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How grey wolf optimization affects remanufacturing

Barna Gal[a*], Christine Zeh[a], Ádám Szaller[b,c]

[a]Fraunhofer Austria Research GmbH, Theresianumgasse 7, A-1040 Wien, Austria
[b]Institute for Computer Science and Control, Kende str. 13-17, 1111 Budapest, Hungary
[c]EPIC InnoLabs Nonprofit Ltd., Kende str. 13-17, 1111 Budapest, Hungary

* Corresponding author. Tel.: +43 676 88861606; *E-mail address:* barna.gal@fraunhofer.at

Abstract

While in 1971 the Earth Overshoot Day was on December 25th, in 2022 this day for Austria was already reached on July 28th. And since uncertainties in the remanufacturing production planning occur, companies are forced to take in trade-offs like increased production capacity available at short notice. These uncertainties result in financial losses and production waste, as well as bottlenecks in the supply of materials for gas engine assembly. For this reason, this paper explores the use of a grey wolf optimizer for the reduction of the cycle time of a gas engine remanufacturer. A discrete event simulation is used for evaluation purposes and the results from the scheduler are compared with benchmarks of the current production planning of manufacturers.

Keywords: Sustainable Manufacturing; Circular Economy; Remanufacturing; Production Planning; Grey Wolf Optimizer

1. Introduction

Although the term circular economy is still open, various definitions exist. Based on corresponding state-of-the-art reviews, which were examined by Suzanne et al. [19], the term circular economy (CE) can be defined as follows according to [6]:

CE is an economic system that opposes the linear open-ended system (produce, consume, dispose) with the aim of achieving sustainable development that simultaneously creates environmental quality, economic prosperity and social justice for the benefit of current and future generations [6].

In the literature, product life extension options are discussed under different terms such as reconditioning, reuse, refurbishment, and remanufacturing. As they tend to overlap in meaning, the definitions of these trending concepts become blurred and mixed. In the production planning literature, two product life extension terms stand out, namely refurbishment and remanufacturing [19]. Refurbishment is a recovery process in which waste is collected, tested, repaired, cleaned, and resold as used, functional products without being disassembled. Remanufactured products are often returned to warranty. Meanwhile, remanufacturing is most commonly referred to as the recovery of used products, which involves the collection, repair, disassembly, and replacement of worn components to bring the products back to the quality level of newly manufactured products. The main feature of remanufacturing is the disassembly of the product, which is the first and most important step in the markets for spare parts or remanufacturing operations in production [19].

To illustrate how CE reshapes the classical linear production approach, it is important to understand how the interference between backward and forward flows affects the production planning process. This interference includes i) the planning of the recovery and procurement of raw materials; ii) the planning of the production activities required to transform input

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materials into finished products to meet customer demand, taking into account both remanufactured and new products; and iii) the returns that have varying degrees of impact on the decision-making levels of production systems [19].

In the following, the individual process steps of the remanufacturing process are described, in which the old parts are regenerated:

- **Disassembly**: In disassembly, the uncleaned old part is disassembled into individual parts or components and sorted for reuse. components and presorted according to reusability, whereby wear parts such as seals and bearings are sorted out and later replaced by new parts in the remanufacturing or reassembly process [17].
- **Cleaning**: All components are cleaned chemically and/or mechanically. This production step is most often a bottleneck, as machines with fixed cycle times and limited capacity are used. cycle times and limited capacity [17].
- **Inspection and sorting**: During inspection, the components are non-destructively for damage and for their reusability. If a component is worn or damaged, it is either sent to the component reconditioning production step or disposed of [18].
- **Component reconditioning**: In component reconditioning ("reconditioning" for short), mainly machining processes are used to bring the components back to the same quality level as the new part [17].
- **Reassembly**: In reassembly, the replacement products or regenerates are produced using new parts. This production step deviates the least from new production but tends to have a higher manual share [17].

