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Leveraging Digital Twins for Integrated Capacity Planning in Remanufacturing Systems

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Abstract

The transition towards circular production challenges the assumptions of traditional production planning and control systems, which were designed for stable, linear supply chains. By contrast, remanufacturing is characterised by irregular product returns, uncertain quality conditions, and variable process routes. Such dynamics necessitate planning mechanisms that are adaptive and continuously updated. This paper presents a Digital Twin–enabled framework for capacity planning in remanufacturing production systems. By connecting tactical and operational planning horizons, the framework maintains synchronisation between planning and execution through information integration and event-triggered orchestration. The paper proposes a multi-time-frame digital twin architecture to transform classical horizon planning into a feedback-driven system that can adapt to stochastic disturbances in real time. This concept establishes the basis for data-driven, event-responsive capacity planning, thereby supporting the development of resilient, resource-efficient remanufacturing operations.

Keywords: Remanufacturing; Production Planning; Digital Twin

1. Introduction

Manufacturers are facing increasing pressure from both regulatory and consumer demands to produce sustainable and durable products. At the same time, global supply disruptions and raw material shortages have underscored the need for resource security and operational resilience. In response, many companies are adopting circular production systems that recover and reuse existing products to maintain competitiveness and reduce dependence on critical materials. [1] Among the R-strategies, remanufacturing is especially promising because it restores used products to an equal or superior condition [2], thereby maximising both environmental and economic benefits.

At the same time, Digital Twin (DT) technologies are transforming production planning and control. Digital twins are virtual representations of physical assets and processes that remain continuously synchronised with real operations through sensor data, analytics, and simulation. Their integration enables predictive, adaptive, and data-driven decision-making, improving real-time visibility, scheduling, and coordination across planning horizons [3].

However, the transition from linear to circular manufacturing exposes the limits of traditional Production Planning and Control (PPC) frameworks such as the Aachen PPC Model and the Hanoverian Supply Chain Model, which rely on stable demand, deterministic processes, and one-directional material flows. These assumptions do not hold in remanufacturing, where stochastic returns, variable quality, and re-entrant flows dominate. Addressing these dynamics requires a feedback-driven PPC approach that connects planning levels dynamically rather than sequentially.

This paper presents a digital twin–based orchestration framework that integrates tactical and operational decision-making to enable adaptive and resource-efficient capacity planning in remanufacturing environments.

2. Production Planning Approaches and Tasks

Production planning and control (PPC) in classical manufacturing is formalised through frameworks that define decision levels and planning tasks across multiple time horizons. These models distribute production, material, and capacity decisions,

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highlighting capacity planning as the link between program feasibility and shop-floor execution.

Ackers presents a time-oriented hierarchy of PPC functions, where programme planning acts on the long horizon, quantity and capacity planning on the medium horizon, and order release and monitoring on the short horizon [4]. Scheduling and capacity planning form the central tactical activity, translating aggregate production volumes into feasible workloads. Capacity planning ensures production targets remain executable under limited labour and machine resources while maintaining utilisation efficiency.

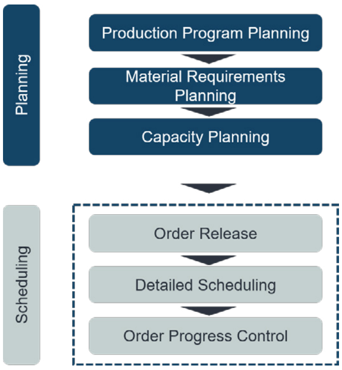

Fig. 1. PPC-Tasks According to Acker [4]

The Aachen PPC model [7] defines five task fields: programme planning, material requirements planning, capacity planning, order release, and order control. As in Acker's model, capacity planning serves as the interface between programme and control, ensuring resources are available in the required quantity and timing. Its position underscores its coordinating role by linking planning intent with executable shop-floor capacity.

The Hanoverian Supply Chain Model (HaLiMo) [6] links PPC tasks with logistical objectives such as delivery reliability and throughput time. It distinguishes three temporal layers of capacity planning [5]:

- *Long term, order anonymous capacity planning*, checking programme feasibility over one to two years at the product group level;
- *Mid term, rough capacity planning*, balancing required and available resources over weeks or months through shift changes or outsourcing;
- *Short term, capacity resource planning*, assigning work to personnel and machines and compensating overloads through overtime or rescheduling.

