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Dynamic reassembly control in flexible remanufacturing systems using Ant Colony Optimisation

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ABSTRACT

Remanufacturing demands flexible operational management because fluctuations in return volumes, component conditions, and processing durations can spread through the process steps and quickly undermine fixed plans. While research has largely focused on disassembly, dynamic control of reassembly remains neglected despite its variant-dependent matching requirements. This paper proposes a new Ant Colony Optimisation (ACO) formulation that treats reassembly as a sequential decision-making process, rather than building complete schedules, employing pheromone adaptation to guide effective matching decisions under uncertainty. Embedded within a discrete-event simulation model, the proposed single-shift approach is evaluated across scenarios of increasing complexity. Results show substantially improved adherence to production programs compared with heuristics, with benefits growing as system complexity rises.

1. Introduction

Remanufacturing has attracted increasing attention in recent years due to its potential to improve resource efficiency while offering economically viable business opportunities [1]. However, effective operational control of remanufacturing systems remains challenging due to the inherent uncertainty in core returns, component conditions, processing times and the need to balance workloads of new and remanufactured products [2]. This uncertainty introduces significant stochasticity, preventing the use of static, predetermined schedules.

Existing research on remanufacturing has predominantly focused on the disassembly stage [3], while significantly less work has examined the control of reassembly, often assuming that the reassembly of a remanufactured product is analogous to conventional assembly. This assumption does not apply to integrated manufacturing and remanufacturing systems (IMRS) in which disassembly, remanufacturing and reassembly of cores are closely interlinked with the production of new products. The uncertainty originating in remanufacturing activities propagates downstream, impacting a wide range of decisions, i.e., bills of material (BOMs), disassembly/assembly planning, capacity planning, production planning and scheduling. Thus, IMRS entail a significant increase in management complexity but also enable original equipment manufacturers (OEMs) to implement remanufacturing processes at an industrial scale [4].

OEMs need to meet a specified production program consisting of multiple product variants. The product variants differ in structure but exhibit partial overlap in required components and subassemblies. Components/subassemblies may be compatible with multiple product variants. For each remanufactured component/subassembly a decision is required which product variants it is being reassembled into. Production control must explicitly account for the remaining unmet demand of each variant.

Production planning and control in IMRS needs to take the following decisions: process and material requirements planning (allocation of remanufactured components to product variants) and dispatching and loading (timing and resource allocation of assembly processes). These decisions are taken dynamically, based on the current state of the system, e.g., availability of components and resources, and continuously adapted to its evolution (arrival of new components, failing remanufacturing operations, failures, etc.). This creates a multistage solution space evolving over time, where future decisions are constrained by current ones, matching the class of future-proof production scheduling and control approaches [5] and making exact optimisation approaches infeasible and conventional heuristic rules insufficiently adaptive [6]. This paper aims for a simple, computationally efficient, and directly applicable approach. To reach this, an adapted Ant Colony Optimisation (ACO) is used, as it provides a general optimisation framework that can be tailored to the specific set of decisions and constraints. Furthermore, ACO allows for leveraging pheromone mechanisms to incorporate feedback from previous decisions and the dynamic evolution of the system without prior training.

2. Related work

Effective operational control in remanufacturing requires dynamic decision-making under uncertainty. Existing approaches apply dynamic decision-making primarily in disassembly, while reassembly control remains simplified.

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2.1. Dynamic control of reassembly

In [7] a multi-priority-rule approach dynamically controls task and resource allocation in a job-shop disassembly system. A similar setting is explored in [8], where control is performed by a reinforcement learning agent. In [9] a dynamic policy selects the next disassembly operation and routing whenever disturbances occur. Although these approaches enable dynamic process selection, they do not account for the availability of other components, thereby overlooking a key complexity inherent to reassembly.

Reassembly, when addressed, is typically considered as one subsystem of a larger remanufacturing system. Control decisions are mostly limited to sequencing orders at resources in single-step [10] or multi-step [11] reassembly systems, whereas more extensive decision-making is confined to proactive scheduling [12] broadens the decision space by explicitly modelling component selection, allowing interchangeable components to be assigned to a product while still assuming a fixed one-to-one component−product relationship [13] captures component commonality more realistically by modelling interchangeable parts as a shared resource pool, enabling flexible allocation across products. Although [13] provides the most appropriate representation of reassembly requirements, it is formulated as a static optimisation problem and cannot react to real-time shop-floor conditions.

