However, this project is delimited to a theoretical ML model. Thus, the two last steps of deploying and monitoring is not included in the methodology (Thornberg, 2019).

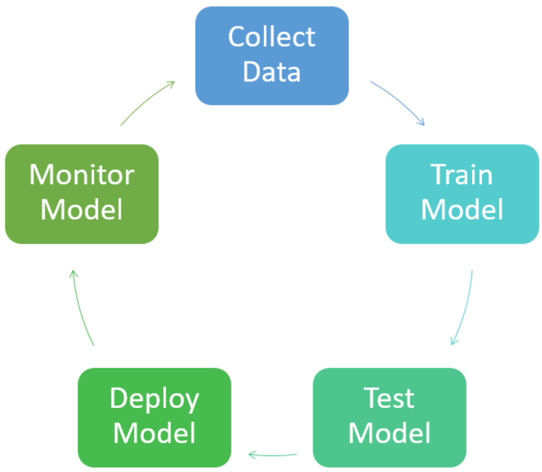

Figure 13 The structure of an ML project.

Accordingly, each iteration starts with collecting data and cleaning it. The cleaning is performed in Excel and includes erasing erroneous rows and superfluous columns. A script is used to import the cleaned data into MATLAB and split it into matrices containing training data and testing data. The imported data is randomly divided into 80% training data and 20% testing data, except for in the learning iteration. The model creation, training and testing are performed with MATLAB's application called Classification learner.

Within the application, various ML algorithms can be used. Although, it is decided to only use one algorithm consistently, namely Fine tree. The decision to only use one method is justified by limiting the factors affecting the model's performance. Furthermore, it is reasoned that the models created within this project are only having the purpose of giving an indication whether ML is applicable for evaluating geometrical relations or not. Consequently, the developed models are not intended to be used without optimization and should be considered only as theoretical models. However, an evaluation of different algorithms is conclusively performed. The model is trained within the application, then exported as a function and used within the script for predicting responses on the testing data. The MATLAB script used is found in Appendix C.

The overall prediction accuracy for both testing and training is examined and presented in the result for each iteration. Furthermore, for deriving the result of how well the model is predicting certain response classes, confusion matrices are used. A confusion matrix presents a comparison between the output class given by the model and the target class including the correct classification. Hence, illustrating the model's shortcomings but also its benefits. A confusion matrix enables different analysis. Thus, showing the percentage of how many correct classifications made but also the percentage of how many incorrect classifications made. Furthermore, the usage of confusion matrices enables analyses of the model's potential since certain fallacies in classifications imply greater impact than others. For example, a CP with a target class of NOK that is given the output class OK can have critical impact. Whilst an instance with target class of OK that is given the output class of NOK does not indicate any critical impact more than a need for evaluation of an engineer. Thus, the resulting confusion matrix of each model is thoroughly analysed for better understanding of the models' potential.

5.2 Learning Iteration

To get acquainted with MATLAB's classification learner, a learning study is conducted early in the project. At this stage, only data from an older project in DPA[0] is accessible. The result was therefore of ulterior use during the user analysis and planning of the forthcoming iterations.

5.2.1 Dataset in Learning Iteration

DPA[0] is based on the same calculations as the more modern MIP system, hence it is considered justified for this purpose. The dataset contains more than 111 000 historical CPs from a previously finalized project. As ML algorithms increases its performance with increasing data size, the large number of CPs is theoretically optimal for the task. However, such large dataset requires very high computer capacity to run in a reasonable time frame. Thus, the data is reduced in order to save time. The data also needs to be divided into two datasets. One for training and one for testing. The training data is cut to 10 000 instances by selecting the top rows without further consideration and the testing is done on the following 1 000 instances. Furthermore, the data contains a large number of categorized columns. For convenience and to adopt the dataset to the ML algorithms, empty and erroneous columns are deleted. The columns represent information about the CP in various forms. Although, only certain columns are of interest to be used as inputs, so-called predictors in the ML model. Furthermore, the data includes one column with the response. The response refers to the classification which is to be predicted. In the data from DPA[0] the response is whether the CP was classified as OK, NOK or Not Evaluated. Thus, the aim of using this data is to investigate the possibility and accuracy for an ML algorithm to predict a classification of either OK, NOK or Not Evaluated for CPs depending on their predictors.

5.2.2 Data Analysis of Learning Iteration

The data is taken from a finalized project; hence the CP statuses only represent the very final stage of the project. Consequently, each row in the dataset represent one of the CPs from the very last moment of the project and the CP's status at that time. As a result, almost no CP has the NOK status. This since in the end of the project, the status checking is more frequent and important than earlier during the development. The distribution of CPs' status, used as response classes, is seen in Figure 14. About one third of the data have the status Not Evaluated. Conclusively, the dataset will not perfectly represent the data which the algorithms will encounter during actual use, but it will work as a replacement that enables testing of algorithms and evaluation of predictor's influence.

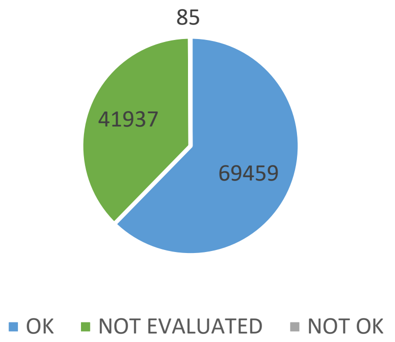

Figure 14 Distribution of response classes in DPA[0] dataset.

A first screening of predictors is conducted by removing obviously unnecessary columns. Left after the first screening are 40 predictors and one response (OK, NOK or Not Evaluated). Reasons for removing the columns and predictors are for instance irrelevant information such as repetitions and highly fragmented, uncomplete or even missing data. A second dataset with only six predictors is also created to test if it would affect the outcome. The six predictors are chosen by guessing the factors that would impact the result most.

5.2.3 Result of Learning Iteration

The results of the two models are presented in Table 3 below.

In general, Model 1 performs with higher overall accuracy, both in training and testing. Although, Model 2 only includes six predictors, in comparison to Model 1's 40 predictors, it performs with an overall accuracy of 83.7%. However, Model 1 is not able to classify any of the NOKs correctly whilst Model 2 is able to classify 46.1% correctly. This means that Model 1 only classified instances as OK or Not Evaluated while Model 2 managed to classify instances in all classes. Consequently, Model 1 is not utilizable since it is unable to predict NOK.

Table 3 Results of model testing in learning iteration.

	Model 1	**Model 2**
Nr of Predictors	40	6
Overall prediction accuracy on training data	98.3%	89%
Overall prediction accuracy on test data	97%	83.7%
Prediction accuracy for Not Evaluated	97%	80.7%
Prediction accuracy for NOK	0%	46.1%
Prediction accuracy for OK	98.9%	92.8%

Furthermore, the results indicate a tendency of overfitting. This since the prediction accuracy are higher for the training data in comparison to the test data for both models. However, for Model 1 the difference is 1.3 percentage, which is insignificant. Although, Model 2 has a difference of 5.3 percentages which is significant. Overfitting imply the model being useless or in need for improvement since it is not performing as well on new testing data than on already seen training data (Elite Data Science, 2019).

5.2.4 Conclusions of Learning Iteration

As stated in the beginning of this chapter, this learning iteration is conducted with DPA[0] data. However, some learnings have been drawn from this experiment that will be carried over to the following iterations.

It can be concluded that the number of predictors impact the outcome. A disadvantage of ML is that it is practically impossible to investigate on how the decisions were made by the model. This makes it harder to analyse which predictors that are the most influencing ones.

Furthermore, it is concluded that the data which originates from one moment in time, do not contain the necessary information for predicting NOK. This means that the data only includes the CP's final status. Thus, not covering CPs which have been updated from NOK to OK during the project. Hence, the model is only trained to identify the status of CPs at the last date of the project. Whilst it is desired for the model to find whether the CP would be classified as OK or NOK at any time regardless of its final status. Therefore, information about the CPs history will have to be included among the predictors.

Although, the both models perform with a high prediction accuracy in both training and testing, the results show a skewed prediction accuracy. Model 2 can predict all three responses, although with questionable accuracy. Whilst Model 1 can only predict two responses. Therefore, it is concluded that the data is incomplete and must be completed with improved predictors and a more even distribution of responses.

5.3 Iteration 1

Iteration 1 is performed to test the different concepts presented in chapter 4. Three models are tested with three different responses to match the concepts presented. Consequently, the three models' respective response were:

- Model 1: CP Risk Level
- Model 2: CP Status
- Model 3: Relation Risk Level

5.3.1 Dataset in Iteration 1

The dataset used is extracted from CCDB, meaning that the data is from the MIP system. The original dataset consists of approximately 7000 CPs. Each CP is represented by one row. However, the dataset needs to be cleaned since some CPs are erroneous and consequently erased from the dataset. After the clean-up, the amount is reduced to 6540 CPs with a total of 54 predictors. All included predictors can be seen in Appendix D.

In contrast to the learning iteration, the dataset used is extracted from two different projects. One that is finalized and one that is currently running. The purpose of this was to hopefully access data with more varied responses than in the learning iteration. However, the data is still extracted at a moment in time, meaning that there is no information regarding the history of a CP. The data regarding a CP is only containing information about its current state.

The data contains three columns that can be used as response. The first response contains the CP Risk Level which can be classified into NA, OK, S1, S3, S4 and S5. The second response contains the CP Status, which is classified as NA, NEW, NOK and OK. The third response is the Relation Risk Level which indicates if any relation within the CP is having an issue. This response can be classified as OK, S1 or K1.

5.3.2 Data Analysis of Iteration 1

To get an overview of the data within the models an analysis of the responses is made. Consequently, each of the three responses are analysed by looking at the distribution of classes within each response. Important to be kept in mind is that a model needs many instances of each possible class within a response for predicting with high accuracy. Therefore, if one class dominates the dataset, it is most likely that the model will become good at predicting that certain class whilst less common classes will be harder to predict.

Model 1, with CP Risk Level as response has the most classes, in total six different. As seen in Figure 15, the distribution of classes is skewed with 80% of the CPs being OK. Furthermore, almost no CPs are classified as S4. The level of S5 is not included since no such class where included in the dataset.

Based on the skewed distribution of classes, the probability of correctly predicting OK is naturally high. Likewise, the probability of correctly predict classes such as S1, S3, S4 is naturally low.

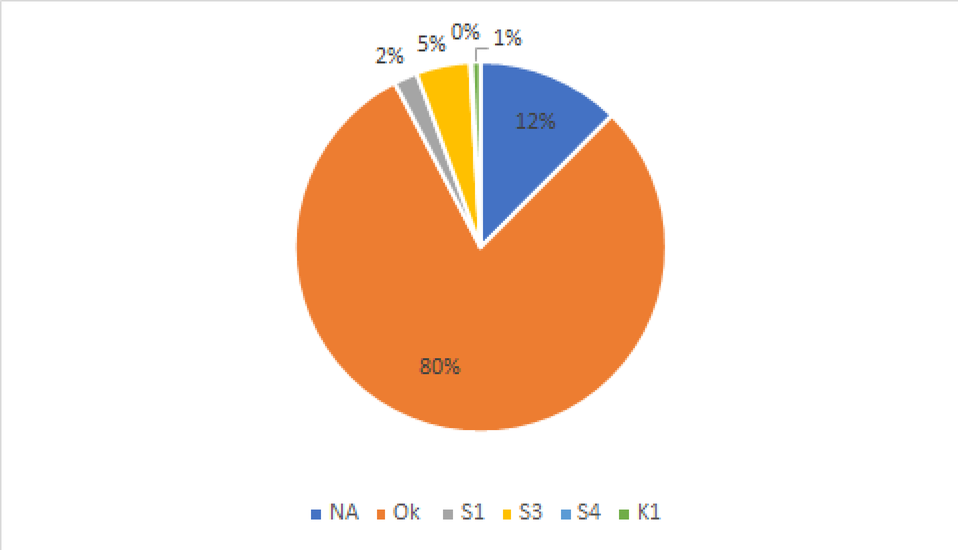

Figure 15 Distribution of response classes in CP risk level data.

Model 2, with CP Status as response, also has a skewed distribution of response classes, see Figure 16. However, the distribution is less divided than for Model 1. The dominating class is still OK with 67%. Almost a fifth of the CPs are classified as NA. Likewise Model 1, it is likely that the results of Model 2 will include a high accuracy of predicting OK correctly. Consequently, having a lower accuracy of predicting the other three classes correctly.

