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Circular 4.0: Digital Intelligence to enable a circular economy

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Executive Summary

This feasibility study investigated how data acquired through the latest advances in digital technologies such as the 4th Industrial Revolution (I4.0) and the Internet of Things (IoT), can provide digital intelligence to shape decisions about the manufacture and utilisation of automotive components for accelerating the implementation of more circular approaches in UK manufacturing. The novelty of this research lies in investigating the application of digital intelligence through the lens of a restorative circular economic model focusing on product life extension and its suitability at a particular point in a product's life cycle.

Through this research, a remanufacturing process was mapped and simulated using Discrete Event Simulation (DES), to depict the decision-making process at the shop-floor level of a hypothetical remanufacturing facility. To understand the challenge of using data in remanufacturing, a series of interviews were conducted. These identified significant variability in the condition of the returned product. To address this gap, the concept of Certainty of Product Quality (CPQ) was developed and tested through a System Dynamic (SD) model to better understand the effects of CPQ on products awaiting remanufacture, including inspection, cleaning and disassembly times.

The wider application of CPQ could be used to forecast remanufacturing and production processes, resulting in reduced costs by using an automatized process for inspection, thus allowing more detailed distinction between 'go' or 'no go' for remanufacture. To scale its impact, CPQ would need to be product-specific and, in the long term, it should be considered when designing a product or component. In the future, considering new technologies such as blockchain would be imperative to secure how data is gathered and analysed, as well as allowing interconnectivity between the product to be remanufactured and the wider operation system. Within the context of a Circular Economy, CPQ could be replicated to assess interventions in the product lifecycle, and therefore the identification of the optimal CE strategy and the time of intervention for the current life of a product i.e. when to upgrade, refurbish, remanufacture or recycle. As demonstrated, data streams would be imperative to understand the factors of influence that affect the product integrity, condition and reliability of a product, and as such developing mechanisms to capture and analyse this data could help to uncover exciting opportunities for creating and quantifying new forms of value within manufacturing.

1. Research Challenge

The Circular Economy offers an alternative model to the traditional linear economy (take, make, use and dispose), decoupling economic value creation from resource consumption by keeping resources in use for as long as possible, extracting the maximum value from them whilst in use and then recovering and regenerating products at the end of each service life.[1] Three Circular Economy strategies for enhancing asset and resource productivity within a manufacturing environment have been identified: i) increasing the utilisation of an asset or resource (product as a service, sharing platforms, greater resource productivity), ii) extending the life of an asset (durable design, predictive maintenance, reuse, remanufacture), and iii) cascading an asset through additional use cycles (component harvesting, recycling).[2] However, the implementation of Circular Economy strategies in manufacturing environments is subject to several risks including the mismatch between fluctuating demand, supply and value of used components, causing uncertainty regarding costs and return on investment[3]; as well as the lack of information concerning the condition, availability and location of in-service assets.[4] However, the emergence and increasing uptake of technologies based on the principles of Industry 4.0 present a way to overcome some of these barriers to fully implement Circular Economy principles in the manufacturing sector.[3]

This research has investigated the feasibility of the application of digital intelligence through the lens of a restorative circular economic model focusing on product life extension, specifically remanufacturing strategies with the aim of assessing the provision of information about the maintenance, enhanced repair and reconditioning, use and reuse of automotive components. The focus is on the automotive sector, as this sector reveals that the sustainability benefits of digitisation could be substantial, arising from 20-30% machine downtime reduction, 12-20% inventory reduction, 30-50% cost of quality reduction and up to 80% improvement in forecasting accuracy.[5] In addition, this sector has succeeded in using data-driven intelligence to enable sustainable practices. However, these have focused on only one Circular Economy strategy (e.g. predictive maintenance) and such risks have prevented successful implementation on other aspects of remanufacture such as the assessment of the stochastic nature of returned products.[6]

2. Context

This feasibility study refers to Circular 4.0 as “data-driven circular approaches” enabled by Industry 4.0. Data-driven intelligence is rapidly becoming a pervasive feature of our economy, where data generated through social, mobile, machine and product networks are being leveraged through data analytics to create new forms of value. In manufacturing industries, through emerging concepts such as Industry 4.0 and Iota, data-driven intelligence is transforming how products are manufactured, sold and used across the value chain.[2] Despite a wealth of research into technological advances in manufacturing, much of it has focused on productivity, flexibility and responsiveness.[7] Pairing the digital revolution with the principles of a Circular Economy model has the potential to radically transform the industrial landscape and its relationship to materials and finite resources, thus unlocking additional value for the manufacturing sector.[8]

