VerSatilE plug-and-play platform enabling remote pREdictive mainteNAnce

Grant Agreement No	:	767561
Project Acronym	:	**SERENA**
Project Start Date	:	1st October 2017
Consortium	:	COMAU S.p.A. Finn-Power Oyj VDL Weweler BV WHIRLPOOL EMEA SpA Kone Industrial Ltd Engineering Ingegneria Informatica S.p.A. OCULAVIS GmbH SynArea Consultants S.r.l. DELL EMC Laboratory for Manufacturing Systems & Automation Fraunhofer Gesellschaft zur Förderung der angewandten Forschung VTT Technical Research Centre of Finland Ltd TRIMEK S.A. Politecnico Di Torino

Title	:	Quantification, comparative analysis and improvements
Reference	:	D6.6
Dissemination Level	:	PU
Date	:	2021-03-31
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Circulation	:	EU/Consortium

Summary:

This deliverable provides a quantification of the outcomes of tasks 6.5 and 6.6 including a comparative analysis to reported baseline values, existing solutions as well as improvements that were performed in the validation process of the SERENA solutions.

Contents

List of Abbreviations

CMM	:	Coordinate Measuring Machine
FMECA	:	Failure Mode, Effects and Criticality Analysis
IIoT	:	Industrial Internet of Things
KPI	:	Key Performance Indicator
ML	:	Machine Learning
MTBF	:	Mean Time to Repair
MTTR	:	Mean Time to Repair
OEE	:	Overall Equipment Effectiveness
OEM	:	Original Equipment Manufacturer
PDM (PdM)	:	Predictive Maintenance
RCA	:	Root Cause Analysis
RUL	:	Remaining Useful Life
VR	:	Virtual Reality
TCM	:	Total cost of maintenance
TRL	:	Technology Readiness Level

Executive Summary

The purpose of this document is to report the outcomes of **SERENA** WP6: Demonstrators Realization, describing the results of the related tasks, namely:

- Task 6.6: Quantification and comparative analysis
- Task 6.7: Final improvements and documentation

From this, it aims to provide a representation of the main benefits obtained with **SERENA** in contrast to the original situation within the industrial sectors represented in each use case, in terms of maintenance, besides the comparison of the **SERENA** approach with other research work and systems, and, with a description of the debugging and identified improvements of the technical systems developed.

The document is structured as follows:

- Chapter 2 contains a benchmarking of the **SERENA** solution with other commercial system solution and research and development works.
- Chapter 3 is referred to a quantitative and qualitative comparison of the scenario with and without the project solution for the different use cases, about maintenance needs, maintenance KPIs. For this second part, the information is detailed within the following industrial applications:
    - Refrigerator cabinet polyurethane foaming process [WHIRLPOOL]
    - Metal sheet punching and bending production line [KONE]
    - Bridge type measuring machine [TRIMEK]
    - Rolling mill machine [VDL WEWELER]
- Chapter 4 describes the identified improvements of the technical systems developed based on the needs previously identified at the beginning of the project, focusing on the following aspects:
    1. Remote factory condition monitoring and control
    2. AI condition-based maintenance and planning techniques
    3. AR-based technologies for remote assistance and human operator support
    4. Cloud-based platform for versatile remote diagnostics

    The primary results of this deliverable include the following:

- A general benchmarking of **SERENA** solution against similar works in research status or development systems/approaches.
- The identification of the **SERENA** systems current status based on the target-specific metrics and KPIs defined by each use case at the beginning of the project plus other general maintenance KPIs for representing the final improvements that **SERENA** could represent in the related industrial sectors where it was implemented; through a quantitative comparative analysis of the before and after scenario.
- A description of the procedures and findings, debugging and identified improvements of the technical systems developed (based on the needs previously identified at the beginning of the project).

1 Introduction

This document aims to identify, analyze and report the predictive maintenance-related improvements coming from the various industrial demonstrators in the **SERENA** project.

These improvements are gathered through the analysis of the following:

- Benchmarking of **SERENA** with similar works and systems
- Description of the state with the adoption of **SERENA** solutions and quantification of the benefits through KPIs, metrics and its analysis.
- Mapping of the industrial accomplishments under the four main technological groups of **SERENA**, including the procedures and finding, lessons learned, etc.

