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Development of a Data Model for Production Program Planning in Remanufacturing

Master's Thesis

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II Abbreviations and Symbols

Abbreviation	Unit	Description
ARIMA		Auto-Regressive Integrated Moving Average
BOM		Bill of Material
CAD		Computer Aided Design
CAM		Core Acquisition Management
CBR		Case-Based Reasoning
CE		Circular Economy
CPOF		Capacity Planning using Overall Factors
CPS		Cyberphysical Systems
CRM		Customer Relationship Management
CRP		Capacity Requirements Planning
DPP		Digital Product Passport
EC		Exclusion Criteria
ECD		Electronic Control Device
EEE		Electrical and Electronic Equipment
ERP		Enterprise Resource Planning
ESG		Environmental, Social, and Governmental
EV		Electric Vehicle
IC		Inclusion Criteria
IDEF0		Integration Definition for Process Modeling
IoP		Internet of Production
IoT		Internet of Things
LLC		Low-Level-Code
LLM		Large Language Model
LSR		Lot-sizing Rule
MD		Master Data
MRR		Material Recovery Rate
MRP		Material Requirements Planning

MRP II		Manufacturing Resource Planning
MPS		Master Production Scheduling
OEM		Original Equipment Manufacturer
PLM		Product Lifecycle Management
PLT		Planning Lead Time
PPC		Production Program Control
PPP		Production Program Planning
QR		Quick Response
RCCP		Rough-cut Capacity Planning
RFID		Radio Frequency Identification
RS		Rough-set
UML		Unified Modeling Language
UN		United Nations
WEEE		Waste Electrical and Electronic Equipment
WWL		World Wide Lab
C	€	Sum of all costs caused by the product p
$D(\tau)$		Product quantity in interval $\Delta\tau$
$D_{r,m}$	h	Deviation of available capacity from required capacity
$GD_{c,m}$		Gross demand for component c in month m
$\mathrm{h}_{\mathrm{req,r,t}}$	h	Hours needed on resource r in planning period t
$I_{o,c}$		Current inventory of component c
$I_{0,p,m}$		Current inventory of product group p
$I_{c,m}$		Inventory of component c in month m
$I_{max,c}$		Maximum inventory of component c
$I_{mix,c}$		Safety stock of component c
$ID_{component}$		Unique Component Identifier
ID_{group}		Unique Product Group Identifier
$ID_{product}$		Unique Product Identifier
l_p	€	Warehousing costs per product
$L_{t,p}$		Stock volume in planning period t

$\mathrm{N}_{\mathrm{coresAvailable}}$		Number of cores available for purchase
$N_{\mathrm{p,t}}$		Needed quantity of product group p in planning period t
$\mathrm{N}_{\mathrm{remanSales}}$		Number of expected sales of remanufactured products
$N_{productInMonth}$		Number of the product in this month
$Name_{component}$		Name of a component
$ND_{c,m}$		Net demand for component c in month m
$ND_{p,m}$		Net primary demand for product group p in month m
$OIP_{p,m}$		Orders in production of product p in month m
p		Product group
$PT_{c,r}$	h	Processing time of component c on resource r
r		Resource
r_c		Reliability of the damage probability
$S_{p,m}$		Expected sales of remanufactured products in month m
$\mathrm{S}(\tau, \mathrm{t})$		Disposal distribution
$SR_{c,m}$		Scheduled receipts of component c in month m
t		Planning period
$TAPT_{r,m}$	h	Total available processing time on resource r in month m
$TRPT_{r,m}$	h	Total required processing time on resource r in month m
u_{t}	€/h	Costs per extra hour
U_{t}	h	Number of extra hours
$\mathrm{x}_{\mathrm{p,r}}$	h	Production time for a product of type p on resource r

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1 Introduction

1.1 Motivation and Objectives

The manufacturing-oriented companies assume the main share in global industrial activities, transforming natural resources, capital, and technology into products. Besides the positive impacts of manufacturing on economic growth and employment, there are severe environmental impacts in terms of waste creation as well as energy and material consumption (Sutherland et al. 2020, p. 1). Furthermore, the industrial sector accounts for one-third of the global annual CO2 emissions, which were 11.6 Gt in 2018 (International Energy Agency 2019). The exploitation of resources poses a significant challenge for the manufacturing industry, as it leads to fluctuations and increases in material prices as well as to increasing political power of the nations that control these resources (Ellen MacArthur Foundation 2017, p. 6). In the current situation, the resources of two earths are needed to maintain the level of consumption sustainably. This is estimated to worsen if no drastic measures are taken (Sutherland et al. 2020, p. 2), as with the still growing population, more resources will be needed in future (Ellen MacArthur Foundation 2017, pp. 19–20). Therefore, there is a continuous movement towards anchoring sustainability in the manufacturing industry. Additionally, legal regulations such as the European Green Deal (European Commission 2019) and the Circular Economy Action Plan (European Commission 2020), as well as investment incentives like the ESG-criteria (Park and Jang 2021), make considering sustainable development almost inevitable in strategic production management (Schuh and Schmidt 2014, p. 16).

A strategy to become more sustainable is implementing a Circular Economy, which aims to close material loops, to use resources more efficiently, to decouple economic growth from the use of resources, and to ensure long-term competitiveness (European Commission 2020, p. 2). Manufacturers play a key role here (Andersen et al. 2022), but are still looking for guidance when implementing methods that enable circularity (Murray et al. 2017, p. 1).

Circularity can be achieved by, e.g., the reuse of products, their repair and reconditioning, and remanufacturing. Remanufacturing is a standardized industrial process in which products are returned to their original, as-new, and improved condition with full warranty (Remanufacturing Industries Council 2022). The largest sectors of the remanufacturing industry in Europe are aerospace and automotive parts supply. In 2019, Mercedes-Benz had 20.000 components in their remanufacturing portfolio, including classic elements of the powertrain and HV batteries of electric and hybrid vehicles (Daimler 2019, p. 48). Caterpillar, a leading global manufacturer of earth-moving equipment, offers a wide variety of remanufactured products and aims to increase sales and revenues from remanufacturing offerings by 25 % from 2018 to 2030 (Caterpillar Inc. 2021, p. 7). Other big companies engaging in remanufacturing are Kodak, Xerox, Delphi, and Volkswagen (Subramoniam et al. 2013; Volkswagen AG 2021, p. 63).

While remanufacturing is already used in industry, there is often a lack of standardized, efficient processes (Östlin 2008, p. 1). In remanufacturing, products that have reached the end of their life cycle become core components of new products, turning the customer into the supplier (Östlin 2008, p. 6). This affects the creation of the production programs, which are an essential component of production planning. The feasibility of the production program depends sensitively on the availability and condition of the returning products and their components. Production program planning in remanufacturing is therefore subject to an elevated level of uncertainty.

In literature, the challenges of remanufacturing have so far been approached in several ways. ACERBI et al. (Acerbi et al. 2022) propose a data model for intermediate to long term strategic decision making on which strategy to implement when dealing with circular economy, but the model does not facilitate production program planning in intermediate planning horizons. ANDERSEN et al. (Andersen et al. 2022) discuss data management systems needed for implementing circular strategies but do not explain the effects on production program planning. Models specifically intended for creating a production program using mathematical approaches like the work of GIGLIO et al. (Giglio and Paolucci 2014) incorporate sales planning to a limited extend and make assumptions about the available data. GAO et al. (Gao et al. 2023), MUSTAJIB et al. (Mustajib et al. 2021), and JIANG et al. (Jiang et al. 2019) propose models that predict the quality of components or process sequences, but partially rely on data points that must be collected when cores are returned and do not elaborate further on the effects on the production program. In the automotive industry, production program planning can be conducted several months before production (Klug 2010, p. 372). At this point in time, key information on which existing planning models are based is not yet available.

A data model covering all data points needed to create a production program in remanufacturing before a core returns to the remanufacturer could reduce the uncertainties and short planning lead times, making production program planning in remanufacturing more reliable. Therefore, the research question for this thesis is:

How can a data model be designed for data-based production program planning in remanufacturing?

1.2 Structure of the Thesis

To systematically derive the answer to the research question, chapter 2 describes the processes and methods that are part of production program planning. It also analyzes which data, and data classes are used. In addition, insights into the Internet of Production and the Digital Product Passport provide information about infrastructures that are currently gaining importance in data-based production planning. Then, remanufacturing is explained as one approach to a more sustainable production with lifecycle-spanning planning. In doing so, the specific contexts and challenges of production program planning in remanufacturing are elaborated. By analyzing the equivalent processes in the automotive industry, it is shown how highly complex products influence in the planning processes. The chapter also serves to define the scope of the thesis.

Chapter 3 then analyzes the current state of research by conducting a systematic literature review. For this purpose, consideration criteria are defined that narrow down the scope of the selected literature, which is then analyzed regarding predefined evaluation criteria. Only literature that shows intersections from production program planning and remanufacturing is considered. The selected literature is analyzed based on evaluation criteria with regard to the core planning processes of the production program planning. Those are sales planning, primary demand planning, and gross resource planning. Other evaluation criteria for the literature are the comprehensiveness of the proposed models and their scalability.

Based on the findings from chapter 2 and 3, the concept of the developed solution for the research question is presented in chapter 4. The basis of the model building is defining the remanufacturing process. Then, the activities of production program planning in remanufacturing are derived, and the data required to implement the activities is identified. In the next step, the data is combined into a data model.

In chapter 5, the process for obtaining the detailed solution is explained. The activities in the activity model are described using the IDEF0 method, dependencies between the activities are clarified, and the corresponding data requirements for input, constraint, resource, and output data are derived. This data is categorized into classes, and relationships of classes are defined using the Unified Modeling Language (UML) to obtain the data model.

In chapter 6, the data model is validated. For this purpose, a prototypical simulation model is developed that reflects core aspects of the data model and of the activity model. The simulation model is evaluated with components from the production of electric vehicles, and it is used to create a prototypic production program for an example scenario in remanufacturing. Finally, the limitations of the developed solution are analyzed.

Chapter 7 provides a summary of the results obtained throughout this work and gives an outlook for the need for future research and action.

2 Fundamentals and Scope

2.1 Scope within Production Planning

For the definition of this work's scope within production planning, German, English, and Spanish literature is reviewed to outline similarities and differences between the established fundamental concepts which result in a production plan. The scope is then defined based on commonalities of the definitions.

2.1.1 Production Planning and Control

In German literature, the task of production management is to design, plan, monitor, and control production, using the company's available resources such as employees, materials, machinery, and information. In this context, operative production management aims to produce products in the required quantity and quality at a defined time while minimizing costs (Lödding 2016, p. 7; Schuh and Schmidt 2014, p. 1). One of the core processes in operative production management is production program planning (PPP, literal translation of the German term *"Produktionsprogrammplanung"*), which results in a feasible production program (Lödding 2016, p. 110; Wiendahl 2010, p. 272). A feasible production program is essential for high delivery reliability (Lödding 2016, p. 110).

PPP is a sequence of the three subtasks sales planning, primary demand planning, and gross resource planning, which are conducted periodically. The sequence is shown in Figure 2.1 and can be seen as a modular method, where each of the three modules requires a certain input and delivers a defined output for the subsequent module (Wiendahl 2010, p. 258). There are various levels of detail for the subdivisions of the general process, like naming the management of customer orders and the determination of delivery times as separate entities, which the three-step sequence includes implicitly as cross-modular tasks (Wiendahl 2010, pp. 257–259). The production program is developed in close coordination between production and sales, because in order to sell, production must be capable of providing the products in time, with the limiting factors being production capacity and the availability of resources. The sales plan incorporates demand forecasts and direct customer orders. Consecutively, to ensure a balanced usage of resources and to check whether primary demand can be matched, a gross resource planning is conducted. Primary demand includes final products for the customer and pre-produced standard components. PPP uses different types of information and focuses on different tasks depending on the underlying production type, like make-to-order or make-to-stock. (Schuh and Schmidt 2014, p. 64)

If the delivery times demanded by customers are shorter than the necessary manufacturing time, (pre-)production or purchasing, and warehousing is necessary up to a certain point in production, called decoupling point. Another reason for decoupling can be high machine setup costs for small customer order quantities. (Lödding 2016, p. 168; Schuh and Schmidt 2014, p. 64)

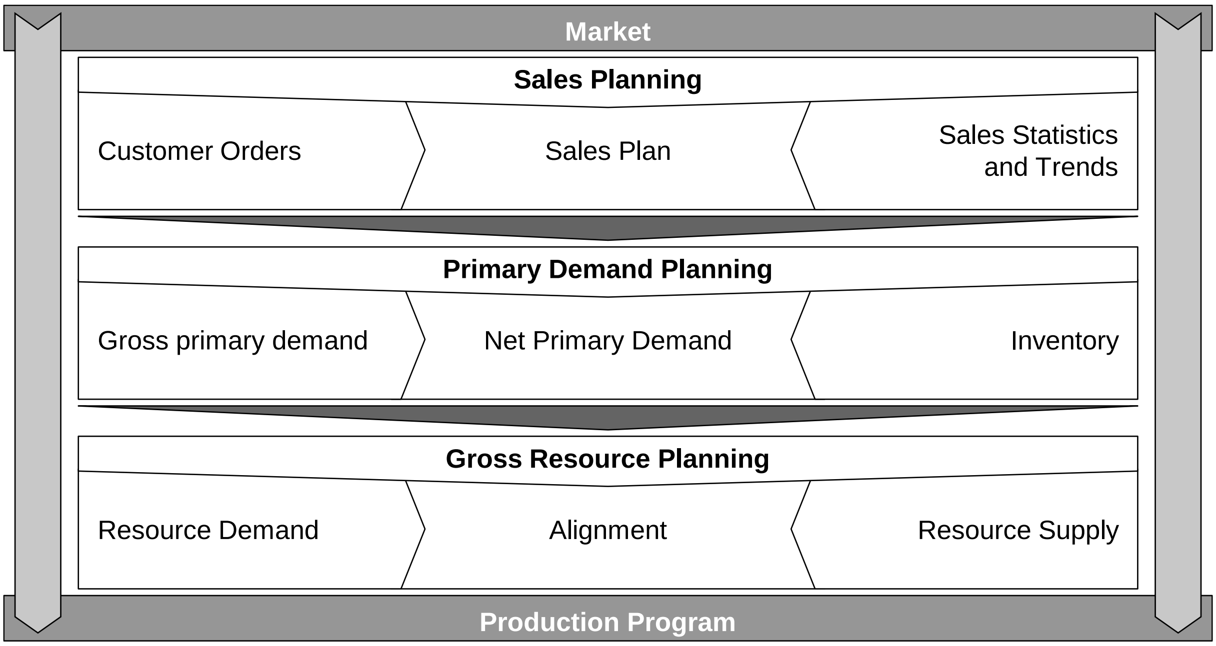


Figure 2.1: Sequence of tasks in production program planning (Schuh and Schmidt 2014, p. 65)

The aim of sales planning is to determine when a certain quantity of a product needs to be available. This can be done for product groups to save costs in case of a large number of final products. One example is the automotive industry, because the exact specifications of a car are determined just before entering the assembly line (Hopp and Spearman 2000, p. 237). In the sales plan, existing customer orders are considered as well as sales statistics and trends or profit targets. Sales forecasts are particularly important for companies which produce to stock, without assigning products to a specific customer before they are sold. Also, a forecast for standard products and components is necessary to check in gross resource planning if the sales plan is achievable. Different forecasting methods are used depending on the sales trend's behavior. A sales trend can rise, be constant or fall, and have seasonal dependencies. (Schuh and Schmidt 2014, p. 67)

Depending on the model, a development plan can be considered independently from the sales plan. It is created in parallel with the sales plan and describes the necessary technical developments of the products and services. The development plan is based on current weaknesses and strengths of the products and identifies development opportunities. It includes the costs associated with the development and compares the expenses with the expected sales. Developments can be functional enhancements to existing product families, changes in production processes, or, in rarer cases, new product developments. (Wiendahl 2010, p. 59)

Primary demand is derived from the demand stated in the sales plan, from existing orders, and, if necessary, from other internal demands. For primary demand planning, product groups must be disaggregated, if the sales plan was conducted at group level. Therefore, the quantities of the different end products as members of a product group must be known. Customer-related orders do not have to be fully specified at the instant they are planned for production. In this case, it is necessary to temporarily assign similar parts for planning purposes. The result is a preliminary production program stating net primary demand, which is the quantity of products that must be produced after deducting stock and orders, which are currently being produced. The production program also includes external demand. (Schuh and Schmidt 2014, pp. 67–68; Wiendahl 2010, p. 60)

Resources are staff, material, and operating or auxiliary tools. The resource requirements for the items defined in the preliminary production program, like type, quantity, and date or period, are roughly planned and compared with the available resources to check whether net primary demand can be produced. The result is the production program. If representative or summarized data is used, the requirements from the preliminary production program must be assigned to the substitute products which were used. (Schuh and Schmidt 2014, p. 68)

2.1.2 Manufacturing Resource Planning

The corresponding English term for an integrated production planning and control process is manufacturing resource planning (MRP II), which includes a subset of processes that facilitate planning and control for short-, intermediate-, and long-term planning horizons. The processes in MRP II can be seen in Figure 2.2.The long-term planning horizon is of 6 months to 5 years and includes long-term demand forecasts, resource planning at the level of investing in new plants or expanding existing ones and aggregate planning, which determines long-term production-, staff-, and other capacity-requirements. (Hopp and Spearman 2000, pp. 136–137)

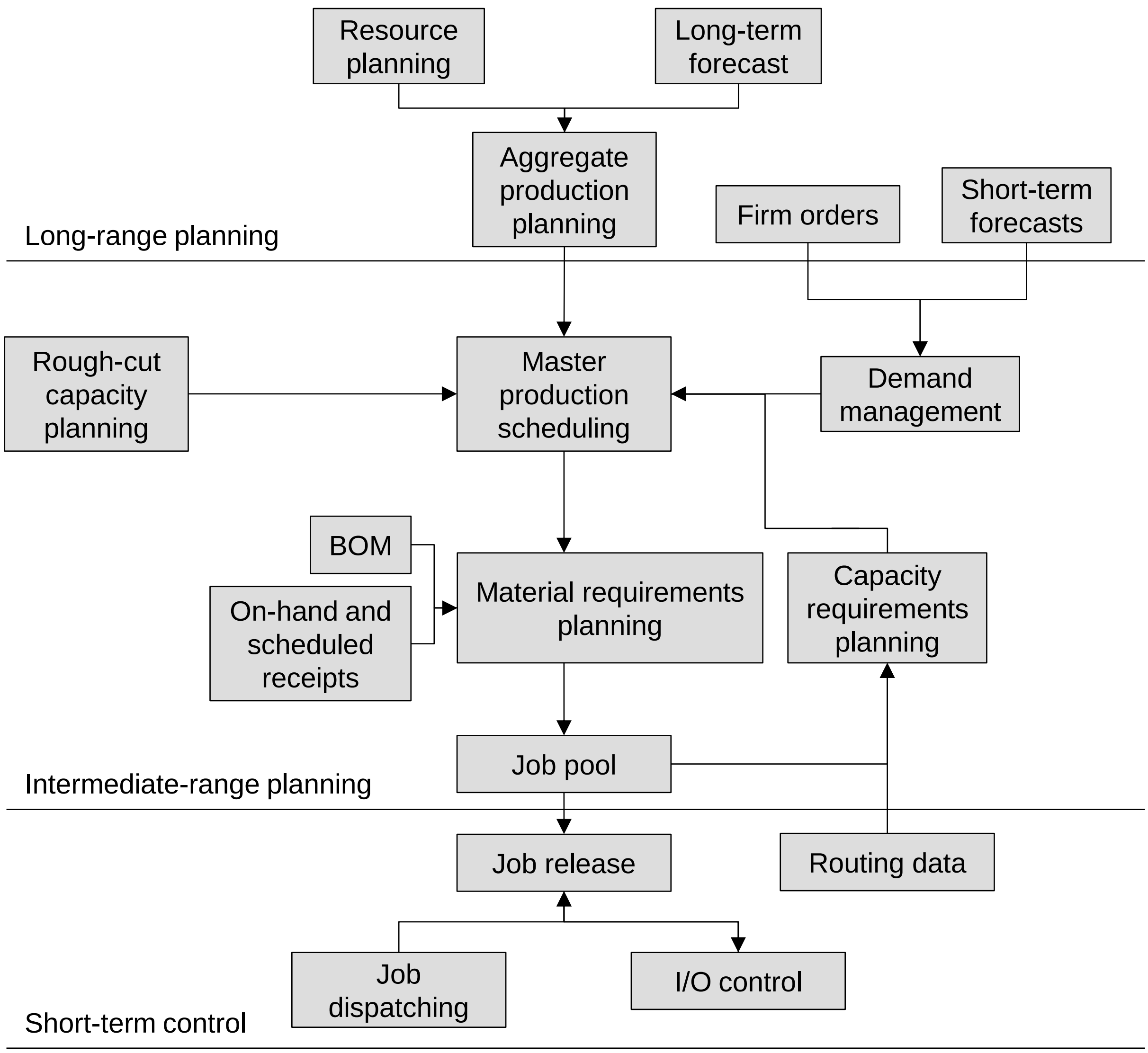


Figure 2.2: MRP II flow chart (Hopp and Spearman 2000, p. 136)

At the intermediate range, a first important step is demand management, which aims to narrow down the aggregated forecasts into detailed and, if applicable, customer specific demands for the next planning periods. Here, it is crucial to determine the already committed orders and the available capacity for new ones which can be promised to a customer. These so-called firm orders, are orders which are fixed and will not be altered, which helps to stabilize production. (Hopp and Spearman 2000, p. 137)

Then, in master production scheduling (MPS) the specific quantity and due dates for all parts of independent demand, including the demand for end parts and the demand for external sub-parts is determined (Jacobs et al. 2018c; Hopp and Spearman 2000, p. 114). In MPS, independent demand is any external demand while dependent demand is the underlying demand for components that comprise the products of independent demand (Hopp and Spearman 2000, p. 110). If the products are complex and therefore the MPS planned at group level, a final assembly schedule determines when the exact end items are produced. Such planning requires a superbill of material which contains forecast percentages for the different variants of each group or model (cf. automotive industry) (Hopp and Spearman 2000, p. 137).

To check the viability of the MPS regarding the availability of resources, a rough-cut capacity planning (RCCP) is conducted (Jacobs et al. 2018b). A simple example of RCCP is shown below. RCCP uses a bill of resources, which states how many hours $\mathrm{x}_{\mathrm{p,r}}$ are needed for a product of group p on resource r to fabricate each part on the MPS and their sub-parts. The first step is to calculate the total hours $\mathrm{h}_{\mathrm{req,r,t}}$ needed on each resource in each planning period t. This is shown in equation 1, where $\mathrm{h}_{\mathrm{req,r,t}}$ is the sum of the products of the quantity $N_{\mathrm{p,t}}$ of each product needed and of $\mathrm{x}_{\mathrm{p,r}}$.

$$h_{req,r,t} = \sum_{p=1}^{P} N_{p,t} * x_{p,r} \quad \textbf{(1)}$$

The hours required are then compared to the available hours on that resource. Should there be significant differences, adjustments can be made at an early stage in production planning. The method is also known as capacity planning using overall factors (CPOF) or, when routing information and BOMs are used, as capacity bill procedure (Jacobs et al. 2018b). Inconsistencies with the available resources can be adjusted by either changing due dates for the orders on the MPS or by augmenting or reducing the available resources. Limitations of RCCP are, that there is neither offsetting nor netting considered, meaning that on the one hand the presumption is that one part can be fabricated within the same period. On the other hand, subassemblies and stock are ignored, making RCCP an optimistic estimate of what can be realized realistically. (Hopp and Spearman 2000, p. 139)

A core process of MRP II is material requirements planning (MRP). There, the MPS is taken as an input to schedule jobs and purchase orders. It also considers the dependance of end items from lower-level parts. This dependence is described in the bill of material (BOM), which specifies the demand for lower-level items caused by each end items (Jacobs et al. 2018a). All items are assigned with a low-level-code (LLC), which refers to the first moment the product is needed in production, based on its level in the BOM. An end item has LLC zero. The first layer of products which is used to produce the end item is LLC one, as long as it is not needed for the production of any other part at an even lower level. The LLC always refers to the lowest level where the part is needed first in production. Figure 2.3 shows an example of a BOM for the two products A and B and the associated LLCs. The LLC is especially necessary for MRP because it is used to organize the iterations over the sub-level items, starting with items of LCC zero and moving on to higher numbers. (Hopp and Spearman 2000, p. 111)

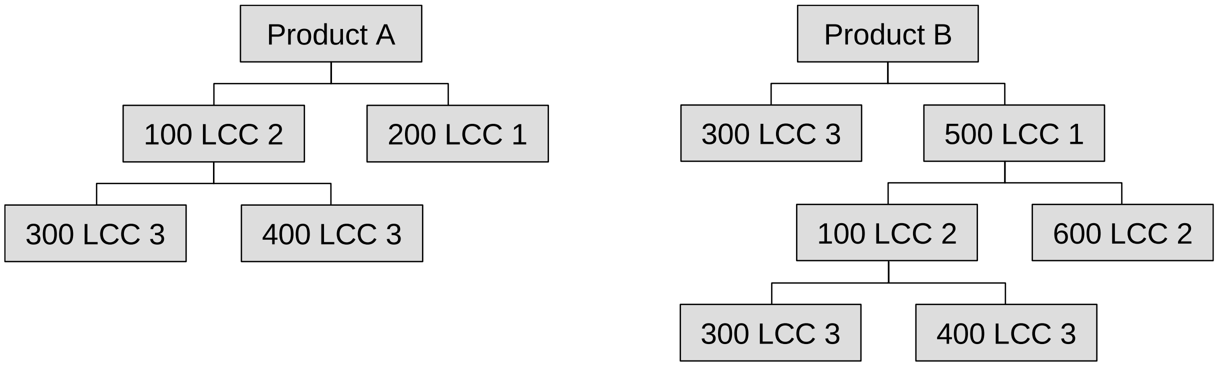


Figure 2.3: Example of a BOM with part numbers and LLCs for two different products (Hopp and Spearman 2000, p. 111)

The main steps to perform an MRP for each level within the BOM can be seen in Figure 2.4. In summary, the necessary minimum information which must be provided by MPS as input to MRP are a part number, a need quantity, and a due date for each order. Additionally, the BOM and the current inventory status is needed. The part numbers are typically linked to an item master file which contains other processing information, like lot sizing information, and planning lead times.

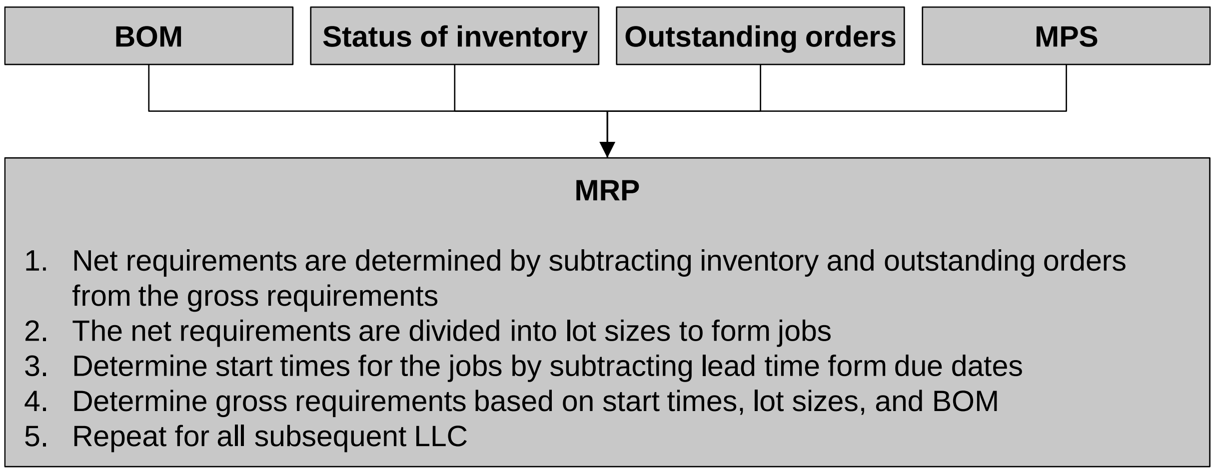


Figure 2.4: MRP scheme (Hopp and Spearman 2000, pp. 111–112)

A typical MRP without firm orders can be seen in Table 2.1 with a lot size of fifteen and a lead time of 1 planning period. There is also an adjustment in the scheduled receipts, postponing the receipts from period one to period two and forwarding the one hundred pieces from period three by one period. In the first case, the stock is sufficient to cover the demand; in the second case, the gross requirements exceed the stock. As a basic rule, scheduled receipts are adjusted before launching new orders, as long as they are not marked as firm orders.

Table 2.1: Example for the calculation of planned orders and receipts of part A (Hopp and Spearman 2000, p. 119)

Part A	Periods:	1	2	3	4	5	6	7	8
Gross requirements		15	20	50	10	30	30	30	30
Scheduled receipts		10	10		100				
Adjusted SRs			20	100					
Inventory	20	5	5	55	45	15			
Net requirements							15	30	30
Planned order receipts							45		30
Planned order releases						45		30	

The last step in the intermediate planning horizon is capacity requirements planning (CRP), which is used to predict job completion times and loads for each process center. CRP requires planned order releases, existing work-in-progress positions, routing data, capacity, and lead times for all process centers as input information. CRP creates a profile of the planned order releases over the planning periods as can be seen in Figure 2.5. The intermediate-term planning results in a collection of planned order releases, called the job pool, which is assigned for production. (Hopp and Spearman 2000, p. 139)

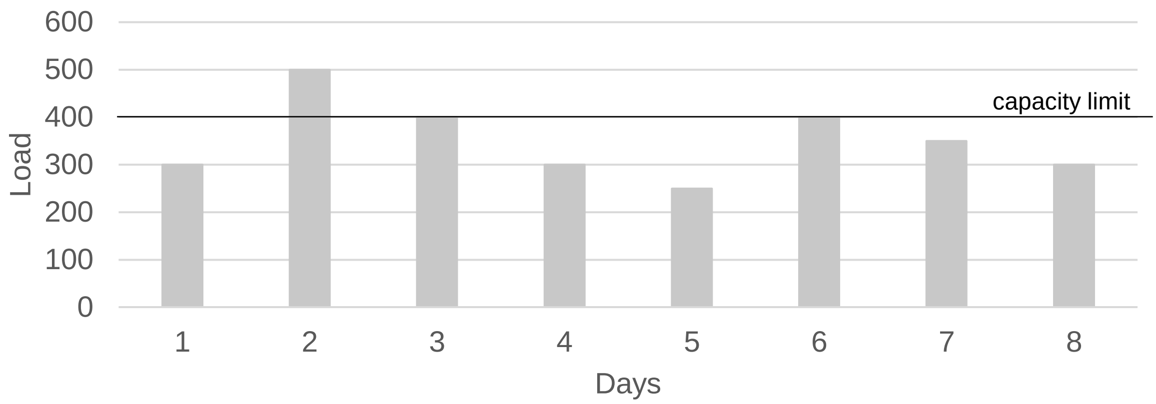


Figure 2.5: CRP load profile (Hopp and Spearman 2000, p. 140)

In case the capacity limit is exceeded, no corrective action is performed because an infinite capacity is assumed, which is a general flaw of both MRP and CRP. Therefore, both methods are only useful in the intermediate planning range. There is also no information regarding the cause of the overload. To resolve an overload, reports that disaggregate the load to determine which jobs are causing the problem are needed to trace back the problem to the MPS.

Furthermore, there are vast amounts of data required and the processes are very time-consuming. The root of these problems is the assumption of constant lead times. There are other methods, which consider capacity limits and adjust lead times. This yields a more realistic result and thus the number of companies using CRP is decreasing. (Hopp and Spearman 2000, pp. 140–141)

All planning results from the intermediate-term phase are given to the short-term control entity, where job releases are scheduled and conflicts in the production of lower-level items are resolved. That includes defining rules for dispatching jobs to certain process steps. Those rules are necessary to maintain the due dates and low manufacturing times while keeping machines at their maximum capacity. (Hopp and Spearman 2000, pp. 141–142)

2.1.3 Excursion into Spanish Literature

The Spanish *“Planificación de la Producción”* defines a *“Plan Maestro”* or master plan based on orders, demand forecasts, and stock. In the master plan it is determined which products are to be manufactured and in what quantities for the next planning periods (Heredia and José 2004, p. 122), which is the equivalent of MPS and MRP in English terms.

Also, the other processes in Spanish literature are similar to MRP II because the English concepts are used as a basis. A standard period for establishing a master plan is two months. For the first periods, the explosion of material requirements for the different parts is done. The term explosion refers to iterating over all levels of the BOMs needed for each product. Knowing the demand in end- and sub-parts, a capacity analysis is performed. The result is a production plan stating the quantities of products to be manufactured in the different process centers of the factory and the demand for materials that need to be purchased. The order of production is not determined, and therefore the effect that the different sequences may have on change-over times is not considered. If the capacity analysis shows that there is not enough capacity available, the master plan is adjusted manually. The actual situation of the manufacturing processes is not taken into account. (Heredia and José 2004, p. 152)

The subsequent step after establishing the master plan and estimating capacity is scheduling the jobs for each process step while following certain rules and resolving bottlenecks (Heredia and José 2004, pp. 147–150). This is the equivalent of what in ERP II is called short-term control.

2.1.4 Definition of Scope

While the literature from English authors like HOPP and JAKOBS, and from the Spanish author HEREDIA ALVARO on methods for production planning are similar in their content and their definition of scopes, the German authors SCHUH, LÖDDING and WIENDAHL define slightly different terminologies and areas for the processes necessary to obtain a production plan. The correlations are shown in Figure 2.6, where the scope of this work regarding production planning is marked by the dark grey areas.

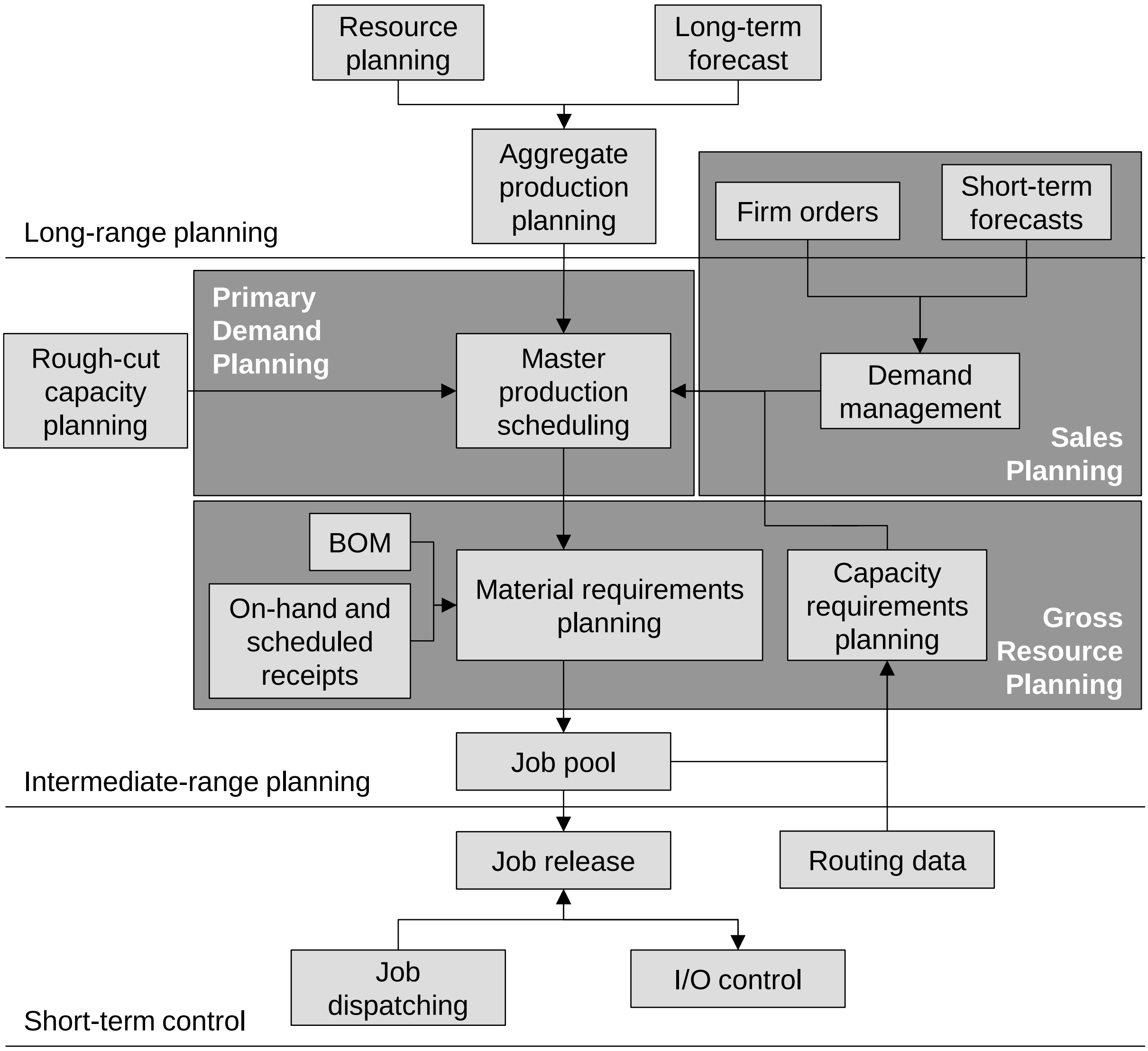


Figure 2.6: MRP II (Hopp and Spearman 2000, p. 136) and PPP (Schuh and Schmidt 2014, p. 65) process

PPP is located mostly at the intermediate planning range of MRP II. Sales planning may exceed the intermediate range depending on the time frame used for forecasts and firm orders, but it is in its core similar to demand management in MRP II and results in an MPS. Planning horizon and duration of a planning period can vary widely depending on the product and company but there is a recommendation for a minimum planning horizon of eight weeks while the minimum planning period is one week (Heredia and José 2004, p. 123). The MPS is part of primary demand planning. The calculations done for MRP at component level are part of gross resource planning. Although the BOM and scheduled receipts are not explicitly mentioned in PPP, it requires the very same information. Gross resource planning also includes CRP in MRP II.

The conditions determined by long-term planning with a planning horizon of more than six months contribute to the intermediate planning period, where the core processes of PPP are located. Those conditions are recognized as an input to PPP but excluded from the scope of this work. The short-term control, which is carried for processes with a maximum planning period of two months, uses the plan developed in the intermediate planning period. It is a subsequent process which is also excluded from the scope of this work.

2.1.5 Methods for Demand Forecasting

Due to the high number of variants and uncertain markets, it is very difficult to reliably forecast demand and to establish reliable production programs (Lödding 2016, p. 3). Demand forecasts can be based on a variety of data, have different levels of aggregation, contain different assumptions about the market, and must therefore be adequate for the application before being used for planning and control activities. They have a continuous influence on all processes and decisions made in PPP, so a forecasting method must be well suited for the actual characteristics in demand development. Mathematically predictable demand development can be stationary, follow a trend, or show seasonal or intermittent profiles. These profiles are shown in Figure 2.7. They can also appear in mixed forms. An intermittent profile shows clear peaks in demand, which can be irregular and return to zero after a certain time. Trendy demand shows an approximately linear development that either increases or decreases over time. Nonlinear trends can also be predicted mathematically as long as there is no inflection point in the demand function. The seasonal profile, unlike the intermittent profile, exhibits a degree of repeatability that can be, for example, weekly, monthly, or annual. The stationary demand profile oscillates irregularly around a mean value. (Schuh and Schmidt 2014, p. 71; Wiendahl 2010, p. 302)

Fluctuations in demand are amplified in supply chains, which is known as the Bullwhip-Effect. The further away the partners of a supply chain are from the end customer, the higher are the fluctuations in demand. In a supply chain consisting of customers, a final producer, a supplier, and a sub-supplier, the final producer experiences the lowest fluctuations in demand and the sub-supplier the highest. (Lödding 2016, p. 139)

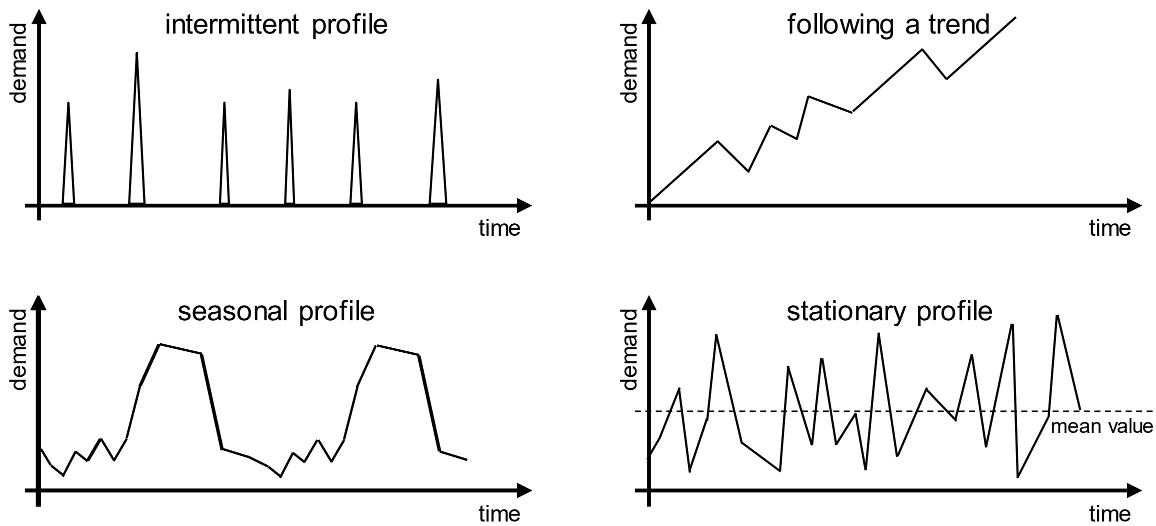


Figure 2.7: Characteristic demand profiles (Schuh and Schmidt 2014, p. 71)

The shown demand profiles can be analyzed using mathematical analysis. Random demand, nonlinear trends, and general structural changes in the demand profile only allow for an empirical-intuitive prediction or a delayed reaction. (Wiendahl 2010, p. 302)

Mathematical forecasting can be done in a simple way, using only the demand of the past periods as input variable to the forecasting model. The forecasting models get more complex if a multivariable approach is used, where the underlying assumption is that future demand depends on several independent influential factors. In models which are based on just one variable, being the demand over the previous periods, the underlying data is obtained by sampling of adjacent points in time, which is why the models are also known as time series analysis (Acerbi et al. 2022, p. 1).

