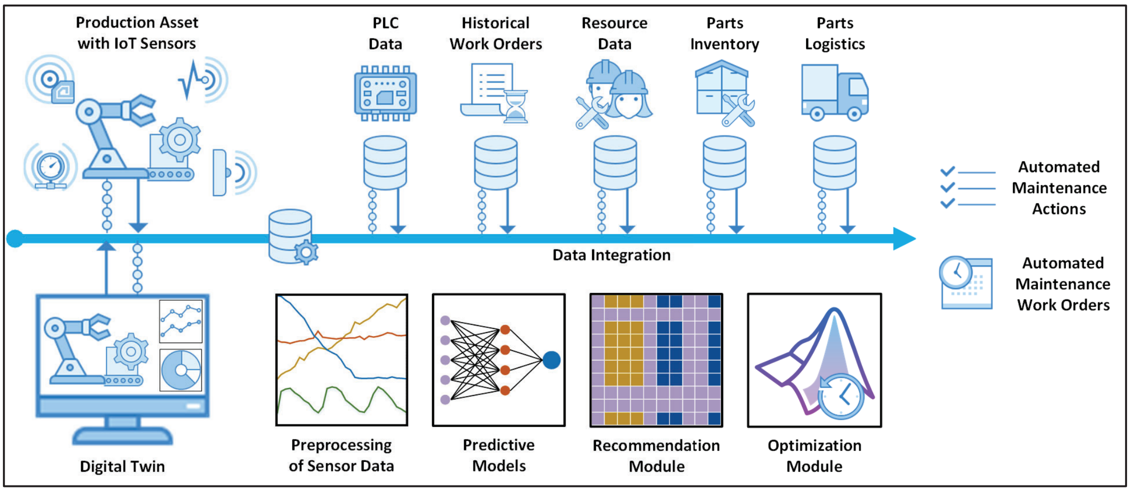
Integrated Manufacturing Analytics Platform for IoT Enabled Predictive Maintenance

Public report



Project within FFI Sustainable Development

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FFI in short

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1. Summary

The project aimed at combining core Industry 4.0 technologies of industrial IoT, digital twins and analytics to realize the full potential of predictive maintenance and pave the way towards prescriptive maintenance. The core idea was to supplement and validate data from existing IoT infrastructure with simulated data from lean digital twins, preprocess and integrate these multiple sources of data into the CMMS, and use machine learning, analytics and optimization techniques to monitor the health of equipment, thereby predicting the need for maintenance in advance.

The project consortium is composed of (i) University of Skövde as the project coordinator, (ii) Chalmers University of Technology as the academic partner, and following five industry partners who will provide use-cases and support various project-related activities, (iii) Scania CV (iv) Volvo Cars Corporation (VCC) (v) Volvo Group Truck Operations (VGTO), (vi) Automotive Components Floby, and (vii) Jernbro Industrial Services.

The project addressed six industrial use-cases across three problem domains:

- *Condition Monitoring of Ball-Screw Drives:* This focused on detecting anomalies and estimating the Remaining Useful Life (RUL) of ball-screw drives in CNC machines. Ball-screw health data from multiple sensors were analyzed using signal processing and machine learning techniques. Significant progress was achieved in fault prediction and localization, though one use-case had limited analysis due to time constraints.
- *Fault Detection in Sheet Metal Glue Lines*: This use case aimed to reduce false positives in detecting faults in sheet metal glue lines using vision sensor data. Unsupervised deep learning models were applied, along with data augmentation and robustness experiments, to improve accuracy and adapt to real-world conditions.
- *Fault Prediction in Hydraulic System*: Predictive models analyzed MES and SCADA data to identify faults in hydraulic accumulators in CNC machine clusters. Techniques like SMOTE and machine learning models helped classify faults and identify critical predictive features, though data quality issues limited further progress.

Through these use-cases, the project demonstrated how anomaly detection in predictive maintenance, enabled by IoT sensor data integration, advanced analytics, and machine learning, can improve maintenance operations.

2. Sammanfattning på svenska

Projektet syftade till att kombinera centrala Industri 4.0 teknologier som industriell IoT, digitala tvillingar och analys för att realisera den fulla potentialen hos prediktivt underhåll och bana väg för preskriptivt underhåll. Den huvudsakliga idén var att komplettera och validera data från befintlig IoT-infrastruktur med simulerade data från "lean" digitala

tvillingar, förbehandling och integrering av flera datakällor i CMMS samt användandet av maskininlärning. Samt, analys och optimeringstekniker för att övervaka utrustningens hälsa och därigenom förutsäga underhållsbehov i förväg.

Projektkonsortiet bestod av (i) Högskolan i Skövde som projektkoordinator, (ii) Chalmers tekniska högskola som akademisk partner och följande fem industripartners som tillhandahöll användningsfall och stöd för olika projektaktiviteter: (iii) Scania CV, (iv) Volvo Cars Corporation (VCC), (v) Volvo Group Truck Operations (VGTO), (vi) Automotive Components Floby och (vii) Jernbro Industrial Services.

Projektet behandlade sex industriella fallstudier inom tre problemområden:

- *Condition Monitoring of Ball-Screw Drives*: Fokus låg på att upptäcka avvikelser och beräkna den återstående livslängden (Remaining Useful Life, RUL) för kulskruvsdrivningar i CNC-maskiner. Hälsodata från flera sensorer analyserades med signalbehandling och maskininlärningstekniker. Betydande framsteg gjordes i att förutsäga och lokalisera fel, även om ett användningsfall hade begränsad analys på grund av tidsbrist.
- *Fault Detection in Sheet Metal Glue Lines*: Detta användningsfall syftade till att minska falska positiva resultat vid feldetektering i limlinjer på plåtdelar med hjälp av sensordata från visionsystem. Oövervakade djupa inlärningsmodeller användes, tillsammans med dataaugmentation och experiment för att avgöra robusthet och förbättrad noggrannhet vid verkliga industriförhållanden.
- *Fault Prediction in Hydraulic System*: Prediktiva modeller analyserade MES- och SCADA-data för att identifiera fel i hydraulackumulatorer i CNC-maskinkluster. Tekniker som SMOTE och maskininlärningsmodeller användes för att klassificera fel och identifiera kritiska prediktiva egenskaper, även om problem med datakvalitet begränsade vidare framsteg.

Genom dessa fallstudier visade projektet hur avvikelsedetektering inom prediktivt underhåll, möjliggjort genom IoT-sensordataintegration, avancerad analys och maskininlärning, kan förbättra underhållsoperationer.