2 Similar research work and systems

2.1.1 Commercial solutions

This section describes some commercial solutions with a focus on machine learning and predictive analytics. A few years ago, predictive analytics and machine learning may have been looked at as niche and accessible for a select few, but now, more and more companies are using them in their day-to-day. They are most commonly used for security, marketing, operations, risk and fraud detection, healthcare, entertainment content, weather patterns, sports, employee growth and predictive maintenance. Below are just a few examples of how predictive analytics and machine learning are utilized in different industries:

- **Banking and Financial Services:** In the banking and financial services industry, predictive analytics and machine learning are used in conjunction to detect and reduce fraud, measure market risk, identify opportunities and much more.
- **Security:** With cybersecurity at the top of every business, predictive analytics and machine learning play a key part in security. Security institutions typically use predictive analytics to improve services and performance, but also to detect anomalies, fraud, understand consumer behaviour and enhance data security.
- **Retail:** Retailers are using predictive analytics and machine learning to better understand consumer behaviour; who buys what and where? These questions can be readily answered with the right predictive models and data sets, helping retailers to plan and stock items based on seasonality and consumer trends – improving ROI significantly.

Focusing a bit more on the last point of the previous list, some highly known commercial solutions use machine learning and predictive analytics tools in their procedures and functioning; some are listed below:

- **Google:** Google has mastered these two areas. It takes advantage of machine learning algorithms and provides customers with a valuable and personalized experience and it is already embedded in its services like Gmail, Google Search, Google Maps, Google Translate, Google Photos, Speech Recognition, Google Adsense, and more. Furthermore, Google Analytics automatically enriches customer data by bringing Google machine-learning expertise to bear on particular datasets to predict the future behaviour of the users. With predictive metrics, it is possible to learn more about customers just by collecting structured event data.
- **Amazon:** Has a cloud-based machine learning services called Amazon Machine Learning (Amazon ML), a service that makes it easy for anyone to use predictive analytics and machine-learning technology. Amazon ML provides visualization tools and wizards as guides through the process of creating machine learning (ML) models without having to learn complex ML algorithms and technology. After they are ready, Amazon ML makes it easy to obtain predictions for customer application using API operations, without having to implement custom prediction generation code or manage any infrastructure. Using the same deep learning technology which drives Amazon.com and ML services, implementing dynamic pricing to stay competitive, screenings purchase and returning requests for signs of fraud, encouraging people to buy more with each order, using data to change physical stores, depending on the information to run fulfilment centres and more.

2.1.2 Research work

In this section are described other research and development projects included in the ForeSee Cluster related to novel design and predictive maintenance technologies or initiatives with a focus on increasing the operating life of production systems and maintenance process improvement.

- **ZBRE4K** main scope is the development of Strategies and Predictive Maintenance models wrapped around physical production systems for minimizing unexpected breakdowns and maximizing the operating life of production systems.
- **PRECOM** deploys and tests a predictive cognitive maintenance decision-support system able to identify and localize damage, assess damage severity, predict damage evolution, assess remaining asset life, reduce the probability of false alarms, provide more accurate failure detection, issue notices to conduct preventive maintenance actions and ultimately increase in-service efficiency of machines by at least 10%.
- **PROGRAMS** seeks to develop a model-based prognostics method integrating the FMECA and PRM approaches for the smart prediction of equipment condition, a novel MDSS tool for smart industries maintenance strategy determination and resource management integrating ERP support, and the introduction of an MSP tool to share information between involved personnel. The proposers' approach can improve overall business effectiveness concerning the following perspectives: increasing Availability and Overall Equipment Effectiveness, continuously monitoring the criticality of system components, building physical-based models of the components, determining an optimal strategy for the maintenance activities, providing in a machine condition monitoring system, developing an Intra Factory Information Service. The production and maintenance schedule of complete production lines and entire plants will run with real-time flexibility to perform at the required level of efficiency, optimize resources and plan repair interventions.
- **UPTIME** aims to design a unified predictive maintenance framework and an associated unified information system to enable the predictive maintenance strategy implementation in manufacturing industries. The UPTIME predictive maintenance system will extend and unify the new digital, e-maintenance services and tools and will incorporate information from heterogeneous data sources to more accurately estimate the process performances.