Mean value methods

Using the arithmetic mean of the demand recorded in the past is one of the simplest methods for demand forecasting. It is possible to use either the average of all demand recorded in the past or to define a time frame for the considered past demand. The demand for each considered previous period is summed and divided by the number of considered periods. The method smooths out trend-like behavior, especially if many prior periods are used to calculate the mean. Forecasting using mean values is therefore only suitable for stationary demand profiles. (Schuh and Schmidt 2014, pp. 72–73; Wiendahl 2010, p. 303)

Exponential smoothing

First order exponential smoothing is a special case of mean value forecasting. It assumes that more recent demand development is more relevant for demand forecasting, so there is a weight applied to the errors made in the previous demand forecasts. The weight causes errors made further in the past to have a decreasing influence on the current demand forecast. The higher the weight, the more the forecast is prone to fluctuations caused by the most recent demand development. Smaller weights increasingly smooth out the forecast. The method needs less historical data, since only the most recent forecast value is included in the calculation of the new forecast. It is also easy to adjust by changing the applied weight. The forecast follows the real course with a time lag and is not suited for stationary demand profiles. (Wiendahl 2010, p. 304; Schuh and Schmidt 2014, pp. 74–75)

Second order exponential smoothing can be used if the demand curve follows a trend, since changes in demand from period to period are considered individually. The method uses an additional weight to consider the slope of the demand development over the previous period. One of the prominent methods for second order exponential smoothing was developed by HOLT (Holt 2004). In contrast to other methods that include linear trends in the forecast, HOLT's method has the advantage that new forecast values are very easy to calculate and only a small amount of data is needed. (Schuh and Schmidt 2014, pp. 75–76)

The method from HOLT can be extended to the method from WINTERS by introducing a seasonal factor to forecast seasonal demand profiles. The actual demand is additionally divided by the seasonal factor of the previous period (Winters 1960). WINTERS' method requires assuming an initial arbitrary value for the seasonal factor, so the initial values for the forecast can derivate significantly from the actual demand. Nonetheless, the forecast adjusts rapidly to the real demand profile. When a large value for the seasonal factor is chosen, the current magnitude of the seasonal development is weighted more heavily relatively to the past development and recent demand developments have a higher influence on the forecast. The method is suited for both trend-like and stationary demand with seasonal influences. But it requires high implementation effort and a previous observation period of at least three to four seasonal cycles to determine a reasonable initial value for the seasonal factor. (Schuh and Schmidt 2014, pp. 77–79)

Forecasting intermittent demands

Intermittent demand leads to major problems in production planning, as it complicates forecasting demand and controlling inventories. The reason for this lies in the variability of the demand quantity and in the irregularity. An often-recited method for forecasting intermittent demand is Croston's method, which is specifically made for intermittent demand. The method is based on exponential smoothing, but periods of zero demand are excluded from the forecast. It is also assumed, that demand sizes are normally distributed. The occurrence of demand in every review period is random and described by a Bernoulli distribution, while the inter-demand intervals follow a geometric distribution. (Syntetos and Boylan 2001)

Regression models

The linear regression method is well suited for forecasting linear demand profiles which can be stationary, or continuously increasing or decreasing. It uses the least squares algorithm to calculate the linear equation which best approximates the previous demand values (Wiendahl 2010, p. 302). The linear equation is then used to forecast the demand for the next planning period. Regression models can also consider more than one independent variable, in which case they are called multiple regression models. Those models are suited for seasonal demand profiles. The independent variables (independent meaning not depending on each other) are often time-dependent. Multiple regression can generally be done with dummy variables, where certain parameters are activated by binary variables to take seasonal influences into account. If seasonal influences show a regularity, the demand can be forecasted using trigonometric functions. The approximation of the function is also done with a least squares method. Trigonometric functions need less parameters, which increases the quality of the estimation given that the underlying assumption of regularity is correct. (Schuh and Schmidt 2014, pp. 81–84)

ARIMA Models

In multiple regression models, the demand is only influenced by the current values of the independent variables. Theoretically, past values of all the variables can influence the current demand. Therefore, regression models often do not capture all underlying dynamics of the demand development (Shumway and Stoffer 2017, p. 75). Auto-Regressive Integrated Moving Average (ARIMA) or Box-Jenkins models, can capture these dependencies by interpreting the time series as a purely stochastically determined series of random values. ARIMA-models are extremely complex and require appropriate software (Jiménez Guerrero et al. 2006).

2.1.6 Methods for Gross Resource Planning

The aim of gross resource planning is to achieve a cost-optimized match between the production quantities in the individual planning periods and the available resources. Therefore, it is necessary to check if the net primary demand can be matched, or, if adjustments are necessary. For gross resource planning, orders can be anonymized. All adjustments can be positioned in between two extreme cases, the first being adjusting the available resources to follow the net demand exactly. This can lead to severe fluctuations in production, but also eliminates the need for warehousing, which reduces the associated costs. The second extreme is to decouple demand and resource availability while maintaining a constant capacity. Should there be less demand than capacity, items can be produced to stock. Should the demand exceed the capacity, orders can be taken from the stock. If the stock is empty, orders will be delayed. Costs to be considered include inventory costs, resource costs including overtime, and outsourcing costs. It is recommended, however, to maintain a certain flexibility to be able to compensate for short-term fluctuations. (Lödding 2016, p. 109; Schuh and Schmidt 2014, pp. 87–89)

Resource smoothing using tabular methods

Tabular methods are an easy way to find an optimal balance between conflicting goals, such as following demand and minimizing costs. Increasing production capacity through overtime or external procurement can compensate for strong fluctuations and enables following demand, but also causes higher short-term costs. In the tabular method, it is assumed, that a product requires a known additional capacity on a certain resource. It is necessary to define an objective for the optimization, for example minimizing inventory costs, and to know the correlation between the objective and the produced items. In the case of inventory costs this can include the costs per period in stock and the costs of added capacity. (Schuh and Schmidt 2014, pp. 89–90)

Resource smoothing using linear optimization methods

More complex problems, where for example more than one product is considered, can be solved using linear optimization methods. The first step is to define an objective function C as can be seen in equation 2. In the given example, C is the sum of all costs caused by the product p and the aim is to find the minimum. The warehousing costs per product are given by l_p, which is multiplicated with the stock volume $L_{t,p}$ in the planning period t. The other part of the equation represents the costs related to overtime, with $\mathrm{u_t}$ being the costs per extra hour and $\mathrm{U_t}$ the number of extra hours. (Schuh and Schmidt 2014, pp. 90–92)

$$Min \rightarrow C = \sum_{p=1}^{P} \sum_{t=1}^{T} l_p * L_{t,p} + \sum_{t=1}^{T} u_t * U_t \quad (2)$$

The solution space of the target function can then be constrained. For example, equation 3 shows that there is a fixed relationship between the stock levels at the beginning $(L_{t-1,p})$ and end $(L_{t,p})$ of a period, the production quantity $X_{t,p}$, and the demand, or the products withdrawn $n_{t,p}$.

$$X_{t,p} + L_{t-1,p} - L_{t,p} = n_{t,p} \quad (3)$$

Other constraints can be:

- The maximum storage capacity that cannot be exceeded, even if it would be cheaper to store more items
- The maximum possible overtime and production capacities
- The non-negativity condition, which all variables must satisfy. Non-negativity means that all variables must be greater than or equal to zero.

Resource profiles for closer analysis of lead times

Simple planning methods for resource utilization do not take into account the specific timing of workloads at individual workstations. By considering resource profiles, planning can be made more precise. Here, production lead time data is considered to create time-phased projections of capacity requirements for individual production facilities. The method requires BOM information and routing data. Resource profiles are a more sophisticated approach to gross resource planning because they are more detailed. In gross resource planning, the time periods for the capacity plan can be of various durations (e.g., weeks, months, quarters). If the time periods used for planning are significantly longer than the lead times, much of the value of the time-phased information can be lost when aggregating the data. This means that planning periods longer than a week may hide important fluctuations in capacity requirements. (Jacobs et al. 2018b)

2.1.7 Limitations of PPP and MRP II in Remanufacturing

Regarding all in- and outputs it is crucial to consider that the analyzed models show certain flaws regarding remanufacturing. MRP II and PPP assume that the needed materials for production can be purchased. But the availability of parts which can be put through a process of remanufacturing depends on the customer, who is also the supplier. MRP II and PPP are highly integrated processes over several departments, which can have opposing interests within the company (Heredia and José 2004, p. 120). The external interfaces are procurement and sales. For remanufactured products, a logical step would be to integrate the customer and the product during its use-phase into the planning process, broadening the scope of MRP II and PPP.

2.1.8 Data in Production Program Planning

Data are a combination of characters that can be converted into information after applying a defined logic. They are structured messages that provide information about past, current, or future states of a system (Philippson and Schotten 1999, p. 219). In the context of production management, there are different approaches to organizing and structuring data. Data can be differentiated by field of application, like product, production, staff, customer, and supplier data, or by function, like master data and movement data, inventory data and change data, as well as application data and control data. (Schuh and Schmidt 2014, p. 44)

Figure 2.8 is a structured representation of typical data and data types found in a manufacturing company. They are explained below. The classification of the data serves only as an example and to improve the overview. No claim is made to completeness.

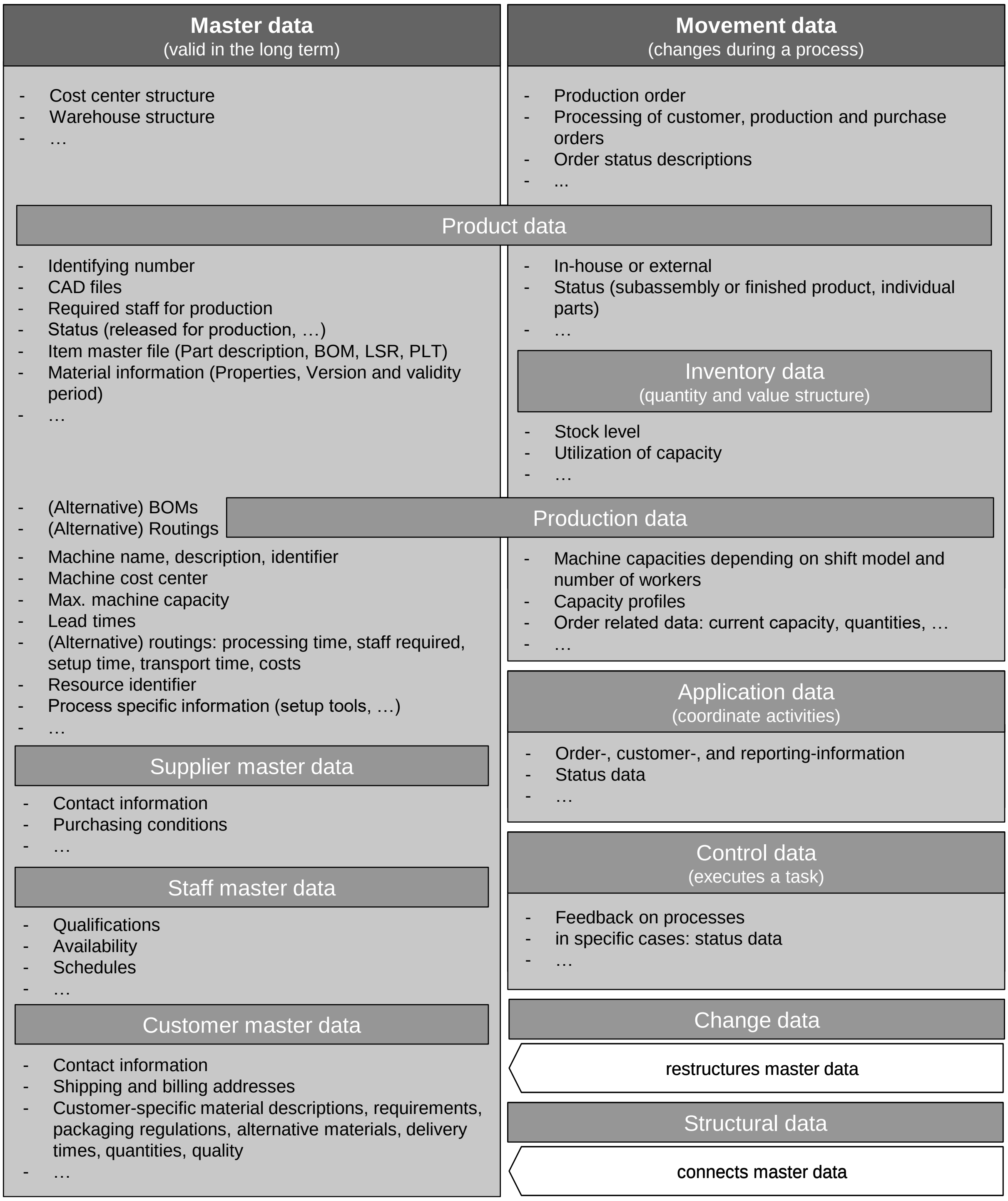


Figure 2.8: Data in production planning

Modern production planning is carried out using enterprise resource planning (ERP) systems that manage data and information from the entire organization. ERP systems digitalize and facilitate the established MRP II planning methods and enable a series of advancements for production planning, like implementing Just-In-Time without Kanban cards or designing processes that combine several techniques to tailor production to the organization. (Heredia and José 2004, p. 116)

Master data

Master data represents the structure of the company and its products (Philippson and Schotten 1999, p. 219). It is frequently accessed in the planning process and requires extensive maintenance efforts. Master data is independent of the orders within a company and includes information that is valid in the long-term, such as the cost center structure and the warehouse structure, the BOM, or the capability to produce certain products. Other typical types of master data are staff master data, customer master data, vendor master data, material master data, and routings. (Schuh and Schmidt 2014, p. 44)

Structural Data

Master data is independent of other data, meaning that there is no additional information needed to interpret it. Another category of data is structural data, which establishes relationships between the characteristics of master data and can therefore not be interpreted independently. (Eigner and Stelzer 2009, p. 80)

Movement data

Information that refers to persons, production orders, machines, and warehouses in the work process, like the processing of customer, production, and purchase orders, belongs to the category of movement data. It is input information to a business process, where it is transformed into input information for a subsequent process. Movement data has two essential characteristics. In contrast to master data, it is only valid for a limited amount of time, like the warehouse stock (Wiendahl 2010, p. 309). The second characteristic is the management of different statuses. For example, production orders can be blocked, released, in process, and completed. Movement data is liked to specific master data information. For example, a production order is linked to the BOM of the ordered part. (Schuh and Schmidt 2014, pp. 42–44)

Inventory data and change data

The terms inventory data and change data can be found in business informatics. They are related to a change in the state of data. Change data is process-oriented information that can cause structural changes to master data while inventory data refers to the quantity and value structure, such as the stock level of an item or the utilization of capacity. By processing movement data, inventory information is frequently changed. (Schuh and Schmidt 2014, p. 45)

Application and control data

In production management, a distinction regarding the use of information is made between application data and control data. Application data is processed during the execution of a business process to coordinate several activities. It includes order, customer, and reporting information. In contrast, control data activates the execution of a task in a process and contains feedback on the progress of the process. Application data often contains status data but depending on the design of a production system, status data can also represent control data, such as a planning board in production or a process instruction. (Schuh and Schmidt 2014, p. 45)

Product data

Properties and components of materials and items in a production system belong to the material master data (Eigner and Stelzer 2009, p. 91). Materials are grouped into in-house production parts, externally procured parts, and externally produced parts. They can further be differentiated according to the degree of processing into finished products, assemblies, and individual parts. Other subdivisions are possible and may be specific to the company or production system. Material master data can be related to other data, like a BOM and routing information for in-house produced items, and standard suppliers for externally procured items. Additionally, every material has a unique identifying number. (Schuh and Schmidt 2014, p. 46)

Attributes of different materials vary with the material's type, like the normed description, dimensions, weight, numbers of associated CAD drawings, unit of measure for procurement, inventory, and production. Product data must still be available after many years, e.g., for spare parts production (Wiendahl 2010, p. 130). Most of the material properties are stored in ERP systems. Materials can be linked to associated alternative materials needed in case of supply bottlenecks or for different lot sizes. In the operations of the assigned routing, the technical and human resources are defined with which the material is produced. There can also be alternative BOMs and routings, which are used when a higher production lot size is required. (Schuh and Schmidt 2014, p. 46)

Forming material groups allows sales planning at product group level. Adding additional attributes, like material and capacity profiles to material groups, enables gross requirements planning for items for which BOMs or routings are not entirely available. Another group of material properties are the status (e.g., released for production), version, and validity period of a material. This information is used to determine the relevance of the data for each department involved in order processing. (Schuh and Schmidt 2014, p. 46)

Key information for manufacturing a product is maintained in the item master file. The item master file contains a description of the part, BOM information, lot-sizing information, and planning lead times. The lot-sizing information is a combination of the lot-sizing rule (LSR) and the planning lead time (PLT). The LSR is needed to define a trade-off between opposing interests in production, like maintaining a small inventory but trying to make use of the full production capacity. The PLT is used to calculate the necessary start time for a job. In MRP this means to subtract the lead time from the planned order receipts. (Hopp and Spearman 2000, p. 114)

Production Data

Production data includes information about the available resources within the factory, like descriptions of machines, how the machines are grouped and what capacity they have depending on the availability of workers and the shift model. Just as products, resources have a unique identifying number. Some information in production is stored linked to a specific process, for example the specific tools or devices needed for a machine setup. Some of this information can additionally be store as machine master data, if it is valid for a long term, like information on the machine number, the name of the machine, the cost center, and the potential capacity. Lead times and alternative routings also belong to the production master data (Eigner and Stelzer 2009, p. 91). The most important machines required to produce a specific item and its capacity requirements are summarized in capacity profiles, which are useful for gross resource planning. (Schuh and Schmidt 2014, p. 47)

The production process for an item is organized by routings, which consist of several operations. Routing information includes the routing status, the validity period for the routing data, and alternative routings. An operation needs information on the processing time on the machine, required staff, setup time, time for transports, as well as the corresponding costs. (Schuh and Schmidt 2014, p. 47)

The control of a production process is based on order-related operational data, which is collected at a specific time and includes current quantities, capacity, and other order-related information. Order-related information changes its state during the production process, so it belongs to the category of movement data. During production planning, master data and movement data is constantly accessed. (Schuh and Schmidt 2014, pp. 47–48)

Another category of data in production planning is warehouse data. Warehouse master data includes the part number of the warehouse item, the storage location, and the minimum stock level. In contrast to warehouse master data, warehouse stock data is movement data because it changes every time an item is stored or removed. Warehouses maintain separate inventory accounts for all item and product master data, where expected and actual input to the warehouse are recorded on the asset side and actual and expected outputs are recorded on the liability side. (Schuh and Schmidt 2014, pp. 47–48)

Production data also includes relevant data related to the production workforce, like the qualifications of the staff, availability and schedules, wage cost rates, and the period of assignment to a machine or machine group. (Schuh and Schmidt 2014, p. 47)

Customer and supplier data

Data related to customers includes contact information, shipping, and billing addresses. Customers can be grouped depending on the objective. To facilitate the handling of markets, groups can be product-based, customer-based, or based on the customers location within a similar region. There can also be material data connected to individual customers or customer groups for the specific material of a specific customers, like customer-specific material descriptions, alternative materials, delivery times and delivery quantities, as well as customer-specific quality requirements and packaging regulations. Like the sales conditions negotiated with a customer, supplier materials can be linked to purchasing conditions, which are specific to a supplier or material. Supplier data also includes contact information for external procurement and external production of material. (Schuh and Schmidt 2014, pp. 49–50)

2.1.9 Identification and Classification Systems

An identification system consists of numbers, letters, or special characters, which are organized in a defined way and describe and classify master and movement data in operational IT systems (Wiendahl 2010, p. 166). It is recommended that numbering systems are simple to use, as short as possible, and adaptable in future (Biedermann 2008, p. 134).

As the previous chapter on data in production planning showed, there are various sources, types, and groups of data. Identification systems help to organize this data and are categorized into part-number systems, staff-number systems, and order-number systems. A part-number system is used to assign products, assemblies, auxiliary and operating materials, or machines to each other. Staff number systems identify employees, customers, suppliers, and representatives. In an order-number system, order-specific data such as sales orders, production orders, or purchase orders are specified. Using identification systems facilitates fast and easy correlation of similar assemblies or BOMs, simplifies managing product variants, and improves procurement coordination. Identification systems also enable a more efficient use of operational IT systems because they simplify the processing of information. The identifier of an article or material number can be used for different data that refer to the same object, like technical drawings, BOMs, or routings. The classification number then serves to assign each object to a group. The number must be constant, systematic, and clear. (Schuh and Schmidt 2014, p. 51; Wiendahl 2010, p. 167)

There are three main types of numbering systems: the parallel number system, the compound number system, and the classification system. Although many more can be found in literature. (Meyer and Sander 2008, p. 134)

Parallel number system

Parallel numbers are used, for example, when the same item has its own identification numbers in different numbering systems or in different areas of application of the same numbering system (Norm DIN 6763 1985, p. 6). The parallel number system consists of classifying and identifying parts. The latter are unique to the object while the classifying part is independent and describes the object. In most cases, the identifying part is formed by a simple, consecutive number. It is possible to assign several classifiers to an identifying part, which is a mayor advantage of this system. It is very flexible and can be changed, reduced, or extended if needed. The system also requires less alphanumeric characters than other systems which reduces the data entry effort and the susceptibility to errors. (Schuh and Schmidt 2014, p. 53)

Compound number system

Features can be dependent on each other or independent of each other. In the case of dependence, the numbering systems are called branched, hierarchical, or compound numbering systems (Wiendahl 2010, p. 169). Compound numbers also consist of a classifying part and an identifying part but there is a rigid connection of both parts within a single number, causing the system to be less flexible than the parallel number system because changes in the classification directly affect the identification. If the classification of a part is changed, its compound number must also adapt to this change. To uniquely identify a part, the complete number must be known. A compound number cannot be extended but an advantage of compound number systems is that numbers can be assigned decentrally. They are also more user friendly, since the classification can be identified directly from the number. (Schuh and Schmidt 2014, p. 53)

Classification systems and feature bars

Classification systems organize objects according to certain properties by which they can be grouped into classes (Norm DIN 6763 1985, p. 3). Each element within a class has a unique classification number. Classification systems simplify the access to information of already existing parts and assemblies which are frequently used. For example, the manufacturing costs of a new item can be estimated by comparing similar parts with a similar cost structure. Another tool for this comparison is a feature bar, which is recommended for companies with modern IT infrastructure. (Schuh and Schmidt 2014, p. 53)

The structure of a classification system and the individual classification criteria highly depend on the specific application. Product requirements, function, form, or manufacturing-related requirements can influence the criteria. For example, the manufacturing requirements of a workpiece are derived from the desired final shape, accuracies, and the surface qualities. A classification system then makes it possible to characterize the individual workpieces according to their technological requirements and to derive classes of components that are similar in terms of manufacturing technology. A disadvantage of classification systems is their limited capability of managing complex part spectrums because either the classification system becomes extremely large, or the accuracy of the description decreases. (Schuh and Schmidt 2014, p. 53)

Feature bars

Feature bars summarize all characteristics and features relevant for a group of items in a structured form (Norm DIN 4000-1 2019). They are used to search for identical and similar items, and simplify the recording or calculation of already existing, similar articles in the processing of orders. This includes access to routing information of similar products, which can be modified and used in production management for the scheduling of orders without creating new routings from scratch. Feature bars simplify the handling of product variants by standardizing them. They allow simple and fast access to a wide range of planning information and documents, and enable shortening setup times by forming setup families. (Schuh and Schmidt 2014, pp. 55–56)

2.1.10 Limits of Classical Data Handling in Remanufacturing

The general data structure of a manufacturing company primarily revolves around the data pertaining to activities taking place within the company itself. However, a gap exists once the products are no longer under the company's control, as there is currently no established infrastructure in place to monitor and track the subsequent journey of these products. This lack of oversight beyond the company's boundaries presents a challenge in terms of maintaining a comprehensive data flow throughout the entire lifecycle of the product.

2.1.11 Internet of Production

There are vast amounts of data in production, which are often hard to access, difficult to interpret, and insufficiently interconnected. The Internet of Production (IoP) is designed to overcome these boundaries. It is to a certain extent similar to the Internet of Things (IoT), which transfers the internet as a worldwide network to the physical world. Main advantages of the IoT are high reliability and accuracy in data collection, high data-storage capacities, fast transmission of data, and the possibility to automate processes (Alarcón et al. 2016, p. 75). In production, the ratio of data to parameters is low, making it difficult to transfer the IoT approach to physical production systems, where information assets with high volume, high velocity, and high variance are needed (Wulfsberg et al. 2019, p. 533).

Within the IoP, the abilities of cyberphysical systems (CPS) are applied to the manufacturing industry. CPS have often been considered isolated from production, even though they can develop higher economic potential by overcoming existing product and industry boundaries (Trauth et al. 2021, p. 275). They are tightly interconnected resources, which contain embedded computers that control physical actuators while receiving and processing information from sensors. The combination of these components creates an intelligent control loop with a certain degree of autonomy, which is adaptive, and can improve efficiency (Zanero 2017, p. 1).

A major advantage of CPS is that they offer a wide range of opportunities for data monetization, especially when connecting different domains. For production planning, data from the production of a material supplier can be used to adapt the parameterization of one's own production processes to any fluctuations in the supplier's processes. Data generated in an IoP extends experimental data and enables improving existing engineering models using data-driven methods. The IoP is meant to be the infrastructure for providing data in real time in a semantically adequate manner and adapted to the application context of the viewer (Wulfsberg et al. 2019, p. 535). A central concept for the realization of the IoP is the digital shadow. (Trauth et al. 2021, p. 277)

In contrast to a digital twin, a digital shadow does not provide a fully comprehensive digital copy, it is not suited for a complete simulation but also does not require a high-resolution database (Wulfsberg et al. 2019, p. 536). Instead, it combines the necessary subset of available data, like field data, simulation data, or data from production engineering models. The information is then processed and displayed in a domain- and application-specific manner, facilitating a cross-domain use of IoP-data. The digital shadow depends on the perspective from which a physical system is viewed, because for each domain the relevant information can be different. Since the data is aggregated and abstracted in a context-specific manner for decision-making, digital shadows enable a reduction of the latency of decision-making situations in production. (Schuh et al. 2020a, p. 7) Digital shadows can be applied to production planning, for example to obtain an optimal production schedule (Becker et al. 2021).

Production includes complex interactions that are often not fully understood. Existing models that represent physical relationships are typically subject to simplifications and specifically designed for their use case. To obtain an improved understanding of the complex mechanisms involved in production, a large number of experiments are required. A major goal of the IoP is creating a World Wide Lab (WWL) where large amounts of field data are made available, resulting in a close connection between manufacturing industries, and science and research. Every data-generating process in the IoP is understood as a potentially valuable experiment. The experiments complement the digital shadows of the production processes, as a digital shadow can be reused for subsequent tasks and continuously improves with use, as the underlying production models are tested, validated, and extended with each successive experiment (Wulfsberg et al. 2019, p. 536). Data-driven methods such as machine learning can derive patterns and models from large amounts of data without a priori knowledge of the underlying physical relationships. Therefore, they assume an important role in the IoP to transform data into decision bases and to further develop and complement existing knowledge-based models. Conversely, the integration of existing expert knowledge and contextual information into data-driven modeling is an important challenge to achieve higher robustness. (Wulfsberg et al. 2019, p. 353; Trauth et al. 2021, p. 278)

Production is currently characterized by various domain silos, each of which uses models and data tailored to the domain. This results in a high degree of heterogeneity, which makes it difficult to use data and knowledge across domains, so that work is often carried out with outdated or incorrect information from other areas. Each domain within the product development, production and use phase of the product should therefore contain all the relevant information for the respective domains (Wulfsberg et al. 2019, p. 534). IoT models use vast amounts of data for multiple parameters and have a high resolution, which is usually neither necessary nor feasible in the context of cross-domain model usability in production. IoP aims to enable an overall exchange of data and information between product development, production, and the use phase, and to enhance productivity and agility in production, which goes beyond the existing organizational boundaries (Wulfsberg et al. 2019, p. 534). Key challenges of IoP lie within the area of data-driven modeling as well as the needed infrastructure. (Trauth et al. 2021, pp. 275–276)

Creating, maintaining, applying, and continuously developing digital shadows requires a cross-domain-functional infrastructure that includes data, models, and decision-makers from all phases of the product's lifecycle. An exemplary depiction of this infrastructure and its levels can be seen in Figure 2.9.

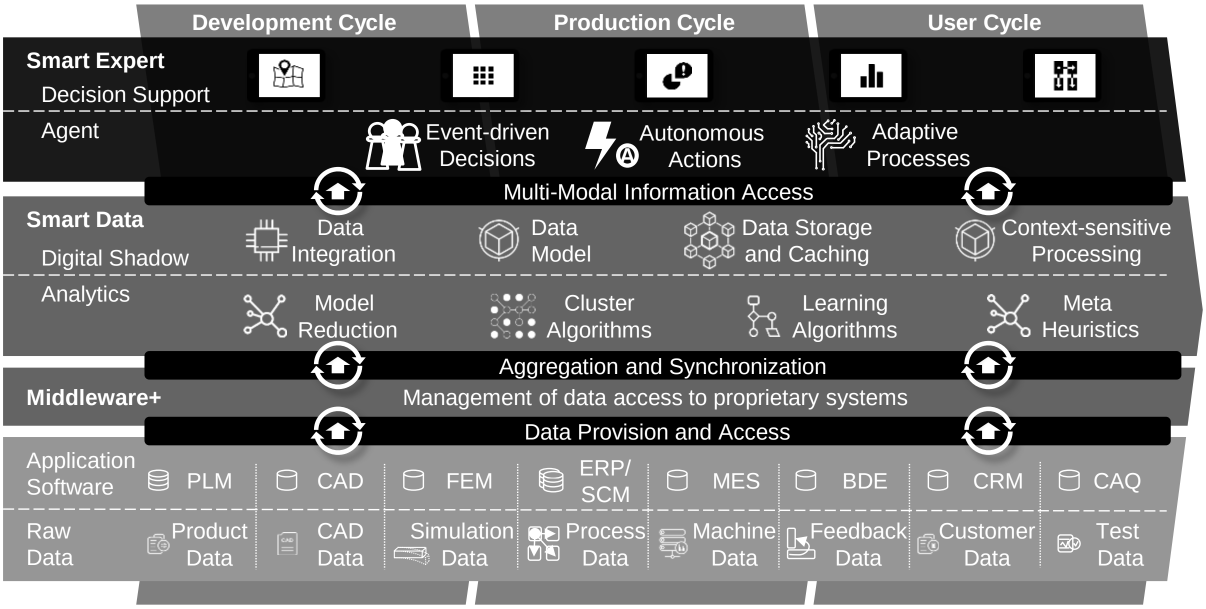


Figure 2.9: Infrastructure of the IoP (Schuh et al. 2020b)

The base level contains vast amounts of raw data from the software-systems used in production, e.g., product data in a PLM system or process data in an ERP system. The raw data can often only be accessed and understood by specialists. Interfaces and data queries must be tailored to the respective systems. Accordingly, the implementation of interfaces which enable recognizing production-related correlations between different domains is costly and time-consuming. The top level is formed by experts who contribute to an intuitive and interactive decision-making process, which is supported by virtual agents. Virtual agents control event-based decisions, autonomous actions, and adaptive processes. They can learn and make decisions autonomously if necessary. This requires an intelligent data layer between the intelligent expert layer and the raw data layer. The layer uses analytical methods and digital shadows that are horizontally and vertically integrated and help to refine the raw data. Comprehensive data models with data storage and caching functions are used to integrate the data. The data is processed context-specifically with minimal latency and made available to the Smart Expert Layer. Methods such as correlation analysis and cluster algorithms capture patterns in data, models, and processes. A Middleware is required as a semantic interface to access the raw data. (Wulfsberg et al. 2019, p. 537)

The biggest challenges of the IoP are controlling and storing large amounts of data from distributed sources and ensuring real-time collaboration through model mappings between proprietary application systems, while complying with data privacy regulations within and across the boundaries of a single organization (Pennekamp et al. 2019, pp. 36–37; Wulfsberg et al. 2019, p. 537). Increasing computing and storage resources will enable new use cases in production in the future, based on complex operations that are not supported by today's networks, models, and available resources. Therefore, an infrastructure for the IoP must be adaptable to new use cases, making the realization of a global infrastructure a challenging, interdisciplinary task (Pennekamp et al. 2019, p. 37).

The IoP can support decision-making in production management in an increasingly uncertain and complex competitive environment, which is characterized by shorter product life cycles, individualization, and disruptive innovations. The volatile environment requires efficient implementation of changes. The IoP can help to improve the quality of the decisions made and increase the speed of decision-making and implementation at all levels of production management (Wulfsberg et al. 2019, p. 538). It can lower product development costs while augmenting profit margins and generally improve product quality and safety (Pennekamp et al. 2019, p. 36).

2.1.12 Digital Product Passport

The Digital Product Passport (DPP) is a set of data that summarizes specific information about a product. This can include components, materials, and chemical substances, information on repairability, spare parts or guidelines for proper disposal. The data originates from all phases of the product life cycle (development-, production-, and user-cycle) and can be used for various purposes in all these phases. Structuring environmentally relevant data in a standardized, comparable format enables all actors in the value and supply chain to work together toward a circular economy. At the same time, the digital product passport is an important basis for reliable consumer information and sustainable consumption decisions. (BMUV 2022b)

The DPP is mentioned in the European Green Deal (European Commission 2019, p. 8) and the Circular economy Action Plan (European Commission 2020, p. 17) of the EU as an essential instrument for a climate-friendly and resource-efficient economy. It is also a key enabler of circular, sustainable supply chains. (Jansen et al. 2022, p. 5)

The DPP is more important for products with complex compositions than for products with few components. Initial approaches already exist, although they have often not yet been institutionalized through mandatory standard data sets or central databases. Accordingly, there are still no concrete and comprehensive concepts at the political level as to how such a comprehensive product passport should be designed and implemented in the future. (Götz et al. 2021, p. 7) A depiction of the concept can be seen in Figure 2.10.

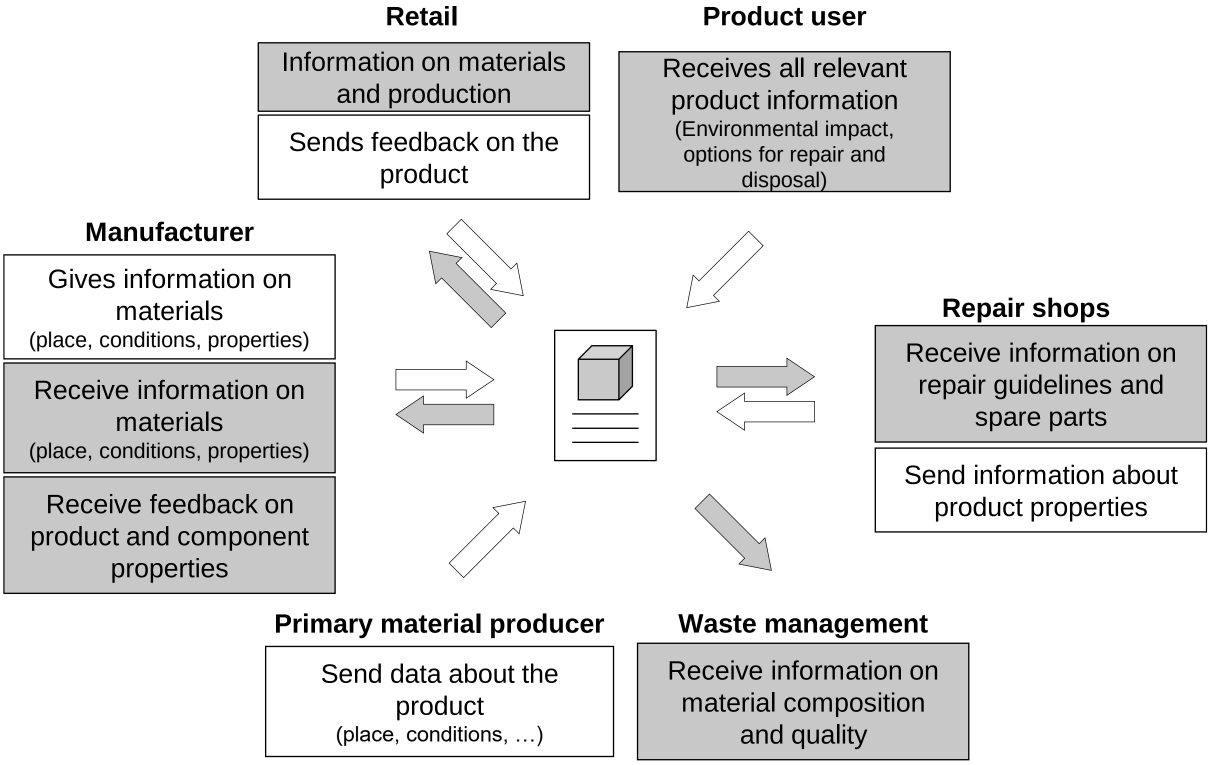


Figure 2.10: Digital Product Passport (BMUV 2022a)

There are legal or voluntary requirements that regulate information flows in production, use, repair, and disposal. But the respective goals and characteristics are depending on various factors. Regulations vary if the requirements are mandatory or voluntarily adapted. Respective information differs by type (database or labeling on the product), by the product group (electronics, chemicals), accessibility (public, non-public), information density (selected aspects, life cycle analysis) and target group (consumers, politics, etc.). There is no coordinated data collection or management system for the consolidation of product-relevant information flows from the different existing systems and sources, which is a challenge for manufacturers and suppliers, who have to comply with numerous information obligations with a wide range of data requirements. (Götz et al. 2021, p. 11)

The majority of current DPPs can be found in the private sector in individual companies or company networks (Jansen et al. 2022, pp. 11–12). DPPs have different characteristics depending on their application. A material pass for example, comprises information about a material so that it can be reused while a cycle passport or cradle-to-cradle passport is more prominent for complex products like passenger cars. Here, manufacturers or the responsible actors provide information on raw materials, dismantling plans, and recycling plans. These aspects should be included in product development. Also, the data has to be available as up-to-date as possible in every phase of the product life cycle. This means that data must be collected not only at the end of the life cycle to show which materials can be returned to the material cycle in which way, but also right from the start to facilitate the design or maintenance in a targeted manner. (Götz et al. 2021, pp. 19–21)

2.2 Fundamentals of Remanufacturing

2.2.1 History and Definitions of Sustainability

A popular definition of sustainability originates from the 1987 Brundtland Report of the United Nations (UN), which defines sustainable development as lasting development that meets the needs of the present without risking that future generations will not be able to meet their own needs (Brundtland 1987, p. 37). The report had significant impact on future efforts such as the Environment and Development Conference held by the UN in 1992 in Rio de Janeiro which led to the so-called *Agenda 21* (Hajian and Jangchi Kashani 2021, p. 1). Nonetheless, the Brundtland report has also been subject to critique. It is a good documentation of many environmental problems but does not identify their fundamental causes and suggests solutions which do not have the desired effect (Trainer). Also, a lack of serious commitment could be seen. For example, the *Agenda 21* provides a framework for sustainable development, but no nation is lawfully bound to follow up on it (Hajian and Jangchi Kashani 2021, p. 3). The chair of the German Sustainable Development Council evaluates the Brundtland report twenty years later (in 2007), stating that many of the defined goals were not accomplished because of a lack of systematic sustainability management and a poor linkage of the objectives with the private sector (Hauff 2007, pp. 8–9).

For the EU this changes with the Circular Economy Action Plan in 2020, where the European Commission commits to working towards several objectives to anchor sustainability in the European economy. For the manufacturing industry, important aspects to consider in future are the right to repair, requirements for batterie manufacturing, and closing material loops. The action plan states that manufacturing companies' material costs make up an average of 40 % of their cost and that closed material loops can increase profitability while protecting from material price fluctuations. (European Commission 2020)

Other incentives for sustainable development have been set by the financial sector by evaluating companies based on environmental, social, and governance (ESG) criteria (Syed 2017, p. 2). These developments require transferring the paradigm of sustainability to the manufacturing industry, where sustainability can be subdivided into the three pillars of economic, ecologic, and social sustainability. Examples for goals for economic sustainability are minimizing the operational expenditure of resources and the operational use of energy. That includes the use of renewable raw materials and energy sources, increasing the efficiency of raw material and energy use as well as productivity per unit area, to avoid the use of hazardous materials, and to develop environmentally friendly products and manufacturing processes. (Schuh and Schmidt 2014, pp. 17–18)

Sustainability requires holistic thinking which, if truly successful would enable decoupling economic growth from the exploitation of natural resources and environmental damage (Murray et al. 2017). In this thesis, the sustainability-definition from the Brundtland report will be used, including economic, ecologic, and social sustainability.

2.2.2 Circular Economy

Circular Economy (CE) is an approach to target the previously mentioned challenges and goals. It emerged as the adversary of past manufacturing principles, which are also known under the name linear economy and characterized by an extraction-production-dispose (Arruda et al. 2021, p. 1), or a take-make-dispose (Ellen MacArthur Foundation 2017, p. 11) pattern. The term linear economy arose simultaneously to CE because a linguistic antonym was needed when discussing circularity (Murray et al. 2017). The difference is illustrated in Figure 2.11. Linear economy ultimately results in the disposal of products and materials. This waste is an environmental burden, resulting in pollution, climate change, and biodiversity loss (Kampker et al. 2016, p. 1).

On the other hand, decisions towards circularity in one sector can have a damaging effect on another sector. For example, many green technologies rely on rare earth materials, the extraction of which has a severe environmental impact. Additionally, a product designed for having a long lifespan can ultimately bare a higher ecologic burden than a product that can easily be disassembled or degraded after use. (Murray et al. 2017)

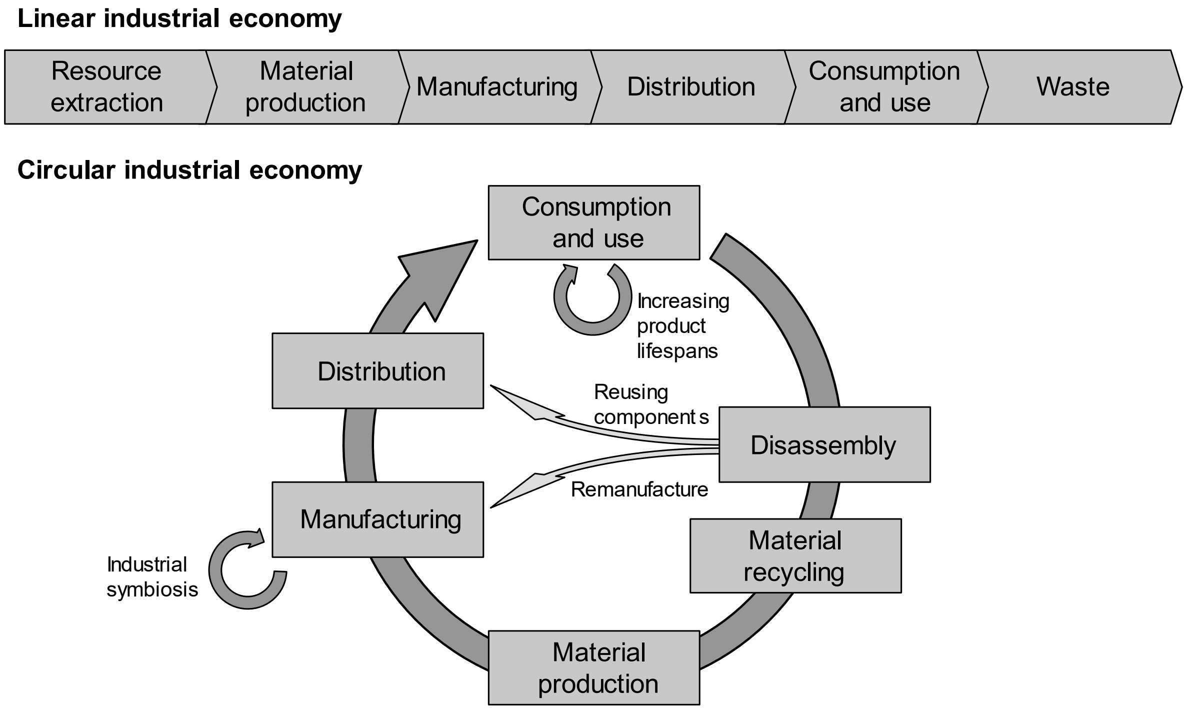


Figure 2.11: Comparison of linear and circular economy (Sutherland et al. 2020, p. 8)

There is an ongoing discussion on the definition of CE. The Ellen Macarthur Foundation defines it as "*an industrial system that is restorative or regenerative by intention and design*" (Ellen MacArthur Foundation 2017, p. 7). It is meant to replace the 'end-of-life' thinking concepts, allow restoration, and include a shift to using renewable energy, eliminating toxic chemicals, which cannot be reused, and to eliminate waste. This is achieved by advancing in the design of materials, products, systems, and business models.