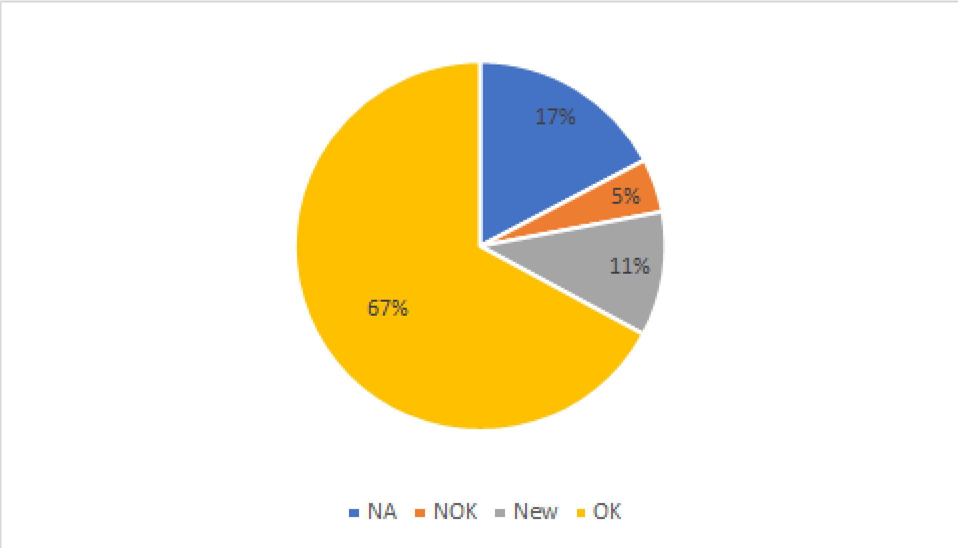

Figure 16 Distribution of response classes in CP relation status data.

Finally, Model 3 with Relation Risk Level as response is having a highly skewed data, see Figure 17. The dataset contains 99% CPs with Relation Risk Level classified as OK. Only 1% of the CPs are classified as K1 and 0% is classified as S1. Thus, Model 3 is likely to predict everything as OK since this is the only situation the data represents.

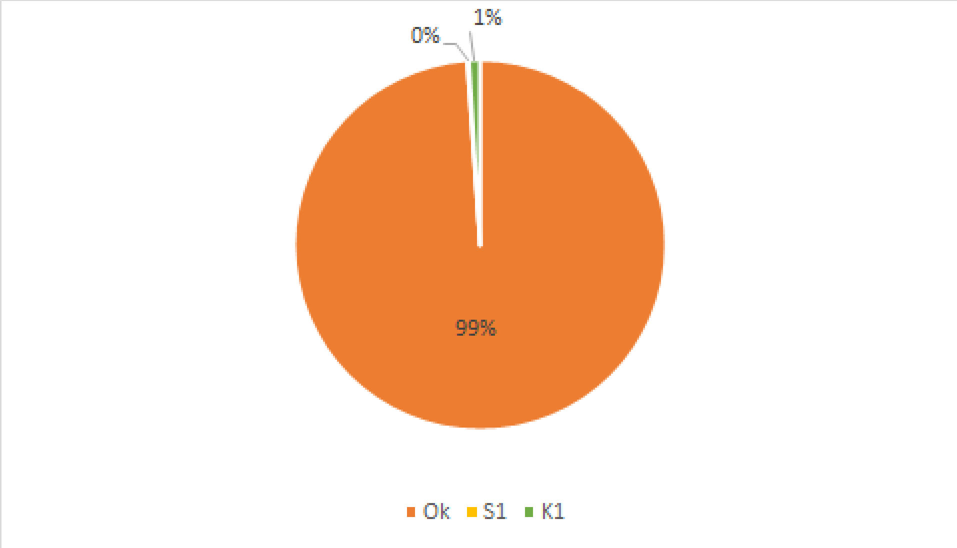

Figure 17 Distribution of response classes in Relations risk level data.

5.3.3 Result of Iteration 1

The resulting prediction accuracy both during training and testing for the three models are presented in Table 4 below. Since the training accuracy and the test accuracy do not differ significantly, there is no indication of overfitting. Although the accuracy seems high, the results need to be further screened. Thus, confusion matrices are plotted for each of the models' result during testing.

Table 4 The models´ overall prediction accuracy.

	Model 1	**Model 2**	**Model 3**
Overall prediction accuracy on training data	92.5%	93.9%	99%
Overall prediction accuracy on test data	92.4 %	95.3%	98.5%

Model 1's confusion matrix is seen in Figure 18. The result shows that none of the Risk Levels K1, S1, S3 and S4 were correctly predicted. Instead the model predicts all CPs with a risk classification as OK. Although, all CPs with a target class of NA were correctly classified. Furthermore, all of the CPs with target class OK are correctly predicted. The result indicates that Model 1 can classify NA and OK correctly. However, Model 1 cannot predict Risk Level.

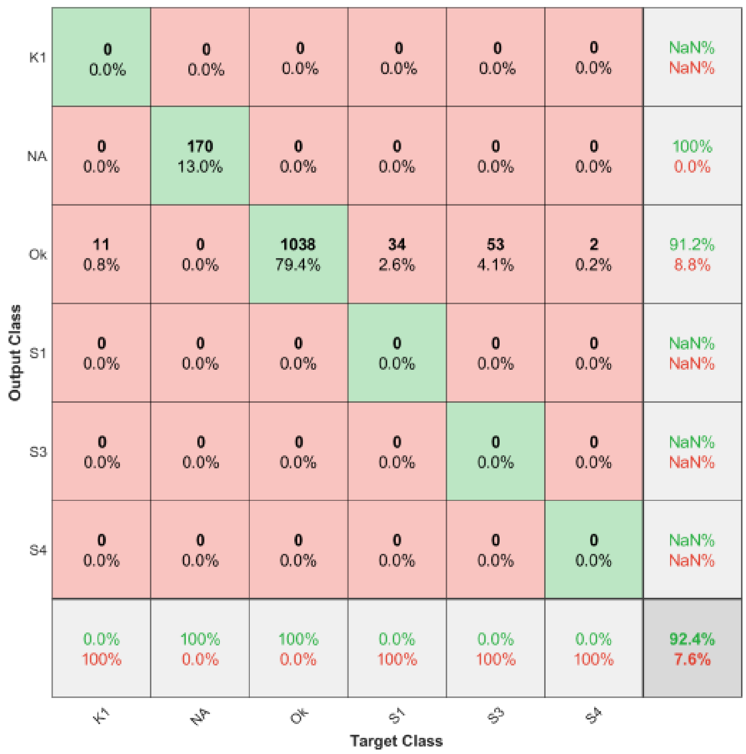

Figure 18 Confusion matrix of testing model 1 of iteration 1.

Figure 19 presents the confusion matrix for testing of Model 2. The results indicate that Model 2 can predict NA, NEW and OK. As seen, the model predicts NA with an accuracy of 98.7%, NEW with 98.6% and OK with 98.9% accuracy. Although, Model 2 shows weak performance in predicting NOK, with 16.4% accuracy.

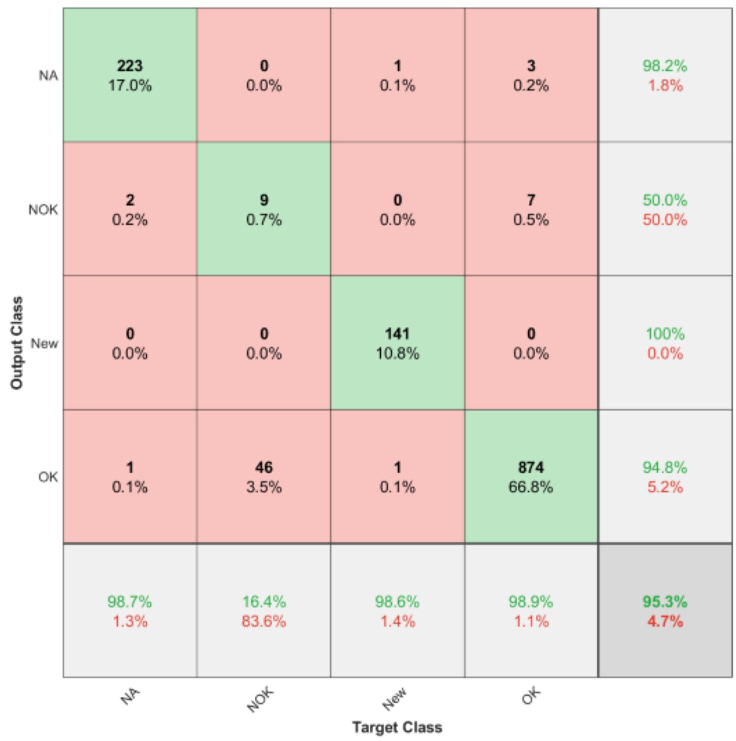

Figure 19 Confusion matrix of testing model 2 of iteration 1.

Lastly, Model 3 results are found in the confusions matrix in Figure 20. The skewed data clearly affects Model 3 since almost every CP is classified as OK. During testing, only three CPs have the output class of K1. Furthermore, 15 instances have target class K1, but only one of them was predicted correctly. In addition, at total of three CPs that have target class S1 were included in the testing and none of them were predicted correctly. Model 3 predicts OK correctly with an accuracy of 98.8%. Although, the probability is in favour of predicting OK by chance because of the skewed data. Thus, making the result trivial.

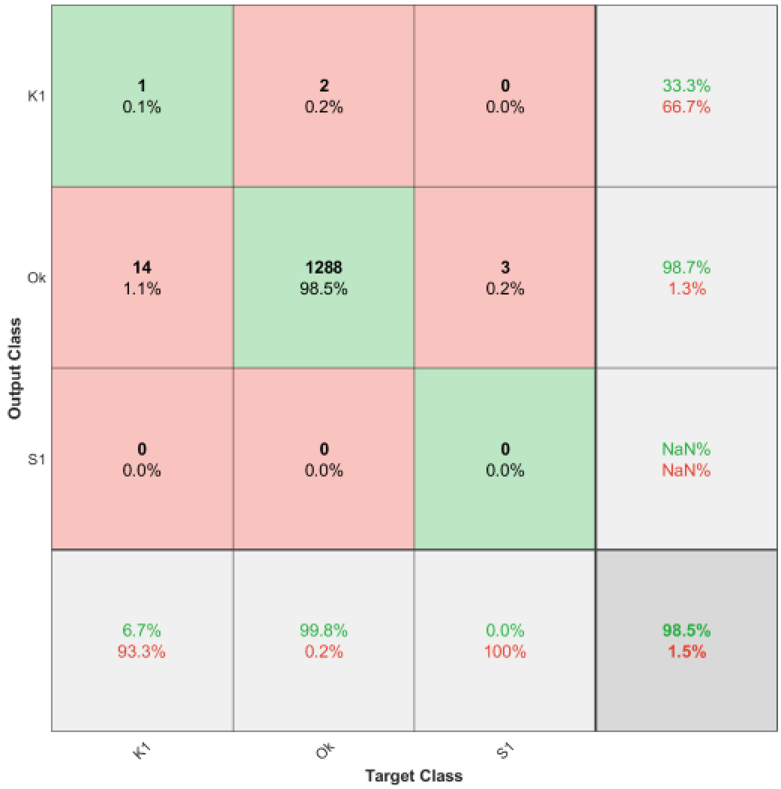

Figure 20 Confusion matrix of testing model 3 of iteration 1.

5.3.4 Conclusions of Iteration 1

In Iteration 1, weak results of predicting the three suggested models' responses are observed. All models have trouble to find patterns that distinguish the response values from each other. The models predict most CPs to be either OK or NA, indicating that the data does not contain the necessary information in order to support a correct prediction of a risk level. Furthermore, the data is heavily skewed with the majority of the responses being OK, thus resulting in a deceptively high prediction accuracy. Just like predicting every CP as OK would also give a high prediction accuracy but would be equally futile for the DEs. The models are however predicting the NA status with high accuracy. This is likely because almost all carryover parts have the target class NA, which gives the model a clear pattern to follow.

In the data, few CPs with higher risk levels, such as S4 and S5, are observed. Hence, the models have few such instances to learn from, which further decreases the models' capability of predicting issues. From the result we can conclude that the prediction of risk levels is very inaccurate. Furthermore, since each CP with a risk appointed to it also is represented with status NOK, it was decided that it is not efficient to continue with using Risk Level as response, but rather only look at the OK/NOK status. It was concluded that a first step would be to find CPs that indicate any form of risk (e.g. NOK) rather than finding the specific level of risk (K1-S5). Thus, the further work will not include the response of Model 1. In addition, it is concluded that there is no utility in using relation risk level as a response since the data lacks enough instances of target class S1 and K1. This is emphasised by the previous user study where it was stated that K1s are not frequently used by the DEs. Therefore, Model 3's responses are excluded from further work.

An improvement drawn from analysing the result is that the status NEW will be removed from further work. All CPs are classified as NEW when it is entered into the MIP system by default. Hence, it is not justified to analyse the predictability of the class NEW.

5.4 Iteration 2

Iteration 2 is conducted with one response class, namely CP Status, based on the result from iteration 1. The work strived for improving Model 2 from the previous iteration.

