

# Data-driven prediction of the viability of remanufacturing for heavy-duty vehicle components

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## ABSTRACT

The production of a heavy-duty road vehicle is a major contributor to the overall financial cost and environmental impact of the vehicle. In recent times, closing the material loops using circular practices has emerged as a promising approach to reduce the environmental impact of the vehicle production. The most common circular practice is material recycling, however, it is a low-value process, as any embodied value in the product apart from the material refinement is lost. In addition the recycling process might be cumbersome if the product is composed of multiple materials that cannot be easily separated. A promising approach to circularity is remanufacturing where a product is disassembled and the constituent components are cleaned and inspected. The components which pass the inspection are then reused in new products, while maintaining quality and warranty equal to new products. This preserves the value in the reused products and not only reduces the consumption of raw materials, but also manufacturing effort. In order for the remanufacturing process to be worthwhile, some conditions need to be satisfied. Firstly, the product needs to be valuable enough for the remanufacturing effort to make economic sense. Secondly, the state of a product that is returned from a customer must be able to be ascertained with a certain degree of confidence in a quick manner. One way to evaluate the state of a returned product

is by using the historical usage data of the vehicle it comes from. The goal of the work presented here is to study the feasibility of remanufacturing for different heavy-duty road vehicle components based on the economic benefits as well as the availability of data for the component in question, as well as identifying the relevant data for evaluating its remanufacturability. The economic feasibility is evaluated by considering the purchase price of the component compared to the costs and cost savings associated with the remanufacturing process. Criteria for the available data, meanwhile, are formulated based on four publicly available datasets that are used in the prognostics literature.

## 1. INTRODUCTION

As issues of sustainability become ever more prevalent in the contemporary political debate, so does the need for resource efficient manufacturing practices. While this could mean manufacturing practices similar to the traditional ones but simply more efficient, there is another, completely different way of viewing manufacturing and resource consumption, that being the circular economy.

In a traditional, linear manufacturing scheme, virgin material is extracted, processed and converted to finished goods in the manufacturing process. After a product has reached its End Of Life (EOL), the product is discarded and thrown away (Potting, Hekkert, Worell, & Hanemaaijer, 2016).

In a circular economy, a product that has reached its EOL is instead fed back into the economy, preserving not only the materials used to manufacture the product, but also some of the value embodied in the product through the manufacturing process. There are a number of possible strategies that can be implemented in order to achieve a more circular resource flow, these are referred to as circular strategies. Out of these strategies, recycling is arguably the most famous and most widely adopted. However, it is very low in the hierarchy of circular strategies, as only the value of the processed materials is recovered, and the recycled material has to be put through a new manufacturing process to be turned into new products (Potting, Hekkert, Worell, & Hanemaaijer, 2016). In (Potting, Hekkert, Worell, & Hanemaaijer, 2016), ten different strategies are identified. These are known as R-strategies and consist of, in order of decreasing circularity: Refuse, Rethink, Reduce, Re-use, Repair, Refurbish, Remanufacture, Repurpose, Recycle and Recover. The focus of the work presented in this paper is on the strategy remanufacturing. Before proceeding, however, it would be prudent to more precisely define what is

actually meant by remanufacturing, as multiple definitions appear in the literature.

In (Potting, Hekkert, Worell, & Hanemaaijer, 2016), remanufacturing is defined as the use of components from a discarded product in a new product with the same function. However, the use of the word *remanufacturing* is used in a variety of contexts in the literature.

A common definition of remanufacturing is that the remanufactured product should be returned to a “as good as new” condition and be covered by the same warranties as a new product (Du, Cao, Liu, Li, & Chen, 2012), (Zhang, et al., 2022) and (Jensen, Prendeville, Bocken, & Peck, 2019). In (Kerin, Hartono, & Pham, 2023) remanufacturing is used to describe the entire process that follows the decision to actually recover an EOL product. This includes a number of possible decisions regarding what happens to the product. One of these options is called *reincarnation*, and means that components that are of good quality in the EOL product are salvaged after disassembly and combined with new, purchased components in new products. This is basically the same as remanufacturing as defined in (Potting, Hekkert, Worell, & Hanemaaijer, 2016). Other possible strategies are *reuse* (direct resell of components to the second-hand component market) and recycling.