3. Background

Artificial intelligence, big data analytics, industrial internet of things (IoT) and digital twins are among the most important technologies driving Industry 4.0 transformation in the manufacturing sector. One of the areas where a combination of these technologies can bring significant improvements is predictive maintenance. The basic principle of predictive maintenance is to leverage real-time data coming from IoT devices such as sensors, transducers, cameras, switches and other instruments with approaches like statistical process control and machine learning to monitor the health of various manufacturing assets and predict when equipment anomaly or failure could occur. As opposed to reactive maintenance, where corrective actions are taken only upon the failure of assets, or preventive maintenance, where maintenance is done at regular intervals of usage, predictive maintenance aims at carrying out maintenance activities as close to the predicted end-of-life of parts or components as possible. There are several immediate benefits to implementing predictive maintenance systems, some of which are increase in equipment uptime and availability, which leads to increased productivity, and reduction in time required for planning and performing maintenance, which in turn can lead to a lean maintenance team and hence lower overall maintenance costs. Other consequential advantages are reduced maintenance inventory requirement, improved operational safety, a lean and efficient supply chain for spare parts and overall reduction in indirect emissions and thus carbon footprint.

4. Purpose, research questions and method

Early adopters of predictive maintenance systems face several key challenges that limit their potential. First, since real-time data is crucial, IoT devices must remain synchronized, connected, and operational throughout production. Second, the lack of interoperability standards among IoT devices from different vendors complicates data integration, requiring compatibility with existing systems like CMMS. Third, predictive analytics poses challenges, as customized models are often needed to handle diverse data types. Limited failure events also hinder training machine learning models for metrics like Remaining Useful Life (RUL) and failure risk. Lastly, selecting corrective actions and generating work orders is difficult due to poor data integration and unstructured maintenance records. Overcoming these challenges is critical to advancing digitalized maintenance in vehicle manufacturing.

The four challenges described above can be formulated into the following research questions which have been the focus of this project:

- **RQ1.** How can clean, continuous, and reliable data be obtained from industrial IoT devices despite their current hardware and connectivity issues?
- **RQ2.** How can real-time IoT device data be integrated with multi-source multi-format data from other sources and made compatible with an existing CMMS?
- **RQ3.** Which statistical and machine learning methods are best suited for predicting maintenance critical metrics like RUL, failure risk and machine reliability?
- **RQ4.** How can appropriate maintenance actions be generated automatically and the associated work orders be optimized with respect to given resources, production plan and maintenance inventory?

The methods used to address these research questions included workshop and factory visits, data collection, data quality assessment, statistical analysis, time-series analysis, signal processing, data integration procedures, simulated experiments, classification algorithms, image processing, computer vision techniques, deep learning methods, reinforcement learning, and multi-criteria decision analysis.

5. Objective

The project had the following six objectives connected to these research questions:

O1. *Supplement and/or validate IoT device data with lean digital twins*
Objective O1 involves the use of what we call "lean" digital twins, whose main purpose is to simulate the assets of interest with just enough detail to reproduce the actual IoT device signal in real-time for either supplementing chunks of missing data, or validating signals when devices are restarted or reconfigured after malfunction. Digital twins also allow simulation of pre-failure equipment behavior for diagnostics, virtual verification of maintenance tasks and operating conditions of new equipment.

O2. *Perform statistical time-series analysis and signal processing of IoT sensor data*
Objective O2 is needed to prepare raw sensor data for running analytics. It involves the use of time-series analysis for imputing missing data points, identifying intermittent and periodic trends, correlation analysis for dimensionality reduction, etc. Signal processing is also required for resampling the signal, perform time-frequency analysis for noise reduction, and feature extraction. These preprocessing techniques can later improve the reliability of predictive models.

O3. *Develop a global schema to integrate maintenance data into CMMS*
Objective O3 deals with merging different sources of data by developing a global schema (data model) which will enable different formats of data to be represented within a unified structure. Such data integration is necessary for analytics solutions to be scalable. In addition to sensors on physical machines and their digital twins, data can also come from other sources such as PLCs, Manufacturing Execution Systems (MES) or even from an Enterprise Resource Planning (ERP) system.

O4. *Employ machine learning to predict RUL and other maintenance metrics*
Objective O4 deals with the training and testing various machine learning algorithms on integrated data. Labeled pre-failure historical data is typically needed for training predictive models through supervised learning methods. However, since such data may not be readily available, either an unsupervised approach of anomaly detection or a reinforcement learning approach which relies on digital twins can be used. A balance between predictive power and explainability can also be achieved depending on specific needs in various use cases.

O5. *Generate automated maintenance actions based on historical work orders*
Objective O5 is focused on determining what type of maintenance activity should be undertaken for an impending problem with the equipment. This requires a record of historical work orders. In the ideal situation, generating maintenance actions could be as simple as locating the failure in a lookup table. However, if the work order database is unstructured or qualitative, the complexity of the tasks increases. Moreover, the

relationship between failure and appropriate maintenance activity may not be as direct, in which case data mining methods have to be employed to find patterns.

O6. *Optimize maintenance schedule to generate automated maintenance work orders*
Objective O6 is related to optimizing the schedule for prescribed maintenance actions given the constraints of production plan, resource availability and personnel competence. The optimal solutions take the form of work orders to be executed. More than one conflicting objective may be involved in specific use cases, in which case multiple Pareto-optimal work orders can be found using multi-objective evolutionary algorithms. In this case, an additional decision-making step is needed.

These objectives can be grouped into the three typical stages of analytics as follows: (i) descriptive analytics (**O1** and **O2**), predictive analytics (**O3** and **O4**), and prescriptive analytics (**O5** and **O6**). Taking the project as a whole, all six objectives have been fulfilled. However, objective **O6** was only achieved in a hypothetical case based on the real industrial scenario. The use-cases handled in this project and the results for each are described in the next section.