And beyond the cluster, some predictive maintenance startups also impacting Industry 4.0 are listed:

- *Predictive-Sigma – Smart Predictive Maintenance:* Predictive maintenance is the analysis of a network of assets that enables the prediction and notification of potential outages. It promises maximum protection of machinery and minimum productivity impact, also at the same time without necessarily increasing the overall system complexity. Spanish startup Predictive-sigma offers a technological platform for predictive maintenance that allows accessing information to increase asset availability and improve the performance of industrial machinery.
- *Semiotic Labs – Smart Condition Monitoring:* Smart condition monitoring is the application of condition-based monitoring technologies, statistical process control or equipment performance. It is used in the early detection and elimination of equipment defects, that could lead to unplanned downtime or unnecessary expenditures. Condition monitoring technology takes into account sensor data, previous inspections, the location and condition of the plant, and historical data. Semiotic Labs, a startup from the Netherlands, offers smart machine-monitoring technologies to the manufacturing industry.
- *Seebo – Root Cause Analysis:* Root Cause Analysis (RCA) is the process of identifying factors that cause defects or quality deviations in the manufactured product. RCA can be performed using machine learning and big data analytics, and these methods are unbiased and based purely upon historical and real-time data straight from the production floor. Seebo, a startup in the USA, focuses on solutions such as predictive maintenance, predictive analytics and offers root cause analysis, using machine learning and probabilistic graphical models.

2.1.3 Benchmarking with SERENA

The progressive and pervasive digitization of industry brings a paramount opportunity to enhance the productivity of manufacturing and assembly operations. In this context, state-of-the-art production systems implement Predictive Maintenance (PdM) solutions to complement preventive maintenance scheduling and avoid costly unexpected breakdowns and corrective maintenance actions, and this where the **SERENA** R&D project is framed. **SERENA** was built upon the needs for saving time and money, minimizing the costly production downtimes, covering the requirements for versatility, transferability, remote monitoring and control by a) a plug-and-play cloud-based communication platform for managing the data and data processing remotely, b) advanced IoT system and smart devices for data collection and monitoring of machinery conditions, c) artificial intelligence methods for predictive maintenance and planning of maintenance and production activities, d) AR-based technologies for supporting the human operator for maintenance activities and monitoring of the production machinery status.

In this sense, the main difference of **SERENA** with the above-mentioned projects is based on the operator support service; integrated along with the entire predictive maintenance solution and real-time data monitoring. This interface helps technicians to identify the source of the error and go through determined steps in the problem-solving procedure, including all visualization systems and AR tools, as well as the scheduling options integrated, or working along, with this system.

3 Quantification and comparative analysis

3.1.1 WHIRLPOOL Use Case

Baseline values are provided by the end-user based on its own experience and company practices.

3.1.1.1 Target specifics metrics and KPIs status

WHIRLPOOL	BASELINE	INTENDED ACHIEVEMENT	**SERENA**
Overall Equipment Effectiveness (OEE)	80%	+15%	80,4% (+5.5%)
Mean Time to Repair (MTTR)	7h	-20%	3h (~-40%)
Mean Time Between Failures (MTBF)	180d	+20%	>360d (double)
Total cost of maintenance (TCM)	17400€	-60% to -70%	8000€ (-54%)

3.1.1.2 Quantitative comparison and analysis of SERENA within the use case

- **Maintenance KPI**

	BASELINE	**SERENA**
Mean Time Between Failures (MTBF)	180d	360d
Mean Time to Repair (MTTR)	7h	3h
Percentage planned maintenance/Percentage of emergency repair work	-	Difficult to calculate but included in the Analysis Outcome

The Mean Time Between Failure indicates the frequency of a specific failure. As said the average number of events of the blocked head is 2/year and thus the MTBF is 180days. With a prediction system in place, we can expect this to increase at least to double.