HaLiMo therefore aligns capacity planning with system behaviour to support feasible programmes and reliable delivery.

Among PPC tasks, capacity planning most directly determines whether planned output can be achieved. Material and order plans can be revised, but capacity feasibility defines whether the system can operate within a given time frame. It also reflects economic trade offs: too little capacity limits fulfilment, while excess capacity increases costs and lowers efficiency [8]. As it defines both physical and economic boundaries, capacity planning becomes central for analysing how planning systems adapt under uncertainty.

2.1. Orchestration of Planning Levels in Digital-Twin Environments

Traditional PPC frameworks rely on hierarchical decomposition, where strategic, tactical, and operational decisions are defined sequentially and exchanged through fixed information flows. This provides structure but also creates rigidity, as higher level plans often lose validity when shop floor conditions change. In cyber-physical production systems, this motivates a shift to Digital Twin–enabled coordination, where a continuously synchronized system model helps interpret deviations and propagate them across planning levels.

In distributed computing, orchestration denotes supervisory control of interacting services. Applied to manufacturing, it governs how planning models exchange information and synchronise internal states [9, 10]. It adds a dynamic control layer that manages timing, dependencies, and interactions between analytical and physical models. Rather than periodic updates, orchestration supports event driven adaptation, keeping decisions aligned with production conditions. Foresighted Digital Twins demonstrate this by assessing disturbances and selecting suitable control strategies in real time [11]. Planning or decision making modules, data exchange, or reoptimisation can be initiated through the following types of triggers (excerpt): [12]

- *Event-based*, responding to machine failures, order changes, or inspection outcomes;
- *Request-based*, when lower-level models signal infeasibility to higher levels;
- *Capacity-based*, utilising available computational resources for recalibration or scenario testing.

Through these mechanisms, orchestration replaces one-way information flow with bidirectional, data-driven feedback. Tactical planning can immediately respond to operational disturbances, while operational control receives updated constraints from the tactical layer. This interaction establishes a closed-loop planning cycle where analytical models and physical systems remain continuously synchronised through digital-twin coordination.

3. Capacity Planning in Remanufacturing

Production planning in remanufacturing differs markedly from conventional forward production, as it must account for uncertain returns, variable core quality, and complex reverse process chains. These sources of input and process uncertainty make planning inherently stochastic and require continuous adjustment to changing system conditions. The following subsection outlines the resulting challenges and reviews state-of-the-art approaches for addressing them.

3.1. Uncertainties in Remanufacturing

The challenges of remanufacturing lie in the various uncertainties, which were partly already introduced. The varying inflow of used products depends on customer behavior, product life cycles, and collection efficiency, leading to asynchronous supply and demand situations that can cause either shortages or overloads [13]. Each returned unit exhibits an individual degradation profile that affects feasible process routes and processing times [14]. Inspection and rework loops introduce feedback and variability that conventional material requirements planning cannot represent accurately [15]. In addition, the uncertain condition of incoming cores complicates the prediction of remaining useful life and the selection of optimal reprocessing strategies [16]. Further complexity arises from additional stages such as disassembly, cleaning, and reassembly, which require the coordination of forward and reverse material and information flows [17]. These interacting uncertainties create a stochastic and information-intensive environment for remanufacturing, where traditional deterministic planning methods often fail to ensure robustness and responsiveness.

3.2. Remanufacturing Production Planning

Capacity planning in remanufacturing has progressed significantly in the past two decades, reflecting the increasing uncertainty and complexity of circular production systems. Early work relied on linear manufacturing assumptions, whereas recent research focuses on adaptive and reconfigurable systems that respond to uncertain return flows and variable product conditions.

Franke et al. [18] presented one of the first integrated approaches to capacity and program planning using mobile phones as a case. Their combination of linear optimization and discrete event simulation showed how stochastic returns shape capacity needs, emphasized the importance of manual labour under fluctuating workloads, and demonstrated that automated disassembly becomes economical only for stable, high volume products. The study highlighted the need for continuous facility adaptation and anticipated multi level dynamic planning.

