Preprints of Control Conference Africa 2024
Balaclava, Mauritius, 16-17 September 2024

Optimization of resource allocation in remanufacturing systems: A labor and automation perspective

Moritz Hoffmann *,**, **Steffi Knorn** *

* *Chair of Control, TU Berlin, Germany.*
** *Robert Bosch Automotive Steering GmbH, Germany.*

Abstract: Remanufacturing depicts a pivotal strategy within the circular economy framework to conserve and reintroduce high-quality components after their end-of-use period. Despite its acknowledged labor-intensive nature, existing literature lacks comprehensive models to aid decision-makers in allocating resources efficiently. Moreover, there is a conspicuous absence of scheduling approaches tailored to optimize labor resource allocation amidst fluctuating supply and demand dynamics. In response, this paper introduces a quantitative optimization model that enables optimal resource allocation over discrete time intervals, that facilitate industrial decision-makers to plan their remanufacturing systems accordingly. Through an illustrative example, we evaluate the feasibility of our model by applying a dynamic programming algorithm to find the optimal resource allocation strategy. Here, we find that due to the variety of complexities associated with remanufacturing the achievement of an optimal solution necessitates judicious simplifications.

Keywords: Remanufacturing; Resource allocation; Optimization; Modeling

1. INTRODUCTION

Remanufacturing depicts an industrial process that sorts, inspects, disassembles, washes, reprocesses or reconditions, assembles, and tests end-of-life (EOL) products (so-called cores) to their original specification (Tolio et al., 2017). While these processes seem simple in contrast to highly industrialized production lines, the dependency on old cores involves random failures of components, product variability, technical incompatibility, demand and supply uncertainties, and a reliance on well trained human labor (Liu et al., 2019; Sitcharangsie et al., 2019; Goodall et al., 2014). Particularly, in the context of central Europe (Tolio et al., 2017) and China (Wei et al., 2015), the reliance on skilled labor in remanufacturing is mentioned as a major challenge. Despite the associated cost considerations as an implementation barrier, Rizova et al. (2020) point out that there are no labor scheduling models for enhanced remanufacturing decision-making in current literature.

While traditional manufacturing enterprises have adapted automation technologies on a wide scale, remanufacturing is still in its infancy (Pfrommer et al., 2022). However, recent advancements such as automated disassembly (Tolio et al., 2017), human robot collaboration (Chu and Chen, 2023) or autonomous core quality inspection (Kaiser et al., 2022) are becoming more popular in literature and industrial applications. These robotic appliances offer reliable production quality and quantity. Nevertheless, these technologies are mostly only applicable to a single process step or specific components within the remanufacturing lines. Also, the high product variability and the lack of information towards these variants poses great challenges. As highlighted in Tolio et al. (2017) and Wei et al. (2015), remanufacturing is still highly reliant on human labor. In contrast to machines that are mostly applicable to only a minor number of process steps, human labor is highly versatile (Chang, 2004). This enables a flexible deployment for fluctuating demands or the compensation of local bottlenecks. Despite their wide applicability to different processes and product variants, manual workforces are less efficient and prone to errors (Myszewski, 2010).

The labor utilization in remanufacturing literature is limited to the qualitative consideration of cost associations. However, the lower demand streams and higher product complexity of remanufacturing require a higher level of versatility than traditional manufacturing. Thus, this paper embarks on this topic and develops a quantitative model for resource allocation and scheduling under human factor consideration in remanufacturing.

2. MATHEMATICAL MODEL OF REMANUFACTURING SYSTEM

For our mathematical model we assume there is a generic remanufacturing system that consist of the traditional remanufacturing production operations (as displayed in Fig. 1). The edges ($\rightarrow$) symbolize the remanufacturing process steps p evolving over an observed discrete time interval k with $k \in [0, K]$, the nodes ($\circ$) depict the quantities of pieces acting as inputs and output of the respective edges, i.e. remanufacturing processes. In this model, intralogistical processes or transport routings between the processes p are not taken in consideration.

