In4Uptime

A project within *Transport Efficiency*

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Content

FFI in short

FFI is a partnership between the Swedish government and automotive industry for joint funding of research, innovation and development concentrating on Climate & Environment and Safety. FFI has R&D activities worth approx. €100 million per year, of which half is governmental funding. The background to the investment is that development within road transportation and Swedish automotive industry has big impact for growth. FFI will contribute to the following main goals: Reducing the environmental impact of transport, reducing the number killed and injured in traffic and Strengthening international competitiveness. Currently there are five collaboration programs: **Vehicle Development, Transport Efficiency, Vehicle and Traffic Safety, Energy & Environment and Sustainable Production Technology.**
For more information: www.vinnova.se/ffi

1. Executive summary

Keeping commercial heavy-duty vehicles in good operational condition is crucial from a financial, safety and environmental point of view. Haulers and transporters require OEMs to provide close to 100% uptime, i.e. no unplanned stops and guarantees on optimal performance of all components, ensuring acceptable levels of CO_2 emission and fuel consumption. The In4Uptime project shows how combining different kinds of data (e.g. on-board and off-board, structured and unstructured, private and public), leads to increased ability to manage uncertainty, variation and unreliability of decisions. In particular, adapting maintenance plans to the needs of individual customers and individual vehicles increases the attractiveness and profitability of the service contracts, and in the end leads to fulfilling more transport assignments, decreasing unplanned stops and accidents on the roads.

The primary objective of the In4Uptime project has been to investigate benefits that increased usage of data analytics can bring to the uptime area, in particular by increasing the penetration and quality of service contracts (maintenance) and related services.

In the project we have delivered four main results that each focus on a somewhat different aspect of the primary objective, and together present a coherent analysis of the costs and benefits related to data analytics for predictive maintenance and uptime domains. The first result is an off-board data analytics environment, focusing on the IT solutions and architectures; hardware and software for data collection, integration and storage; evaluation of available data, including reliability, availability and relevance, as well as algorithms for predicting component failures. The second result is a platform for collecting, visualising, processing, and combining large amounts of public and private data, for example from Trafikverket (Swedish Transport Administration) and from Volvo; we have shown how this combined data allows for new services to be created, by developing methods to estimate how much trucks are delayed due to road accidents; we have also analysed what additional information should be collected to improve the accuracy of those methods, as well as to enable additional analysis. The third result is development of methods for predictive maintenance based on on-board data streams; continuous long-term data collection on a fleet of buses in Kungsbacka (started in 2012); algorithms for detecting deviations and abnormal operation based on comparing individual vehicles against the rest of the fleet; combining on-board and off-board data to identify the best knowledge representation formalisms for various types of signals, as well as to correlate observed anomalies against reference data from the workshops. The fourth result is related to identifying the innovation potential of data-driven methods within the uptime area; analysis and synthesis of current best practices as well as existing and new business models.

Finally, the conclusions from the In4Uptime project are summarised in a short animated movie, which we believe to greatly enhance the visibility of the project.

Technical results are summarised in multiple internal deliverables, as well as six published conference and journal articles (with three more in progress).
Ongoing projects such as BIDAF and BADA will benefit from the In4Uptime results. We have created an animated movie that explains what we have done and how we see our results could be used today as well as in the future. A natural step would be to involve and demonstrate the complete chain from prediction to repair involving fleets and workshops. From an academic viewpoint, future research could include improving the COSMO method, refining the reference group for defining the nominal working condition based on usage patterns and exploring more generic models for fault detection and isolation

2. Background

Unplanned stops for heavy vehicles are particularly problematic, not only are the repairs more costly if they have to be carried out away from appropriate facilities, but also, it often results in extra costs such as additional damage to components, failures to meet delivery deadlines and possibly loss of confidence among clients. Last but not least, the effects on the traffic flow could be devastating. It is also known that many vehicles operate for long periods of time in conditions that are far from perfect, since customers usually only visit workshops once problems render trucks or buses unusable.
One way of improving the situation is to collect and exploit as many sources of information about individual vehicles as possible, including both on-board data about their operation and off-board data about their environment. Earlier projects including ReDi2Service and InnoMERGE have shown that predictive maintenance is effective in the short term and offers tangible benefits, and the natural next step is to extend this idea with additional sources of data. An increased penetration of service contracts and other services in the uptime area is an important key to ensure regularly maintained vehicles. Avoidance of unplanned stops and breakdowns not only improves the financial margins for the OEM, dealer and transport operator but it also improves traffic flow and road safety, which is beneficial for the society as a whole.
Research on different ways to combine information coming from diverse sources with the goal of increasing uptime is one of the core directions within the research profile of the Centre for Applied Intelligent Systems Research (CAISR) at Halmstad University. The focus of the centre is on awareness, in particular on self-aware intelligent systems. This concept means that systems should be able to use available data to build a representation of their own internal state, as well as their operation, both current and intended. The data used for this purpose can come both from internal sensor and control signals, but also from external information sources. Behavior of a group of systems can then be analysed, and anomalous individuals can be detected, enabling predictive maintenance. For vehicle applications, we have combined such deviation detection with historical repair information, thus creating knowledge about the state of health of a given vehicle, as well as whether and when it requires a workshop visit.

We are creating a world where we are surrounded by intelligent systems. Data flows in many directions and is readily available through public APIs in real-time. By combining different data sources we can enrich the user experience and design intelligent systems. Recorded Future continuously monitor trends on the Web and bring experience from big data analytics and processing.