2. Literature review and state of the art

2.1. Production planning in remanufacturing

In their literature review on meta-heuristics in production planning for remanufacturing plants, Ansari and Daxini [1] cover the state of the art of applied algorithms as well as current trends. Significantly, the genetic algorithm (GA) is the most widely used, along with artificial bee colonies, particle swarm optimization, ant colony optimization, simulated annealing, tabu search, variable neighborhood search, and hybrids of these approaches. They also emphasize that the use of meta-heuristics to solve production planning problems has become increasingly important, not only in the field of remanufacturing. Following this literature review by Ansari and Daxini [1], nine other publications on production planning in remanufacturing have appeared in the scientific database Scopus, which are summarized below. These include the scenario analysis by Khakbaz and Tirkolaee [7], which examined six different cases of the ability of manufacturing and remanufacturing processes to develop a sustainable manufacturing/remanufacturing policy that maximizes expected profit. The results found indicate that as the substitution rate increases, the expected profit and the remanufacturing rate increase [7]. Lahmar et al. [10] investigate the best trade-off between manufacturing new products and remanufacturing recycled products based on economic and environmental considerations. A mathematical multi-objective model is developed and an approach based on a non-dominated sorting genetic algorithm (NSGA-II) is proposed [10].

Quezada et al. [16] attempt to optimize the production scheduling of a three-season remanufacturing system under uncertain input data. They consider a multi-stage stochastic integer programming approach and use scenario trees to represent the uncertain information structure. Their numerical results show that the proposed solution approach provides near-optimal solutions for large instances with a reasonable computational cost [16]. Cheng [4] studies a multi-period dynamic production scheduling problem in a hybrid manufacturing and remanufacturing system (HMRS). To solve the problem, they first use the hazard rate function and the information about the products in use to obtain an estimator of the replenishment quantity. Then a dynamic programming model is formulated and proven that a smooth-value policy is optimal when demand is uniformly distributed [4].

Due to the divergent material flow, production systems with loosely coupled stations are particularly suitable, and due to the risk of state-dependent operational disturbances, the emergence of hybrid disassembly systems combining manual and autonomous workstations is expected. By comparing the reinforcement learning (RL) approach with a heuristic control approach, the potential of the RL approach can be simulated using two different test cases [20].

Yu [22] models a new mixed-integer program to support various tactical decisions in remanufacturing reverse logistics, i.e. remanufacturing setup, production planning and inventory levels, core procurement and transportation, and remanufacturing line balancing and utilization.

Lahmar et al. [9] tackle the HMRS problem A mathematical multi-objective model is established and an approach based on the NSGA-II is introduced; moreover, a technique of ranking performance by similarity to the ideal solution is used to find the best trade-off solution under the Pareto front obtained by the NSGA-II algorithm [9].

Assid et al. [3] investigate how companies could benefit from such an integrated control policy to assist their managers in determining production rates, the order and size of follow-up orders, and the size of samples to be inspected. The corresponding problem aims to propose an efficient inspection policy that integrates four key decisions to coordinate remanufacturing, production, replenishment of returns, and quality control while minimizing overall costs and meeting a quality constraint demanded by customers [3].

Assid et al. [2] addresses the problem of production planning and scheduling in an HMRS where demand is satisfied either by remanufacturing returned items or by manufacturing new items. It explores how companies can benefit from changeable system settings with two production lines operating in a stochastic and dynamic context [2].

2.2. Grey wolf optimizer

The grey wolf optimizer (GWO) was originally published by Mirjalili [14] in 2014 and has since received attention in its application to a wide variety of mathematical problems. Before

Table 1: Conceptual Framework for this research after Peffer et al. [15].