2.1 Product variants

One of the major challenges in remanufacturing is the high product variability (Tolio et al., 2017). Thus, we consider j product variants which may be taken from the set $j \in \{1, \ldots, n_{\mathrm{j}}\}$. In dependence of the type and the architecture of the observed remanufacturing product, there may be some compatibilities between these variants j. When equipped with such information, the remanufacturing facility can derive insights from the bill of materials (i.e. list of assembled components for variant j), elucidating which components are compatible for which variants (Graham et al., 2015). We assume that components from variant j can be recombined quite freely; only the same components l from the set $l \in \{1, \ldots, L\}$ of variant j need to be utilized, but they do not have to be identical. For instance, in the case of an alternator (e.g., in Tolio et al. (2017)) it must be assembled from a housing, a rotor and other components again, but the respective parts do not necessarily have to originate from the exact same product under compatibility consideration. Nevertheless, it is important to note that particularly independent remanufacturers are not affiliated with the original equipment manufacturer and thus may lack depth of information in this regard.

Also, one must consider that the same number of disassembled components L is required to form a re-assembled product. As arbitrary failures incur in remanufacturing (Liu et al., 2019), the minimum quantity of reconditioned components define the maximum quantity of possibly assembled variants. For example, if two cores of one variant are diassembled into three components $\{2, 2, 2\}$ and, one of those is unusable due to the occurrence of failures, from the remaining components only one variant can be assembled.

2.2 External Supply and Demand

In order to start the remanufacturing process, a supply of EOL products are required. Thus, we assume that at each k a quantity of $s_j(k) \in \{0, 1, 2, \ldots\}$ of cores is supplied.

After the successful execution of all remanufacturing processes, the output of the final process can be delivered to the customer, to fulfil its required demand $d_j(k)$. As applied in Lage Junior and Godinho Filho (2017) and Ferrer (2003), we assume that the supply of cores $s_j(k)$ and the customer demand $d_j(k)$ are reliable and determined. This also means that there are no pre-disassembly inspection efforts required. As remanufacturing systems operate in value networks, the observed time period to fulfil the customer demand is limited to one production cycle K. We assume that the number of remanufactured variants j post-testing is temporarily accumulating to meet the demand at the end of the time interval, e.g. $d_j(K)$. Moreover, we suppose that the accumulated number of supplied variants j in the production cycle surpasses the number of requested customer demands with $s_j(K) \geq d_j(K)$.

2.3 Resources

To execute the remanufacturing processes p of the variants j a subset of resources i is required. For resource allocation we distinguish between human labor and automation technology scheduling. For instance, in the model's most simple form, the resource i depicts 1 for human operators and 2 for automation machinery. In more detail one can also differentiate between differently skilled and trained operators. This may include specialists for specific processes or all-rounders that are versatile to a variety of processes and variants. Similarly to these considerations for human labor, one could also distinguish between different states of autonomy for automation machinery. In addition, the inclusion of machines with human intervention constraint or human robot collaborations (as in Chu and Chen (2023)) could be considered.

When applying and comparing different resources in production processes or remanufacturing systems, in particular, the productivity $\eta_{p,i,j}$ of resource i, process p and variant j over time step k depicts a crucial performance indicator. We adapt the traditional definition of productivity by Björkman (1992), to a variable performance metric that evolves over the time k and takes the learning capabilities of human operators in consideration. This allows the development of specific skills that raise the productivity of allocated resource i over time. Thus, we define $\eta_{p,i,j}(k)$ as

$$\eta_{p,i,j}(k) = \eta_{0_{p,i,j}} + (1 - e^{-\alpha_{p,i,j}(k - k_{0_{p,i,j}})})\eta_{\mathrm{t}_{p,i,j}} \quad (1)$$

where $\eta_{0_{p,i,j}}$ represents the initial value of production output at the observed time frame $k_{0_{p,i,j}}$ that increases by the constant time value $\alpha_{p,i,j}$ to raise the effective output over time k of allocated resource i by repeatedly execution of process p and variant j. The additional learning capability is limited to a maximum value of $\eta_{\mathrm{t}_{p,i,j}}$, as with a converging $k \to \infty$ the maximum productivity of the process p for resource i of variant j can be simplified to $\eta_{p,i,j}(k) = \eta_{0_{p,i,j}} + \eta_{\mathrm{t}_{p,i,j}}$.

Usually, it is assumed that the application of automation technology achieves a higher throughput and, thus, higher values of η than human labor. However, as we will see later, human operators are typically able to handle a higher variance of processes p and variants j whereas machinery is statically applicable to specific processes p and variants j; such that $\eta_{p,i,j} = 0$ for many combinations of p, i and j under machine deployment considerations.

2.4 Failures

As mentioned above, remanufacturing is subject to arbitrary failure rates of cores and core components. Hence, we assume upon an incurred failure, the defective piece is identified immediately and disposed out of the system.