The Mean Time To Repair is the average time used to restore a condition after a failure. Only when SERENA will be able to reduce completely the breakdown of the machine we can improve MTTR, which, in that specific case, will be reduced to zero.

In case of an unexpected breakdown, AR support can reduce time to substitution by 14-15% enabling also untrained operator to work it out.

- **Maintenance costs**

	BASELINE	**SERENA**
Maintenance Direct Costs (Personnel costs, consumables, spare parts, sensors/systems/connections maintenance, etc.)	17400€	8000€

- **Efficiency and overall productivity**

	BASELINE	**SERENA**
OEE	80%	80,4%
Percentage Emergency Work	-	Difficult to calculate but included in the Analysis Outcome
Schedule Compliance	-	Difficult to calculate but included in the Analysis Outcome

- **Human factor**

From operator/user perspective:	BEFORE	**SERENA**
Maintenance personnel satisfaction related to maintenance procedure/system subject of the project	*The maintenance procedures before SERNA were limited to reactive and preventive.*	***SERENA** predictive capacity allows for a better work organization and is reducing the need to work in an emergency. A better work organization has a very positive impact on worker satisfaction.*
The efficiency of instructions of maintenance activities	*SMP -Standardized Maintenance Procedures (static files printed on paper – or excel files) are the only guide to the maintenance operator.*	***SERENA** platform and wearable device support are not only enabling a quicker and safer operation but also improves the richness of details (e.g., video) and interaction not available in SMP.*
Operator specific skills needed to use **SERENA** system or tools? It is complex? Reskilling needed?	*N/A*	*The platform is easy to use, however, the basic skill to use it requires an understanding of data used to predict, RUL concept and a period of training with glasses to use them comfortably.*

3.1.1.3 Analysis outcome

The impact of **SERENA** in the WHR use case is very clear in term of potentiality even though not proven on real data. The impossibility to test the platform on real-time data was generated by a reorganization of the production of the factory happened in August 2020. A strategic reconfiguration of the factory of production leads to the decision of closing the Double Door production line and, consequently, shutting down the foaming machine. So, all the consideration done on KPI is based on the data gathered in one year of functioning of the machine with the new head sensor installed. However, some assumptions can be done and they have been used to estimate the KPI.

1) All the consideration are done on the Mixing Head component and not on the entire Foaming Machine
2) The process under evaluation (i.e., the Mixing Head) is quite stable and we recorded an average of two unexpected breakdowns per year. This means that is quite difficult to have a solid statistical base of data to support our statement.
3) The typical procedure of repairing a broken mixing head is quite straightforward: WHR always keep a spare part in its warehouse and the broken head is substituted with the new one. The broken one is then sent to a third party to be restored.

With these two elements, we can make a chain of consideration that will help the KPI projection not only on the past but also for the future. Based on this, the main outcome of **SERENA** is that it was proved the system able to predict the break of the mixing head with the necessary anticipation that allows to supersede the preventive maintenance plan and to avoid the breakdown.

- To stay on the safe side (i.e., assuming the initial prediction accuracy to be further improved) we can estimate that at least one of the two breakdowns can be avoided. This has an immediate impact on the OEE which can improve from 80% to 80.4%. This number seems quite low, but we need to take into account that while the OEE is representing the overall machine efficiency, **SERENA** is actually impacting on a subsystem (the mixing head) and only to the *Availability* element of the OEE.

- This number can for sure improve whether a predictive maintenance approach is extended to other parts of the machine.
- The same reduction of an unexpected event is also the cause of the improvement of MTBF (two breaks in a year 180d, one break 360d).
- MTTR, which is represented by the time needed to substitute the head, is currently 3,5h. This time is not impacted by SERENA ability to predict, but by SERENA AR Assistant: the improvement of guidance can shorten up the time to repairing up to 15% and is enabling a broad population of maintenance workers to be assigned the task.
- The TCM cost of maintenance is mainly due to the restoring cost (performed by third parties) and the labour cost of the substitution. Since every rework is costing currently 8700€ we estimate that instead of 17400€/year we can achieve a TCM of 8000€/y (one external restoration, less labour, less warehouse cost).

3.1.2 KONE Use Case

Baseline values are provided by the end-user based on its own experience and company practices.