Steps from Peffer et al. [15]	Implementation
i) problem identification and motivation	increased production capacity because of remanufacturing
ii) defining goals for a solution	reduce cycle time by an optimized schedule
iii) designing and developing	constrain GWO for schedule optimization
iv) demonstrating	implementing and validating GWO in Python with Plant Simulation
v) evaluating and publishing	evaluate GWO with simulation

discussing the planning problems in particular, a brief general overview of the idea of the GWO should be given. The idea originates from the hierarchical structure of real grey wolves, whereby here their hunting behavior has been investigated. In the original formulation, there are four groups: alpha -, beta -, gamma-, omega -wolves. The alpha-wolves are the ringleaders. The beta-wolf obeys the alpha-wolf but dominates the wolves of the other levels. The third group, the gamma-wolf, is led by the alpha- and beta-wolves but dominates the other wolves. Omega-wolves are at the lowest level in the group. They obey all wolves at higher levels [14].

In the literature, the necessity of four groups is critically discussed and results have shown that a division into only two groups, alpha and omega, simplifies the hierarchy structure of the wolves. This version is known as the improved grey wolf optimizer (IGWO) [11].

2.3. Grey wolf optimizer in remanufacturing

A literature search in Scopus on the use of grey wolf in remanufacturing using the keywords "remanufacturing" and "grey wolf" yielded eight publications. Six of these were relevant to this search, five of which used a multi-objective grey wolf optimizer (MOGWO) approach and one of which used an improved IGWO approach. In comparison to other meta-heuristics, the field of applications with the GWO is still quite new and therefore needs more applied research.

The IGWO is proposed by Li et al. [11] to solve a distributed flexible job shop scheduling problem, which is an extension of the flexible job shop scheduling problem. In this algorithm, new coding and decoding schemes are developed to represent the three subproblems and convert the coding into a feasible schedule. [11]

Multi-Objective (MO) optimization considers more than one objective function at a time. In Makhadmeh et al. [13] , the multi-objective formulation is retained and a MOGWO is used to estimate the Pareto optimal solutions that represent the best trade-offs between the objectives [13].

In further literature review, only MOGWO is used to solve shop floor scheduling problems. Among others, for blocking flow shop scheduling problems, which have an important application in manufacturing due to the imprecise and vague temporal parameters in real production. Therefore, Yang and Liu [21] propose a fuzzy flow shop scheduling problem with fuzzy processing time and fuzzy due date to minimize the fuzzy margin and maximize the average matching index [21]. For flexible job scheduling with variable processing speeds, Luo et al. [12] attempt to minimize production margin and total energy consumption simultaneously [12].

For a line balancing problem Guo et al. [5] consider real cases to investigate the efficiency and feasibility of the proposed algorithm MOGWO. Comparisons with discrete gray wolf optimization, genetic algorithm II with non-dominated sorting, multi-population evolutionary algorithm, and multi-objective evolutionary algorithm show the superiority of the proposed approach. [5]

3. Methods

The method used in this research was divided into five steps, which include problem identification, goal definition, development, demonstration, evaluation, and publication. The focus is on the development and demonstration, in which the GWO is adapted for the use case and run through the simulation. The exact implementations of the research steps can be seen in Table 1.

4. Case Study

4.1. Description

At a remanufacturing facility, castings from returned cylinder heads are returned when they reach end-of-life status. After disassembly, machining, cleaning, and reassembly, the cylinder heads are returned to the customer, where they can be reworked a total of three times before being scrapped. Uncertainty about the timing, quality, and reusability of the returned components and assemblies creates scheduling problems for the manufacturer. The trade-offs for the manufacturer are increased inventory and increased need of production capacity available at short notice. These uncertainties result in financial losses and production waste, as well as bottlenecks in the supply of materials for gas engine assembly.

In the plant itself, cylinder heads can pass through three different lines, depending on size and series, with a total of eleven different variants in constant circulation.