Similarly to the progressing effectiveness η, the failure occurrence can be expressed as a time dependent variable λ. Thus, we adapt the stochastical model of Myszewski (2010) as a variable failure rate $\lambda_{p,i,j}(k) \in [0, 1]$ that is dependent on the process p, the deployed resource i, and the variant j that develops over time:

$$\lambda_{p,i,j}(k) = \lambda_{\mathrm{rf}_{p,i,j}} + e^{-\beta_{p,i,j}(k - k_{0_{p,i,j}})}(\lambda_{0_{p,i,j}} - \lambda_{\mathrm{rf}_{p,i,j}}). \quad (2)$$

The failure rate consists of the random failure $\lambda_{\mathrm{rf}_{p,i,j}}$ that affects any deployed resource, the initial failure $\lambda_{0_{p,i,j}}$ at time $k_{0_{p,i,j}}$, and the time constant $\beta_{p,i,j}$ that defines the decrease of failures over progressing time. We assume that for human operators the failure rate $k_{0_{p,i,j}}$ which can be compensated through training and the resulting learning effects (see further, in (Myszewski, 2010)). For automation technology, we assume that for any i and j, the

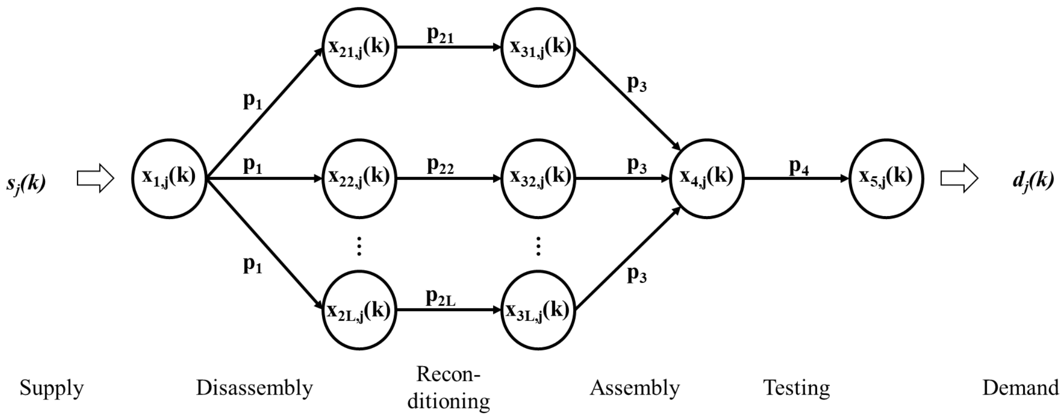

Fig. 1. Generic remanufacturing system

time constant $\beta_{p,i,j} \to \infty$ which simplifies to $\lambda_{p,i,j}(k) = \lambda_{\text{rf}_{p,i,j}}$. The remaining random failure might be caused by resource-independent effects as outlined above.

2.5 Decision variable

We further denote the decision variable $u_{p,i,j}(k)$ that indicates how many resources i are deployed on process p for variant j over time k. The outlined model aims to optimize the resource efficiency that is controlled by the number of resources deployed with $u_{p,i,j}(k)$. For example, under given resource considerations, the deployment of the optimal number of human operators as resource 1 in process 3 of variant 5 is required; when $u_{3,1,5}(k) = 3$, the optimal deployment policy is three human operators.

2.6 State equations

Based on the previously defined parameters and their respective variables, we outline our state equation $x_{s,j}(k)$ that dynamically evolves over the progress of time k. Considering the outlined generic remanufacturing system, the states are indicated by the nodes (∘) of the Petri net in Figure 1. The index s increases incrementally with the successful pass of one process step p with $s \in \{1, \ldots, n_\text{s}\}$. For example, the state of an assembled product has the state $x_{4,j}$ that transforms after passing process p_4 to the state $x_{5,j}$. For the nodes within our generic remanufacturing system in Figure 1, we outline the following state equations over time:

$$x_{1,j}(k+1) = x_{1,j}(k) + s_j(k) - \sum_i \eta_{1,i,j} u_{1,i,j}(k) \tag{3}$$

$$x_{2_l,j}(k+1) = x_{2_l,j}(k) + \sum_i (1 - \lambda_{1,i,j}(k)) \eta_{1,i,j} u_{1,i,j}(k) - \sum_i \eta_{2_l,i,j} u_{2_l,i,j}(k) \quad \forall l \in \{1, \ldots, L\} \tag{4}$$