In a situation where the customers expect access to their vehicles at all times, being able to avoid unplanned stops is crucial. To do that, monitoring the health of vehicles and components is very important and could enable dynamic maintenance planning. Being able to quickly react to events is important but being able to predict issues and taking proactive measures is the key to keeping the customers' vehicles and business on the road.

3. Objective

The primary objective of the In4Uptime project has been to investigate benefits that increased usage of data analytics can bring to the uptime area, in particular by increasing the penetration and quality of service contracts (maintenance) and related services. Well maintained vehicles will lead to less environmental impact, safer and more efficient traffic, as well as lower costs and increased competitiveness.

Deeper comprehension of how customers use heavy-duty vehicles, actual component life-cycle and wear under real conditions, and the effect individual vehicle's health can have on the full logistics operation are all important for automotive OEMs to understand. There was some amount of data already available related to all of those areas, but neither scope nor quality of it was well analysed.

The In4Uptime project aimed to analyse all three lynchpins of this issue. The first objective was focused on the data: understanding what is available, and what more can be collected. The second objective was to develop new algorithms for analysing the information and to evaluate their accuracy, computational requirements, etc. The third objective was to analyse the business needs and opportunities related to Data Science.

4. Project realization

The general approach of the project followed a typical Data Mining process. We began by identifying available data sources, selecting the ones that are relevant for our goals, and collecting the information within analytics environment. Once there, the data needed to be preprocessed, and finally analysed. Based on conclusions drawn from the analysis, we have investigated new business models and services. Overall, all those steps were followed successfully and most energy was spent on the data (collection, preprocessing and analysis). The project has, in terms of the final step, taken a high level approach as looking for methods that could be applied generally when Big Data services are developed. The final demonstration of the In4Uptime results will take place after the project has finished.

The major data sources used in the project consist of:

- Databases including truck maintenance history, configuration data and logged usage data.
- Fleet management data from trucks operating in Sweden.
- On-board signal stream data collected on a bus fleet in Kungsbacka, logged solely for the purpose of predictive maintenance.
- Accident and weather sensor data continuously harvested from Trafikverkets public data channel.
- Accident data from global open source media analyzed by RF natural language processing Web Intelligence Engine.

From the start it was planned to have one common analytics environment, however, it turned out to be a challenge, mostly from a legal perspective, to share data between partners. To resolve data sharing issues, a combination of separated environments and anonymisation of data was applied. In addition, different partners had different needs regarding the computational capabilities.

5. Results and deliverables

The results of the project consist of almost fifty deliverables, both internal and external, in the form of algorithms, software, reports, scientific publications, presentations, workshops, processes, guidelines, animations, etc. Those are grouped in five major areas:

Data analytics environment. We have worked within a big initiative at Volvo Group for building a data warehouse that gathers internal information about trucks in one place. This work consisted of designing the architecture for analytics software and hardware, identifying and evaluating relevant data sources, as well as collecting and aggregating the information. With that environment in place, we have developed several prediction algorithms. One example of an algorithm show promising results; 15% of the air compressor repairs are preceded by a warning, while keeping the false warnings as low as 20%. Meaning that 8 out of 10 vehicles predicted to fail actually fails within 90 days.

Combining internal and external data sources. We have created a platform for collecting, visualising, processing, and combining large amounts of public and private data. We have demonstrated it by aggregating accident information provided by the Swedish Transport Administration with fleet management data from Volvo. Another example is sentiment analysis on Twitter and other social media data.

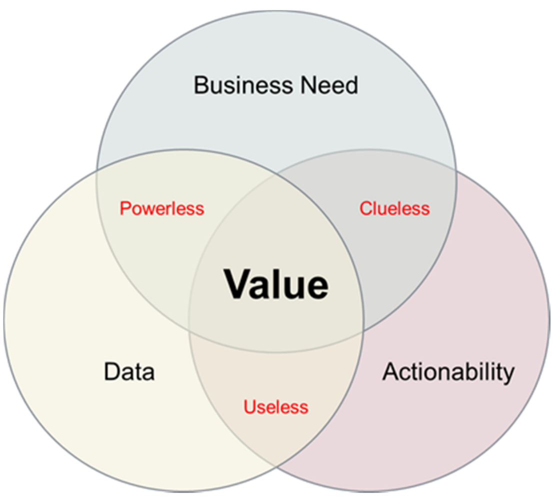
The use cases are showing benefits of combining many diverse sources of data, especially the combination of Trafikverket data and fleet management data where results are being important input for evaluating the benefits of data analytics in the uptime domain.

Predictive maintenance based on onboard data streams. In the project we have continued working with predictive maintenance algorithms developed earlier as collaboration between Volvo Technology and Halmstad University. This includes updates to the COSMO algorithm, with component models based on on-board data collected from a fleet of buses, in operation in Kungsbacka. New results include quantifying the effects of a broken component on the data models and deviations, algorithms to correlate onboard and off-board data, and tools for interpreting semantic information.

Innovation potential. In the beginning of the project we performed interviews in the Volvo organization to understand the maturity of the organization in terms of being able to develop and generate revenue from services based on Big Data. We have also theoretically applied such a service to a vehicle maintenance scenario to see how the process would be affected. Another important step was to create a method to help identifying potential value in complex business ecosystems.

Final project presentation in the form of animated movie. To help explaining what we have done and how we see the effect that the results of this project will and could have on the transportation industry and other projects, we have created a professional animated movie. The movie is suitable for a wide audience and will be used internally as well as externally.

Below we describe some example results from the project in more detail.



