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Manufacturing Reliability and Cost Improvements through Data Analytics: An Industry Case Study

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Abstract

Industry has entered a new age of industrial change which is revolutionising how products are manufactured. Driving this industry change are newly developing digital technologies such as robotics, artificial intelligence, advanced analytics and the industrial internet. This convergence of technology and manufacturing is driving the digital transformation of every industrial segment from operations to logistics, and from aeronautics to retail product manufacture. The technology advances evident from Industry 4.0 will result in industry disruption and build competitive advantages for the organisations who can master the technologies in their manufacturing processes. However, organisations are struggling to develop a tactical methodology to introduce these technologies while simultaneously transforming their organisation cultures and organisations and maximising the benefits. One of the key reasons for the Fourth Industrial Revolution called Industry 4.0 is the need to strengthen the competitiveness of Western European economies, which as a result of the progressing globalization process and rising labor and business costs [1]. A key benefit of the introduction of Industry 4.0 initiatives in a manufacturing plant is to help overcome current operations management limitations, such as, the lack of knowledge on how the process is performing at a specific point in time. This paper will investigate the impact of deploying a range of Industry 4.0 technologies to access machine and operations performance data, to improve equipment reliability and to reduce the costs associated with the maintenance of equipment. With the introduction of the operational data analytics as a result of data extraction from manufacturing equipment, along with integrating other data sources, the business has realised improvements in key metrics like OTIF (On Time in Full), OEE (Overall Equipment Effectiveness), MTBF (Mean Time Between Failure), MTTR (Mean Time to Return), CuC (Consumable Unit Cost), and Lead Time. This paper discusses this project and the results obtained at Zimmer Biomet while also discussing the research carried out for ZOML to begin its journey on manufacturing digitalisation.

The paper starts with a background in Industry 4.0. The next section provides a background on the company where the problem statement and project have come from with some detail on their digitalisation journey. The following section details the problem and the project that the research is derived from and the final section is in relation to the results of the research and the project.

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1. Research Context

1.1. Case Description

Zimmer Orthopedics Manufacturing Ltd. (Zimmer Ireland - ZOML) was set up in 2008 in Shannon, Ireland, and manufactures femorals for the global market. At the time, ZOML consisted of just one site in Shannon. The original start up strategy for the Shannon site was to transfer the existing process as it was from the headquarters site in Warsaw, Indiana and to optimise the process later. The as-transferred process relied heavily on paper-based records and manual controls. As the site scaled in capacity and complexity, this became a limiting factor to achieving the company vision, which was to have zero lost working days due to accidents, zero recalls, one day lead time and build a femoral product at a lower cost in line with the business' strategy. The Company needed to standardise its processes and move from compliance by verification at the end of the process to compliance at source, in order to scale up to full production capacity at Shannon. This led to the company deploying MES as a strategic transformational project that would begin the company's journey in relation to Industry 4.0 and digitalisation. The advantages of MES that are widely discussed are increased productivity, improved product quality and downtime reduction [2] however what is typically not realised until post implementation is the value in the data that is generated on the process. The technology advances in Industry 4.0 will result in industry disruption and build competitive advantages for the organisations who can master the technologies in their manufacturing processes. This rapid growth of technologies interconnected with electronics and the internet of things is enabling the development of manufacturing which has led to the paradigm shift and has become defined as the fourth industrial revolution or Industry 4.0 [3]. Thus, the aim of Industry 4.0 is to transform the manufacturing factories of today using these advancements in technology, into "smart" factories using solutions like, the Industrial Internet of Things, Cyber Physical Systems, Machine Learning and Cloud Computing, to empower these manufacturing processes with flexibility and adaptability. However, rather than specific technology solution, it is necessary to consider the overall interaction of implementing various combinations of Industry 4.0 enabling technologies which can deliver impact in companies [4]. This vision of Industry 4.0 aims to incorporate vertical and horizontal integrations of all core functions, from manufacturing, procurement and warehousing, all the way to sales of the final product which leads to more rapid product development, customised production, improved management of manufacturing environments, faster supply chains, and so on. This high level of integration allows transparency across business processes, which enables greater efficiency including clear decision recommendations for users [5].