3.1.2.1 Target specifics metrics and KPIs status

KONE	BASELINE	INTENDED ACHIEVEMENT	**SERENA**
Technical Availability Rate	~60%	+10%	~+4% (~64%)
Availability	~30%	+10%	~+3% (~33%)

3.1.2.2 Quantitative/qualitative comparison and analysis of SERENA within the use case

- **Production breakdowns**

	BASELINE	**SERENA**
Mean Time Between Failures (MTBF)	80min	187min
Percentage planned maintenance/Percentage of emergency repair work	-	Difficult to calculate but included in the Analysis Outcome

- **Maintenance costs**

	BASELINE	**SERENA**
Maintenance Direct Costs (Personnel costs, consumables, spare parts, sensors/systems/connections maintenance)	N/A	-10%

- **Efficiency and overall productivity**

	BASELINE	**SERENA**
Percentage Emergency Work	-	-5%
Schedule Compliance	-	+5%

- **Human factor**

From operator/user perspective:	BEFORE	**SERENA**
Maintenance personnel satisfaction related to maintenance procedure/system subject of the project	*No systems available for predictive maintenance for the project testbed. Therefore, the satisfactory level not high.*	*Testbed components have predictive maintenance data available for maintenance personnel. Higher satisfaction level.*

The efficiency of instructions of maintenance activities	*Maintenance activities instructed for new personnel. No documented maintenance activity instructions.*	*VR/AR instructions for punching tool change and punching tool sharpening. Standardized way makes activities more efficient.*
Operator specific skills needed to use **SERENA** system or tools? It is complex? Reskilling needed?	*N/A*	*Production operators, maintenance technicians, supervisors and staff personnel at the factory need to be further trained for the* ***SERENA*** *system and its features and functionalities.*

3.1.2.3 Analysis outcome

Technical availability and availability have both increased due to the **SERENA** project and other maintenance development activities. Very good results were also made by increasing the MTBF value. Since there were no predictive maintenance applications before **SERENA**, maintenance personnel and upper staff now have a better understanding of the testbed's condition. This enables timely maintenance activities so that necessary actions are done before monitored components fail. Correctly timed maintenance activities have a big impact on machine production efficiency since before **SERENA** implementation, weekly scheduled maintenance downtimes often were pointless. Overall assessment from KONE personnel for the **SERENA** system is positive. The **SERENA** project testbed plays a critical role in the production facility. With the project outcomes, the occurrence for failures has dropped, assuring the better flow of production and ultimately timely delivery of elevators

3.1.3 TRIMEK Use Case

Baseline values are provided by the end-user based on its own experience and company practices.

3.1.3.1 Target specifics metrics and KPIs status

TRIMEK	BASELINE	INTENDED ACHIEVEMENT	**SERENA**
Soft Breakdown	≈ 1 per 2 years	+ 2 years	Indirectly affected by: (+) 5-10% machine availability (-) 5-10% unexpected failures
Hard Breakdown	≈ 1 per 5 years	+ 2 years	Indirectly affected by: (+) 5-10% machine availability (-) 5-10% unexpected failures
Cost of repairing and maintenance activities	N/A	~ -20%	~ -15%
Extension of measuring machine lifecycle	10-15 years	+1 year	+ 0.5 years
Correct maintenance personnel to be sent to the right customer	1-2 people once or twice depending on the problem	-1 person	Achieved

3.1.3.2 Quantitative comparison and analysis of SERENA within the use case

- **Production breakdowns**

	BASELINE	**SERENA**
Mean Time Between Failures (MTBF)	-	(+) 5-10%
Percentage planned maintenance/Percentage of emergency repair work	-	(+) 5%

- **Maintenance costs**

	BASELINE	**SERENA**
Maintenance Direct Costs (Personnel costs, consumables, spare parts, sensors/systems/connections maintenance)	N/A	~ -15%

- **Efficiency and overall productivity**

	BASELINE	**SERENA**
Percentage Emergency Work	35% of total maintenance work	(-) 15,4%
Schedule Compliance	-	Difficult to calculate but included in the Analysis Outcome