360 Value Framework

The framework is designed to support stakeholders in identifying, defining and answering business questions. The framework supports the transformation of unknown questions into known question to support full insight and to bring forward potential value in complex business ecosystems by focusing on the interactions among three critical dimensions. It is particularly useful if many stakeholders, in the early phase of the analysis, try to collaborate in discovering potential/undefined value. In this context it is important to understand how the three aspects interact with each other. *Business need* defines what are the relevant challenges and opportunities that have the potential to bring revenue or reduce costs. *Data* defines what information is available, how relevant it is, and whether any more can be collected. And the *Actionability* defines what kind of actions or decisions can be made as a result of the analysis that will be performed. The focus in on decreasing the lead time and increasing the quality within the same budget as before.

Often the framework is triggered by a business sponsor: an illustrative example would be a football manager who aims to win Euro 2016. In order to succeed, it is necessary to identify the needs of the team, the data that can be used to make decisions, and the resources that are available. A potential player who does not address the need, one that the manager cannot afford, nor one whose abilities are unknown are going to bring value to the team. It is only at the intersection of those three aspects that the true value can be found.

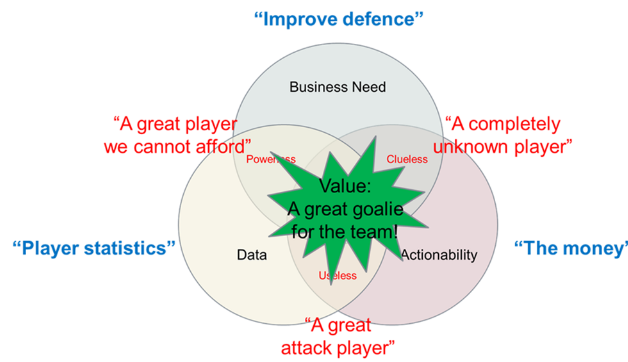
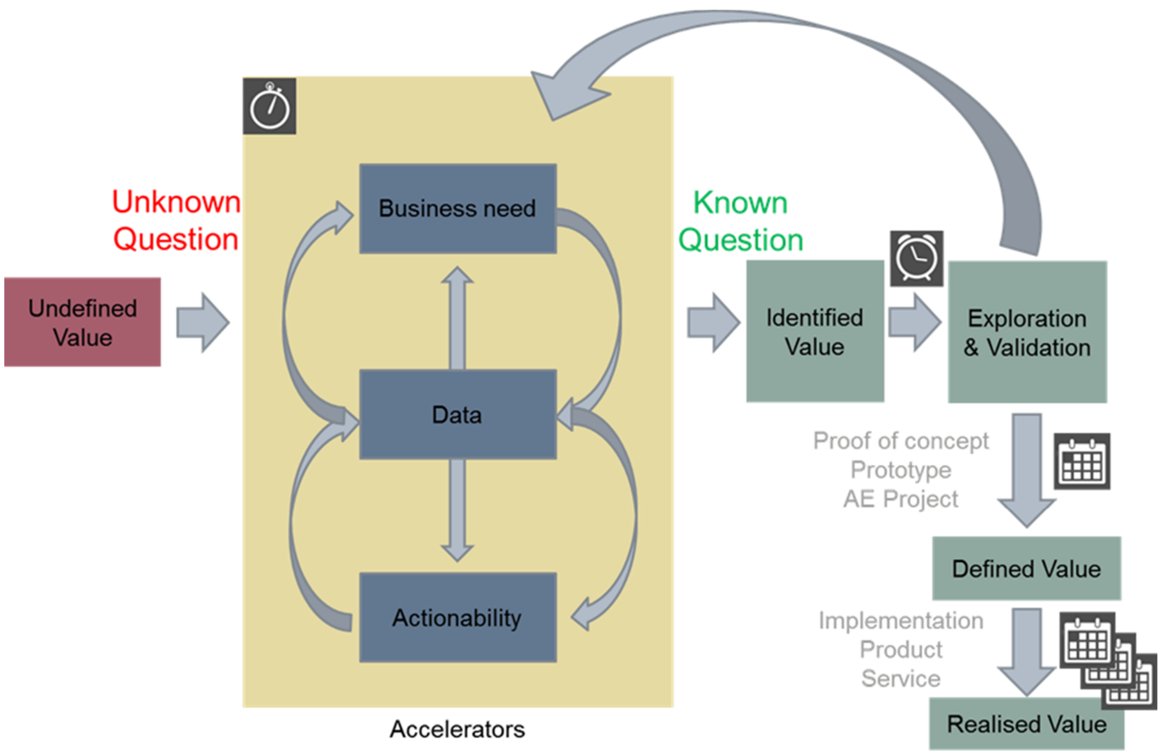
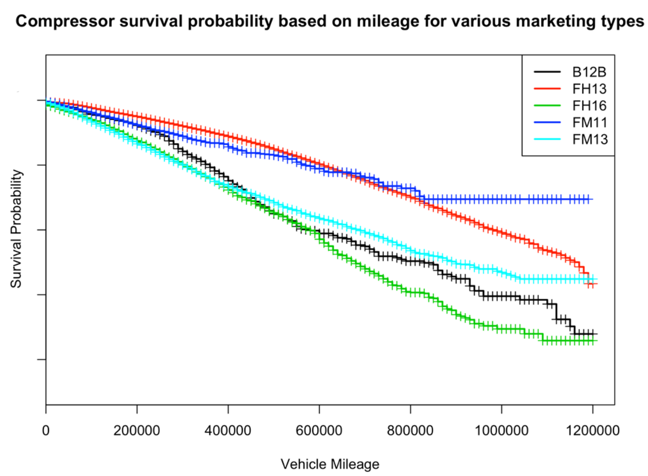


Figure below describes how does the *360 value method* fit in existing processes: it is designed for quick initial analysis, followed by validation step.



