

Planning Flexible Maintenance for Heavy Trucks using Machine Learning Models, Constraint Programming, and Route Optimization

Jonas Biteus
Scania CV AB

Tony Lindgren
Stockholm University

ABSTRACT

Maintenance planning of trucks at Scania have previously been done using static cyclic plans with fixed sets of maintenance tasks, determined by mileage, calendar time, and some data driven physical models. Flexible maintenance have improved the maintenance program with the addition of general data driven expert rules and the ability to move sub-sets of maintenance tasks between maintenance occasions. Meanwhile, successful modelling with machine learning on big data, automatic planning using constraint programming, and route optimization are hinting on the ability to achieve even higher fleet utilization by further improvements of the flexible maintenance. The maintenance program have therefore been partitioned into its smallest parts and formulated as individual constraint rules. The overall goal is to maximize the utilization of a fleet, i.e. maximize the ability to perform transport assignments, with respect to maintenance. A sub-goal is to minimize costs for vehicle break downs and the costs for maintenance actions. The maintenance planner takes as input customer preferences and maintenance task deadlines where the existing expert rule for the component has been replaced by a predictive model. Using machine learning, operational data have been used to train a predictive random forest model that can estimate the probability that a vehicle will have a breakdown given its operational data as input. The route optimization takes predicted vehicle health into consideration when optimizing routes and assignment allocations. The random forest model satisfactory predicts failures, the maintenance planner successfully computes consistent and good maintenance plans, and the route optimizer give optimal routes within tens of seconds of operation time. The model, the maintenance planner, and the route optimizer have been integrated into a demonstrator able to highlight the usability and feasibility of the suggested approach.

CITATION: Biteus, J. and Lindgren, T., "Planning Flexible Maintenance for Heavy Trucks using Machine Learning Models, Constraint Programming, and Route Optimization," *SAE Int. J. Mater. Manf.* 10(3):2017, doi:10.4271/2017-01-0237.

INTRODUCTION

To efficiently transport goods it is important that vehicles have a high degree of availability or uptime and in particular avoid failures causing unplanned stops by the road side and hence failure to carry out the transport mission. An unplanned stop by the road does not only cost due to delivery delays, but can also lead to damaged cargo. One important tool to uphold uptime is to perform proper maintenance. However, too much maintenance is not optimal due to costs for planned downtime and workshop actions. Therefore, the maintenance should be planned to gain the optimal balance between maintenance and risks for failure.

We have investigated how machine learning using big data, constraint programming, and route optimization could be used for improving the maintenance of heavy trucks. The aim is to achieve improved alignment between the maintenance program of a product and its actual maintenance needs. Existing operational data collected by on-board sensors in the vehicles have been utilized to train a

predictive random forest model, here after named as the model. For a single vehicle, the model is evaluated with its operational data as input and the result is used to compute its optimal maintenance plan.

The paper is divided into four parts where first the prognostic modelling method is described, then follows, the alert engine, the maintenance planner, and the route optimizer. Finally, the demonstrator is presented.

As an application example we have used the air dryer system which is a common cause of unplanned stops. However, the methods should be equally applicable to other similar components.

BACKGROUND

Scania Commercial Vehicles is a manufacturer of heavy trucks, coaches and engines for industrial and marine usage and a supplier of vehicle related services such as financing, logistic planning, and repair and maintenance.

Scania trucks are famous for their customizability, where each truck can be specified to exactly match the customers' needs. For example the number of axles - typically two to eight, power take-off position, different brake systems, engine power, fuel, such as natural gas, bio fuels and diesel, handful of different gear boxes, cab height, auxiliary equipment or seat type. In addition to the above flexibility there are an uncountable number of different potential body builds that could be added to the trucks.

However, for maintenance, this diversity presents a challenge as there are very few vehicles that are identical and therefore from a modelling perspective, the number of parameters that have to be taken into consideration increases. Further, the trucks are used in very different modes, such as long haulage, construction works, and garbage collection, which also affect the predictive models and planning algorithms we aim at producing.

Traditional Maintenance at Scania

Historically, the maintenance plan for a vehicle is set when the vehicle is sold. This is typically done by sales personnel together with the buyer by selecting one of a set of predefined maintenance plans that best matches the vehicle specifications and the buyers intended usage. To this is added maintenance for body builds such as tail lifts and hook loaders.

The predefined maintenance plans are developed and maintained by skilled personnel having knowledge about both the products and how the customers use the vehicles. The vehicle usage is partitioned into six typical application types such as long haulage or distribution. Each maintenance plan consists of cyclic fixed maintenance tasks based on mileage or calendar time.

Maintenance was always done in a cycles of small, medium, and large maintenance occasions where different maintenance modules of tasks for maintaining different sets of components are included. The name indicates the number of components to be maintained.

Flexible Maintenance at Scania

Nowadays, Scania offers Flexible maintenance, commonly denoted as condition based maintenance, where the maintenance program is partitioned into smaller sets of maintenance tasks performed at irregular intervals. Typically for Scania, which have a very modular system, each truck will have a more or less unique number of maintenance tasks.

Data driven expert rules can be used to adapt the maintenance program such that sub-sets of maintenance tasks can be moved to earlier or later maintenance occasions.

To minimize the cost for the customer it is important to only perform maintenance that are really needed. In [1] and [2] we presented the basis of such a maintenance system based on expert rules. In this paper we utilize a similar algorithm but feed it with alarms from the prognostic model.

Data for Training Prognostic Models

Data from three different sources have been extracted for use in this work.