CE does not necessarily cover all areas of sustainability. CE, as defined by the Ellen Macarthur Foundation, does not mention the social sustainability component, which is one of the problems that the term CE faces. It is said to focus on environmental and ecological challenges (Arruda et al. 2021, p. 1), and to show definitional ambiguities and conceptual uncertainties (Schöggl et al. 2020, p. 1). One reason the concept of a CE shows several weaknesses is that is driven by actuators outside the scientific community (Arruda et al. 2021, p. 1).

Another proposed definition of CE, which includes the social dimension, is: "*The Circular Economy is an economic model wherein planning, resourcing, procurement, production, and reprocessing are designed and managed, as both process and output, to maximize ecosystem functioning and human well-being.*" (Murray et al. 2017) This definition for CE will be used in this thesis. It is based on a review of 114 circular economy definitions, where CE is often described as a combination of reduce, reuse, and recycle activities. The activities which help establishing circularity are known as 9R-Framework. They are shown in Figure 2.12.

Smarter product use and manufacture	Refuse	Make products redundant by abandoning its function or by offering the same function with a radically different product
	Rethink	Make product use more intensive (e.g. by sharing product)
	Reduce	Increase efficiency in product manufacture or use by consuming fewer natural resources and materials
Extend lifespan of product and its parts	Reuse	Reuse by another consumer of discarded product which is still in good condition and fulfills its original function
	Repair	Repair and maintenance of defective product so it can be used with its original function
	Refurbish	Restore an old product and bring it up to date
	Remanufacture	Restore an old product in a new product with the same function
	Repurpose	Use discarded product or its parts in a new product with a different function
Useful application of materials	Recycle	Process materials to obtain the same (high grade) or lower (low grade) quality
	Recover	Incineration of material with energy recovery

Figure 2.12: The 9R-Framework (Kirchherr et al. 2017, p. 224)

2.2.3 Definition of Remanufacturing

Remanufacturing is a central element of a CE. It enables the recovery of products or components for further use (Kampker et al. 2016, p. 1) in closed-loop supply chains, which consist of a forward and a reversed supply chain. The forward chain refers to how products reach the customer, the reverse chain describes their way back to the supplier. (Östlin 2008, p. 4)

The Remanufacturing Industries Council defines remanufacturing as a "*comprehensive and rigorous industrial process by which a previously sold, leased, used, worn, or non-functional product or part is returned to "like-new" or "better-than-new" condition, from both a quality and performance perspective, through a controlled, reproducible, and sustainable process*" (Remanufacturing Industries Council 2022). The used products, which are returned to the manufacturer are also called cores (Golinska-Dawson and Nowak 2015, p. 1; Parker et al. 2015, p. 0).

Older definitions of remanufacturing include the term *core* but are less precise on the condition of the returning product. They also do not mention the sustainability component, meaning that modern remanufacturing implicitly requires social sustainability, while older definitions focus on ecological or economic benefits. (Ijomah et al. 2004, p. 6; Sundin 2004, p. 2; Östlin 2008, p. 2)

The definition distinguishes remanufacturing from other R-strategies. The reuse of a product does not require any processing activities (Östlin 2008, p. 33). For recycling, mixed streams of post-consumption or post-production waste are processed to recover raw materials at the end of the product's life cycle (Reike et al. 2018, pp. 256–257). In a repair process, defects are repaired to restore the product's functionality, which does not result in a "like-new" condition that includes warranty for the entire product and additional product life. Meanwhile refurbishing includes activities that make a product appear new but does not include activities that restore the original functionality corresponding to a new condition. (Kampker et al. 2016, p. 3)

2.2.4 Core Acquisition Management

The task of core acquisition management (CAM) is to ensure the supply of cores. It aims to minimize the uncertainties of timing, volume, and quality in core acquisition while maintaining low costs. An important activity in CAM is acquisition control, which helps the manufacturer to influence the return of cores by augmenting or lowering incentives for the customer. This is combined with the forecasting of returns and implementing return strategies. CAM also classifies cores according to their quality, evaluates their price, and creates channels for product returns. There are several models of customer relationships which enable gathering used products from customers. Each has a different effect on the remanufacturing system. (Östlin 2008, p. 1; Wei et al. 2015, pp. 5–6; Östlin 2008, pp. 39–44)

Cores can emerge from a market stream or a waste stream. The market stream includes used products, which are still useful, but are not used anymore by their owners. The waste stream refers to products, which can no longer be used, like a car damaged during an accident. (Andrew-Munot and Ibrahim 2013, p. 489)

The sources for cores can further be categorized into end-of-life returns, end-of-use returns, commercial returns and secondary channel goods, and reusable components. End-of-life returns are removed from the market to prevent environmental or economic damage. Examples of such products, for which disposal is regulated by law, are vehicles, packaging materials, batteries, tires, and construction waste. End-of-use returns are given back by the user after a certain period of time, e.g., because leasing contracts end, or because products are replaced. These products are still in good condition, making them well suited for remanufacturing or resale. Commercial returns are products that are returned shortly after sale. The phenomenon is particularly prevalent in e-commerce, where up to 25 % of purchase volumes are returned. Reusable items include components that are related to the consumption, use, or distribution of the actual product without being part of the actual product. (Krikke et al. 2004, p. 26)

Leasing and renting are part of the end-of-use and reusable components, and a main source for cores. They are more predictable than other types of returns because the time of return is easier to estimate. Another model to ensure the availability of cores is to request the customer to sell the core to get a new product. One example is an exchange cycle in the automotive industry, where a remanufactured engine is only sold if a used engine is returned (Seitz and Peattie 2004b, p. 81). There are also voluntary systems where the user may freely return the cores to a remanufacturer or sell it to a core broker. And there can be financial incentives like product-discounts if the user commits to returning the core after use. This way a company can avoid losing cores to competitors (Östlin 2008, p. 41).

Return forecasting

Cores are not immediately available when a product is released on the market (Guide 2000). They appear when the demand for remanufactured products has reached its maximum, i.e., there is a period of time when demand can no longer be met. Also, the total amount of cores which are available over time exceeds the demand for remanufactured products (Östlin 2008, p. 72). Functional updates that bring the product up to the current state of the art can create stronger demand at the end of the product life cycle (Kampker et al. 2016, p. 5).

Past sales data can be used to make predictions about when products are likely to be returned. Figure 2.13 shows how the failure of a product quantity $D(\tau) * \Delta\tau$ after the average lifetime μ can be approximated with a normal distribution $S(\tau, t)$. If only components are considered instead of whole products, the disposal distribution can be represented as a function of the product quantity in the market and the failure rate of the individual components. (Umeda et al. 2005, pp. 7–9)

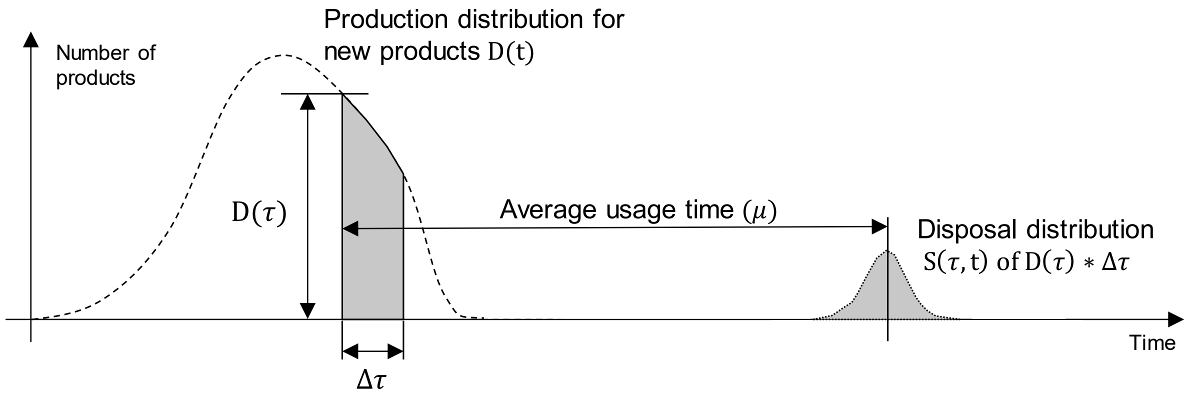


Figure 2.13: Model linking production and disposal distributions (Umeda et al. 2005, p. 9)

Predicting the availability of cores is necessary to level the supply and demand of remanufactured products. It enables reducing the stock of cores, disposal of surplus cores, and avoiding supply bottlenecks. It also reduces the overall uncertainties in the system and lowers the cost of remanufacturing. Balancing core-demand and -supply in a remanufacturing system affects resource and materials planning, lot sizing, production decisions, and scheduling. (Östlin 2008, pp. 39–44)

Product Cannibalization

Product cannibalization causes a decline in sales of a product that results from the introduction of another product from the same company, brand, or product line (Wildemann 2008, p. 71). In remanufacturing, customers may decide to buy an older, remanufactured version of the product at a lower price (Okuda et al. 2018, p. 114).

Cannibalization depends on the product. It is less likely for consumer products because there is little overlap in bidders between the new and remanufactured products. This overlap is bigger for commercial products and therefore the risk of direct cannibalization is higher. (Guide Jr. and Li 2010, p. 1)

2.2.5 Remanufacturing Process

The remanufacturing process is not standardized, i.e., the activities and their sequence within the process depend on the application and the requirements for the specific components. Remanufacturing includes activities such as inspection, disassembly, storage, reassembly, cleaning, and testing, which in the case of household appliances can be carried out in that precise order (Sundin 2004). In other cases, the order might be different or certain steps can be ignored (Östlin 2008, p. 4); Andrew-Munot and Ibrahim 2013, p. 488). Also, the location of the activities may vary. A first assessments of a core's quality and its disassembly can be done by a technician on site, while further process steps may be carried out in a central factory.

The organization of the processes is influenced by decisions that must be made during the process. For example, if a core has defective components, a decision must be made whether to replace or repair them (Östlin 2008, pp. 5–6). Figure 2.14 shows an exploratory remanufacturing process. It can be described in more detail and include cleaning, sorting, and inspection activities or the replacement of certain parts in underlying process steps (Kampker et al. 2016, p. 3).

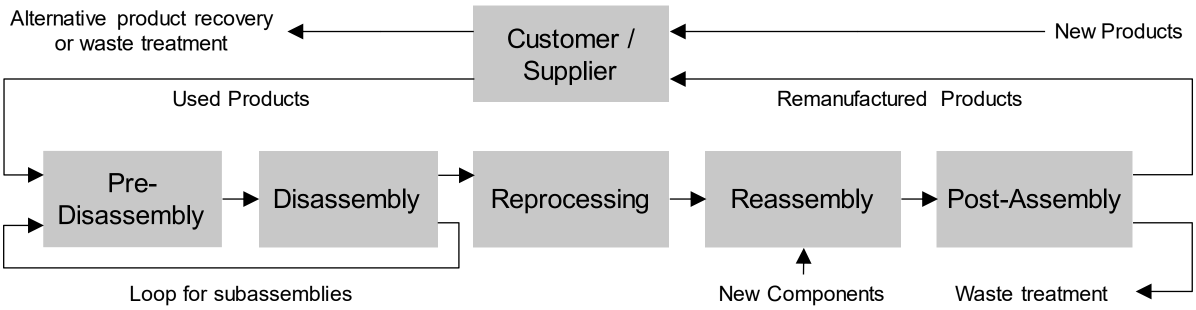


Figure 2.14: Remanufacturing process (Östlin 2008, p. 7)

Pre-Disassembly

The cores are first introduced to a quality control to assess their ability to be remanufactured (Östlin 2008, p. 44). This can be done, for example, by means of a visual inspection. Inspection times for similar types of cores from the market stream are also similar. However, high variations in quality conditions can occur within the waste stream, and between the waste stream and the market stream, which can result in varying inspection times. Cores from the waste stream tend to have longer inspection times and require special inspection tools. The percentage of cores that can be classified as suited for remanufacturing can vary depending on the batch due to the uncertain quality condition of the cores. The cores suited for remanufacturing can be classified into several quality groups, and the best quality group should be given the highest priority for reprocessing. Furthermore, the variability of quality groups in the waste stream is expected to be higher than in the market stream. (Andrew-Munot and Ibrahim 2013, pp. 489–490)

The cores must also be cleaned because grease, oil, dirt, paint, and rust can complicate the disassembly process (Östlin 2008, p. 44). The cleaning operation can be the most time-consuming (Sundin 2006, p. 431) and there can be products which are impossible to inspect without cleaning them (Sundin 2004, p. 27). Meanwhile LIU et al. argue that the availability, quality, reprocessing costs, and remaining service life of the remanufactured product depend directly on the used cleaning methods and the corresponding cleaning quality (Liu et al. 2013). They further state that cleaning can also introduce impurities into the remanufacturing process, which limits the technical application.

Disassembly

After the inspection process, the cores that have not been classified as scrap are sent to the disassembly process. Disassembly involves breaking down cores into their subassemblies and their individual components (Östlin 2008, p. 44). General-purpose tools such as drills are often used here and although robotic arms may also be used for the disassembly of complex cores, automation is rarely found in disassembly processes (Östlin 2008, p. 44). In contrast to inspection times, disassembly times are largely independent of the quality or origin of the cores, but they do depend on their complexity. Cores with a complex product structure require more disassembly time than those with a simple product structure. In addition, disassembly times can be reduced by more skilled labor or automated systems. (Andrew-Munot and Ibrahim 2013, p. 490)

The disassembly can be accompanied by further inspection and sorting of subcomponents, which is why a loop was added to Figure 2.14. The processes for subcomponents can be carried out in parallel or sequentially, depending on the product structure. Parallelism is possible for large-volume cores with a simple product structure, as well as for cores with a small number of components and a complex product structure. Large-volume cores with complex product structure are usually first disassembled, then inspected. (Andrew-Munot and Ibrahim 2013, p. 491)

Disassembly yields of components from high quality cores are higher than those from the lowest quality group. In addition, the disassembly yield for cores from the market stream is higher than that of cores originating from the waste stream. Besides the product structure, the product design also influences the disassembly yield, as products that are not designed for disassembly may be damaged in the disassembly process. (Andrew-Munot and Ibrahim 2013, pp. 491–492)

The yield of reusable components of a core is measured with the material recovery rate (MRR) as can be seen in equation 4. (Guide 2000, p. 473)

$$MRR = \frac{number\ of\ reusable\ components}{number\ of\ total\ components} \tag{4}$$

Reprocessing

Reprocessing aims to repair or to improve the quality of the core (Östlin 2008, p. 44). It includes cleaning, surface treatment, and repair activities. The aim is to restore the components to their original condition and functionality. The number of processes and the process duration depend mainly on the quality group of the components. High quality components may require only cleaning and surface treatment, while low quality components may require additional repair. The more complex the product design, the more repair steps such as cutting, welding, and deburring is necessary. Therefore, lead times vary widely, and planning of the corresponding process steps, the necessary machines, and materials is also required (Andrew-Munot and Ibrahim 2013, p. 492).

Reassembly

In reassembly there can be a cannibalization of parts, meaning that components obtained from one item are used to repair or rebuild another unit of the same product (Rogers and Tibben-Lembke 1999, p. 256). Reassembly can also be done with reused, reprocessed, and new components (Östlin 2008, p. 45). If the remanufactured parts show a fluctuating, predictable demand, MRP is a well-suited method to plan the necessary materials and components for reassembly because it uses fixed planning horizons which buffer fluctuations (Östlin 2008, p. 51).

Components that cannot be reused are replaced. In the case of original equipment manufacturers (OEMs), spare parts can be manufactured. Otherwise, they are procured externally. Replacement components are especially important in the remanufacture-to-order business model, where the customer sends cores to the manufacturer for remanufacturing. The same uncertainties in quality apply to subcomponents as to the original cores. In reassembly, mainly universal tools are used to assemble the components into remanufactured products. Complex cores may require the use of robotic arms to assemble components. (Andrew-Munot and Ibrahim 2013, p. 492)

2.2.6 Effects of Remanufacturing on PPP and Refinement of Scope

The design of a product influences its ability to be remanufactured (Sundin 2004, p. III). As design is not part of PPP, it is excluded from the scope.

The inherent characteristics of a production system affect the remanufacturing process. These unique characteristics are a challenge for production planning and control and must therefore be considered accordingly. (Andrew-Munot and Ibrahim 2013, p. 488)

Sales planning and demand forecasting are the first step in PPP. They are often performed at group level meaning that for remanufacturing one of the main challenges is to balance the demand for remanufactured products with the supply of cores, which are not always synchronized. Their ratio depends on the rate of technological innovations and the expected life of a product. (Östlin 2008, pp. 106–107)

In primary demand planning, the demand for products gets broken down into components. The resulting uncertainty at component level poses a challenge for MRP, because the actual need for components is determined in the process but planned one to six months ahead. For example, disassembly generates an uncertain number of components, cannibalizing components requires having them in stock and if new components are needed, lead and delivery times must be considered for procurement. Manufacturers therefore often plan according to demand and supply of cores and then break the demand down to the components. A graphic interpretation of the decision process at component level and the consequences was developed by ÖSTLIN and can be seen in Figure 2.15. (Östlin 2008, pp. 106–107)

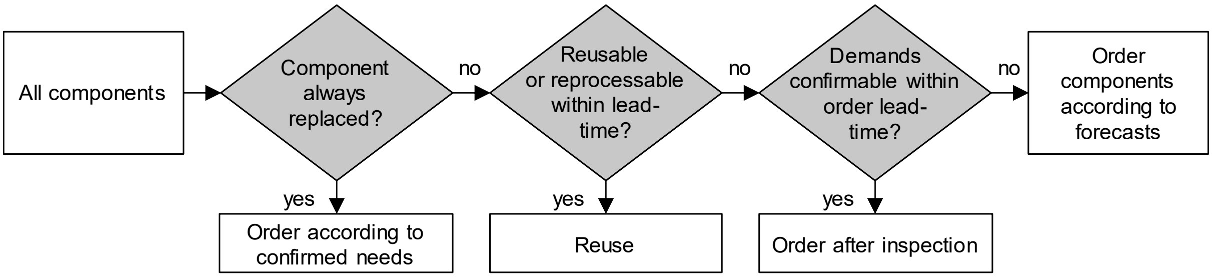


Figure 2.15: Material planning for components in remanufacturing (Östlin 2008, p. 108)

The decisions made in the disassembly process are part of the short-term control, which was excluded from the scope (see page 11). Nonetheless, confirmed needs for components that are always replaced and demand forecasts for components which cannot be procured or made within the order lead-time are an important input for primary demand planning and gross resource planning in PPP (see: decoupling point, described by SCHUH for PPP (Schuh and Schmidt 2014, p. 64)).

When products reach the end of their previous life cycle, it is difficult to report the status of the products to the remanufacturer (Wang et al. 2014, p. 1). The inspection of cores gives information that can be used for material planning, but this information is often not collected or used because there is no efficient way to gather and analyze it. Also, the administrative costs can be greater than the potential benefit of having the information. Especially components with low sourcing lead-times and low minimal order quantities would benefit from such information because instead of having an inventory they could be ordered just-in-time. (Östlin 2008, p. 113)

There are further challenges which are inherent to a remanufacturing system and differentiate it from a normal manufacturing system which must also be resolved in production planning but are no direct part of PPP or can be placed at interfaces of PPP where specific activities overlap. The implementation of a reverse supply chain and especially CAM is a challenge in remanufacturing, but the overlapping activities of CAM and PPP are the forecasts for core supply and demand considering MRRs. Also, the optimal mix of remanufactured and new products put into production must be determined. The general need for an efficient disassembly process with multiple key remanufacturing stages which are interdepended and hard to automize are also crucial for production planning at process level but not included in PPP because existing facilities and routings are an input to PPP. Regarding this, the important challenges lie within the multiple types of subcomponents and the quality-dependent varying lead times as well as finding transparent methods for tracking materials and their requirements while dealing with small lot sizes. (Andrew-Munot and Ibrahim 2013, p. 492; Guide 2000; Östlin 2008, pp. 6–9)

Lean principles can be difficult to implement in remanufacturing because they require standardized, robust, and predictable processes when manufacturing new products. In remanufacturing systems, predictable processes can only be realized to a certain extent because of the fluctuations in core quality. (Östlin 2008, p. 1)

In summary, uncertain core demand, return quantity, quality, and timing result in variable inspection yields and variable disassembly yields, reprocessing effort, and reprocessing times which leads to fluctuations in capacity requirements. While there are many references for the challenges inherent to remanufacturing, there is no generally accepted framework on how to resolve them from a PPP perspective, which describes which information to gather, and how to process them.

2.2.7 Remanufacturing Market

A report from the US International Trade Commission states, that from 2009 to 2011 the US was the largest remanufacturer in the world. In this period, the value of US remanufactured production reached $43.0 billion, growing by 15 % and supporting 180,000 full-time jobs. The most contributing industries were aerospace, consumer products, electrical apparatus, heavy-duty and off-road equipment, information technology products, locomotives, machinery, medical devices, motor vehicle parts, office furniture, restaurant equipment, and retreaded tires. In export, U.S. remanufacturing generated $11.7 billion in 2011. The report also states that in 2011 the US and Europe assumed the main share in remanufacturing activities and associated trade. The foreign markets face challenges in regulations, import bans, and lack a common definition of remanufactured goods, which limit trading remanufactured goods and cores. (Treat et al. 2020)

In the past, the remanufacturing sector has extended from smaller companies to OEMs such as Caterpillar, Kodak, Xerox, and Delphi (Subramoniam et al. 2013). Caterpillar, a leading global manufacturer of earth-moving equipment, offers a wide variety of remanufactured products and aims to increase sales and revenues from remanufacturing offerings by 25 % from 2018 to 2030 (Caterpillar Inc. 2021, p. 7). For OEMs, remanufactured versions of their products can have higher profit margins than new products (Guide Jr. and Li 2010, p. 4).

In 2015, the remanufacturing industry in Europe had an annual turnover of 30 billion euros while supporting 190,000 employees. Germany is the European pioneer and leader in remanufacturing. With sales of 2.4 billion euros, Germany accounts for 31 % of European remanufacturing sales. By 2030, growth to 90 billion euros and an additional 75,000 jobs are expected in the European remanufacturing industry. 80 % of remanufacturing activities take place in the aerospace industry (42 %), in the supply of automotive parts (25 %), and in heavy-duty and off-road applications (14 %). Up to 80 % of the material used can be reused in remanufacturing products. As a result, 2.260.000 t of material and 8,255,000 t of CO_2 are saved per year in Europe. (Parker et al. 2015, pp. 42–49)

Remanufacturing is often not operated as a core business, but as a service in aftersales. The share of sales accounted for by remanufacturing cannot always be clearly determined, as data here are available in an aggregated form (Östlin 2008, p. 5) but remanufacturing is playing a crucial role in the currently occurring paradigm shift from selling a product to providing products and services (Ijomah 2009, p. 91).

2.3 Fundamentals in the Automotive Industry

2.3.1 Production Program Planning in the Automotive Industry

In the automotive industry, PPP is a part of tactical production management, which deals with the medium-term implementation of strategic goals over a planning horizon of up to five years and determines production capacity and production technology. Tactical production management aims to adapt the production structure and work organization to changing processes and products, taking into account legal requirements and collective agreements. (Herlyn 2012, p. 17)

Program planning deals with production capacities, while program control is responsible for drawing up specific production programs in the factories, which are the link to operational production management. In the automotive industry, program planning and control is also a cross-sectional discipline that assumes an integrative function for the brands, sites, and divisions of a customer-driven manufacturer. It includes the company's own production, as well as suppliers, their sub-suppliers, and the vehicle handover to the customer. (Herlyn 2012, pp. 17–18)

The automotive industry differentiates between PPP and production program control (PPC). They are multi-stage, cyclical and recursive planning processes that are based on the sales plans and gradually decrease the planning horizon, so the planning terms become more specific, resulting in a steady increase in planning accuracy (Herlyn 2012, p. 121). PPP and PPC must be viewed holistically as an interaction between the internal production of vehicles and aggregates and external suppliers (Kropik 2009, p. 23).

Production plans and production programs are clearly distinguished. They differ in time frame and aggregation. Production plans are created for aggregated products (Hopp and Spearman 2000, p. 237), while production programs contain the individual products (Günther and Tempelmeier 2003, pp. 141–142). The tasks of PPP and PPC are the preparation of production plans for the vehicles and aggregates, the preparation of production programs for manufacturing all fully specified vehicles and aggregates, and the commissioning of the assembly of all vehicles and aggregates with optimal use of resources at the highest possible utilization of the available capacities. The aim of PPP is to assure the manufacturing of all vehicles and associated assemblies as ordered by the customer and on schedule (Herlyn 2012, p. 18). An example for the planning horizons depending on the aggregational level is shown for VW in Figure 2.16.

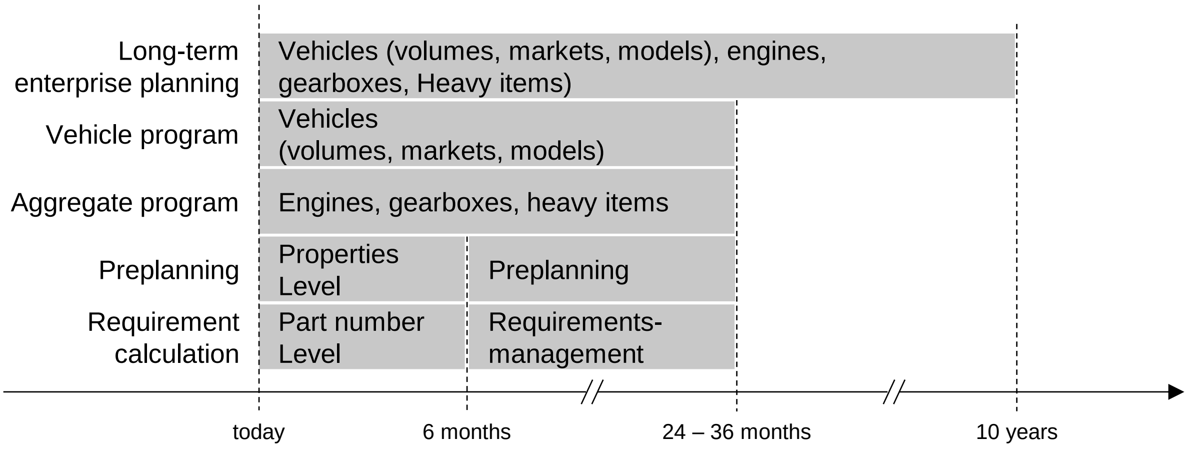


Figure 2.16: Program planning stages using the example of VW (Klug 2010, p. 372)

Production plans and programs are created for the entire international production network of an automotive manufacturer, including the production companies and external suppliers that manufacture vehicles or assemblies on behalf of the OEM. The production programs contain the binding basis for the actual production of goods and services at operational level. (Herlyn 2012, p. 19)

The production programs refer only to the vehicles and assemblies (primary programs), while the manufacturing programs refer to the required components (assemblies, parts, production material), which are also called secondary programs. Furthermore, there are tertiary shipping programs, which are created for both the products and the components. The secondary requirements for the components are derived from the primary and secondary programs with the aid of the BOMs. (Herlyn 2012, pp. 19–20)

Automotive manufacturing is a build-to-order industry, so PPP starts with the customer and his order (Herlyn 2012, p. 57). Vehicle ordering takes place at product level, which is why only this level is relevant for PPP of vehicles and assemblies. The structural, parts-related, and material-related variants and their relationships play no role in vehicle ordering and program planning (Herlyn 2012, p. 79). The vehicle order begins with the specification of the series vehicle with various configuration options or the selection of a special model. Series or special models can be converted into functional vehicles when choosing special equipment. The vehicle types can be further individualized according to the customer's wishes until a unique vehicle is created. Special, functional, and individual equipment are technical modifications to the series vehicle and have a major impact on the production processes, as they cannot be fully integrated into the series process and are therefore given special consideration in PPP (Herlyn 2012, p. 66).

The PPP and PPC process and their dependencies are shown in Figure 2.17. PPP begins in sales with market-related sales plans, which are developed cooperatively by the importers and the OEM's sales department. Sales plans are created for countries, for groups of countries or for regions, since legislation and customer requirements can vary greatly (Grebe et al. 2021, p. 21; Ohl 2000). Market-specific sales plans form the basis for market-specific distribution plans, which depend on the competitive situation, brand positioning, and customer segmentation in the respective market. In addition, the broadness and diversity of the product range as well as the introduction or discontinuation of models and ongoing model adjustments are considered. The distribution plan is an agreement between sales and production for the quantity of vehicles that can be assured to the importer by the manufacturer. (Herlyn 2012, p. 122)

Vehicle production plans are derived from market-related distribution plans, i.e., the market-related sales figures are distributed to the production sites across brands, taking into account certain restrictions. This way, changes in sales between brands and markets can be balanced out in production and a flexible response can be made to changes in customer demands. Vehicles of several brands are bundled in one plant to save production, procurement, and logistics costs. The production plans of all brands are therefore coordinated by a companywide program planning committee. Here, the distinction between vehicle factories and aggregate factories becomes important, which also have to be coordinated with each other (Zernechel 2007, p. 368). The demand for aggregates for all vehicle plants is distributed among the aggregate factories to create their production plans. An aggregate factory can supply several vehicle plants and aggregate variants can be built in parallel in several factories. (Herlyn 2012, p. 123)

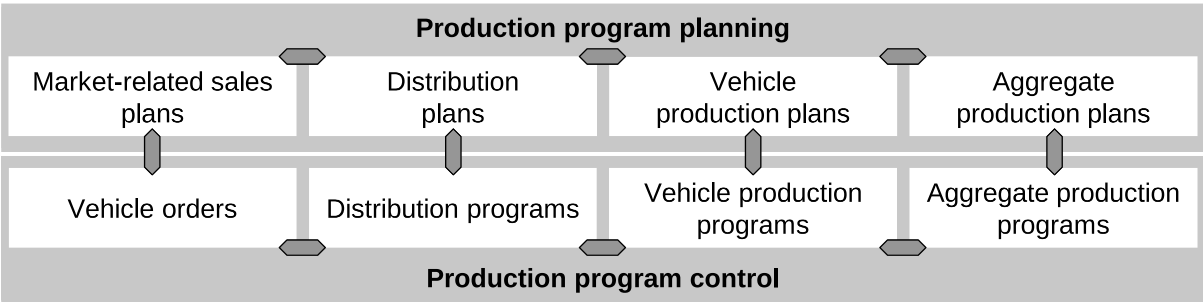


Figure 2.17: PPP and PPC in automotive manufacturing (Herlyn 2012, p. 123)

PPC starts with the vehicle-orders, which form the basis for the distribution programs and, later, for the vehicle production programs. Dealers and importers can use the orders to identify current demand trends at an early stage and may influence them with marketing measures (financial incentives). If there is a shortage of confirmed orders, vehicles are ordered without existing customer orders. Vehicle orders can also be scheduled later if the demand exceeds the sales plans. In this case, however, the delivery date is postponed. Vehicles can also be exchanged between market segments if production exceeds demand in one segment while the demand in another market segment is higher than expected. (Herlyn 2012, pp. 123–124)

The distribution program is intended to meet the distribution plan's targets for vehicle volumes and variants. Discrepancies between the planned sales figures in the sales plan and actual customer orders require adjustments, which are reconciled with production and procurement capacities. In the event of a shortage of customer orders, the distribution program can be filled by the dealers and importers with their own orders. Surplus vehicle orders remain in the order backlog and are included in the next distribution program. The vehicle orders in the distribution program are transferred to the production programs for the vehicle assembly plants. (Herlyn 2012, p. 124)

With the vehicle programs, production periods are defined for all vehicle orders and assigned to a factory. In the factory, the vehicle programs are then implemented in the various production areas and assembly programs are derived for the assembly lines. Based on the vehicle production programs, the production programs for the aggregate factories can be created. Therefore, the delivery times of the aggregates, and the capacities and distribution rules between the aggregate factories are required. In addition to the demand for aggregates by the vehicle plants, the production programs of the aggregate factories must also consider the production of spare parts and demand for aggregates from other companies. (Herlyn 2012, p. 124)

The distribution and production plans only contain production capacities or production volumes, but no quantities of specific vehicles or units. The sales and production programs, on the other hand, contain specific vehicle orders from which the binding production orders for the vehicle and aggregate factories are derived. (Herlyn 2012, p. 124)

2.3.2 Remanufacturing in the Automotive Industry

Remanufacturing in the automotive industry is already implemented for components and for special purpose vehicles, but not yet for passenger cars and light commercial vehicles (Kamper et al. 2019, p. 281). There is, however, high potential in applying remanufacturing to electric vehicles (EVs). Currently, they are more expensive to purchase and have a higher total cost of ownership than conventional cars with a combustion engine despite having lower operating costs. An EV that can be remanufactured can further reduce these costs, making it cheaper than a conventional car (Kampker et al. 2016, p. 3). EVs are also more suited for remanufacturing than conventional cars because they have more conceptual freedom in their product and functional structure. Also, the disassembly, processing, and reassembly of an EV is easier because its engines (Kampker 2014, p. 22) and gear boxes (Kampker 2014, p. 231) are less complex.

2.3.3 Challenges in PPP for Automotive Remanufacturing

HERLYN states that for PPP of vehicles and aggregates, the ordering phase is of particular importance, while the information and usage phases play a subordinate role and can be neglected. For PPP in remanufacturing, chapter 2.1.12 and 2.2 showed that the later phases of the product life cycle should be incorporated in the planning process to reduce uncertainties in production planning. (Herlyn 2012, p. 67)

A challenge for demand forecasting in the automotive industry is that the simple time-series models described in chapter 2.1.5 predict trends or seasonal dependencies, but they are not suited for capturing complex market-influences or do so only in a very specific and limited way. For vehicles, the forecast variable usually refers to aggregate demand sizes or to the demand for a specific new product category. Since disaggregated demand is not modelled within the framework of the demand forecast models, these approaches do not provide much basis for explaining product-specific life cycles (Eggert 2003, p. 21), which poses a challenge to remanufacturing because it needs information about return quality, quantity, and timing from the use phase of the product. As in other remanufacturing activities, vehicle remanufacturing relies on the availability of cores (Sitcharangsie et al. 2017, pp. 13–14). Vehicle remanufacturers must therefore maintain a long-lasting relationship with customers which is complicated by the fact that customer loyalty to OEM service schemes decreases over time (Seitz and Peattie 2004a, p. 82).

For pre-processing, it is important to differentiate mechanical components from mechatronic systems when performing functional tests to evaluate the quality of cores. The damage patterns of mechanical components are often easier to detect, e.g., by visual inspection, than those of mechatronic systems. In addition, electronic control devices (ECDs) provide OEMs with limited access to records of user data because they often lack open communication interfaces. While error messages are transmitted, this makes the underlying causes untraceable, and the overlap of damage patterns of linked systems complicates the prediction of such damages. Furthermore, different usage patterns and environmental conditions during the vehicle lifecycle lead to different levels of wear and tear, making recurring damage patterns even more difficult to detect and the total reprocessing effort in the remanufacturing of vehicles hard to determine. (Kamper et al. 2019, p. 286)

The efficiency of production systems for more complex products is more sensitive to deviations, which can reduce profitability and therefore increases the planning effort. Vehicles also use frictional, positive, and adhesive connections, which often cannot be disassembled economically. Therefore, a comprehensive initial assessment of the components' condition is required to derive the necessary remanufacturing steps (Sitcharangsie et al. 2017, p. 13). Furthermore, the storage of cores or additional resources, is not intended in an efficient and lean production as desired in the automotive industry. (Kamper et al. 2019, pp. 286–287)

The quality assessment must be able to process various input variables from different sources such as status information, error messages, life cycle data from ECDs and sensors, and individual assessments performed in the factory. Due to this complexity, incorrect assessments cannot be avoided, which leads to unplanned or deviating processes and additional material requirements. A PPC system for automotive remanufacturing must have additional information, dynamic scheduling, and allow continuous reassessment of the profitability of remanufacturing orders (Kamper et al. 2019, p. 287). On the other hand, long-term planning can be better suited for aggregate production planning in the automotive industry than short-time decision making because it mitigates the effects of uncertainties of material matching and material routings in remanufacturing (Sitcharangsie et al. 2017).

3 State of Research

The aim of this thesis is the development of a data model for PPP in remanufacturing. The data model must contain all data points, which are required to create the production program in remanufacturing, in a structured form. Therefore, in addition to the data required for the classic PPP in manufacturing (demand, sales volume, routings, BOMs, assembly capacities, etc.), the data requirements implied by remanufacturing (sales mix of new and remanufactured products, quality classes of cores, disassembly capacities, etc.) must be included in the data model.

Chapter 2 analyzes the basics of PPP, remanufacturing, and data handling in manufacturing companies. Chapter 3 examines the current state of research on existing data-based approaches, which result in a production program, or which deal with the handling of planning uncertainties that arise from remanufacturing in PPP activities. At first, requirements and evaluation criteria for the literature are defined. The identification and analysis of existing approaches is then carried out within a systematic literature analysis. Finally, the selected approaches are presented and evaluated according to the previously defined requirements in order to identify the research gap addressed in this thesis.

3.1 Criteria for the Evaluation of Existing Approaches

The examined literature should propose a data-based model which deals with sales planning, primary demand planning, and gross resource planning within PPP in remanufacturing. Therefore, a model found in literature should indicate the specific remanufacturing process and the product or product group for which it is intended. All underlying assumptions must be clearly specified, and the literature should include a comprehensive description of the necessary data and information. The literature must also deal with one of the planning uncertainties identified in chapter 2.2.6 and 2.3.3. Those uncertainties are the basis for the evaluation criteria:

- **Ability of the proposed model to <u>handle uncertainties in sales planning with remanufacturing</u>:**
  The literature should propose a data model for feasible processes that allow an economic balance of remanufactured products and new products. This includes the forecasting of core supply, of core quality, and decision making on the introduction of new products to minimize negative effects of product cannibalization.
- **Ability of the proposed model to <u>handle uncertainties in primary demand planning</u>:**
  The data model should reflect how uncertain core quality affects component yields, and how those yields in combination with uncertain core return quantities and timings affect inventories, total recovery rates, and new component requirements, in remanufacturing or combined systems. This may include methods on how to facilitate the initial assessment of cores.

- **Ability of the proposed model to <u>handle uncertainties in gross resource planning</u>:**
  The data model should reflect how uncertain core quality, quantity, and timing affect routings, lead times, or processing times, and thus capacity requirements, in remanufacturing or combined systems.
- **<u>Comprehensiveness of the data model</u> for PPP in remanufacturing and incorporation of data from different phases of the product life cycle:**
  Crucial information about cores originates in the use-phase of the product, which then affects the (re-)manufacturing phase. The literature should propose a framework on how to identify the relevant data, be precise in its definitions, explain how to obtain and handle the needed information, or describe the underlying logical or communicational infrastructure.
- **<u>Transferability</u> of the proposed model to the automotive industry:**
  PPP in remanufacturing can be very depending on the product. The planning effort rises with the product complexity and remanufacturing processes for small parts can differ from those of more complex ones. Also, products of similar complexity but with other properties that vary (size, area of application, type of components like hazardous substances, etc.) may need different information and processes which affect the PPP. The model should also adapt to the planning horizons of two to three years at vehicle level in the automotive industry.

3.2 Method for a Systematic Literature Review

The identification and analysis of existing research approaches is conducted using a systematic literature analysis based on Kitchenham. The literature is examined as broadly as possible and narrowed down to a target area on the basis of predefined criteria. This allows for a comprehensive, scientific representation of the current state of research and research gaps can be identified. (Kitchenham 2007, pp. 3–4)

The approach can be seen in Figure 3.1 and has three phases. In the first phase, the literature analysis is planned. This includes the definition of the objective, the selection of the databases, and the definition of the search terms. In addition, inclusion and exclusion criteria are defined, which serve to narrow down the literature to the target area. In the second phase, the databases are searched for the search terms and the hits are exported and stored in a preliminary database. In this thesis, the preliminary database is created with Excel and narrowed down to the target area in various filter stages, taking into account the previously defined criteria. The final database is created by a forward and a backward search in the preliminary database. In the backward search, the bibliographies of the publications in the preliminary database are analyzed to find additional candidates for the final database. In the forward search, literature that cites the present article is searched for. In the third phase the results are documented and represented in a clear and comprehensive manner, and the publications which are part of the final database, are represented. The final step is to evaluate the literature with respect to the objective and the evaluation criteria. (Kitchenham 2007, pp. 7–39)

Planning the review	Conducting the review	Reporting the review
- Definition of the objective - Selection of the databases - Definition of search terms - Definition of inclusion and exclusion criteria	- Identification of publications - Publication exporting - Filter and analyse results - Forward and backward search	- Overview on the results of all previous steps - Presentation of the final results - Evaluation of the final results

Figure 3.1: Systematic literature review (Kitchenham 2007, p. 6)

Figure 3.2 states the relevant information of the planning phase. The objective is defined based on the planning uncertainties identified in chapter 2.2.6 and 2.3.3. The evaluation criteria of the literature were explained in chapter 3.1 and the selected databases were chosen with the aim to broadly cover the field of scientific publications. The search is carried out in English, for electronically available literature only. The search in the databases is limited to title, abstract and keywords of the publications. In order to obtain an overview of the current state of research, only publications with a publication date since the year 2000 are considered. Additional information on the final database is given in Appendix A.1.

Objective	
Investigate the state of research on data-based production program planning with remanufacturing to identify research gaps.	
Databases	**Search terms**
IEEE Xplore (www.ieeexplore.com) Scopus (www.scopus.com) Google Scholar (www.scholar.google.com)	Remanufacturing, data model, production program planning, automotive industry (the term *automotive* yielded no additional results and was discarded for the search string) (remanufacturing data model) OR ((remanufacturing) and (production program planning)) OR ((data model) AND (remanufacturing) AND (planning))
Inclusion criteria (IC)	**Exclusion criteria (EC)**
IC 1: Literature focusing on data-based PPP with remanufacturing and its underlying activities **IC 2:** Consider title, abstract and keywords	**EC 1:** Literature which is not accessible electronically **EC 2:** Literature which needs to be purchased **EC 3:** Redundant literature **IC 3:** Publications in languages other than English, German, or Spanish

Figure 3.2: Planning parameters for the systematic literature review

The search and export of the results from the databases were conducted in the period from Jan 1st to Jan 31st, 2023. Due to the special characteristics of the Google Scholar database, the export of this database was limited to the first 500 entries. Table 3.1 shows the hits and exports of the different databases.