Data-driven approaches for a Circular Economy in manufacturing is strongly related to the concept of Industry 4.0, also known as smart manufacturing or the 4th industrial revolution.[3,9] Industry 4.0 is based on a manufacturing system driven by information technologies such as cyber-physical systems, cloud manufacturing, IoT, additive manufacturing and big data.[10] It involves a combination of smart factories and product enabled communication through the aforementioned technologies.[9] Industry 4.0 allows decision making through real-time information on production, machines and flow components as well as constant monitoring of performance and the tracking parts and products.[11] Industry 4.0 technologies have the potential to unlock a Circular Economy through the tracking of products in use by embedded sensors embedded in order to monitor maintenance requirements[3]; monitor products in use to extend their lifetime by recovery of components for reuse or remanufacture or to inform end of life strategies such as disassembly and recycling[12]. A ‘product passport’ would be required that could display information about materials contained in the product to facilitate reverse logistics and therefore Circular Economy strategies.[8] In addition, information technologies could be used to monitor and control operational performance to assess real-time efficiency to predict maintenance or refurbishment of components/product[13]; provide services alongside the physical product, for example, to customise products using 3D printing[14], or remove the provision of physical products, by replacing them with virtual ones.[3]

As seen, there has been growing interest in exploring the relationship between a Circular Economy and Industry 4.0.[3,12,15] However, a deeper knowledge and understanding is required on how data acquired from digital technologies can really unlock the potential of a Circular Economy. Table 1 identifies the data flows between the product, the user (including the customer, client and operator) and the conjunction of activities that occur between the designer, the manufacturer and the supply chain, referred to as 'Big M' in manufacturing[16]; mapped against circular strategies to identify new models of material use and value creation.

This study focused on investigating the value of capturing and analysing data streams to inform decision making processes in remanufacturing of automotive components as a starting point (darkest shaded) and will explore crossover with other product life extension strategies (light shaded) and sectors.

In context, remanufacturing is the process of disassembly and recovery of an asset at a product and component level[8], and it is considered as one of the product life extension strategies of a Circular Economy to keep a product or component at its highest utility and value[17]. Remanufacturing is already common in the automotive sector as it has one of the largest economic impacts[18], and will become even more imperative as we move from fossil fuel-powered cars to hybrid and electric vehicles. Therefore, it is vital and timely to invest in post-manufacturing strategies such as remanufacturing of critical parts of these vehicles.

Table 1 Data flows and circular strategies

			Data Flows			
			Product - Product	Product - User - Product	Product - Big M - Product	User - Big M - User
Circular Strategies	End-of-Current-Life	Cascading & Recycling	Component harvesting	Assess material & product value	Assess material & supply chain value	Inform end of life behaviour
	Product Life Extension	Refurbish / Remanufacture	Share upgrade needs	Identify upgrade options	Share product integrity	Identify user preferences
		Reuse / Redistribute	Adjust lifetime expectancy	Inform second life role	Inform design for second life	Inform second life preferences
		Maintenance	Share product faults	Assess product performance	Assess product degradation	Assess service performance
	Increasing Utilisation	Product as a Service / Sharing Platforms	Share product status	Assess product and service faults	Predict servitisation	Identify user patterns

3. Approach

The key partners of this study included PSS – an independent remanufacturing company of automotive components, RiverSimple – a hydrogen fuel cell car manufacturer, The High Speed Sustainable Manufacturing Institute (HSSMI) and the European Centre for Remanufacture – consultancies with expertise in remanufacturing. These organisations were involved throughout the research to enable a more informed understanding of remanufacturing and to investigate data acquisition and interaction in the remanufacturing process between the product, the use and the Big M (Figure 1).

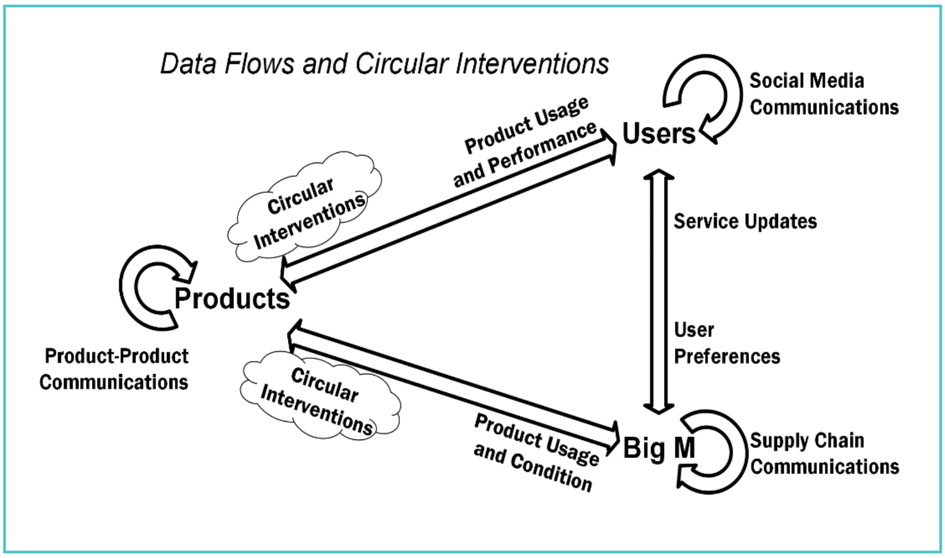

Figure 1: Data flows enabling circular strategies

Through a state of the art literature review in remanufacture and a series of interviews with companies involved in remanufacture (five in total with two OEM companies, two independent remanufacturers and a consultancy - see: Okechukwu et al.[19]) a remanufacturing process was mapped (see Figure 2 below), and simulated using Discrete Event Simulation (DES), to depict the decision-making process at the shop-floor level of a hypothetical remanufacturing facility. It is important to mention that remanufacturing is either performed by the Original Equipment Manufacturer (OEM) or a third-party independent remanufacturer. The difference being that the OEM can leverage upon product knowledge and brand name, whilst the independent remanufacturer has better accessibility to cores with extensive expertise in remanufacturing and has dedicated facilities for this [18]. The DES Model was developed in AnyLogic, for an independent remanufacturer processing an electric motor, and focussed on the remanufacture of two major components: a rotor (an electrical component) and a shaft (a mechanical component).

