Optimization of a Remanufacturing Production Planning System with the Help of Artificial Intelligence

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Abstract. Although production planning in remanufacturing systems has attracted great interest from the research community, only a couple of real industrial applications can be perceived. Additionally, in real cases, companies are faced with manufacturing multiple products, which further complicates remanufacturing production planning (RPP). Therefore, there is a need to optimise RPP where manufacturers are involved in remanufacturing multiple products. Also optimized systems should consist of a number of uncertainties, such as the uncertain quality of the returned products.

Because of these uncertainties the manufacturers have to use new parts or components - with both higher environmental impacts, as well as costs. In the present paper a line balancing scheduler of a remanufacturing system is presented - focusing on the disassembly, machining and reassembly of parts. The objective of the paper is the reduction of usage of the energy and cost intensive new parts with production scheduling using a genetic algorithm (GA). The achievements are illustrated and presented with a real industrial use case from a gas engine producer. A discrete event simulation (DES) is used for evaluation purposes and the results from the scheduler are compared with benchmarks of the current production planning of the gas engine manufacturer.

Keywords: remanufacturing · genetic algorithm · production planning · simulation · uncertainties

1 Introduction

Humanity currently requires the equivalent of 1.7 planets to compensate for resource consumption by human activities [17]. Furthermore the manufacturing industry is one of the main consumers of material and energy resources, in addition to generating significant amounts of waste. Due to the scarcity of resources, the concept of circular economy based on remanufacturing has become an important approach for resource-efficient sustainable development, representing one of

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the most significant aspects of waste management [15]. Remanufacturing is most commonly referred to as a recovery process for used products that involves the collection, repair, disassembly, and replacement of worn-out components to bring the products back to the quality level of newly manufactured products [14]. In remanufacturing, there are particular challenges for production planning systems (PPS) that do not exist in traditional manufacturing [1]. These characteristics, unique to remanufacturing, require a change in the fundamental concept of traditional PPS [4].

1.1 Motivation of This Research

To highlight the research gaps within RPS systems for this paper, the identified research needs from two literature reviews are used. For example, in an analysis of 160 scientific journal publications, Suzanne et al. [14] state that although from an academic perspective RPS have attracted a lot of interest, but only weak links with industrial applications can be perceived. In addition, Ansari and Daxini [2], in an analysis of 123 scientific journal publications, point out that in real cases, companies are faced with manufacturing multiple products, further complicating remanufacturing production planning. Therefore, they call for future research to optimize RPS in a way, that manufacturers are involved in remanufacturing multiple products and the system consists of a number of uncertainties, such as uncertain quality, time, return, and demand [2]. In addition to the research needs from academia, those challenges presented in [1] can be observed in a remanufacturing plant for gas engines. The uncertain timing as well as the quality and reusability of the recirculated components and assemblies pose the problem to the manufacturer that the regular use of energy- and cost-intensive new parts has to be accepted. From the above findings, the central research question for this paper results in how the use of a genetic algorithm can minimize the use of energy and cost intensive new parts through production schedule sequence optimization. The main objective of this work is to develop an approach to optimize RPS, taking into account the uncertain quality of the returned products as well as the diversity of variants. Subordinately, this work attempts to remedy the above-mentioned research gaps of Suzanne et al. [14] and Ansari and Daxini [2] by developing a procedure with stronger connections to industrial applications and by incorporating uncertainties from reality into the optimization.

The paper is structured as follows. First, a literature review is presented regarding RPS and the addressed research gaps are discussed. The following chapter deals with the method description and the research question. Than the simulation model is introduced that is used to evaluate the genetic algorithm, which was designed to optimize the production plan sequence of the company partner.

2 Literature Review

2.1 State of the Art

Research activities in the field of PPS for remanufacturing often focus on *disassembly planning* and scheduling. Jeunet and her coauthors present an approach for solving practical sequencing problems [8]. Lage Junior and Godinho Filho [9] propose a stochastic dynamic programming model considering stochastic routings. They apply their model to a real case of automotive clutch remanufacturing. Mao et al. [11] combine genetic algorithm with Petri net modeling and stochastic programming for used car parts under uncertain conditions. Wang presents a parallel partial disassembly line balancing model with stochastic disassembly time [16]. In the paper of Rent et al. the desassembly planning is extended with end-of-lyfe consideration aiming at the maximization of the recovered value [13].