5.4.1 Dataset in Iteration 2

The same data as in iteration 1 is basis for iteration 2, although it is further cleaned. Based on the results from iteration 1, showing the data being incomplete to predict Risk Level accurately, it is decided to only use the CP Status as response. Furthermore, all CPs with target class NEW is excluded. Therefore, the responses in Iteration 2 are NOK, NA and OK. After this reduction, a total of 5838 CPs remains.

In addition, the dataset is complemented with three new predictors. These predictors are intended to ease finding a pattern in the data. The following predictors are added:

- Amount of relations each CP include
- Smallest distance between DIs in the CP
- Average distance between DIs in the CP

From previous iterations it was understood that the data needed to be modified for it to be readable by the ML algorithm. Each CP contains several relations with correlating clearing distances. In some cases, a CP can hold more than 500 relations. Thus, since the analysis is made on CP level, a way of gathering the information of all the relation clearing distances into one or a few predictors was necessary. Combined with learnings from the user analysis the new predictors were created by transforming data from relation level and adding it to the CP dataset. Consequently, a total of 20 predictors were used after the inclusion of the three predictors. All included predictors can be seen in Appendix D.

5.4.2 Data Analysis of Iteration 2

The new dataset's responses are distributed as shown in Figure 21. A skewed distribution does still exist. The distribution of responses could theoretically be evened out by reducing the number of CPs classified as OK. Although, reducing the number of instances would also reduce the ability for the model to learn, thus making it less valid. Hence, reducing the dataset more could be affecting the result more than skewed data.

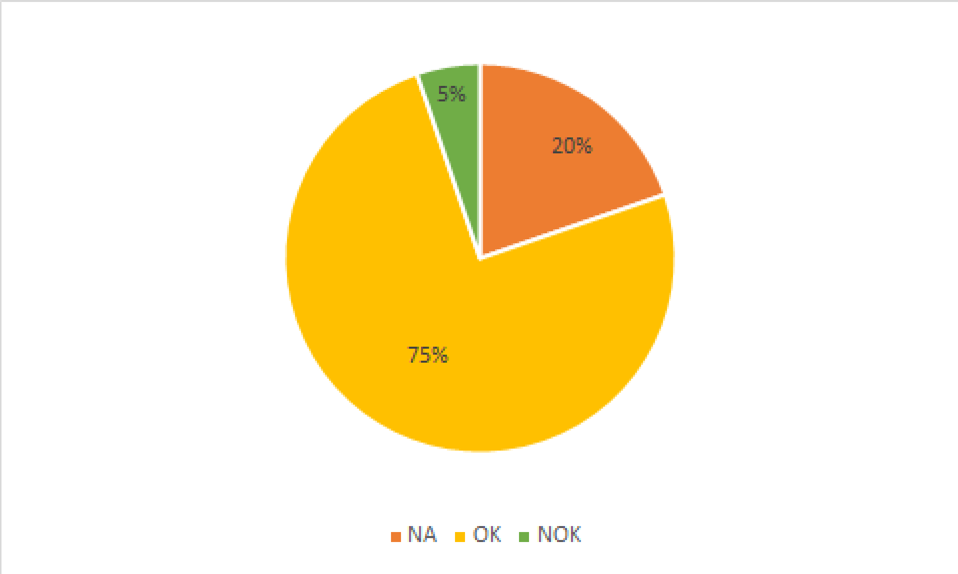

Figure 21 Distribution of responses in dataset.

5.4.3 Result of Iteration 2

The model's prediction accuracy is presented in Table 5 below. The table includes the overall accuracy for both training and testing. Also, included is the accuracy of predicting each class in the response. The model predicts OK with an accuracy of 99%. However, the model is not able to predict NA nor NOK with equally high numbers. The prediction accuracy for NA is 18.5% whilst the prediction accuracy for NOK is only 4%. The model's overall accuracy corresponds well between training and testing, 76.7% during training in comparison to 76.5% during testing.

The confusion matrix in Figure 22, further shows the comparison of target and output class. Noteworthy, only 52 of the total 1168 CPs are given an output class different from OK. Which means that the Model classifies almost each CP as OK regardless of target class.

Table 5 The models prediction accuracy.

	Accuracy
Prediction accuracy on training data	76.7%
Prediction accuracy on test data	76.5%
Predictions Accuracy of NA response	18.5%
Predictions Accuracy of NOK response	4%
Predictions Accuracy of OK response	99.5%

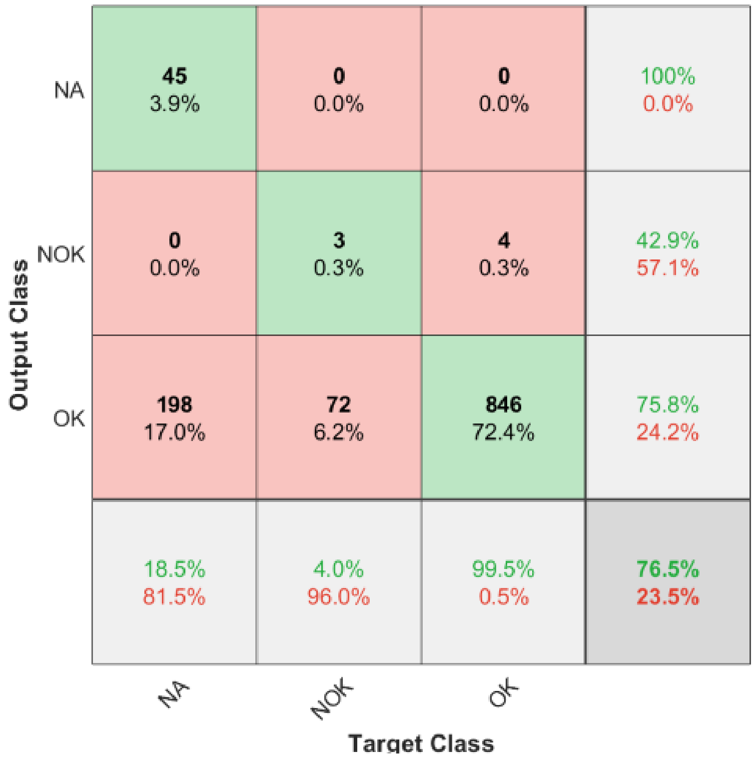

Figure 22 Confusion matrix of testing the model of iteration 2.

5.4.4 Conclusions of Iteration 2

The result shows that the accuracy of predicting NOK is still very low, only 4%. This imply that the model is predicting 96% of the CPs with target class NOK to be OK, thus not performing nearly good enough to be useful for any of the concepts presented in the user analysis.

As in iteration 1, the dataset is extracted at one moment in time and does not include any information whether the CP once been classified with a risk or not. Hence, the dataset and the response are not including enough information for a model to learn if a CP is having a risk or not more than in just the exact moment the data is representing. Thus, the response must be updated to include historical data indicating if the CP’s status has been changed over time.

Moreover, CPs are classified with NA whenever there is no need for them to be evaluated by MIEs or DEs. As found in the user study, DIs that are carryovers are linked to be CPs that are unnecessary to evaluate. Thus, there is a correlation between carryover DIs and the class NA. CPs with the class NA does not have to be classified by an ML model, instead a filter can be used to simply sort these CPs. Therefore, the response can be simplified to only including two different output classes, NOK or OK by removing NA. Hence, CPs with the class NA will be excluded from future dataset.

So far, the different existing predictors has not been closely evaluated. It would be beneficial to evaluate the impact of the predictors in order to improve the accuracy. Predictors that are including many categories can possibly impair the result by confusing the model and making it harder to find useful patterns. If simpler but informative predictors are used, patterns are easier to find for the model. Thus, before moving on to the third iteration an evaluation and testing of predictors are made in order to find the most influencing predictors.

5.4.5 Evaluations of Predictors

For evaluating the predictors influence, the training environment within MATLAB's classification learner is used. The same dataset and response as in Iteration 2 is used during the evaluation. Within the training environment, multiple models are created with different combinations of predictors. A first elimination of clearly impairing predictors is done. Consequently, the predictors indicating variants are eliminated. Furthermore, predictors including whether the CP is validated by MIE or DE are eliminated since they involve human evaluation which will not be accessible for a future ML model. This led to 17 remaining predictors which are further eliminated.

The process of optimizing predictors is a matter of trial and error and can be seen as an experimental progression (Yufeng, 2017). Therefore, the remaining predictors are evaluated by stepwise train new models with different combinations of predictors. The model's ability to predict NOK is the crucial factor during the evaluation. Thus, the predictors that improved the performance are decided to be kept. Whilst predictors that reduced the performance are eliminated. The evaluation is summarized into an elimination matrix which is shown in Table 6 Elimination of predictors.

Table 6 Elimination of predictors.

Predictor name	Decision	Comment
Project ID	Eliminated	Includes only two classes in the dataset. Does not improve the performance.
CP validated by MIE	Eliminated	Involves human evaluation, will not be accessible for future ML models.
Relation validated by MIE	Eliminated	Involves human evaluation, will not be accessible for future ML models.
Relation validated by DE	Eliminated	Involves human evaluation, will not be accessible for future ML models.
Event checked by DE	Eliminated	Involves human evaluation, will not be accessible for future ML models.
ART name	Continued	Includes 79 unique classes, indicated the location of the DI in the vehicle.
Unit name	Eliminated	Indicate the unit owner of the DI. Does not improve the performance.
Variants	Eliminated	Includes a great number of classes. Reduces the performance.
Function groups	Continued	Indicates the function group the DI belongs to. Improves the performance.
DI program	Eliminated	Indicates whether the DI is included in a vehicle project or not. Does not improve the performance.
DI code number	Continued	Is a unique number for each DI, can possible ease the finding recurrent DIs.
DI position number	Continued	Indicates that the same DI occurs on a different location.
DI revision number	Continued	Indicates how many times the DI's geometry has been updated.
DI name	Continued	States the name of the DI. Is kept but simplified into keywords.
Position names	Eliminated	Includes 500 classes and is not consequently used on all DIs. Reduces the performance.
Carryover	Continued	Unclear impact.
Is electric	Eliminated	Does not improve the performance.
Amount of relations	Continued	Improves the performance.
Smallest clearing distance	Eliminated	Does not improve the performance.
Average clearing distance	Eliminated	Does not improve the performance.

The elimination results in eight predictors being kept. Although, the predictor DI name will be simplified into keywords for easing the model's interpretation. However, a model with the remaining predictors, except DI name, is trained and tested. This model resulted in an overall prediction accuracy of 89.9% during test. The prediction accuracy for all response types is illustrated in Table 7. Although, most prominent is the improvement in the model's ability to predict NOK. The model's prediction accuracy for NOK with seven predictors is 48.6%. This is in comparison to the result of the model in iteration 2, where 20 predictors are used but the model's prediction accuracy for NOK are 4%. Meaning an improvement of 44.6 percentages. The model's prediction accuracy for each response class is found in Figure 23. Consequently, it is decided to proceed with eight predictors and complete the dataset with parameters including historical data to improve the model's performance even further.

Table 7 Prediction accuracy of different response classes.

	Accuracy
Prediction accuracy on training data	89.6%
Prediction accuracy on test data	89.9%
Predictions accuracy of NA response	81.7%
Predictions accuracy of NOK	48.6%
Predictions accuracy of OK	95.6%

Figure 23 Confusion matrix of influencing predictors test.

5.5 Iteration 3

Iteration 3 is made in order to optimize the model's performance. The iteration is performed with the same data as in iteration 2. However, the class of NA is excluded from the response classes, meaning the model only includes the response classes OK and NOK. In addition, the aspect of historical changes taken into consideration in the response class. Furthermore, changes regarding the predicators are made in order to improve the model's performance,

5.5.1 Dataset in Iteration 3

In earlier iterations the data has been extracted from the system at one specific moment in time. By running the model on such data, training of CPs that earlier have had a risk is lost. This results in poor prediction accuracy since the model has incomplete data to learn from and test on. To solve the problem with missing NOK instances, each CP is checked against its status history data and whenever a previous NOK status was detected, the CP is updated to exhibit that.

The predictors declared in chapter 5.4.5 are used in Iteration 3. However, the predictor DI name is changed. Previously, it did not give satisfying results and instead a system with keywords is tried. From the DI names, some frequently recurring keywords were extracted. The keywords were selected manually with the intention of helping the algorithms to categorize and classify component types, materials and likewise. The keywords are seen in Table 8.

Table 8 Keywords introduced in model of iteration 3

Nut	Cap	Cable	Hose	Padding	Rubber	Carpet	Fixing
Gasket	Bolt	Hinge	Insulation	Shaft	Spacer	Snap ring	Screw
Bracket	Plug	Seal	Fastener	Carrier	Cover	Clip	Flange
Sensor	Pipe	Spring	Latch	Housing	Absorber	Attach	Injector
Lid	Bushing	Harness	Panel	Washer	Bearing	Valve	Strut
Lock	Joint	Trim					

Furthermore, to increase the likelihood of the models to find useful pattern in the data, a new predictor was constructed. This new predictor is a measurement of the amount of relations that is of penetrating type. A complete list of the predictors of iteration 3 can be seen in Appendix D.