Wurster et al. [19] advanced this direction with a condition aware framework for hybrid disassembly systems. Their mixed integer model integrates product condition data and probabilistic process outcomes, representing networks of manual and robotic stations. Through an adaptive rolling horizon, they periodically reoptimize system configuration and capacity, linking long term system design with short term responsiveness and moving capacity planning toward feedback driven reconfiguration.

Huster et al. [20] examined strategic capacity planning for EV battery remanufacturing and showed that outcomes depend strongly on return rates and product quality. Their results underline that strategic decisions require stochastic feedback from operations to remain valid.

Despite these contributions, current methods seldom synchronize operational, tactical, and strategic decisions. In manual remanufacturing, operational planning assigns workers to stations, tactical planning regulates overtime and temporary staff, and strategic planning defines overall workforce levels. If these layers are misaligned, overloads or idle labour can occur even when nominal capacity appears sufficient. Coordinating the layers ensures flexible and efficient use of manual resources. This logic extends to resilient circular factory architectures, where transformer cells switch between assembly and disassembly modes as needed [21], with long-term planning defining cell capacity and short-term planning managing configuration.

3.3. State of the Art of Digital Twins in Remanufacturing

Recent research has explored the use of Digital Twins (DTs) to enable adaptive and data-driven production planning and control in response to these challenges. DTs establish a real-time, two-way link between physical assets and their virtual counterparts, facilitating monitoring, simulation, and predictive decision making [23]. In remanufacturing, DTs can improve visibility of core condition, support dynamic scheduling, and optimise resource use across uncertain and distributed settings.

At the *process level*, DTs have been developed to model disassembly, cleaning, and inspection under uncertainty. Chen et al. [22] present a DT based framework that enhances information sharing across remanufacturing supply chains, reducing diagnostic delays and improving coordination. Kerin et al. [16] propose a generic asset model for product DTs that enables prediction of disassembly effort and processing routes from uncertain core quality.

Current DT applications in remanufacturing tend to be limited in scope, frequently focusing on individual processes rather than integrated systems. They also rarely address issues such as data gaps, scalability, and computational effort. The practical implementation of DTs is further constrained by issues relating to data quality, connectivity and interoperability. Nevertheless, DTs offer a pathway towards event-driven remanufacturing by linking heterogeneous data and enabling real-time feedback between planning and execution. This facilitates a transition from reactive to predictive and adaptive operations. However, the use of DTs for production planning, particularly for capacity decisions in the face of uncertain returns and variable process conditions, remains largely unexplored.

4. Digital Twin–Enabled Planning in Remanufacturing

Remanufacturing systems operate under conditions that cause production plans to shift as soon as they meet real operations. Irregular returns, changing routes, and variable process dynamics mean that plans created with forward production assumptions lose validity quickly, making planning dependent on timely feedback and rapid adjustment. A DT can support this need by linking planning models directly to real time data from inspection, disassembly, and reassembly processes. While traditional rolling horizon planning updates plans at fixed intervals, a DT framework enables event driven adaptation, allowing digital representations to trigger reoptimisation whenever disturbances such as unexpected core arrivals or condition deviations occur.

To manage the volatility in remanufacturing, the proposed framework extends traditional planning concepts into a closed-loop system that adapts the timing and content of reoptimization according to the current system state. Two functions of the concept are central: (i) information integration, which maintains consistency between virtual and physical models across horizons, and (ii) model orchestration, which governs when and how reoptimization occurs through event, constraint, or resource-based triggers. Together, these functions create an adaptive DT planning structure that remains coherent and responsive to stochastic disturbances across horizons. The proposed DT for remanufacturing production planning is shown in 2.