Table 3.1: Search results of the systematic literature review

Database	Hits	Exported hits
Google Scholar	17.800	500
IEEE Xplore	89	89
Scopus	445	445

The exported 1.034 publications are filtered in Excel. The first filtering step is to delete duplicates, which result from searching multiple databases. Then, the content is further restricted by a blacklist filter. The blacklist filter automatically removes titles that contain terms from non-relevant domains. The remaining 426 publications are manually filtered first by their title, then by abstract, and finally by full text. Whether to consider a publication or not is decided based on the defined objective and the inclusion and exclusion criteria. Through the manual filter, 46 publications remain after the title filter, 29 publications remain after the abstract filter, and five publications remain after the full text filter. Additional research and forward and backward searches add seven publications to the database. Care was taken to avoid duplicating similar approaches that perform the same planning steps but use different calculation methods. The final database contains 12 publications. These approaches are presented in section 3.3. The final evaluation and thus the answer to the objective of the systematic literature analysis is given in section 3.4. The filtering steps can be seen in Figure 3.3.

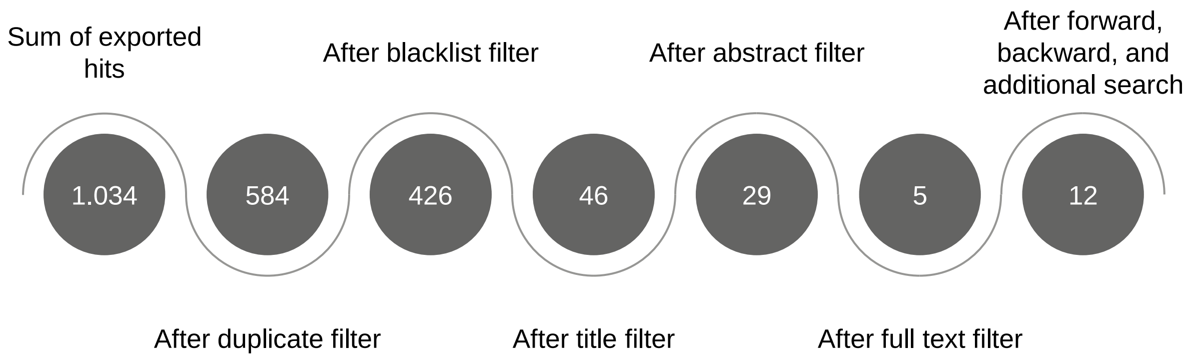


Figure 3.3: Filtering steps of the systematic literature review

3.3 Presentation and Evaluation of the Results

3.3.1 A Conceptual Data Model promoting Data-Driven Circular Manufacturing (Acerbi et al. 2022)

Acerbi et al. propose a data model which captures all the data and information which must be available to implement a circular production. The required data and information are divided into the main classes of product, process, management, and technology, which in turn are subdivided into a total of 29 subclasses. A simplified version of the complex model can be seen in Figure 3.4. The model language is UML. The data which needs to be gathered depends on the chosen strategy but there can be overlaps in the data needs of different circular processes. Remanufacturing, e.g., is mentioned as a separate class from the disassembly class because disassembly can be necessary before engaging in recycling or repair processes as well. By filling in the available data and by raising awareness for the missing data, manufacturers can better decide either which strategy they want to choose, or which information still needs to be obtained in order to implement, for example, a remanufacturing process. (Acerbi et al. 2022, 854-545)

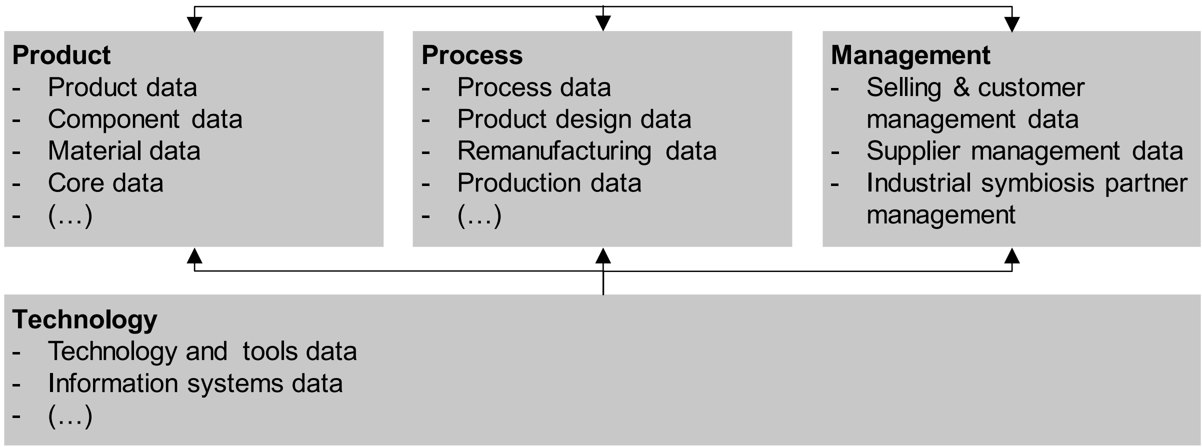


Figure 3.4: Conceptual data model (Acerbi et al. 2022, p. 840)

Evaluation: The data model provides an initial basis for important data and information that must be available or obtained when implementing a remanufacturing process. All phases of the product life cycle are considered, and the model is comprehensive, even if the information is not explicitly assigned to a specific phase. Due to the general validity of the model, it is also transferable to a complete vehicle in the automotive industry. In addition, important information and data that are required in the PPP are mentioned, but their relationship to each other and how they are interdepend is not explained. An example of this is naming the BOM, and the capacities and routings in separate classes. These are not directly related to each other in the data model. In PPP, the BOM influences the routing, and thus the use of capacity. Therefore, the consequences that uncertain core quality, quantity, and timing have on sales planning, on primary demand planning, and on gross resource planning are only assessed to a limited extent in this model.

3.3.2 Sustainable Information Management for Waste Electrical and Electronic Equipment (Lɪ et al. 2012)

Lɪ et al. propose a data model that helps to implement distributed information services which enable convenient and secure handling of electrical and electronical equipment (EEE) information. The model is intended to assist companies in the traceability of information about their components to facilitate recovery and remanufacturing. The information that should be known about a product is divided into the eight categories factory information, tracing information, technological information for recovery, feedback information, recovery/remanufacture-oriented design support information, legal information, economic information, and ecological information.

Lɪ et al. transform this information into a data model for factory information (see Figure 3.5) and into a separate data model for recovery and remanufacturing information (see Figure 3.6). For Lɪ et al., the factory information is considered the most important for remanufacturing. Together with the product information, which shows the type of components and physical properties, the treatment strategy can be determined. This includes non-destructive and destructive dismantling. The manufacturer and supplier classes are inherited from the role in SC. The role in SC, the material, and the products have a unique identification number. The MBOM is a tree structure in which a node represents a component or part. Each node has corresponding information on the material composition, the process flows, and the types of joints used. The models are based on defined manufacturing and disassembly processes using the example of an LCD screen. The required information is derived from the LCD screen's manufacturing process. (Li et al. 2012)

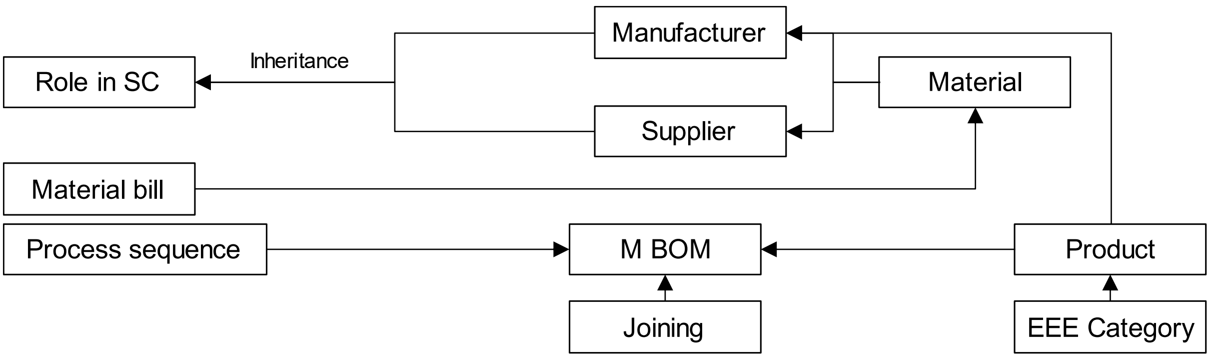


Figure 3.5: Conceptual information model of factory information (Li et al. 2012, p. 880)

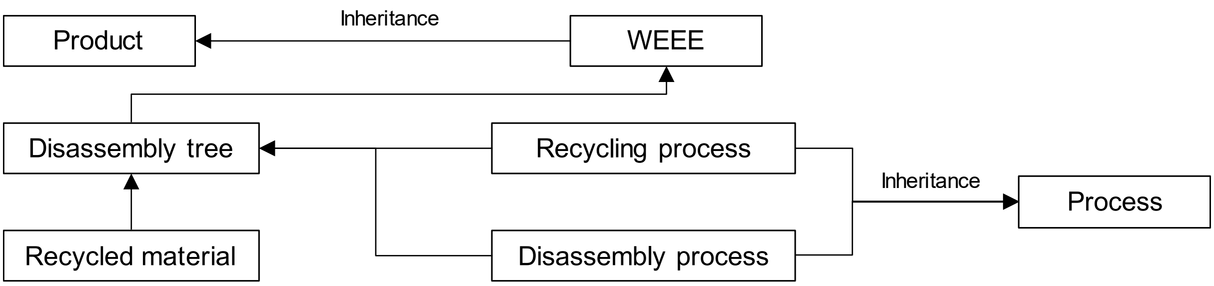


Figure 3.6: Conceptual information model for recovery and remanufacturing (Li et al. 2012, p. 880)

Evaluation: The data model is tailored to EEE, and in particular to an LCD screen. This results in specific features in the data model that cannot be transferred to the automotive industry. These include, for example, the EEE category class and the recycling information and process. The model provides a structured approach to data required for PPP in remanufacturing but does not assign individual classes to specific planning steps. Nevertheless, important dependencies that also play a role in the PPP are included. For example, the BOM is linked to the materials and process steps used in manufacturing, and the disassembly tree is derived from the manufacturing process. In addition, no quality classes for returns are mentioned in the model, and there is no time stamp that could be used to record important developments for individual products over its life cycle. Only the average service life is recorded here. The model therefore does not take into account any quality- or quantity-related influences on the PPP, but nevertheless captures a large part of the necessary data for gross resource planning. Also, the publication does not explain the classes and variables sufficiently, and the model is neither tested nor validated.

3.3.3 Information Systems and Circular Manufacturing Strategies: The Role of Master Data (ANDERSEN et al. 2016)

ANDERSEN et al. investigate which master data is required for different circular strategies, such as reuse, circular design, and remanufacturing. They also explain how the data is related to the information systems used in the manufacturing industry. The term information systems includes technologies such as computer-aided design (CAD) for product development, customer relationship management (CRM), product lifecycle management (PLM), and ERP. Table 3.2 shows the results of the publication. The table is intended here for better understanding and only shows an excerpt of the results. It shows which master data is relevant depending on the strategy, as these are supported by different information systems, technologies, and activities. The strategies are enumerated in the initial column and subsequently allocated to corresponding activities in the second column. In column two, a distinction is made between internal company processes and inter-company processes. In the third column, the domain that is influenced by the strategy is mentioned. The different domains are the product, the process, and the business domain. For remanufacturing, only supply chain activities between main actors are considered. Specific activities for the different information systems and circular economy strategies are not taken into account. The last column additionally gives examples of the relevant master data. (Andersen et al. 2022, pp. 28–29)

Column four states the information system, which in case of remanufacturing and disassembly is, for example, PLM. The selection of the relevant master data in PLM is based on the research from MYUNG et al. and includes parts data, design data, BOM, docs/specification, configuration data, work instructions, product quality data, product compliance data, and product service data. (Myung 2016, p. 776)

Table 3.2: A framework for master data management for circular manufacturing strategies (Andersen et al. 2022, p. 29)

CM strategy	Activity	Domain	Information System	Master Data element	Examples
(…)					
Remanufacturing	Return to manufacturer	Process Product	PLM (CLSC) BC (OLSC)	MD for products MD for manufacturing	Material composition, MD for utilization of parts
Disassembly	Return to manufacturer	Process Product	PLM (CLSC) BC (OLSC)	MD for products MD for manufacturing	Material composition, MD for utilization of parts
(…)					

Evaluation: For remanufacturing and disassembly, the publication specifies which information systems should be utilized. As the publication is very general and because it solely focuses on supply chain activities for remanufacturing, there is no actual differentiation made between remanufacturing and disassembly. Consequently, the according entries in the table are identical. The framework can theoretically be used in the automotive industry, but its practical value remains uncertain as it has not been validated in ANDERSSON et al.'s research. Moreover, the explanations are incomplete. The abbreviations BC and OLCS, mentioned as information systems in column four, are left unexplained. There is also no further specification of the master data (MD) for utilization of parts, which is mentioned in the last column. Thus, the publication falls short in fulfilling most of the defined evaluation criteria. Nonetheless it shows, that master data must be managed in a PLM system due to the elevated level of complexity involved in disassembly and remanufacturing.

3.3.4 A Cloud-Based Approach for WEEE Remanufacturing (WANG et al. 2014)

WANG et al. present a web-based, service-oriented platform for cloud remanufacturing. The model is tailored to waste electrical and electronic equipment (WEEE) and aims to provide an interoperable, adaptable, and distributed infrastructure to assist the manufacturing industry in recycling, reusing, and remanufacturing products with a cloud-based information system. (Wang et al. 2014, p. 409)

The structure of the model can be seen in Figure 3.7. In the user layer, the user operates a web browser. Users are both customers and remanufacturers looking for synergies. For the consumer, the relevant product data is stored in a quick response (QR) code attached to the product, so the customer does not need to have any knowledge of the product or its reprocessing. The data model containing the product information is based on the ISO 10303, which enables computer-aided representation and exchange of product data over the entire life cycle of a product (Norm ISO 10303 - 1 1994, p. 5). The web-interface offers various service requests, which are documented in a standardized format. They are passed on to the cloud service coordination layer. Here, the broker agent assigns the available reprocessing services to a request. The selection of the appropriate services is made taking into account their cost, duration, and resource consumption. The user can then check the offers communicated to him. The selection of the optimal remanufacturing processes is supported by a quantifiable lifecycle analysis integrated into the service layer, which finds the options with the lowest ecological impact and the highest economic benefit. The negotiated service is then carried out and controlled by the supervision agent. (Wang et al. 2014, pp. 410–411)

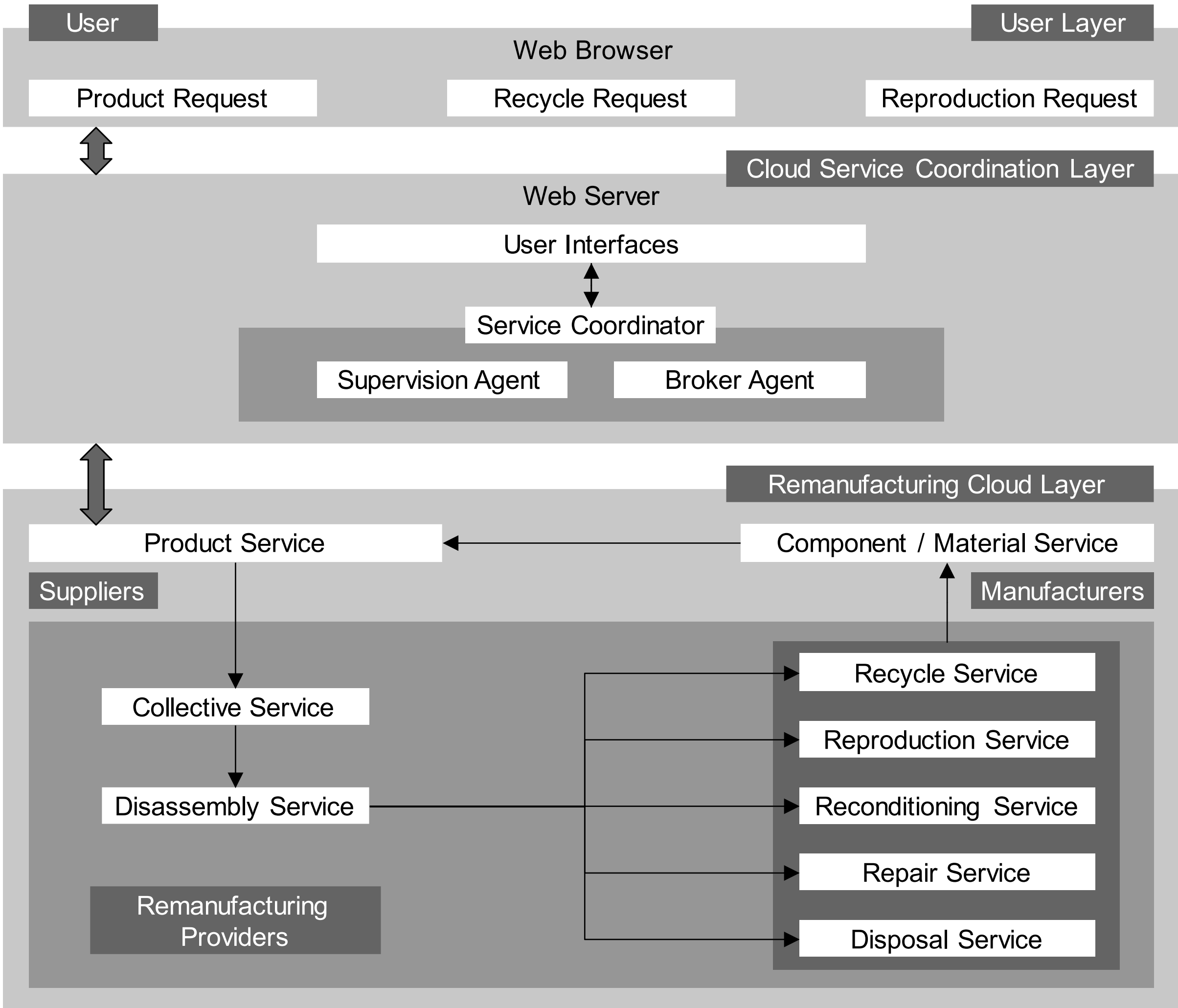


Figure 3.7: Cloud remanufacturing service infrastructure (Wang et al. 2014, p. 410)

Evaluation: The storage of product information with QR codes is limited to products with little complexity. Therefore, the model is not scalable to a complete vehicle. Furthermore, it is not specified which product data is used exactly and there is no possibility for the user to specify product-specific damage characteristics in the web interface. Thus, quality differences in the cores are not communicated to the manufacturers before the core arrives and cannot be considered when planning production in an intermediate planning horizon. However, the model does provide the ability to better estimate the demand for remanufactured products, as the time of arrival of a core is known as soon as the user requests a remanufacturing process. In addition, by linking the user to remanufacturers through the service layers, a high level of integration of data across the product life cycle is achieved.

3.3.5 Development of a Sales Planning Methodology for the Remanufacturing of Complete Vehicles in the Automotive Industry (Frank 2022)

Frank proposes a model for profit-optimized sales planning of remanufactured vehicles and new vehicles over several planning periods. All vehicles to be sold are produced or remanufactured within the same period and sold at the end of the period. The planning horizon can be determined flexibly but there is a recommendation of eight years given for vehicle sales plannings. The planning horizon is also limited by fundamental new developments to which a core cannot be remanufactured with the available remanufacturing methods. An example of this is a fundamental modification of the chassis. The model can be seen in Figure 3.8. Its central output is the profit over all periods. In addition, the profit-maximizing sales of the new and remanufactured vehicles are determined. The forecast is made on the basis of various input factors. These include, for example, the life cycle distribution of the vehicles, which determines the timing and volume of the returned cores, and the sales prices, which have an impact on demand, and determine the margins of the different vehicle types in the sales model. The model also considers product cannibalization effects in different sales scenarios. (Frank 2022, p. 86)

Another important input to the model is the demand forecast, which serves as an upper bound for the maximum number of vehicles that can be sold in each planning period. The model is specifically tailored to electric vehicles and whenever possible, remanufacturing is favored over new vehicle production. Additionally, the probability of a core of a defined quality class being returned depending on the business model is taken into account. Cores can be bought, and surplus cores are sold if they are not needed to meet the demand in a certain period. In the start period, no remanufacturing takes place because no cores are available yet. If a core needs to be upgraded, the associated costs in the model increase. (Frank 2022, pp. 90–95)

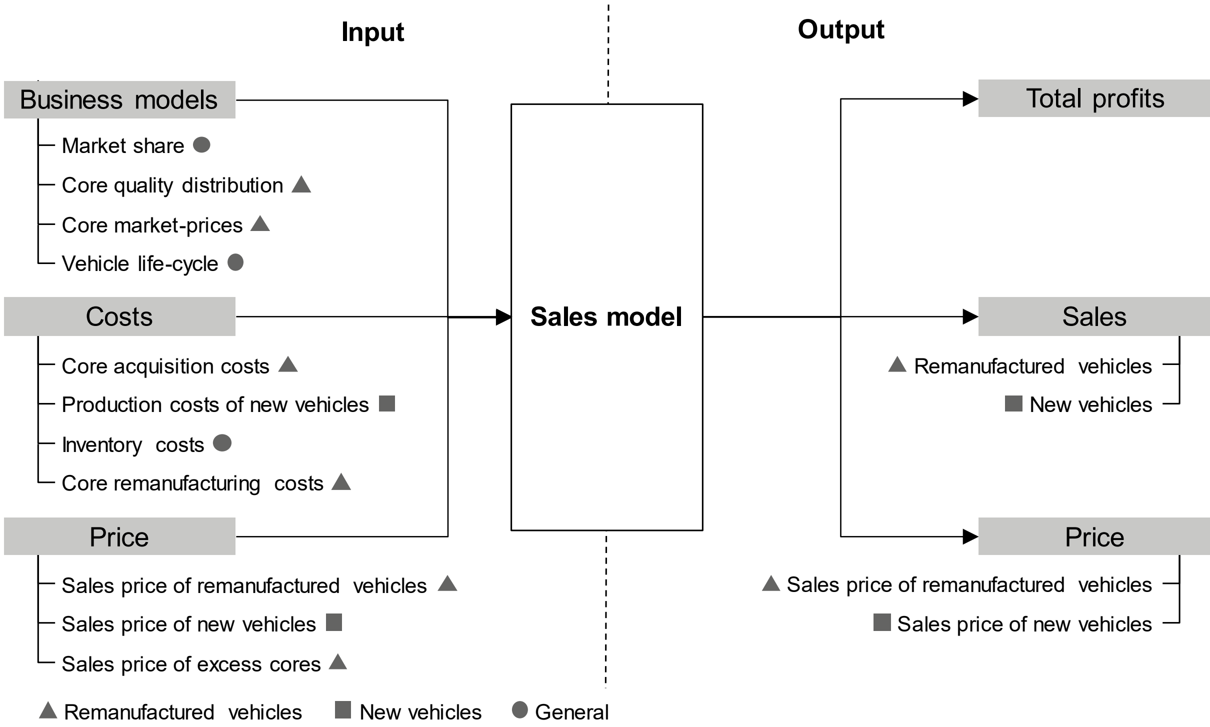


Figure 3.8: Input and output factors of the sales model (Frank 2022, p. 87)

Evaluation: The model is very well suited for the application in the automotive industry. Moreover, uncertain core quality and quantity are considered in the sales planning. Since it is a sales model, the consideration of primary demand and gross resource planning is omitted. However, the model provides a solid and comprehensive basis for subsequent steps of PPP and addresses essential information of sales planning in the automotive industry.

3.3.6 A Mixed-Integer Mathematical Programming Model for Integrated Planning of Manufacturing and Remanufacturing Activities (Giglio et al. 2014)

Giglio et al. investigate the creation of a production program for a hybrid manufacturing / remanufacturing system as shown in Figure 3.9. In the system, new products are manufactured in multi-step assembly operations. The goal is to determine the number of components and finished products to be manufactured, the quantity of new basic parts to be bought, the number of basic parts to be recovered from returned products, and the quantity of returned products to be acquired in order to match a predefined deterministic demand per planning period. The model minimizes the costs incurred in the system. (Giglio and Paolucci 2014, pp. 1–3)

On the manufacturing side, the products are broken down into their components via a BOM, which also contains the lead times of components or products. Furthermore, a number of existing machines is defined, and which machines are suitable for processing which components. In addition, the maximum capacity of the machines is taken into account. The same applies to the remanufacturing side. Here, the quantity of available remanufactured components, the quantity of returns in the current period, and the quantity of cores that start the remanufacturing process in the current period including their quality, and the quantity of cores in inventory at the end of a period are considered. (Giglio and Paolucci 2014, 3–5)

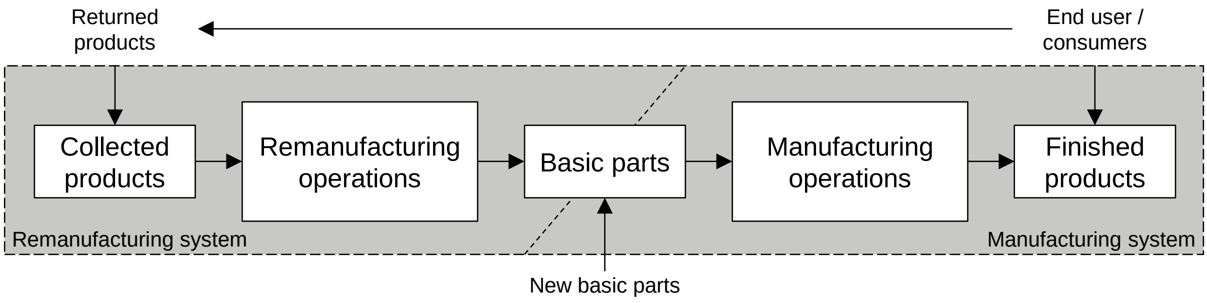


Figure 3.9: Remanufacturing system model (Giglio and Paolucci 2014, p. 2)

Evaluation: Despite its similarity to other periodic planning models, the model is included in the evaluation because it explicitly considers the effects of uncertain core quality and quantity on machine utilization and routings. Other models are more general in this aspect and do not break down the production program to the machine level. Therefore, this one fills a gap in the consideration of gross resource planning in connection with different routings. However, it lacks consideration of the problem that routings can change during disassembly depending on the quality of cores. The model can be scaled to the total vehicle but is not precise in which data is used to classify the quality of cores. Also, sales planning is not part of the model.

3.3.7 Supply Planning Model for Remanufacturing System in Reverse Logistics Environment (Kim et al. 2006)

Kim et al. propose a mathematical model that helps manufacturers decide whether needed parts should be ordered from external suppliers or remanufactured internally. The decision is made by maximizing total cost savings and determines the quantity of parts to be processed at each remanufacturing facility. (Kim et al. 2006, p. 279)

The basic structure of the model can be seen in Figure 3.10. After use, products are returned to a collection site, where a decision is made as to whether they will be passed on to a subcontractor or disassembled and refurbished at company-owned sites. The demand for products is a known input and can be flexibly adjusted, as can the planning horizon. From the demand for products, the demand for components is derived based on the BOM. Another known input is the number of cores that will be returned by the customer in each planning period. If demand cannot be met by the returns, missing components must be procured externally. In addition, the maximum capacity of the collection plant, the dismantling plant and the reprocessing plant is taken into account and a maximum disposal quota is defined. The individual process steps are then assigned their costs and the cost optimal solution is calculated. (Kim et al. 2006, pp. 284–285)

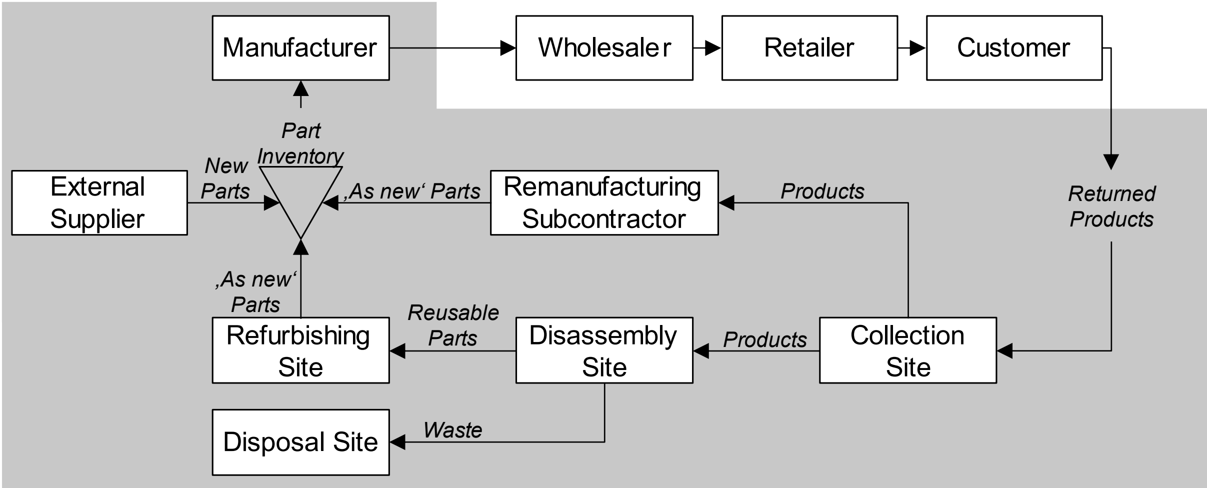


Figure 3.10: Conceptual framework for a remanufacturing system – the shaded region (Kim et al. 2006, p. 281)

Evaluation: Based on the known inputs, the model can provide information about the cost-optimal mix of new and remanufactured parts and is thus also suitable to determine a feasible mix of remanufactured components and new components which are converted into a new product. This is important in sales planning, but the model assumes a known cumulative demand in which no distinction is made between new and remanufactured products. For the same reason it is only suited for the production of vehicles for which the customer does not care what parts were used to build the new vehicle and product cannibalization is also not considered. Quality-dependent planning uncertainties are mostly neglected in the model, since, for example, no MRR is considered and no classification of the quality of the cores takes place. In addition, the model relies on the timing and quantity of returns being known. Since the capacity of the factories is taken into account by moving production quantities to later time periods, planning uncertainties in gross resource planning caused by fluctuating core supply can be reduced to some extent. However, the effects of changing routings are neglected.

3.3.8 Production Planning in Remanufacturing/Manufacturing Production System (Kasmara et al. 2001)

Kasmara et al. introduce a model that generates a production plan in a hybrid manufacturing-remanufacturing system. The model is based on a material flow diagram which can be seen in Figure 3.11. It is a linear programming model, which is implemented in the mathematical programming tool XPRESS-MP and evaluated with three products with six common components. Although, it can be applied to any number of products with any number of components. An important assumption is modeling the sales of a product as a variable which has an upper limit, namely, the demand. The demand may not be matched in certain periods if the overall system does not allow for it economically. The BOM information are contained in a product structure parameter, which relates components to their products. Also, the model considers a variety of costs, which are related to the activities shown in the material flow diagram (manufacturing costs, remanufacturing costs, inventory costs, etc.) as well as revenues obtained from selling products. The expected time of return of cores is modeled by a probability distribution and there is a limited probability that a core can be successfully remanufactured. Additionally, KASMARA et al. define a minimal remanufacturing ratio to account for possible environmental regulations. The calculation of the inventories after each activity are given constraints like a maximum and minimum inventory and the activities themselves are constraint by a maximum capacity. The model aims to maximize the profits per planning period and determines the optimal numbers of sales, disassembly, assembly, disposal or lower recovery strategies, remanufacturing, manufacturing, and remanufactured parts to be used in assembly. (Kasmara et al. 2001, pp. 711–712)

In addition, KASMARA et al. point out several important considerations for the information needed in remanufacturing systems and how they influence the planning process. Increasing product complexity leads to increasing process costs. Also, part commonality can help balancing inventories when the demand fluctuates. Fluctuating demand causes return fluctuations and the longer a product takes until it is returned, the worse its condition and the higher the remanufacturing costs. Longer lead times in returning cores also require a longer planning horizon for production planning. Remanufacturing generally generates higher profits than manufacturing if the cores have a high quality and if collection rates are high. Also, general incentives for increasing the remanufacturing ratio are inflated costs of material, manufacturing, and disposal while having low costs in collection and remanufacturing. (Kasmara et al. 2001, p. 713)

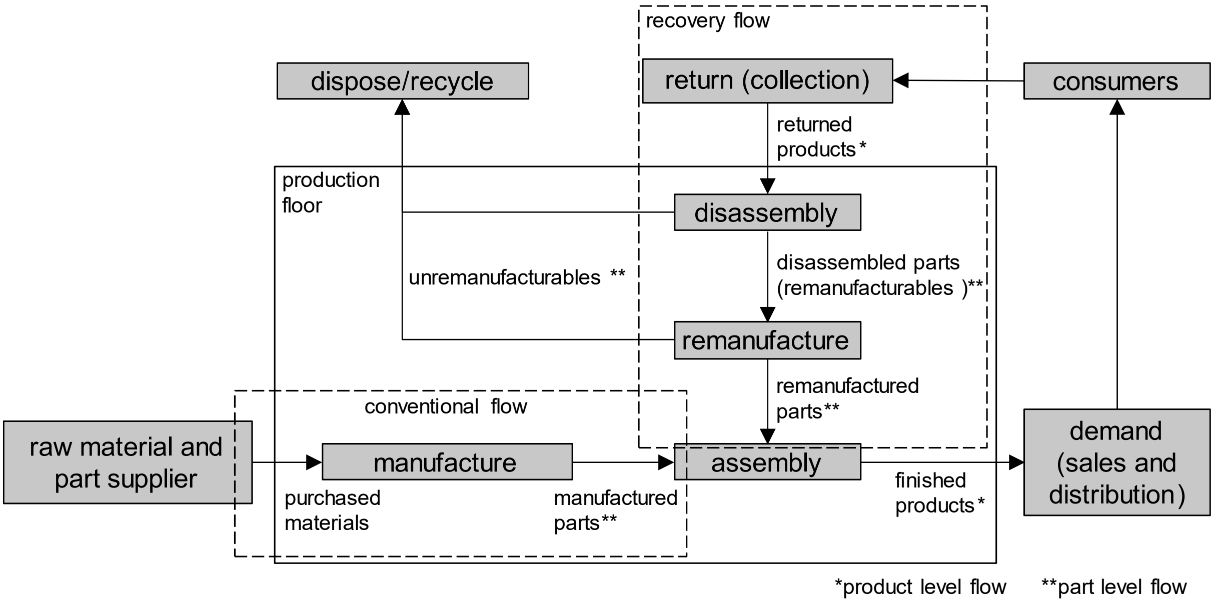


Figure 3.11: Material flow diagram for a hybrid manufacturing-remanufacturing facility (Kasmara et al. 2001, p. 711)

Evaluation: The model is one of the most comprehensive in the handling of planning uncertainties in PPP. The publication does not explain the exact calculation steps, but it describes the data on which the model is based. It takes into account quality- and quantity-dependent planning uncertainties in statistical form, including capacity limits and inventory constraints. Costs are considered, but the effects of different core qualities on reprocessing costs and specific routings are omitted. These could be included, for example, by using a probability distribution of qualities that calculates increasing costs and process times for cores of lower quality. Furthermore, the model does not address which data exactly is the basis of the statistical core quality distribution. The model can be scaled to an entire vehicle, since it has no restriction for the number of components or products, or for the definition on the planning horizon and periods. However, the demand is only modeled for one product type, no new products are sold separately from remanufactured products, and sales planning is not part of the model.

3.3.9 Material Planning for a Remanufacturing facility (Ferrer et al. 2000)

Ferrer et al. propose a model to determine the optimal remanufacturing and purchase quantities of cores, parts, and components per planning period. The model is based on MRP and requires an MPS as an input. As in the classical MRP, demand for components is derived with the BOM and comparison with the inventory yields the primary demand. The core supply is estimated as a percentage value of sales per planning period. Ferrer et al. use a reverse BOM to determine the disassembly yield of the incoming cores. Should the disassembly yield not be sufficient to cover the demand for the assembly of components, either cores, parts, or components must be purchased from the market. The objective is to minimize the purchase quantities. Although, the authors state, that the model would work equally well minimizing the inventory level. Purchases have a lead time of four planning periods. For each planning period, the model defines the on-hand inventory, and which cores, parts, and components to buy, to disassemble, and to assemble. (Ferrer and Whybark 2001, pp. 118–122)

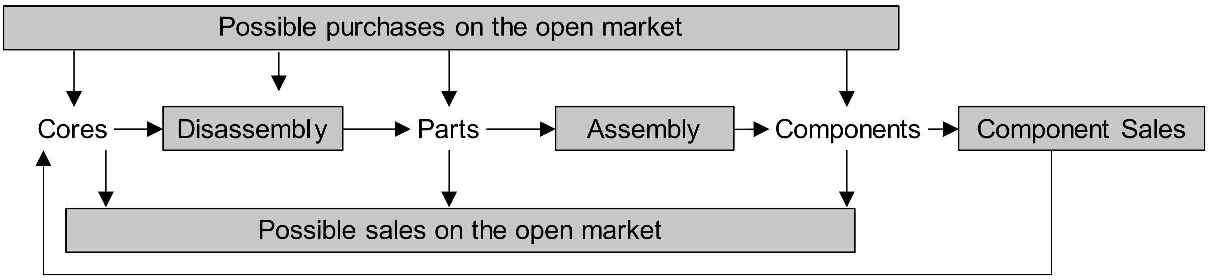


Figure 3.12: Material process flow diagram for component remanufacturing (Ferrer and Whybark 2001, p. 114)

Evaluation: The model deals with core processes of primary demand planning and with parts of gross resource planning. Its limitations for PPP are that there is no sales planning considered and that capacity limits in production are ignored. The model assumes that all parts which are remanufactured have the same routing. Also, various kinds of failure modes are neglected. More precisely it can be seen in Figure 3.12, that there is no process step mentioned, where parts are restored to an as-new condition. Also, the disassembly BOM values are based on experience and the model is made for a pure remanufacturing facility, so there is no possibility to manufacture missing parts or components in-house and the sold components will always be an uncertain mix of purchased and remanufactured parts. Therefore, the model cannot be used for a facility which considers demand for remanufactured and new products. The model was evaluated for automotive starters but could be scaled to a full vehicle remanufacturing facility. The failure modes of the cores are not described. The model does not explain which data is needed to determine return rates and qualities.

3.3.10 A Data-Driven Method of Selective Disassembly Planning at End-of-Life under Uncertainty (GAO et al. 2023)

GAO et al. propose a model for determining disassembly sequences. The model calculates a trade-off between the minimum number of disassembly operations and the maximum feasibility in order to remove target components or high-value parts from a core as quickly and feasibly as possible for reuse, remanufacturing, or recycling activities. It is a data-driven method where dismantlability describes the degree of difficulty with which components can be removed under uncertainty. For this, random and fuzzy evaluation data are converted into qualitative values, and then a prediction of the disassembly steps is made. The prediction of the time at which the disassembly must take place is based on historical data. (Gao et al. 2023, p. 365)

The model is tested on an electric motor drive system, which has a defined set of components. Those have a simplified shape and are provided with information about their junctions, like the access side and the disassembly direction. A predefined graphical model shows the sequence of screws to take out or junctions to open, in order to obtain a specific component. The quality of screws can influence if a part can be recovered easily, and therefore a motor drive in bad physical condition has a high probability of component damage in the disassembly process. (Gao et al. 2023, pp. 567–568)

The defined criteria to evaluate the uncertainty in disassembly can be seen in Figure 3.13. A distinction is made between component characteristics and disassembly characteristics with a total of six criteria against which each component of a core is evaluated. The physical condition describes the degradation status of the component that influences the disassembly sequence. In addition, the accessibility captures the ease of access to each component. A screw that is in a tight, deep spot is more difficult to access than exposed components that can be easily moved, positioned, or removed with a tool. Thus, accessibility depends on the relative location of the connections to other components. Disassembly tools and methods are accounted for by the disassembly pattern, which can vary depending on how the components are connected. The mating face captures the complexity of the disassembly process. For example, complexity increases when multiple joint components need to be disassembled. The connection type criterion takes into account that it is easier, for example, to remove fasteners such as bolts and clamps, than it is to remove welded or soldered connections. Additionally, removing components during the disassembly process may cause damage to the component, e.g., when opening welded joints. Finally, the number and variety of joints are also recorded as criteria. The model also specifies briefly where and how the necessary data can be obtained. (Gao et al. 2023, pp. 568–569)

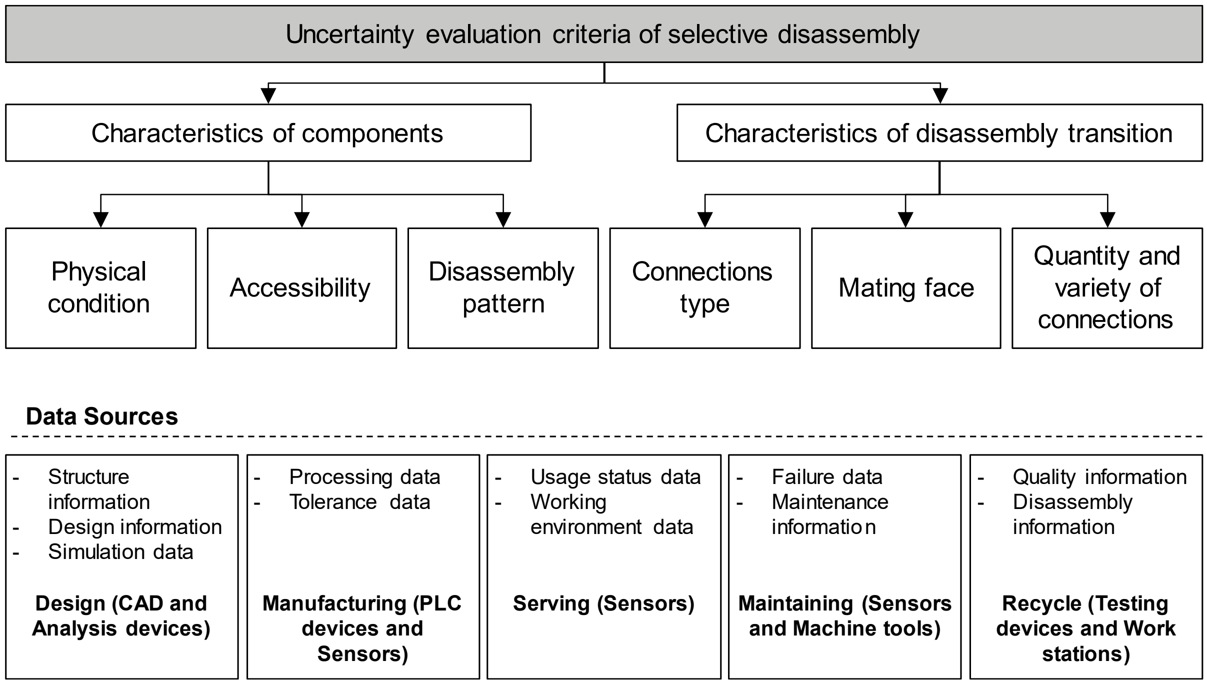


Figure 3.13: A representation of the evaluation criteria used to assess uncertainty of EOL products and their data sources (Gao et al. 2023, pp. 568–569)

Evaluation: The model provides a solid data basis for the determination of disassembly sequences with uncertain core quality. Expected return times are also taken into account, but here the specific data sources are not discussed further. However, they are described precisely for the quality categories used and they are also assigned to distinct phases of the product life cycle. Although the model does not deal with problems of sales planning or concrete periodic PPP, it does provide an important basis for the data requirements in disassembly, which is a necessary process step in PPP. The model can be transferred well to mechanical components of a vehicle because the defined criteria for evaluating dismantlability are formulated in a generally valid manner. It is a comprehensive approach to handling uncertainties in gross resource planning.