As an organisation the business needed a scalable and sustainable solution for any data integration tool introduced, particularly for processes in the regulated medical sector. The Company selected Wonderware as an appropriate platform for development, as their research showed the Wonderware Platform outperformed other similar solutions in design simplicity, operational flexibility, and information processing capabilities [6]. Advanced Analytics is the umbrella term given to the likes of predictive analytics, prescriptive analytics, data mining and other analytics that apply high level data science methods, such as, Artificial Intelligence (AI), to cope with far more complex datasets and produce far deeper insights and predictions. The ultimate goal is to deploy suitable predictive analytics and prescriptive tools to ensure that the company has the knowledge to run the business as efficiently as possible to provide the customer with what they wanted, when they wanted it. This knowledge is a critical asset for a manufacturing enterprise, which enables businesses to differentiate themselves from competitors and compete efficiently and effectively to the best of their abilities [7]. Organisations that use advanced analytics can act quicker and with a greater degree of confidence about future outcomes. It enables organizations to make data-driven decisions and gain deeper insights on market trends, customer preferences, and key business activities by prompting potential outcomes rather than relying on end users to identify the trends from visualisation of their data sets. However, increasing applications of machine learning and data science techniques present a range of procedural issues including those that involved in data, assumptions, methodologies, and applicable conditions. Each of these issues may increase difficulties for implementation in practice, especially associated with the manufacturing characteristics and domain knowledge [8]. The positive side of Industry 4.0 is the creation of value, which include both an increase in effectiveness and the development of contemporary business models. Moreover, Industry 4.0 introduces new possibilities that will likely disrupt the traditional business models. [9]

While it is positive to have this data-driven knowledge, the rise in complexity brings with it a need for new skills in the company's business. Adapting to these new skill requirements is a challenge in the manufacturing industry, where it is rare to find the personnel with advanced data analytics skills and it is common for businesses to have problems finding qualified people to organise, manage, and analyse big data. The technology and tools around big data are advancing rapidly, but there aren't necessarily enough skilled people who can operate this technology at an expert level. It's much harder to collect, manage, and build actionable reports from big data if your team simply doesn't have the know-how [10].

1.2. Methodology

The research project, developed in conjunction with the IDEAM Research Institute at Technological University Shannon (TUS), set out to investigate the impact of developing reliability data analytics on the potential for a reduction in the costs associated with the maintenance of equipment. The research work aimed to develop a solution for data extraction and collection from the company's equipment and processes to provide subject matter experts with the relevant data that can improve the reliability of the equipment, in turn improving the OEE metric and providing the business unit with more stability and confidence in the capacity plan while also reducing the maintenance costs.

A participatory action research approach was taken for the project. By using this approach, the people most impacted by the problem could be relied upon to be motivated to work and help in solving this problem. Using frequent and clear communication to the stakeholders was key to keeping engagement high and ensuring the users were contributing to finding an effective solution. Throughout the project requirements for upskilling of individuals and changes to their daily work schedules become apparent, as the solution developed to remove the non-value add activity from the end users and to provide insight into their daily responsibilities they have not had before. Benchmark visits were carried out across a number of businesses within the manufacturing industry to better understand what has been carried out on this subject elsewhere, as well as learning from others the positives and negatives regarding solution deployments.

1.3. Digitalisation Strategy

It is the Company's strategic view that Manufacturing plants more than ever need to integrate their decision making based on facts and a complete data set. Traditionally businesses differentiated themselves through achieving high quality, reliable service and improved agility. These elements are now simply a qualifier to do business. Building a "digital thread" from raw material to finished product and from supplier to customer is a key enabler to maintain the qualifiers but also to drive a competitive advantage in the area of collecting real-time manufacturing data, marrying the design process with manufacturing, acquiring customer information and feeding it back to the manufacturing site. This enables manufacturing to meet the true needs of our customers in a competitive way [11]. The Company places a clear focus on data being key to delivering this strategy, and that the tools and systems that have become available under Industry 4.0 enable improvements in the company's reliability and reduce the compliance risk in the company's processes. The data philosophy is based on a hierarchy of Machines, Connectivity, Data and People, as shown in Fig.1.