6. Results and deliverables

The project dealt with the following six company use-cases over the three-year period:

UC1. *AMC + PAS Condition Monitoring Data for Ball Screw (VGTO + Jernbro)*
This use-case involved the use of data from Siemens SINUMERIK Integrate Analyze MyCondition (AMC) system, together with data from Jernbro's Predictive Analysis Servo (PAS) system, to predict faults and estimate the remaining useful life (RUL) of CNC machine tool ball-screw drives. The ball-screw (see Figure 1) is a critical component of CNC machines as its degradation can severely impact the machining precision and quality of cylinder blocks and cylinder heads. The AMC system provides test cycles for equability, circularity, and universal axis tests that are periodically carried out on each machine, while the PAS system measures the current and voltage of the servo motors during these tests. The equability axis test provides the torque/force measurements over the axis position. The circularity test results in a polar plot of the circular path for each of there machining planes and circularity-specific characteristics, such as deviation and hysteresis. Finally, the universal axis test determines the characteristics that define the coulomb and viscous friction characteristics, as well as the moment of inertia and a torque offset.

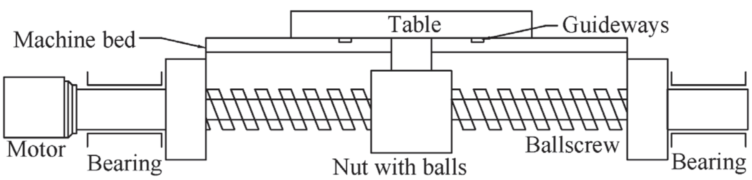

Figure 1: Schematic showing the key mechanical components of a ball-screw drive.

UC2. *SICK Vision Sensor Data for Sheet Metal Glue Lines (Volvo Cars)*
This use-case involved using grayscale images taken by the SICK Inspector PIM60 vision sensor for detecting faults in the glue lines deposited by a robotic arm on sheet metal parts. The SICK system includes a toolbox that can be detect deviations from a predefined geometry of the glue lines. However, due to the changing lighting conditions in the production environment and other factors such as vibrations and humidity, the system triggered unnecessary production stops based on flagged anomalies in images that turned out to be false positives (OK images of normal glue lines tagged as NOT OK). The company wanted to reduce the false positive rate using advanced deep learning techniques. In total, data for 20 distinct components, each containing approximately 300 images of size 480*640 pixels, were provided. There were no images of faulty glue lines in the datasets. Figure 2 shows a schematic representation of the vision system. Figure 3 shows two images of normal glue lines – the one the left is tagged OK by the vision system, while the one on the right is tagged as NOT OK, probably due to a change in the lighting condition.

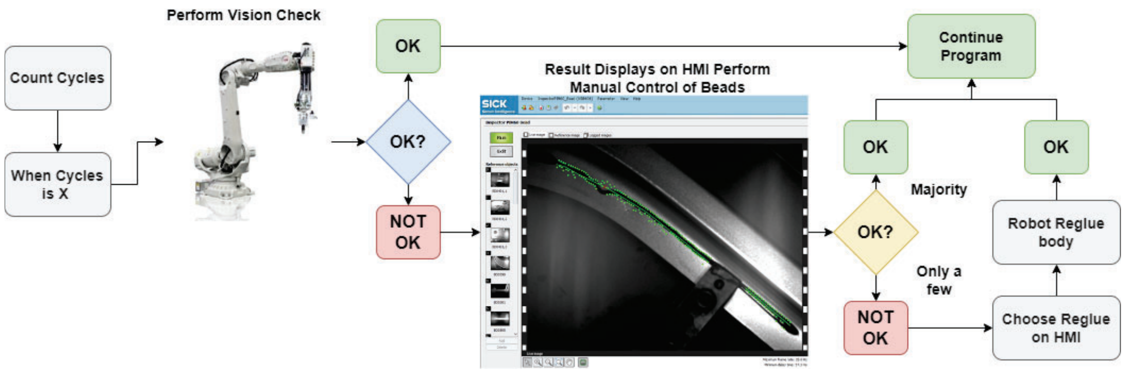

Figure 2: Schematic showing the operation of the vision system in ***UC2****.*

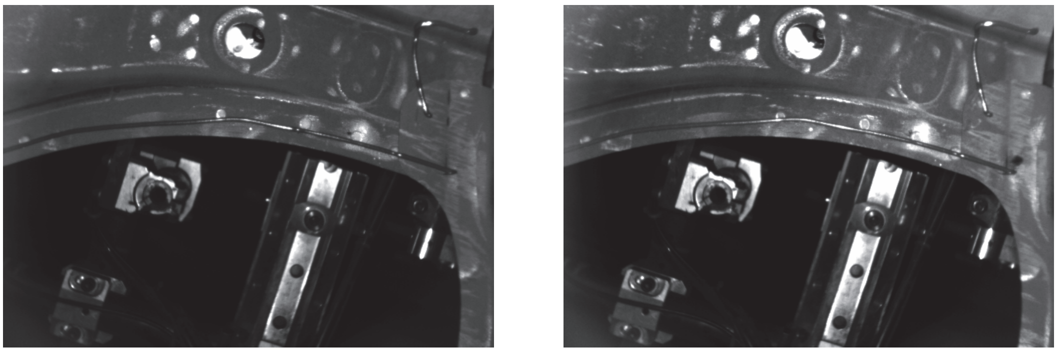

Figure 3: Images of normal glue lines tagged as OK (left) and NOT OK (right).

UC3. *SPM Condition Monitoring Data for Ball Screw (Volvo GTO)*
This use-case involved the use of vibration data measured by SPM Instrument accelerometers mounted directly on the ball-screw on each axis of the CNC machine. The company switched from using the AMC+PAS system data to SPM measurements in order to reduce the time required for testing the condition of ball-screw drives. Another potential

advantage of using accelerometer measurements is that the fault can be localized to either the nut assembly or the ball-screw, as well as along the length of the ball-screw.

UC4. *MaintMaster IoT Vibration Sensor Data for Ball Screw (AC Floby)*
This use-case involved CNC machines where no health data was previously being collected. The company purchased multiple IoT vibration sensors from MaintMaster and mounted them as follows: (i) IoT1 (Portal cross slide motor), (ii) IoT3 (X-Slide), (iii) IoT4 (Stand X-Axis), and (iv) IoT5 (Support Bearing Ball Screw X-Axis). The data from these sensors, as well as production volume data for a two-month period was provided. However, the vibration data was found to be too noisy and contaminated with environmental factors to be used for predictive analytics. The IoT sensors also tended to go offline due to network connectivity issues, and this went unnoticed for some time as no notifications were setup. Due to these reasons, this use-case was not pursued further.