Through the interviews conducted, a taxonomy of manufacturing data was defined in three categories: structured data (spreadsheets, relational databases, enterprise data warehouse, files sorted in manufacturing PCS), semi-structured data (data from sensors, relays, RFID, XML, time series data structures) and unstructured data (operator shift reports, machine logs, error logs, texts, images, audio/video, manufacturing collaboration on social platforms) (see: Okechukwu et al.[19]). These findings helped to understand the challenge of using data in remanufacturing, especially as data comes in different formats, which can influence the assessment of the returned product, without knowing for sure the significant variability in the condition of the returned product.[20] To address this gap, the concept of Certainty of Product Quality (CPQ) was developed. Furthermore, a System Dynamic (SD) model developed in AnyLogic for the remanufacturing process of a fuel cell at RiverSimple was used to better understand the effects of CPQ on the product awaiting to be remanufactured, including inspection, cleaning and disassembly times.

The CPQ concept delivers a novel feature to the remanufacturing process as it is a value between 0.1 and 1 that quantifies how certain you could be about the quality of a returned product. CPQ brings a new way of quantifying forms of value within remanufacturing based on the amount of data that is available to provide information about the returned product. Some important facts of CPQ are:

- CPQ is a function of Physical Condition (PC), Part Remanufacturing History (PRM), Part Replacement History (PRH), and Data from sensors (DS).

- If you were certain/confident about the quality of the returned product, the number would be around 0.8-1.0. If you were uncertain, the number would be between 0.1-0.5.

- CPQ would affect the Disassembly time, Cleaning time, Inspection time of the product.

- CPQ has an impact on the time spent in a remanufacturing process and associated costs.

- 80% of products are going through an inspection process to be remanufactured into reusable products; the remaining 20% are expected to be disposed of.

- The nature of the product determines the CPQ and the level of disassembly a component might go to. Data from sensors could help to determine the uncertainty and CPQ.

In the final stage of research, the main partners of this study were interviewed to validate the CPQ concept and its effects on the decision making of the remanufacturing processes as well as its challenges and benefits.

4. Implementations

Discrete Event Simulation Model:

A DES Model showing the sequence of remanufacturing processes of a rotor and a shaft were depicted as shown in Figure 2.

These are: Inspection & Sorting, Disassembly, Cleaning, Inspection & Grading, Fault Diagnosis & Prognosis, Reconditioning, Reassembly, Testing and Final Assembly. The top half and the bottom half illustrate the remanufacturing processes for the rotor and shaft respectively. Some key features of the model are described overleaf:

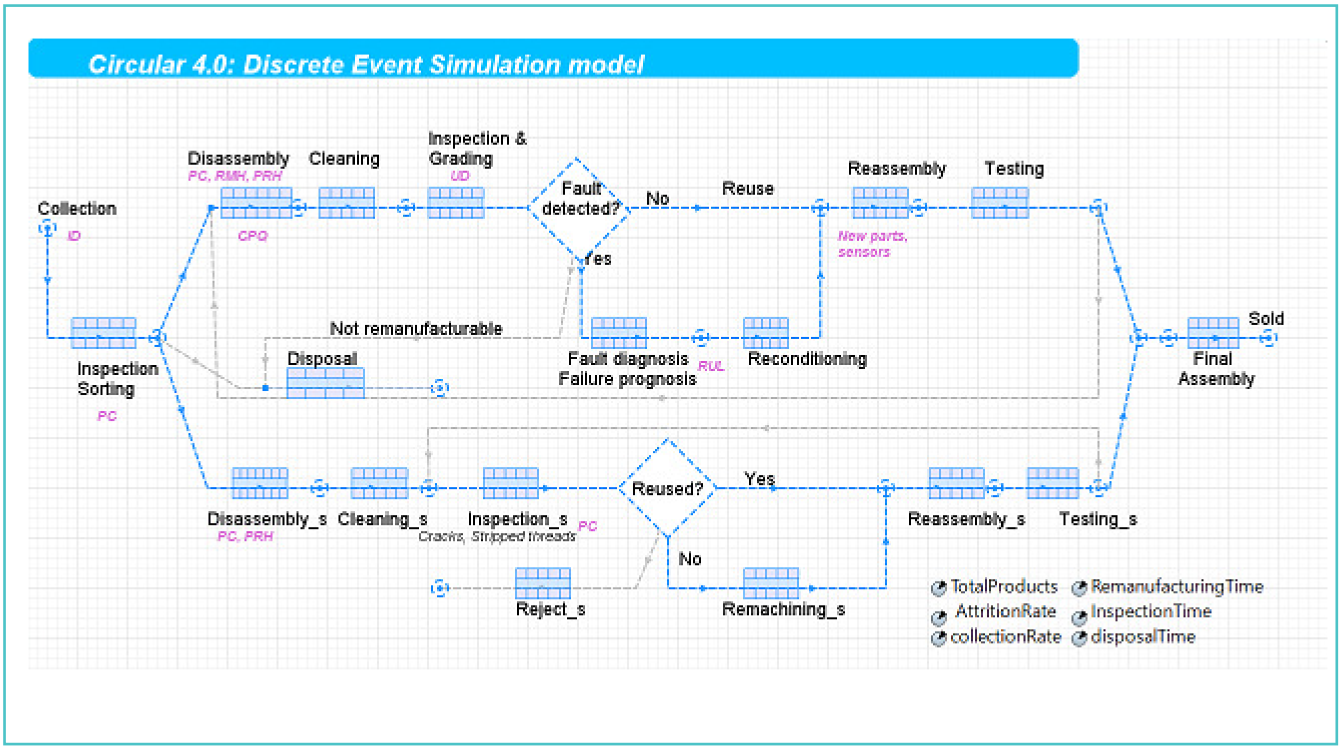

Figure 2: Discrete Event Simulation (DES) Model of two components of an electric motor

- **Collection (returned products):** The remanufacturing process starts with the collection of returned products. The attrition rate for electrical products, as suggested in the literature, was kept at 3%.[21]

- **Inspection and sorting:** After collection, the products are inspected based on their physical condition (PC) and the product identification number (ID). Approximately 10% of the products are rejected and sent for disposal at this stage. The electric motor is then disassembled and sorted into electrical components (rotor) and mechanical components (shaft).

- **Disassembly**: Actual disassembly of a return is not necessarily an exact reversal of its assembly sequence due to various factors: degradation of components, damage to components during use, missing components, product upgrade during maintenance and remanufacturing tasks.[22] Some components of an electric motor e.g. rotor can be reused directly without the need for full disassembly whereas other components e.g. shaft require proper reconditioning and disassembly so that they can be reused in a remanufactured product.[23]

- **Time spent in disassembly, cleaning and inspection:** CPQ of the returned product would affect the disassembly time, cleaning time and inspection time in the remanufacturing process. For example, if the CPQ for the product is very high, then in most cases you can directly inspect/disassemble/replace the faulty part and may not need to go down to the lowest level of disassembly. The time spent in the above-mentioned remanufacturing processes is directly proportional to the associated labour costs and the costs associated with the repair/replacement of parts. Hence, CPQ of a product could be useful for predicting the remanufacturing time and costs.

- **Inspection and grading:** Inspection is required to measure and detect the current condition of a component. Generally, the components are graded into three categories:[24] (a) directly reusable, (b) reusable after proper repair or reconditioning, and (c) cannot be repaired or reconditioned.

- **Fault Diagnosis and prognosis:** Diagnosis detects the failure that has occurred in a component, and isolate and identify the root of the failure, based on the data collected by the embedded sensors. Prognosis estimates the time at which a component will fail to operate at its stated specifications based on its current condition as well as the future load and environmental exposure i.e., the prediction of the remaining useful life (RUL) of the component.

- **Reconditioning and Repair:** The reconditioning strategies are dependent on the current condition and the failure mode of the used parts. A damaged or worn part can be repaired either by removing the damaged area or by adding new material to the area, depending on the severity of the damage.[25] The PRM, as well as the performance and reliability of the previous remanufactured versions of a component, will provide insight into the effectiveness of the reconditioning methods.

- **Reassembly and Testing:** Generally, the reassembly sequence is the same as the original new product but may differ if there has been a significant upgrade during remanufacturing.

System Dynamics Model:

A SD model was used to understand the remanufacturing operation and decision-making process at a systems level as shown in Figure 3. Some key features of the model were obtained from direct conversations with RiverSimple and are described below:

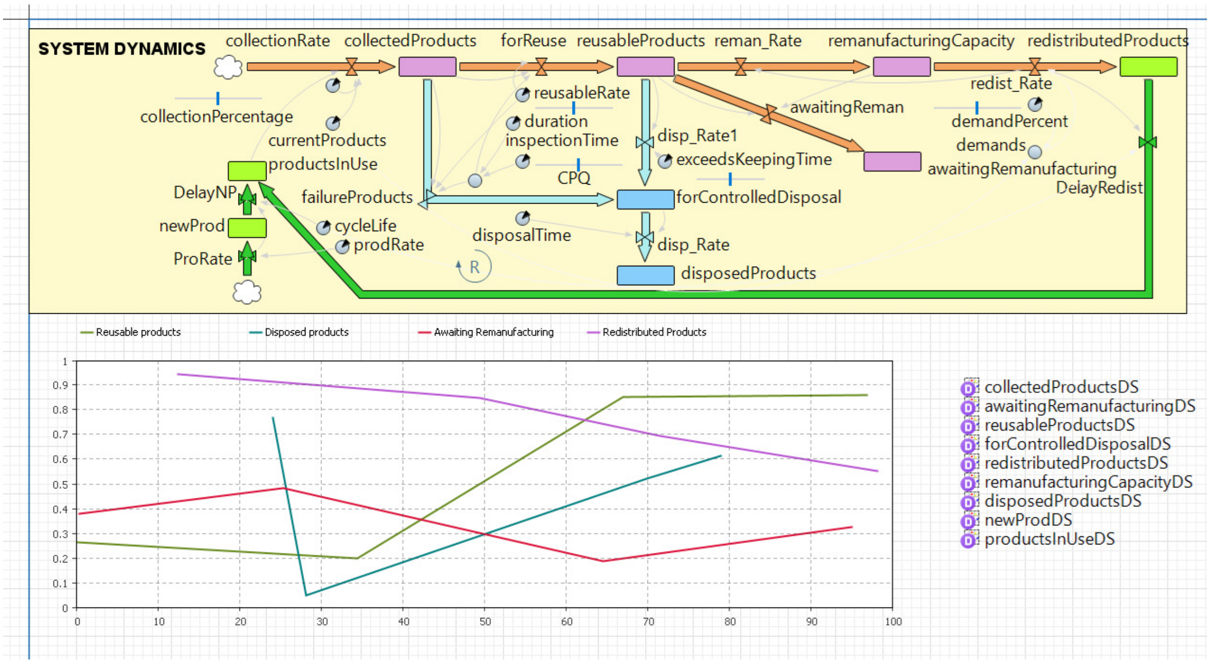

Figure 3: System Dynamic Model of a fuel cell for RiverSimple

- **Collection (returned products):** The remanufacturing process starts with the collection of returned products. The attrition rate for fuel cells, as suggested in the literature, was kept at 3%.[21]

- **Reusable products:** 80% of products going through the inspection process are expected to be remanufactured into reusable products, the remaining 20% will be disposed of.

- **Inspection Time:** CPQ of the returned product would affect the inspection time in the remanufacturing process.

- **Controlled disposal:** 20% products are going through the inspection process for controlled disposal. They will be disposed of with respect to disposal time and rate. Some products (valid in the case of batteries etc) that exceed the keeping time will also be sent for disposal. The number that exceeds the keeping time is 1%.

- **Demand:** This element controls the remanufacturing rate and redistribution rate.

- **Awaiting remanufacturing:** Products that have passed the inspection and are awaiting remanufacture.

- **Redistributed products:** Are given a product lifetime of 5 years. After 5 years, they will automatically join the collected products (returned products).

- **New products:** Are given a production rate and cycle lifetime of 5 years and after that they will automatically join the collected products.

5. Summary of Results: The value of data

The DES Model helped to understand that the data obtained from embedded sensors in the product is critical in determining the CPQ of that product. Figure 2 demonstrates the effect of CPQ on the time spent in disassembly, cleaning and inspection. For example, during remanufacturing of 100 products with high CPQ (ranging between 0.8-1), 75% of the products spent 31-35 hrs in disassembly, cleaning and inspection, with a mean of 31 hrs. However, during remanufacturing of 100 products with low CPQ (ranging between 0.1-0.3), 75% of the products spent 46-52 hrs in disassembly, cleaning and inspection, with a mean of 47 hrs, as shown in Figure 4 and 5 respectively. Figure 4 depicts the *Probability Distribution Function (PDF)* of time spent in disassembly, cleaning and inspection. Vertical bars correspond to time spent in the system with heights proportional to the density of products. Solid lines represent the mean time spent in the system. Figure 5 depicts the variations in the time spent in disassembly, cleaning and inspection.

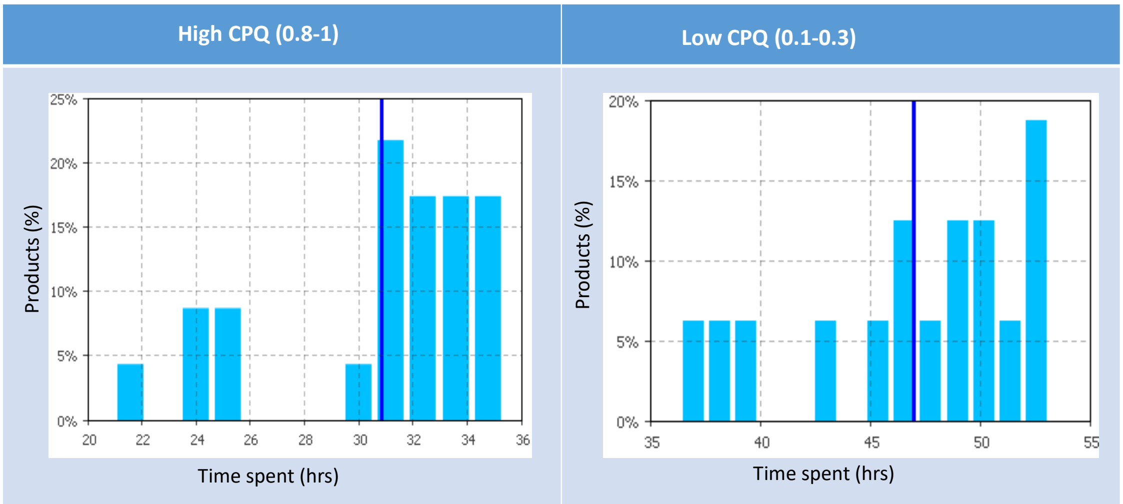

Figure 4: Probability distribution function of time spent in disassembly, cleaning and inspection