5.5.2 Data analysis of Iteration 3

Since NA is erased as a response category, the response now only contains two classes: NOK and OK. The distribution of the two classes within the response is seen in Figure 24. CPs classified as OK is still dominating making the data slightly skewed. A total of 4645 instances are included in the dataset. Likewise, iteration 1 and 2, 80% of the instances is used for training while 20% is used for testing the model. However, the 80% randomly chosen instances are duplicated so the model is trained on the same data twice. This means that the data is trained on a total of 7430 instances with 3715 unique characteristics. Consequently, the remaining 20% that the model has not been trained on is used for testing. The reason for duplicating the training data is to improve the number of instances making it easier to find pattern.

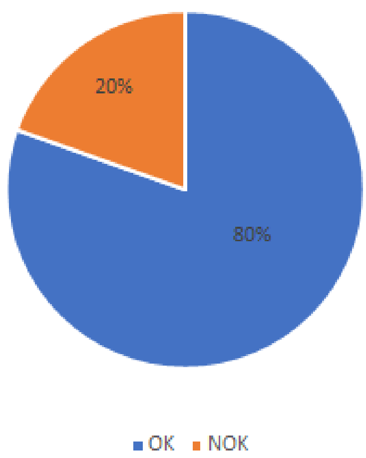

Figure 24 The distribution of response classes.

5.5.3 Results of Iteration 3

The prediction accuracy of iteration 3 is shown in Table 9. The overall prediction accuracy has increased in comparison to the result of iteration 2. Although, the difference in accuracy between training and testing is noteworthy due to it showing a tendency of the model being overfitted since the model is performing worse on testing data than on training data. However, the prediction accuracy during testing is still better than in iteration 2.

The result during testing is showing significant improvements in the model's ability to predict NOK. As shown in Table 9 the predication accuracy of NOK is 59.5% and of OK 90.1%. In comparison to iteration 2, with a prediction accuracy of 4% for NOK, the model has improved with 55.5 percentages. In addition, the performance is improved by 10.9 percentages in comparison to the prediction accuracy 48.6% of the model used when evaluating influencing predictors.

Table 9 Prediction accuracy of model in iteration 3.

	Accuracy
Prediction accuracy on training data	87.7%
Prediction accuracy on test data	84%
Predictions Accuracy of NOK	59.5%
Predictions Accuracy of OK	90.1%

The confusion matrix in Figure 25 is showing the result of the model's prediction on testing data. It is shown that certain instances with target class OK is categorized as NOK. However, the severity of this problem is less than the other way around since a NOK entails a human examination of the CP anyways. However, instances with target class NOK that are classified as OK are indicating a fallacy in the model. If such a model is used, a potential risk would not be detected by the engineers. Thus, the number in the lower left corner is of the greatest interest to evaluate the model's potential.

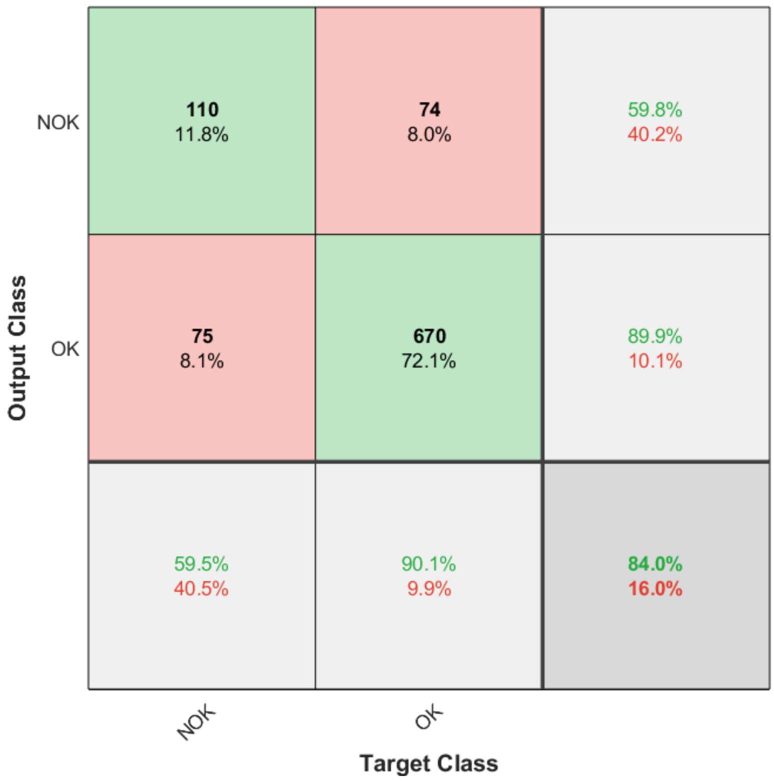

Figure 25 Confusion matrix of testing the model of iteration 3.

5.5.4 Conclusion of Iteration 3

As seen in the result, the model can predict NOK with an accuracy of 59.5%. This is a clear improvement from previously models. It is concluded that the new combination of predictors highly improves the model's performance. However, a deeper analysis of the impact of each respective predictor must be conducted to optimize the model even further. At this stage, it can be concluded that the model clearly can identify NOKs from OKs in more than half of the instances.

The update of the response by firstly sorting out NA and secondly include historical aspects is also beneficial for the performance. Although, the dataset is the least skewed dataset used so far, which might have affected the performance as well. Since the data is less skewed and only two response classes are used, the probability of guessing the correct answer increases.

In summary, the model's performance has improved significantly throughout the iterations. Although, to full declare whether an ML model can be useful in the evaluation of geometrical relation further investigations are needed. As seen in the result, the used predictors influence the performance along with the response class. Consequently, a throughout investigation of predictors is of interest.

5.6 Final iteration

A final iteration is performed in order to declare the predictors with most impact. Furthermore, an attempt to optimize the model is done by experimenting with the algorithm for the model. The same data used in iteration 3 is used for making the result comparable.

5.6.1 Full Factorial Design experiment

As concluded in Iteration 3, a deeper analysis of the impact of each predictor is needed for optimizing the performance. Thus, a full factorial design (FFD) experiment is carried out. The purpose of an FFD is to investigate factors, in this case predictors, and their combined effect on the outcome. An FFD leads to all possible combinations of predictors that are tested. Consequently, models are created and trained for all the possible combinations. The training result of each model is evaluated and likewise 5.4.5 Evaluations of Predictors the model's ability to predict NOK is used as the crucial factor during the evaluation (Antony, 2014).

FFD commonly includes factors that are set at two levels, either a high or a low value. In this experiment predictors are set as either on or off, thus being included in the model or not. Hence, a so called FFD in two levels is used. Subsequently, the number of models in the FFD depends on the number of factors and levels. The formula for number of models R is based on the number of factors, k, and the number of levels, *n*. The exact equation for determine R is $R = n^k$. Therefore, with nine predictor and two levels the number of models to be evaluated are $2^9 = 512$ (Anup K. Das, 2018).

Although, since an FFD with nine parameters would imply 512 experiments, it was reasoned to ease the process by screening the predictors and reduce the number to only seven. This led to the number of models created being $2^7 = 128$ instead. It could be argued that a so called Fractional Factorial Design could be used, meaning that nine predictors could be kept but fewer models are needed. Although, a Fractional Factorial Design decreases the resolution of the experiment (Jamshidnezhad, 2015). Instead it was reasoned that a screening of obvious none-influencing predictors could be made reducing the number of predictors to seven. Seven predictor and 128 models were considered a manageable amount to evaluate while keep a high resolution due to the use of FFD.

5.6.1.1 Pre-FFD screening

A screening session is conducted for reducing the number of predictors to seven. This screening session is conducted by testing the performance of the model by running it repeatedly with one predictor excluded each time. In this test one predictor stood out as the least important, namely Keywords. With

Keywords turned off, the overall accuracy of the model went up significantly, from average 55.3% to 63%. The result can be studied in Figure 26.

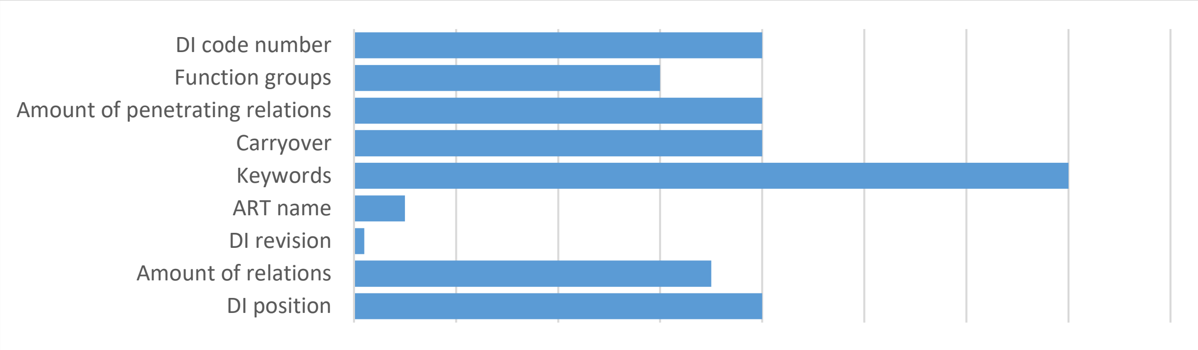

Figure 26 Normalized result from the first screening test with respective predictor turned off. A longer bar indicates better performance of the model without the predictor.

The test was then reiterated in the same fashion, but this time with Keywords also turned off at every test run. Another predictor was found lacklustre in this session, namely Carryover. When Carryover was excluded from the predictors the accuracy went up from the test average 61% to 65%. The result can be studied in Figure 27.

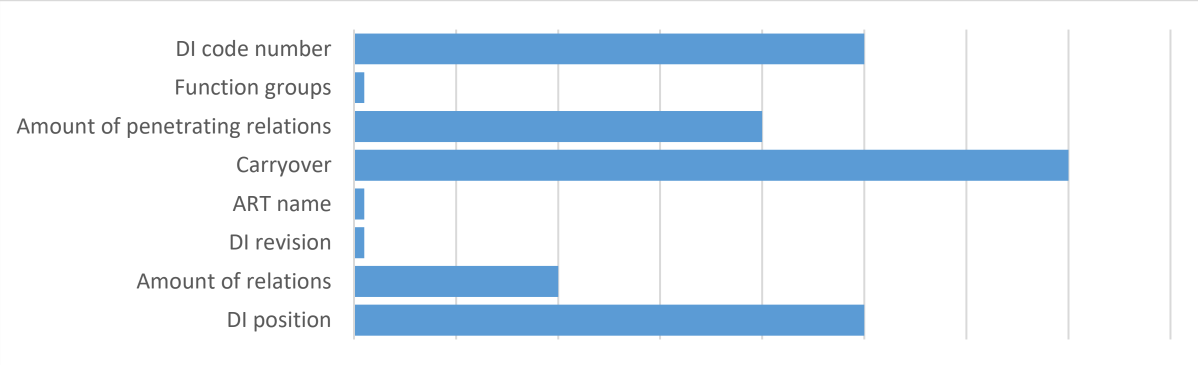

Figure 27 Normalized result from the second screening test with respective predictor turned off. A longer bar indicates better performance of the model without the predictor.

Conclusively Keywords and Carryover are screened away, leaving only the seven remaining predictors for the FFD test.

5.6.1.2 FFD test

As stated before, the test of seven predictors imply 128 tests. A system of all possible combinations is created and written down in a spreadsheet. The testing is then conducted by following the pre-entered scheme of combinations. Each test resulted in an accuracy value of the ability to predict NOK. The whole test protocol, sorted in ascending order from the lowest score to the highest, can be seen in Appendix E.

By analysing the scores conclusions can be made. Firstly, the result shows that Amount of penetrating relations and DI position have very small effect on the outcome. In most cases it rarely impacts the result when those predictors are turned off compared to on. Secondly, DI revision and Amount of relations have relatively weak but still noticeably positive impact on the result. The model performs worse when any of those predictors are turned off compared to on. Thirdly, ART name and Function groups have large impact on the result. Those predictors are clearly the most important ones overall. However, looking at specific combinations shows that no predictor performs strong on its own, it is rather a matter of combinations to achieve a high result. The combination of ART name, DI revision and DI code number is particularly impactful to reach high accuracy. In fact, the best accuracy was achieved with all seven predictors turned on, although only with a small margin to the second-best result.

Conclusively this test is conducted to understand the impact of each predictor on the result. It is important to know this to understand how the best possible performance of a model can be achieved. The test shows that no predictor is strong alone, but some combinations are stronger than others. The most distinct result from this test is however that Amount of penetrating relations and DI position have very little effect on the result. Those predictors are thusly removed from further analysis to simplify the model. The five remaining predictors are presented in Table 10**.**

Table 10 The five important predictors.