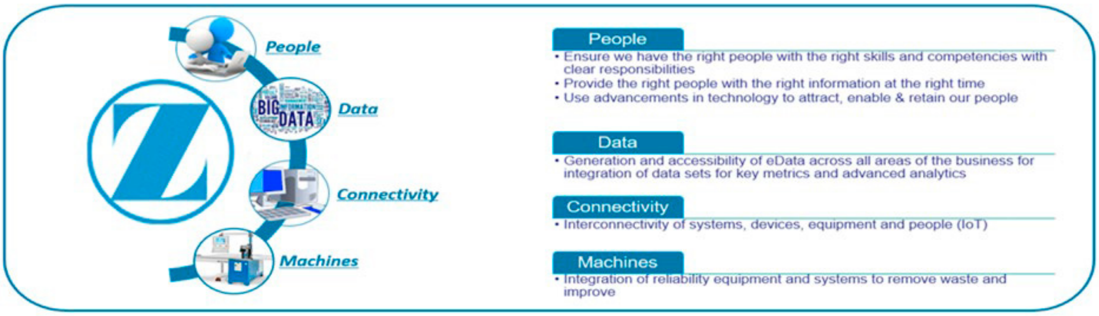

Fig. 1. Zimmer Biomet Digitalisation Strategy.

When building a strategic roadmap regarding data, it was decided to use a philosophy of starting with being reliable, then becoming agile and with a view to becoming predictable. In addition, from a quality assurance perspective for a medical device company it is also crucial for the company's validated equipment to run exactly within the validated specifications approved. Thus, a standardized data extraction solution needed to be developed that could be deployed on the process equipment (CNC Machines / Cleanlines) to extract the critical parameters and alarms from the PLC in order to monitor the operations.

2. Industry Case Study

2.1. Problem Definition

A problem-solving session (2018) with the Business Unit where a CNC machine had required a spindle change-out within four months of a new spindle being installed was carried out. A spindle change-out is costly for the company's business exceeding €60,000 once the labour, tools, spares and external vendor costs are factored in. This cost mentioned above, does not include the cost of disrupting the company's manufacturing schedule. The problem solving was thorough and identified that four bolts fastening the spindle has not been tight enough on original spindle change out. This was identified as the root cause for failure of the new spindle within four months of installation. It was commented that "there was no way we could have known". This prompted an investigation into whether there were any leading indicators that the machine was approaching a catastrophic failure and could the maintenance and operations teams have limited the damage or eliminated the risk of failure. It was discovered that in the lead up to this event, the business had in fact used up to four times the budgeted (expected usage) number of cutters(tool) in the three weeks leading up to the event. Had this been reviewed or highlighted to the relevant people the business could have indeed avoided the failure of a four-month-old spindle and corrected the issue. It led to questions on what other indicators would have been available that could have removed the risk to downtime and availability of the machine. Based on feedback taken from benchmark visits at other companies, the researcher began to look for solutions regarding data availability and accessibility. Identifying there is a difference between operational business intelligence and analytical business intelligence allowed the team to begin deploying the solution for accessing data and to deliver a visualisation to the end user to provide insights and drive action. The maintenance function became the focus of the project as there were obvious cost saving potential through reduced downtime, reduced consumables and optimized maintenance operations.

2.2. Solution

A solution was developed to enable the end user to view their data and better equip themselves to make business decisions with more confidence. The solution consisted initially of connecting a machine (Haas Grinder) to a Wonderware tool for data extraction and then transferring this data into Qlikview to build visuals for the end user. During the execution of this project the scope was widened to include extracting the process parameters from cleanline equipment and critical alarms and triggering a "hold" functionality in MES as a result. The scope also grew to include other data sources that provided additional processing data and tool/consumable usage that would provide more valuable information for end users regarding delivery and cost of production. Figure 2 shows the control and data acquisition architecture for the project.