$$x_{3_l,j}(k+1) = x_{3_l,j}(k) + \sum_i (1 - \lambda_{2_l,i,j}(k)) \eta_{2_l,i,j} u_{2_l,i,j}(k) - \sum_i \eta_{3,i,j} u_{3,i,j}(k) \quad \forall l \in \{1, \ldots, L\} \tag{5}$$

$$x_{4,j}(k+1) = x_{4,j}(k) + \sum_i (1 - \lambda_{3,i,j}(k)) \eta_{3,i,j} u_{3,i,j}(k) - \sum_i \eta_{4,i,j} u_{4,i,j}(k) \tag{6}$$

$$x_{5,j}(k+1) = x_{5,j}(k) + \sum_i (1 - \lambda_{4,i,j}(k)) \eta_{4,i,j} u_{4,i,j}(k) \tag{7}$$

The first state equation in (3) describes the number of intermediate products for $x_{1,j}(k+1)$ at stage 1 during time step $k+1$. This includes the sum of the parts that have been at this state during the previous time step $x_{1,j}(k)$ and the supply of new cores $s_j(k)$; from this accumulation of parts, the number of required pieces for the following process step 1 (i.e. disassembly) $\sum_i \eta_{1,i,j} u_{1,i,j}(k)$ are subtracted as disassembly removes a piece (core) from node 1 and adds a component to each node 2_l.

The second state equation in (4), follows the same principle. First, aside from the pieces $x_{2_l,j}(k)$ of the previous time step, the supply of disassembled parts (i.e. components) l from the previous process 1 under consideration of failure occurrences by the applied resources i are considered with $\sum_i (1 - \lambda_{1,i,j}(k)) \eta_{1,i,j} u_{1,i,j}(k)$. Similarly, to the state equation (3), the number of required components to proceed with the process step 2 (i.e. reconditioning) $\sum_i \eta_{2_L,i,j} u_{2_L,i,j}(k)$ are subtracted.

Similarly to the state equation in (4), (5) describes the number of component l after successful reconditioning under failure occurrence consideration $\lambda_{2_L,i,j}(k)$. However, as the following process step 3 assembles $\sum_i \eta_{3,i,j} u_{3,i,j}(k)$ pieces, the same number of reconditioned components is required, for all l states (as outlined in 2.1). Here, we assume that the components are only compatible within their respective variant j (i.e. there are no compatibilities between the different variants n_j).

The fourth state equation (6) describes the state of all assembled components at time frame $k+1$. This includes the sum of the previously assembled products $x_{4,j}(k)$ and the supply of reconditioned components under failure reduction consideration as $\sum_i (1 - \lambda_{3,i,j}(k)) \eta_{3,i,j} u_{3,i,j}(k)$ accumulated for all deployed resources i. From this sum the parts for the final testing step 4 are subtracted.

The last state before the successfully remanufactured pieces are delivered to the customer is described in (7). This includes the accumulation of the parts $x_{5,j}(k)$ that have been in this state since time k and the parts that are without defects after process 4 (i.e. testing) $\sum_i (1 - \lambda_{4,i,j}(k)) \eta_{4,i,j} u_{4,i,j}(k)$ for all resources i. The sum of these parts are considered serviceable parts accumulate until the end of production cycle K to fulfil the demand $d_j(K)$.

The vector containing all states $x_{s,j}$ is denoted $\mathbf{x}$ below.

3. OPTIMIZATION PROBLEM

3.1 Objective function

The rationale of a remanufacturing production system is to remanufacture parts in the most efficient manner to fulfil customer orders. The aspect of production efficiency arises from the associated costs of the respective processes. As failures or other inefficiencies accumulate, they cause costs that decrease the profit of the system as a whole. Thus, it is important to take these influencing factors in consideration to *maximize* the value $V(K)$ by applying the *optimal* number of resources $u_{p,i,j}(k)$. For that, firstly the value $V(K)$ can be defined as

$$V(K) = r(K) - c(K) \tag{8}$$

where $r(K)$ describes the generated revenue and $c(K)$ describes the incurred accumulated costs at the end of the production cycle K. The revenue is defined as

$$r(K) = \sum_j P_j \min\{x_{5,j}(K); d_j(K)\}. \tag{9}$$

In essence, the equation above assumes that the demand $d_j(K)$ equals the production quantity $x_{5,j}(K)$ and is sold to the customer at price P_j. However, if the produced quantity $x_{5,j}(K)$ is lower than the demand $d_j(K)$ ($x_{5,j}(K) < d_j(K)$) only the number of successfully remanufactured product variants j can be sold. Furthermore, a surplus that extends the customer demand ($x_{5,j}(K) > d_j(K)$) cannot be sold because it was not requested from the customer. This surplus is then transferred to the inventory and can be used in the following production cycle.