UC5. *MES + SCADA Data for CNC Machine Cluster (Scania)*
This use-case involved the use of MES and SCADA data for a cluster of CNC milling machines to predict and classify faults in the hydraulic system, specifically in a component called the hydraulic accumulator. It plays a critical role in regulating oil pressure to ensure smooth operation. Any malfunction in the accumulator can lead to system-wide disruptions, resulting in machine stoppages and production delays. In a production line of interconnected machines, the operational status of each machine can be inferred from its interactions with neighboring machines. By examining how the state of one machine correlates with those of the machines immediately preceding and succeeding it, a clearer picture of its operational health emerges. This relationship, combined with extensive sensor data, forms the foundation for predicting and diagnosing faults. Figure 4 shows the cluster of machines whose MES and SCADA data were provided for fault analysis.

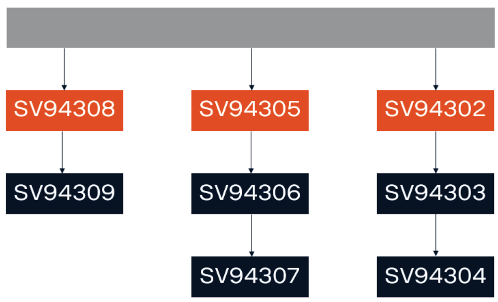

*Figure 4: Cluster of CNC machines used for hydraulic accumulator fault analysis in **UC5**.*

UC6. *STMicroelectronics Vibration Sensor Data for Ball Screw (AC Floby)*
This use-case involved a sensor setup and vibration data that is similar to those in **UC3**. Therefore, the same analytics techniques could be applied. However, as this use-case started just three months before the end of the project, the analysis was somewhat limited.

In summary, (i) **UC1**, **UC3**, **UC4**, and **UC6** dealt with anomaly detection and RUL estimation of ball-screws in CNC machines, (ii) **UC2** dealt with anomaly detection and segmentation in images of sheet metal glue lines, and (iii) **UC5** dealt with hydraulic accumulator fault prediction in a cluster of CNC machines. Figure 5 shows an overview of the type of research problems and data that were handled in the project altogether.

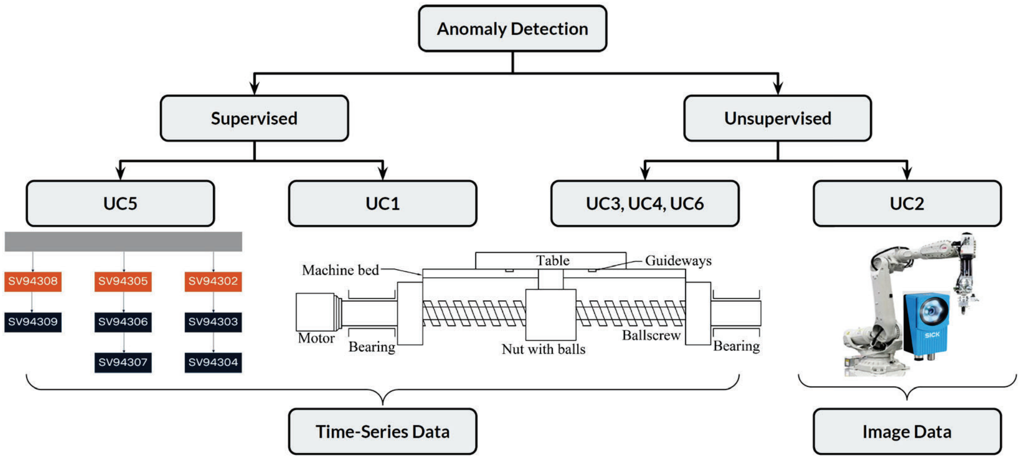

Figure 5: A summary of the research problems and data types handled in the project.

Table 1 shows the degree to which the six project objectives were achieved in each of the aforementioned use-cases. It can be seen that **UC2** and **UC3** were the most successful use-cases, followed by **UC1**. Though the prescriptive analytics stage could not be reached in **UC5** and **UC6**, adequate progress was made that provided valuable insights to the industry partners. As mentioned above, **UC4** was discontinued due to the poor data quality.

Table 1: Goal fulfillment in various use-cases of the project. Checkmark in parenthesis represents partial fulfillment of the corresponding objective.

Use-Cases	Industry Partners	Descriptive		Predictive		Prescriptive	
		O1	O2	O3	O4	O5	O6
UC1	VGTO + Jernbro	✓	✓	✓	✓	✕	✕
UC2	VCC	✓	✓	✓	✓	✓	(✓)
UC3	VGTO	✓	✓	✓	✓	✓	✕
UC4	AC Floby	✓	✓	✕	✕	✕	✕
UC5	Scania	✓	✓	(✓)	(✓)	✕	✕
UC6	AC Floby	✓	✓	(✓)	(✓)	✕	✕

The main challenge in achieving the project objectives in some use-cases was the delay in gathering relevant data for analytics. Reflecting on the project timeline, Table 2 highlights when the first dataset for each use-case was received and when the use-cases either ended or were discontinued. It is evident that use-cases with significant delays in data collection naturally experienced a lower degree of goal fulfillment. Some objectives that were partially fulfilled either involved hypothetical use-cases based on the real use-case from the companies, or had to be ended due to lack of time in the project.

Table 2: The timeline of the use-cases within the project duration. The starting point of the use-case is denoted by Ⓢ, and the endpoint is denoted by Ⓔ.

Use-Cases	Industry Partners	Project Timeline		
		Dec.2021-Nov.2022	**Dec.2022-Nov.2023**	**Dec.2023-Nov2024**
UC1	VGTO + Jernbro	Jul2022Ⓢ → ⒺJan2023		
UC2	VCC		Feb2023Ⓢ →	→
UC3	VGTO		Oct2023Ⓢ →	→
UC4	AC Floby		Sep2023Ⓢ → ⒺFeb2024	
UC5	Scania		Oct2023Ⓢ →	→
UC6	AC Floby			Sep2024Ⓢ →

6.1 Anomaly Detection and RUL Prediction in Ball-Screw Drives

The proposed condition monitoring methodology in **UC1** for ball-screw drives consists of four main steps: data collection, data preprocessing and feature engineering, model building, and anomaly detection. The machine tool drive system is operated under no-load condition at regular intervals to capture AMC health data. Subsequently, the data is preprocessed and features are extracted from raw signals using the discrete wavelet transform approach. The unsupervised machine learning technique, principal component analysis, is used to reduce the dimensionality of the dataset and find feature combinations that capture most of the variation in the data. Next, Hotelling's T^2 statistic is computed for each sample on a rolling basis, and anomalous behavior is detected based consistent deviations beyond the moving median of Hotelling's T^2 statistic.