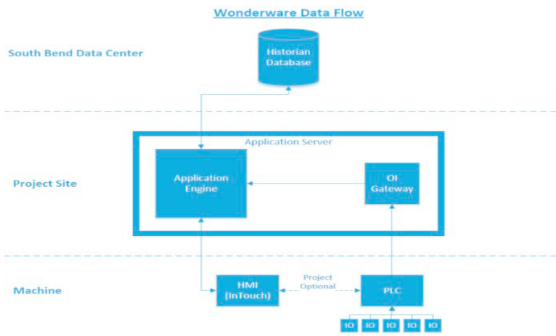

Fig. 2. Control and Data Acquisition Architecture.

In addition to the deployment of operational business intelligence, it was decided to investigate the use of a predictive model to determine the "time to next alarm" using alerts, motor speed, motor current and motor temperature extracted from the equipment. It was clear that further work is needed to define the key inputs of alerts leading to mechanical faults in order to apply predictive analysis.

3. Results

With the introduction of operational data analytics as a result of data extraction from manufacturing equipment along with processing data sources the business has realised improvements in key metrics like OTIF (On Time in Full), OEE (Overall Equipment Effectiveness), MTBF (Mean Time Between Failure), MTTR (Mean Time to Return), CuC (Consumable Unit Cost), and Lead Time. It was concluded that the introduction of data analytics has reduced the costs of the maintenance function and the costs of consumables usage across the business unit included in the proof of concept. In addition, the Data Analytics has improved the reliability of the equipment and reduced the costs of consumables in the process. The fact the business is now using these tools is proof of the value that they are bringing to the business. An example of the Maintenance function dashboard is shown below in Fig.3.

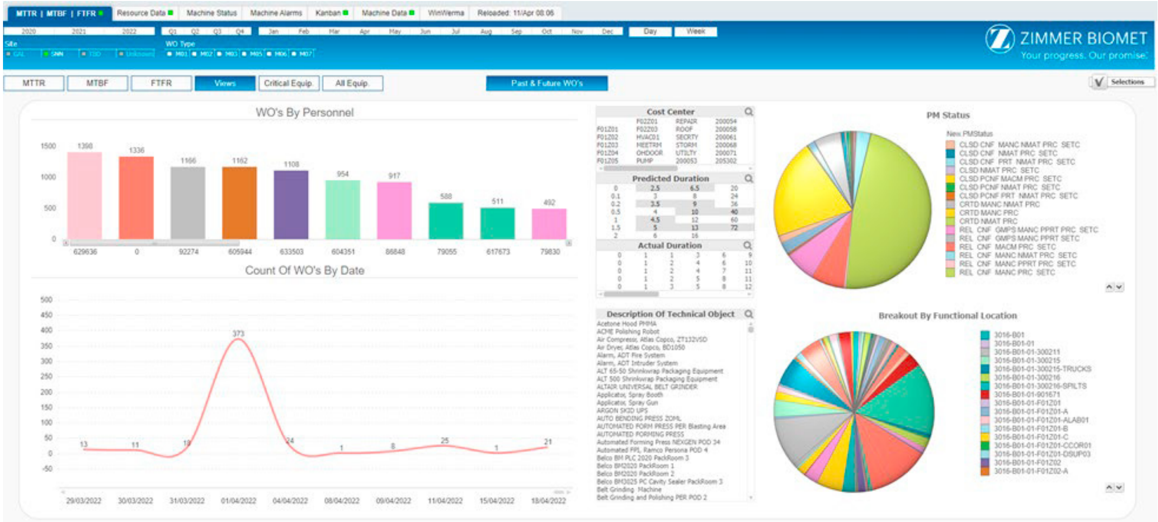

Fig. 3. Data-driven Maintenance Dashboard.