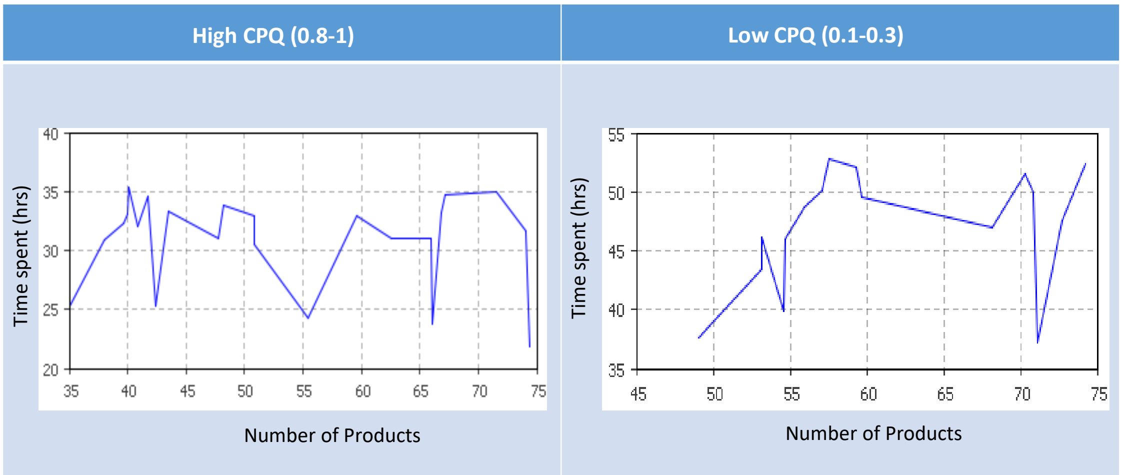

Figure 5: Time spent in disassembly, cleaning and inspection for a high and low CPQ in a small number of products

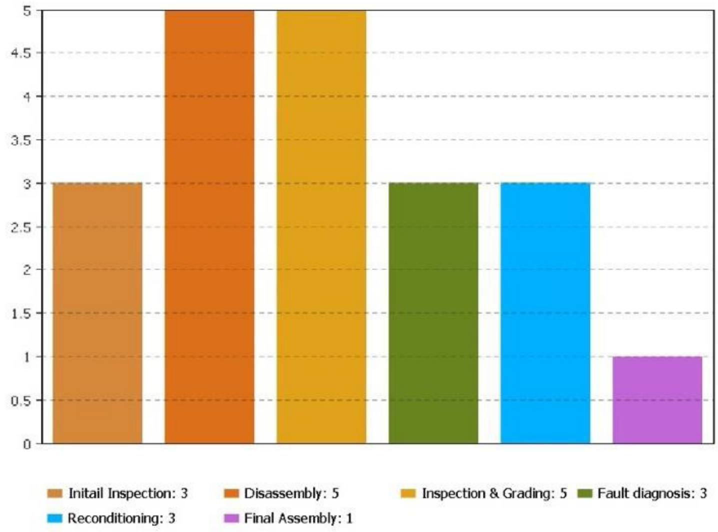

Figure 6: Maximum utilisation of pallet racks in each section of a remanufacturing facility