The Discrete Wavelet Transform (DWT) transforms a signal into different scale and shift parameters. It is implemented using a pair of low-pass and high-pass wavelet filters, using a selected wavelet function and its corresponding scaling function. The preprocessed signals are transformed using the DWT by selecting the optimal mother wavelet from the Python package 'PyWavelets'. After decomposing a signal using the DWT with s levels, wavelet coefficients are obtained from each level. Energy, root mean square, and kurtosis are calculated for each level and included as features. Figure 7 shows a two-dimensional Principal Component Analysis (PCA) projection of the extracted features. From this figure, it is observed that normal and abnormal behavior occupy different regions of the first two PCs. Each region describes the corresponding degradation of the ball-screw over time. The monitoring samples A, B, and C show the normal behavior of the ball-screw. Furthermore, the monitoring samples D and E show an abnormal region, which is surrounded by the similar abnormal behavior of the ball-screw.

Hotelling's T^2 statistic is shown in Figure 8 for each monitoring sample, with their respective threshold limit T^2_{limit}. The T^2_{limit} is observed to decrease rapidly and then constant, due to the increase in sample size of the training dataset. The monitoring samples B and C show high Hotelling's T^2 statistics, which can be taken after continuous operation of the machine. Therefore, it is necessary to base decisions on moving statistic of the Hotelling's T^2 statistic. The ball-screw is observed to be in a healthier condition before the monitoring sample D, but it started to deteriorate significantly afterward. There are consistent monitoring samples above T^2_{limit} around the monitoring sample D, indicating the degradation of the ball-screw.

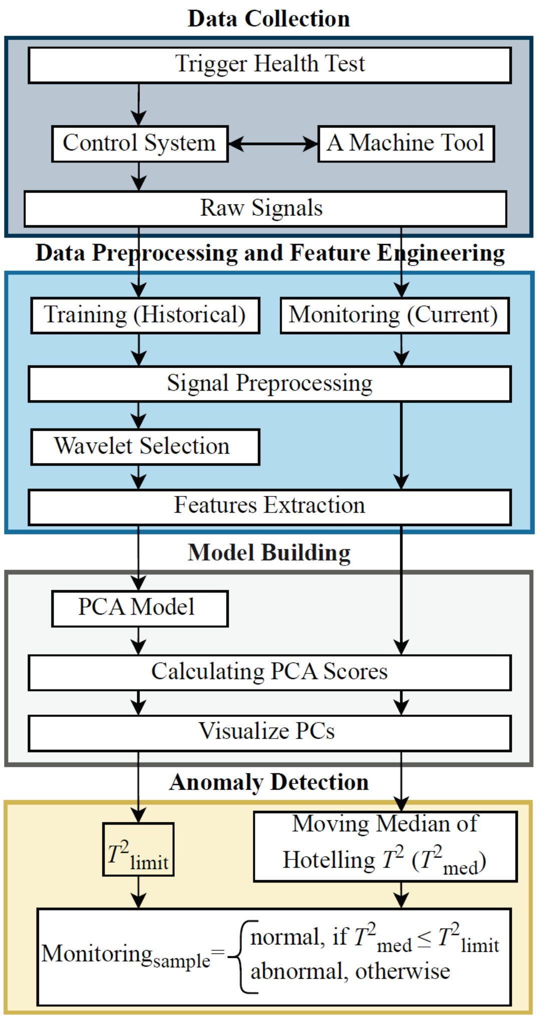

Figure 6: Proposed methodology in **UC1**.

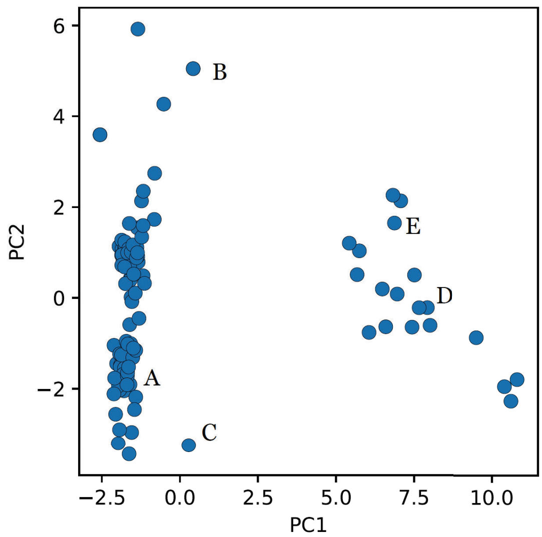

Figure 7: PCA Visualization.

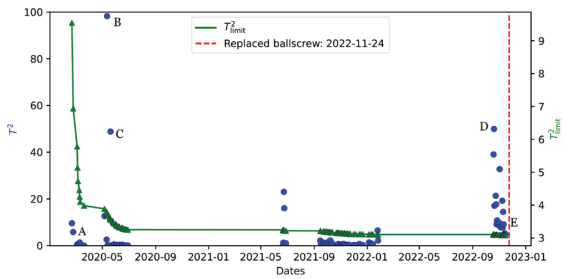

Figure 8: Anomaly detection with T^2.

A similar methodology for vibration data analysis in **UC3** and **UC6** was also proposed which includes the use of an additional calculated feature called Ball-Pass Frequency (BPF) for fault isolation.

6.2 Anomaly Detection and Segmentation in Glue Lines

Due to the unavailability of images of faulty glue lines, unsupervised deep learning models for anomaly detection were employed in **UC2** to significantly reduce false positive rates. A comparative evaluation was conducted on 17 unsupervised deep learning models for anomaly detection, spanning various categories and incorporating 28 backbones, using datasets of approximately 300 glue line images per part. To address the challenge of limited training data and improve generalization, data augmentation techniques were applied, and robustness experiments were performed to ensure applicability in real-world industrial conditions. Table 3 shows various image-level and pixel-level predictive performance metrics for the 17 deep learning models on one of the 20 components studies in **UC2**. Figure 9 shows the segmentation results for some of the best performing deep learning models. Additionally, Figure 10 shows the inference times and throughput (number of images processed per second) of all models. Overall, the findings demonstrated that deep learning approaches effectively detect and localize anomalies, significantly reducing false positives and gluing machine downtimes compared to the existing system. A multi-criteria decision analysis approach was also used in **UC2** for model selection, allowing decision-makers to achieve optimal trade-offs between accuracy and inference time, thereby improving operational efficiency.