4.2. Simulation Model

Using a discrete event simulation model developed in Siemens Tecnomatix Plant Simulation, the remanufacturing process was analyzed. Simulation technology is capable of investigating system performance and comparing the effect of different parameters used as input, without modifying the real

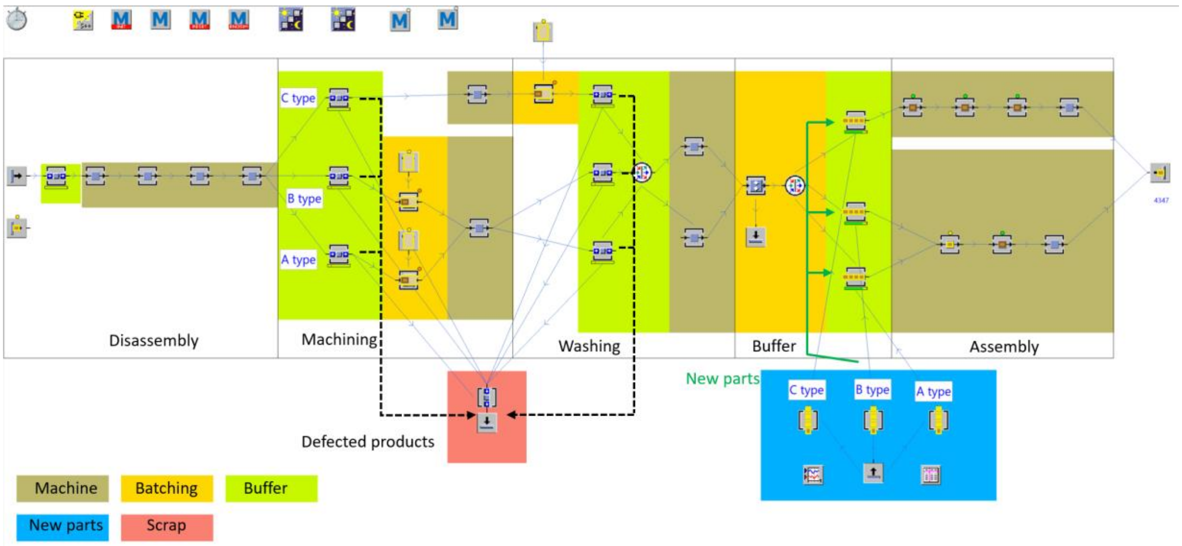

Figure 1: Simulation model of the investigated manufacturing system

system. The model (shown in Figure 1) includes distinct manufacturing stages such as disassembly, machining, washing, and assembly. Parallel resources are dedicated to each product type, ensuring that the specific production line operates efficiently. Prior to and following the machining stage (as indicated by the black arrows in Figure 1), non-remanufacturable parts are eliminated from the system. New parts are introduced into the system before the assembly stage (green arrows), if the number of parts in any of the three buffers falls below four, a new cylinder head is brought into the system to guarantee continuous assembly line operation.