It might be assumed “remanufacturing” involves some type of more advanced repair techniques. This is also present in parts of the literature, where remanufacturing is used to describe the process where a EOL product with actual damage is repaired and can be put back into service. This is described using the term *value added treatment*. Examples of this are found in (Qin, Yang, Huang, Xu, & Liu, 2015), where scratched hydraulic cylinder bores are repaired using honing, in (Lei, Huajun, Hailong, & Yubo, 2017) where laser cladding is used to return material to damaged impeller blades, and (Wilson, Piya, Shin, Zhao, & Ramani, 2014), where laser deposition is used to repair damaged turbine blades. This type of treatment is considered out of scope for the presented work.

The work in this paper focuses on remanufacturing in the sense that components from EOL products that are of satisfactory quality are salvaged and can be used in conjunction with new components in new products.

The process of remanufacturing then consists of returned EOL products, also known as *cores*, being disassembled, the components cleaned and inspected, and the components that pass the inspection being returned to the manufacturing pipeline and the other components being recycled (Kroner, Luo, & Bertsche, 2020).

One large problem with the current remanufacturing practice is that the quality of the returned cores can vary significantly, and it is only at the final inspection step that the actual quality of the components can be ascertained. This means that products of low quality will go through the cumbersome and costly disassembly and cleaning phases, despite providing little to no value at the end of the process (Kroner, Luo, & Bertsche, 2020).

A possible way to reduce the uncertainty is to pre-screen the returned components and evaluate their condition before making the decision whether they should be put through the remanufacturing process, with the intention of sorting out the cores that are likely to be of low quality (Kroner, Luo, & Bertsche, 2020). This pre-screening could be done based on the recorded diagnostic and usage data of the product. Developing such a decision-making tool is not a trivial problem, though, and would have to be done for every type of product individually. This means that in order for the industry to embrace such a decision-making tool, the economic gain from the remanufacturing process has to be great and the pre-screening has to be technically feasible and practical to perform. Here, technical feasibility means that there exist sufficient data on the core in order to evaluate its state when it is returned.

This is the main focus of the presented work. The goal is to establish the foundations of a framework for evaluating the economic benefits and data availability in order to decide what whether to develop a remanufacturing decision-making tool for a certain product. The economic benefits are evaluated by comparing the cost of a new product with the remanufacturing cost, whereafter the remanufacturing cost is broken down into its different components. The data availability is treated by going through four publicly available product datasets that are featured in the prognostics literature and comparing their similarities to establish common features.

The paper is structured as follows: Section 2 first deals with the economic evaluation criteria, followed by what data needs to be available for a successful product state evaluation. Section 3 then discusses the results and concludes the paper.

## **2. PRODUCT EVALUATION**

### **2.1 ECONOMIC FEASIBILITY**

In order for the remanufacturing of a product to be economically feasible, there has to be sufficient cost savings to warrant the remanufacturing process.

Approaching the problem from a component perspective, the net gain of replacing a new component with a recovered one can be formulated as

$$P_i = C_{p,i} - C_{r,i}, \tag{1}$$

where  $P_i$  is the profit associated with replacing component  $i$  (an index) and  $C_{p,i}$  and  $C_{r,i}$  are the costs associated with purchasing a new component (or manufacturing a new one) and recovering an old component from a core, respectively. The recovery cost can be further broken down into the costs of the different steps of the manufacturing process. In (Jiang, Wang, Zhang, Mendis, & Sutherland, 2019) the recovery cost is broken down into cost for disassembly, value recovery (cleaning and inspection in this case) and reassembly. The contribution from reassembly can be ignored, as the new product is assumed to have the same assembly procedure, and therefore cost, independently of the amount of recovered components present. The recovery cost can then be formulated as,

$$C_{r,i} = C_{D,i} + C_{C,i} + C_{I,i}, \tag{2}$$

where  $C_{D,i}$ ,  $C_{C,i}$  and  $C_{I,i}$  are the disassembly, cleaning and inspection costs, respectively.

Since the goal is to evaluate the profitability on a product basis, the profit is calculated on a product basis by summing the contributions from each component in the product,

$$P = \sum_{i \in I}^N C_{p,i} - \sum_{i=1} C_{r,i}, \tag{3}$$

Where  $N$  is the total number of components in the product and  $I$  is an index set of the components that pass the inspection. The reason that the purchasing price is not summed over all components is that only the components that pass the inspection can replace new components in the new product.