*Table 3: Predictive performance comparison of all deep learning models used in **UC2**.*

Model	Backbone	Image AUROC	Image F1 Score	Pixel AUROC	Pixel F1 Score
CFA	ResNet18	0.810 ± 0.015	0.950 ± 0.007	0.984 ± 0.001	0.453 ± 0.020
	WideResNet50	0.889 ± 0.026	0.960 ± 0.008	0.993 ± 0.000	0.544 ± 0.002
CFlow-AD	WideResNet50	0.871 ± 0.042	0.950 ± 0.007	0.993 ± 0.000	0.539 ± 0.008
CSFlow	EfficientNet-B5	0.822 ± 0.015	0.943 ± 0.000	0.955 ± 0.002	0.224 ± 0.006
DFKDE	ResNet18	0.130 ± 0.000	0.943 ± 0.000		
	WideResNet50	0.120 ± 0.000	0.943 ± 0.000		
DFM	ResNet50	0.320 ± 0.000	0.943 ± 0.000	0.986 ± 0.000	0.342 ± 0.000
	ResNet18	0.280 ± 0.000	0.943 ± 0.000	0.983 ± 0.000	0.316 ± 0.000
DRAEM		0.934 ± 0.037	0.970 ± 0.016	0.982 ± 0.006	0.635 ± 0.079
DSR		0.968 ± 0.026	0.966 ± 0.016	0.971 ± 0.016	0.683 ± 0.051
Efficient_AD		0.981 ± 0.007	0.978 ± 0.004	0.954 ± 0.000	0.674 ± 0.004
FastFlow	ResNet18	0.935 ± 0.022	0.967 ± 0.008	0.994 ± 0.001	0.560 ± 0.028
	WideResNet50	0.982 ± 0.010	0.982 ± 0.004	0.997 ± 0.000	0.638 ± 0.009
	cait	0.837 ± 0.040	0.969 ± 0.008	0.996 ± 0.000	0.662 ± 0.014
	deit	0.948 ± 0.024	0.977 ± 0.011	0.992 ± 0.002	0.597 ± 0.033
GANomaly		0.737 ± 0.251	0.948 ± 0.007		
MMR	WideResNet50	0.980 ± 0.004	0.997 ± 0.002	0.997 ± 0.000	0.597 ± 0.012
PaDiM	ResNet18	0.901 ± 0.040	0.969 ± 0.004	0.997 ± 0.000	0.660 ± 0.013
	WideResNet50	0.962 ± 0.012	0.973 ± 0.008	0.997 ± 0.000	0.614 ± 0.012
PatchCore	WideResNet50	0.944 ± 0.006	0.975 ± 0.005	0.996 ± 0.000	0.571 ± 0.002
Reverse_Distill.	WideResNet50	0.943 ± 0.036	0.969 ± 0.008	**0.998 ± 0.000**	0.662 ± 0.016
	ResNet18	0.871 ± 0.026	0.965 ± 0.005	0.997 ± 0.000	0.656 ± 0.006
SimpleNet	WideResNet50	0.983 ± 0.000	0.969 ± 0.011	0.967 ± 0.000	0.538 ± 0.006
stfpm	ResNet18	**0.985 ± 0.009**	0.982 ± 0.011	0.997 ± 0.000	0.673 ± 0.008
	WideResNet50	0.981 ± 0.004	0.976 ± 0.005	**0.998 ± 0.000**	**0.696 ± 0.003**
UFlow	mcait	0.951 ± 0.010	**0.986 ± 0.006**	0.996 ± 0.000	0.578 ± 0.015
	ResNet18	0.935 ± 0.019	0.967 ± 0.005	0.993 ± 0.000	0.538 ± 0.030
	WideResNet50	0.941 ± 0.033	0.967 ± 0.011	0.993 ± 0.001	0.475 ± 0.039

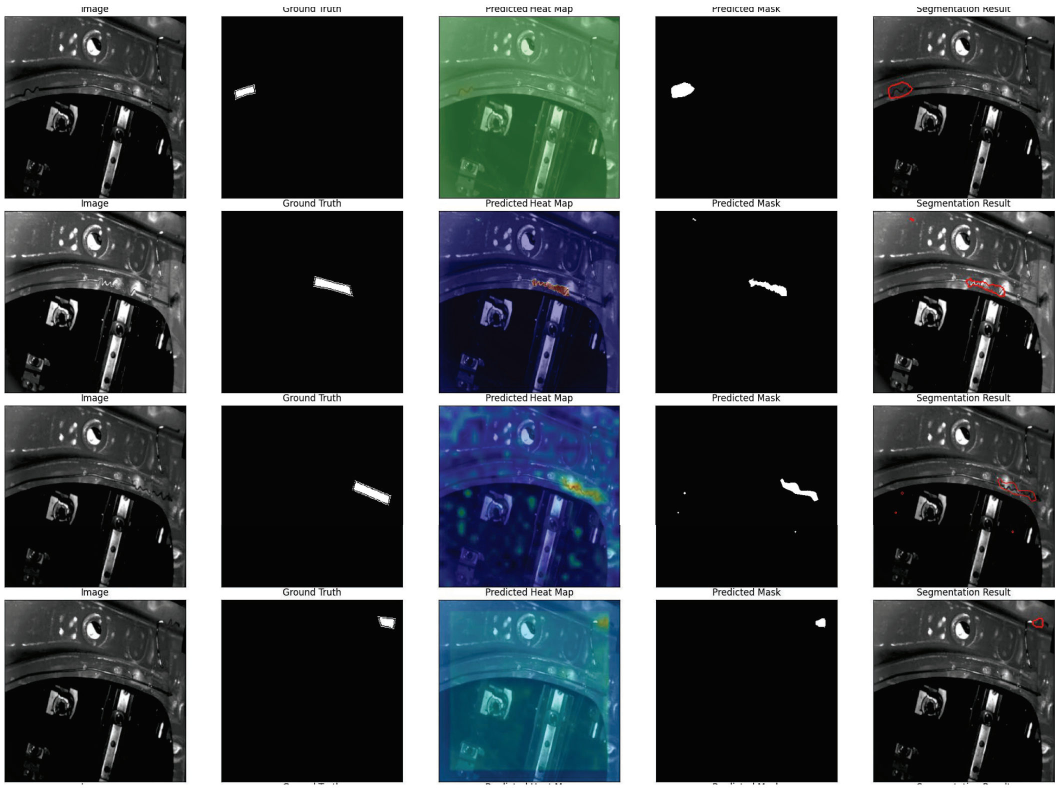

Figure 9: Segmentation result for models stfpm, DSR, fastflow, and Efficient_Ad.