With the introduction of the Maintenance function dashboard the accountability is in place and the ownership is now in the hands of the maintenance technicians to ensure that all activities due are closed out on time and the recognition is now also an incentive to do so. Benefits to the business have been seen in a number of areas, including;

3.1 Mean Time To Repair

This is an important metric to understand how the maintenance team are tracking the return of equipment fit for use to Operations. It is also important to the leader of the maintenance function to measure how the team is performing in relation to time taken to repair equipment. Over the fifteen-month pilot period, the monthly average time to repair time reduced by 40% from 1.89 hours to 1.14 hours. This also accounts for a 40% reduction on the actual time recorded for maintenance work orders, from 955 hours to 575 hours.

3.2 Unplanned Maintenance Occurrence

Over the pilot period of 15 months, the average occurrence of an unplanned maintenance related event has reduced from every twelve days to currently being twenty-seven days. This improvement can be attributed to a couple of factors. The fact that the data is called out earlier is now providing the Maintenance team with more visibility of their performance along with detail of the equipment has enabled the team to focus on the correct issues and increase the average time between failures.

3.3 Better Diagnostic Data

Providing variable data from the Haas grinding machine enables better trouble shooting for the maintenance team. The correlation of historical data sets has shown that an unplanned maintenance work order was raised for this machine just after erratic behaviour was seen on the spindle temperature, which could have been flagged earlier. It is also apparent that the duration of the alarm provides a greater indication of the impact of the alarm on the machine in relation to downtime. For example, during the pilot period, for the Haas Grinder, the third highest alarm and the longest duration alarm was in relation to coolant. In the same period, while reviewing the reasons for unplanned maintenance work orders on the same machine, “Coolant” was called out as the highest reason for maintenance to work on the machine.

3.4 Consumable Usage

It was identified by the business that there was a lack of knowledge regarding the usage of consumable tools in the manufacturing process. Through the application of a spares vending system, linked with the maintenance dashboard, the business now has a true reflection of usage for the first time. This has also enabled the visualization to show the trend of usage across each machine for all tools. Over the pilot period, the Consumable Unit Cost (CuC) has reduced by 10% from the value in the first quarter of 2021. This was successful by highlighting by tool how the business unit was performing against the budgeted usage and enable a "finger on the pulse" type dashboard using the data extracted from the electronic kanban(dispenser) so that Engineering and Operations teams were able to identify issues and resolve that at the time of the issue rather than reviewing the data on paper at the end of the month when the event could be a number of weeks in the past.

3.5 OEE

In relation to OEE, the availability of the equipment is key to the calculation. The business measures the availability of the equipment from the amount of time that the equipment is in a "Productive" state as defined per MES (the equipment is placed in an "unproductive" state by maintenance technician when they are working on the machine) and use this in the OEE calculation. As can be seen in the appendix, from January 2020 a positive trend can be seen in the number of hours that equipment in being set in an unproductive state. Reviewing the data for the previous year 2021, its can be identified that May and July were particularly poor months for availability of the Haas fleet. Across 2021 the average result across the Haas machines was 95.37%, while 2022 to date is recording an average availability of 95.49%. See Figure 4. At a glance this does not necessarily show a significant increase in availability but over just one week this is twenty-six hours of machine time across eighteen machines that is now available to Operations that they did not have across 2021. This is just looking at the eighteen Haas grinding machines in one business unit. This is scalable across all equipment in the manufacturing plants without a massive amount of effort as the functionality is out of the box from the MES. Taking this into account within the Ireland plants we have approximately ten other types of CNC machines on the production floor with over one hundred machines in all groups. The company has the potential to retrieve significant capacity in additional machine hours. See Haas fleet OEE in Figure 4.