3.3.11 A Novel Multi-Criteria Sorting Model Based on AHP-Entropy Grey Clustering for Dealing with Uncertain Incoming Core Quality in Remanufacturing Systems (Mustajib et al. 2021)

Mustajib et al. propose a quality grading method for cores based on the data criteria shown in Figure 3.14. The main criteria are the physical condition, the technological condition, and the usage condition. The obsolescence is a parameter that evaluates how up to date the product is. It refers to the technological advances made during the product life cycle and serves to evaluate if the product can keep up with the emerging new technological innovations when surpassing its intended lifespan. The upgradability measures how easily the product can be functionally adapted or enriched by features in the remanufacturing process. It serves to evaluate how hard it is to upgrade the product with a modern technology to avoid obsolescence. Then, the model accounts for the products having limited life cycles. The multiple life cycles parameter counts how many life cycles the product may have before being passed on to another, lower-grade circular strategy. The disassemblability sub-criteria captures how easy it is to disassemble the core and the damage level captures the degree of physical defects like wear, cracks, and corrosion. Products may also return without containing all their parts, which is why the components completeness is evaluated as well. Also, the traceability of the product information such as model or type are important for the quality grading. If the manufacturer's identification number is known or readable on the core, the product is considered to have a higher quality. As important is knowing the allowable geometric and dimensional tolerances and the frequency of use, which counts the number of times the product was used in the use phase. Another sub-criterion is the maintenance frequency, which captures how intensely the product is maintained during the use phase. This is done by establishing an expected load level as the average and then moving up the quality scale when the product was used under normal load, and moving down the quality scale when the product was used above normal load. The final sub-criterion is the remaining useful life. (Mustajib et al. 2021, p. 23)

Most of the criteria are qualitatively evaluated on a scale from one to five. An exception is the component completeness, which is a percentage value of the complete product. There is also more detailed information given on the meaning of the scale from one to five in the different criteria. The obsolesce scale, e.g., reaches from "*overtime*" to "*equal as new technology*" and the upgradability from "*minimal repair*" to "*replacement with new parts*". The disassemblability is evaluated by weather complex processes and machines are needed. It considers how time consuming the process is if there are permanent joints, or if damaging parts is inevitable when disassembling. The damage level can take on precise quantifiable measurements, for example when there are measurable levels of wear and tear. Regarding the traceability of the parts identity, the scale reaches from having a fully functional radio frequency identification (RFID) to incomplete identification numbers. (Mustajib et al. 2021)

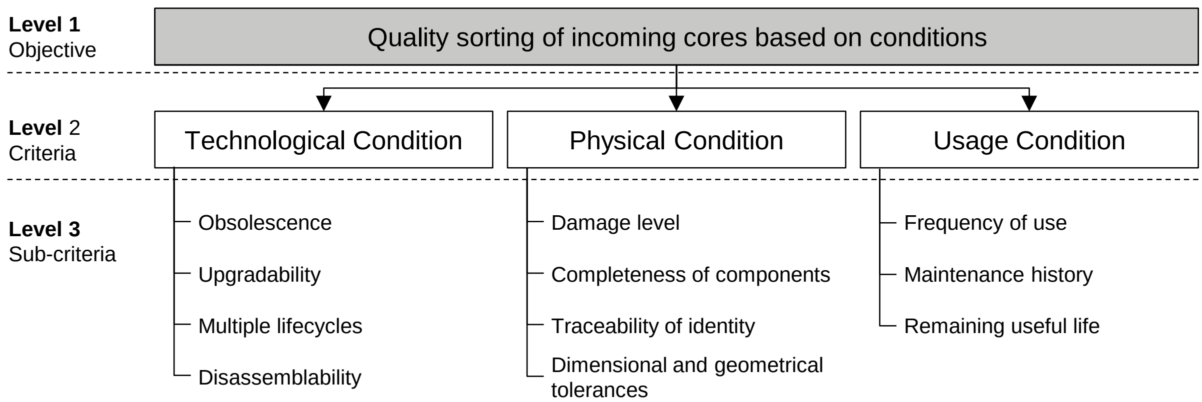


Figure 3.14: Hierarchy of decision levels for the incoming core quality sorting problem (Mustajib et al. 2021, p. 11)

Evaluation: The model provides a very good overview of the data that needs to be known about a product in order to plan the remanufacturing process based on uncertain quality. It is also a good approach to handling the relevant data from the use phase and goes into more detail about what exactly this data looks like. Nevertheless, it only represents a small part of the complex PPP, since return quantity and timing, demand, and concrete process steps are not considered. The model can be applied to the analysis of the components in vehicle production and is comprehensive in the description of the data points. Its value for PPP in remanufacturing lies mainly in gross resource planning.

3.3.12 A Hybrid Approach of Rough Set and Case-Based Reasoning to Remanufacturing Process Planning (JIANG et al. 2019)

JIANG et al. address the impact of different quality states and fault patterns in cores on routings in the remanufacturing process to reduce the processing time and effort. For this purpose, they use a hybrid model based on rough-set (RS) reasoning on the one hand and case-based reasoning (CBR) on the other. RS is used to automatically identify the relevant features of a core and to determine the weights of the features. CBR is used to calculate the similarity of processes in a database to find the optimal reprocessing techniques and routings for a new core. (Jiang et al. 2019, p. 19)

The steps from the model are shown in Figure 3.15. A new core is called a case and is described by a set of features. The case-based reasoning is used to fill information gaps like unknown features by comparison with similar parts. The RS then removes redundant features, since a case can theoretically have features which are not necessarily important for determining the reprocessing steps. The weights of the remaining features are calculated automatically. Then, the case is compared to other cases from the database using a nearest neighbors algorithm to determine the best process flow for that case. For the presentation of a case, the features case number, condition feature description, and process solution are used. The condition feature description includes the name of the component, its type, material category, brand, material hardness, surface roughness, straightness, failure location, and machining allowance. The information related to the process solution contains data about processes and equipment, as well as process parameters and the sequence of process steps. (Jiang et al. 2019, pp. 21–22)

As a validation example, the work uses a saddle guide with the following characteristics: Guide type, guide number, material brand, machining accuracy, failure symptom, failure position, failure degree, heat treatment, horizontal straightness, vertical straightness, hardness, and surface roughness. (Jiang et al. 2019, p. 25)

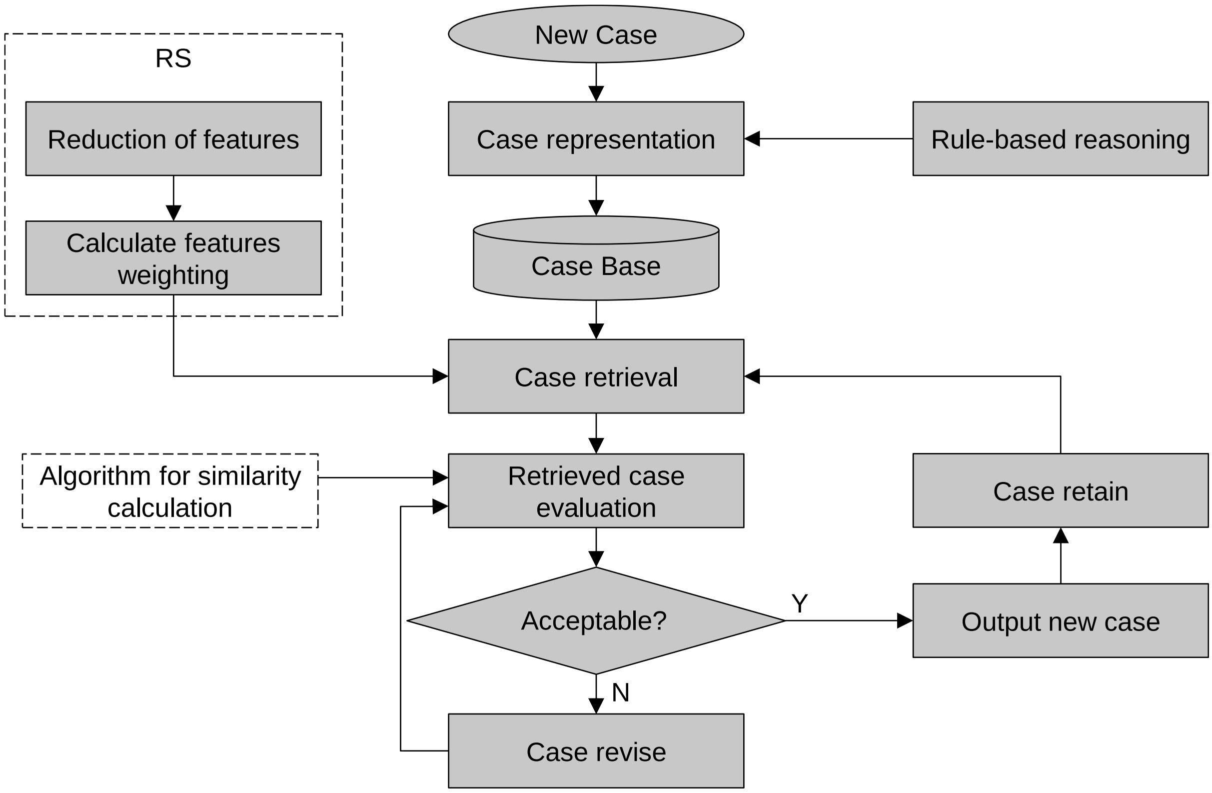


Figure 3.15: Process flow for the selection of a restoration process with rough-set and case-based reasoning (Jiang et al. 2019, p. 22)

Evaluation: The model is well suited for estimating the effects of different core qualities and specific fault symptoms on routings. It provides a basis for gross resource planning since optimal routings are suggested. In the model, however, it remains open at which point in time the failure symptoms are known. These may only be detected during a detailed analysis upon arrival at the factory. The model is therefore only partially transferable to vehicle production. For PPP in the automotive industry, the core qualities would have to be known over a long planning horizon and, in the sense of a lean production, the cores would have to go directly through the remanufacturing process as soon as they arrive at the factory, so that no unnecessary storage costs are incurred. In addition, no consideration is given to capacity limits and no consideration is given to separate demand for new or remanufactured products.

3.4 Evaluation of the Existing Approaches

Table 3.3 presents a summary of the evaluation outcomes. The analyzed research on PPP in remanufacturing can be classified into four categories. The first category examines deeply the required data and information, classifying them into distinct classes. However, such models do not account for several essential interdependencies of PPP in remanufacturing. The second category of models relates to the description of information flow infrastructures in remanufacturing or circular strategies in general. However, these models lack precision in terms of the exact data points that should be communicated. The third category of models addresses the periodic production planning in remanufacturing facilities. Such models involve uncertainties in core qualities and supply, and incorporate effects on routings, capacity, or inventory constraints. However, these models simplify the input data. Demand, core quality, and core availability are estimated based on historical values or approximated by statistical distributions that must be gathered over long periods of time. As a result, they require a long planning lead time. They also do not specify the exact data points which are used to perform the quality assessment.

Models of the fourth category specifically determine optimal assembly, disassembly, or repair processes by using defined data points from different phases of the product life cycle. These models do not connect the data to all planning activities in PPP. However, they show the potential of data-based PPP in remanufacturing. Models of category four still rely to some extent on quality assessments performed during an initial inspection when being returned. By gathering data about the core before it returns, namely, during the user phase, long planning lead times, and uncertainties due to fluctuating core condition and availability could be reduced. Therefore, the user phase data needs to be combined with the relevant manufacturing and remanufacturing processes data, referenced to the activities of PPP in remanufacturing, and represented in a structured in a comprehensive data model. As the literature analysis shows, such a model does not exist yet. Hence, there is a research gap in data-based PPP in remanufacturing and the derived research question is:

How can a data model be designed for data-based production program planning in remanufacturing?

Table 3.3: Evaluation results of the relevant literature

Rating scale

- ○ unsatisfied
- ◔ mostly unsatisfied
- ◑ partially satisfied
- ◕ mostly satisfied
- ● fully satisfied

Authors	Category		Handling of uncertainties in sales planning	Handling of uncertainties in primary demand planning	Handling of uncertainties in gross resource planning	Comprehensiveness of the data model	Transferability to the automotive industry
Authors	**Category 1** Focus on data collection	ACERBI et al. 2022	◔	◔	◔	◑	◕
		LI et al. 2012	○	◔	◔	◕	○
	Category 2 Focus on infra-structure	ANDERSEN et al. 2016	○	○	○	◔	○
		WANG et al. 2014	◔	○	◑	◑	○
	Category 3 Focus on periodic production program planning	FRANK 2022	●	◔	◔	◑	●
		GIGLIO et al. 2014	○	◕	◑	◔	◑
		KIM et al. 2006	◑	◔	◑	◔	◕
		KASMARA et al. 2001	○	◑	◕	◔	◕
		FERRER et al. 2000	○	◔	◑	◔	◑
	Category 4 Focus on (dis-) assembly processes based on defined data points	GAO et al. 2023	○	○	◕	◕	◕
		MUSTAJIB et al. 2021	○	○	◕	◕	◑
		JIANG et al. 2019	○	○	◕	◔	◑

4 General Model Structure

4.1 Definition of the Remanufacturing Process

Chapter 4 establishes the foundation for building the data model for PPP in remanufacturing. The literature on periodic planning in chapter 3.3 shows that PPP is process specific. For example, in the case of a pure remanufacturing company that does not offer new products for sale separately, product cannibalization resulting from a mix of new and remanufactured products would not be considered and therefore would be excluded from sales planning. In this work, a product mix of new and remanufactured products is chosen. Similar considerations apply to individual process steps, since inventories, capacities, and qualifications must be defined for each process step. Therefore, the basis of the data-driven PPP is the definition of the remanufacturing process including the individual process steps. The remanufacturing process defined for this work is shown in Figure 4.1.

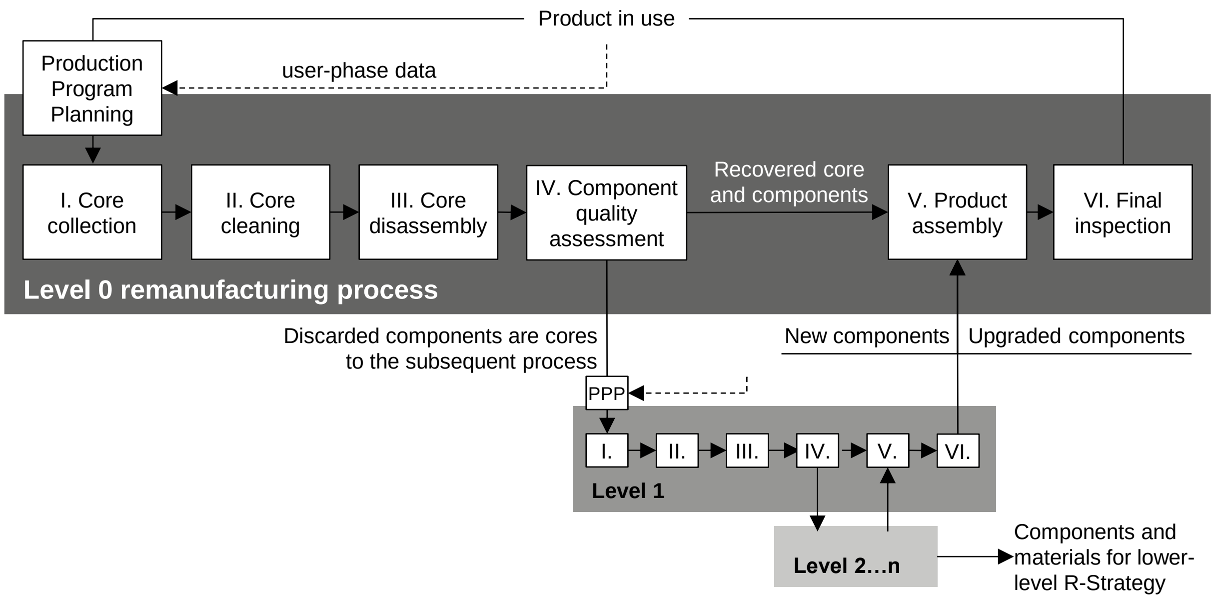


Figure 4.1: Cascaded remanufacturing process with defined levels for production program planning

The process model shows, PPP is the first step in the remanufacturing process as it is defined for this work. The planning can be performed while some cores are still in use with the customer. In PPP, the product's user-phase data is considered so that uncertainties caused by the returning cores can be incorporated at an early stage. The second process step is the collection of cores after a user cannot or does not want to continue using the product. Cores are also collected when a company that retains ownership of the cores while they are in use at the customer's site requests the return of its cores. The collection step is highly relevant to the data model because, the nature of the business model influences how, when, and in what condition cores are returned for reprocessing (Frank 2022, p. 86). After collection, the cores are cleaned. This processing step is important because, as discussed in chapter 2.2.5, it reveals defects and facilitates the disassembly and reassembly processes. In the third process step, the cores are then disassembled into their components.

Afterwards, the components undergo a quality assessment. After the assessment, reusable components are transferred to assembly. It is important to note that product requirements may change during their life cycle, resulting in certain components of a core not being reused despite having no technical defects. This is because new standards imposed by legislators may force the manufacturer to modify the product. Additionally, products and components are continuously being developed and upgraded through innovations, resulting in the new product receiving an upgrade and thus an increase in value compared to its predecessor generation, which also appeals to the customer. As a result, reusable components are only those that are functional, desired by the customer, realizable by the manufacturer, and tolerated by the legislator (Chierici and Copani 2016, p. 1).

Components that cannot be reused due to the reasons mentioned above are returned to their respective manufacturers as cores and undergo their respective remanufacturing process. By implementing the cascading process, each remanufacturer is solely responsible for the products that they manufacture in-house. The remanufactured components from lower cascades are then returned to the next higher level as new components. Meanwhile upgraded components are obtained from a different source. The remaining useful core and the useful components are then assembled with new and upgraded components into the new product. Before the product can be given to the customer, it needs pass the final assessment. Components which cannot be reused in any of the cascades, are passed on to a lower-level circular R-Strategy.

4.2 Derivation of the Planning Activities for PPP in Remanufacturing

Based on the remanufacturing process defined in chapter 4.1, the planning activities of PPP in remanufacturing can be derived. The thereby created activity model contains an initial description of the most important input and output information for the individual activities and forms, together with the remanufacturing process, the basis of the data model. For remanufacturing, core acquisition management (see chapter 2.2.4) is added as a planning element to PPP in addition to the classic elements of sales planning, primary demand planning, and gross resource planning as explained in chapter 2.1.1. Core acquisition management for PPP in remanufacturing is primarily responsible for the information management of core availabilities and qualities, as well as their communication with the classic elements of PPP. The activity model can be seen in Figure 4.2.

The activity model starts in sales planning with the demand forecast at product-level. As shown in chapter 2.1.5, the input information requirements of the demand forecast depend on the selected forecasting method. Accordingly, once the forecasting method has been selected, the forecast parameters must be determined. In addition, historical sales data is used, if available.

As in classic PPP, the demand forecast, and the already existing customer orders form the basis for sales planning at product level. When creating the sales plan, the aim is to achieve a profit-optimized mix of remanufactured products and new products. Therefore, the costs and prices of the new products and the costs and prices of the remanufactured products must be known. At the same time, the core acquisition management needs to provide the core-procurement costs and the revenues that can be generated by selling surplus cores on the market. In addition, the expected core availabilities must be known, as well as their expected quality distribution. The prediction of core availabilities and qualities is also the task of core acquisition management and depends on the business model. The availability of cores can be estimated using core return probability distributions. The quality of a core is determined by the quality of its components. An estimation of the overall core quality can therefore be based on the component's quality distribution, and on the probability of how many and which components can be recovered. The sales plan is then divided into a separate sales plan for new products and one for remanufactured products. The sales plan for new products is passed on to a normal manufacturing facility.

With the sales plan completed, primary demand planning can be initiated. Primary demand planning consists in deriving the net primary demand for products, which is obtained by comparing the desired sales to the inventory level of products and to the already existing orders in production. The net primary demand is then used in gross resource planning to determine the gross demand for components using the BOMs. At this point, all desired and necessary component upgrades are also taken into account. By subtracting the inventories while considering safety stock, and the expected component yield via disassembly, which is estimated by the core acquisition management, the net demand for new components can be derived. Also subtracted here are component quantities that were ordered in earlier planning periods and whose arrival is therefore expected within the current planning horizon. The net demand for components is passed on as an order to the according component manufacturers or production facilities and must be available at the start of product assembly. Additionally, each core now is matched with a new product to be converted in. All components which have to be removed from the core are now known and based on the lead times for each component in disassembly and in assembly, the according lead times can be determined.

The quantity of cores to be disassembled, as determined by the sales plan, is the basis for gross resource planning in disassembly. Gross resource planning for assembly, in turn, requires the net primary demand for products as an input. In combination with the routings and other process information, such as processing times, the required capacities can be derived. As a core is ideally only striped of components, which can no longer be used, each core can have a different configuration or composition of components after disassembly, and therefore has a unique remanufacturing process. This means that each core must be identified individually when entering production. The final step is to compare the required capacities with the available capacities in all processing steps to check the feasibility of the production program.

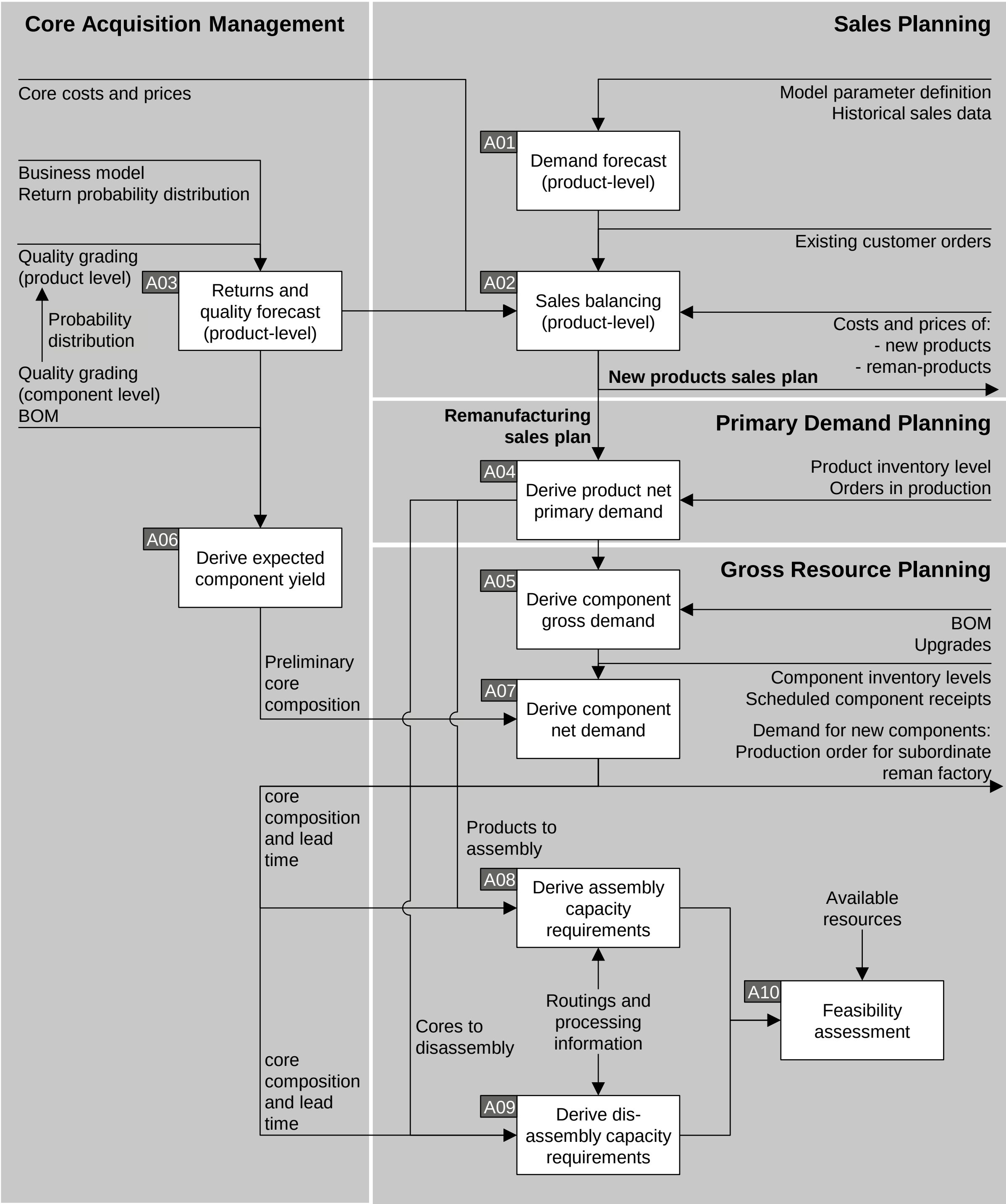


Figure 4.2: General model of data-based production program planning in remanufacturing

4.3 Conceptualizing the Data Model

The activity model is examined with the IDEF0 method to deduce the data required for the respective activities. The data is transferred into a data model, which is written in UML. The general structure of the model is shown in Figure 4.3. The procedure for building the final data model is to sort the data from the activity model into classes. For this purpose, UML provides class diagrams that assign attributes and methods to a class. Instances of these classes then represent the real objects of PPP in remanufacturing. In addition to the division into classes, data that is to be assigned to the master data is highlighted accordingly in order to simplify the future management of the data. Furthermore, data is highlighted that is related to the use phase of the product and should therefore be part of a digital product passport to support the PPP in remanufacturing.

The aim of the PPP is to create a production program. The production program is therefore the central class in the UML diagram. A production program stands in relationship with other classes, which contain the necessary data of their instances. These relations can have different characteristics, which is represented by the labeling and end symbols of the lines. Accordingly, products are added to a production program, as well as cores that have many of the attributes that a product also has. Products are composed of components. To better structure the model, the production program receives a separate sales model, and the sales model receives a separate demand model. In addition, the production program registers the facilities for which it is created, and these in turn have several associated resources with the corresponding process parameters. The data is also marked as master data or as part of a DPP if applicable.

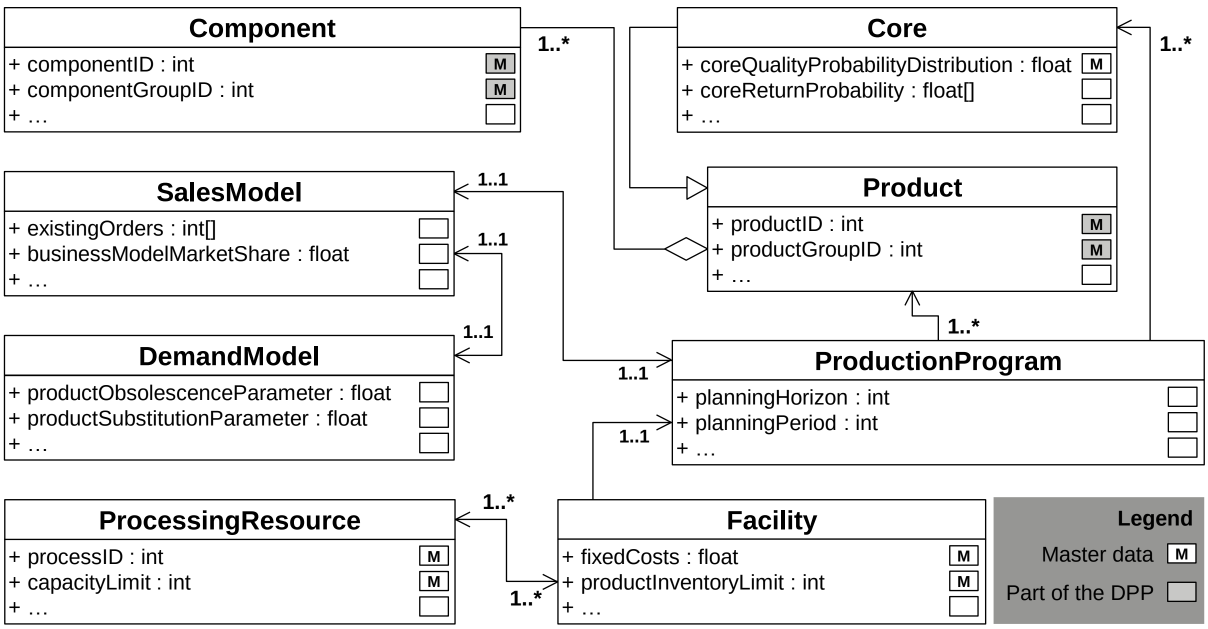


Figure 4.3: General UML data model for PPP in remanufacturing

5 Detailing of the Model

5.1 Methodological Approach and General Model Theory

The data model is methodically derived based on the process model and the activity model defined in chapter 4. The activity model already contains the most important input and output information for the activities in PPP. In order to obtain a systematic and complete coverage of the data requirements, they must be derived in a structured way from the existing activity model. The data requirements are classified in order to obtain the final model, which then contains all data points about the respective products, components, and processes that are needed for PPP in remanufacturing as defined in chapter 4. The basis of the model construction are general requirements that are imposed on models.

A model must have certain characteristics and meet certain requirements to be considered as such. STACHOWIAK (Stachowiak 1973, pp. 131–133) identifies three main characteristics of models in his general model theory. Those are the illustration characteristic, the shortening characteristic, and the pragmatic characteristic. The data model is evaluated against these characteristics to determine how the requirements of a model are met.

- **Illustration characteristic:** A model is a representation of natural or artificial objects or processes. These objects or processes can be observed or created by humans or machines. Models can be simplified versions of the originals, which themselves can be models. Any object that can be experienced or constructed by a person can be considered the original form of one or more models.

The data model represents the database required for carrying out a PPP in remanufacturing, and thus fulfills the illustration characteristic.

- **Shortening characteristic:** Models do not necessarily capture all attributes of the original they represent. They contain only those entities that seem relevant to the respective model creators and/or model users. However, the simplification made by the modeler assumes that the modeler has fully understood the original in order to make an informed decision about which entities are relevant.

With the presentation of the characteristics of PPP in remanufacturing, this thesis shows that the topic of PPP in remanufacturing has been comprehensively analyzed and understood, including the weaknesses of classical approaches. Thus, an informed decision can be made about which entities the data model must represent and the shortening characteristic is fulfilled.

- **Pragmatic characteristic:** Models are not necessarily uniquely assigned to their originals. They are created to replace the original by application of the model. The application takes place in defined time intervals and under restriction to certain mental or actual operations. Thus, models are not only representations of an original, but have a, often human, user. They are time-related and have a defined purpose. A model has to consider not only the question of what it represents, but also for whom, when, and for what purpose it is made with respect to its specific functions.

The data model represents all data required for PPP according to the defined remanufacturing process. By applying and filling in the model, all data required for PPP in remanufacturing can be obtained. The application is the responsibility of the production planner and is conducted in the PPP cycle defined by the company. Thus, the pragmatic characteristic is fulfilled.

5.2 Systematic Derivation of the Information Requirements

The model of PPP in remanufacturing is based on activities, which require defined information for their execution. To determine the information requirements of all activities, the Integration Definition for Process Modeling (IDEF0) method can be used. It is suitable for the structured design and analysis of systems, as well as for the improvement of productivity and communication in computer-integrated manufacturing systems. In addition, it is explicitly proposed for the development and specification of working methods. A working method is a combination of activities, methods, and tools, which serve the achievement of a defined purpose. (Presley and Liles 2015, p. 1) PPP in remanufacturing is such a sequence of activities and its purpose is to create the production program.

The IDEF0 logic for mapping processes is based on a block structure. A classic IDEF0 block is shown in Figure 5.1 on the left. It contains an activity that requires an input and provides an output. The activity is subject to constraints and requires resources. The blocks can be combined into arbitrarily complex models by connecting inputs and outputs of different blocks and combining them in different aggregation levels, as shown in Figure 5.1 on the right. (Presley and Liles 2015, p. 2; Dorador and Young 2000, pp. 431–433)

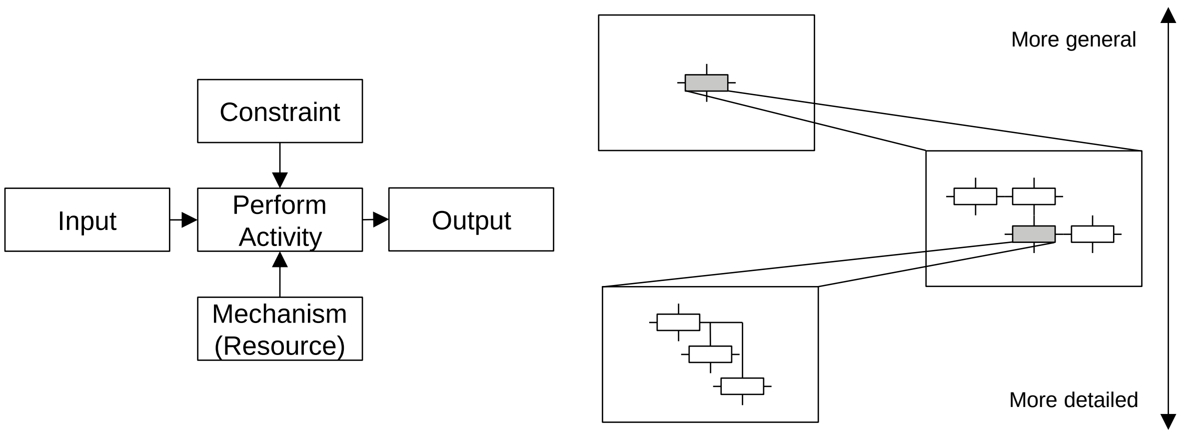


Figure 5.1: Representation of an IDEF0 block (left) and of a decomposition-structure (right) (Presley and Liles 2015, p. 3)

The placement of the blocks is not bound to a strict order of precedence, making the IDEF0 method suitable for mapping flows where multiple activities occur simultaneously, and where the actual order in which tasks are executed varies depending on the specific implementation. (Presley and Liles 2015)

In the following, the individual components of an IDEF0 block are integrated into the context of this work, and the meaning of activity, input, output, constraint, and resource are explained in more detail. A graphic description of the final, general IDEF0 block as used in this thesis is represented in Figure 5.2.

Activity: An activity is a task that must be carried out in PPP in remanufacturing. All activities are predefined as shown in Figure 4.2. As PPP in remanufacturing is a planning process, all activities convert non-physical inputs into non-physical outputs, meaning that the activities only convert information and no actual products or materials.

Input: The input is the information needed to perform the activity and to obtain the output. Depending on the activity, the type of information varies significantly. In sales planning, mostly market information is needed. Meanwhile core acquisition management requires information about the condition of cores, which are then passed on to primary demand planning. Primary demand planning uses product related information and inventory information. Finally, gross resource planning requires capacity information in order to verify the production program.

Output: The set of information generated by an activity is called the output. Apart from two exceptions, all outputs are inputs to a subsequent activity. Those exceptions are the new products sales plan, which is handled in a classic PPP, and the final feasibility check.

Constraint: Constraints are here considered a special kind of input information that limit the solution space of the output. In the context of PPP in remanufacturing such constraints can be maximal or minimal inventories, capacity constraints, availabilities of cores, etc.

Mechanism/Resource: Resources are needed to conduct the task or activity. As could be seen in chapter 3.3, the mechanism or resource to create a production program is often a mathematical optimization, which performs several activities at the same time, given certain variables, parameters, and constraints. Whenever a block has no specific assigned resource, the field is left empty.

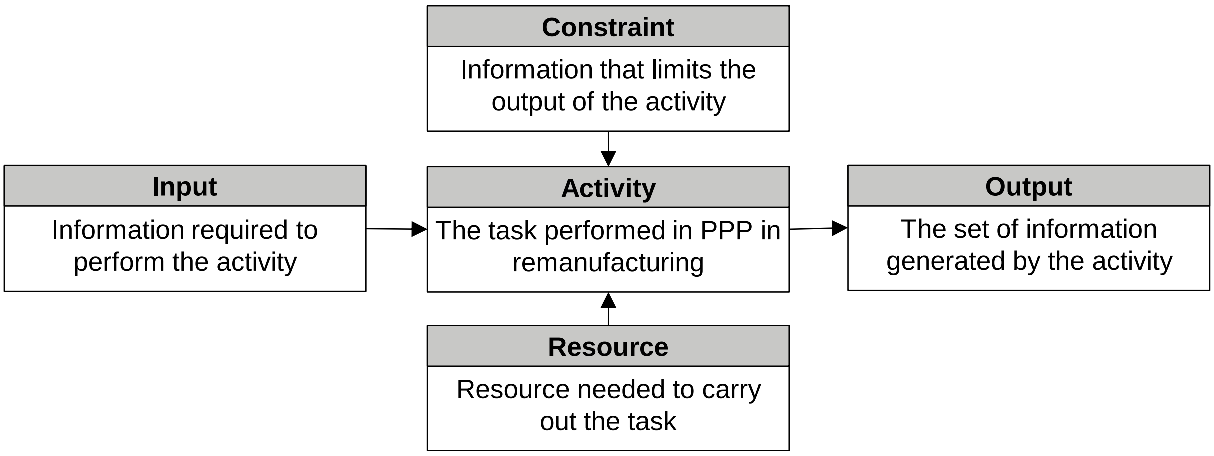


Figure 5.2: General IDEF0 block in the context of PPP in remanufacturing

5.2.1 IDEF0 and the Distinction between Data and Information

The terms data and information are often not clearly distinguished from each other. In literature, a distinction between data, information, and knowledge is common, but the terms are defined differently depending on the context. In computer systems, data is the term for coded invariants. It also often refers to statistical records or, in its most basic form, a sequence of symbols that cannot be interpreted without context. Information in computer systems is data with an assigned meaning. Information is interpretable data and can be used to generate knowledge. (Zins 2007, pp. 480–486)

For this work, the distinction between data and information is particularly important since the final goal is to create a data model. In the literature on the use of the IDEF0 logic, there is not always a clear distinction made between these two terms. For example, DORADOR et al. refer to data as information or objects (Dorador and Young 2000, p. 431), and PRESLEY et al. mainly use the term data in their explanations of how to use the IDEF0 method (Presley and Liles 2015). Therefore, it is assumed that IDEF0 is suitable for mapping both data and information.

However, by this definition a data model needs context to be applicable and understandable. Therefore, the IDEF0 blocks are first filled with information to allow for an understanding of the purpose of the corresponding model fragments. The data needed for each piece of information is then decontextualized and represented only by a variable name and the data type. The explanation on how to use the data must therefore be taken from the information blocks and is partially lost during translation into the data model. The following example illustrates the issue. A constraint for sales planning is that only as many remanufactured products can be sold as there are cores available. Formulated as an understandable equation and thereby an information this means:

$$N_{remanSales} \leq N_{coresAvailable} \quad \textbf{(5)}$$

A data model then reduces the context to the mere variables, which in this case are $\mathrm{N_{remanSales}}$ and $\mathrm{N_{coresAvailable}}$, without mentioning their relation to each other or how they are used.

Accordingly, IDEF0 serves as a methodical approach for identifying the data. The data model finally summarizes this data, classifies it, and represents it in a from the activity model abstracted form. This avoids duplications and simplifies the handling of the data. The procedure is illustrated in Figure 5.3.

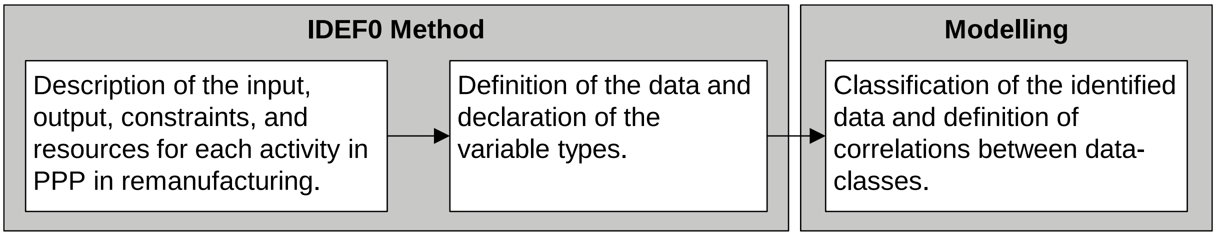
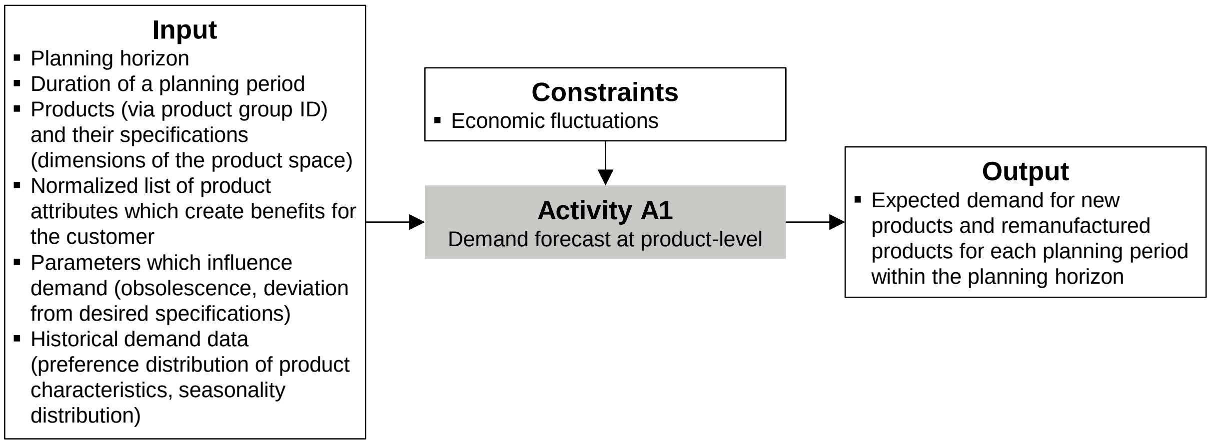


Figure 5.3: Method for deriving the data model from the activities of PPP in remanufacturing

5.3 IDEF0 Information Requirements and Derivation of Data Requirements

Activity A1 – Demand forecasting at product-level (Figure 5.4)

Input – The information needed to predict demand varies depending on the used prediction method. For the IDEF0 block, the EGGERT demand model is used as a reference (Eggert 2003, 197–209). Independently of this, the planning horizon and the duration of the planning periods are defined. In addition, it is determined which products are included in the demand forecast. Those are identified by their product group ID, which also distinguishes between remanufactured and new products and is assumed to be a sequence of integer values. In addition, according to EGGERT, the product attributes that are valued by the customer are an input to the demand forecast. Such attributes can be of different types and units, which is why they must be normalized in advance to make them comparable (Eggert 2003, pp. 199–200). The demand forecast also requires product-group-specific variables as an input. The obsolescence is a measure of the customer's loss of interest in products as they age (Eggert 2003, p. 156). In addition, the customer is only willing to accept a certain level of deviation of product specifications from his personal preference. By incorporating historical demand records for the products under consideration, seasonality can also be taken into account and the accuracy of the model can be improved. If there is no seasonality to be seen in the previous demand, the parameter is set to zero.