DI code number
Function groups
ART names
Amount of relations
DI revision

5.6.2 Algorithm evaluation

Previous models have consistently used the algorithm tree. However, the model's performance is affected by the algorithm used. The choice of algorithm is unique for each application of ML. Thus, experimenting with algorithms is a possible way of optimizing a model's performance.

In MATLAB's Classification Learner, eleven different algorithms are built in. These eleven algorithms are the once used for evaluation. Like the previous iterations, data is used to train the model. Although the choice of algorithm is now alternated creating one model for each algorithm. Consequently, the five predictors declared in the previous section are used. This means that eleven models were created and trained.

The result of the testing of each model is seen in Table 11. The result varies from 78.1% to 85.5% in overall accuracy. The variation of this accuracy is greater, varying from 9.7% as lowest up to 74.9% as highest accuracy. The model with the highest accuracy of predicting NOK is the model using the algorithm RUS Boosted trees. However, the model with highest overall prediction accuracy is the one based on the algorithm bagged trees. The result varies from 78.1% to 85.5% in overall accuracy. The model's accuracy in predicting NOK is of interest. The variation of this accuracy is greater, varying from 9.7% as lowest up to 74.9% as highest accuracy. The model with the highest accuracy of predicting NOK is the model using the algorithm RUS Boosted trees. However, the model with highest overall prediction accuracy is the one based on the algorithm bagged trees.

Table 11 Result of model testing in algorithms evaluation.

Model name	Overall	NOK accuracy
Fine tree	82.5%	52.3%
Logistic regression	80.3%	12.3%
Gaussian naïve bayes	78.1%	19.5%
Kernel naïve bayes	79.2%	15.4%
Linear svm	80.5%	9.7%
Quadratic svm	80.6%	10.8%
Cubic svm	80%	11.3%
Fine gaussian svm	80.4%	9.7%
Boosted trees	84.3%	46.2%
Bagged trees	85.5%	52.3%
RUS boosted trees	78.8%	74.9%

The prediction accuracy of NOK which the RUS boosted tree algorithm performs is the highest achieved throughout the project. Moreover, the results show that the algorithms based on decision trees; fine tree, boosted trees, bagged trees and RUS boosted trees all performs with a high accuracy of predicting NOK. The boosting method used both in the algorithm boosted tree and RUS boosted trees is a well-known technique to use within the field of ML when the distribution of data is skewed (Govindaraj & Lavanya, 2013). The tendency of skewed data has been seen throughout the previous iterations. Furthermore, the method of RUS boosted also includes the improvement of weak predictors in addition to evening out the skewed distribution.

It is concluded that the data used throughout the project is clearly affecting the results by its skewed distribution. Furthermore, predictors can either be strong or weak meaning that they influence the model's accuracy differently. Since RUS boosted tree was the algorithm performing best regarding predicting NOK, a tendency of weak predictors still exists in the five used predictors. Finally, the usage of an algorithm based on a decision tree is justified to use.

5.7 Conclusion of Data Analysis & Model Enhancement

It is concluded that the risk level will not be evaluated. Each CP associated with a risk also has a NOK status and the model show weak performance in differentiating between the degrees of risk. Thus, it is enough to only predict at status level, rather than at the risk level. Moreover, the data from relation level contained very few instances of risk. It was therefore concluded that data from relation level was not applicable for the ML model. Hence, relations data was discontinued in the analysis.

Furthermore, it is concluded that all CPs with NEW status must be removed since they do not add any training value for the model. A CP classified as NEW has by definition not been evaluated, hence will only distort the data with a trivial response. Furthermore, it is concluded that CPs with the status NA will be removed from the data.

The data analysis is performed on a dataset extracted from the MIP system database at one specific moment in time. At that instance, the CPs have a specific status, either OK or NOK. However, some CPs have changed from NOK to OK at an earlier moment in time, likely since the geometrical issue was resolved. These CPs would therefore not train the ML model to identify NOK correctly. To combat this issue, the historical changes to each CP are examined and whenever applicable the status is changed. Conclusively, the data that is extracted from the database does not take changes through time into consideration, but alteration of the data can combat this problem.

In the final iteration, an FFD experiment was conducted to examine the impact of each combination of predictor. In the test, five predictors where found as the optimal combination to get the best performance from the model. These five predictors were later used to evaluate the impact of different algorithms. Conclusively, an alteration of the tree algorithm showed the best performance, namely RUS boosted trees.

The prediction accuracy is improved from 4% to almost 75% when predicting NOK. This improvement is accomplished by modification of the data through successively eliminating predictors and forming new ones. The significant increase in accuracy understates the importance of predictor engineering. It is concluded that the data that exists today needs to be cleaned and reformed to be functional in an ML application.

Conclusively, the developed model can predict NOK at CP level with a certain accuracy. However, the model is still in need of further development by deploy and monitor it before its practical performance can be determined.

6 Converged Result

In the converged result chapter, the results and conclusions of Chapter 4 and 5 are merged. It intends to conclude on which concepts are feasible. Consequently, the potential of how the work of MIP can be eased by applying ML is determined.

6.1 Concept Evaluation

Six concepts are presented in the user analysis, but only five are procced with as opportunities for easing the work of the MIP users. The five concepts from the user analysis are compared and matched to the found potential from the data analysis & model enhancement below.

Concept 1 –OK/NOK recognition. This concept has its basis in the ability to predict OK or NOK at relation level in MIP. From chapter 5 it is stated that the ML model cannot predict at relation level, but rather on CP level due to the adequate and incomplete data. Therefore, the concept is forfeit.

Concept 2 - CPs' risk tendency. A 75% accuracy of predicting NOK is achieved. This means that the model can find 3 out of 4 of the CPs with risk based on the MIP data. However, the concept is not able to predict the right risk level. Concept 2 propose that the model shall support the user by classifying the CPs that might be imposed with a problem as a risk. By identifying 75% of such CPs and presenting these to the user the objectives of concept 2 are still considered practicable.

Concept 3 – Relations' risk tendency. Likewise concept 1, the ML model has no ability to predict at relations level, thus is concept 3 forfeit.

Concept 4 – High-risk notification. With the same reasoning as for concept 2, High risk notification on CP level is feasible. The model can identify 75% of the NOKs which implies the ability to identify CPs with a risk and consequently notify the user of it. However, High-risk notification of relations is not possible.

Concept 6 – Decision verification. To support the users of MIP, a verification function based on the predictions from the model can be used. The user takes a decision, then the model returns if it coincides with the prediction or not. This function is within the capabilities of the model, but only to some extent sine the model is not predicting at 100% percent. The function is still feasible as an supporting feature to the MIP system.

In summary, three out of the five proposed concepts have the potential to ease the work of the MIP users. Namely, concept 2, 4 and 6. These concepts are considered as opportunities of how ML can be applied in MIP based on the possibilities of the developed theoretical ML model. Conclusively, the found opportunities in the User analysis is matched with the developed ML model, meaning that there is a potential for ML to be applied and facilitate the work of MIP users.

7 Risk, Ethical and Environmental Considerations

This chapter includes the ethical and environmental considerations regarding the application of ML in MIP. By examine the European Commission's principles of how to develop trustworthy AI, the key aspects needed to be considered in this project is highlighted. In addition, a risk analysis is performed. The risk analysis aims to emphasize the consequences the application of ML can mean.

7.1 Ethical Considerations

Stated by the European Commission's High-Level Expert Group on AI (AI HLEG) there are four principles to ensure ethical deployment of trustworthy AI systems. Moreover, they also present seven key requirements for realization of the same. The principles and requirements are of general sort and the ML application discussed in this report is not touched by all of them. In this chapter only a discussion of the relevant ethical aspects with regards to this report is held, however, in the creation of any AI system, all of these guidelines should be fulfilled prior to deployment.

In the MIP data, information about the DEs and MIEs is stored. It is possible to identify the person making an action, for instance changing a CP or relation status. By letting the ML model take this personal data into account when predicting, it will present a result based on individuals' historical pattern. It will be possible to distinguish and highlight individual's patterns in a way that was much harder to accomplish without ML. By doing this, interference with the *principle of prevention of harm* and *principle of fairness* might occur (European Commission, 2019). The Principle of prevention of harm states

> *"AI systems should neither cause nor exacerbate harm or otherwise adversely affect human beings. This entails the protection of human dignity as well as mental and physical integrity… Particular attention must also be paid to situations where AI systems can cause or exacerbate adverse impacts due to asymmetries of power or information, such as between employers and employees"* - *(European Commission, 2019)*

The principle of fairness states that fairness implies:

> *"…ensuring equal and just distribution of both benefits and costs, and ensuring that individuals and groups are free from unfair bias, discrimination and stigmatisation."*- *(Ibid.)*

If the ML model could be used for identifying people's deficiency or differences, it would imply the risk of potentially go against this principle. However, if the personal information is removed from the data, the usage of ML in MIP discussed in this report should apply to the principles presented by AI HLEG in the 2019 report.

Explicability is crucial for building and maintaining users' trust in the ML model (European Commission, 2019). This means that the process should be transparent, and the possibilities and purpose of the model should be openly communicated to those affected by it. If no such information is delivered, the predictions cannot be contested by the users and in time flaws in the model‘s outcome might not be detected.

If an ML model would be allowed to perform decisions in MIP such as changing the status on a CP or relation, the question of accountability for that decision would naturally arise. AI HLEG presents accountability as a requirement for trustworthy AI and states that it necessitates that mechanisms be put in place to ensure responsibility and accountability for AI systems and their outcomes before and after their development, deployment and use. Thus, it is recommended that Volvo Cars set up governance frameworks, ensuring accountability for the decisions taken by the ML system both prior to development and during use of it. Moreover, it is found that there are two possible ways to use ML in MIP, evaluating and supporting. If application of ML in MIP will be a supporting feature rather than an evaluating one, the decision making will remain in the human domain, thus reducing the need for a governance framework.

7.2 Environmental considerations

No environmental aspects have been found within the subject of this report.

7.3 Risk analysis

Throughout the project, factors are detected that potentially can induce risks with applying ML in MIP. These factors are analysed to determine and declare what risks the usage of ML in MIP would possibly imply. Furthermore, the analysis includes recommendations in form of an action plan for mitigate the risks.

The factors and their risks are classified. In order to classify the risk, a risk matrix is used (Ulrich & Eppinger, 2011). Thus, the risk is evaluated depending on likelihood of occurrence and the consequences it would imply if it occurs. Based on these two factors, the risk is given a class of either low, medium, high or extreme. The risk matrix is presented in Table 12. The consequences of the identified risks imply mainly loss in time and increased costs. For example, if an ML model is implemented and makes an incorrect prediction regarding a CP, the consequence includes delay in the development processes. Moreover, consequences can include the need for late costly changes in projects.

Table 12 The Risk matrix used for classifying the identified risks.

Likelihood	**Consequence**				
	Insignificant	Minor	Moderate	Major	Critical
Rare	LOW	LOW	LOW	MEDIUM	HIGH
Unlikely	LOW	LOW	MEDIUM	MEDIUM	HIGH
Possible	LOW	MEDIUM	MEDIUM	HIGH	HIGH
Likely	MEDIUM	MEDIUM	HIGH	HIGH	EXTREME
Almost Certain	MEDIUM	MEDIUM	HIGH	EXTREME	EXTREME

Eight main risk factors are found. These are presented in Table 13, followed by a risk description, their risk class. In addition, a suggested action plan for each of the risks are given. The action plan strives for mitigating the risk. The importance of mitigating the risks are relevant since the consequences of an incident imply loss in form of both time and money.

Table 13 Identified risk factors, their class accompanied with action plan.

Risk Factor	Risk description	Risk class	Action plan
No one to hold accountable for errors.	The accountability for a faulty prediction is unclear, making it hard to track the origin of the fallacy.	LOW	Communicate between business units and set up a clear framework of how to handle the accountability.
The ML model is biased.	The data used to train the ML model have made it biased. Consequently, the model is not able to predict accurately.	MEDIUM	Deploy and monitor the model thoroughly before using it live.
An ML model would lead to less awareness of geometrical environment.	The implementation of ML implies less usage of MIP by DEs, leading to loss of geometrical awareness. Consequently, DEs' design process requires more redesigns.	MEDIUM	Introduce a checking tool in CATIA that is easy for DEs to use for ensuring geometrical awareness.
The ML model is not trusted.	The uses of MIP do not trust the ML model. Thus, the value of the ML implementation is greatly reduced.	MEDIUM	Be transparent and arrange training for the users to prove the trustworthiness of the ML model.
The ML model's prediction accuracy and users trust is not aligned.	If the model is trusted more than it can perform, risk are that wrongly predictions goes unnoticed.	MEDIUM	Be transparent and arrange training for the users for gaining trust and deploy and monitor the ML model before using it live.
Hidden fallacies in the ML model exists.	The ML model has hidden fallacies making it unable to make sudden incorrect predictions.	HIGH	Deploy and monitor the model thoroughly before using it live.
The ML model is overfitted.	The ML model is overfitted making it unable to use with new projects and components.	HIGH	Deploy and monitor the model thoroughly before using it live.
Data structure changes over time.	If the data structure changes, caused by e.g. system updates, the model needs to be retrained.	EXTREME	Communicate between business units in order to prepare for system updates.