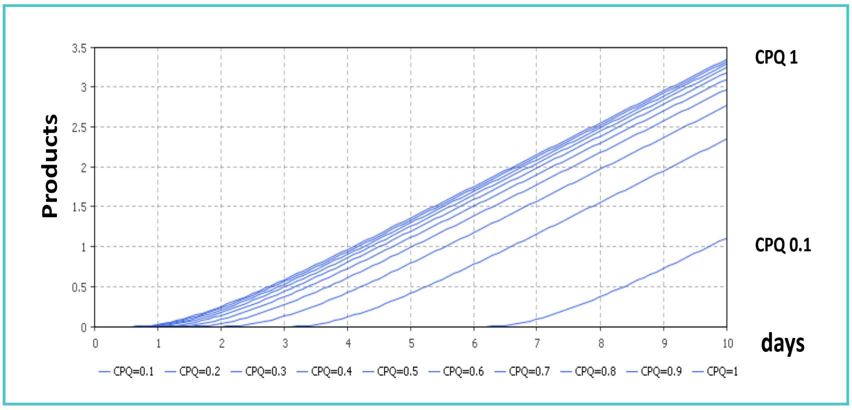

Figure 7: Effect of CPQ on resuable products

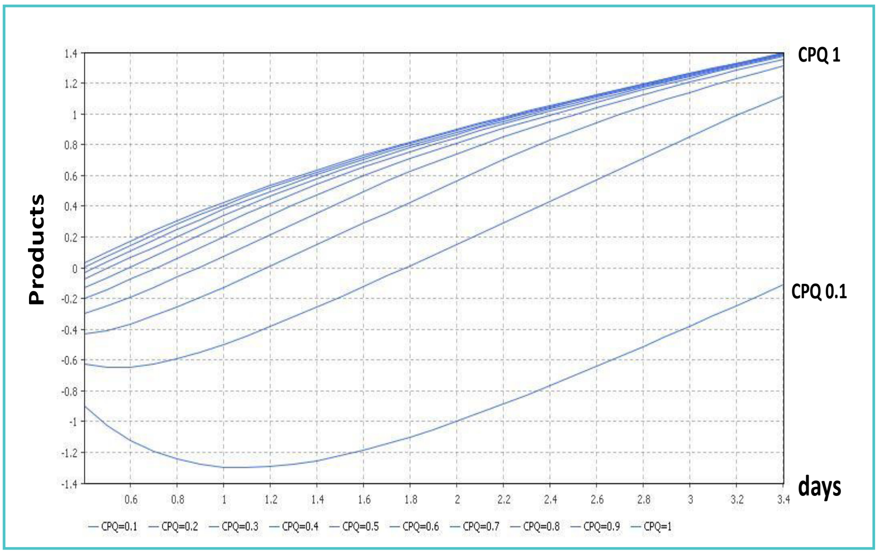

Figure 8: Time spent for remanufacture depending on the CPQ value

The DES model showed that storage/work space has been allocated for each station in the form of pallet racks. Figure 6 depicts a bar graph showing the maximum utilisation of pallet racks in each section of the remanufacturing plant. This feature is useful to determine the optimum resources required to meet the product demand, such as the number of workstations being used.

The SD Model demonstrates the effect of CPQ on the products awaiting remanufacture in the system. For example, if a batch of CPQ 0.1 is received for remanufacturing, then after 10 days only 1 product would complete the disassembly and inspection stage and would reach the 'awaiting remanufacture' stage. Whereas, if a batch of CPQ 1 is received for remanufacturing, the number of products at 'awaiting remanufacture' stage would be three times higher, as depicted in Figure 7.

In addition, Figure 8 demonstrates the effect of CPQ on the reusable products. For example, if a batch of CPQ 0.1 or 0.2 arrives then after 3 days there would not be any product in remanufacturing.

6. Wider Applications

The feasibility study has demonstrated that capturing CPQ rates could be used to predict not just the time but also the number of products that could be remanufactured enabling a forecast that can be used to plan remanufacture and production processes. In addition, adding a degree of automation in inspection would be key for the aforementioned forecasting. However there is a need for a system that can process and analyse historical data based on the PRM and PRH. Experienced inspectors would be key to gather as much information as possible to develop and calibrate this system. The challenge is to find a mechanism to do so, that could also help to standardise the data for each product. If this challenge is overcome, data sets can then be used to differentiate one product from another to make the remanufacturing process as efficient as possible. Another challenge would be to replace manual with automated inspections for components that pass a quality threshold. This could be overcome by assessing the CPQ when disassembling a part, as this information could be captured by the CPQ to increase its certainty. Therefore, there will be a point where the product does not need to be further inspected, and the decision would be automated based on the CPQ value.

CPQ has the benefit of reducing costs by using an automated process for inspection as it allows a more detailed distinction between 'go' or 'no go' for remanufacture. To scale its impact, CPQ would need to be product specific and in the long term it should be considered when designing a product or component. In the future, considering new technologies such as blockchain would be imperative to secure how data is gathered and analysed, as well as allowing interconnectivity between the product to be remanufactured and the wider operation system.
Within the wider context of a Circular Economy, CPQ could be replicated to assess interventions in the product lifecycle, and therefore the identification of the optimal Circular Economy strategy and the time of intervention for the current life of a product. As demonstrated, data streams would be imperative to understand the factors of influence that affect the product integrity, condition and reliability, and as such developing mechanisms to capture and analyse this data could help to uncover exciting opportunities for creating and quantifying new forms of value within manufacturing.

7. Conclusions and future plans

Through investigating remanufacture within the automotive industry, the feasibility study identified that i) the analysis of in-service data from automotive components can influence decisions surrounding remanufacture and can lead to significant cost, material and resource savings by reducing the uncertainty in the condition of components returned for remanufacture, ii) there is a need for fundamental research into how interactions between products, users and manufacturers can inform opportunities for circular approaches, and iii) to enable a transformational change in resource use across the manufacturing sector a wider spectrum of Circular Economy strategies needs to be investigated across multiple industrial sectors.

This research has taken the first step in investigating the relationship between emerging technologies that contribute to Industry 4.0, the Internet of Things and the Circular Economy. The development of the CPQ concept has provided evidence that data on Physical Condition, Part Remanufacturing History, Part

Replacement History and Data from sensors can support a more efficient and intelligent remanufacturing process resulting in substantial cost, material and resource savings. Furthermore, this study has evidenced the significant potential to upscale this research through the use of social, mobile, machine and product network data, leveraged through data analytics to create new forms of value to transform the industrial system within the context of a digitally enabled circular economy.

The team has secured subsequent funding from the Engineering and Physical Sciences Research Council (EPSRC - grant number: EP/R032041/1) for a 3-year project to address some of the challenges presented in this feasibility study and extend its scope to identify how data from products in the automotive and aerospace sectors can further inform decisions surrounding the implementation of Circular Economy strategies within manufacturing.