- **Human factor**

From operator/user perspective:	BEFORE	**SERENA**
Maintenance personnel satisfaction related to maintenance procedure/system subject of the project	*The maintenance procedures before **SERENA** were limited to reactive and preventive.*	*By having the real-time monitoring of such important system as the air bearings, the maintenance approach can be more predictive and preventive; more practical and beneficial concerning the personnel activities. Besides the maintenance operator support helps to understand the tasks needed to be performed, so the satisfaction in a general perspective is improved.*
The efficiency of instructions of maintenance activities	*Maintenance procedures were presented in the form of manuals or through presential training*	***SERENA** platform and maintenance operator support represents a user-friendly and effective way to perform training to new personnel, besides it improves the level and value of detailed information by having it on videos, audios, etc., allowing the company to organize such processes more effectively.*
Operator specific skills needed to use **SERENA** system or tools? It is complex? Reskilling needed?	*N/A*	*Like all new software and hardware, it is needed to learn how to used and install it, but TRIMEK's personnel is used to manage digital tools*

3.1.3.3 Analysis outcome

In the TRIMEK use case, the solution was implemented and tested in TRIMEK's laboratory although the final benefits are thought for a situation where the machine is already sold to a customer and it's placed in the client facility or factory. This, for the time of the project, influences the KPIs calculation and it brought a sort of difficulty when giving an exact quantified measure for many of the KPIs. However, these KPIs were selected as they are the current way for TRIMEK to assess the efficiency of their processes. The impact of **SERENA** is assessed by the personnel with expertise in the use of the machine, its maintenance, the client's involvement, operators and operations coordinators.

In general words, **SERENA** represents a maintenance approach with a lot of potential and value from TRIMEK's perspective. The different systems and services developed for TRIMEK and concentrated in **SERENA** platform, working together as a "chain of services" have a positive influence on the occurrence and early detection of breakdowns, as well as in the time for solving the issues stopping the machine availability; by having the opportunity to monitor the state of an important subsystem for the machine accuracy assurance and visualize this valuable data, allowing the operator to assess the situation, with real-time and historical data, for making the best decision on the maintenance actions that need the machine in an early stage. This, for sure, impacts the lifecycle of the machine.

3.1.4 VDLWEW Use Case

Baseline values are provided by the end-user based on its own experience and company practices.

3.1.4.1 Target specifics metrics and KPIs status

VDLWEW	BASELINE	INTENDED ACHIEVEMENT	**SERENA**
Products produced by segments	Every 18.000 produced pieces, used as preventive maintenance	+100%	2021Q1: Every 18.500 pieces (+3%), not caused by Serena
Reduce maintenance costs	60000€/year	-50%	€30000/year, by better procurement, not affected by Serena
Operational Machine Downtimes	104hours/year	-50%	Not affected by Serena
Downtime in new product release	2-4 hours/change	-50%	Not affected by Serena

3.1.4.2 Quantitative comparison and analysis of SERENA within the use case

- **Production breakdowns**

	BASELINE	**SERENA**
Mean Time Between Failures (MTBF)	20 days	2021Q1: 16 days, not affected by Serena but by higher volume per day
Percentage planned maintenance/Percentage of emergency repair work	-	Not possible to calculate, as segment replacement is still done as planned maintenance

- **Maintenance costs**

	BASELINE	**SERENA**
Maintenance Direct Costs (Personnel costs, consumables, spare parts, sensors/systems/connections maintenance)	60000€/year	€30000/year, by better procurement, not affected by Serena

- **Efficiency and overall productivity**

	BASELINE	**SERENA**
Percentage Emergency Work	-	Not possible to calculate, as segment replacement is still done as planned maintenance
Schedule Compliance	-	Segment exchange is still done as weekly planned maintenance

- **Human factor**

From operator/user perspective:	BEFORE	**SERENA**
Maintenance personnel satisfaction related to maintenance procedure/system subject of the project	*Operators are trained conventionally*	*The operator support services (WP4) bring great value in deploying untrained operators on jobs that require expertise. A prerequisite for this being successful is good content.*
The efficiency of instructions of maintenance activities	*Operators had to use work instructions on paper. No recording/feedback on the execution.*	*The system has proved to be user-friendly. The trick is in the content. Steps can be forgotten, because they are trivial to the engineer, but not to the operator*
Operator specific skills needed to use **SERENA** system or tools? It is complex? Reskilling needed?	*N/A*	*The engineers, maintenance personnel and operators should require further training on SERENA.*