8 Discussion

Throughout the project several results have been presented. However, before a final conclusion can be made, a discussion is needed for justifying the concluding thoughts. The discussion includes a critical view of the project and the choices made as the prominent aspect.

The data is always a main factor of an ML project and so also in this project. In the early stages of the project, it was found that there is no clear perception of when a relation is OK or NOK. As presented in the user analysis, the status notation in MIP is rather a case of marking if the user is aware of the relation or not. This unclarity in the system has divided the users into groups were several interpretations of the status notation exists. In some cases, the users do not change status to YES until the geometry is perfected, and some users put the status on YES even though the geometry has major errors. As long as the CP status is not set in a way that correlates with the actual state of the geometry, the data will be lacklustre and not consistent enough to train the ML model properly. Furthermore, the data used for training is not using the same vocabulary. Instead for YES and NO, OK and NOK is used. This further complicates the understanding and connection between the usage of the MIP and the data. Simply put, the lack of a common interpretation of when a CP is OK or NOK is confusing for users and complicates the application of ML.

The consequences of not having a common interpretation of when a CP is OK means that the data used within this project for training the model is inferior. Since the status of OK is interpreted as OK by the model it means that certain predictions are faulty predicted since the OK might have been set before the CP actually was OK. This means that the ML model is only able to predict if the CP would have been evaluated as OK or NOK but not if any further actions were needed to complete the geometrical relation. Based on this arguing, it is clear that the current alternatives for marking the CP status in MIP is not usable, complicates the user situation and the application of ML. Instead, new alternatives for the marking of CP status should be implemented giving the users the opportunity to mark the CP as OK, NOK or Needs update. The change would imply that the new data will be much more suitable for an ML model to learn from. Furthermore, the user experience would potentially improve.

This project is delimited to only use data extracted from MIP. The quality of the data is of importance since its quality is directly correlating to the potential performance of an ML model. The foundation of this investigation lays on the data including enough pattern for an ML model to learn how to make justified predictions. Although, Senior Machine Learning Engineer Lars Thornberg at Volvo Cars states:

"A good starting point when developing an ML model that is supposed to evaluate something people usually evaluate, is to find how the person in question evaluates the matter."

From what has been learned through the user analysis, it is known that evaluations in MIP is not simply a matter of looking in the MIP data but rather a matter of visual inspection and experience-based knowledge. This is directly contrary to the approach of this project of using the data within MIP. However, the data in MIP includes aspects such as what kind of component it is and which ART it belongs to, which are stated as underlying knowledge when evaluating the CP. Furthermore, the results from the Data analysis and Model Enhancement in chapter 5 indicates that the data is adequate to predict 75% of the NOK CPs. These results mean the data must contain enough information for making the choice of OK or NOK with a certain accuracy. Moreover, this project is delimited to only develop a theoretical model, which must be kept in mind. This implies that the model is not ready to be deployed live and more extensive evaluations needs to be done to ensure that that the model do not have fallacies. Yet, with the right data and further development, tendency is that an ML model can grow more accurate with time. Also, in the long run, the process of evaluating geometrical relations could be fully automated.

Based on the above arguing, it is still hard to clearly state if an ML model based on the data directly extracted from MIP is beneficial to apply in MIP. Instead, an approach including data from other systems, such as Teamcenter, are perhaps of more use since it could represent the user's behaviours better. In that case, even image recognition could be used. If an ML model instead were to be trained to classify penetration as OK or NOK based on 3D models the evaluation would be more humanlike. However, this would imply extensive development since no such data with correct response included are currently accessible.

Found in the user analysis there are comprehensive discussions involving many divisions and blocks regarding the evaluation of certain CPs. These discussions often occur at mechanical integration meetings or simply between DEs. During these discussions, action plans and decisions are made. Potentially, these discussions could be funnelled down to be used as predictors, stating errors in the design etc. However, statements as the two below are frequently found in the user analysis:

> *"...there is no documentation of the evaluation process."*
>
> *"It is never documented why something is considered to be OK or not."*

This lack of documented evaluation implicates the concept using the discussions as predictors. Although, an easier way of using MIP is still desired which paves the way for a change in MIP where the right data can be gathered and in the future lead to an easier system including an ML model.

Benefits of applying an ML model in MIP implies possible savings in time and cost by a more time efficient mechanical integration. However, before deciding on applying ML, the findings in the user analysis must be considered. Namely, the users strongly believe that MIP is necessary for ensuring the design quality. Also, without using MIP, the risk is that awareness of the geometrical environment is lost. Many DEs states that MIP is a tool that ensures them that they have designed as good as possible. However, MIP is only periodically used which weakens the utility of MIP's potential. By only using MIP close to geofreeze, DEs are minimizing their time in MIP while simultaneously stating that it is necessary for them to use MIP. In the case of applying ML into MIP, the aspect of when MIP is used is of great importance for making the ML model useful. Deeper analysis of the timing of when the ML model should be used is needed for not turning it into an annoying feature of MIP.

This project's approach of including data from only two projects is discussable. Since the model is only trained and tested with this data, no results can prove the performance on various projects. One risk is that the data varies from project to project, making an ML model inconsistent in its predictions. Thus, the need for deploying and monitoring the model is emphasized. Furthermore, the aspect of data changing over time is something to take into consideration when concluding on the utility of ML in MIP. If the prerequisites for the model changes, one needs to be aware of this in order to not lose the models utility. According to the consultation made, Volvo Cars is not currently running any type of projects like the application of ML in MIP would imply. Therefore, it is necessary to be clearly aware of the prerequisites of the model before deploying it. In addition, since this project is delimited to a theoretical model, the prerequisites for a deployed model is not included although they are of high importance.

In the model enhancement process described in chapter 5**,** the predictors were modified and altered in the search for higher accuracy when predicting NOK. This is referred to as predictor engineering, a must for all ML model development. The idea of predictor engineering is that the algorithm must get input data that it can understand and interpret in a way that make sense for finding patterns. In the search for predictors that translates the data into a language that the algorithm can interpret, the DI code was spilt into separate elements. The tests show that the model performs better with the DIs current revision number as a predictor compared to without it. However, it is questionable if this number is applicable in the real situation of finding NOKs in MIP. If the model is trained with the revision number for identifying NOK CPs, it would have a hard time finding NOKs early in the project, when the revision number is low and the ability to identify NOK is the most rewarding. The revision number is inherently connected to the likelihood of NOK. This since a faulty geometry must be changed, which entails a new revision. Hence, a CP has a high likelihood of having a high revision number if it has ever had the status NOK. Therefore, the recommendation is to not include the revision number as a predictor in future work.

Time is an important aspect when working with the data from MIP. In this project, the data has been extracted from the database at one specific moment in time. At that time, some components in the car are very well developed and others might be at an early stage. In MIP this means that some CPs are fresh and have only had the status OK, whilst others might be several months old and have a long history of status changes. The fresh CPs might however become a NOK at a later stage, for instance if the geometry is altered. If the model is trained with data like this, the model will learn to identify CPs as OK, but in reality, they might become NOK at a later stage. Thus, a fallacy will be introduced in the model. It is therefore recommended to only train the model with data from well-developed projects that are in the later stages of its lifespan.

Another aspect with time is that the model presented in this report is trained to identify CPs without the aspect of time in mind. In practice this means the model will predict a CP as OK or NOK without taking its degree of matureness in mind. Thus, when a new CP appear in MIP, the model will evaluate as if it were in the project's final state. Even though a geometry might be perfectly fine at that specific time in the project, the model will mark it as NOK if it recognizes the CP as NOK. This issue originates in the data structure. Since the data only represent one state per CP, it does not include the changes in time. If the model were to be trained on each CPs all states, the model would theoretically be able to predict with the aspect of time in mind. A suggestion is to use the historical data of each CP when training the model. The historical data shows every change that have occurred to each CP. For instance, the historical data would show if a CP was evaluated as OK at time *A*, then evaluated as NOK at time *B* and lastly OK again at time *C*. Each event as one separate node in the dataset. The model will theoretically be able to distinguish between these separate states if at least one other predictor changes in between them, for instance time and revision of the DI.

9 Final Conclusion

This thesis aims to investigate the potential of applying ML in MIP. To achieve this, three main hypotheses are stated. Consequently, the hypotheses are answered in the following texts.

1. *There is a potential for easing the work of MIP users by applying ML*

An extensive user analysis resulted in six concepts to use ML in MIP were identified. These concepts had the jointly aim to ease the evaluation of geometrical relations. However, the two users of MIP, DEs and MIEs, have different ways of using MIP. Thus, they have different needs. It is concluded that the potential of easing the work of DEs are greater than for MIEs, as DEs evaluate at relation level leading to a more extensive use of MIP.

It is concluded that only three of the six identified concepts are feasible. The first feasible concept intends to identify a CP's risk tendency. In this concept, an ML model predicts and evaluate the status of a CP and change its status to OK or NOK. Hence, the notation of NOK indicates that the CP has a risk tendency. Following, the second concept builds on the first concept, but instead of evaluating, the concept intends to notify the user when a CP is evaluated to be of high risk. This means that the user can prioritize the CPs by the level of risk. Hence, focus on the most critical objectives first. Finally, the third concept intends to verify the users' evaluation. The ML model is used to support the users by confirming their evaluation based on the model's prediction. The functions of all the three concepts are within the capabilities of the developed model. However, the three feasible concepts are only functional at a CP level. Thus, only supporting the work of MIEs and not DEs. Since it is concluded that the greatest potential lays in easing the work of DEs, the feasible concepts are inferior with the prominent needs.

Moreover, it is concluded that there are two possible ways of using ML in MIP. The ML model would either be evaluating or supporting. In the user analysis the users state that MIP is necessary for ensuring the design quality. Without using MIP, risks are that awareness of the geometrical environment is lost. Therefore, it is concluded that an evaluating ML model is inappropriate to develop since it could erase one of the main functions of MIP; giving DEs awareness of their geometrical surroundings. Instead, a supporting ML model is concluded to be the best fit. This, since it implies easing the work at the same time keep the human involvement.

In summary, there exists three potential concepts for easing the workload of users by applying ML in MIP.

2. *Geometrical relations can be evaluated by an ML model based on available data from MIP.*

Results show an ML model being able to predict NOK with an accuracy of approximately 75% based on data extracted from MIP. The ML model is based on a RUS boosted tree algorithm and uses five predictors. By modifying the data through successively eliminating and creating new predictors the model's prediction accuracy was improved from 4% to the final 75%. It is concluded that comprehensive cleaning and reforming of the accessible data must be done for it to being functional in an ML application. Furthermore, it was not feasible for the ML model to evaluate at relation level. This, since the data from relation level contained very few instances of risks, making the data inadequate for the development of an ML model predicting risk level. Hence, the model developed is only able to predict at CP level.

Furthermore, the ML model is only theoretical since it has not been deployed or monitored. Thus, its true utility is still to be determined. To fully determine the ML model's utility, it is required to deploy the model, evaluating on a live project. Although, the results indicate a high prediction accuracy, there are multiple aspects contradicting the utility of ML. Potential fallacies in the model have been identified and discussed. Due to doubts of using revision number as a predictor, the CP status not being set correlating to the actual state of the geometry and the model's lack of time considerations. The resulting accuracy of predicting NOK might not correlate to the real-world scenario.

This project is delimited to use historical data from MIP that is available today. Consequently, the results only show what is possible in the current state. ML has the potential to be applied in MIP at Volvo Cars. However, the utility of it is questionable due to the needs not aligning with the current possibilities. Therefore, the recommendation is to not implement ML in MIP as long as the model is only able to predict at CP level.

If Volvo Cars is able to change the users' behaviours, MIP's interface or both, relevant data can be collected making it possible to utilize an ML model for predicting at relation level. Thereby, enabling alignment of the needs and the possibilities.

3. *The application of ML in MIP can be executed with ethical, environmental and risk aspects taken into consideration.*

Based on the European Commission's principles of how to develop trustworthy AI, the application of ML in MIP must exclude any personal information in the data that is used to train the ML model. Furthermore, the process and purpose of the ML model must be transparent and openly communicated to the ones affected by the application of the ML model. This for building and maintaining users' trust in the ML model.

Consequently, the application of ML in MIP induces certain risks. The consequences of the risks are mainly loss of time and money. In total, eight risks are identified. The most critical is the risk of the ML model making a faulty decision. This may occur due to the model being biased, overfitted or an update in the system being made. Each risk is accompanied with an action plan aiming for mitigating the consequences. It is concluded that no environmental aspects needed to be considered exists.