Sometimes the remanufacturing company incentivizes customers to return cores through buyback schemes, thus a third term can be added to Eq. (3), the core buy-back price  $C_B$ ,

$$P = \sum_{i \in I} C_{p,i} - \sum_{i=1} C_{r,i} - C_B. \quad (4)$$

In Eq. (4) it is already seen how the quality of the returned core affects the profit from the remanufacturing process. The second sum and the third term are constant, as all components go through the remanufacturing steps up to and including inspection and the buy-back price is constant. In contrast, only the components that pass the inspection contribute to the first term. Inserting Eq. (2) into Eq. (4) yields,

$$P = \sum_{i \in I} \sum_{i=1}^N C_{p,i} - \sum_{i=1} (C_{D,i} + C_{C,i} + C_{I,i}) - C_B. \quad (4)$$

Although simple, Eq. (4) gives some indication of the desired properties of the product. Ignoring questions regarding the core quality, the first sum is maximized when the individual component purchasing prices are as large as possible.

The second sum is minimized when the product disassembly cost and component cleaning and inspection costs are low. This means that the product should be easy to disassemble and the individual components should be easy to clean and inspect.

Finally, in order to keep the buy-back price low, the core itself should have a low value on the second-hand market in order to incentivize the customer to sell it back to the OEM instead of selling it on the second-hand market.

There are other possible costs associated with, for example, recycling the discarded components. Modelling these costs are outside of the scope of the presented would have to be done in a more comprehensive study that takes into account multiple different R-strategies. The same holds for the assessment of the environmental impacts and the circularity performance of the remanufacturing process. While such assessments would complement economic feasibility with a measure for environmental and resource efficiency, they would require more detailed, process-specific data and would, in most cases, be conducted at a later stage of the decision-making framework.

## 2.2 TECHNICAL FEASIBILITY

### PROGNOSTICS

As is mentioned in the introduction, the ultimate goal of the research is to create a decision-making model that can make the decision about whether or not to recover a core based on the quality of the core, as estimated using data about the vehicle and its usage history. While there are many possible metrics for evaluating the quality, in the literature on remanufacturing it is common to use the residual useful life (RUL) or the reliability of the product as a measure of the overall quality (Psarommatis & May, 2025). It is common to define some type of condition on the RUL or reliability and the product is declared fit for remanufacturing if the condition is satisfied. In (Hu, Liu, Lu, & Zhang, 2014) and (Zhang, et al., 2022), the reliability is used as a measure of when to remanufacture roller bearings. Similarly, in (Chen, Wang, Zhang, Zhang, & Dan, 2019) the reliability is used to determine the optimal remanufacturing point of engine blades. In (Hu, Liu, & Zhang, Remanufacturing decision based on RUL assessment, 2015), the reliability of a fictional product with a crack is used to determine when the product should be remanufactured.

The estimation of RUL of a product is a field known as prognostics and has two main branches, model/physics based and data-driven (Kim, An, & Choi, Introduction, 2017). In model-based prognostics, the degradation process modelled using a mathematical model, and the prognostic process then becomes about fitting the model parameters based on the data recorded from the product during usage, usually through a Bayesian filter, such as a particle filter. An example of such a model is the Paris-Erdogan law for crack propagation (Kim, An, & Choi, Tutorials for Prognostics, 2017).

In data-driven prognostics, there is no model for the degradation, instead a large amount of recorded data from the product is used to find patterns relating to the state of the product (Kim, An, & Choi, Introduction, 2017). Tools from the field of machine learning can be used to unearth patterns between the data and the degradation state (Kim, An, & Choi, Introduction, 2017).

The work presented here will exclusively focus on data-driven prognostics. The reason for this is that developing a model of the degradation is too difficult for an assembled product with multiple possible failure modes and very complex behaviour. Data-driven methods, on the other hand, only requires large amounts of sensor and usage data from the product, which is often collected by vehicle OEMs.

Given that the goal of the presented work is to evaluate what data is needed in order to successfully construct prognostic tools, the focus of this section will be on the datasets that are used in the literature, rather than the methods used.

Four publicly available datasets have been chosen to illustrate the required properties of recorded data. These four are the NASA battery dataset (Saha & Goebel, 2007), the FEMTO bearing dataset (FEMTO Bearing Data Set, 2012), the Scania Component X dataset (Kharazian, Lindgren, Mangússon, Steinert, & Andersson Reyna, 2025) and the SCADA wind turbine dataset (Wind turbine scada signals 2016, n.d.).