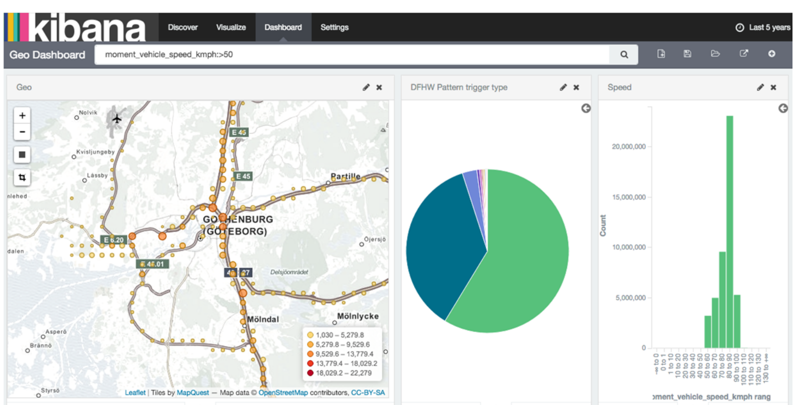
Understanding Component Life-Cycle

One important step towards improving reliability and uptime of heavy duty vehicles is understanding the life-cycle of individual components, i.e. to get an overview - based on actual usage data, not only on design-time predictions, of when do they fail and what are the factors that contribute to those failures. With the data made available within the *In4uptime* project, we have been able to create tools for performing such an analysis.



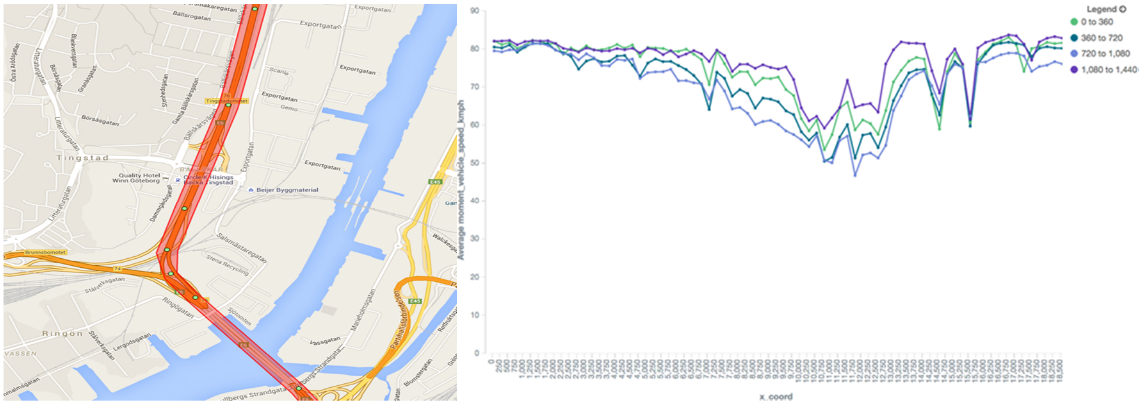
An example is “survival analysis”, which can be used to model how does the risk of a certain component failing, change over time. However, in general those risks are different for different fleets, based on factors such as vehicle configuration and usage patterns. Therefore, the analysis should not be done only once, but continuously, for populations of different vehicles.

As an example, the plot (at left) shows how compressor survival probability changes based on vehicle mileage differ among various marketing types. Censored data is an important source of information since the data from more than 90% of vehicles are only available during a short period of their lifetime. The result of survival analysis is shown in the Figure for five marketing types with the highest number of vehicles in the dataset. This result is obtained by using the Nonparametric Kaplan-Meier estimator. The results from the figure can be easily explained by the expected usage pattern of different types of vehicles. On the other hand, large differences also exist within each marketing type, and therefore even more accurate models can be obtained based on the usage statistics data that is available nowadays. The failure rate estimated by this method can be used as one of the features in a classifier predicting failures for each individual vehicle.



Combining Diverse Data Sources

To visualize and explore the collected data we built several apps, including the publicly available web app [in4uptime.recfut.com]() and the iOS app *4uptime*. The web app allows the user to make detailed heat maps and show seasonal distributions. RF also created a private web app and data analytics platform to visualize fleet management data (see figure above). A proof of concept dashboard for fleet overview was developed with big data scalability in mind.



The fleet management data was queried for events from a narrow corridor for a 19 km path along E6 in Gothenburg. Not surprisingly there is a speed dip close to Tingstadstunneln, and the average speed is slower during daytime.

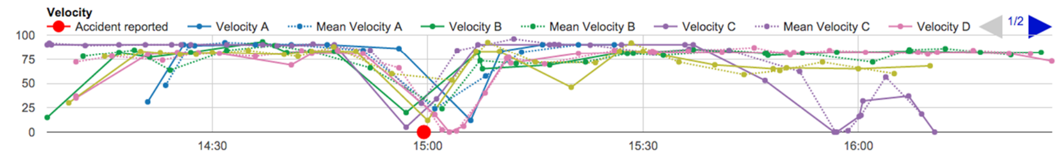
A big data analytics platform can also be used to calculate average vehicle speeds, as exemplified above. Using both accident and truck sensor data truck delay time of accidents can be calculated as seen below. In this example an accident in Jönköping has caused 5 different trucks to slow down and be delayed in total more than 70 minutes. Using data over a period of one year, some 12,000 accidents were correlated. At least 1,000 of them were found to cause delays for at least one heavy vehicle (in the analysed population) and caused delays of more than 360 hours.