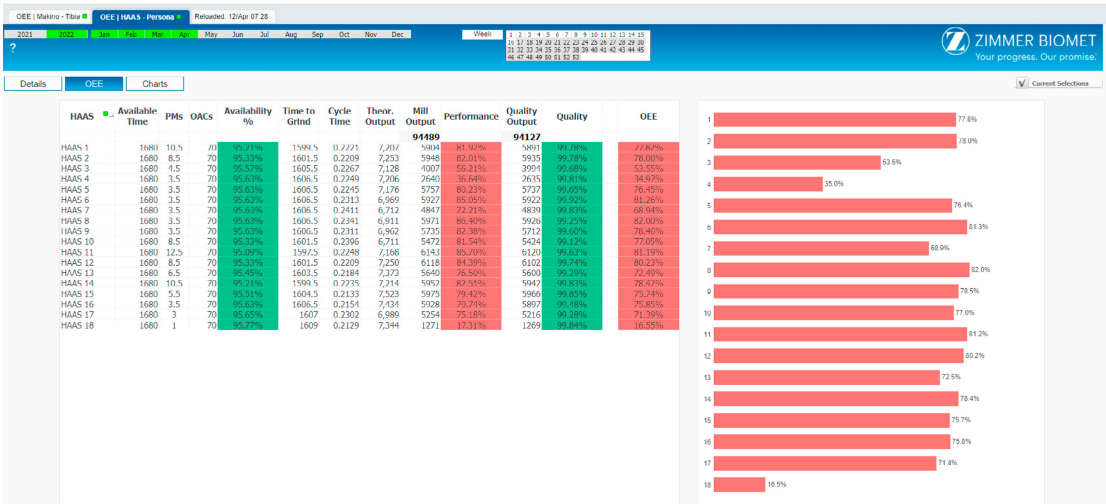

Fig. 4. OEE

3.6 Other Benefits

Connecting the Maintenance function dashboard to the MES data has also enabled other initiatives which are showing benefits for the business. This includes the opportunity for 'campaign building' of sequencing SKUs to reduce the number of change-overs and decrease set-up times. For example, in 2021 there were eighteen different SKUs built on the Haas Grinder, while in April 2022 there were only five different SKUs manufactured. This allows the machine to run optimally and reduces the inspections required on product. Additional, adding a requirement in MES for the operator to record the data of the grinding wheel balancing process has provided the Maintenance team visibility on a significant source of unplanned downtime, and has shown a reduction in spindle related issues since its introduction.

The team agreed to build a visual in the QV application to trend alarms. It was agreed that this would be a useful representation of the data to enable end users to track particular alarms of interest and provide an indicator on if a particular alarm pattern is reducing after action has been executed to resolve that particular issue. As shown in Fig.4., the overview of alarms generated on the Haas Grinder over the study period are shown, with a significant decline in occurrence. The alarms are alerts of all levels that the machine.

Fig. 5. Data-driven Maintenance Dashboard.

Based on all of the above detail, it was concluded that the introduction of data analytics has reduced the costs of the maintenance function and the costs of consumables usage across the business unit included in the proof of concept as can be seen on the business' key performance indicators.

4. Conclusions

Should the company continue in the plan and roadmap proposed through this project and continue to roll-out the data analysis to the fleet (>20) of Haas Grinders and to other production machines (>100), they can expect to see a significant reduction in over usage of tooling and consumable materials and increased production capacity available to the business. This will continue to reduce the costs for the business and improve the reliability of the equipment as unplanned events would become rarer and eventually eliminated through a predictive model. The pilot study has demonstrated that data analysis has improved the reliability of the equipment and reduced the costs of consumables, with the improvement in reliability providing more capacity for the company to grow their business. It could be argued to make an improvement you must first measure what you are improving and while this is true in this scenario using data analytics has improved the business across multiple metrics and also reduced the transactional waste that employees were carrying out in the daily duties. Removing this waste and providing clean data allows for a paradigm shift from independent automated and human activities towards a human-automation symbiosis (or 'human cyber-physical systems') characterised by the cooperation of machines with humans in work systems and designed not to replace the skills and abilities of humans, but rather to co-exist with and assist humans in being more efficient and effective. [12]

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