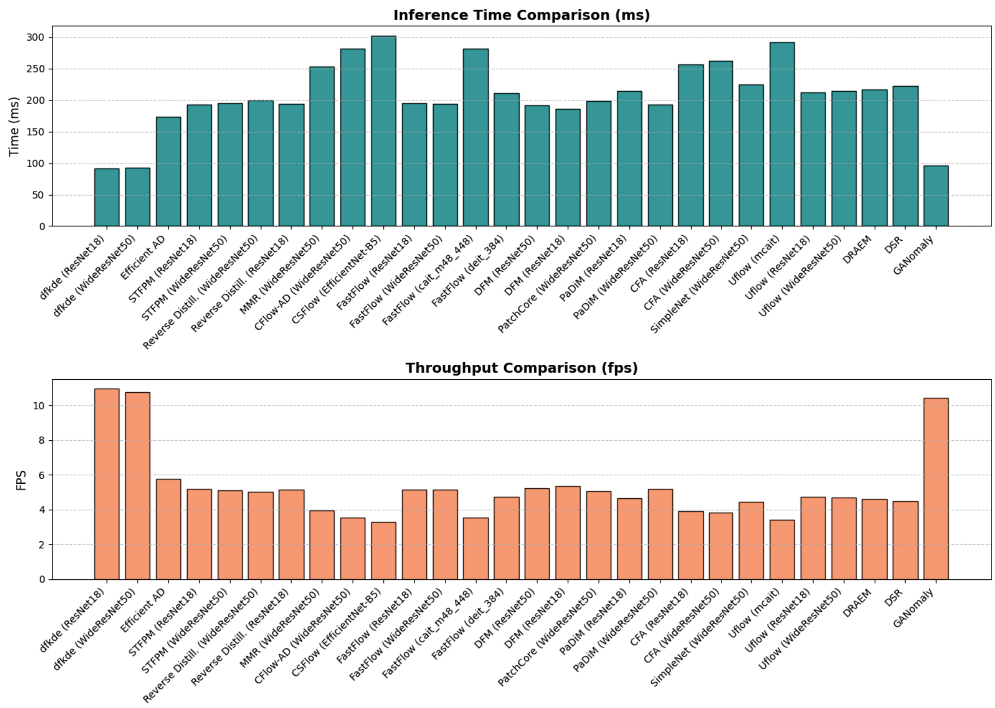

*Figure 10: Inference times and throughput of all deep learning models used in **UC2**.*

6.3 Anomaly Detection in CNC Machine Cluster

The approach incorporates data from MES and SCADA, including sensor measurement for vibration, compressed air levels, hydraulic temperature, and hydraulic pressure. There were some concerns regarding the data quality, but these could not be resolved within the remaining project time. The Synthetic Minority Over-Sampling Technique (SMOTE) is used to address data imbalance problem. Two different classification models, namely Random Forest and XGBoost, are employed to identify which features are most relevant to failure prediction. Table 4 shows the F1-score performance metric for these two models under various scenarios. The light signal features should ideally not be used for prediction. The extracted time-series features are also helpful for improving the prediction performance of both models. It can also be seen that SMOTE helps significantly improve the performance of Random Forests, with a slight deterioration for XGBoost.

Table 4: F1-scores for different data and feature scenarios.

Scenarios	Random Forest	XGBoost
With Light Signal Features Without Time-Series Features	0.5833	0.9855
Without Light Signal Features Without Time-Series Features	0.0571	0.3673
Without Light Signal Features With Time-Series Features	0.1053	0.3077
Without Light Signal Features With Time-Series Features SMOTE	0.2174	**0.3051**

Figure 11 shows the feature importance scores obtained from the trained XGBoost model for the top 10 features. Even though the predictive performance of the model is relatively low, the top features can be used to diagnose the root causes of the faults in the CNC machine cluster.

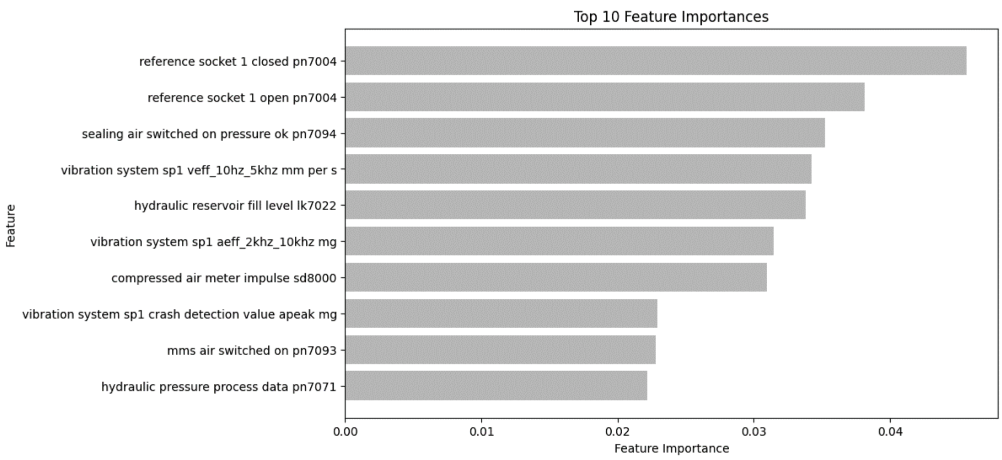

*Figure 11: Top 10 features extracted from the XGBoost classification model in **UC5**.*

FFI’s Sustainable Production program identifies digitalization at various points within the value chain as a precursor to the true integration of sustainability perspectives. IoT enabled predictive maintenance, where large amounts of data are gathered and analysed to make decisions, is a form of digitalization that can have a positive impact on the structure of the production maintenance systems and associated supply chains from a life cycle perspective. All use-cases in this project dealt with anomaly detection using time-series and image data collected by IoT sensors. Anomaly detection is an important part of predictive maintenance as it is another step towards improving resource utilization and reducing wastage, in turn leading to higher productivity and shorter lead times. Thus, the results of this project directly contribute to the overall program goal. Additionally, FFI – Sustainable Production places high emphasis on research results that can be quickly translated to practical application. The use cases addressed in this project required close collaboration with industry partners. Real production and maintenance data collected during actual operations were used to test and validate the developed methodologies and algorithms. As a result, the deliverables of this project achieved Technology Readiness Levels between 4 and 6.