Dynamic control remains confined to disassembly-oriented approaches that overlook the dependency of reassembly on component availability. Approaches considering reassembly address only fragments of the actual control problem or rely on static scheduling without dynamic control. Demand fulfilment is rarely incorporated. Reassembly assumes that each component can only be reassembled into a single product variant.

2.2. Dynamic control through ACO

Ant Colony Optimisation (ACO) adapts to uncertainty and dynamic environments by balancing learned patterns with the exploration of alternative choices. Thus, ACO offers a framework for modelling and controlling the reassembly decision processes in IMRS where decisions must be made iteratively, adaptively and under uncertainty.

In production planning and control, some ACO-based approaches exist; however, they are limited to proactive scheduling and do not provide dynamic, state-driven control. ACO was first introduced comprehensively in [14]. In [15] ACO is applied to parallel-machine scheduling in batch processing to determine machine assignments and batch sequences. Due to its computational efficiency, ACO is frequently employed for rescheduling tasks [16] proposes ACO to reassign resources to open operations in a hybrid flow-shop system. Broader job-shop formulations additionally extend the decision scope to operation selection. In [17] a Petri-net−guided ACO is used for rescheduling under machine breakdown, while [18] uses ACO to construct an initial schedule and iteratively reschedule in response to periodic rush orders. In [19] ACO does not construct the schedule directly; instead, agents negotiate the schedule based on pheromone-guided probabilities. These approaches all generate complete holistic schedules and do not enable the dynamic, state-driven control required under the uncertainty of remanufacturing.

Outside the production domain, ACO has been applied to dynamic control problems. For example, [20] tackles the dynamic vehicle routing problem by updating pheromone levels as new delivery requests arrive.

Existing ACO approaches for production control remain limited to classical holistic scheduling and do not interact with the runtime system. Given the proven success of ACO in dynamically evolving domains, there is significant potential in adapting ACO to support real-time, state-dependent control decisions in remanufacturing.

3. Approach

The approach presents a novel modelling of ACO for production control. In classical ACO scheduling approaches, ants represent entire schedules and the graph captures all possible sequencing decisions. Here, each ant represents a single component and traverses a graph that encodes all reassembly options. Decisions are made sequentially. The graph is evaluated for each matching step rather than once for a full solution. The approach is executed continuously in parallel to the shift, enabling real-time, demand-driven control under uncertainty and shifting ACO from offline scheduling to online decision making.

The overall goal of the reassembly subsystem is to fulfil the overall product demand $D = (D_1, \ldots, D_v)$ of each product variant $(1, \ldots, v)$, within one shift. The objective is to fulfil the demand as exactly as possible, avoiding over- and underproduction. To evaluate how well this goal is met, the product-specific deviations from the target production program are drawn upon. For each product variant v with a target quantity D_v and produced quantity I_v, the unweighted absolute deviation is defined as $\Delta_{abs} = \sum_v |I_v - D_v|$. To prioritize deviations of high-demand variants, the weighted absolute deviation is defined as $\Delta_{w,abs} = \frac{1}{D}\sum_v D_v \times |I_v - D_v|$. While the unweighted metric treats all product variants equally, the weighted metric explicitly emphasises variants with large target quantities. The corresponding relative deviations are defined analogously by normalizing each term with D_v.

Each product variant v consists of a set of component types C_v which is a subset of all unique component types within the system $C_v \subseteq C_{Total} = \{C_1, \ldots, C_n\}$. For each product, the components are assembled in a variant-specific structure. The same component can be requested by multiple product variants

$(\exists (v, v') : C_v \cap C_{v'} \neq \emptyset)$. Therefore, decisions must be made dynamically regarding which components or subassemblies should be reassembled. Furthermore, assembly operations must be assigned to available resources that match the required capabilities, assuming a job-shop environment.

The decision space is schematically outlined in Fig. 1, where nodes represent components, subassemblies and fully assembled products. Directed edges represent feasible matching operations and are annotated with the corresponding transition probability; e.g., component W can be assembled with components X, Y, or Z to obtain intermediate assemblies WX, WY, or WZ. Thus, every path from a component node to an end-product node corresponds to a feasible reassembly route for that product.

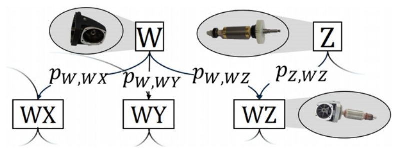

Fig. 1. Schematic excerpt of modelling approach for the decision space.