Data

Input
- planningHorizon : int
- planningPeriod : int
- productGroupID : int
- normalizedProductAttributes : float[]
- productObsolescenceParameter : float
- productSubstitutionParameter : float
- seasonalityParameter : float
- productDemandHistory : int[]

Constraints
- economyFluctuationParameter : float

Output
- expectedDemand : int[]

Figure 5.4: IDEF0 block of information requirements and derivation of data requirements for product-level demand forecasting

Constraints – Demand can be constrained or spurred by economic fluctuations. Therefore, an economic fluctuation parameter is included in the model.

Output – The demand forecast provides a separate demand distribution for each product across all planning periods within the planning horizon.

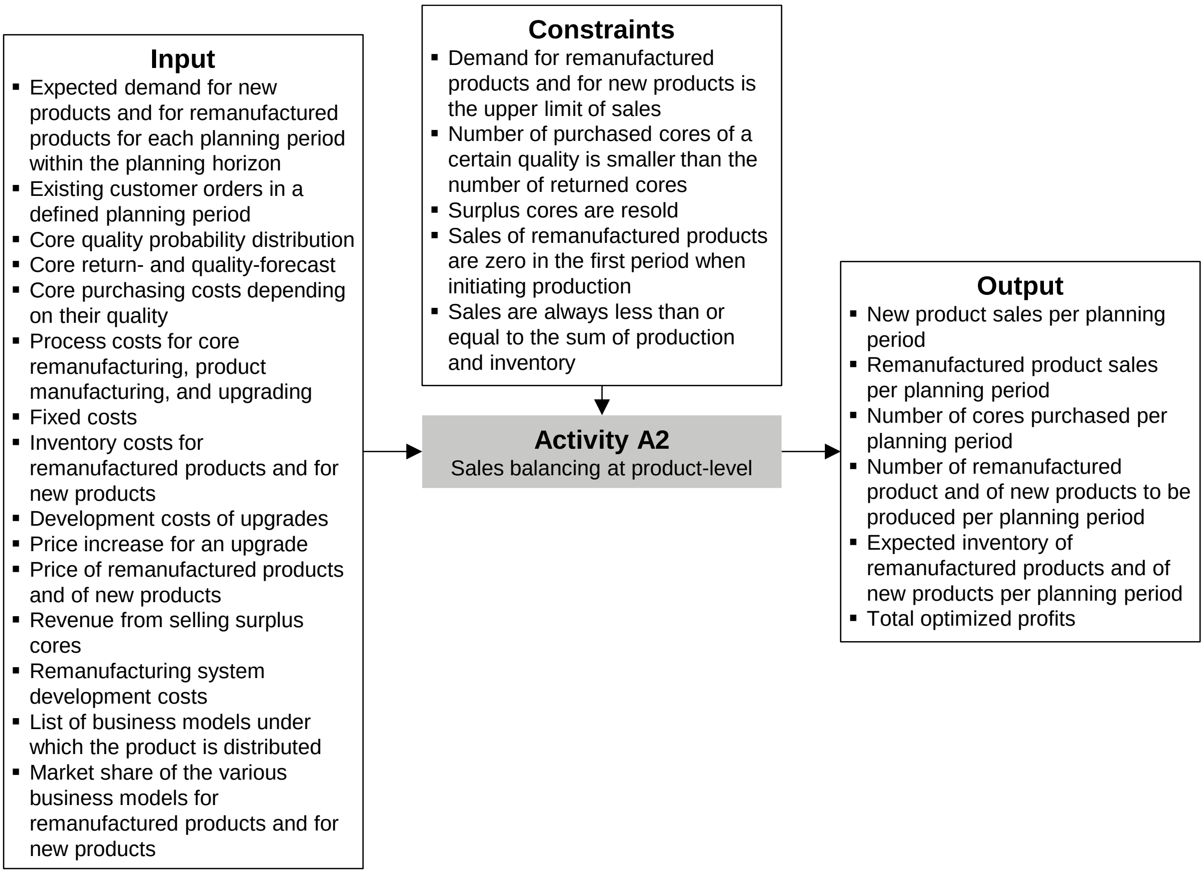
Explanation of the derived data – The planning horizon and the planning period are assumed to be integers. The list of normalized product attributes contains an associated set of normalized attributes for each product. A normalization can be done to a range from zero to one, therefore the floating-point number is chosen as data format. A list structure is also proposed for the output, assigning a time series of integer demand forecast values to each product. The length of the list always corresponds to the number of planning periods.

Activity A2 – Sales balancing at product-level (Figure 5.5)

Input – The balancing of sales figures of remanufacturing and new products is based on the sales model from FRANK (Frank 2022, pp. 85–96). The activity requires above all the demand forecast from activity A1. Furthermore, already existing customer orders are taken into account, which have to be produced in addition to the expected demand. For the cores, the quality probability distribution must be known, which determines how likely it is that a core can be remanufactured. In addition, the prediction of core availability and their qualities are included in the balancing of sales. Core quality and availability depend on the business model and are core specific. Therefore, in addition to the product group ID, a unique product ID is introduced, which can identify every single product individually. On the cost side, estimations of the quality-dependent procurement costs of the cores are required, and estimations of the processing costs for remanufacturing, for new production, as well as for upgrades. The inventory costs are needed as input, as well as the fixed costs of the production. Further costs are caused by the development of the remanufacturing system and by the development of the upgrades. Both can be zero if there were no developments made within the current planning horizon. The costs of the cores correspond to the price that can be achieved by selling surplus cores. Furthermore, the achievable prices of all products are needed, as well as information about what price increase can be obtained with an upgrade.

Constraints – Sales are constrained upward by demand. There may be periods in which a potential increase in profits justifies selling less products than the demand would allow. In addition, the maximum number of cores that can be purchased is the number of cores available on the market. If, at the end of a period, more cores are purchased than are needed for remanufacturing, the surplus cores are sold. In addition, the sales of remanufacturing and new products are at most as high as the sum of the inventory of a period and the products (re)manufactured in that period.

Output – The main output of the activity are the sales figures to be achieved for all products per planning period. The activity also determines the number of cores purchased per period, the required inventory and production quantities, and the total expected profits.



Data

Input
- productID : int
- expectedDemand : int[]
- existingOrders : int[]
- coreQualityProbabilityDistribution : float
- coreReturnProbability : float[]
- manufacturingProcessCosts : float
- remanufacturingProcessCosts : float
- fixedCosts : float
- productInventoryCosts : float
- productPrice : float
- coreAcquisitionCosts : float
- businessModel : string
- businessModelMarketShare : float
- upgradingProcessCosts : float
- upgradeDevelopmentCosts : float
- upgradePriceIncrease : float

Constraints
- expectedDemand : int[]
- coresAvailableFromReturns : int[]
- coresPurchased : int[]
- coresResold : int[]
- remanufacturedProductInventory : int[]
- newProductInventory : int[]
- remanufacturedProductProduction : int[]
- newProductProduction : int[]

Output
- remanufacturedProductSales : int[]
- newProductSales : int[]
- coresPurchased : int[]
- remanufacturedProductInventory : int[]
- newProductInventory : int[]
- remanufacturedProductProduction : int[]
- newProductProduction : int[]
- totalProfits : float

Figure 5.5: IDEF0 block of information requirements and derivation of data requirements for product-level sales balancing

Explanation of the derived data – The probability of a core to have a sufficient quality for remanufacturing is a floating-point number. Furthermore, all data that changes with a planning period is represented as a list. This concerns all outputs and constraints, whereby the total profits form an exception as they represent the sum over all profits and planning periods. Profits, prices, and probabilities are generally represented as data of type float. The business model types are a list of strings, each of which is assigned a market share. The latter is a normalized value between zero and one, which is thus also defined as a floating-point number.

Activity A3 – Returns and quality forecast at product-level (Figure 5.6)

Input – Chapter 2.2.5 showed that core return times are statistically distributed. This distribution must be known for a product, including the time the core was sold to the customer. If additional information from the past is available, historical data can be used, similar to the demand forecast. A corresponding forecasting model may require further parameters. As described in the general model, the probability of a core to have a certain quality is estimated based on the quality probability distribution of its components. The component quality distributions are derived from the individual component qualities, which are logged over time and cumulated for each component group. The combined quality probability distribution of the components then yields the probability for a core to have a sufficient quality to be remanufactured.

Output – The objective of the prediction is to determine the core quality, the time at which a product is expected to be returned, and the probability with which a core will be returned in a specific business model and with a defined quality. Core acquisition management also communicates the procurement costs for cores, which depend on the quality of the cores, to sales planning.

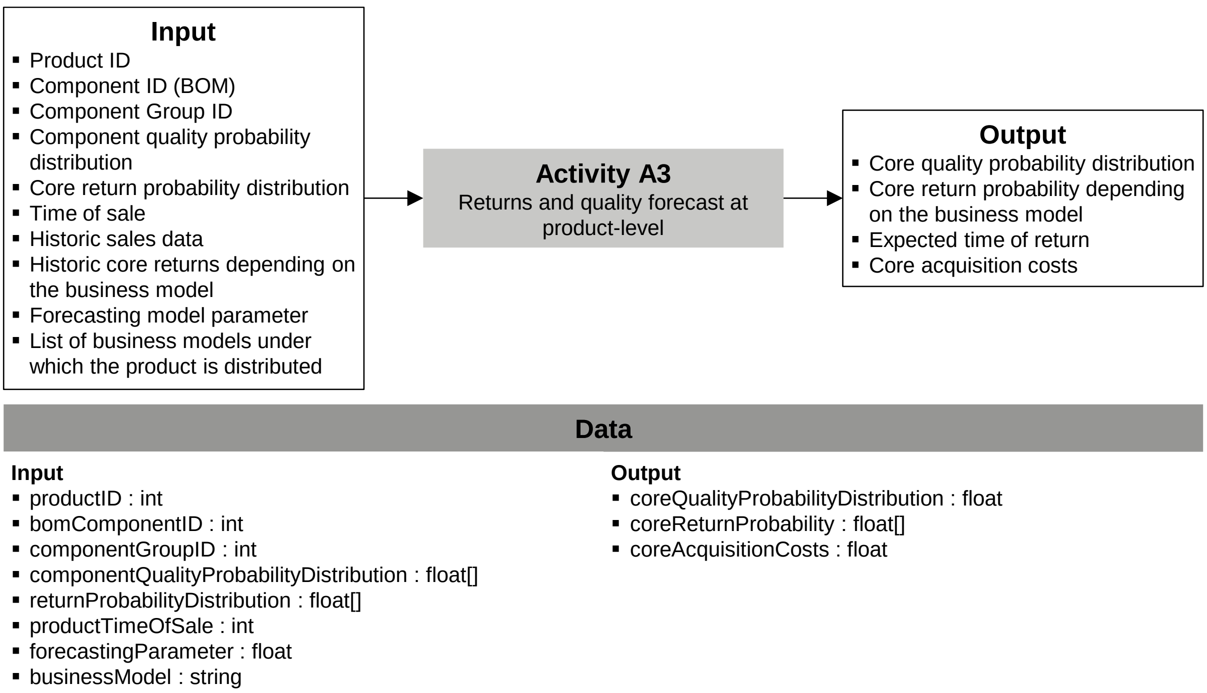


Figure 5.6: IDEF0 block of information requirements and derivation of data requirements for product-level returns and quality forecast forecasting

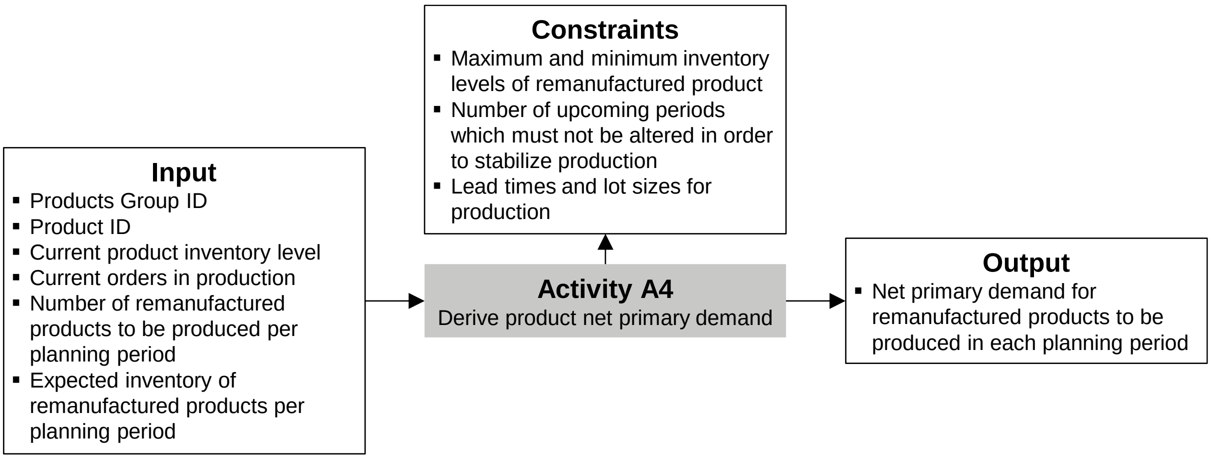
Explanation of the derived data – As before, the time-dependent variables are represented as a list. The output can be summarized in four data points. On the one hand, the quality distributions are floating point numbers which define how likely it is that a core consisting of a known set of components can be remanufactured, and on the other hand, the list format of the return probability also captures the period in which the return is expected to occur. Costs are floating-point numbers.

Activity A4 – Derive product net primary demand (Figure 5.7)

Input – The gross primary demand recorded in the sales plan is reduced by the current inventories in the determination of the net primary demand for products. In addition, orders currently in production are subtracted, which also do not have to be included in new product orders. The distinction between the individual product ID and the product group ID is necessary at this point in order to first identify the products of the same type, and then to use the Individual ID to check compliance with the exact product specifications defined in the sales plan.

Constraints – For all products, maximal and minimal inventory limits are defined, which may neither be exceeded nor undercut. The upper limit of the inventory can be chosen based on the available space, and the minimal inventory is a safety stock that must be maintained in order to be able to react to deviations from the plan. In addition, it can be specified that no changes are made to the production program within a defined number of subsequent periods in order not to destabilize production. The lead times are average values for the product group and the lot sizes constrain the flexibility in meeting demand.

Output – The result of the activity is the net primary demand of the products, i.e., the number of pieces that are ordered per product and period in the production. As lot sizes and lead time must be considered in this activity, the inventories calculated in the sales plan must be updated.



Data

Input
- productGroupID : int
- productID : int
- remanufacturedProductInventory : int[]
- ordersInProduction : int[]
- remanufacturedProductSales : int[]

Constraints
- productInventoryLimit : int
- productSaftyStock : int
- frozenPeriods : int
- productLeadTime : int
- lotSize : int

Output
- netProductDemandRemanufacturing : int[]
- netProductInventory : int[]

Figure 5.7: IDEF0 block of information requirements and derivation of data requirements for deriving the remanufacturing product net primary demand

Explanation of the derived data – The data structure for deriving the net primary demand is less complex than that of the preceding activities. All data are integers. The output is then a list of orders that are put into production for a product in a specified planning period. Although only one product ID is recorded as a variable, the ID is recorded for all the products considered, and thus for each product a list of orders is submitted to production.

Activity A5 – Derive component gross demand (Figure 5.8)

Input – To determine the gross demand for components, the respective product IDs, and their associated component compositions from the BOMs are required. In remanufacturing those BOMs are also product specific, and each component has a unique ID. This causes complex data management but is necessary to be able to record the individual operating conditions of a component in the use phase. The BOM of a new product already includes all upgrades. In the data model, the ID of a product and the ID of a core are not formally distinguishable, as they both refer to products. The distinction becomes apparent only when looking at the specific ID that identifies the product.

Output – The BOMs are used to calculate the gross demands of components for production. The gross demands do not include any inventory or planned component receipts.

Explanation of the derived data – The BOM must assign the component ID and the quantity of components required to each product ID. In addition, BOMs may have a tree structure if additional BOMs exist for the components themselves. However, according to the process defined in chapter 4.1, subcomponents are taken care of within a lower-level cascade in the remanufacturing process. Thus, the BOM needed to manufacture the product within one cascade has only one sub-level. This is due to the cascading of the process, in which each component demand is transferred to a sub-production as a customer order.

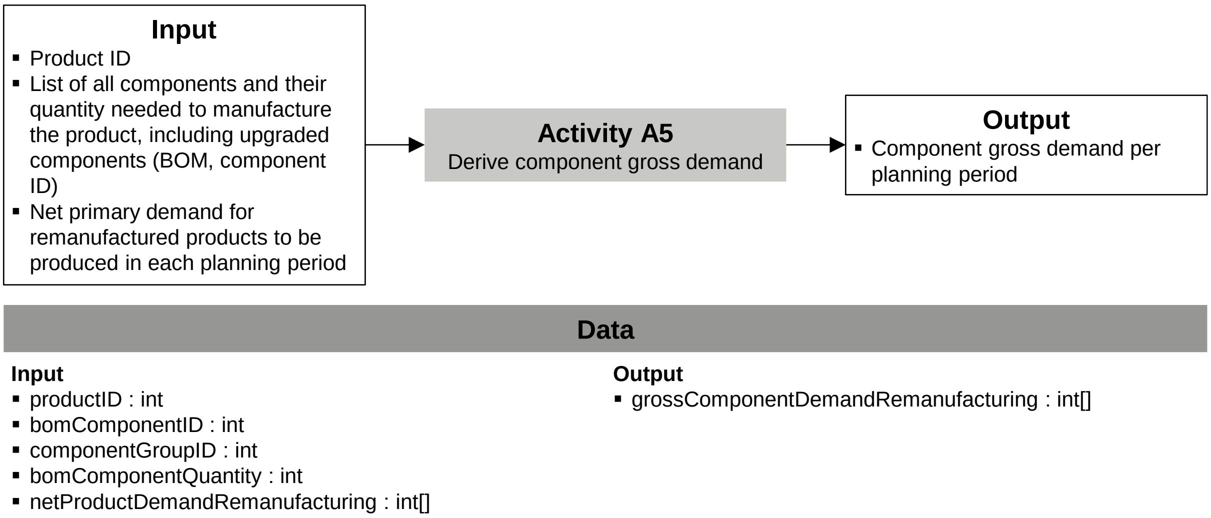


Figure 5.8: IDEF0 block of information requirements and derivation of data requirements for deriving the component gross demand

Activity A6 – Derive expected component yield (Figure 5.12)

Deriving the expected component yield is a complex task which is displayed here in three consecutive IDEF0 blocks. Those blocks combined then form the activity as can be seen in Figure 5.9. At first, the components contained in a core are identified (A6.1). Then, the remaining useful life of each component is estimated (A6.2) and finally the gross component yield is determined (A6.3).

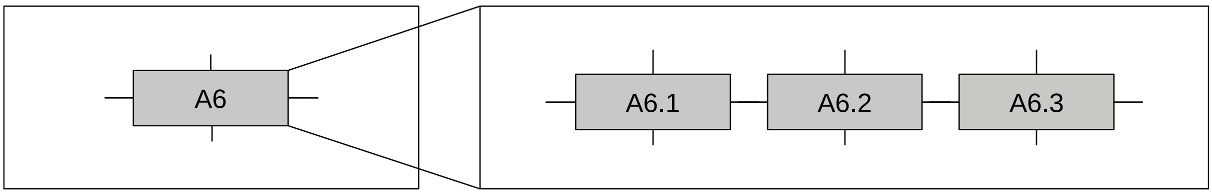


Figure 5.9: IDEF0 decomposition structure of activity six into three consecutive sub-activities

Activity A6.1 – Identify core components (Figure 5.10)

Input – Each core is identified individually, as it is composed of individual components which all have a quality that depends on their unique usage conditions during the use phase. The BOMs are therefore not generic anymore as in classic PPP, where one BOM can be used to decompose several products which consist of components of the same type.

Output – The activity yields a list of all the individual component IDs that are installed in the product. Such a list is created for all the cores that are expected to return in a specific period.

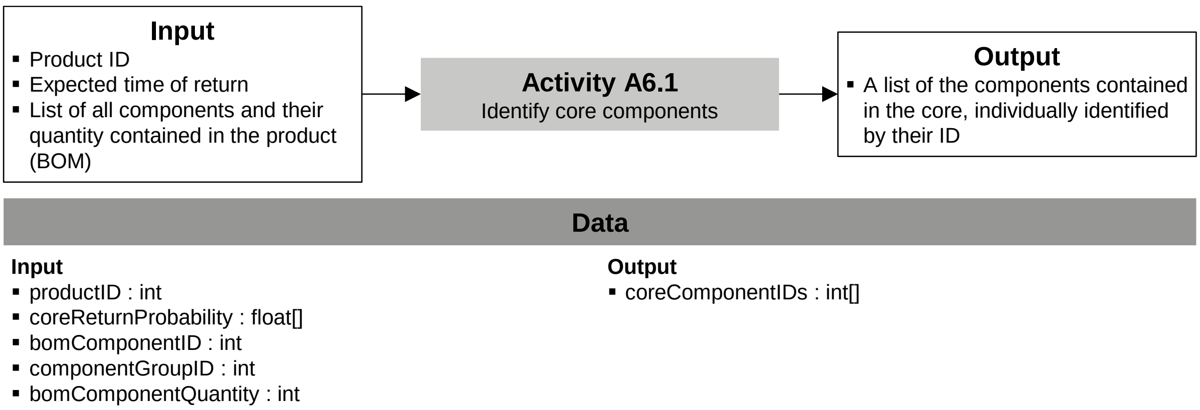


Figure 5.10: IDEF0 block of information requirements and derivation of data requirements for identifying the components of a core

Activity A6.2 – Estimation of the remaining useful life of the components (Figure 5.10)

Input – The quality of a component in the data model is determined by its remaining useful life. Components which have a sufficient remaining useful life can be reused in new products. The estimation of the remaining useful life requires several pieces of information. These are primarily based on MUSTAJIB et al. (Mustajib et al. 2021). This information includes the component age. In addition, there may be components that can only go through a defined number of life cycles. For this purpose, the number of previous life cycles is recorded. Besides, physical damage is recorded in the form of the damage level. The tolerances of geometry and dimensions must be known, and the frequency of use. A component that has been serviced more often is likely to have a higher remaining useful life. This also applies to components from products that are returned earlier.

The categories listed are general criteria intended to cover as wide a range of data and components as possible. In individual cases, the challenge is to identify exactly those data points that influence the lifetime of components. For this purpose, a placeholder for additional data is added to the data model. The following examples illustrate how versatile the possibilities are.

Machine tools often have ball screws that are used to translate a rotary motion into a translational motion. In ball screws, the screw pitch error has a considerable influence on the operating behavior, internal load distribution, stiffness, and component life (Mei et al. 2003, p. 1).

Such a data point is rather specific but can be included in the tolerance parameter mentioned in this IDEF0 block. A different example is a lithium-ion battery. The life of lithium-ion batteries depends, among other things, on whether they are used outdoors, exposed to uneven road surfaces or temperature fluctuations, and on the load changes (Wu et al. 2016, p. 1). Another publication uses voltage, current, temperature, and the discharge capacity to predict the capacity of a lithium-ion battery (Ansari et al. 2021, p. 3), showing that even within one type of component, there is no general consent about which data to use. To predict the remaining useful life of engine oil in internal combustion engines, oxidation, antioxidant breakdown, additive depletion, soot accumulation, total acid or base number, oil consumption, and wear metals can be used (Jagannathan and Raju 2000, p. 3511).

Output – The activity outputs the expected remaining useful life of each component in the component list.

Explanation of the derived data – The data used to estimate the remaining useful life of a component cannot always be estimated objectively. MUSTAJIB et al. use subjective ratings for all categories except for the completeness of the component. This is a quotient of the number of parts that make up the component and the number of parts that the component should have. In remanufacturing with a cascaded process, the formation of the quotient is obsolete, since components are remanufactured by their respective manufacturer should they not be complete. Therefore, a boolean value is used here, which allows a yes-no distinction.

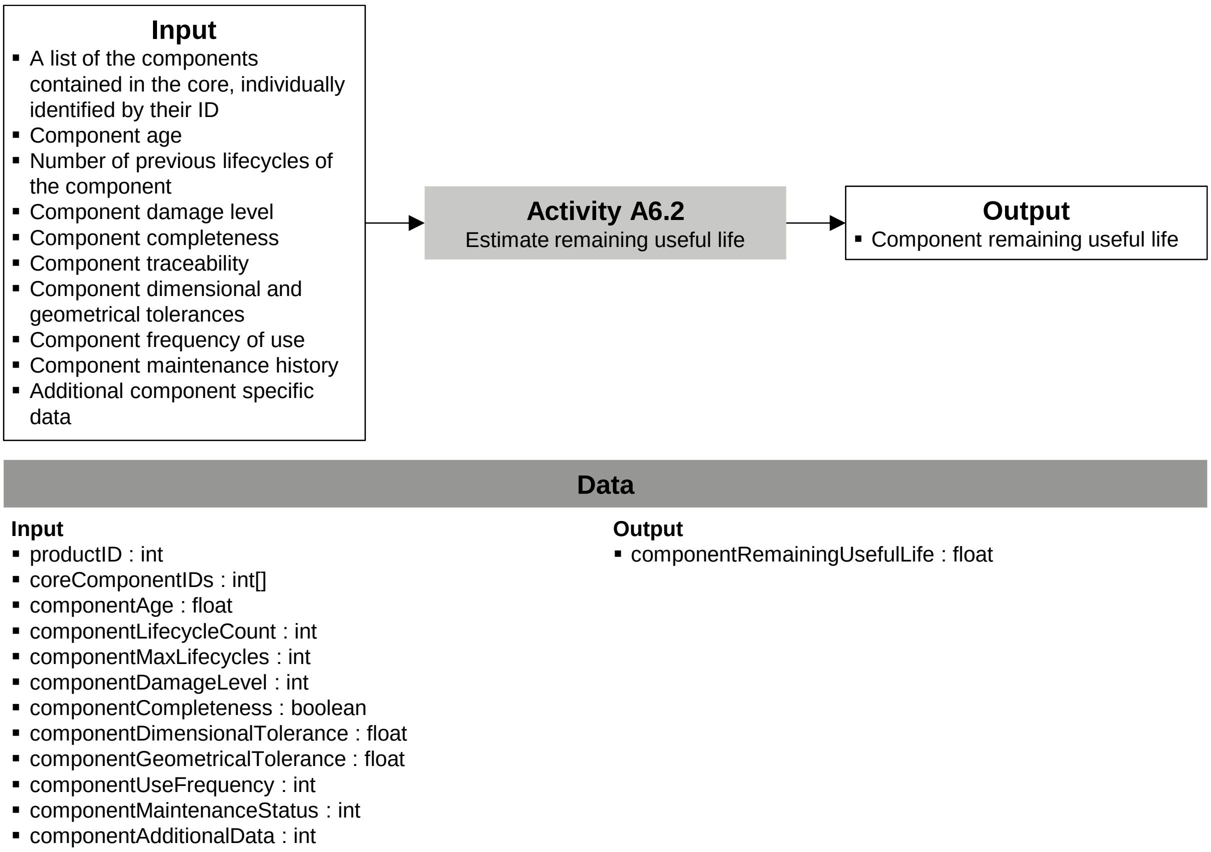


Figure 5.11: IDEF0 block of information requirements and derivation of data requirements for determining the remaining useful life of the components

Activity A6.3 – Determining the gross component yield (Figure 5.12)

Input – The gross component yield is determined for each product and its components. Those components, which have a remaining useful life superior of the necessary one, can be included in a new product. Additionally, the components are analyzed with respect to their obsolescence and their upgradability.

Output – The output is a list of all components which can be reused. At the same time, components which have no sufficient remaining useful life, are obsolete, or not upgradable, cannot be used again in a new product. Storing this information is important in order to return such components to their manufacturer.

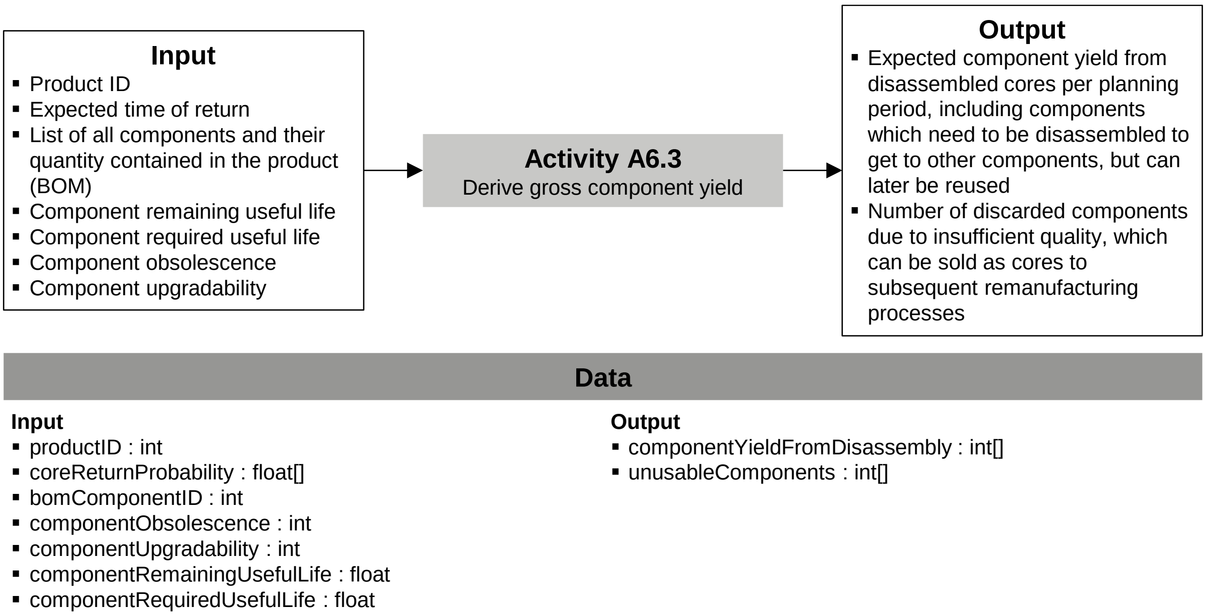


Figure 5.12: IDEF0 block of information requirements and derivation of data requirements for deriving the expected component yield

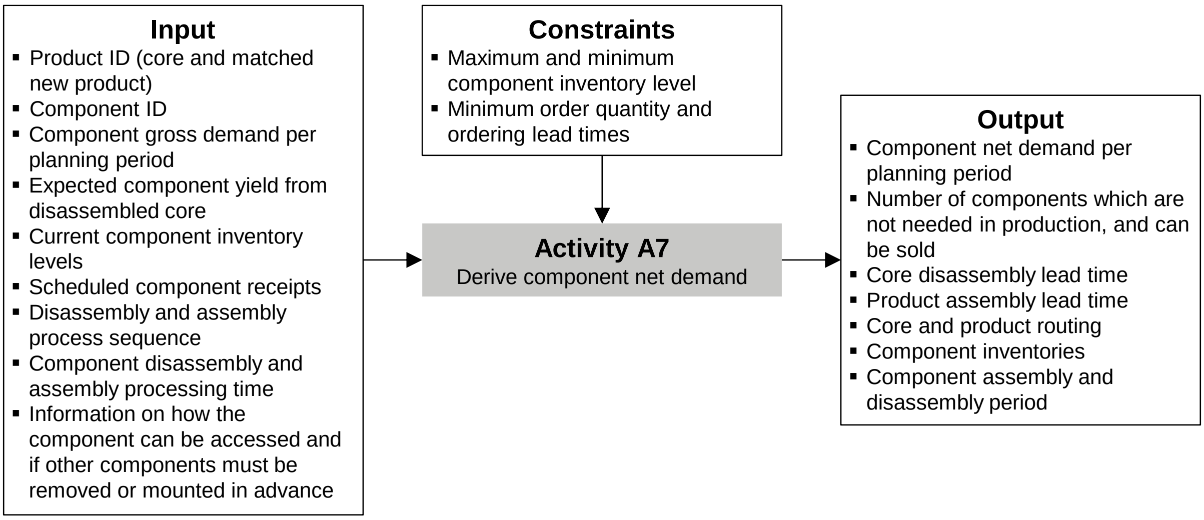
Activity A7 – Derive component net demand (Figure 5.13)

Input – For the calculation of the net demand of components, the gross demands are needed as input information. From this, the expected component yields from the cores, the current inventories and the components already ordered that will arrive at the factory within the planning horizon are subtracted. An additionally needed information is how the components can be accessed. There may be components needing replacement, which cannot be removed without removing other components of acceptable quality first.

Constraints – Similar to the determination of net requirements from the products, the maximum allowable inventory levels and component safety stock levels are required. Also, the minimal order quantities and ordering lead times must be considered as constraints.

Output – The activity has several objectives. One of them is to determine the number of components that need to be ordered from subsequent production lines or suppliers. There is also a quantity of components that will not be used in remanufacturing. Such components may meet quality requirements but are not installed in new product because they are either replaced by an upgrade, or simply not desired by the customer. In the automotive industry, for example, a core may have a trailer coupling, while the customer of the new product does not want it. Since the high quality of the component has already been verified at this point, it can be resold, or put into stock. Another main objective is determining which components must be removed in disassembly, and which must be reassembled. Therefore, a core is matched with a new product based on the estimated availability of a core and their level of similarity. Knowing the process sequence of all components in assembly and in disassembly, as well as the individual lead times, the core-specific remanufacturing process can now be planned because the routing is known. Therefore, the component net demand is already adjusted for when the components are needed, so that the final product can be delivered in the planned period. Additionally, each component is marked with a timestamp of the period in which it needs to be disassembled or assembled.

Explanation of the derived data – The variable used to describe the combined routing of a core and later, a product, is determined by the sequence of process IDs, which refer to the component's disassembly and assembly processes. The variable is a list of integer IDs, which in this case is not related to the planning periods.



Data

Input
- productid : int
- bomComponentID : int
- componentGroupID : int
- grossComponentDemandRemanufacturing : int[]
- componentYieldFromDisassembly : int[]
- currentComponentInventory : int[]
- componentReceipts : int[]
- componentAssemblyProcessID : int
- comonentDisassemblyProcessID : int
- componentAssemblyPredecessorID : int
- componentDisassemblyPredecessorID : int
- componentAssemblyProcessingTime : int
- componentDisassembllyProcessingTime : int

Constraints
- componentInventoryLimit : int
- componentSafetyStock : int
- minimalorderQuantity : int
- orderingLeadTime : int

Output
- netComponentDemandRemanufacturing : int[]
- componentInventory : int[]
- componentsForSale : int[]
- coreDisassemblyLeadTime : int
- productAssemblyLeadTime : int
- coreDisassemblyRouting : int[]
- productAssemblyRouting : int[]
- componentDisassemblyPeriod : int
- componentAssemblyPeriod : int

Figure 5.13: IDEF0 block of information requirements and derivation of data requirements for deriving the component net demand

Activity A8 – Derive assembly capacity requirements (Figure 5.14)

Input – The required capacities in assembly can be determined on the basis of the routings and process times already known for the respective component assemblies. The planning period, in which a component is assembled is specified in the previous activity. The sum of all component assemblies together with the IDs of the respective processes is the total required capacity on a resource in a defined period.

Output – For each process, uniquely identified by its ID, the required capacities are specified and expressed as the time the resource is occupied.

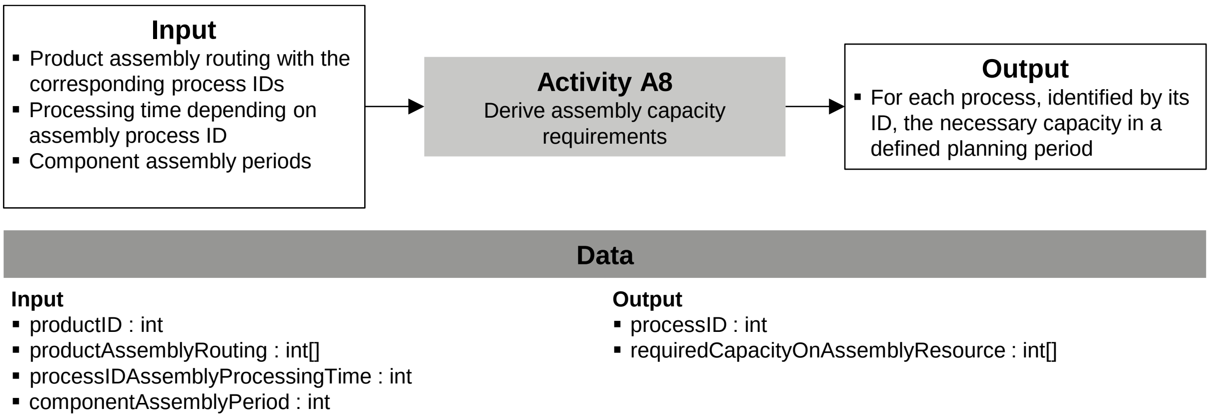


Figure 5.14: IDEF0 block of information requirements and derivation of data requirements for deriving the assembly capacity requirements

Activity A9 – Derive disassembly capacity requirements (Figure 5.15)

Input – As in assembly, the required capacities in disassembly can be determined using the routings and process times already known for the respective component disassembly. The planning period, in which a component is disassembled is specified in the previous activity. The sum of all components to be disassembled, together with the IDs of the respective processes, is the total required capacity on a resource in a defined period.

Output – For each disassembly process, uniquely identified by its ID, the required capacities, e.g., expressed as the time the resource is occupied, are specified.

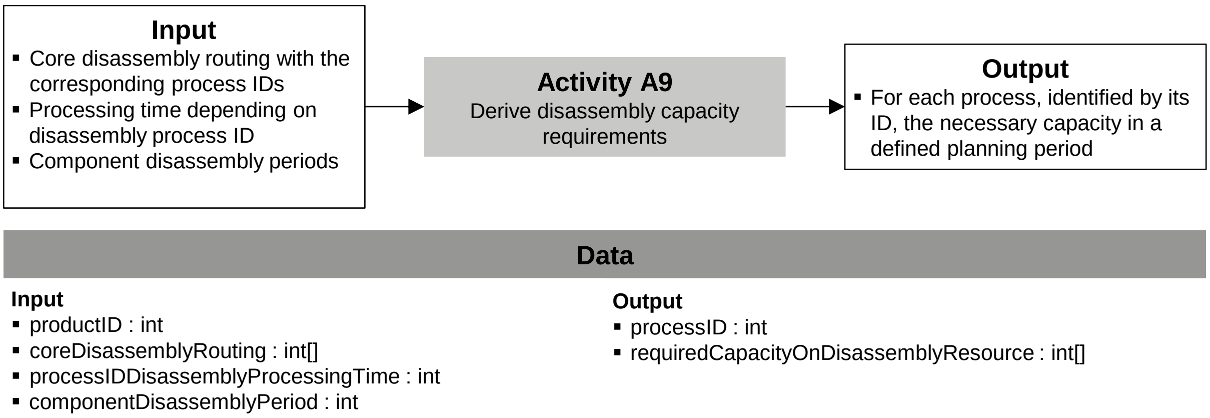


Figure 5.15: IDEF0 block of information requirements and derivation of data requirements for deriving the disassembly capacity requirements

Activity A10 – Checking the feasibility of the production program (Figure 5.16)

Input – To check the production program and the availability of resources, the process ID and the total process times in a planning period are required. Formally, it is not necessary to distinguish between disassembly and assembly, since this information is linked to the process ID.

Constraints – The feasibility of the production program is limited by the maximum available capacity.

Output – The result of the activity is a comparison between the available and the required capacity for each period and resource. If these do not match, changes must be made in the production program to relieve the resources, or additional capacity must be made available.

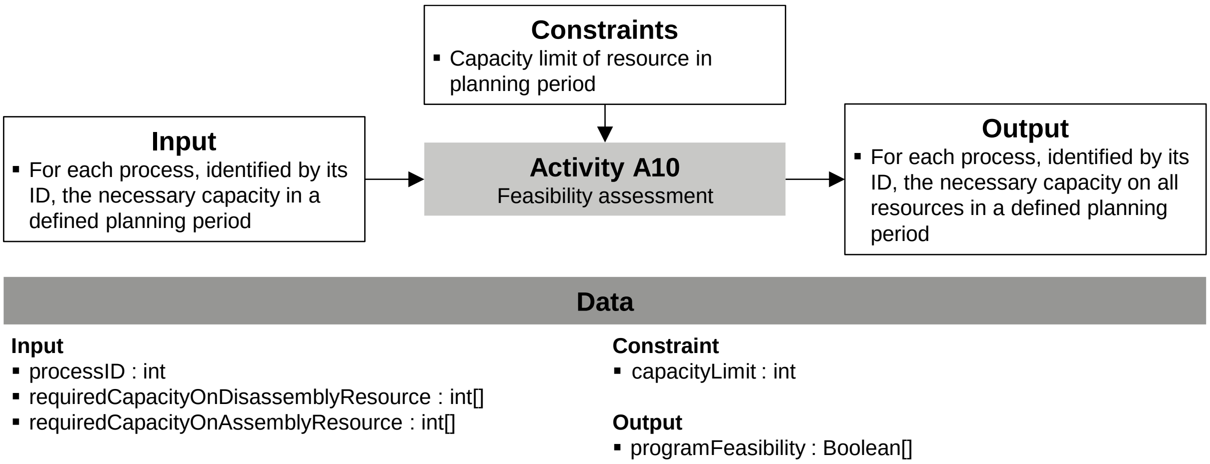


Figure 5.16: IDEF0 block of information requirements and derivation of data requirements for the feasibility assessment of the production program

5.4 Model Building in UML and Data Classification

5.4.1 Basics and Applications of UML

UML is a standardized modeling language that is applied in the context of processes. There are several types of UML diagrams. These include UML use case diagrams, which describe system functionality, as well as class diagrams, and behavior diagrams. UML class diagrams depict relationships between classes and define which classes inherit from each other. A UML diagram forms the basis of an object-oriented data base, which comprises all relevant data for an information model (Dorador and Young 2000, p. 430). Therefore, UML is used to create the data model. In addition, UML can be used to build on IDEF0 information diagrams. The derivation of data needs in a UML diagram from information needs defined in an IDEF0 logic is called a bottom-up approach to model building (Dorador and Young 2000, p. 435).

DORADOR et al. use the IDEF3 method as an intermediate step when transferring an IDEF0 model to a UML class diagram. IDEF3 is a further development of IDEF0, which was developed for the object-centric description of physical processes, with the goal of capturing every possible status of an object in a real process (Dorador and Young 2000, p. 433). Since the goal of this work is the development of a data model for PPP in remanufacturing, and not that of a data model that represents the physical remanufacturing process in the factory, the intermediate step of IDEF3 modeling is omitted.

In a UML class diagram, a class describes a group of objects with common properties, behavior, relationships to other objects, and semantics. A class is represented as a rectangle, which, in addition to the class name, contains all the attributes of the class and the methods available to the class (Dorador and Young 2000, p. 435). The methods are not considered further in the data model, since the goal is not representing the handling of the data, but the definition of the data, which must be obtained depending on the class. Attributes have a name and a type, and describe the state of a class. The type refers to the basic data types such as int, a class, or an interface. Classes, attributes, and methods can have modifiers specifying the visibility, insatiability, and modifiability. For example, they can be public, protected, private, or readonly. Graphically, this is indicated by "+", "#", "-" and "?" (Rumpe 2012, p. 35).