Hybrid systems that use both raw materials and returned products in the production process are often addressed in the literature as well. Fang [5] optimizes the operation strategy (determining the amount of new and remanufactured products) considering the related costs, uncertainty about recycling, demand substitution, capacity limitations and component durability. Han and his coauthors [7] focus on uncertainties of quality, process times, remanufacturing costs as well as market demands and using robust optimization. Polotski et al. [12] concentrate on manufacturing and remanufacturing costs, holding costs, backlog and set-up costs. Benkherouf et al. investigate an inventory system with production, remanufacturing and refurbishing activities using mathematical programming [3].

3 Methods

The procedure in this research was divided into five steps, which includes problem identification, goal definition, development, demonstration, evaluation, and publication. The focus is on the development and demonstration, in which the GA is adapted for the use case and coupled with the simulation. The exact implementations of the research steps can be seen in Table 1.

4 Simulation Model of a Real Remanufacturing Application

In an remanufacturing shop, cast housings of returned cylinder heads are basically disassembled, machined, and reassembled after reaching end-of-life status. The remanufactured cylinder heads, which are an essential part for gas engines, can be used for a maximum of three product life cycles. The two-shift cylinder head production system specialized in refurbishment with several disassembly, machining, storage and assembly stages is designed as a simulation in a multi-line discrete event simulation (DES) model after [6], which is run through by a work piece agent population, shown in Fig. 1

Table 1. Conceptual Framework for this research after Pfeffers et al. (2007)

Steps from Pfeffer et al. (2007)	Implementation
i) problem identification and motivation	RPS have only weak links with industrial
	Applications and to optimize RPS such that manufacturers are involved in remanufacturing multiple products and the system consists of a number of uncertainties, such as uncertain quality
ii) defining goals for a solution	Usage reduction of energy and cost intensive New parts of an industrial remanufacturer
iii) designing and developing	Constrain a GA for the given industrial use case
iv) demonstrating	Implementing and validating GA in Python
	with Anylogic simulation
v) evaluating and publishing	Evaluate GA with simulation and publish findings

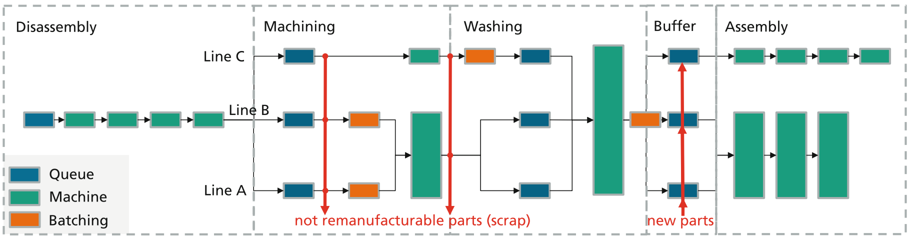

Fig. 1. Flowchart and simulation model

In order to follow the call of Ansari and Daxini [2] and to optimize RPS in such a way that different product variance and a system with different uncertainties are taken into account, the population within the agent is defined with different influencing factors, such as series, product variants, production times. The DES that the agents run through acts with the uncertainties of the reject rate, which varies randomly per series and station, as it was measured in reality. The exact used agent parameters and system parameters can be found in Table 2.

The evaluation of the simulation is carried out by means of a monthly production plan of the company partner. The total number of assembled cylinder heads at the end of the month are known, as well as the number of units of which variants were assembled and the sequence in which the lines are planned. The sequence is done in always alternating push into the lines (as an example: A_1, B_1, C_1, A_2, B_2 ,C_2, A_3,...). The simulation needed 22 h (4,44% deviation) more, then the real remanufacturer (496 h), whereby a start-up time of the simulation must be taken into account, i.e. the filling up of the lines. This small difference validates the DES model.