At each decision point, an ant located at a node i selects its next node j from the set of feasible successors N_i according to the standard ACO probabilistic state transition rule

$$p_{ij} = \frac{(\tau_{ij})^{\alpha} \times (\eta_{ij})^{\beta}}{\sum_{s \epsilon N_i} (\tau_{is})^{\alpha} \times (\eta_{is})^{\beta}} \tag{1}$$

where τ_{ij} denotes the pheromone-level associated with the matching operation represented by edge (i,j), η_{ij} is the heuristic desirability of this operation, and $\alpha > 0$ and $\beta > 0$ control the relative influence of pheromone information and heuristic guidance. In our modelling eq. (1) becomes related to reassembly: Parameter η_{ij} enables the implementation of preferred reassembly decisions or incompatibilities (η_{ij}=0). In the proposed approach, the heuristic term is defined as $\eta_{ij} = \frac{1}{t_{ij}}$, with t_{ij} denoting the processing time of the associated reassembly operation. Shorter operations are therefore preferred, which biases the search toward time-efficient reassembly sequences while still allowing exploration through a random choice. The resulting probability distribution is sampled once per decision event, yielding a single reassembly decision. Accordingly, the ant attempts to initiate the reassembly operation with a compatible partner ant (a required component of the reassembly step). If no partner is available, the ant waits at this node and the physical order is stored in the buffer before the corresponding process step. If no compatible partner arrives within a predefined waiting time t_R, the ant makes a new

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probabilistic edge choice from its current node. The physical order remains in the buffer.

If a compatible partner ant is present at the target node, the two are matched, according to a first-in-first-out rule based on the waiting time at the node. The reassembly is allocated to a free processing cell using an external dispatching rule, executed, and the corresponding edge is appended to both ants' paths. In line with the underlying order logic of the remanufacturing model, only one ant continues its path after successful matching.

Pheromone adaptation is driven by the deviation from the target production program. A pheromone update is triggered when a finished product, e.g. of variant v, is fully reassembled. For all edges (i,j) that belong to the combined paths of the ants that produced this unit, the pheromone level is updated according to Eq. (2).

$$\tau_{ij}' = (1-\rho)\tau_{ij} + L_v \tag{2}$$

Hereby, ρ denotes the evaporation rate and the reinforcement term L_v is defined as

$$L_v = 1 + \frac{D_v - I_v}{D_v} \tag{3}$$

where D_v is the target quantity and I_v is the currently produced quantity of product v. The reinforcement increases with the relative underproduction of the product variant v. Ants are attracted to paths that contribute to products with a high remaining demand. A local pheromone reduction after each edge traversal supports continued exploration and avoids premature convergence.

To limit overproduction, a dedicated pheromone reset mechanism is introduced. Once the target quantity of a product variant is reached, the pheromone values on edges relevant solely to this product are reset to zero, making them unattractive to future ants. An extended backtracking until branching reset strategy traces upstream from the satisfied end product and resets all edges that exclusively feed this product, stopping at branching nodes with alternative paths to products with remaining demand.

Overall, the proposed approach differs from classical offline ACO applications in three central aspects. First, ants are bound one-to-one to dynamically arriving orders rather than being generated in artificial iterations. Second, the search space is an order matching graph that explicitly incorporates intermediate assemblies and reprocessing steps. Third, pheromone reinforcement and reset are directly coupled to a multi-product target-production program rather than a single scalar tour length. The computational effort is minimal. Learning is reduced to lightweight pheromone updates based on simple aggregation and evaporation rules. Decision making is constant-time, requiring only a probabilistic selection (single random draw) without solving an optimisation problem. No offline training or function approximation is required, enabling immediate applicability.

4. Results

To assess the performance of the proposed approach, a discrete-event simulation environment is used to implement the IMRS described. In this environment, the dynamic reassembly control is implemented, together with an alternative control mechanism, to evaluate their impact on system performance. Different configurations of IMRS with increasing complexity were implemented. The configurations differ in product variants that are reassembled and in processes that are equipped on the stations. An overview is given in Table 1.

Table 1
Overview of the different configurations.