Accident SE_STA_TRISSID_1_4356232

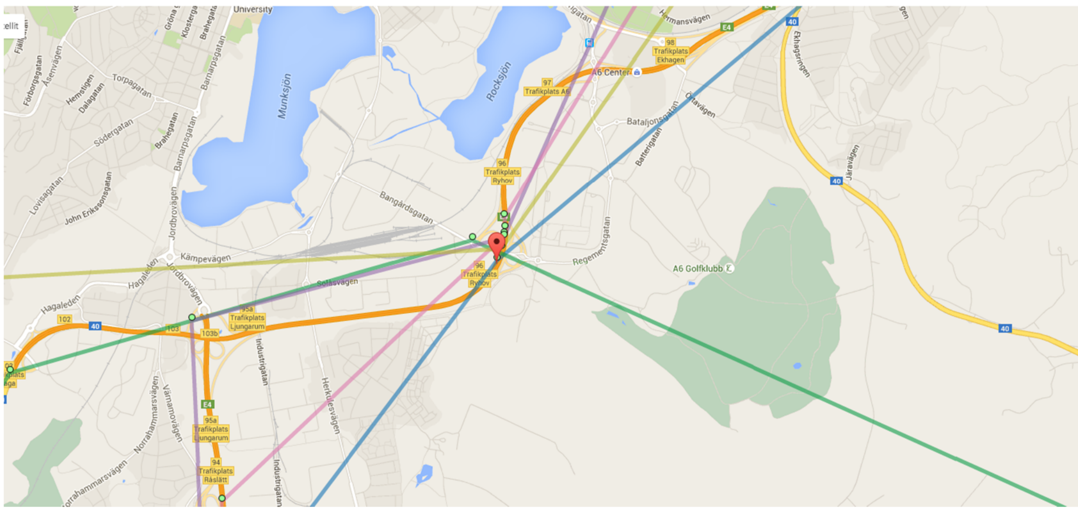
Report: Olycka med 2 personbilar. Begränsad framkomlighet.

Version Time: 2015-06-02T15:33:21Z UTC **Probability:** certain **Severity:** high **Site:** **Position:** (57.7626343, 14.1883745)

#	Vehicle Number	Delay Distance	Max Velocity Before	Max Velocity After	Between	Actual Time	Expected Time	Delay Time
A	2001686812	8 km	90 km/h	90 km/h	14:56 - 15:10	14m 10s	5m 20s	8m 50s
B	2001721317	15 km	93 km/h	85 km/h	14:47 - 15:07	20m	10m 7s	9m 53s
C	2001738028	24 km	90 km/h	90 km/h	14:47 - 15:07	20m	16m	3m 60s
D	2001762539	15 km	82 km/h	82 km/h	14:51 - 15:11	20m	10m 59s	9m 1s
E	2001790991	16 km	83 km/h	83 km/h	14:50 - 15:06	16m 45s	11m 34s	5m 11s



Mean velocities between measurements are calculated on vehicle *event_time*. Distances between measurements are calculated with *flying bird distance* with GPS positions or Odometer distance (accuracy 1km). It does not always give the actual distance driven.



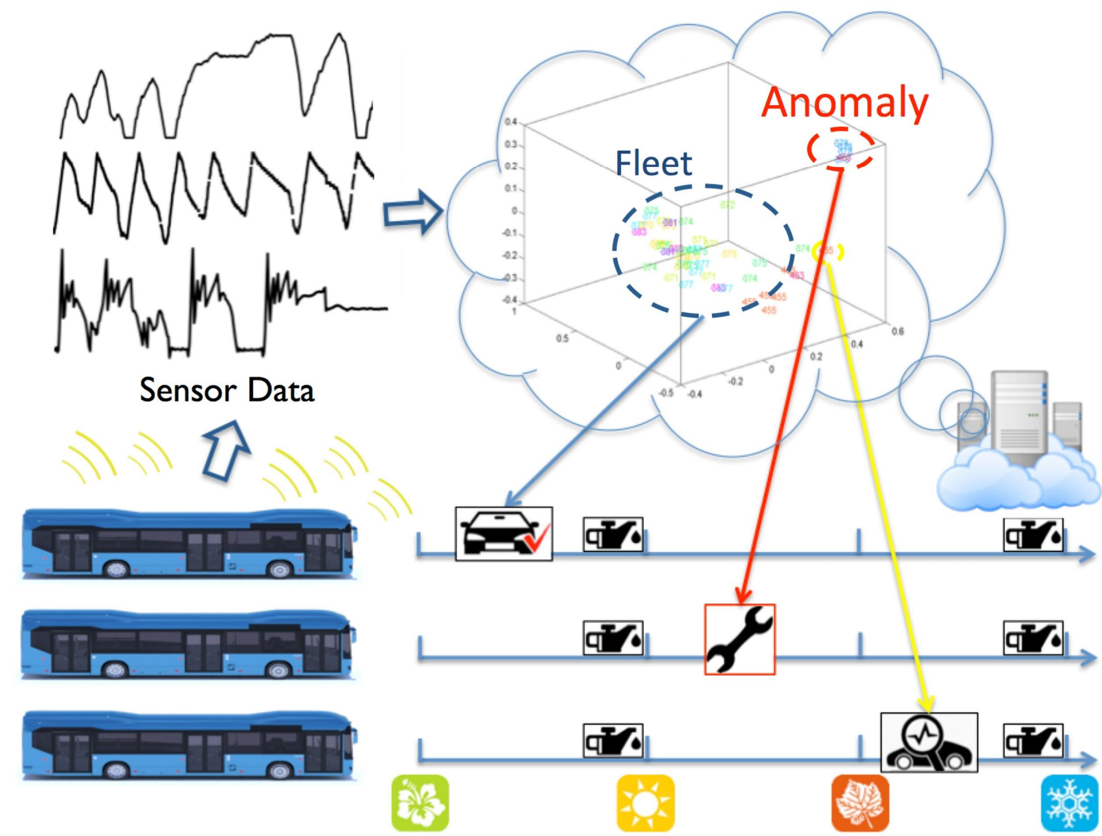
A traffic accident in Jönköping has caused 5 vehicles to be delayed.