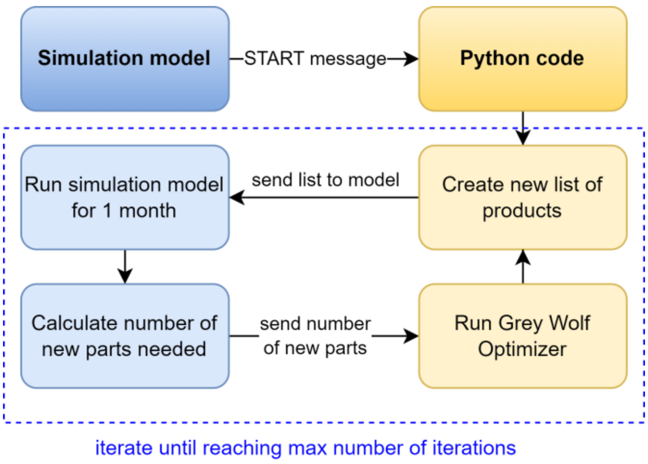

Figure 2: Flowchart of the communication between the model and the optimizer

Using the simulation model, experiments were run to investigate the effect of applying the GWO on the production schedule (order of used parts sent to the system as input). The main KPIs are the number of used and new parts and the overall output of the system after running the model for 1 month. Since simulation models are only capable of evaluating system performance and not suitable on their own to optimize parameters, GWO was programmed using Python language and communicated with the model through a socket interface. Figure 2 shows the flowchart of the communication between the model and the optimizer. The optimizer, after receiving a start message from the model, sends a list of product IDs as a comma-separated text to the model (first, an initial list is sent). After, an iteration starts where (1) the simulation model is run for 1 month, (2) the number of new parts needed in 1 month is determined as the result of the model run, (3) it is sent to the optimizer and (4) the optimizer determines the new schedule. The exit criteria for the optimizer is a given number of iterations, which in this case was 1000 (based on the results, after this the results do not change significantly).

4.3. Adaptation of the GWO

To optimize the simulation using the GWO the input schedule must be transformed. This is necessary as the GWO is not able to work with a discrete result set but expects a multi-dimensional interval as the search space. In equation (1) this transformation process is stated. Using the proposed approach of Komaki et al. [8] the order of the parts is defined by the values of a n-dimensional real number $\mathbf{z}$, with n the length of the schedule. Each part is assigned one canonical basis vector independent of its position in the schedule. During initialization, z is built by linear combination of random values from the interval $[-5, 5]$ as scalar components and the basis vectors. By comparing the values of the components of z, the parts are sorted to create the initial schedule. By adapting z the schedule can be changed as the sorting is done before each simulation run. This calculated schedule is then provided to the simulation, which returns its fitness defined by the new parts needed.

$$\mathbf{z} = \begin{array}{c} \begin{pmatrix} -4.3 \\ 2.9 \\ 0.1 \\ -3.74 \\ 1.5 \\ 2.94 \end{pmatrix} \end{array} \begin{array}{l} A_1 \\ A_1 \\ A_2 \\ B_1 \\ B_1 \\ B_2 \end{array} \in R^6 \Rightarrow [\mathrm{A_1 B_1 A_2 B_1 A_1 B_2}] \qquad (1)$$

Table 2: Results of the GWO highlighting the quantitative benefits in comparison.

	A_{new} (pcs)	B_{new} (pcs)	C_{new} (pcs)	A_{old} (pcs)	B_{old} (pcs)	C_{old} (pcs)	Sum_{month} (pcs)	Sum_{new} (pcs)
Random production plan	14	234	648	658	428	740	2722	896
GWO	162	377	1072	679	464	745	3499	1611

By applying this transformation the schedule needs to be of fixed length. However, the scrap parts can cause the simulation to need more than the planned parts for one month. To provide a sufficient schedule length the dropout probability needs to be taken into account.

5. Results

To validate the simulation, a real production schedule from the manufacturer was run through and the lead time of the entire production schedule was measured. There is a deviation of 4.44% of the monthly cycle time, where the simulation is slightly slower, but is still considered usable for further consideration of the GWO.

In order to validate the production plan generated by the GWO, a random monthly production sequence was first run and the total number of parts produced was measured. These results are shown in the first row of Table 2. The GWO was then coupled to the simulation and run through 1000 iterations with 10 wolves in total. The results are shown in the second row of Table 2. It can be seen that the total number of parts iterated has increased significantly. Due to the fact that the production plan could be processed more quickly, new parts were subsequently used due to the remaining time from the simulation. The number of new parts that have gone through more can be interpreted as open capacity in the comparison of the production plans of the plant, whereby a positive functionality of the GWO can be determined.

6. Conclusion and Outlook

In order to deal with the uncertainties within a remanufacturing plant, this study proposes a GWO for the application of production schedule optimization. By specifically transforming the production schedule to provide it as an input to the GWO, it can be effectively applied to such problems. The results show a reduction in both lead time and open capacity within the remanufacturing plant. Further research will compare this application of GWO with other meta-heuristics discussed in the literature to identify other performance indicators.

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