‘Resource efficiency in production’ and ‘SMART production’ are two programme areas in FFI – Sustainable Production that this project has directly contributed to. Description of the former area specifically points to connecting equipment and systems, thereby enabling production resources to be optimized for a climate-neutral and competitive production. Similarly, description of the latter area refers to automating entire processes by combining data from different sources and analyzing it with AI techniques to give decision makers an optimal basis. The digitalization focus seen in these descriptions is analogous to the central contribution of the project results - IoT devices on production assets feeding real-time data to the CMMS, which is used by machine learning models to predict imminent anomalies or failures that are proactively corrected through automated maintenance actions, performed with an optimized schedule. Both programme areas also mention increasing competitiveness through an efficient production system as a challenge. The far-reaching benefits of predictive maintenance suggest that implementing the results of this project in production can lead to increased competitiveness in the long run.

7. Dissemination and publications

7.1 Dissemination

How are the project results planned to be used and disseminated?	Mark with X	Comment
Increase knowledge in the field	X	Ball-screw is a critical component of the CNC machines. The conditioning monitoring tests used in this project are common in many manufacturing facilities. The developed method can not only predict

		but also localize the faults, which has not previously been addressed in the literature. The thorough empirical comparison of unsupervised anomaly detection models on real industry use-cases does not exist in the literature.
Be passed on to other advanced technological development projects	X	The project results are ready to be implemented in production. They will be passed on to internal development projects at the companies. New research project applications within the predictive maintenance area are being developed based on the project results.
Be passed on to product development projects	-	Not applicable
Introduced on the market	-	Not applicable
Used in investigations / regulatory / licensing / political decisions	-	Not applicable

The results and learnings from this project have been communicated both internally and externally through meetings, presentations, and publications. Overall, all industry partners in the project are satisfied with the outcomes and have expressed interest in continuing the collaboration through future research projects.

7.2 Publications

Published Papers:

1. Kumbhar, M., Bandaru, S., & Karlsson, A. (2024). Condition Monitoring of a Machine Tool Ballscrew Using Wavelet Transform based Unsupervised Learning. Procedia CIRP, 130, 342-347. https://doi.org/10.1016/j.procir.2024.10.098.
2. Chen, S., Lopes, P.V., Marti, S., Rajashekarappa, M., Bandaru, S., Windmark, C., Bokrantz, J. & Skoogh, A. (2024). Enhancing Digital Twins with Deep Reinforcement Learning: A Use Case in Maintenance Prioritization. In 2024 Winter Simulation Conference (WSC) (pp. 1611-1622). IEEE. https://doi.org/10.1109/WSC63780.2024.10838867.

Submitted Papers:

3. Chen, S., Bandaru, S., Marti, S., Bekar, E.T., & Skoogh, A. Comparison of Unsupervised Image Anomaly Detection Models for Sheet Metal Glue Lines.
4. Kumbhar, M., Bandaru, S., & Karlsson, A. Anomaly Detection and Fault Isolation in Ballscrew Drive System using Vibration Data Analysis.

Master’s Theses:

- Nagarajan, A.V. & Janaswami, G. (2024). Data Synchronization in Digital Twin for a Lab-Scale Drone Factory. Department of Industrial and Materials Science. Chalmers University of Technology. http://hdl.handle.net/20.500.12380/308662.
- Subramanian, S.K. & Hedin, L. (2025). Deployment of an Unsupervised Anomaly Detection Model Using Anomalib and PyTorch, Is it feasible on a low-powered edge -device?. Department of Industrial and Materials Science. Chalmers University of Technology. http://hdl.handle.net/20.500.12380/309089.

8. Conclusions and future research

This project aimed to integrate core Industry 4.0 technologies – industrial IoT, digital twins, and analytics – to optimize predictive maintenance and pave the way toward prescriptive maintenance. By using IoT sensor data from real production, the project used machine learning, analytics, and multi-criteria decision analysis techniques to monitor equipment health and predict maintenance needs. The project focused on six industrial use-cases: condition monitoring of ball-screw drives, fault detection in sheet metal glue lines, and fault prediction in hydraulic systems. Ball-screws are vital components in CNC machines, and the condition monitoring tests used in this project are widely applied across various manufacturing facilities. The developed method not only predicts faults but also localizes them, a capability not previously explored in the literature. Additionally, a comprehensive empirical comparison of unsupervised anomaly detection models in real industry use-cases is lacking in existing research. These use-cases demonstrated the potential of predictive maintenance by leveraging IoT sensor data integration, advanced analytics, and machine learning to improve maintenance operations.

The project's results align with FFI's Sustainable Production program, which emphasizes digitalization for improved resource efficiency and sustainable production systems. By analyzing time-series and image data from IoT sensors for anomaly detection, the project contributed to reducing unplanned downtimes thereby improving productivity and reducing wastage. The collaboration with industry partners ensured that real production data was used to test and validate methodologies, achieving TRLs between 4 and 6. The project's contributions to ‘Resource efficiency in production’ and ‘SMART production’ further support the goal of enhancing competitiveness and driving climate-neutral, efficient production systems through digitalization and AI-driven maintenance solutions.

The project results are ready for implementation in production and will be passed on to internal development teams at the participating companies. Building on these outcomes, new research proposals focused on predictive maintenance are being developed with new and existing industry partners.

9. Participating parties and contact persons

Participating parties	Contact persons	Gender
University of Skövde	Sunith Bandaru, Mahesh Kumbhar, Alexander Karlsson	3M
Chalmers University of Technology	Anders Skoogh, Siyuan Chen, Ebru Turanoglu Bekar, Silvan Marti	1F, 3M
Automative Components Floby	Samuel Awe, Erik Kowalczyk, Fredrik Andersson, Kevin Hodgson, Patrik Johansson	5M
Jernbro Industrial Services	Mats Ahrling, Jim Fransson, Christer Sundqvist	3M
Scania CV	Arash Mousavi, Yoones Sanjabi, Evy Svensson, Adithya Thaduri, Jesper Gordon	1F, 4M
Volvo Car Corporation	Per Andersson, Marcus Sörensson, Edwin Larsson, Mickael Svensson, Krister Mattsson	5M
Volvo Group Truck Operations	Kanika Gandhi, Sven Wilhelmsson, Linus Nordström, Andreas Gustafsson, Kemily Lopes	2F, 3M