In summary, the application of ML in MIP can be executed with ethical, environmental and risk aspects taken into consideration.

10 Recommendations and Future Work

Since the model is delimited to be of theoretical character, this future work is recommended to expand on the project's result:

- Deploy and monitor the ML model presented in the report in a small scale.
- Ensure a consistent use of MIP throughout its users.
- Investigate the cost of implementing ML.
- Investigate the time to develop a fully operational ML model.

Although, the recommendation is to not apply ML. Thus, further actions are suggested as follows:

- Further investigate and improve the MIP interface based on the user analysis.
- Make it possible to screen the exposed relation in MIP directly in TCVis.

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Appendix A Interview Questions

Design Engineer

MIP USAGE

1. What is your title and your profession?
    a. What ART do you work within?
2. How do you use MIP?
3. Can you describe the process of you using MIP?
    a. What is the first step?
    b. How do you know that the CP/relation is your responsibility?
    c. How do you sort the CPs and relations?
        i. What is it that you start with?
    d. How do you validate the relations?
    e. Are you considering the distance shown in MIP?
        i. Are you considering the value of the distance as you evaluate the relation?
        ii. Are there any relations that are easy to validate? If so, how are you treating them?
4. What is the main reason for your department needing MIP?

CHECKED BY DESIGN ENGINEER (YES/NO)

5. What does a yes mean to you?
6. Are you evaluating all your CPs and relations?
    a. If no, which do you not evaluate
    b. Are you using the function of "Distance Required"?
    c. Are there any CPs that you know since before are already OK?
7. Do you believe that the YES/NO system works well?
    a. If no; Why and how can it be clearer?
    b. If yes; In which ways is it easing your work? Can it improve?
8. Would a "relation OK" button be useful in MIP?
    a. Explain your thoughts!
    b. Do you see any potential problems with such a button?
    c. DO you believe there are any risks with such a button?

ISSUE

9. Do you use the Issue-function?
10. How is an issue solved?
11. In which ways are an issue followed up?

MISCELLANEOUS

12. Do you believe that MIP is adding value in you work?
13. What is the most time consuming in the work you do that involves MIP?
14. How can MIP be improved in your opinion?
15. What are your thoughts regarding if an AI would be used within MIP?
    a. What could be potential advantages, disadvantages and risks with that?

Mechanical Integration Engineer

MIP USAGE

16. What is your title and your profession?
    a. What block do you work within?
1. How often do you use MIP?
17. How do you use MIP?
18. Can you describe the process of you using MIP?
    a. What is the first step?
    b. How do you know that the CP/relation is you responsibility?
    c. How do you sort the CPs and relations?
        i. What is it that you start with?
    d. How do you validate the relations?
    e. Are you considering the distance shown in MIP?
        i. Are you considering the value of the distance as you evaluate the relation?
        ii. Are there any relations that are easy to validate? If so, how are you treating them?
2. Regarding the ownership of CPs:
    a. How is the owner determined?
    b. How come the owner of the checkpoint is not automatically owner of the underlaying relations?
    c. If X is owner of component 1 and Y is owner of component 2 that are in relation with each other, who is assigned the ownership of the relation? Praxis?
19. What is the main reason for your department needing MIP?

OK/NOK

3. How do you use the functions of OK/NOK?
    a. Can you show and describe your thoughts?
4. What is affecting whether the checkpoint is classified as NOK or OK?
20. Do you believe that the YES/NO system works well?
    a. If no; Why and how can it be clearer?
    b. If yes; In which ways is it easing your work? Can it improve?
    a.
5. How is the decisions and evaluation documented?
21. Are you evaluating all you CPs?
    a. If no, which do you not evaluate
    b. Are you using the function of “Distance Required”?
    c. Are there any CPs that you know since before are already OK?

ISSUE

22. Do you use the Issue-function?
23. How is an issue solved?
24. In which ways are an issue followed up?
6. How is the risk function used in you work?

MISCELLANEOUS

25. Do you believe that MIP is adding value in you work?
26. What is the most time consuming in the work you do that involves MIP?
27. How can MIP be improved in your opinion?
28. What are your thoughts regarding if an AI would be used within MIP?
    a. What could be potential advantages, disadvantages and risks with that?

Appendix B User study KJ-method

KJ for DEs

The assessment processes

- "Yes" in the column of checked by design owner do not mean that the relation is okay, it just means that I am aware of the relation
- I evaluate regarding to material, squeak, rattle, tolerances, risks and so on
- I check all the relations in TCVis
- "Yes" means that I have checked the relation, if something has to be done about it, I can write a comment
- I do not make any notes or comments, I just change the button for checked by design engineer to either "Yes" or "No"
- "Yes" means that it is ok, I can add a comment if the relation is not okay
- I evaluate the relation visually in TCVis
- If there is any problem, I leave the checked by design owner red
- Sometimes, parts that is in relation in MIP is having parts in between them. Meaning that there is no real conflict
- I evaluate the relations based on my experience, for example for example gaskets are made to be in conflict and I know that
- I do not take the value of the distance into consideration; I rather look in TCVis
- "Yes", do only mean that I am aware of the relation not that I am sure that the relation is OK
- "Yes" means that I have checked the relation and that it is OK
- Sometimes I just look at the distance in MIP and know that the relation is OK
- I check the relations by open up the whole geometrical surrounding in TCVis and then I control each part on at the time
- If I notice any problem in TCVis, I usually opens the geometry in CATIA as well for controlling it an extra time
- It is possible to guess whether a relation is OK or not
- My component is having a rather fixed position in the car and is not moved. If it interferes with something, the counterpart has to be changed
- Instead of looking in MIP, I sometimes manually measure the distance between parts in either TCVis or CATIA
- I check all the CPs within my ART, it is about 200 CPs
- All DEs prefer CATIA before TCVis
- I control all the relations in TCVis, but sometimes I just put a "Yes" into the checked by design owner without thinking too much about it
- I look at the distance in MIP and change the checked by design engineer to "Yes"
- I do not check all relations in TCVis because I know since before that it is alright. Although, sometimes I have to doublecheck, then I open the relation in TCVis
- It is never documented why something is considered to be OK or not
- I load all the relations into TCVis and then I do a clearance analysis and finds the same distances as in MIP, then I can control them
- Sometimes, one wants to have sub-owners included because they have been involved in the CAD process
- Some CPs are intuitively classified as problems
- I do not dare to classify something as "Yes" without checking the geometry in TCVis or CATIA

- I control the relations in TCVis, but if I am unsure, I can use CATIA since TCVis sometimes has some visually problems

When MIP is used

- I am trying to do MIP when I have time, to avoid having too much to do in MIP close to a release
- I only use MIP close to a release
- MIP is used after the geofreeze when the surrounding geometry are OK
- Every twelfth week, when a release is due, we use MIP. It is unnecessary to do it before
- Geofreeze occurs two weeks before a release
- I do not need MIP, since I am already aware of the surrounding geometry when I start using CAD
- I use MIP because of quality reasons, but only before a release
- I use MIP continuously a few times a week. However, very rarely in the early phases of a project
- There cannot be any geometrical clashes when simulations are done
- It is often very stressful in new projects with a lot of new components, at that time MIP is very useful since it is easily happened that a geometrical clash is missed
- MIP should be done continuously, but we only do it before a release
- Immature projects and concepts can create a lot of clashes, but it is unnecessary to check since they will eventually mature
- MIP is used when the project grows close to the end and suppliers are needed
- I use MIP when people complain, and the project requires it
- I forget how to use MIP because I use it rarely

Benefits of MIP

- Without MIP we lose the integration quality
- MIP ensures me that I have designed my parts a good as possible considering the surroundings
- MIP is good for double checking your work
- MIP helps by making me aware of conflicts
- MIP is definitely useful
- I check so that we do not have penetrating geometries
- MIP is used to make sure everything will fit in the car
- MIP is helpful for getting to know the surrounding geometries
- "Yes"/”No” works better than it did in DPA[0]

Disadvantages of MIP

- It is cumbersome that is says “Yes" even if the thing is not ready
- OK/NOK should be clearer so that everybody works the same way
- Some CPs is unnecessary because of our tight tolerances. The part is supposed to be close to each other
- Some conflicts are repetitions that occurs in several projects
- Carryover parts and variant parts consume a lot of time; they look the same but still needs to ticked off
- It would be an improvement if reoccurring conflicts was automatically removed, same part with the same distance
- Personally, MIP do not add any value, but it can be useful for the project management

- The MIP system is used as a verification-tool that I use for my own sake
- A big problem is that people do not know how to use MIP
- MIP is used to communicate the status to the project management. In some way it is used to calm down the project management and measure the performance of the project
- An improvement would be to include a carryover filter in MIP
- I do not look at carryover parts, I filter then away
- Some lines are checked by the MIEs and is therefore less stressful to handle
- Carryover parts and clips are the most time-consuming parts to handle
- The problem is that the MIP interface is hard to understand and that everyone works in diverse ways

Redundant CPs

- Fasteners is such stuff that you always need to check off without looking
- Some conflicts are the same as in other cars, in such instances I just mark them as OK since I know it from before
- Some CPs have the same problem and you just need to check it off
- Items with large distance between each other is no problem
- You know how some components will behave in real life, cables for instance. Then I set it as OK even if they are in contact

Sorting CPs

- I check relations and sub-relations, one at a time
- I assess all my CPs
- Clips can be set to "Yes" without looking
- I check all rows that are marked red red first, then red green
- I just start from the top of the list that is presented when I start MIP
- I choose the "My CPs"-tab and go through all the red marked lines
- I sort by project and filter away everything except my ART. Then I search for my name and get a list of things that has a relation with my parts
- A lot of checks are a matter of ticking them off
- I sort the relations so that I get the one with the largest negative distance first
- When a relation is checked, I put it as "Yes"
- I check my CPs against the most critical ARTs first
- DIs can be grouped in such way that I only need to check off one variant
- I sort by ART

Usage of the issues function

- I do not use the issue function, If I discover a problem, I contact the responsible person via Skype, email or directly (mentioned five times)
- It is less cumbersome to contact the person outside of MIP then using the issue function
- I want to solve problems directly, so I do not use the issue function
- An issue with "K1" means more work than just contacting the person directly
- If something needs to be done with the design, I take a snapshot and add it to my to do list

Time consuming tasks

- Sometimes CPs that I have already check are reoccurring, it is unnecessary work
- The thing that takes the longest is to go through all the relations

- MIP would have been better if there were an OK button
- It is complicated and I have to filter the information in MIP
- Sometimes DIs that do not contain any parts are added, then CPs that are not relevant are added
- Should be good if relations were zoomed in on immediately after loaded from MIP into TCVis
- A preview of the geometry in MIP would be good, it takes very long time to load it into TCVis
- It takes a long time to load it into TCVis and then find the relations

The user experience of MIP

- It should be a better connection between TCVis and MIP, now I have to do a clearance analysis in TCVis to find the distance shown in MIP
- An autogenerated email that was sent out when an update in MIP was done would be great, just to inform when I actually have an issue in MIP
- "Yes" = I have checked
- Send an email whenever a problem is encountered so that people can check their CPs and relations
- An OK button/column would be an good idea to make it more clearer that the relation is actually OK
- The "Yes"/”No” system is unclear
- “No” is equally to me needing to do CAD immediately
- MIP could be improved by simplify the user interface
- MIP is so messy so I cannot do it very often
- MIP should not only display numbers of distances, it should show a figure of the problem or even a 3d model so one could turn it around
- MIP could improve by reducing the number of columns, the number of columns makes it very confusing to find the important information
- "Yes" means to me that I have seen the relation and that is alright right now
- It takes very long time to load the relations and geometry from MIP into TCVis
- I would like an email whenever I have important CPs
- I wish I was notified if something in the environment around my part was changed
- MIP is consisting of too many columns
- I see a problem in TCVis since it is so hard to use and requires me to change a lot of setting to use it
- It is bad that MIP is keeping a lot of old projects

Thoughts of AI and ML in MIP

- Using AI in MIP would probably mean that MIP would be used more continuously
- Can one trust predictions done by AI?
- AI cannot oversee anything important
- AI should highlight problems and present a view of the geometrical issue
- It feels dangerous using AI or ML, what if it misses 1 case?
- Such an algorithm has to take everything into consideration, but I guess it could be tried at cases that is not that critical
- AI or ML should be able to decide whether a part is likewise an older part, and if the old part was geometrically OK the new one should also be considered OK
- If ML is used, it should still be possible to look at the CPs and relations that the ML have evaluated

KJ for MIEs

For what is MIP used

- MIP is used for creating an overview of all geometries
- MIP is used as a scorecard where I log all issues on different CPs
- MIP is used for following up the project's status
- MIP is used for making sure we have the correct speed of solving problems
- MIP helps you to avoid having to remember a lot of stuff manually
- MIEs are acting as a helping hand between DEs
- MIEs are mainly checking CPs but also relations
- We are contacting the DE if we see any problems
- MIP is used to ensure that everything is checked