3.1.4.3 Analysis outcome

The VDL Weweler use case is challenging. We experienced challenges to produce accurate measurements. Once these were available, the tests showed no correlation between the calculated RUL and the manually measured layer thickness. There was no time left in the project to re-engineer the RUL calculation. Besides that, the business circumstances have changed since the start of the project:

- New products have been introduced, having a greater (negative) impact on the lifetime of the segments. After having recognized this, the production method is adapted, almost restoring the original lifetime. So SERENA was shooting on a “moving target”.
- A new layer application method was introduced, giving a much longer lifetime. This changes the business case assumptions: RUL is much longer (about 30.000 products), exchange less frequent, benefits lower.
- COVID-19 affected our business negatively in 2020, shifting the company’s focus to survival projects. This caused the late delivery of accurate measurements.

Due to the fact the main KPI “Products produced by segments” is not significantly affected by the SERENA project, it can be safely supported that the other three KPI’s are also not affected: Reduce maintenance costs, Reduce Downtime, Reduce Downtime in new product release.

Despite this negative result, VDL Weweler is impressed by the versatility of the SERENA platform. It can be adapted to this very broad range of use cases. The AR operator support is a valuable part of this.

4 Final improvements and documentation

This section describes the debugging procedures and final improvements of the following technical systems developed in collaboration between **SERENA** partners during the project:

- Remote factory condition monitoring and control
- AI condition-based maintenance and planning techniques
- AR-based technologies for remote assistance and human operator support
- Cloud-based platform for versatile remote diagnostics

Finally, this section concludes with an overview of the key lessons learned during the **SERENA** project.

4.1.1 Identified issues and improvements

Since demonstrators experiments and results are already in detail documented in D6.2-D6.5 to avoid unnecessary repetition, this sub-section provides a summary of final improvements done during the last months of the testing and validation cycle.

4.1.1.1 Remote factory condition monitoring and control

During the past months, as a result of continuous improvements in the area of remote factory monitoring, the reliability and accuracy of collected data were improved as well as the potential security bugs in the network were identified and resolved. Finally, the solution for the remote data collection, processing and storage was validated with the industrial pilots to ensure that the developed system fits well in the real production environment and satisfies the technical requirements established at the beginning of the project.

4.1.1.2 AI condition-based maintenance and planning techniques

Additionally, several small improvements were made to the algorithms that predict the wear of machine components to accurately schedule the preventive maintenance before the actual failure. Even though the developed monitoring solution already carefully collects data through sensors the predictive AI and machine learning principles were double-checked to be able to determine the best timing for scheduling of the maintenance activities. These improvements were done to ensure that the software accurately predicts the likelihood of component failure, the ordering of the spare parts is done in advance and the daily production process is not interrupted. As a result of the revision, the predictive maintenance scheduling solution is made as practical as possible, maintenance visits are scheduled on optimal time (not after the machine fails but also not before an operation is needed) and therefore industrial companies can avoid unnecessary costs related to the production loss. Furthermore, since the user can easily modify the threshold values to fit the different factory-specific environments, the AI condition-based maintenance and service scheduling solutions developed during the **SERENA** project can be utilized by a wide range of European manufacturing companies.

4.1.1.3 AR-based technologies for remote assistance and human operator support

During the final round of improving the AR-based remote assistance, the developed solution was tested with the machine operators and field technicians to make sure that even complex guidance is easy to follow and it boosts productivity in the field. As a result of a few small improvements, according to the user feedback, the usability and interactivity of the animated and video instructions improved and the average fix time decreased. The final versions of guidance that were developed during the **SERENA** project are considered very practical and successful in replacing paper-based manuals and cutting the training time.