To apply (8), we need to introduce the different types of costs for the remanufacturing system. These include the investment costs c_{i_0} for machinery or upfront training opportunities for the respective resources, costs of supplied cores $c_{\mathrm{c},j}$, operational costs $c_{\mathrm{o}_{p,i,j}}(k)$ for wages or maintenance in dependence of the resource, and costs of lost demand c_{d}, see Puchkova et al. (2015), that encompass contractual penalties $c_{\mathrm{cp},j}$ for each missing unit $x_{5,j}(K)$. Considering all these types of costs, $c(K)$ is defined as

$$\begin{aligned} c(K) = &\sum_i c_{i_0} + \sum_j s_j(k) c_{\mathrm{c},j} \\ &+ \sum_{p,i,j} \sum_{k=1}^{K} u_{p,i,j}(k) c_{\mathrm{o}_{p,i,j}} \\ &+ \sum_j \max\{(d_j(K) - x_{5,j}(K)); 0\} c_{\mathrm{cp},j}. \end{aligned} \tag{10}$$

The first line includes the sum of the costs for allocated resources and supplied cores. In the second line of (10) the operational costs for the optimal resource policy for all p, i, j until K is outlined. In the last line, the cost of lost demand for $x_{5,j}(K) < d_j(K)$ with the contractual penalty $c_{\mathrm{cp},j}$ for each missing variant j is described. When the demand is fulfilled or even surpassed ($x_{5,j}(K) \geq d_j(K)$), this line simplifies to $\max\{(d_j(K) - x_{5,j}(K)); 0\} = 0$.

The optimisation is subject to constraints as $u_{p,i,j}(k)$ has to be chosen such that $x_{s,j}(k) \geq 0 \ \forall p, i, j, k, s$. Further, overall resources may be limited by $\bar{u}_{p,i,j}$ and $\bar{u}_i$ leading to $u_{p,i,j}(k) \in [0, \bar{u}_{p,i,j}]$, $\sum_{p,j} u_{p,i,j}(k) \in [0, \bar{u}_i]$. Here, $\bar{u}_i$ and $\bar{u}_{p,i,j}$ depict the resource limit as the upper bound that cannot be exceeded. This may arise from a shortage of labor availability or space restrictions within the remanufacturing facility.

3.2 Finite-Time Horizon Optimal Resource Allocation

Here, it will be discussed how to obtain the optimal resource allocation, that is choosing $u_{p,i,j}(k)$ for all p, i, j and $k \in \{1, \ldots, K\}$ to maximize the revenue at the end of the time interval K. We assume that no non-causal information is available and the decisions on how to choose $u_{p,i,j}(k)$ are made for each time step k based on the current state of the system.

A resource allocation policy is a set of functions to determine $\{u_{p,i,j}(k)\}$. It is feasible if the constraints above are almost surely (a.s.) satisfied for all $k \geq 1$ and admissible if it is further based only on the causal information containing the current state space, e.g. no knowledge whether a failure will occur in a consecutive processing step.

The finite-time horizon optimal resource allocation problem which maximizes the expected revenue over a finite horizon subject to constraints is given by

$$\begin{aligned} &\max_{u_{p,i,j}(k): 1 \leq k \leq K} \mathbb{E}\left[v(K)\right], \\ &\text{s.t. } u_{p,i,j}(k) \in [0, \bar{u}_{p,i,j}], \sum_{p,j} u_{p,i,j}(k) \in [0, \bar{u}_i], x_{s,j}(k) \geq 0 \end{aligned} \tag{11}$$

a.s. for all s, p, i, j and $1 \leq k \leq K$, and $x_{s,j}$ satisfy the state space equations as depicted in (3-7).