Attribute	Basic	Moderate	Complex
# Product variants	6	10	10
# Comp. per product	4	6	6
# Comp. types	8	12	12
# Unique processes	20	42	48
Assembly depth	3	5	6
# Stations	20	42	48
# Processes per station	2	3	4

All evaluations in this study are conducted over a fixed horizon of one 8-hour production shift. The considered system operates in one-piece flow with short processing times (0.5–1 min), resulting in product lead times that remain well below 8 h. All results are based on the average over 20 independent simulation runs per scenario to account for the stochasticity of arrivals (modelled via exponential distribution) and processing times (modelled via lognormal distribution). For each configuration, a predefined target production program with deliberately differentiated product demands is specified to explicitly test the demand adaptive behaviour of the control approach.

A systematic grid based hyperparameter tuning was conducted to identify a robust ACO configuration for the high complexity setting. The pheromone influence α, heuristic influence β, evaporation rate ρ, initial pheromone level τ_0, reactivation time limit t_R, and the pheromone reset strategy were varied across predefined ranges ($\alpha\epsilon[0.5-1.5]$, $\beta\epsilon[1-5]$, $\rho\epsilon[0.25-0.75]$, $\tau_0\epsilon[0.5-10]$, $t_R\epsilon$ $[15-45]$), with the tuning objective being the minimisation of absolute and weighted deviations from the target production program. Low evaporation rates led to premature convergence and persistent overproduction of dominant product variants, whereas excessive evaporation destabilised the control and increased variance in the product mix. Intermediate values ρ provided the best trade-off between reactivity and stability. The best-performing configuration across varying production program scenarios was obtained with $\alpha = 1.5$, $\beta = 1$, $\rho = 0.5$, $\tau_0 = 1$, $t_R = 45$, and the backtrace-until-branching-reset strategy.

The proposed ACO approach is benchmarked against three heuristic matching rules: Waiting Time (WT) prioritises the order with the longest waiting time at a matching node. Shortest Processing Time (SPT) selects the feasible matching option with the shortest processing time. Demand Driven (DD) selects the matching option that leads to the product variant with the highest remaining deviation from the target production program. These fulfil the requirements of a simple and computationally efficient approach and were therefore chosen as a baseline. More complex approaches, like Reinforcement Learning, require extensive training. For all approaches, including ACO, the same downstream dispatching rule (lowest buffer utilization) is applied after matching to ensure direct comparability.

Fig. 2 illustrates the performance of ACO control compared to WT, SPT, and DD in a complex environment configuration. Each policy was tested with 20 simulation runs. Within each policy the observed variance is minimal, therefore mean values are reported. ACO achieves an absolute demand deviation of 13.7 units and a weighted absolute deviation of 2.22 units, as well as a relative deviation of 9.83 % and a weighted relative deviation of 10.54 %. In contrast, all three heuristic rules exhibit substantially higher absolute and relative deviations from the target program, reflecting pronounced over- and underproduction of individual variants. This confirms that purely time-driven (WT), processing-oriented (SPT), and static demand-driven (DD) matching strategies are not sufficient to ensure demand-accurate production under high complexity, whereas ACO maintains stable demand compliance by continuous, state-dependent adaptation.

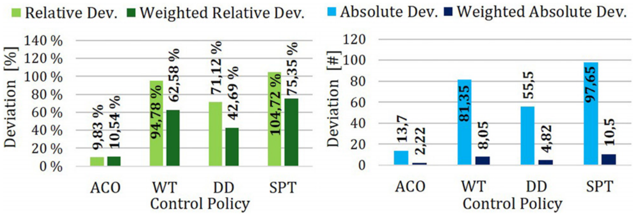

Fig. 2. Comparison of production program fulfilment per control policy.

Fig. 3 provides a detailed view of the distribution of the produced end products compared to the target production program. While all heuristic matching rules exhibit significant deviations from the target production program, ACO control closely tracks the specified target quantities across all product types. In particular, variants with low

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target demand that are heavily overproduced by the heuristics remain tightly controlled under ACO, while high-demand variants are reliably prioritised. This distribution level analysis directly confirms that the demand for accurate performance of ACO in Fig. 2 is rooted in a consistently balanced product mix rather than in isolated effects on individual variants.

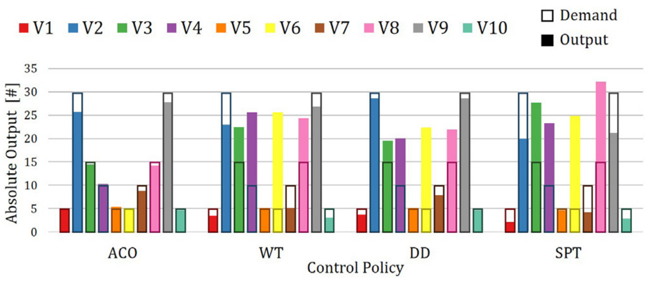

Fig. 3. Achieved output per variant and control policy.