4.1.1.4 Cloud-based platform for versatile remote diagnostics

Finally, small improvements were made to the interface of the **SERENA** platform to optimize the usability of different dashboards with predictive analytics and enhance user experience. Since the data collected from the machine can be difficult to understand for novice users, the goal was to ensure that the **SERENA** dashboard provides interactive visualizations that do not require extensive training or any specific advanced skills for using it on daily basis.

4.1.2 Lessons learned

While the predictive maintenance solutions developed during the project and implemented are considered successful and practical from the pilot perspective, several lessons learned can be pointed out throughout the project lifecycle.

As a result, it was discovered that the low-cost solution (like Raspberry PI) can be quite successfully used in ***remote machine condition monitoring*** despite some performance issues. The lesson to learn here is that even though the low-cost solution requires a minimum initial investment, at the later stages it requires a lot of customization and tailoring to the factory environment, which results in additional expenses. In the future, these problems can be avoided through careful assessment of different solutions for data collection and processing existing on the market before the beginning of the project to find a good fit between cost and quality.

Taking into count that the AI capabilities and computer vision are continuously improving, it is important to regularly keep track of the latest technology trends to improve ***SERENA AI condition-based maintenance and scheduling solutions*** in the future. For example, the machine learning algorithms should be further trained, validated and tested in different industrial contexts to help AI become self-learning and autonomous assistant (to humans) that accurately predicts the likelihood of component failure.

Similarly, with the increasing levels of automation, there is still room for improvements and further upgrades of the ***AR-based software for remote operator support*** with even smarter visual assistance elements (e.g., by using computer vision and audio guidelines). Also, the availability of assisting technology on a larger set of devices (e.g., tablets, smart glasses etc.) can be improved further.

As a result of the **SERENA** project, it becomes clear that the adoption of predictive Industry 4.0 software solutions is a challenging process on both individual and organizational levels and it will take time before these applications are widely used. As a result, companies should be ready to face resistance from employees who will refuse to change their traditional routines and adopt new ways of doing work. Furthermore, with the steadily increasing complexity of the ***cloud-based platform for remote factory monitoring,*** companies should consider offering training sessions to employees on how to be data scientists or data translators to ensure that they correctly interpret big data and derive the right insights from it. Additionally, to increase the adoption of the **SERENA** dashboard and use of the ***cloud-based platform for remote factory monitoring*** on daily basis among employees there is a need to organize regular training sessions and provide easy to understand manuals to users.

Another takeaway from the project is that the user interface of the **SERENA** dashboard should be continuously tested with different users (e.g., machine operators, technicians etc.) and improved based on their feedback to ensure that visualization dashboards are interactive and reflect the current production needs.

One more lesson learned during the **SERENA** project is that there is a need in the future to remotely collect 1) more diverse data from the sensors in industrial equipment and surroundings and 2) improve data quality to make machinery and software even more robust and automated so that it requires minimum involvement from humans. Due to the limited scope of the **SERENA** project, it was decided that data will be collected only from a limited number of objects, however, a ***remote factory condition monitoring system*** has a huge potential and it can provide much more value through a larger and more heterogeneous data collection.

5 Conclusions

This deliverable reports the outcome of the activities carried out within **SERENA** WP6 during the project's lifetime.

SERENA is based on a predictive maintenance approach focused on versatility, transferability, remote monitoring data collection and analysis, remote communication platform and data processing. It stands out the work on artificial intelligence methods for predictive maintenance and planning of maintenance and production activities along with AR-based technologies for supporting the human operator for maintenance activities and monitoring of the production machinery status, one of the most valuable aspects for the end-users in general.

However, for the particularity of the use cases, some constraints and important aspects affected the quantification of some of the KPIs defined at the beginning of the project. Some of these aspects are the implementation in laboratory environments in some of the cases, other improvements made in parallel into the production line for other cases, period of data gathered and data availability, among others. Nevertheless, based on the expertise of personnel involved in each demonstration scenario and use case, some aspects were considered for estimations on how **SERENA** impacted and can bring benefits on the different industrial production environments: that were positive in most of the cases.

Throughout the project duration, technical issues were improved for each system/service to work properly according to the use cases particularities. More data and more time are required to further train the algorithms and generate more accurate analysis. And definitely, all services have the potential to be further exploited.