The relations between the classes are described by means of lines, which end in symbols. An example of such a generic UML class diagram is shown in Figure 5.17. The figure shows, that the subclass Class_2 inherits from superclass Class_1. An inheritance relationship can exist between two classes. Here, the superclass inherits its attributes and methods to the subclass. In the subclass, further attributes and methods can be added, or those of the superclass can be redefined. In doing so, the restrictions imposed by the modifiers must be adhered to. According to the so-called substitution principle, instances of the subclass can also be used where instances of the superclass are required. Another element of the UML-logic are associations, which are binary relationships between classes that are used to realize structural information. An association has a name, a cardinality, and an indication of navigation directions. The cardinality expresses multiplicity and is specified for each association. A cardinality of "0..1" means, that there can be zero or one objects of another class associated with the class, while “0..*" allows for multiple objects to be associated with the class (Rumpe 2012, p. 35). An example of an association in which a class can have an aggregation of objects from another class is the relationship between Class_3 and Class_1. The UML diagram states that Class_1 can be aware of zero or several objects of Class_3.

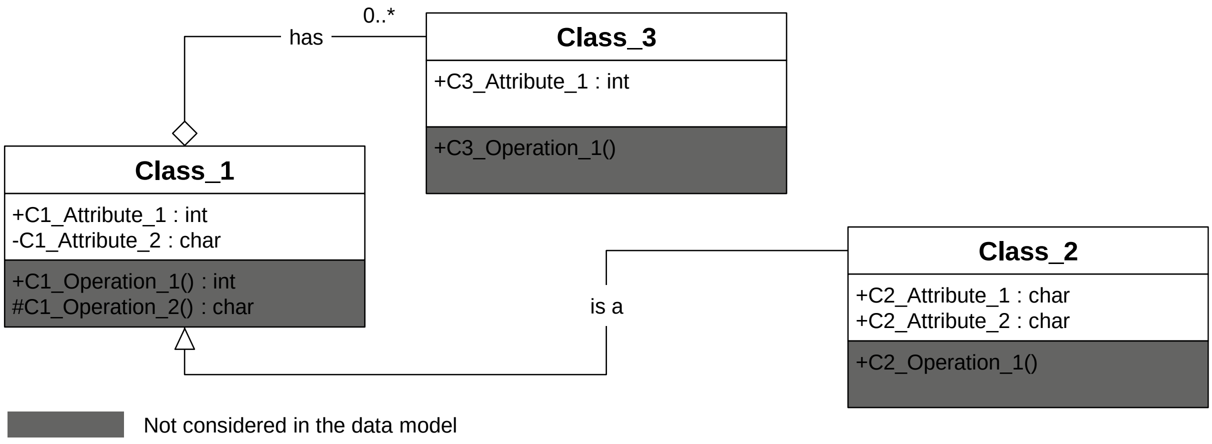


Figure 5.17: Representation of a basic structure for a UML class diagram combined from DORADOR et al. (Dorador and Young 2000, p. 435) and RUMPE (Rumpe 2012, p. 37)

5.4.2 Building of the UML Class Diagram for PPP in Remanufacturing

Since UML is an object-oriented modeling language, the basis of the UML model for PPP in remanufacturing is the definition of the classes, their respective attributes, and their associations with each other. The result is shown in Figure 5.18.

The ProductionProgram-class

The production program is the central object of PPP in remanufacturing. It is defined by the planning horizon, the number of planning periods, and by the frozen periods in which no change is made to the current production program. To create it, the current product inventories are needed, as well as the number of current orders in the factory for the upcoming periods. Then, the expected inventories over the next periods are determined, both for new products and for remanufactured products. The gross component demand is derived from the net demand for remanufactured products. By matching component inventories, components already ordered, and expected component yields from core disassembly, the net component demand is determined as well as the quantity of components that cannot be reused. In addition, the production program records the required disassembly capacity for each core and the required assembly capacity for each product, so that these can then be compared with the available resources to check the feasibility of the production program.

The other data needed to create the production program are attributes of other classes. A production program has a unidirectional association to at least one product. This is marked by an open arrow and means that a production program can know several objects of the Product-class, but these in turn have no knowledge about the production program itself. The production program has an identical unidirectional association with one or more cores. There is also a bidirectional relationship with one or more facilities and with one sales model. Here, the associations are bidirectional, so that an object of the SalesModel-class and of the Facility-class is aware of the existence of its respective production program and vice versa. This is necessary because the objects of the SalesModel-class and the Facility-class need to identify the products for which the production program is made.

The SalesModel-class

The sales model provides further data points for the production program, which are outsourced to a separate class to improve the diagram structure. Through the bidirectional relationship, the sales model can identify the products for which the production program is to be created. The sales model records the existing orders for a product, as well as the market shares of the business model under which a product was sold. It stores information about when cores are expected to be returned, how many cores need to be purchased, and how many cores will be resold. The sales model also defines for each planning period how many products of the same type are to be produced and sold and it can be adjusted by another parameter to make the prediction more precise.

The class has another bidirectional association with exactly one demand model. Thus, the demand model in turn can provide the prediction for the demand of all products contained in the sales model.

The DemandModel-class

A demand model is integrated into the sales model and stores information about the product obsolescence and about its substitutability. It also stores the demand history of a product and includes a parameter for seasonal fluctuations as well as for economic ones. Based on this data the class estimates the expected demand for a product group.

The Facility-class

A facility has associated fixed costs and processing costs for manufacturing and remanufacturing products. Additionally, the facility accounts for the process costs of an upgrade. It also defines a safety stock and an inventory limit for all products and components.

Regarding the bidirectional association to the production program, it should be noted, that a production program can include several facilities, while a facility only has one assigned production program. Each facility is composed of one or more processing resources.

The ProcessingResource-class

Each resource has a process ID and a capacity limit. The dismantlability of components is assumed, so all resources needed to process the product are available and have defined processing times in assembly and disassembly.

The Product-class

Each product is an object that has a unique ID and belongs to a product group. This distinction is necessary to enable the individual determination of the installed components and their data. A product has normalized attributes, causes inventory costs, and can be sold at a certain price. If the product has been upgraded, the resulting increase in value is recorded. The development costs for an upgrade are also recorded in the product data. Each product is sold under a specific business model, at a defined time. In addition, the product-specific data includes the lead time for assembly and the routing. Also, the lot sizing information must be known for a product. As the last relevant data point, a list of unique component IDs is added to represent the BOM.

The Core-class

A core in PPP is a product, which is given back to the manufacturer. Thus, a core has the attributes that a product has, such as an individual ID, normalized attributes, etc. In UML notation, this relationship can be depicted as an inheritance. The inheritance is marked with a white triangle. In addition to the inherited attributes, a core has a quality distribution, a return probability, and acquisition costs. Furthermore, the disassembly lead time and the disassembly routing are recorded for each core.

The Component-class

A product is an aggregation of one or more components. Each object of this class has an individual ID and a group ID. In addition, each component receives a statistical distribution of its quality. This is determined based on several data points, which here serve as orientation and do not have to be raised necessarily for each component, or can also be extended, should very specific data points for the determination of the remaining useful life of a component be needed. After determining the remaining useful life, the obsolescence and upgradability are used to filter for the components which can be reused. In addition, a component has a process ID that links it to its respective assembly and disassembly process, as well as the corresponding processing time and period in which the component is likely to be disassembled or reassembled. To determine components to be disassembled or reassembled before others, the process IDs of the preceding production steps are also stored. In normal manufacturing facilities without remanufacturing, components would also have lot sizing information. In the defined remanufacturing process, as new components are ordered and not produced, the equivalent of lot sizes for components are minimal order quantities from the supplier.

Classification as master data

In Figure 5.18 there are also remarks given on which data is master data. Following the definition of master data in chapter 2.1.8, there are fundamental differences in what is the master data when comparing regular PPP to PPP in remanufacturing. In PPP, routings, processing times and BOMs are master data. In PPP in remanufacturing, on product level all this information is individual for every product due to the individually identified components. The product routing depends on the component yield of each product and so do the processing times. As every component is unique, and has a unique ID, the BOM of a product changes every time a component is replaced. Therefore, these data points should not be treated as master data in the data management system of the remanufacturer. The equivalent of the processing lead time is the ordering lead time.

Integration into a digital product passport

Many of the in the data model mentioned data points are not inherently known to the manufacturer, as the data emerges or changes during the use phase. As shown in chapter 2.1.12, such data can be collected in a structured way in a DPP. This work does not define a complete DPP but provides data that should be part of it to facilitate PPP in remanufacturing.

The DPP should include the product ID and the product group ID in order to identify the product. The time of sale should be included as well as all individual component IDs which identify the components the product is made of. Those components should also keep their group ID, to facilitate the creation of component group specific quality statistics. The key parameters which help build these statistics at component level should also be included in the DPP to serve as a basis for the evaluation of a core's quality. These parameters change during the useful life of the component. That includes the age, the number of life cycles, the damage level, the completeness, and the deviancy of the dimensional and geometrical tolerances from their tolerable values. Also included should be the use frequency and the maintenance status. The additional data parameter is also recorded because there may be more product specific data points necessary to determine the remaining useful life of a component. The upgradability and the respective price increase should also be part of the DPP, so that a component that breaks can be replaced in a repair shop, or upgraded in case the customer wishes to do so.

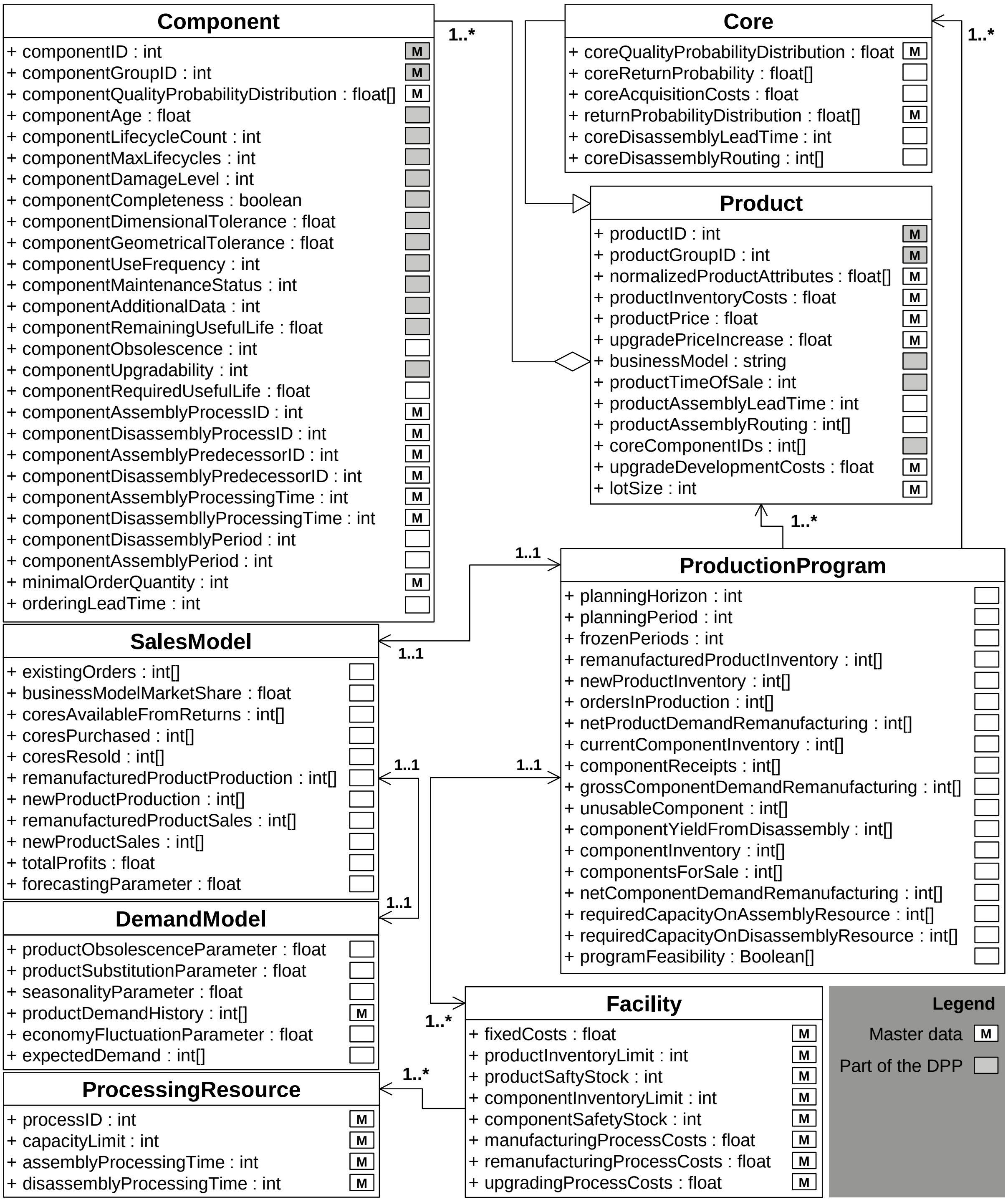


Figure 5.18: UML data model for production program planning in remanufacturing, categorization as master data, and assignment to a DPP

6 Validation

6.1 Conceptualization of a Prototypical Simulation Model

To validate the data model, a prototypical PPP is conducted in remanufacturing with the aim to show that the PPP can be performed with a simulation model based on the data listed in the data model. Since this is a concept validation, the data model is reduced to a selected set of essential elements, which are shown in Figure 6.1, and only core functions are implemented.

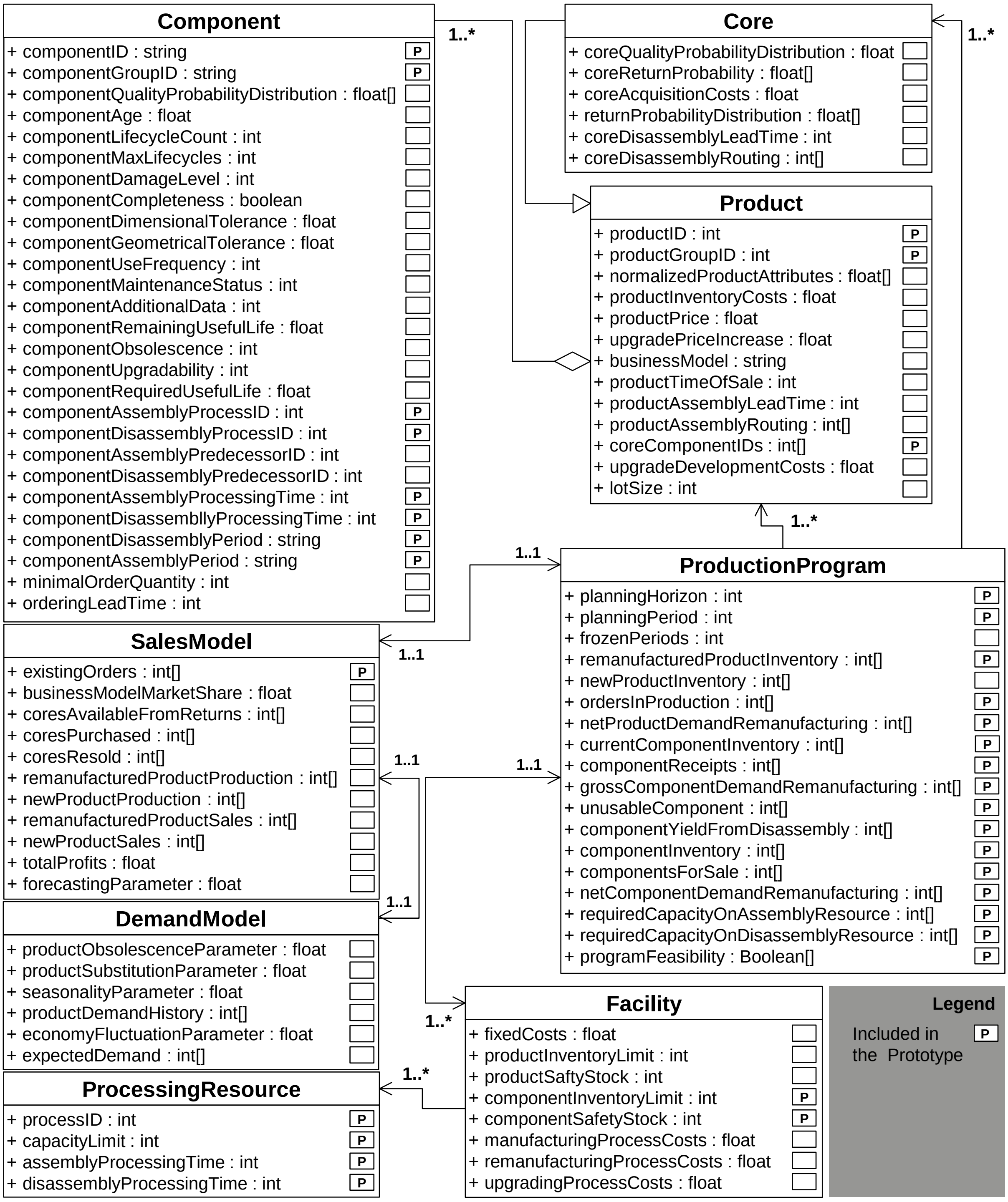


Figure 6.1: Depiction of the data used for the prototype of the simulation model

Development Tools

The simulation model is implemented in Python in the Spyder development environment. Additionally, the large language model (LLM) ChatGPT is used to assist in writing parts of the model code. The model code is shown in Appendix A.2 and all parts that were created using the LLM are marked accordingly. The LLM was used solely to assist in writing program code. No text passages or other content of the thesis were written using an LLM and no LLM was used in the interpretation of results. This is important because LLMs can have severe biases in the interpretation of data and text and are therefore generally not acceptable as authors of scientific publications (Norris 2023, p. 1).

Definition of the remanufacturing product and process

The simulation model is created for an electric vehicle remanufacturing process. This requires a dataset, which defines the components of an electric vehicle, and which contains the required processing information. Such a dataset is described by HOLLAH (Hollah 2019, pp. 190–192). The dataset contains the components of an electric vehicle, and for each component an operation number, a damage probability, a disassembly probability, and the duration of the disassembly and reassembly process. In addition, the predecessor processes are defined, and process IDs are specified as several components are (dis-)assembled on the same resource. The data is thus suitable for simulating the PPP for an electric vehicle remanufacturing process. The components and their processing information are shown in Appendix A.3.

The PPP is carried out for an example scenario over a planning horizon of six months. The planning horizon is divided into six planning periods of one month each. Since a model for sales planning in remanufacturing already exists[1], its output data structure is used to define the inputs for the prototype simulation model of PPP in remanufacturing. The scope of the prototype simulation model is shown in Figure 6.2.

[1] The sales model from FRANK described in chapter 3.3.5

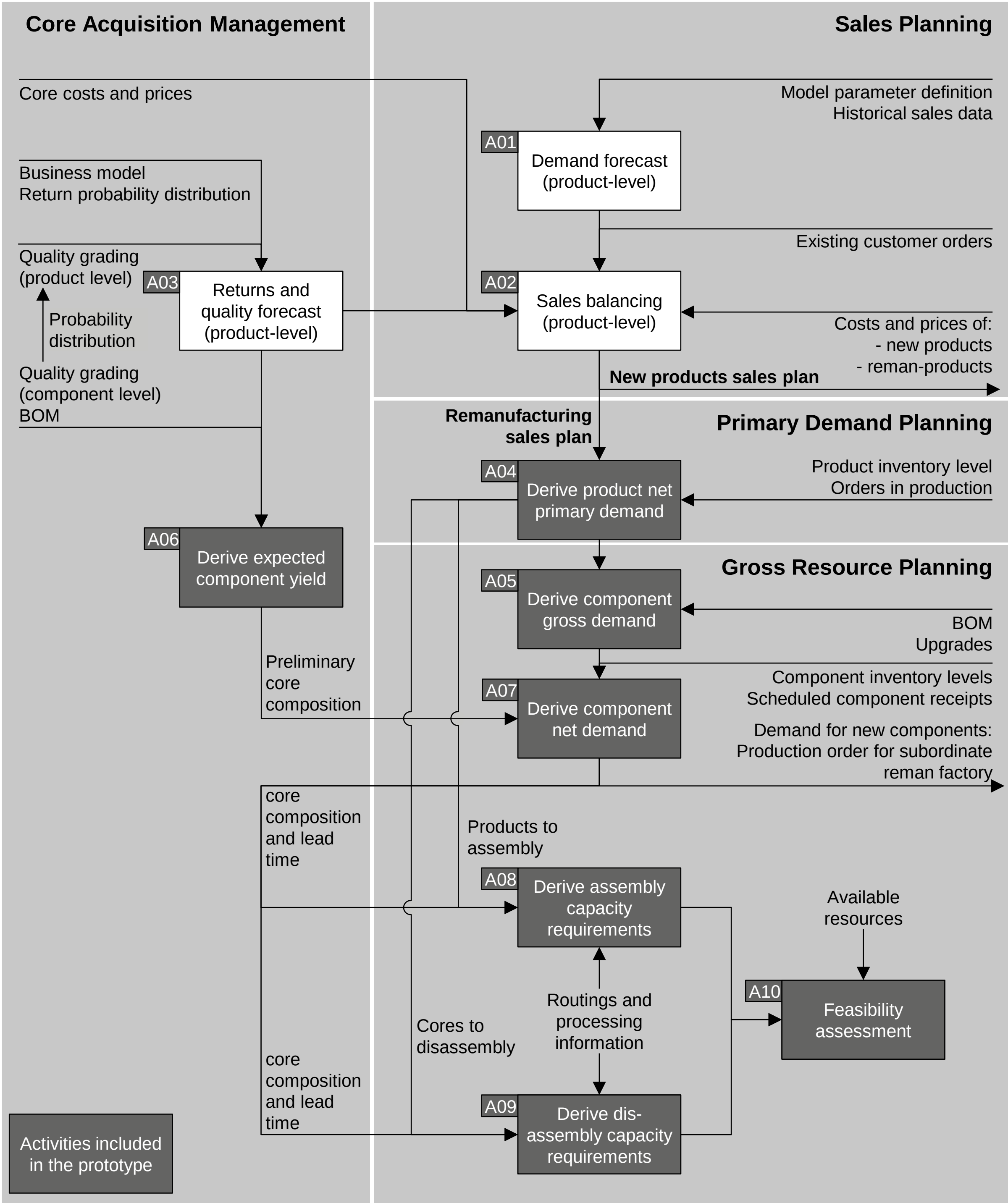


Figure 6.2: Activities of PPP in remanufacturing which are included in the prototype simulation model for creating the production program

6.2 Implementation and Analysis of the Results

A04 – Deriving the product net primary demand

The PPP is conducted for electric vehicles of product-group p. The expected sales figures $S_{p,m}$ of products in that group in month m, the orders in production $OIP_{p,m}$ and the current inventory $I_{0,p,m}$, are known inputs. They are listed in Table 6.1 for the next planning periods.

Table 6.1: Expected sales figures, current inventory, and orders in production for the simulation model

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Expected sales of remanufactured products $S_{p,m}$	300	200	200	300	200	300
Remanufacturing orders in production $OIP_{p,m}$	50	0	0	0	0	0
Current inventory of remanufactured products $I_{0,p,m}$	20	0	0	0	0	0

The net demand $ND_{p,m}$ for electric vehicles within a group is calculated using equation 6.

$$ND_{p,m} = S_{p,m} - OIP_{p,m} - I_{0,p,m} \tag{6}$$

The results can be seen in Figure 6.3. As the current inventory and the orders in production only change the net demand for products in the current month, the other planning periods are unaffected by the calculation of the net primary demand.

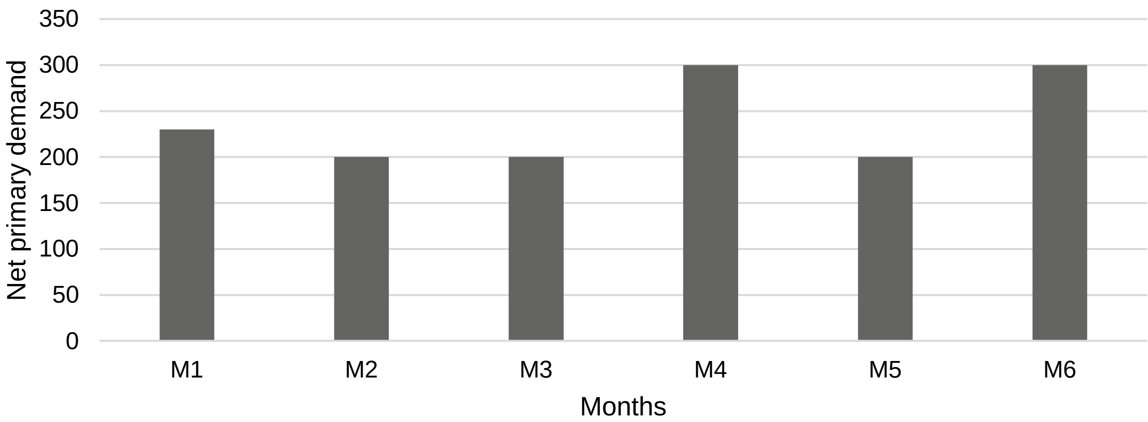


Figure 6.3: Net primary demand for products per month within the planning horizon

A05 and A06 – Deriving the expected component yield and component gross demand

The net demand for electric vehicles per month is used to create a database of the cores, which are to be used in the remanufacturing of the vehicles. Therefore, each product is assigned a unique ID. The ID is composed of a string for identifying the product group, an integer number corresponding to the month of remanufacturing, and an integer number assigned to each product within a month. Equation 7 illustrates this relationship. An example of an ID generated for the tenth product of group “P” in month five is: “P510”.

$$"ID_{product}" = "ID_{group}" + "Month" + "N_{productInMonth}" \tag{7}$$

The components defined by HOLLAH are used to create the BOM for the product group. The components can then be assigned to a specific product in order to create the product specific BOM. All components in the product specific BOM must also be uniquely identifiable, including the assignment to the product in which they are installed. This can be achieved by creating a component ID according to equation 8. The component ID is composed of the product ID and the component name, which is also representative for the component group ID. An example of a component ID generated in this way is: "P510-engineHood".

$$"ID_{component}" = "ID_{product}" + "Name_{component}" \tag{8}$$

For the prototype of the simulation model, there are no updates considered. Therefore, the group BOM of a new product is identical to the group BOM of a core.

Creation of the individual core BOMs

For the simulation model, the dataset with the component processing information is preprocessed. The operation number and predecessor operations are omitted. Thus, the removal probability is no longer representative. In the simulation model, the damage probability is used to simulate the comparison of the remaining useful life estimate based on the component data with the required useful life. As the determination of the remaining useful life is highly individual to each component, the corresponding prediction models must be developed and validated for each component individually. The damage probability is a floating-point number between zero and one. For the simulation, a random number is generated, which also lies between zero and one. If this number is below the damage probability of a component, the component must be removed. In the list of cores, these components are given a "-REPLACE" identifier associated with the component ID. The list of cores, stripped of the components which contain a "-REPLACE" identifier now represents the gross component yield of each individual core. On the other hand, the gross component demand is the sum of all components within a month, which are marked with a "-REPLACE" identifier. The gross component demand for the engine hood, mirrors, the driver door, and the headlights can be seen in Figure 6.4. A table of all component gross demands is shown in Appendix A.4.

The gross component demand in month four and in month six is elevated compared to month one, two, three, and five. This can be explained by the higher net demand for products in the respective months. Within one month, the gross demands for the engine hoods and mirrors vary slightly but are of a similar order of magnitude. The driver door on the other hand exceeds the demand of the other components while there is little gross demand for headlights. The reason for the higher demand for passenger doors is the elevated damage probability of the component. In the processing data, components of type engine hood and mirrors have a damage probability of 0,3. The driver door has a damage probability of 0,7, which causes the component to be replaced more frequently. Meanwhile the headlights only have a damage probability of 0,05, meaning that in most cases, they can be reused in a new product.

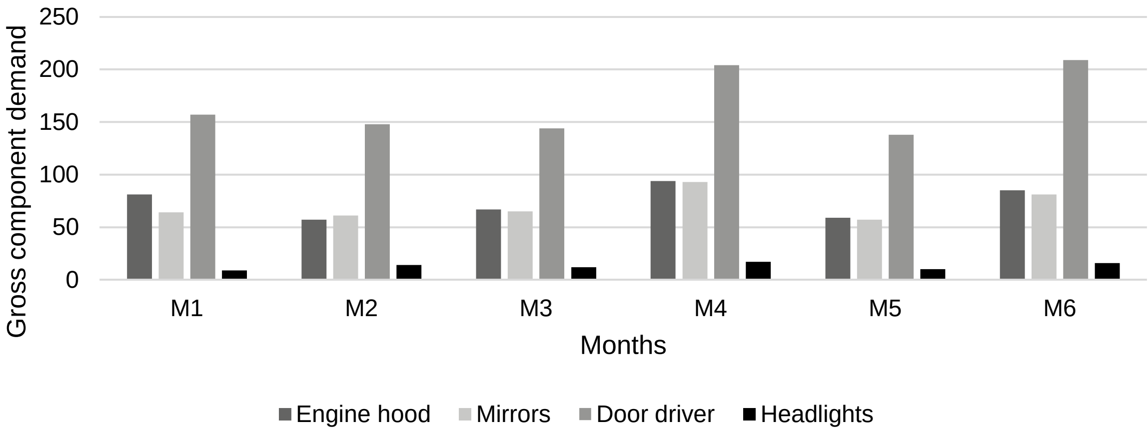


Figure 6.4: Gross component demand for selected components over all planning periods

A07 – Deriving the net component demand

The gross requirements for components are compared with the current inventories and with the component orders already placed with the respective component remanufacturers, in order to determine the net demand for components. The calculation of the component yield is deterministic, i.e., components are either exchanged or further used with a fixed probability. There has so far been no consideration of the probability, to which this deterministic assignment component yields leads to a correct result. Corresponding statistics about the reliability of the damage probability must be made component-individually. To validate the data model, the reliability of the damage probability is also expressed by a random number in the simulation model. In the context of the component data, the reliability of a re-use prediction increases, when historically many similar components had a similar component-specific dataset on which they were evaluated, or when key data about the component is known. The less comparable cases of a component that has a defined condition there are, the less reliable is the re-use or replace prediction.

An approach to incorporate the reliability in the production program is by specifying the safety stock accordingly. If the reliability of a component-related damage probability is low, the safety stock is increased to account for fluctuations in the actual component yield. The reliability is a floating-point number in between 0,4 and 0,9. For each component c, equation 9 defines the safety stock $I_{min,c}$ and equation 10 defines the inventory limit $I_{max,c}$. For the current inventory $I_{o,c}$ at the beginning of the planning horizon applies $I_{o,c} \in [I_{min}, I_{max}]$.

$$I_{min,c} = (1 - r_c) * 40 \quad \textbf{(9)}$$

$$I_{max,c} = I_{min,c} + 30 \quad \textbf{(10)}$$

The net demand $ND_{c,m}$ for components of type c in month m is determined by equation 11. Here, the inventory $I_{c,m-1}$ of the previous month and the scheduled component receipts $SR_{c,m}$ of the current month, are subtracted from the gross component demand $GD_{c,m}$.

$$ND_{c,m} = GD_{c,m} - I_{c,m-1} - SR_{c,m} \quad \textbf{(11)}$$

If the inventory and the scheduled receipts exceed the gross demand, the surplus components are stored in the inventory of the current planning period. If the safety stock is undercut, the necessary additional demand is added to the net demand. If the maximum inventory is exceeded, either more space must be made available, or the assembly of the respective products is delayed. Adjustments for the maximum inventory are not included in the prototype. The scheduled receipts data is shown in Appendix A.5 and the inventory data is shown in Appendix A.6. The results of the net demand calculation are shown in Figure 6.5, for the components engine hood, mirrors, the driver door, as well as for the headlights. A full list is shown in Appendix A.7. As before, the driver door shows the highest demand. The development of the net demand for headlights indicates that there are more scheduled receipts and surplus inventory in the first two months than there is gross demand.

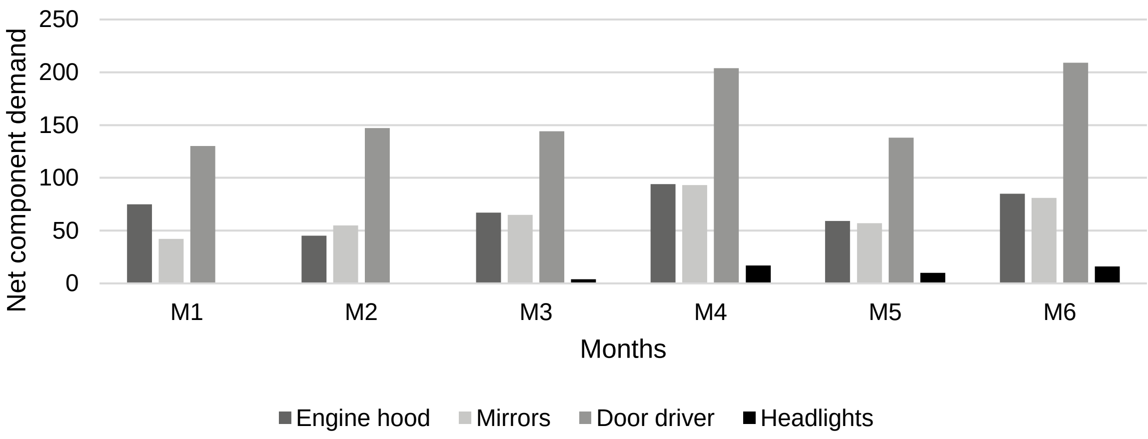


Figure 6.5: Net component demand for selected components over all planning periods

A comparison with the inventory of the headlights depicted in Figure 6.6 reveals that the result from the net demand calculation is plausible. In the first two months, the inventory ranges in between the safety stock and the inventory limit. In month three, the gross demand for components exceeds the receipts and the surplus inventory. Hence, in month three, the net demand for headlights appears, while being zero in month one and two. The inventory then remains at the level of the safety stock. The underlying assumption of the prototype, that components can be ordered by piece, and thereby ignoring minimal order quantities, causes this behavior of the model.

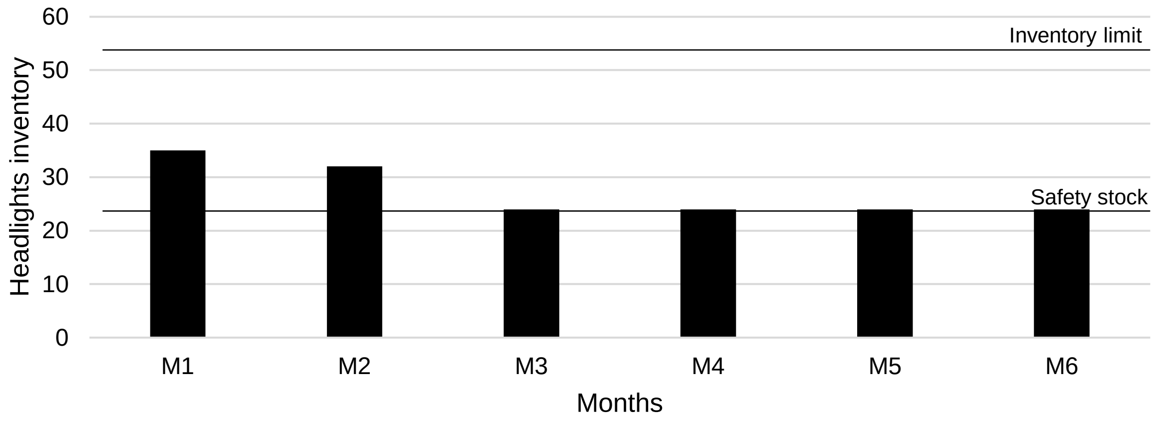


Figure 6.6: Inventory of headlights over all planning periods

A08 and A09 – Deriving the assembly and disassembly capacity requirements

The capacity requirements are calculated as hours on a processing resource. This is shown in equation 12. The resource needed to disassemble and assemble a component is obtained using the assigned ID contained in the group BOM. The gross demand for components is multiplied with the processing time $PT_{c,r}$ of the component c on resource r to obtain the total required processing time $TRPT_{r,m}$ needed on a resource r in each planning period. The result is divided by 3600 to convert the processing time contained in the group BOM from seconds to hours. The results of the calculations for each resource and month are shown in Appendix A.8.

$$TRPT_{r,m} = \frac{1}{3600}\sum_{c=1}^{C} GD_{c,m} * PT_{c,r} \tag{12}$$

A10 – Feasibility assessment of the production program

The total available capacity of the factory is shown in Appendix A.9. To facilitate the analysis of the production program, the total required processing time is subtracted from the total available processing time $TAPT_{r,m}$ as shown in equation 13, to get the deviation $D_{r,m}$ of the two values.

$$D_{r,m} = TAPT_{r,m} - TRPT_{r,m} \tag{13}$$

The result of the comparison is shown in Figure 6.7, and the respective data can be found in Appendix A.10. When the result of the comparison is negative in a given month on a specified resource, the required capacity is exceeded. Such is the case for resource two in month one, where 18,6 h cannot be covered with the available processing time. For this month, the production program is not feasible. In month two and in month five, all resources show surplus capacity. In month three, the required processing time exceeds the available one by 2,5 h. Months four and six are not feasible either, because in both months all required capacity is higher than the available one, except for resource zero in month six.

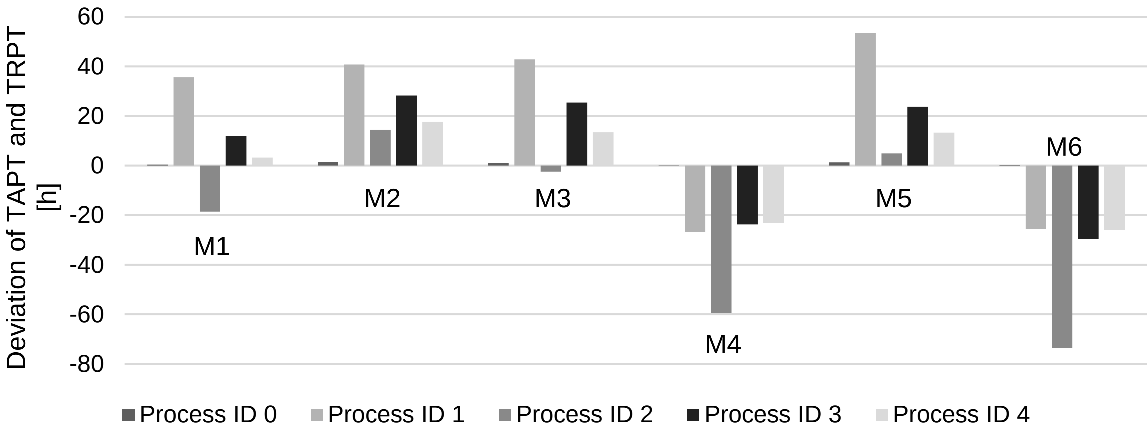


Figure 6.7: Feasibility assessment of the production program

The reason for the capacity to be exceeded significantly in month four and six is the higher net primary demand. The primary demand in month one is 220, the primary demand in month two, three, and five is 200. The net primary demand in month four and six is 300, and thereby exceeds the previous demand by 33 %.

Adjustments

To adjust for the demand peaks in month four and six, the additional capacities in the following months can be used. This causes a delay in delivery, because in remanufacturing the option to produce to stock in the previous months is limited to the available cores. Assuming, that the cores used in the calculation of the production program arrive in the respective month, the demand cannot be met, if no additional capacity is provided. This is a crucial difference to a regular production, where producing to stock is usually an option. Another solution is to adjust the sales planning. Initially, the sales plan yields the most profitable sales figures assuming that all net demand can be met. Should this not be the case, it is the task of sales planning to re-adjust the sales figures to the demand that can be matched. This may change the net demand in all planning periods.

6.3 Critical Reflection on the Obtained Results

The simulation model validates the concept of the defined remanufacturing process, of the activity model, and of the data model. However, the data model for the PPP is based on much more extensive data than used in the simulation model. The simulation model assumes that the probability with which a component can be reused is known. This assumption is based on real data, but the exact comparison of the remaining useful life with the required useful life would have to be included in a complete simulation model. Other component data that is not considered is the minimum order quantity and the ordering lead time. In addition, preceding operations are not taken into account in the calculation of the routings.

By decoupling the sales model from the prototype, only core data is considered that is also used in the product data and inherited by the cores. Lot sizes in production are also not considered. Although the prototype does not output the assembly and disassembly routing directly in a sorted form, these are implicitly contained in the data sets of the cores and can be provided by simple readout of the generated tables.

In its current state, the simulation model does not encompass all the data points from the comprehensive data model. Consequently, certain contents within the data model still require validation. To ensure the accuracy and reliability of the simulation results, it is imperative to address these outstanding contents and validate them accordingly. By validating the remaining data model contents, a more comprehensive and robust simulation can be achieved, providing greater insights and confidence in the comprehensiveness of the data model, in the correctness of the activity model, and in the accuracy of the simulation model's predictions and outcomes.

Nonetheless, a production program has been created in which each product and component can be individually identified and tracked, component inventories are output and subject to defined constraints, and resource requirements are matched against the available resources to analyze the validity of the production program.

7 Summary and Outlook

Implementing a circular economy through remanufacturing can help the manufacturing industry to become more sustainable by using resources more efficiently while ensuring long-term competitiveness. However, there is a lack of standardized and efficient processes for remanufacturing, which imposes challenges on the production program planning. Current literature has not yet adequately addressed this issue. Therefore, this work proposes a data model to cope with the uncertainties in production program planning caused by remanufacturing. The data model is obtained by analyzing the state of the art in production program planning and remanufacturing. The challenges are systematically identified, and the potential of managing those challenges using a defined set of data is analyzed. The data model is obtained by breaking down the production program planning process into activities, which are then analyzed for their information and data requirements using the IDEF0 method. The data is then structured and categorized into a UML class diagram which contains the attributes needed for each instance entangled in the production program. The purpose of the data model is to provide a structured framework showing the data needed to create a production program, which can be made before cores return to the remanufacturer, and which allows for incorporating the effects of planning uncertainties such as product specific routings, fluctuating processing times, and core conditions.

The data model is evaluated using a simulation model, which uses core activities within the production planning process, based on several core data points from the previously developed data model. As a practice-oriented example, the simulation is conducted for electric vehicle remanufacturing, based on a real component data set, which includes processing times, damage probabilities, and process IDs for each component. The results show that the data model is suited for developing and analyzing a production program. However, as the simulation model is a prototype, some of the constraints imposed by remanufacturing on the production programming process are not yet considered. These include preceding operations and an individual analysis of component data to determine their condition.

The simulation also reveals a major drawback in production program planning in remanufacturing, compared to the normal production program planning process. When adjusting for capacity shortages, surplus capacity from previous months cannot always be used to stock more products, as the cores needed for production might not be available this early. The feasibility of the production program therefore depends sensitively on the reliability of the forecasts, and higher safety stocks are needed if such reliability is not provided.