When MIP is used

- MIP is used several times every week, the goal is 30 min per day
- MIP is used after the concept phase
- Once every week I check for new CPs in the project
- I use MIP about 1 h a week

MIEs responsibilities

- The new CPs are yours if they are positioned within your block area
- We are five MIEs in our block plus one team manager
- We have integration meetings every week

Usage of the Issue function

- It is often known where issues will occur since the people working in the concept phase can inform us
- If a relation looks visually incorrect, it gets an "Issue"
- An experienced MIE can with time tell where issues will occur
- It is very easy to handle a case with a relation in MIP, then you can simply create an issue
- When creating an issue, the MIE writes about the problem and holds a meeting. When the issue is closed, the MIE writes a short note about what changes solved the problem
- When an issue is closed, the reason is usually noted by me
- MIEs can see issue history
- In some project that I been involved in during a long time, I am aware of all the parts and can see clashes and problems without consulting MIP
- We at propulsion do not use the issue function

MIEs' usage of MIP

- Some parts are designed to be in contact and then that CP is simply ignored
- In our block we look at many parameters when deciding the outcome of a relation. For instance, assembly requirements, NVH calculations (sound and vibrations), clearance (when you drive up a ramp), corrosion, tolerances, crash test results and simulations
- Between some components you know by experience that there must be some kind of play in order to work
- New CPs are given owners and sub-owners etc

- Sometimes old CPs need to get new owners
- The OK/NOK can be misleading
- OK/NOK works very well in general, it is very clear
- NOK is automatically set when a MIE creates an issue
- I check the geometry in TCVis

Complications within MIP

- Carry over parts are not evaluated because they have already been evaluated in another project
- Often are geometrical relations examined in CATIA
- If a component is positioned in between two block areas, they might not show up in the list of CPs belonging to any block. Every now and then you have to look for such CPs manually
- It is cumbersome when a component lies within more than one block, since the ownership situation is not clear. Sometimes bad communication leads to that the CP is overlooked
- If one MIE takes ownership of a component that reaches trough many blocks, it will not appear in the other MIEs list
- Some CPs are already validated and considered OK since they are from old projects
- All DIs creates a CP, although they are not always evaluated since they can be carryover parts
- When a CP is checked, it is never looked at again
- There is a tendency that DEs believes "Yes" and green is that I as a MIE have approved the CP, but it only means that I have checked it
- What happens in MIP stays in MIP, no documentation of the evaluation process
- The system is very slow, and it takes a long time to load the model into TCVis
- In the grey zones between blocks, it is necessary that MIEs agrees on who is responsible
- It is necessary to talk between the blocks

Appendix C MATLAB code

Script for learning iteration

```
Counter1 = 0;
yfit1 = trainedModel1.predictFcn(testdata);
xfit= table2array(facitdata);
for i = 1:length(yfit1)
    if yfit1(i) == xfit(i)
       Counter1=Counter1+1;
    end
end
procent = (Counter1/length(yfit1))*100;
fprintf('Prediction accuracy for model 1 is %d %%\n', procent)
```

Script for the rest of the iterations

```
%% Load data and create training and testing matrices
T = MIPDATAVer3; %loading the excel file
[m,n] = size(T); % creates two variables based on the size of the excel file
P = 0.80 ; % 80 %training 20 % test
idx = randperm(m); % creates a vector with random values
Training = T(idx(1:round(P*m)),:); % creates training data by randomly taking 80%
of the rows in the excel file
Testing = T(idx(round(P*m)+1:end),:); % creates testing data with the rest of rows

%% creates answers
Facit = Testing(:,10);  % creates a column with answers
Facit = table2array(facit); % converts the column
Testing(:,10) = []; % deletes the right answers from the testing matrix

%% predict new answers and compare
predictions = trainedModel.predictFcn(Testing); % uses the function generated in
the classification learner to predict new answers
Counter = 0; % creates a counter for loop
for i = 1:length(predictions)  % compares the predicted values to the answers
    if facit(i,:) == predictions(i,:)
       Counter=Counter+1;
    end
end
procenten1 = (Counter/length(predictions))*100 % calculates the accuracy in %
plotconfusion(facit,predictions) % plots a confusion matrix
```

Appendix D Predictors

Predictors of Iteration 1	
Project ID	The project the DI belongs to
CP validated by MIE	Is CP validated by MIE
Relation validated by MIE	Is all relations validated by MIE
Relation validated by DE	Is all relations validated by DE
Event checked by DE	Is change validated by DE
ART ID	ID for the ART
ART Code	Code for the ART
ART name	Name of DIs ART category
Unit name	DIs unit belonging
Variants	Listing all DIs variants
Function groups	What function groups the DI is included in
DI program	What program the DI is included in
DI code number	Unique identification number for each DI
DI position number	Amount of times the DI is repeatedly used in the car
DI revision number	Current DI revision
DI name	The DI’s name
Block name	What block the DI belongs to
Is carryover	Is DI carryover from another project
DI carryover manually changed	Is the carryover status manually changed
Relation follow up	The relation followed up or not
Relation follow up manually changed	The relation follow up status changed manually
VIE follow up	The VIE followed up or not
VIE follow up manually changed	VIE follow up status is changed or not
Position names	The name of the position
Is electric	Electric component or not

Predictors of Iteration 2	
Project ID	The project the DI belongs to
CP validated by MIE	Is CP validated by MIE
Relation validated by MIE	Is all relations validated by MIE
Relation validated by DE	Is all relations validated by DE
Event checked by DE	Is change validated by DE
ART name	Name of DIs ART category
Unit name	DIs unit belonging
Variants	Listing all DIs variants
Function groups	What function groups the DI is included in
DI program	Volvo Cars' internal program name
DI code number	Unique identification number for each DI
DI position number	Amount of times the DI is repeatedly used in the car
DI revision number	Current DI revision
DI name	Volvo Cars' internal DI name
Is carryover	Is DI carryover from another project
Position names	The positions name
Is electric	Electric component?
Amount of relations	Amount of relations connected to CP
Smallest clearing distance	Smallest clearing distance of relations connected to CP
Average clearing distance	Average clearing distance on relations connected to CP

Predictors of Iteration 3	
ART name	Name of DIs ART category
DI position	Amount of times the DI is repeatedly used in the car
DI revision	Current DI revision
Keywords (DI name)	Keywords based on DI name
DI carryover	Is DI carryover from another project
DI code number	Unique identification number for each DI
Amount of relations	Number of relations connected to CP
Amount of penetrating relations	Percent of relations with negative value in relation to the total amount of relations
Function groups	Function groups the DI is included in

Appendix E Full factorial design experiment

#	DI position	Amount of relations	DI revision	ARTname	Amount of penetrating relations	Function group	DI code number	%	#	DI position	Amount of relations	DI revision	ARTname	Amount of penetrating relations	Function group	DI code number	%	#	DI position	Amount of relations	DI revision	ARTname	Amount of penetrating relations	Function group	DI code number	%	#	DI position	Amount of relations	DI revision	ARTname	Amount of penetrating relations	Function group	DI code number	%
1	0	0	0	0	0	0	0	0	38	1	1	1	0	1	0	0	36	75	1	1	0	0	0	1	1	53	112	0	1	1	1	0	1	0	61
2	1	0	0	0	0	0	0	1	39	1	1	1	0	1	0	1	36	76	0	0	1	1	1	0	0	53	113	1	1	0	1	0	1	0	61
3	1	0	0	0	1	0	0	7	40	0	1	1	0	0	0	1	37	77	1	1	0	0	1	1	0	53	114	0	1	1	1	0	1	1	61
4	0	0	0	0	1	0	0	8	41	1	0	0	1	1	0	0	37	78	1	1	1	0	1	1	0	53	115	0	1	0	1	1	1	0	61
5	0	1	0	0	0	0	0	12	42	0	0	0	1	1	1	0	38	79	0	0	1	1	0	1	0	54	116	0	1	0	1	1	1	1	61
6	1	1	0	0	0	0	0	14	43	1	0	0	0	1	1	0	38	80	1	1	0	0	0	1	0	54	117	0	1	1	0	1	1	1	61
7	0	0	0	0	1	0	1	14	44	0	1	1	0	1	0	1	38	81	0	1	0	0	1	1	1	54	118	0	1	1	1	1	0	1	61
8	0	1	0	0	1	0	0	14	45	0	0	1	0	0	0	1	39	82	1	0	1	0	1	1	0	54	119	1	1	0	1	1	1	1	61
9	0	0	0	0	0	0	1	18	46	1	0	0	1	0	1	0	39	83	1	0	1	1	1	0	0	54	120	1	1	1	1	1	1	0	61
10	0	0	1	0	0	0	0	18	47	0	0	0	1	0	1	1	40	84	1	1	0	0	1	1	1	54	121	0	1	0	1	0	1	1	62
11	1	1	0	0	1	0	0	18	48	0	0	0	0	0	1	1	42	85	1	0	1	1	0	1	0	55	122	1	1	0	1	0	1	1	62
12	0	0	0	1	0	0	0	19	49	1	0	0	1	1	0	1	42	86	1	0	1	1	1	0	1	55	123	1	1	1	1	0	1	1	62
13	1	0	0	0	0	0	1	19	50	0	0	0	0	1	1	1	43	87	0	0	1	0	0	1	1	56	124	0	1	1	1	1	1	0	62
14	1	0	1	0	0	0	0	21	51	1	0	0	1	1	1	0	43	88	0	1	1	1	0	0	0	56	125	1	1	0	1	1	1	0	62
15	1	0	0	0	1	0	1	21	52	1	0	0	0	0	1	1	46	89	0	0	1	1	1	0	1	56	126	1	1	1	0	1	1	1	62
16	0	0	0	0	0	1	0	23	53	1	0	0	1	0	1	1	46	90	1	0	1	0	0	1	1	57	127	0	1	1	1	1	1	1	63
17	0	0	1	0	1	0	0	23	54	0	0	1	0	0	1	0	47	91	1	0	1	1	0	0	1	57	128	1	1	1	1	1	1	1	63
18	0	0	0	1	1	0	0	25	55	1	0	0	1	1	1	1	48	92	1	1	1	1	0	0	0	57									
19	1	0	0	1	0	0	0	26	56	0	1	1	0	0	1	0	49	93	0	0	1	1	1	1	0	57									
20	1	0	1	0	1	0	0	26	57	1	0	1	0	0	1	0	50	94	1	0	1	1	1	1	0	57									
21	0	1	1	0	0	0	0	28	58	1	1	0	1	1	0	0	50	95	0	0	1	1	0	0	1	58									
22	0	0	0	1	0	0	1	29	59	0	1	0	1	0	0	0	51	96	0	1	1	0	0	1	1	58									
23	0	0	0	1	1	0	1	30	60	1	1	0	1	0	0	1	51	97	1	0	1	1	0	1	1	58									
24	0	0	0	1	0	1	0	31	61	0	0	1	0	1	1	0	51	98	0	0	1	0	1	1	1	58									
25	1	1	0	0	0	0	1	31	62	0	0	0	1	1	1	1	51	99	1	0	0	0	1	1	1	58									
26	0	0	0	0	1	1	0	32	63	0	1	1	0	1	1	0	51	100	1	1	1	1	1	0	0	58									
27	0	1	0	0	1	0	1	32	64	0	1	0	0	0	1	0	52	101	0	1	1	1	0	0	1	59									
28	0	1	1	0	1	0	0	32	65	0	1	0	1	0	0	1	52	102	1	1	1	0	0	1	1	59									
29	1	0	1	0	1	0	1	32	66	1	1	0	1	0	0	0	52	103	0	1	1	1	1	0	0	59									
30	1	1	0	0	1	0	1	32	67	1	1	1	0	0	1	0	52	104	1	0	1	0	1	1	1	59									
31	0	1	0	0	0	0	1	33	68	0	1	0	0	1	1	0	52	105	1	0	1	1	1	1	1	59									
32	1	1	1	0	0	0	0	33	69	0	1	0	1	1	0	0	52	106	0	1	0	1	0	1	0	60									
33	1	0	0	0	0	1	0	34	70	0	1	0	1	1	0	1	52	107	0	0	1	1	0	1	1	60									
34	1	0	0	1	0	0	1	34	71	1	1	0	1	1	0	1	52	108	1	1	1	1	0	0	1	60									
35	1	0	1	0	0	0	1	35	72	0	0	1	1	0	0	0	53	109	1	1	1	1	0	1	0	60									
36	1	1	1	0	0	0	1	36	73	0	1	0	0	0	1	1	53	110	0	0	1	1	1	1	1	60									
37	0	0	1	0	1	0	1	36	74	1	0	1	1	0	0	0	53	111	1	1	1	1	1	0	1	60									