Analysis of Diagnostic Trouble Codes Data

Diagnostic trouble codes (DTC) are specified by manufacturers indicating malfunctions within monitored systems. DTCs can be used to identify causes of failures. However, they do not predict future failures. In this study, we have investigated the possibility of reusing the DTCs for predicting maintenance by comparing the daily frequency of failure count for each DTC close to a compressor repair (60 days before the repair) with the daily frequency of failure count for the same DTC in general. The selected DTCs can be included as features in the classifier for prediction of a repair. This analysis has been performed for each vehicle, then, the results were aggregated for all the vehicles. The initial results include DTCs related to components such as compressor control or pumped air volume since last air, which are clearly related to a compressor repair.

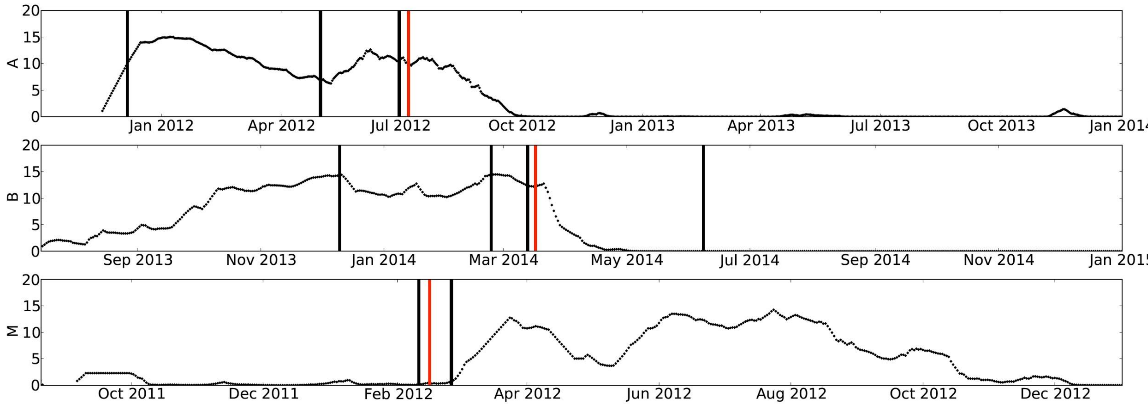
Online Anomaly Detection Using the COSMO Method

One critical factor to achieve high vehicle uptime is the capability of detecting anomalies and capturing abnormal behavior in advance so that problematic components can be diagnosed and fixed, or replaced if necessary, before they cause on-road breakdowns or undesired consequences during regular operations.
An illustration of our anomaly detection system and its usage is shown in the figure below.



The system continuously mines various sensor data streams on-board the vehicle, discovers interesting signal relations, constructs compressed representations of vehicle behaviour and transmits them to a back-office server using telematics. The server runs an algorithm, so-called Consensus Self-Organizing Models (COSMO), to detect anomalies based on the idea of 'Wisdom of the Crowd'. By comparing a compressed representation of each vehicle against the rest of fleet, the system can estimate the probability of each vehicle being deviating from the group, i.e. the system defines nominal behaviour of fleet online and any individual deviates from this reference behaviour can be considered as an anomaly. This information can be utilised for decision support on optimising maintenance scheduling, e.g. eliminating unplanned stops by fixing risky components before it cause vehicle breakdown on road. One key feature of COSMO method is the ability to capture and encode characteristics of the signals by using different representations. For instance, histogram approximates probability distribution of the signal that can be utilised for capturing differences within the spread. They are a memory efficient representation that is robust against noise and easy to compute on-board. On the other hand, a complex representation such as a Recurrent Neural Network captures dynamics, i.e. temporal information, of the signal. By comparing each individual with the rest of the group, the system identifies deviations based on characteristics encoded in representation.