Table 2. Agent and system parameters of the simulation

Cylinder head variant	A_1	A_2	A_3	B_1	B_2	B_3	C_1	C_2	C_3	C_4	C_5
Quantity	n_{A1}	n_{A2}	n_{A3}	n_{B1}	n_{B2}	n_{B3}	n_{C1}	n_{C2}	n_{C3}	n_{C4}	n_{C5}
Machining time	t_{mA1}	t_{mA2}	t_{mA3}	t_{mB1}	t_{mB2}	t_{mB3}	t_{mC1}	t_{mC2}	t_{mC3}	t_{mC4}	t_{mC5}
Assembly time	t_{aA1}	t_{aA2}	t_{aA3}	t_{aB1}	t_{aB2}	t_{aB3}	t_{aC1}	t_{aC2}	t_{aC3}	t_{aC4}	t_{aC5}
Scrap rate After disassembly	srd_A	srd_A	srd_A	srd_B	srd_B	srd_B	srd_C	srd_C	srd_C	srd_C	srd_C
Scrap rate after machining	srm_A	srm_A	srm_A	srm_B	srm_B	srm_B	srm_C	srm_C	srm_C	srm_C	srm_C

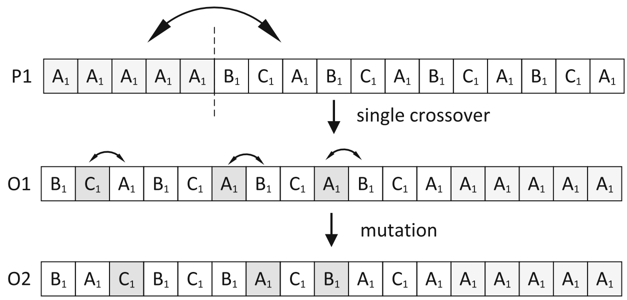

Fig. 2. How the GA changes from population to population

5 Optimization

The GA is designed in [6] following [10] and adapted to this use case. Here one population is used, which presents one monthly production plan and has single crossover and mutation (with a mutation rate of 10% as possibilities to change from population to population each iteration like it is described in [10] and shown in Fig. 2. While single crossover causes a heavy change in the sequence, which can lead to overlooking present minima, it is only used every tenth iteration, if no new minima was found.

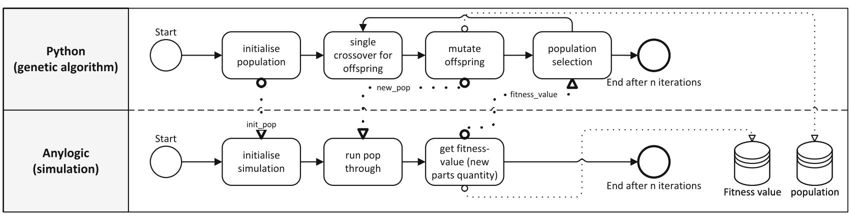

Fig. 3. Communication between simulation and GA

For evaluation of the GA, Python is connected to the simulation software Anylogic through the add-on library Pypline, where Anylogic acts as a mainframe and calls and runs function codes from Python. To run the optimization exactly, Python starts by initializing a random population representing a monthly schedule, as provided by the company partner, in random production order. The initialized population is run through the simulation in Anylogic to obtain the first fitness value, which represents the number of new parts needed. After single crossover and a mutation of the offspring population is triggered by Python, a new run of the new population through the simulation is performed, in order to get a new fitness value. With population selection the fitness values are compared and lowest one is used as new population for the next iteration, till a given number of maximum iteration is reached, as it is shown in Fig. 3.

6 Results and Limitations

As visible in Table 3, the sequence optimization of the production plan by the GA resultes in a decrease of 44.41% of required new parts compared to the real

Table 3. Results of the GA 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)
Real use case	200	240	150	480	220	620	1910	590
Simulation	200	240	150	480	220	620	1910	590
GA	136	136	56	622	326	620	1916	328

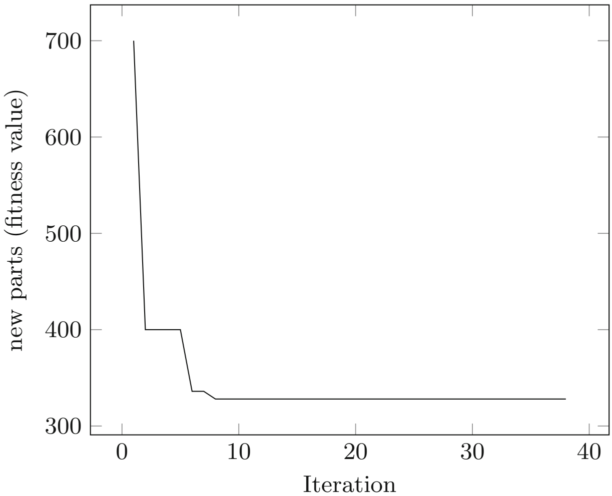

Fig. 4. Fitness value course of the GA per iteration

use case and the simulation. However, a slower cycle time is expected since the GA was compared with the 4.44% slower simulation. An upper limit of available cast housings for machining, as is the case in reality, was not introduced for this simulation in order to be able to determine the maximum production capacity of the lines.