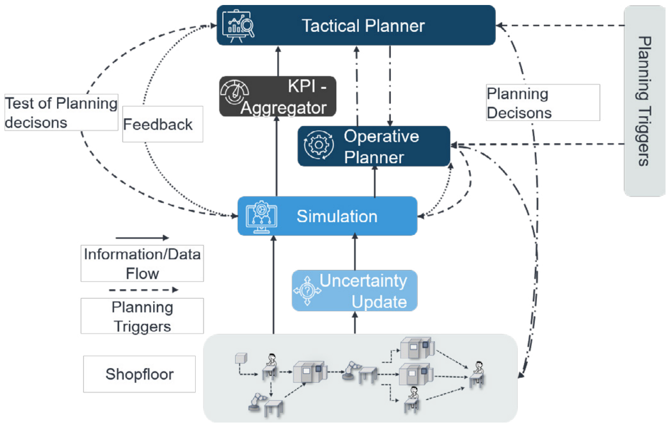

Fig. 2. Two-Level Production Planning Digital Twin

The heart of the proposed DT for capacity planning in remanufacturing consist of the two-level planning approach, where two planner modules ($operational \triangleq short-term$; $tactial \triangleq mid-term$) interact with each other, fed with information from the shopfloor. The logic of the planning modules is illustrated by the capacity planning example, which focuses on staff assignment to workstations and overall labour capacity. This is because remanufacturing processes remain predominantly manual. The further elements and the logic of information flow and model instantation will be discussed in the following sections.

4.1. Information Integration Across Planning Horizons

In a digital twin architecture, information integration creates a continuous synchronisation loop between the tactical and operational planning layers. The tactical digital twin defines feasible capacity envelopes, including workforce availability, machine readiness, and flexibility margins. The operational digital twin then allocates these envelopes to resources at the daily or shift level. This ensures that tactical plans remain feasible in accordance with current shop floor conditions, while the most recent tactical constraints guide operational models.

Information exchange between the two layers is facilitated through a series of modular components that collectively form the core of the digital twin environment. At the lowest level, the shop floor provides live data on machine states, inspection outcomes, and resource utilisation. This information enters the *Uncertainty Update* module, which continuously refines probabilistic estimates of return quantities, product quality, and process times. The output is a belief state b_t, which represents the system's current knowledge and uncertainty.

The *Simulation* module uses this belief state to evaluate the anticipated performance of planning decisions in uncertain conditions. It provides a virtual environment in which operational plans can be tested prior to implementation. The simulation results, such as throughput, lead time, and resource utilisation, are then provided to the *Operative Planner*, who adjusts short-term decisions accordingly and determines feasibility limits, such as achievable overtime or minimum staffing levels. The *KPI Aggregator* summarises these results and consolidates performance indicators, forwarding them to the *Tactical Planner*. This is necessary, as the long term planning necessitates more general KPIs compared to the short term planning levels (e.g. inventory turns vs. schedule adherence). The tactical layer interprets this information and updates the aggregate capacity plans, thereby completing the information loop across all planning horizons. The logic behind each module and connection, as well as the circumstances under which each planning module is triggered, is explained in detail in the following sections.

Uncertainty Integration

As already described, uncertainty in remanufacturing appears in two main forms: the variable quantity and quality of returned cores, and process-related variability such as fluctuating processing times, alternative routing, and rework. Both evolve dynamically as the DT receives new sensor data and inspection outcomes from the shopfloor. The already introduced beliefe state b_t can formally be described as:

$$b_t = (\hat{\Theta}_t, \Sigma_{\Theta,t}, \hat{\mu}_{\tau|q}, \hat{\sigma}^2_{\tau|q}), \tag{1}$$

where $\hat{\Theta}_t$ denotes the estimated system parameters and $\Sigma_{\Theta,t}$ their associated covariance, representing model uncertainty. The terms $\hat{\mu}_{\tau|q}$ and $\hat{\sigma}^2_{\tau|q}$ describe the conditional mean and variance of the process time τ given the observed product quality q. As a result, b_t captures both the current state of knowledge and the remaining uncertainty in the digital twin's information model. After an inspection or an execution that results in a new observation y_t, these estimates are updated via a function $\mathcal{U}$ that stands conceptually for any updating mechanism that incorporates observed evidence into the planner's information base. One examplary update mechanism would be using Bayes Rule, using the above notation updates are formally described as:

$$b_{t+1} = \mathcal{U}(b_t, y_t), \tag{2}$$

From this belief, a predictive workload for the next operational window H_O can be derived, reflecting the expected resource demand and its uncertainty:

$$\widetilde{W}_{t:t+H_O}(b_t) \sim \text{Workload}\big(A_{t:t+H_O}, \Theta_{t:t+H_O} \sim b_t, R, \tau|q \sim b_t\big) \tag{3}$$

Here, R denotes the observation noise covariance, quantifying the uncertainty of new information used in updating the belief state.