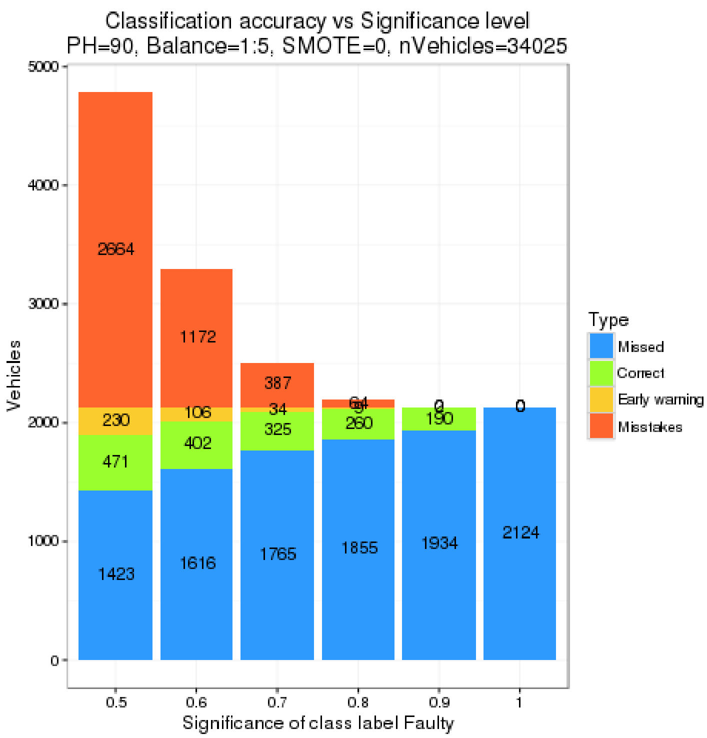
The case study based on a fleet of 19 Volvo buses operated in Kungsbacka shows that our system is able to predict different types of failures including engine cylinder jammed that causes vehicle unable to operate, engine cooling fan overuse that waste 5% more fuel as well as half of the compressor failures that causes buses break down on-road. The Figure below shows the deviation level over time of three buses within this fleet for the Wet Tank Air Pressure signal.



Wet Tank Air Pressure is the only signal collected on-board for the purpose of monitoring air system and deviation level in the plots indicate how likely the vehicle is being deviating from the fleet. Bus A had a long deviation between the end of 2012 and October 2012. During this deviation, there were repairs for air leak problem in December 2011, for gearbox in May 2012, air regulator repair in June 2012 and bus breakdown on road due to compressor failure. Deviation drops gradually afterwards. The sharp increase from November to December 2011 is due to missing data, not a quick deteriorating compressor. Bus B has also had long deviation between June 2013 and May 2014. Compressor failure in March 2014 caused bus inoperable and towed to workshop for compressor replacement. The deviation drops afterwards. The first two cases of deviation level match compressor failures quite well, i.e. bus A in July 2012 and bus B in March 2014. For the case of bus M in February 2012, the deviations start when compressor are replaced. One possible explanation is that the new compressor of this bus performs better than old ones and thus behaves differently from the rest of the fleet during the first couple of months.

Predicting Vehicle Maintenance Using Off-board Data

Vehicle manufacturers, collect various usage and vehicle statistics for customer and quality follow-up. Similarly, maintenance history is tracked for warranty handling and customer invoicing. These, quite different, sources of information can be merged and mined for new and useful insights. Data collection is typically the most expensive part of data analytics and reusing already collected data is thus very cost effective. It is unlikely that exactly the required data is available and in most cases the problem formulation or method for analysis must be adapted to what data is available resulting in an imperfect, but hopefully good enough, outcome.



A concept to derive maintenance predictions based on already available vehicle data has been developed in the project Redi2Service, which also was funded by VINNOVA prior to the In4Uptime project. In4Uptime has continued the development and making it ready for large scale deployment on existing customer owned vehicles. Most part of the work has focused on adjusting algorithms for larger volumes of data and the Volvo internal big data computational infrastructure.

The prediction result, if a vehicle's air compressor needs to be replaced or not is presented in the figure (at left). The figure illustrates the outcome on real predictions (based on a separate test set). The histogram details how the failing vehicles are being predicted by the maintenance prediction algorithm. By increasing the significance level, the algorithm is forced to be more confident in positive (failures) predictions. It reduces the positive mistakes but increases number of missed failures. To proper evaluate the prediction result correctly each vehicle prediction must be classified accordingly:

- **Correct** A vehicle which failed was predicted as failing within a certain time period prior to the failure.
- **Early Warning** A vehicle that failed was predicted as failing long before it actually failed.

- **Missed** A vehicle which failed was never predicted as failing
- **Mistakes** A vehicle which never failed was predicted as failing at some point.

The "Significance of class label Faulty" details how certain the prediction algorithm needs to be of a prediction before the vehicle is actually considered faulty. Increasing the threshold reduces the mistakes but increases the number of missed vehicles. Further details on the algorithm are available in a Volvo internal technical report.

5.1 Delivery to FFI-goals

The data collection required for this project suggests that the studied vehicles are connected. Most likely, the services and business models affected by the results will require connected vehicles. That will contribute to the specific objectives of the program to increase the number of connected vehicles by *50% to 2020*. New business opportunities and new business models themselves, further contribute to the specific objectives.

Since the primary objective of the In4Uptime project has been to investigate benefits that increased usage of data analytics can bring to the uptime area, in particular by increasing the penetration and quality of service (maintenance) contracts and related services one could argue that well maintained vehicles will lead to less environmental impact and less emissions.

Better service, maintenance and improved products and services is another objective that was targeted by the project, mainly by researching predictive maintenance.

Increased uptime as in less unplanned stops, do have positive impact on traffic flows which means that less breakdowns lead to better accessibility and less traffic jams which generally leads to less accidents could in the long run also lead to improved image and status for the transport business. All of which are objectives of the program.

Further, by the nature and setup of the project, we have also contributed to:

- Continued competitive production, research and development in Sweden.
- Research based technology- and competence development.
- Cooperation between SMEs, Universities and research institutes.
- New and essential knowledge, effectively implemented.
- Increased quality of automotive education by cooperation between industry, agencies, universities and the research community.