3.3 Finite-Time Horizon Optimal Resource Allocation Policy

For the causal information case where the future unpredictable occurrences of failures are not a priori known, the solution to the stochastic control problem (11) is given by the following theorem:

Theorem 1. *Let the initial condition be* $\mathbf{x}(0)$*. Then the value of the finite-time horizon maximization problem* (11) *with causal information is given by* $V_1(x_{s,j}(0))$*, which can be computed recursively from the backward Bellman dynamic programming equation*

$$\begin{aligned} V_k(\mathbf{x}(k)) = \max_{u_{p,i,j}(k)} \Big\{ &c_{o,p,i,j} u_{p,i,j}(k) \\ &+ \mathbb{E}\left[V_{k+1}(\mathbf{x}(k+1)) | u_{p,i,j}(k)\right] \Big\} \end{aligned} \tag{12}$$

for $1 \leq k \leq K-1$ *such that the constraints in (11) are met and the dynamics of* $\mathbf{x}(k)$ *are given by (3-7). The terminal condition is*

$$\begin{aligned} V_K(\mathbf{x}(K)) = &r(K) - \sum_i c_{i_0} - \sum_j s_j(k) c_{\mathrm{c},j} \\ &- \sum_j \max\{(d_j(K) - x_{5,j}(K)); 0\} c_{\mathrm{cp},j}. \end{aligned} \tag{13}$$

Proof. The proof follows from the optimality equations for finite-time horizon stochastic control problems, Bertsekas (1995).

The solution to (11) is then given by

$$\left\{u^*_{p,i,j}(k)\right\} = \underset{u_{p,i,j}(k)}{\operatorname{argmax}} \Big\{ c_{o,p,i,j} u_{p,i,j}(k) + \mathbb{E}\left[V_{k+1}(\mathbf{x}(k+1)) | u_{p,i,j}(k)\right]\Big\} \quad (14)$$

for $1 \leq k \leq K-1$ such that the constraints mentioned above are met and with state dynamics (3-7) and V_k is the solution to the Bellman equation (12).

In general the solution to the dynamic programming equation (14) can only be obtained numerically because there is no closed form solution. The numerical solution then relies on computing the optimal policy for a large number of discretised state space values, we assume that this computation is done off-line and stored in a look-up table. In real-time, when the optimal policy shall be deployed, as the control system receives the state space information at each time step, the controller looks up the optimal resource allocation policy for the corresponding nearest discretised values of the state values and applies them.

4. ILLUSTRATIVE EXAMPLE

In order to assess the feasibility of the outlined model, an illustrative example is proposed. In response to the implications of the *curse of dimensionality* inherent in dynamic programming, necessitating significant computational resources, we undertook substantial simplification of the provided model.

We assume that only one variant j undergoes remanufacturing, which streamlines the mathematical operation by one dimension. The demand is limited to the number of remanufactured parts, hence, contractual penalties regarding the cost of lost demand are not taken in consideration. Regarding the remanufacturing process steps, we did not carry out any simplifications. Here, each supplied core undergoes disassembly, reconditioning, assembly, and testing operations before being delivered to the customer. However, as the multi-echelon production line in Fig. 1 includes L components, our example only considers 2 components that are reconditioned and assembled for the defined remanufacturing variant. Further, we define the following resources i with their capabilities η and λ as:

- Specialized worker ($i = 1$): $\eta_{0_{p,1}} = \{2; 6; 0.5; 5; 0\}$, $\lambda_{\mathrm{rf}_1} = 0.05$, $\alpha_1 = 0$, $\beta_1 = 0$,
- Versatile worker ($i = 2$): $\eta_{0_{p,2}} = \{2.5; 4; 1.5; 4; 3\}$, $\lambda_{\mathrm{rf}_2} = 0.05$, $\lambda_{0_2} = 0.1$, $\alpha_2 = 0.1$, $\beta_2 = 0.1$,
- Automated machinery ($i = 3$): $\eta_{0_{p,3}} = \{2.5; 7, 5; 2.5; 6; 0\}$, $\lambda_{\mathrm{rf}_1} = 0.01$, $\alpha_1 = 0$, $\beta_1 = 0$,

where we neglected index j, assuming that λ_{rf_i} and λ_{0_2} do not depend on process p (hence neglecting the index for p) and that the specialized worker and the machine are not undergoing further training. The set given for $\eta_{0_{p,1}}$ contains the value for each process (given in the order of the processes).

The distinction between resource 1 and 2 is that we consider two generic types of operators; one that is more specialized on specific processes (and hence with larger values for specific η) and the other one being more flexibly applicable. While both of them are subject to a random failure λ_{rf}, the versatile worker starts with an additional initial failure λ_0 that improves due to training.