The NASA battery dataset is a dataset developed by subjecting lithium-ion batteries to accelerated aging experiments. The batteries were repeatedly charged and discharged under different conditions and the current, voltage and temperature was measured during each cycle and the battery capacity was measured after each cycle. Similarly, the FEMTO dataset is developed by subjecting ball bearings to accelerated aging in a laboratory environment. An experimental setup was built and the bearing housings were equipped with vertical and horizontal accelerometers and a temperature sensor. The bearings were then spun with a certain angular velocity and under a certain load until the acceleration magnitude reached 20 g (g being the gravitational acceleration).

Other datasets come from recorded industry data. The Scania Component X dataset is based on recorded operational data and repair records for a number of Scania heavy-duty road vehicles. The component itself is an unknown engine component and all of the data has been normalized and the data types have been erased to protect proprietary information.

Another industrial dataset is the SCADA dataset for wind turbines. SCADA is short for Supervisory Control and Data Acquisition and is a system for monitoring industrial processes, but this particular dataset is one recorded from offshore wind turbines (Zhang, Vatn, & Rasheed, 2025). It contains about 80 recorded features, ranging from temperatures of different components, rpm of different components and ambient environmental conditions.

In the NASA dataset, the degradation is defined as the decrease in capacity of the batteries, and failure is often defined as the time when the capacity decreases below a threshold value, usually between 70-80% of the original capacity. Examples of prognostics on this dataset in the literature are (Ma, et al., 2019), (Zhang, Li, & Li, 2020) and (Zhang, et al., 2019). In (Ma, et al., 2019) and (Zhang, Li, & Li, 2020), neural networks (NN) are used to predict the

future degradation based on past degradation. The process is illustrated in Figure 1, which shows the degradation of one of the batteries in the dataset. The dots show the measured data and the crosses show the results of a convolutional neural network (CNN) trained to predict the degradation in capacity. The process will be explained in slightly more detail for clarity.

The green dots in Figure 1 show the training data that is used to train the CNN, this data forms a vector  $x = (x(1), x(2), \dots, x(n))$ , where  $x(i)$  is the capacity measured after load cycle  $i$  and  $n$  is the number of training data points. Now an embedding dimension  $d \in \mathbb{N}$  is chosen and the data is arranged in the following way:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \dots \\ X_{n-d} \end{bmatrix}, X_i = (x(i), x(i+1), \dots, x(i+d-1)) \quad (5)$$

$$Y = \begin{bmatrix} x(d+1) \\ x(d+2) \\ \dots \\ x(n) \end{bmatrix}. \quad (6)$$

Each row in the matrix  $X$  is a window sequence of length  $d$  from  $x$  and the corresponding element in  $Y$  is the element from  $x$  that immediately follows the sequence. The CNN is trained to predict the elements of  $Y$  using the rows of  $X$  as input. The results can be seen in Figure 1 as the blue crosses.

Once the model is trained the future capacity is predicted by inputting the last  $d$  elements of  $x$  into the CNN, thus predicting the capacity one cycle into the future from known data. The prediction can then be fed back into the CNN by including it in the input sequence, thus predicting the capacity 2 cycles into the future. This process is repeated until the predicted capacity reached the threshold. The predicted future capacity can be seen as the black crosses in Figure 1, while the red dots show the actual capacity. For this particular model,  $d$  was selected to be equal to 11.

This method is known as 1-step ahead prediction and is what is done in (Ma, et al., 2019), although with a different NN architecture. In (Zhang, Li, & Li, 2020) a similar approach was used, but one that allowed for prediction multiple cycles ahead.

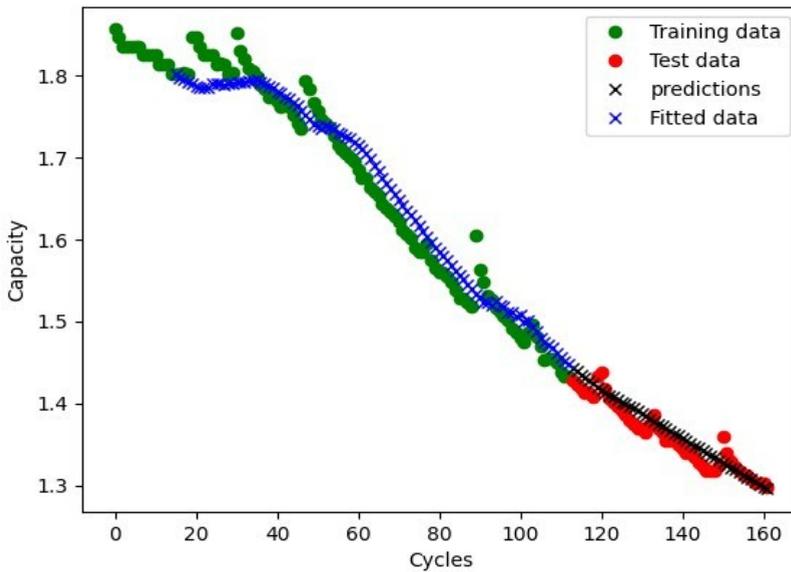


Figure 1. Predicted degradation of battery capacity.