6. Dissemination and publications

6.1 Knowledge and results dissemination

There are other ongoing projects which can benefit from the results of In4Uptime. One such project is BIDAF (“BIg Data Analytics Framework”), funded by the KK foundation in the SIDUS programme. The overall aim of this project is to create a strong distributed research environment for big data analytics. This involves e.g. to develop a computational platform suitable for machine learning of massive streaming and distributed data.

There is also the Vinnova BADA programme and the BADA project. The BADA project takes some of the ideas from In4Uptime one step further and develops a distributed environment where data can be shared also between partners and third parties.

The experience, knowledge of test cases and data that has been gained through the In4Uptime project can be used as an example domain to demonstrate the capabilities of the developed platform in the BIDAF project. This will benefit both the company partners in In4Uptime as it will provide a useful demonstration, as well as the partners in the BIDAF consortium as they will be able to test the platform on realistic data from the automotive domain.

The In4Uptime project will be presented at the Vinnova projektpresentationsdag in September 2016. There will also be an In4Uptime dissemination event at Volvo Technology later this year. Also, the In4Uptime animated movie will be made publically available for streaming.

6.2 Publications

Yuantao Fan, Sławomir Nowaczyk, and Thorsteinn Rögnvaldsson. "Using Histograms to Find Compressor Deviations in Bus Fleet Data." *The Swedish AI Society (SAIS) Workshop 2014, Stockholm, Sweden, May 22-23,* 2014.

Yuantao Fan, Sławomir Nowaczyk, and Thorsteinn Rögnvaldsson. "Evaluation of self-organized approach for predicting compressor faults in a city bus fleet." *Procedia Computer Science* 53 (2015): 447-456.

Yuantao Fan, Sławomir Nowaczyk, and Thorsteinn Rögnvaldsson. "Incorporating Expert Knowledge into a Self-Organized Approach for Predicting Compressor Faults in a City Bus Fleet." *Thirteenth Scandinavian Conference on Artificial Intelligence: SCAI 2015*. Vol. 278. IOS Press, 2015.

Yuantao Fan, Sławomir Nowaczyk, Thorsteinn Rögnvaldsson and Eric Aislan Antonelo. Predicting Air Compressor Failures with Echo State Networks. *3rd European conference of the prognostics and health management society 2016*, Bilbao, Spain, July 5-8, 2016.

Rune Prytz, Sławomir Nowaczyk, Thorsteinn Rögnvaldsson, and Stefan Byttner. Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data. *Engineering Applications of Artificial Intelligence 2015*, 41, 139-150.

Rune Prytz. Machine learning methods for vehicle predictive maintenance using off-board and on-board data. *Halmstad University Press (Licentiate dissertation)*. 2014.

7. Conclusions and future research

Conclusions and Future Innovation Directions

The In4Uptime project has demonstrated that, in the automotive domain, a large number of potential improvements are possible when it comes to generating value by collecting and analysing more data. This is particularly true with regards to combining different data sources. Just as apps have revolutionized how we use our smartphones, bringing together vehicle on-board systems and external data sources can lead to ecosystems of smart integrations with reactive data flows supporting proactive measures.

As the data becomes more readily available, new opportunities will arise for taking advantage of it. In the In4Uptime project we have demonstrated several examples of data that, once collected, becomes an important asset that can be reused for new, originally unforeseen, purposes. One important conclusion is that finding the right business needs to address, and defining the appropriate scope of the questions to be asked remains a challenge. It will certainly require more study; especially with regards to how does the

data-driven (or at least data-conscious) process fit the existing workflow in the organisation.
The In4Uptime project has focused on the predictive maintenance area, however, the primary observations and conclusions are related to importance of collecting, properly describing, understanding and utilising data, which have much broader applications. We have shown that all those steps should be as general as possible, in order to enable additional uses of the data, which not only saves costs and avoids duplicate efforts, but in many cases is the necessary condition for making those additional benefits feasible. The main reason for that is the necessity to have a certain amount of initial data, in many cases months or even years, without which, the analysis cannot be started. Even more importantly, this initial amount of data is often required even to do an initial feasibility study.

Within the predictive maintenance and uptime domain, the In4Uptime project has analysed component life-cycle, diagnostic trouble codes, vehicle usage statistics and streaming sensor signal data in order to predict component failures. We have tested and developed several different algorithms, adapted to the particular challenges in each individual case. Incorporating expert knowledge into the data-driven methods, developing new generic models, exploring and validating the results using both real and synthetic data, shown results that are in many cases reliable and will bring value in a production environment as well as will over time improve the service contract business and other transport and vehicle related services.

At this stage we have not addressed the process of taking failure predictions to the end customer. Predictive maintenance in practice requires precise feedback from workshops on repairs initiated by provided predictions, which is out of the scope of this project. This complete chain, from prediction to repair, is definitely the next step towards the innovative uptime management in the automotive domain. It will require involvement of workshops and one or more fleets, large enough to experience a significant number of faults during the time of this hypothetical future project.

Other directions for future research include refining the reference groups for defining the nominal working behaviour based on factors such as usage patterns and exploring more generic models for fault detection and isolation. Further, an autonomous learning module that can optimize parameters of representation over time, based on occurrences of new faults and failures, is on the shortlist.

We do see that more value can be gained by combining publicly available data sources with internal, private data. In this project we have measured how truck drivers were affected by traffic accidents nearby. That is just one example, but such information is very important in making sure that the customer has the right support to make the right decisions regarding everything from when to take a break to when maintenance of the truck is needed.

8. Participating parties and contact person

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