Information exchange between layers

The DT structure formalizes information flow between planning layers via two complementary mappings:

$$\pi_{T\to O} : (x_T, s_T) \mapsto c_O, \qquad \phi_{O\to T} : (x_O, s_O) \mapsto f_T, \tag{4}$$

where the downward projection $\pi_{T\to O}$ translates tactical decisions into operational capacity envelopes, and the upward projection $\phi_{O\to T}$ aggregates realised performance and feasibility information back to the tactical level. Together, these mappings define the bidirectional information channel that maintains consistency between planning layers under uncertainty.

The projected envelope c_O includes a probabilistic safety margin to ensure feasibility with high confidence:

$$\mathbb{P}(A_O x_O \leqslant C_T) \geqslant 1 - \alpha, \quad (5)$$

or equivalently,

$$A_O x_O \leqslant C_T - q_{1-\alpha}[\widetilde{W}_{t:t+H_O}(b_t)], \quad (6)$$

where $q_{1-\alpha}[\cdot]$ denotes a quantile-based risk buffer derived from the uncertain workload forecast. The operational layer, in turn, reports aggregated feedback f_T which captures realised performance indicators and discovered feasibility bounds such as staffable shifts, achievable overtime, and minimal viable working hours.

Although overtime remains an operational decision variable, its observed feasible range provides structural feedback that gradually refines the tactical capacity planning. This is because overtime and workforce capacity represent substitutive mechanisms for generating production time: persistent reliance on overtime indicates that the tactically allocated capacity is insufficient, while recurring idle time suggests overstaffing relative to the feasible overtime potential. By incorporating these observations, the tactical planner can recalibrate workforce levels and shift structures to achieve a balanced and economically efficient capacity allocation.

Three-way information Exchange

Integration thus establishes a three-way information loop between the shop floor, the operational planner, and the tactical planner. Shop floor data, including inspection results, machine availability, and utilization, inform operational planning. The operational planner aggregates this evidence, determines local feasibility bounds, and passes them upward to the tactical level. The tactical planner, in turn, adjusts aggregate capacity decisions and transmits revised envelopes downward. A belief-aware feedback operator can summarize this interaction

$$\Phi(b_t) = \phi_{O\to T}(\cdot; b_t) \circ \pi_{T\to O}(\cdot; b_t), \quad (7)$$

which links successive horizons through consistent information updates. Integration, therefore, provides the structural and informational backbone that allows orchestration to operate effectively.

4.2. Trigger-Based Planning Orchestration

While integration ensures informational consistency, orchestration governs when and how planning models are updated. Event-driven re-planning, though essential in remanufacturing, lacks the regularity of time-based rolling-horizon updates. Without coordination, irregular triggers could cause instability or excess computation. Orchestration, therefore, provides a supervisory logic that determines when model updates occur and how they are synchronised.

At its core, orchestration operates through complementary trigger mechanisms that activate planning activities across levels, as shown in Figure 3.

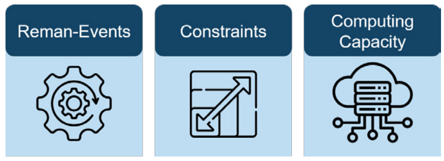

Fig. 3. Trigger Types of Planning Layers

Reman Event-based triggers ($\text{Trigger}_O(t)$) activate short-term replanning when significant remanufacturing events occur, such as the arrival of cores, new orders, or inspection outcomes. Only events with a notable impact on system performance or feasibility initiate updates, while minor fluctuations are filtered out. This ensures selective responsiveness rather than continuous reaction to noise.