Lastly, the developed control algorithm is evaluated under different levels of complexity. For this purpose, the complexity classes defined in Table 1 are applied to systematically vary both product structure and remanufacturing system complexity. In addition, the effect of more heterogeneous demand across product variants is examined by increasing the number of distinct demand profiles from four (Scenario A) to ten (Scenario B). Fig. 4 shows that ACO-based control progressively outperforms the heuristic approaches as system complexity increases. This performance advantage is particularly pronounced when the target production program becomes more heterogeneous.

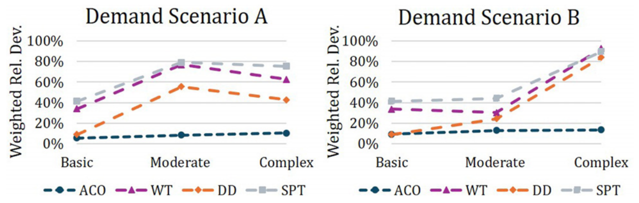

Fig. 4. Weighted relative deviation under increasing complexity.

The underlying decision mechanism of the proposed control approach can be examined through the pheromone distribution at a representative point in time. Fig. 5 presents a snapshot of the pheromone levels in the matching graph after 240 min of operation. At this stage, pheromone intensity is concentrated along reassembly paths associated with product variants for which residual demand exists, whereas edges corresponding to variants with satisfied demand exhibit significantly reduced pheromone levels. This distribution illustrates how pheromone values encode the current fulfilment state of the demand vector D and how ACO dynamically adapts its preference structure to steer local matching decisions toward the required product mix.

5. Conclusion and outlook

This paper introduced a dynamic, demand-adaptive production control approach for reassembly in integrated remanufacturing systems based on ACO. The approach enables continuous, state-dependent control under stochastic arrivals and heterogeneous product demand. The results confirm that the proposed control significantly improves demand compliance compared to classical time-driven, processing-driven, and static demand-driven matching strategies, particularly under high structural complexity. The proposed approach is applicable to a broad range of remanufacturing systems, that involve different product structures with shared components that require coordinated recombination decisions.

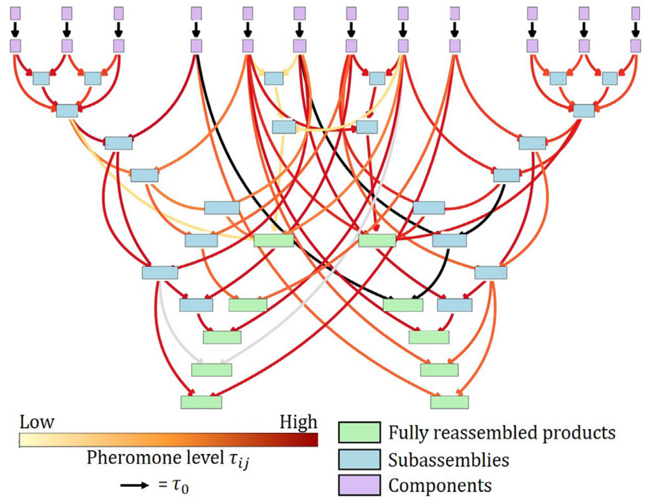

Fig. 5. Pheromone Network at t = 240 influenced by the remaining demand in product variants.

While the present study focused on the bounded horizon of a single production shift, future applications focus a multi-shift operation, especially the carry-over mechanism for initial pheromone levels. In this context, the transfer and controlled adaptation of learned pheromone information across consecutive shifts represents a key research direction. Further developments may include time-varying demand profiles, and adaptive parameter control based on observed system dynamics. The presented approach focuses solely on the objective of demand fulfilment. Also, the transferability of the method to multi-objective scenarios will be addressed in future work.

From an industrial perspective, the proposed ACO-based control constitutes a simple, computationally efficient solution for dynamic reassembly matching in complex remanufacturing systems. It provides a practical foundation for demand-adaptive reassembly and enables a systematic reduction in manual intervention while maintaining high responsiveness to volatile demand patterns. The approach does not require prior training and is therefore directly applicable.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Finn Bail: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicole Stricker:** Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jonas Schwenker:** Writing – original draft, Validation, Software, Investigation, Formal analysis. **Marcello Urgo:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Conceptualization. **Gisela Lanza:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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