Outlook

Future research should focus on addressing the constraints imposed by remanufacturing on the production programming process that were not yet considered in the simulation model. These constraints include preceding operations, inventory limits, and an individual analysis of component data to determine the components' condition. By considering these constraints, it would be possible to develop a more comprehensive production program planning process that takes into account all the relevant factors and ensures effective and efficient remanufacturing.

As the model reliability in the simulation depends sensitively on the reliability of the forecasts used for production program planning in remanufacturing, another research focus should be developing accurate and sophisticated forecasting methods for core return times and component reusability. The developed data model relies on the comparison between the remaining useful life and the required useful life to be known. The remaining useful life is very specific to a component type. Its estimation cannot be based on a generalized set of information for a general component. The dataset must be collected for each component individually.

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VI Appendix

A.1. Results of the Systematic Literature Review

Authors	Title	Year
Gao Y.; Lou S.; Zheng H.; Tan J.	A data-driven method of selective disassembly planning at end-of-life under uncertainty	2023
Acerbi, Federica; Sassanelli, Claudio; Taisch, Marco	A conceptual data model promoting data-driven circular manufacturing	2022
Andersen, Terje; Bressanelli, Gianmarco; Saccani, Nicola; Franceschi, Benedetta	Information Systems and Circular Manufacturing Strategies: The Role of Master Data	2022
Frank, Laurenz	Development of a sales planning methodology for the remanufacturing of complete vehicles in the in the automotive industry	2022
Mustajib M.I.; Ciptomulyono U.; Kurniati N.	A novel multi-criteria sorting model based on ahp-entropy grey clustering for dealing with uncertain incoming core quality in remanufacturing systems	2021
Jiang, Zhigang; Jiang, Ya; Wang, Yan; Zhang, Hua; Cao, Huajun; Tian, Guangdong	A hybrid approach of rough set and case-based reasoning to remanufacturing process planning	2019
D. Giglio; M. Paolucci	A mixed-integer mathematical programming model for integrated planning of manufacturing and remanufacturing activities	2014
Wang, Lihui; Wang, Xi Vincent; Gao, Liang; Váncza, József	A cloud-based approach for WEEE remanufacturing	2014
W. D. Li; K. -M. Chao; G. Q. Jin; K. Xia; L. Gao	Sustainable information management for Waste Electrical and Electronic Equipment	2012
Kim, Kibum; Song, Iksoo; Kim, Juyong; Jeong, Bongju	Supply planning model for remanufacturing system in reverse logistics environment	2006
A. Kasmara; M. Muraki; S. Matsuoka; Sukoyo; K. Suryadi	Production planning in remanufacturing/manufacturing production system	2001
Ferrer, Geraldo; Whybark, D. Clay	Material Planning for a Remanufacturing Facility	2001

A.2. Prototypical Simulation Model Code

```
"""
Created on Wed Apr 26 13:48:56 2023

@author: ESTEBAN
"""
# import productionProgramClass
import csv
import random
import os


def main():
    ## CHATGPT START
    # Replace 'example.csv' with the name of your CSV file
    if os.name == 'nt':
        os.system('TASKKILL /F /IM excel.exe /T')

    filename1 = 'netDemandComponent.csv'
    filename2 = 'startComponentInventoriesUpdated.csv'
    filename3 = 'netDemandComponentNonNegative.csv'
    ## CHATGPT STOP

    ### start variables
    # The output of the sales model are sales numbers for each product group. First step is defining the sales of a group for the next six months.
    remanufacturedProductSalesGroup1 = [300,200,200,300,200,300]

    # Define the current inventory of products of group 1
    remanufacturedProductInventoryGroup1 = [50,0,0,0,0,0] #defines the current inventory

    # Define the number of products which are being produced in the current period
    ordersInProductionGroup1 = [20,0,0,0,0,0]

    # Define a variable which contains the net product demand
    netProductDemandRemanufacturingGroup1 = []

    # calculate net product demand (net demand = sales - inventory - orders in production)
    for x, y, z in zip(remanufacturedProductSalesGroup1, remanufacturedProductInventoryGroup1, ordersInProductionGroup1):
        netProductDemandRemanufacturingGroup1.append(x-y-z)


    # Define a database for the products in the net product demand and give every product a unique ID and unique components with a unique ID.
    databaseProducts = {}

    # components of the products
    components = ["Motorhaube", "Aussenspiegel", "TuerFahrer", "TuerBeifahrer", "Tuerdichtungen", "StossstangeVorne", "Grillabdeckung", "UntererKotfluegelschutz", "Fender", "LampenVorne", "Lampenmasken", "UntereTuerverkleidung", "UntereBSaeulenaussenverkleidung", "LampenHinten", "StossstangeHinten", "Wischersystem", "KlebeverbindungDach", "ASaeulenAussenverkleidung", "Tuerkontaktschalter", "SteckerHeizsystem", "Frontscheibe", "Kabelbaumabdeckung", "Sitzgruppe", "Gurtschloss", "Lenker", "Lenksaeulenverkleidung", "Lenkwinkelsensor", "Serviceklappen", "AbdeckungHintereMittelkonsole", "Handbremshebel", "Instrumentenpanel", "KabelbaumInstrumentenpanel", "Pedalerie", "Deckeninnenbeleuchtung", "Sonnenblenden", "ASaeuleninnenverkleidung", "BSaeuleninnenverkleidung", "Himmelverkleidung", "GurtaufrollerSamtGurt", "Kofferaufbau", "BSaeulenaussenverkleidung", "Heizsystem", "Technikraumdeckel", "Klemmen12VBatterie", "12VBatterie", "12VSchaltkasten", "KlemmenTraktionsbatterie", "Traktionsbatterie", "DcDcWandler", "HochvoltLadegeraet", "HochvoltSchaltkasten", "Ladebuchse", "KabelLeistungselektronik", "Antriebswellen", "Pumpe", "Antriebsstrang", "Handbremssystem", "RaederHinten", "RadhausHinten", "Hinterachse", "FederbeinHinten", "RaederVorne", "RadhausVorne", "Bremsleitungen", "BremssattelVorne", "BremsbelaegeVorne", "BremsscheibenVorne", "Koppelstange", "FederbeinVome", "Servolenkung", "Spurstange", "Motorhalterung", "EMotor", "Vorderachse", "Kabelbaum", "Karosserie"]

    # CHATGPT: loop through the netProductDemandRemanufacturingGroup1 list and create a product entry in the database for each month
    for month, demand in enumerate(netProductDemandRemanufacturingGroup1, start=1):
        for i in range(demand):
            # create a unique ID for each product
            product_id = f"P{month}{i}"
            # create a dictionary entry for each product with its ID, month, and components
```

```
            databaseProducts[product_id] = {"Month": month, "Components": {comp: f"{product_id}-{comp}" for comp in components}}

    ## CHATGPT START
    ### !!!only necessary when start variables change!!!
    # # Open a CSV file for writing the databaseProducts to the CSV file
    # with open('products.csv', mode='w', newline='') as file:
    #     # Create a writer object
    #     writer = csv.writer(file, delimiter=';')

    #     # Write the header row
    #     writer.writerow(['ID', 'Month'] + components)

    #     # Write each product to a row in the CSV file
    #     for product_id, product_data in databaseProducts.items():
    #         month = product_data['Month']
    #         component_ids = [product_data['Components'][comp] for comp in components]
    #         writer.writerow([product_id, month] + component_ids)
    ## CHATGPT STOP

    # There is a CSV file called componentsProcessingData which contains for every type of component the processing information.
    # It needs to be read to a dictionary
    databaseComponents = {}

    # CHATGPT START
    # read component data to a python dictionary
    with open('componentsProcessingData.csv', 'r') as csv_file:
        csv_reader = csv.reader(csv_file, delimiter=';')
        next(csv_reader) # skip the header row

        for row in csv_reader:
            component = row[0]
            number = int(row[1])
            damageProbability = float(row[2])
            processingTime = int(row[3])
            processID = int(row[4])

            databaseComponents[component] = {
                "number": number,
                "damageProbability": damageProbability,
                "processingTime": processingTime,
                "processID": processID
            }
    ## CHATGPT STOP

    # For the prototype, there are no updates considered. The BOMs of the new products are equal to the BOMs of the cores.
    # So now the products which are contained in the sales program are convertet to cores.
    databaseCores = databaseProducts

    # The processing data of the components contains information on their damage probability. In the cores variable, a
    # component is flagged with "-REPLACE" to the existing string in the cell to mark the compoennts which need to be disassembled and replaced
    # The codde also counts how many components of which type must be replaced per month.

    # the following dictionary called components_replaced can be used to count how many components of each type must be replaced in total
    # components_replaced = {}

    # CHATGPT START
    for product in databaseProducts:
        for component, component_id in databaseProducts[product]['Components'].items():
            damage_probability = databaseComponents.get(component, {}).get('damageProbability')
            if damage_probability is not None and random.random() < damage_probability:
                replaced_component_id = component_id + "-REPLACE"
                databaseProducts[product]['Components'][component] = replaced_component_id

                # if component not in components_replaced:
                #     components_replaced[component] = 1
                # else:
                #     components_replaced[component] += 1

    ### !!!only necessary when start variables change!!!
```

```
##Open a CSV file for writing  the core variable to a CSV file called cores to visualize it.
# with open('cores.csv', mode='w', newline='') as file:
#     # Create a writer object
#     writer = csv.writer(file, delimiter=';')

#     # Write the header row
#     writer.writerow(['ID', 'Month'] + components)

#     # Write each product to a row in the CSV file
#     for product_id, product_data in databaseCores.items():
#         month = product_data['Month']
#         component_ids = [product_data['Components'][comp] for comp in components]
#         writer.writerow([product_id, month] + component_ids)
## CHATGPT STOP

# The gross component demand is obtained by reading an empty excel file called grossDemandComponent in a variable.
# The CVS only contains zeros at the beginning
databaseGrossDemandComponents = {}

## CHATGPT START
# read gross component demand data to a python dictionary, the preliminary file is filled with 0s
with open('grossDemandComponent.csv', 'r') as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=';')
    next(csv_reader) # skip the header row

    for row in csv_reader:
        component = row[0]
        month1 = int(row[1])
        month2 = float(row[2])
        month3 = int(row[3])
        month4 = int(row[4])
        month5 = int(row[3])
        month6 = int(row[4])

        databaseGrossDemandComponents[component] = {
            "month1": month1,
            "month2": month2,
            "month3": month3,
            "month4": month4,
            "month5": month5,
            "month6": month6,
        }
## CHATGPT STOP

# create a dictionary for the resource capacity needed, it is filled with 0s for a start
databaseResourceNeeded = {}

# read resources to a python dictionary
with open('resourcesNeeded.csv', 'r') as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=';')
    next(csv_reader) # skip the header row

    for row in csv_reader:
        resource = row[0]
        month1 = int(row[1])
        month2 = float(row[2])
        month3 = int(row[3])
        month4 = int(row[4])
        month5 = int(row[3])
        month6 = int(row[4])

        databaseResourceNeeded[resource] = {
            "month1": month1,
            "month2": month2,
            "month3": month3,
            "month4": month4,
            "month5": month5,
            "month6": month6,
        }
## CHATGPT START
# Search for all entries in databaseCores which have a replace flag and add the component to the gross component demand
for core_id, core_data in databaseCores.items():
```

```python
        month = core_data['Month']
        components = core_data['Components']
        for component_name, component_id in components.items():
            if "-REPLACE" in component_id:
            # remove everything up to and including the first "-"
                prefix_removed = component_id.split("-", 1)[1]
                # remove the "-REPLACE" suffix from the remaining string
                suffix_removed = prefix_removed.rsplit("-REPLACE", 1)[0]
                component_name = component_name.split("-")[0]
                if suffix_removed in databaseGrossDemandComponents:
                    databaseGrossDemandComponents[suffix_removed][f"month{month}"] += 1

    # Write each product to a row in the CSV file to visualize the gross component demand
    with open('grossDemandComponentUpdated.csv', 'w', newline='') as file:
        writer = csv.writer(file, delimiter=';')
        writer.writerow(['Component'] + list(databaseGrossDemandComponents['Motorhaube'].keys())) # write headers
        for component, data in databaseGrossDemandComponents.items():
            writer.writerow([component] + [data[key] for key in data])

    # read inventory data to a variable of type dictionary
    databaseStartInventory = {}
    with open('startComponentInventories.csv', 'r') as csv_file:
        csv_reader = csv.reader(csv_file, delimiter=';')
        next(csv_reader) # skip the header row
    ## CHATGPT STOP

        for row in csv_reader:
            component = row[0]
            currentInventory = int(row[1])
            inventoryMin = int(row[2])
            inventoryMax = int(row[3])
            # the reliability is a random number to simulate how reliable the estimation of a components quality is.
            # if the reliability is low, more safety stock is needed
            reliability = float(row[4])
            month1 = int(row[5])
            month2 = int(row[6])
            month3 = int(row[7])
            month4 = int(row[8])
            month5 = int(row[9])
            month6 = int(row[10])


            databaseStartInventory[component] = {
                "currentInventory": currentInventory,
                "inventoryMin": inventoryMin,
                "inventoryMax": inventoryMax,
                "reliability": reliability,
                "month1": month1,
                "month2": month2,
                "month3": month3,
                "month4": month4,
                "month5": month5,
                "month6": month6
            }


    # read planned component receipts data to a variable of type dictionary
    databasePlannedComponentReceipts = {}
    with open('plannedComponentReceipts.csv', 'r') as csv_file:
        csv_reader = csv.reader(csv_file, delimiter=';')
        next(csv_reader) # skip the header row

        for row in csv_reader:
            component = row[0]
            month1 = int(row[1])
            month2 = int(row[2])
            month3 = int(row[3])
            month4 = int(row[4])
            month5 = int(row[5])
            month6 = int(row[6])

            databasePlannedComponentReceipts[component] = {
                "month1": month1,
                "month2": month2,
                "month3": month3,
```

```
                "month4": month4,
                "month5": month5,
                "month6": month6
            }

    # define a dictionary for the preliminary component net demand, which is not yet adjusted for Min and Max inventories
    # if planned receipts and inventory are higher than the demand, the value can be negative
    preliminaryNetComponentDemand = {}

    for component, component_demand in databaseGrossDemandComponents.items():
        net_demand = {}
        for month, demand in component_demand.items():
            planned_receipts = databasePlannedComponentReceipts[component][month]
            if month == "month1":
                current_inventory = databaseStartInventory[component]["currentInventory"]
                net_demand[month] = demand - planned_receipts - current_inventory
            else:
                net_demand[month] = demand - planned_receipts
        preliminaryNetComponentDemand[component] = net_demand

    # write the preliminary net component demand to a csv for visualization
    with open('netDemandComponent.csv', 'w', newline='') as file:
        writer = csv.writer(file, delimiter = ';')
        writer.writerow(['Component', 'Month1', 'Month2', 'Month3', 'Month4', 'Month5', 'Month6'])
        for component, demand in preliminaryNetComponentDemand.items():
            row = [component, demand['month1'], demand['month2'], demand['month3'], demand['month4'], demand['month5'], demand['month6']]
            writer.writerow(row)

    netComponentDemand = preliminaryNetComponentDemand
    # correct the net Demand, so that all demand is matched, and min inventories are considered

    for component, demand in preliminaryNetComponentDemand.items():
        for month, value in demand.items():
            previous_month = 'month' + str(int(month[5]) - 1)
            if value < 0:
                if month == 'month1':
                    databaseStartInventory[component][month] = abs(value)
                    if abs(value) < databaseStartInventory[component]['inventoryMin']:
                        diff = databaseStartInventory[component]['inventoryMin'] - abs(value)
                        databaseStartInventory[component][month] = databaseStartInventory[component]['inventoryMin']
                        netComponentDemand[component][month] = diff
                    else:
                        netComponentDemand[component][month] = 0
                else:
                    print('ELSEHIT')
                    databaseStartInventory[component][month] = abs(value) + abs(databaseStartInventory[component][previous_month])
                    netComponentDemand[component][month] = 0
                    if databaseStartInventory[component][month] < databaseStartInventory[component]['inventoryMin']:
                        print('ifhit')
                        diff = databaseStartInventory[component]['inventoryMin'] - databaseStartInventory[component][month]
                        databaseStartInventory[component][month] = databaseStartInventory[component]['inventoryMin']
                        netComponentDemand[component][month] = diff

                    # # Set negative value to zero in demand
                    # netComponentDemand[component][month] = 0
                    # # Add the absolute value to the current inventory in databaseStartInventory
                    # databaseStartInventory[component][month] = abs(value)

            if value == 0:
                # The inventory does not change. This requires a check for the first month, which has no predecessor.
                # If the value 0 is hit in the first month, the inventory of the theoretical previous month is 0 resulting from the way the gross demand is calculated.
                # Then, the inventory is set to the Min value and the demand is increased respectively.
```

```
                if month == 'month1':
                    databaseStartInventory[component][month] = databaseStartInventory[component]['inventoryMin']
                    netComponentDemand[component][month] = databaseStartInventory[component]['inventoryMin']
                else:
                    databaseStartInventory[component][month] = databaseStartInventory[component][previous_month]


            if value > 0:
                if month == 'month1':
                    databaseStartInventory[component][month] = databaseStartInventory[component]['inventoryMin']
                    netComponentDemand[component][month] = databaseStartInventory[component]['inventoryMin'] + value

                else:
                    diffInv = databaseStartInventory[component][previous_month] - value
                    if diffInv < databaseStartInventory[component]['inventoryMin']:
                        netComponentDemand[component][month] = databaseStartInventory[component]['inventoryMin'] - diffInv
                        databaseStartInventory[component][month] = databaseStartInventory[component]['inventoryMin']
                    elif diffInv >= databaseStartInventory[component]['inventoryMin']:
                        netComponentDemand[component][month] = 0
                        databaseStartInventory[component][month] = diffInv




    with open('netDemandComponentNonNegative.csv', 'w', newline='') as file:
        writer = csv.writer(file, delimiter = ';')
        writer.writerow(['Component', 'Month1', 'Month2', 'Month3', 'Month4', 'Month5', 'Month6'])
        for component, demand in netComponentDemand.items():
            row = [component, demand['month1'], demand['month2'], demand['month3'], demand['month4'], demand['month5'], demand['month6']]
            writer.writerow(row)

    with open('startComponentInventoriesUpdated.csv', 'w', newline='') as file:
        writer = csv.writer(file, delimiter = ';')
        writer.writerow(['Component', 'currentInventory', 'inventoryMin', 'inventoryMax', 'reliability', 'Month1', 'Month2', 'Month3', 'Month4', 'Month5', 'Month6'])
        for component, demand in databaseStartInventory.items():
            row = [component, demand['currentInventory'], demand['inventoryMin'], demand['inventoryMax'], demand['reliability'], demand['month1'], demand['month2'], demand['month3'], demand['month4'], demand['month5'], demand['month6']]
            writer.writerow(row)

    print(databaseResourceNeeded)

    for component, demand in databaseGrossDemandComponents.items():
        process_id = databaseComponents[component]['processID']
        duration = databaseComponents[component]['processingTime']
        for month, value in demand.items():

            databaseResourceNeeded[str(process_id)][month] += value*duration

    print(databaseResourceNeeded)

    # Open a new file for writing and create a CSV writer object
    with open('databaseResourceNeeded.csv', 'w', newline='') as csvfile:
        writer = csv.writer(csvfile, delimiter = ";")

        # Write the header row
        writer.writerow(['Process ID', 'Month 1', 'Month 2', 'Month 3', 'Month 4', 'Month 5', 'Month 6'])

        # Write the data rows
        for process_id, data in databaseResourceNeeded.items():
            writer.writerow([process_id, data['month1'], data['month2'], data['month3'], data['month4'], data['month5'], data['month6']])



    ## CHATGPT START
```

```
    # Use the 'start' command on Windows to open the file with the default program
    if os.name == 'nt':
        os.system('start "" "%s"' % filename1)
        os.system('start "" "%s"' % filename2)
        os.system('start "" "%s"' % filename3)
    ## CHATGPT STOP



if __name__ == "__main__":
    main()
```

A.3. BOM Data for Electric Vehicle Remanufacturing (Hollah 2019, pp. 190–192)

Component	number	damagePropability	processingTime	processID
Motorhaube	1	0.3	162	0
Aussenspiegel	2	0.3	234	1
TuerFahrer	3	0.7	1236	1
TuerBeifahrer	4	0.3	1236	1
Tuerdichtungen	5	0.3	234	1
StossstangeVorne	6	0.3	498	1
Grillabdeckung	7	0.3	234	1
UntererKotfluegelschutz	8	0.3	138	1
Fender	9	0.3	618	1
LampenVorne	10	0.05	618	1
Lampenmasken	11	0.2	162	1
UntereTuerverkleidung	12	0.2	162	1
UntereBSaeulenaussenverkleidung	13	0.3	162	1
LampenHinten	14	0.05	378	1
StossstangeHinten	15	0.3	498	1
Wischersystem	16	0.15	636	1
KlebeverbindungDach	17	0.3	1080	1
ASaeulenAussenverkleidung	18	0.3	198	1
Tuerkontaktschalter	19	0.05	378	1
SteckerHeizsystem	20	0.05	114	1
Frontscheibe	21	0.1	1080	1
Kabelbaumabdeckung	22	0.05	306	2
Sitzgruppe	23	0.3	1098	2
Gurtschloss	24	0.5	162	2
Lenker	25	0.3	306	2
Lenksaeulenverkleidung	26	0.05	306	2
Lenkwinkelsensor	27	0.05	306	2
Serviceklappen	28	0.05	234	2
AbdeckungHintereMittelkonsole	29	0.15	114	2
Handbremshebel	30	0.15	306	2
Instrumentenpanel	31	0.3	1476	2
KabelbaumInstrumentenpanel	32	0.05	234	2
Pedalerie	33	0.3	438	2
Deckeninnenbeleuchtung	34	0.05	114	2
Sonnenblenden	35	0.05	186	2
ASaeuleninnenverkleidung	36	0.05	234	2
BSaeuleninnenverkleidung	37	0.05	306	2
Himmelverkleidung	38	0.05	498	2
GurtaufrollerSamtGurt	39	0.5	162	2
Kofferaufbau	40	0.45	2160	2
BSaeulenaussenverkleidung	41	0.2	198	2
Heizsystem	42	0.05	618	2
Technikraumdeckel	43	0.05	234	3
Klemmen12VBatterie	44	0	126	3
12VBatterie	45	0.5	126	3
12VSchaltkasten	46	0.05	234	3
KlemmenTraktionsbatterie	47	0	576	3
Traktionsbatterie	48	0.7	864	3
DcDcWandler	49	0.05	306	3
HochvoltLadegeraet	50	0.05	618	3
HochvoltSchaltkasten	51	0.05	234	3
Ladebuchse	52	0.3	306	3

Component	number	damagePropability	processingTime	processID
KabelLeistungselektronik	53	0.05	234	3
Antriebswellen	54	0.05	738	3
Pumpe	55	0.1	306	3
Antriebsstrang	56	0.75	618	3
Handbremssystem	57	0.3	618	3
RaederHinten	58	0.15	216	3
RadhausHinten	59	0.3	186	3
Hinterachse	60	0.4	306	3
FederbeinHinten	61	0.05	360	3
RaederVorne	62	0.15	216	4
RadhausVorne	63	0.3	144	4
Bremsleitungen	64	0.3	978	4
BremssattelVorne	65	0.5	306	4
BremsbelaegeVorne	66	0.5	576	4
BremsscheibenVorne	67	0.5	576	4
Koppelstange	68	0.4	234	4
FederbeinVome	69	0.4	234	4
Servolenkung	70	0.15	306	4
Spurstange	71	0.3	618	4
Motorhalterung	72	0	924	4
EMotor	73	0.1	0	4
Vorderachse	74	0.6	0	4
Kabelbaum	75	0.15	0	4
Karosserie	76	0.75	0	4

A.4. Simulated Gross Component Demand

Component	M1	M2	M3	M4	M5	M6
Motorhaube	81	57	67	94	59	85
Aussenspiegel	64	61	65	93	57	81
TuerFahrer	157	148	144	204	138	209
TuerBeifahrer	65	58	67	102	50	100
Tuerdichtungen	69	58	62	95	64	87
StossstangeVorne	69	64	62	84	54	90
Grillabdeckung	80	64	61	88	63	84
UntererKotfluegelschutz	53	65	58	92	67	88
Fender	62	53	57	87	60	86
LampenVorne	9	14	12	17	10	16
Lampenmasken	45	45	34	61	37	67
UntereTuerverkleidung	43	44	37	58	39	49
UntereBSaeulenaussenverkleidung	52	65	62	88	56	95
LampenHinten	7	6	7	18	13	7
StossstangeHinten	86	62	63	78	61	86
Wischersystem	32	39	23	44	18	42
KlebeverbindungDach	51	64	60	85	60	84
ASaeulenAussenverkleidung	63	63	60	82	66	91
Tuerkontaktschalter	12	7	11	11	6	13
SteckerHeizsystem	8	6	13	7	6	17
Frontscheibe	19	24	25	32	22	27
Kabelbaumabdeckung	10	11	13	12	7	14
Sitzgruppe	60	62	54	95	56	97
Gurtschloss	104	98	108	161	93	150
Lenker	65	50	68	85	65	93
Lenksaeulenverkleidung	13	13	7	8	11	13
Lenkwinkelsensor	10	14	15	16	12	11
Serviceklappen	12	6	9	12	8	14
AbdeckungHintereMittelkonsole	27	27	27	51	25	46
Handbremshebel	29	30	27	43	24	45
Instrumentenpanel	84	53	72	83	71	91
KabelbaumInstrumentenpanel	15	8	8	14	7	14
Pedalerie	78	63	56	104	66	96
Deckeninnenbeleuchtung	7	8	6	9	8	10
Sonnenblenden	10	13	7	15	8	20
ASaeuleninnenverkleidung	7	15	11	10	14	16
BSaeuleninnenverkleidung	12	12	6	13	10	14
Himmelverkleidung	13	10	9	18	16	15
GurtaufrollerSamtGurt	119	105	106	164	90	146

Component	M1	M2	M3	M4	M5	M6
Kofferaufbau	109	80	99	136	89	155
BSaeulenaussenverkleidung	42	41	37	64	34	50
Heizsystem	7	10	15	9	5	12
Technikraumdeckel	11	10	12	8	8	15
Klemmen12VBatterie	0	0	0	0	0	0
12VBatterie	113	122	114	141	99	170
12VSchaltkasten	8	9	7	8	6	20
KlemmenTraktionsbatterie	0	0	0	0	0	0
Traktionsbatterie	153	138	146	207	144	224
DcDcWandler	14	9	13	12	10	14
HochvoltLadegeraet	11	3	8	10	6	24
HochvoltSchaltkasten	15	9	10	17	9	20
Ladebuchse	63	60	55	97	53	83
KabelLeistungselektronik	13	10	9	16	9	11
Antriebswellen	12	12	8	12	14	14
Pumpe	24	19	23	32	20	26
Antriebsstrang	173	147	148	237	148	219
Handbremssystem	68	55	62	84	67	103
RaederHinten	44	21	26	44	27	45
RadhausHinten	67	65	56	109	58	90
Hinterachse	90	74	76	112	90	114
FederbeinHinten	12	8	4	19	10	9
RaederVorne	27	29	26	40	34	46
RadhausVorne	62	52	63	94	60	100
Bremsleitungen	78	50	60	92	65	100
BremssattelVorne	116	96	94	144	97	144
BremsbelaegeVorne	105	102	100	152	105	140
BremsscheibenVorne	106	106	109	128	104	148
Koppelstange	90	81	71	121	77	132
FederbeinVome	98	82	92	109	75	104
Servolenkung	39	29	37	49	25	39
Spurstange	72	61	64	92	64	88
Motorhalterung	0	0	0	0	0	0
EMotor	21	19	13	30	14	24
Vorderachse	131	119	122	181	120	177
Kabelbaum	29	35	24	49	28	50
Karosserie	177	149	147	224	145	228

A.5. Simulated Scheduled Receipts

Component	M1	M2	M3	M4	M5	M6
Motorhaube	6	12	0	0	0	0
Aussenspiegel	14	6	0	0	0	0
TuerFahrer	20	1	0	0	0	0
TuerBeifahrer	6	3	0	0	0	0
Tuerdichtungen	16	11	0	0	0	0
StossstangeVorne	8	2	0	0	0	0
Grillabdeckung	4	17	0	0	0	0
UntererKotfluegelschutz	10	5	0	0	0	0
Fender	8	16	0	0	0	0
LampenVorne	20	11	0	0	0	0
Lampenmasken	16	1	0	0	0	0
UntereTuerverkleidung	7	12	0	0	0	0
UntereBSaeulenaussenverkleidung	16	17	0	0	0	0
LampenHinten	16	12	0	0	0	0
StossstangeHinten	10	10	0	0	0	0
Wischersystem	15	12	0	0	0	0
KlebeverbindungDach	9	15	0	0	0	0
ASaeulenAussenverkleidung	12	19	0	0	0	0
Tuerkontaktschalter	4	20	0	0	0	0
SteckerHeizsystem	3	9	0	0	0	0
Frontscheibe	4	11	0	0	0	0
Kabelbaumabdeckung	5	4	0	0	0	0
Sitzgruppe	1	4	0	0	0	0
Gurtschloss	2	1	0	0	0	0
Lenker	8	1	0	0	0	0
Lenksaeulenverkleidung	8	1	0	0	0	0

Component	M1	M2	M3	M4	M5	M6
Lenkwinkelsensor	13	2	0	0	0	0
Serviceklappen	14	0	0	0	0	0
AbdeckungHintereMittelkonsole	7	1	0	0	0	0
Handbremshebel	0	11	0	0	0	0
Instrumentenpanel	15	4	0	0	0	0
KabelbaumInstrumentenpanel	4	5	0	0	0	0
Pedalerie	12	4	0	0	0	0
Deckeninnenbeleuchtung	8	15	0	0	0	0
Sonnenblenden	1	12	0	0	0	0
ASaeuleninnenverkleidung	4	11	0	0	0	0
BSaeuleninnenverkleidung	9	10	0	0	0	0
Himmelverkleidung	11	14	0	0	0	0
GurtaufrollerSamtGurt	3	14	0	0	0	0
Kofferaufbau	10	14	0	0	0	0
BSaeulenaussenverkleidung	11	4	0	0	0	0
Heizsystem	7	10	0	0	0	0
Technikraumdeckel	4	3	0	0	0	0
Klemmen12VBatterie	5	1	0	0	0	0
12VBatterie	8	5	0	0	0	0
12VSchaltkasten	6	4	0	0	0	0
KlemmenTraktionsbatterie	8	7	0	0	0	0
Traktionsbatterie	11	4	0	0	0	0
DcDcWandler	8	9	0	0	0	0
HochvoltLadegeraet	15	4	0	0	0	0
HochvoltSchaltkasten	15	2	0	0	0	0
Ladebuchse	6	13	0	0	0	0
KabelLeistungselektronik	9	14	0	0	0	0
Antriebswellen	3	9	0	0	0	0
Pumpe	12	5	0	0	0	0
Antriebsstrang	3	7	0	0	0	0
Handbremssystem	3	12	0	0	0	0
RaederHinten	10	8	0	0	0	0
RadhausHinten	11	3	0	0	0	0
Hinterachse	0	12	0	0	0	0
FederbeinHinten	10	9	0	0	0	0
RaederVorne	1	2	0	0	0	0
RadhausVorne	8	9	0	0	0	0
Bremsleitungen	0	4	0	0	0	0
BremssattelVorne	7	6	0	0	0	0
BremsbelaegeVorne	4	3	0	0	0	0
BremsscheibenVorne	12	13	0	0	0	0
Koppelstange	4	1	0	0	0	0
FederbeinVome	9	3	0	0	0	0
Servolenkung	14	8	0	0	0	0
Spurstange	7	5	0	0	0	0
Motorhalterung	1	3	0	0	0	0
EMotor	7	3	0	0	0	0
Vorderachse	11	7	0	0	0	0
Kabelbaum	12	3	0	0	0	0
Karosserie	0	3	0	0	0	0

A.6. Simulated Inventory

Component	currentInventory	inventoryMin	inventoryMax	reliability	M1	M2	M3	M4	M5	M6
Engine hood	19	19	49	0.53	19	19	19	19	19	19
Mirrors	14	6	36	0.87	6	6	6	6	6	6
Door driver	29	22	52	0.47	22	22	22	22	22	22
TuerBeifahrer	10	9	39	0.79	9	9	9	9	9	9
Tuerdichtungen	11	10	40	0.76	10	10	10	10	10	10
StossstangeVorne	13	12	42	0.7	12	12	12	12	12	12
Grillabdeckung	8	7	37	0.83	7	7	7	7	7	7
UntererKotfluegelschutz	32	24	54	0.41	24	24	24	24	24	24
Fender	22	21	51	0.49	21	21	21	21	21	21
Headlights	24	24	54	0.4	35	32	24	24	24	24
Lampenmasken	9	5	35	0.88	5	5	5	5	5	5
UntereTuerverkleidung	17	9	39	0.79	9	9	9	9	9	9
UntereBSaeulenaussenverkleidung	13	13	43	0.69	13	13	13	13	13	13

Component	currentInventory	inventoryMin	inventoryMax	reliability	M1	M2	M3	M4	M5	M6
LampenHinten	13	9	39	0.78	22	28	21	9	9	9
StossstangeHinten	12	7	37	0.83	7	7	7	7	7	7
Wischersystem	13	6	36	0.87	6	6	6	6	6	6
KlebeverbindungDach	28	22	52	0.45	22	22	22	22	22	22
ASaeulenAussenverkleidung	26	19	49	0.54	19	19	19	19	19	19
Tuerkontaktschalter	20	19	49	0.54	19	32	21	19	19	19
SteckerHeizsystem	32	22	52	0.45	27	30	22	22	22	22
Frontscheibe	27	20	50	0.5	20	20	20	20	20	20
Kabelbaumabdeckung	18	18	48	0.56	18	18	18	18	18	18
Sitzgruppe	6	5	35	0.89	5	5	5	5	5	5
Gurtschloss	24	16	46	0.6	16	16	16	16	16	16
Lenker	13	5	35	0.89	5	5	5	5	5	5
Lenksaeulenverkleidung	22	15	45	0.64	17	15	15	15	15	15
Lenkwinkelsensor	13	10	40	0.75	16	10	10	10	10	10
Serviceklappen	21	20	50	0.51	23	20	20	20	20	20
AbdeckungHintereMittelkonsole	13	7	37	0.83	7	7	7	7	7	7
Handbremshebel	17	13	43	0.68	13	13	13	13	13	13
Instrumentenpanel	31	24	54	0.42	24	24	24	24	24	24
KabelbaumInstrumentenpanel	21	19	49	0.53	19	19	19	19	19	19
Pedalerie	11	7	37	0.84	7	7	7	7	7	7
Deckeninnenbeleuchtung	23	13	43	0.69	24	31	25	16	13	13
Sonnenblenden	11	10	40	0.75	10	10	10	10	10	10
ASaeuleninnenverkleidung	16	13	43	0.68	13	13	13	13	13	13
BSaeuleninnenverkleidung	17	14	44	0.66	14	14	14	14	14	14
Himmelverkleidung	22	19	49	0.53	20	24	19	19	19	19
GurtaufrollerSamtGurt	18	13	43	0.68	13	13	13	13	13	13
Kofferaufbau	24	19	49	0.54	19	19	19	19	19	19
BSaeulenaussenverkleidung	21	12	42	0.72	12	12	12	12	12	12
Heizsystem	18	14	44	0.65	18	18	14	14	14	14
Technikraumdeckel	12	12	42	0.7	12	12	12	12	12	12
Klemmen12VBatterie	26	18	48	0.56	31	32	32	32	32	32
12VBatterie	16	16	46	0.62	16	16	16	16	16	16
12VSchaltkasten	16	9	39	0.79	14	9	9	9	9	9
KlemmenTraktionsbatterie	28	22	52	0.46	36	43	43	43	43	43
Traktionsbatterie	11	8	38	0.81	8	8	8	8	8	8
DcDcWandler	19	14	44	0.66	14	14	14	14	14	14
HochvoltLadegeraet	23	14	44	0.66	27	28	20	14	14	14
HochvoltSchaltkasten	18	10	40	0.75	18	11	10	10	10	10
Ladebuchse	22	14	44	0.65	14	14	14	14	14	14
KabelLeistungselektronik	31	22	52	0.47	27	31	22	22	22	22
Antriebswellen	20	14	44	0.65	14	14	14	14	14	14
Pumpe	23	13	43	0.68	13	13	13	13	13	13
Antriebsstrang	18	9	39	0.78	9	9	9	9	9	9
Handbremssystem	6	6	36	0.85	6	6	6	6	6	6
RaederHinten	16	13	43	0.69	13	13	13	13	13	13
RadhausHinten	16	10	40	0.75	10	10	10	10	10	10
Hinterachse	11	11	41	0.73	11	11	11	11	11	11
FederbeinHinten	7	7	37	0.83	7	8	7	7	7	7
RaederVorne	17	12	42	0.72	12	12	12	12	12	12
RadhausVorne	20	18	48	0.57	18	18	18	18	18	18
Bremsleitungen	15	12	42	0.72	12	12	12	12	12	12
BremssattelVorne	17	7	37	0.83	7	7	7	7	7	7
BremsbelaegeVorne	25	15	45	0.64	15	15	15	15	15	15
BremsscheibenVorne	14	14	44	0.65	14	14	14	14	14	14
Koppelstange	14	11	41	0.74	11	11	11	11	11	11
FederbeinVome	12	10	40	0.76	10	10	10	10	10	10
Servolenkung	8	6	36	0.87	6	6	6	6	6	6
Spurstange	10	6	36	0.87	6	6	6	6	6	6
Motorhalterung	11	8	38	0.82	12	15	15	15	15	15
EMotor	19	11	41	0.73	11	11	11	11	11	11
Vorderachse	13	6	36	0.87	6	6	6	6	6	6
Kabelbaum	14	12	42	0.72	12	12	12	12	12	12
Karosserie	6	6	36	0.85	6	6	6	6	6	6

A.7. Simulated Net Component Demand

Component	M1	M2	M3	M4	M5	M6
Engine hood	75	45	67	94	59	85
Mirrors	42	55	65	93	57	81
Door driver	130	147	144	204	138	209
Door passenger	58	55	67	102	50	100
Tuerdichtungen	52	47	62	95	64	87
StossstangeVorne	60	62	62	84	54	90
Grillabdeckung	75	47	61	88	63	84
UntererKotfluegelschutz	35	60	58	92	67	88
Fender	53	37	57	87	60	86
Headlights	0	0	4	17	10	16
Lampenmasken	25	44	34	61	37	67
UntereTuerverkleidung	28	32	37	58	39	49
UntereBSaeulenaussenverkleidung	36	48	62	88	56	95
LampenHinten	0	0	0	6	13	7
StossstangeHinten	71	52	63	78	61	86
Wischersystem	10	27	23	44	18	42
KlebeverbindungDach	36	49	60	85	60	84
ASaeulenAussenverkleidung	44	44	60	82	66	91
Tuerkontaktschalter	7	0	0	9	6	13
SteckerHeizsystem	0	0	5	7	6	17
Frontscheibe	8	13	25	32	22	27
Kabelbaumabdeckung	5	7	13	12	7	14
Sitzgruppe	58	58	54	95	56	97
Gurtschloss	94	97	108	161	93	150
Lenker	49	49	68	85	65	93
Lenksaeulenverkleidung	0	10	7	8	11	13
Lenkwinkelsensor	0	6	15	16	12	11
Serviceklappen	0	3	9	12	8	14
AbdeckungHintereMittelkonsole	14	26	27	51	25	46
Handbremshebel	25	19	27	43	24	45
Instrumentenpanel	62	49	72	83	71	91
KabelbaumInstrumentenpanel	9	3	8	14	7	14
Pedalerie	62	59	56	104	66	96
Deckeninnenbeleuchtung	0	0	0	0	5	10
Sonnenblenden	8	1	7	15	8	20
ASaeuleninnenverkleidung	0	4	11	10	14	16
BSaeuleninnenverkleidung	0	2	6	13	10	14
Himmelverkleidung	0	0	4	18	16	15
GurtaufrollerSamtGurt	111	91	106	164	90	146
Kofferaufbau	94	66	99	136	89	155
BSaeulenaussenverkleidung	22	37	37	64	34	50
Heizsystem	0	0	11	9	5	12
Technikraumdeckel	7	7	12	8	8	15
Klemmen12VBatterie	0	0	0	0	0	0
12VBatterie	105	117	114	141	99	170
12VSchaltkasten	0	0	7	8	6	20
KlemmenTraktionsbatterie	0	0	0	0	0	0
Traktionsbatterie	139	134	146	207	144	224
DcDcWandler	1	0	13	12	10	14
HochvoltLadegeraet	0	0	0	4	6	24
HochvoltSchaltkasten	0	0	9	17	9	20
Ladebuchse	49	47	55	97	53	83
KabelLeistungselektronik	0	0	0	16	9	11
Antriebswellen	3	3	8	12	14	14
Pumpe	2	14	23	32	20	26
Antriebsstrang	161	140	148	237	148	219
Handbremssystem	65	43	62	84	67	103
RaederHinten	31	13	26	44	27	45
RadhausHinten	50	62	56	109	58	90
Hinterachse	90	62	76	112	90	114
FederbeinHinten	2	0	3	19	10	9
RaederVorne	21	27	26	40	34	46
RadhausVorne	52	43	63	94	60	100
Bremsleitungen	75	46	60	92	65	100
BremssattelVorne	99	90	94	144	97	144
BremsbelaegeVorne	91	99	100	152	105	140
BremsscheibenVorne	94	93	109	128	104	148
Koppelstange	83	80	71	121	77	132

Component	M1	M2	M3	M4	M5	M6
FederbeinVome	87	79	92	109	75	104
Servolenkung	23	21	37	49	25	39
Spurstange	61	56	64	92	64	88
Motorhalterung	0	0	0	0	0	0
EMotor	6	16	13	30	14	24
Vorderachse	113	112	122	181	120	177
Kabelbaum	15	32	24	49	28	50
Karosserie	177	146	147	224	145	228

A.8. Simulated Required Capacity in h

ProcessID	M1	M2	M3	M4	M5	M6
0	3.6	2.6	3	4.2	2.7	3.8
1	164.4	159.3	157.2	226.8	146.5	225.6
2	158.6	125.5	142.5	199.5	135.1	213.6
3	113	96.7	99.6	148.8	101.2	154.7
4	96.8	82.4	86.5	123.1	86.8	126

A.9. Simulated Available Capacity in h

ProcessID	M1	M2	M3	M4	M5	M6
0	4	4	4	4	4	4
1	200	200	200	200	200	200
2	140	140	140	140	140	140
3	125	125	125	125	125	125
4	100	100	100	100	100	100

A.10. Simulated Capacity Deviation in h

ProcessID	M1	M2	M3	M4	M5	M6
0	0.4	1.4	1	-0.2	1.3	0.2
1	35.6	40.7	42.8	-26.8	53.5	-25.6
2	-18.6	14.5	-2.5	-59.5	4.9	-73.6
3	12	28.3	25.4	-23.8	23.8	-29.7
4	3.2	17.6	13.5	-23.1	13.2	-26

VII Statutory Declaration

I declare that I have developed and written the enclosed Master Thesis completely by myself, and have not used sources or means without declaration in the text. Any thoughts from others and literal quotations are clearly marked. The Master Thesis was not used in the same or in similar version to achieve an academic grading or is being published elsewhere.

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Place, date Signature