Constraint-based triggers ($\text{Trigger}_{Constr}(t)$) initiate tactical re-planning when cumulative indicators reveal structural imbalances such as persistent backlogs, excessive utilisation, or depleted capacity margins. Once such thresholds are exceeded, the trigger prompts higher-level adjustments of capacity allocations or planning parameters.

Capacity-based triggers ($\text{Trigger}_C(t)$) utilize idle computational resources instead of reacting to production events [12]. When tactical models are not actively solving, available capacity is used for background analyses such as testing alternative configurations, recalibrating parameters, or exploring hypothetical demand and return scenarios. This enriches future planning cycles without disrupting ongoing operations.

Together, $\text{Trigger}_O(t)$, $\text{Trigger}_C(t)$, and $\text{Trigger}_{Constr}(t)$ form a coordinated orchestration logic that balances responsiveness and stability. Model updates occur only when warranted by significant events, structural constraints, or available computing capacity, avoiding unnecessary re-planning while preserving adaptability.

The orchestration logic distinguishes between local and global update mechanisms. When ($\text{Trigger}_{Constr}(t)$) is activated, both upward and downward information flows are executed for full synchronisation between tactical and operational layers. The event-based trigger ($\text{Trigger}_O(t)$) initiates an upward update $\phi_{O\to T}(t)$, while the capacity-based trigger ($\text{Trigger}_C(t)$) causes a downward update $\pi_{T\to O}(t)$. This layered structure avoids excessive re-planning and prevents isolated events from inducing instability.

Using the notation from Section 4.1, the orchestration-aware feedback operator is formalised as:

$$\Phi^O(t) = \begin{cases} \phi_{O\to T}(t) \circ \pi_{T\to O}(t), & \text{if } \text{Trigger}_{Constr}(t) = 1, \\ \phi_{O\to T}(t), & \text{if } \text{Trigger}_O(t) = 1, \\ \pi_{T\to O}(t), & \text{if } \text{Trigger}_C(t) = 1, \\ \text{Id}, & \text{otherwise.} \end{cases} \quad (8)$$

Through this operator, planning updates occur only when justified by observed events, production constraints, or available computational capacity, thereby combining reactive and proactive planning within a single supervisory framework.

5. Pathways Towards Validation

A first proof of concept (PoC) of the short term simulation based planner, implemented as a Semi Markov Decision Process, has already shown promising results for event driven reoptimization of planning policies. In this PoC workers were dynamically allocated to disassembly stations based on the changing needs within a shift, resulting in a more balanced WIP and buffer levels. The next step is a two level orchestration, that links operational simulation with tactical capacity allocation.

Validation will take place with industrial partners through a real life case study on the remanufacturing of automotive electric drives. The pathway begins with creating a digital representation of the teardown, inspection, and reassembly flow using live shop floor data. This model will be used to replay and perturb realistic return patterns, for example irregular inflows of starter motors or electric drives.

In this environment, the operational layer will reoptimize staff to station assignments in response to disruptive events, such as unexpected defect rates that introduce additional processing steps. The tactical layer will adjust overtime, redistribute labour, or activate temporary staffing when medium term workload forecasts shift.

The validation will assess how well the orchestrated setup handles stochastic arrivals, variable rework, and fluctuating manual capacity. Key indicators include throughput stability, work-in-progress behaviour, and disturbance responsiveness. The aim is to demonstrate the technical feasibility and planning benefits of a Digital Twin enabled orchestration framework for remanufacturing contexts dominated by manual disassembly, such as electric motors and household appliances.

6. Conclusion and Outlook

The framework for capacity planning in remanufacturing links tactical and operational decision layers through information integration and orchestration. The approach extends classical rolling horizon planning by introducing event driven adaptation, allowing plans to remain feasible and consistent amid the uncertainty of circular production systems. Future work will extend toward the tactical level and apply it to real life scenarios. The planned validation on automotive electric drive remanufacturing will show how Digital Twins can connect digital planning with real production control. The long term vision is adaptive, and digitally synchronised planning for sustainable circular manufacturing. The framework still has limitations. It has not yet been tested with industrial scale data, and its performance under large stochastic variability remains open. Addressing these aspects will be essential for adoption of Digital Twin supported planning in real remanufacturing environments.

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