First, data from a database with historical operational data have been extracted, which include information based on on-board sensors showing how each truck has been used in average. The data includes parameters such as air pressure, engine load, gear selections, and air consumption from Scania trucks in everyday usage. One characteristic of the operational data is that there are no time series available. Information describing how a vehicle has been used is stored as average scalars and histograms where different variables represent how often specific sensor data is measured within different intervals. For example, [Figure 1](#) shows one such histogram over an ambient temperature parameter for two different vehicles.

Secondly, a database containing the configuration of each vehicle have been used.

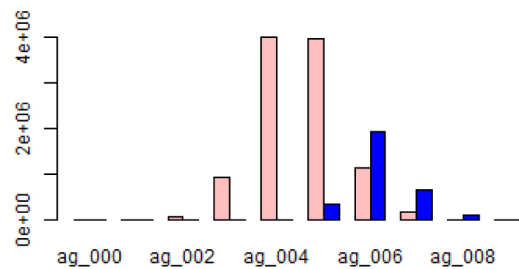


Figure 1. Example of histogram data for two different vehicles (blue and pink). The bin identifiers are ag_000 to ag_009.



Figure 2. Photo of a new air dryer with desiccant cartridge on the top, control unit to the left and purge valve in the bottom.

Finally, we have used information from Scania workshops containing information if components have been replaced or not. We here assume that if a component have been replaced then it was probably faulty.

Application Example - Air Dryer

The air dryer supplies dehumidified air in most heavy trucks. The pressurised air is used for controlling systems such as breaks, suspension, seats, and gearbox. [Figure 2](#) shows a variant of the system.

Since the air pressure system is a fundamental part of the vehicle, a fault in the air dryer often results in disturbance or complete immobilization of the vehicle.

Machine Learning

The prognostic modelling is done using machine learning which is a method of data analysis that automates model building. The algorithms iteratively learn from data and thereby builds more or less complex models that can explain the given data. The utilization and construction of prognostic models using machine learning are given a good introduction in for example [3] which provides both background, details, and further references.

When training a model, a set of feature vectors, i.e. variables, have to be given to the algorithm. Further, in supervised learning, which we are using here, we must give the algorithm a case vector indicating if the specific vehicle have broken or not.

Constraint Programming

The maintenance planning problem is basically a constraint satisfaction problem for which [4] gives a good background.

Constraint programming is typically used to find solutions to scheduling and combinatorial planning problems. Constraint programming have proved to be valuable when dealing with the complexity of many real-world scheduling problems, such as scheduling of air flights, school classes, or logistic planning.

A constraint programming model is expressed in a declarative fashion, using decision variables, constraints and objectives that must be minimized or maximized.

Route Optimization

The standard vehicle routing problem is a combinatorial optimization and integer programming problem which finds the optimal set of routes for a fleet of vehicles to traverse in order to deliver goods to a set of customers.

PART 1: PROGNOSTIC MODELLING

The objective with the prognostic modelling method used here is that it should be simple to understand for engineers, and it should need as little manual work as possible. These objectives are crucial for the ability to maintain the models over time. In this work, we have assumed that no additional sensors should be added to the vehicles and thereby not increasing a vehicle's production cost.

Problem Formulation

For this type of model that operates on statistical data, we do not believe that the accuracy is sufficiently good to base a predictive replacement decision on with all costs related to such replacement, e.g. downtime and repair costs. Instead the model will be used to detect vehicles in risk of having problems and when the model indicates a problem, a component check will be added to the flexible maintenance protocol for the vehicle's next scheduled maintenance stop.

Typically a model is evaluated using statistical measures such as probability for miss classifications. It is however not sufficient to only evaluate a models quality using such measures since these does

not take into consideration the effects of different miss classifications. Therefore, we have here formulated a business case that should be optimized.

In the business case, there are primarily two types of costs that can arise if the model does not behave perfect, either false alarms or missed detections. To further quantify the problem, we have set up a metric based on the costs, where a missed detection costs 500 € (denoted c_m) and a false alarm costs 10 € (c_f). The missed detection is assumed to result in a vehicle breakdown with its associated costs of downtime and repair. The false alarms are assumed to result in component checks that are performed in workshops during scheduled maintenance. The costs are rough estimates derived using figures from Scania's service network in Europe.

A model P predicts the probability for a vehicle to be in the failure class given a set of operational data δ . To be able to take a decision, an alarm, a , is constructed based on the model

$$a = \begin{cases} 1, & \text{if } P(\delta) \geq T \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where T is the alarm threshold.

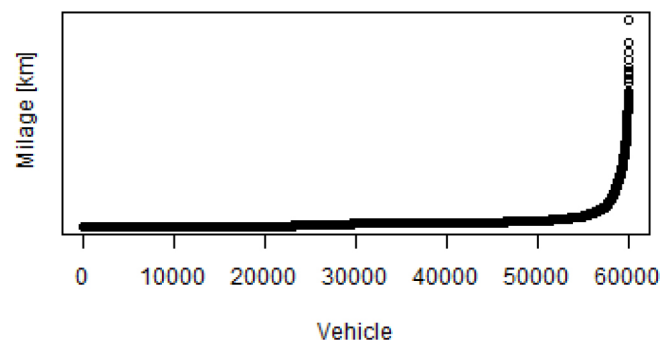


Figure 3. Mileage data in the example data set. The data have been sorted by size.

For a set of vehicles, let f be the number of false alarms, i.e. wasted checks, and m be the number of missed detections. The optimization problem is thereby

$$\min_{P,T} \sum (mc_m + fc_f) \quad (2)$$

and we will here optimize this in two steps starting with optimizing P and then optimizing T .

Example Data

For this paper a subset of data from 80 000 trucks from five EU markets have been used. One data sample is used for each vehicle. In this data, no other specification than that the vehicle is a truck have been used as a feature. The data have intentionally been biased to hide proprietary quality information.