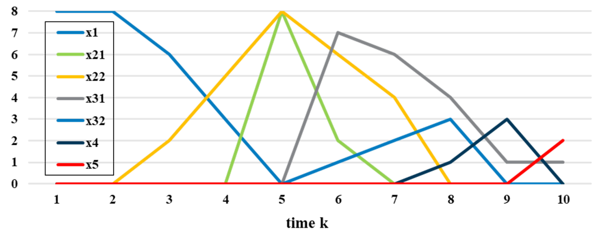

Fig. 2. Illustrative Example: Number of pieces x_s over time.

Resource 3 represents an extreme case of the specialized worker, as the automated machine has a higher throughput than the specialist, with lower failure rate but less versatility than resource 2. In reality, automated machinery is highly efficient in executing certain processes but not applicable to others (e.g., automated disassembly (Tolio et al., 2017)). In our example we assume that resource 3 outperforms all resources for p_{21} and p_3 and is generally more productive than resource 1. The versatile worker is the only resource that is capable of p_5; they are slightly more/less productive than $i = 1$ in the other processes.

Due to computational reasons we needed to limit the resources i to a quantity of one unit, that is $\sum_{p,j} u_{p,i,j}(k) \in \{0, 1\}$ for all i. Furthermore, we observe the time horizon $K = 10$, neglect the investment c_{i_0} and consider a higher $c_{\mathrm{o},p,i,j}(k)$ for the investment intensive resources. Also, we simplify the costs for resource deployment as constant for all processes p with $c_{\mathrm{o},1}(k) = 0.5$, $c_{\mathrm{o},2}(k) = 0.3$ and $c_{\mathrm{o},3}(k) = 1$ (again neglecting indices for p and j). Acknowledging λ_{rf_2}, we assume that resource 2 has the lowest cost. We also assume $P_j = 20$.

We simulated a scenario with $x_1(0) = 8$ and all other initial states being zero. For failures, the random process was simulated by a Bernoulli variable with probability for a failure according to λ. The results can be found in Figs 2 and 3. They show that despite the overall higher values of η for using the machine and a much lower chance of failure, only using human labor (resources 1 and 2) is optimal in the majority of times. Hence, it seems that, indeed human labor may be more profitable than investing into complex machinery as humans are much more flexible and versatile (indeed, it also is evident that the more versatile worker, $i = 2$, is deployed far more often than the specialist worker, $i = 1$). Of course, this must be verified in a more complex investigation of more realistic processes over a longer period of time. However, for this, it is essential that other methods are used to compute the optimal (if even possible) or sub-optimal solutions. In Ansari and Daxini (2022) the authors also find that dynamic programming becomes prohibitively complex and impossible to handle for even small remanufacturing problems.

5. DISCUSSION

In remanufacturing literature, the importance of human operators is vastly acknowledged but also highlighted as a major barrier for high wage countries. Moreover, resource allocation strategies for human labor utilization are scarce and highlighted as a significant research gap for

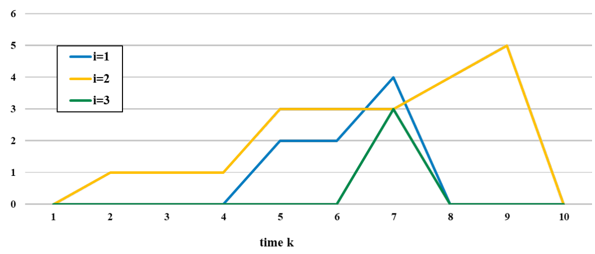

Fig. 3. Illustrative Example: Processes to which resources $i = 1, 2, 3$ are allocated over time.

operational decision-making in remanufacturing (Rizova et al., 2020). A vital challenge here is depicted by the scheduling of workers within the processes as humans possess individual skills and capabilities. Here, Chang (2004) outlines an entropy-related function to describe human labor versatility, but the authors do not delve into its incorporation into the already existing complexities of multi-echelon production networks.

In our developed model we outline human factors such as productivity η and failure occurrence λ that can be enriched by the individual capabilities of resource i. Furthermore, this aspect is not limited to the human operator as a resource, it also takes the possibility of machine deployment or automation technology for optimal scheduling in consideration. As outlined in the illustrative example, the versatile worker is the most sufficient resource for this production case. To verify these assumptions, the developed model should be applied to a remanufacturing case company.