These methods assume that the degradation can be directly and easily measured and that failure can be simply defined using the degradation. This is not always the case and sometime the degradation has to be estimated from other data. Staying with the NASA dataset, in (Zhang, et al., 2019), features extracted from the voltage and current measured during discharging are used to estimate the capacity and RUL indirectly using a neural network.

For the bearing dataset, failure was defined as the point when the acceleration reached 20 g. The research that uses this dataset focuses on extracting features from the vibration data that show clear increasing or decreasing behaviour with regards to RUL. In (Kim, An, & Choi, Applications of prognostics, 2017), the entropy for certain frequencies in the acceleration spectrum was used to estimate the RUL. The frequencies were selected so that the entropy decreased with increasing number of load cycles, as this behaviour was similar for all bearings, despite wildly varying RUL.

In (Zhang, et al., 2022), different features from the vibration signal, both time and frequency features, were used to estimate the reliability of the bearings, with focus being put on determining the best time to remanufacture the machine containing the bearings.

In contrast, the wind turbine dataset contains the operational data of four different wind turbines, as well as the logs when certain events occurred. This also means that failure is not defined by any of the recorded features and the relationship between the signals and the failure has to be learnt by the model. In (Zhang, Vatn, & Rasheed, 2025), a normal behaviour modelling (NBM) approach is used. NBM is based on the concept of defining a normal state when the product is healthy and then using the deviation from this normal state to define how close the system is to failure. A regression model was trained to estimate the temperature at different parts of the wind turbine based on other recorded features, such as rpm. The model was trained on data recorded a long time before failure occurred. This means the model will accurately estimate the temperature when the system is far from failure. As the wind turbine degrades, the relationship between the temperature and other parameters changes, which means that the regression model performs worse. The difference between the result of the regression model and the actual temperature could then be used to estimate the level of degradation.

Finally, the Scania Component X dataset contains operational readouts for 14 different features in time as well as the time that the unknown was replaced (if it was). In (Zhong & Wang, 2024), (Parton, Fois, Veglió, Metta, & Gregnanin, 2024) and (Carpentier, De Temmerman, & Verbeke, 2024), different machine learning algorithms were used to predict the RUL of the component as part of a challenge. For this dataset, the degradation is not directly known, in fact, due to the anonymization of data, not even the types of data collected are known, so the problem of identifying features that relate to failure have to be learnt purely from data, as knowledge about the product and data is non-existent.

### 3. DISCUSSION AND CONCLUSIONS

Based on the four datasets presented and the literature examples using them, some preliminary conclusions can be drawn regarding the necessary data for prognostics to be successfully implemented. One thing that all datasets have in common is that they contain data recorded during a large part of the product use phase, both when the product is healthy, degraded, and when the product fails. For the battery and bearing datasets, the failure is defined in terms of thresholds of the measured data, meaning that, theoretically, no other data is required for a prognostics model, one can simply use time series analysis to predict the future degradation based on past measured degradation. However, as is seen in the bearing dataset, the acceleration remains fairly stable during

a large part of the lifetime and only changes significantly very close to failure, making prognosis difficult. While feature extraction and signal processing can help mitigate these issues, having data on more features could help the prognosis model, as these might be more stable in their change over time.

From the two industrial datasets, the failure of the component is its own category, completely unrelated to any of the recorded data. In both datasets a large number of different data are recorded continuously during operation of the product in question, from a healthy condition all the way to failure.

As the purpose of the presented work is to develop evaluation criteria for if a product has sufficient data recorded during operation to facilitate the development of a prognostics model, the two industrial datasets are deemed most important. This is because the failure of a product in an automotive context usually is discovered during an inspection or due to the performance suddenly worsening, which is unrelated to the recorded data. While a direct measurement of the degradation of health state is useful, the two most important features of a product dataset are that data is recorded from when the product is healthy and all the way until failure and that a large amount of unrelated features are recorded, as the relevant features are unknown a priori and are determined during development of the prognostics model.

Because the proposed criteria are defined independently of any specific product and manufacturing method, they can easily be applied to a large amount of different types of products.

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