This future work will see a characterisation of in-service data streams based on an information-theoretic approach for selecting optimal Circular Economy strategies and timing of intervention.

To achieve this, qualitative research will identify the different types of value generated from Circular Economy strategies and the factors and costs that influence their implementation. Findings from this qualitative research will inform the data streams to be mathematically characterised, to further calculate the types of value and cost. Research findings will be iteratively applied, tested and evaluated through three crosscutting use cases in partnership with Airbus, Rolls Royce and RiverSimple. This work would not have been possible without the findings emanating from this feasibility study.

8. References

1. WRAP. 2017. WRAP and the Circular Economy. Available from: http://www.wrap.org.uk/about-us.

2. Rubmann et al. 2015. Industry 4.0 The Future of Productivity and Growth in Manufacturing Industries. The Boston Consulting Group.

3. Lopes de Sousa B., et al. 2018. Industry 4.0 and the Circular Economy: A proposed research agenda and original roadmap for sustainable operations. In: Big Data Analytics in operations and supply chain Management. Springer.

4. Sue, B., et al. 2013. A review of the circular economy in China: Moving from rhetoric to implementation. Journal of Cleaner Production, 42:215-227.

5. SMMT, 2016. The Digitalization of the UK Automotive Industry. Available from: www.smmt.co.uk/reports.

6. Bocken et al. 2014. A literature and practice review to develop sustainable business model archetypes. Journal of Cleaner Production, 65:42-56

7. Babiceanu and Seker. n/d. Big Data and Virtualization for Manufacturing Cyber-Physical Systems: A Survey of the Current Status and Future Outlook. Computers in Industry, Available at: 10.1016/j.compind.2016.02.004.

8. Ellen MacArthur Foundation. 2016. Intelligent Assets: Unlocking the Circular Economy Potential. Available from: www.ellenmacarthurfoundation.org.

9. Lasi, H., et al. 2014. Industry 4.0. Business & Information Systems Engineering. 6(4): 239–242.

10. Kang H.S., et al. 2016. Smart manufacturing: Past research, present findings, and future directions. International Journal of Precision Engineering and Manufacturing – Green Technology. 3(1):111–128.

11. Lu Y. 2017. Industry 4.0: A survey on technologies, applications and open research issues. Journal of Industrial Information Integration. 6:1–10.

12. Okechukwu O., et al. 2017. A review of data

driven approaches for Circular Economy in manufacturing. 18th European Roundtable for Sustainable Consumption and Production, ERSCP. Skiathos Island, Greece: 18th European Roundtable for Sustainable Consumption and Production, ERSCP. pp. 120–131.

13. Hofmann, E. and Rusch. 2017. Industry 4.0 and the current status as well as future prospects on logistics. Computers in Industry. 89:23-34

14. Despiesse, M., et al. 2017. Unlocking value for a circular economy through 3D printing: A research Agenda. Technological forecasting and social change. 115:75-84.

15. Bressanelli G., et al. 2018. Exploring how usage-focused business models enable circular economy through digital technologies. Sustainability 10(3):639

16. Neely 'Manufacturing Analytics: The Role of Big Data in the Future of Manufacturing', Available from: http://cambridgeservicealliance.eng.cam.ac.uk

17. Towards the Circular Economy Vol. 1-3. Available from: http://www.ellenmacarthurfoundation.org.

18. Savedra Y.M.B., et al. 2013. Remanufacturing in Brazil. Case studies on the automotive sector. Journal of Cleaner Production. 53:267-276

19. Okechukwu, O., et al. 2018. A decision-making framework for the implementation of remanufacturing in rechargeable energy storage systems in hybrid and electrical vehicles. Procedia Manufacturing.

20. Aras N., Boyaci T. and Verter V. 2004. The effect of categorizing returned products in remanufacturing, IIE Transactions, 36(4): 319-331,

21.Warken Industrial and Social Ecology PTY LTD. 2012. Analysis of lead acid battery consumption, recycling and disposal in Western Australia. Available at: http://www.batteryrecycling.org.au/wp-content/uploads/2012/06/120522-ABRI-Publication-Analysis-of-WA-LAB-Consumption-and-Recycling.pdf

22. Fang H. C., Ong S.K., and Nee A. Y. C. 2015. Use of Embedded Smart Sensors in Products to Facilitate Remanufacturing, Handbook of Manufacturing Engineering, Springer-Verlag London 2015 A.Y.C. Nee (ed.) Handbook of Manufacturing Engineering and Technology.

23. Kara, S. et al. 2008. Assessment of products for optimal lifetime. CIRP Annual Manufacturing and Technology Conference 57(1):1–4

24. Steinhilper, R. 1998. Remanufacturing – the ultimate form of recycling. Fraunhofer IRB, Stuttgart

25. Bras, B. 2008. Design for remanufacturing processes. In: Kutz M (ed) Environmentally conscious mechanical design. Wiley, Hoboken, pp 283–318

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The study was conducted by a team of researchers from Cranfield University and the University of Sheffield

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