In particular, the potential for versatility of human labor should be emphasized more prominently when decisions regarding resource allocation are made. Most of the applied models in current literature focus on resource optimization, particularly for high production volumes. The decisions whether automation and human labour are deployed are made based on high/low wage country constraints (Tolio et al., 2017). However, this strategy lacks quantitative evidence and has limited applicability to remanufacturing due to its prevailing challenges and the lower investment capabilities. Considering this, the suitability of existing models is limited in this context. Thus, the developed model can guide decision-makers navigating these trade-offs to determine the optimal solution.

In the future we intend to incorporate core and component compatibility in our developed model. While we assumed in (3)-(7) that the different variants j are not compatible, this incorporation based on a pre-defined compatibility analysis could resolve existing bottlenecks caused by defective parts or low productivity ratios of certain variants. Here, a matching algorithm as in Yu and Lee (2018) could be applied to find the optimal assembly combination of different variants under optimal resource allocation consideration. Furthermore, it would be interesting to apply heuristic approaches to the given example to compare near-optimal solutions with the outcome of the dynamic programming approach. With the application of a heuristic we could additionally tackle more complex problems and take more aspects of the outlined model in consideration.

REFERENCES

Ansari, Z.N. and Daxini, S.D. (2022). A State-of-the-Art Review on Meta-heuristics Application in Remanufacturing. *Arch. Comput. Methods Eng.*

Bertsekas, D.P. (1995). *Dynamic Programming and Optimal Control*. Athena Scientific, 3rd edition.

Björkman, M. (1992). What is Productivity? *IFAC Proceedings Volumes.*

Chang, A. (2004). On the measurement of labor flexibility. In *IEEE Int. Eng. Management Conf.*

Chu, M. and Chen, W. (2023). Human-robot collaboration disassembly planning for end-of-life power batteries. *Journal of Manufacturing Systems.*

Ferrer, G. (2003). Yield information and supplier responsiveness in remanufacturing operations. *European Journal of Operational Research.*

Goodall, P., Rosamond, E., and Harding, J. (2014). A review of the state of the art in tools and techniques used to evaluate remanufacturing feasibility. *Journal of Cleaner Production.*

Graham, I., Goodall, P., Peng, Y., Palmer, C., West, A., Conway, P., Mascolo, J.E., and Dettmer, F.U. (2015). Performance measurement and KPIs for remanufacturing. *Journal of Remanufacturing.*

Kaiser, J.P., Lang, S., Wurster, M., and Lanza, G. (2022). A Concept for Autonomous Quality Control for Core Inspection in Remanufacturing. *Procedia CIRP.*

Lage Junior, M. and Godinho Filho, M. (2017). Master disassembly scheduling in a remanufacturing system with stochastic routings. *Central European Journal of Operations Research.*

Liu, C., Zhu, Q., Wei, F., Rao, W., Liu, J., Hu, J., and Cai, W. (2019). A review on remanufacturing assembly management and technology. *The International Journal of Advanced Manufacturing Technology.*

Myszewski, J.M. (2010). Mathematical model of the occurrence of human error in manufacturing processes. *Quality and Reliability Engineering International.*

Pfrommer, J., Klein, J.F., Wurster, M., Rapp, S., Grauberger, P., Lanza, G., Albers, A., Matthiesen, S., and Beyerer, J. (2022). An ontology for remanufacturing systems. *at - Automatisierungstechnik.*

Puchkova, A., Srinivasan, R., McFarlane, D., and Thorne, A. (2015). Towards Lean and Resilient Production. *IFAC-PapersOnLine.*

Rizova, M.I., Wong, T., and Ijomah, W. (2020). A systematic review of decision-making in remanufacturing. *Computers & Industrial Engineering.*

Sitcharangsie, S., Ijomah, W., and Wong, T. (2019). Decision makings in key remanufacturing activities to optimise remanufacturing outcomes: A review. *Journal of Cleaner Production.*

Tolio, T., Bernard, A., Colledani, M., Kara, S., Seliger, G., Duflou, J., Battaia, O., and Takata, S. (2017). Design, management and control of demanufacturing and remanufacturing systems. *CIRP Annals.*

Wei, S., Cheng, D., Sundin, E., and Tang, O. (2015). Motives and barriers of the remanufacturing industry in China. *Journal of Cleaner Production.*

Yu, J.M. and Lee, D.H. (2018). Scheduling algorithms for job-shop-type remanufacturing systems with component matching requirement. *Computers & Industrial Engineering.*