In Fig. 4 the fitness value improvement of a total of 38 iterations of the GA is shown. It is to be expected that by further GA fine tuning and increasing the number of iterations (this was limited by the Personel Learning Edition (PLE) restriction of Anylogic) further minima can be found, which undercut the value of this research.

7 Conclusion

To address the research gaps within RPS, which show weak links to industrial applications and a lack of optimization with multiple products and multiple uncertainties, a GA optimization with coupled DES is presented and applied to an industrial use case. This approach considers a number of parameters related to the product variance (such as different duration in disassembly, machining and assembly) and uncertainties (such as different scrape rates for each variant) of the RPS. An overall improvement of the cost- and energy-intensive new parts requirement of 44.41% can be achieved. As a next step the environmental impacts of the new and old parts and their optimization will be investigated. On longer term other optimization methods like ant colony optimization, simulated annealing and grey wolf optimization will be tested as well.

References

1. Andrew-Munot, M., et al.: Analysis of production planning activities in remanufacturing system. J. Mech. Eng. Sci. **12**(2), 3548–3565 (2018)
2. Ansari, Z.N., Daxini, S.D.: A State-of-the-art review on meta-heuristics application in remanufacturing. Arch. Comput. Methods Eng. **232**(20),1465 (2021). ISSN: 1134-3060
3. Benkherouf, L., Skouri, M., Konstantaras, I.: Optimal control of production, remanufacturing and refurbishing activities in a finite planning horizon inventory system. J. Opti. Theory Appli. **168**(2) 677–698 (2016)
4. Y. Cui et al. Research on remanufacturing scheduling problem based on critical chain management. In: IOP Conference Series: Materials Science and Engineering 215 (2017), p. 012005
5. Fang, C., Lai, M., Huang. Y.: Production planning of new and remanufacturing products in hybrid production systems. Comput. Indust. Eng. **108**(4), 88–99 (2017). ISSN: 03608352
6. Gal. B.: Study on application-oriented sequence optimization for remanufacturing production planning systems in the circular economy. Tech nische Universität Wien (2022)
7. Han, S.A., et al.: A robust optimisation model for hybrid remanufacturing and manufacturing systems under uncertain return quality and market demand. Int. J. Prod. Res. **54**(17), 5056–5072 (2016) ISSN: 0020-7543

8. Jeunet, J., Croce, F., Salassa. F.: Heuristic solution methods for the selective disassembly sequencing problem under sequence-dependent costs. In: IFAC PapersOnLine , pp. 52–13 (2019)
9. Lage, M., Jr., Godinho Filho, M.: Master disassembly scheduling in a remanufacturing system with stochastic routings. Cent. Eur. J. Oper. Res. **25**(1), 123–138 (2017)
10. Li, W., Wang. S.: Sustainable Manufacturing and Remanufacturing Management. Springer, Cham (2019). https://doi.org/10.1007/978-3-319-73488-0. ISBN: 978-3-319-73487-3
11. Mao, J., et al.: Disassembly sequence planning of waste auto parts. In: J. Air Waste Manag. Assoc. **71**(5) , 607–619 (2021)
12. Polotski, V., Kenne, J., Gharbi. A.: Set-up and production planning in hybrid manufacturing-remanufacturing systems with large returns. Int. J.f Prod. Res. **55**(13), 3766–3787 (2017). ISSN: 0020–7543
13. Ren, Y., et al.: A Multiobjective disassembly planning for value recovery and energy conservation from end-of-life products. In: IEEE Transactions on Automation Science and Engineering 1vol. 8, pp. 791–803 (2021)
14. E. Suzanne, N. Absi, and V. Borodin. Towards circular economy in production planning: Challenges and opportunities. Eur. J. Oper.l Res. **287**(1) , 168–190 (2020). ISSN: 03772217
15. VDI Zentrum Ressourceneffzienz. Studie VDI ZRE: Potenziale der schwachen künstlichen Intelligenz für die betriebliche Ressourceneffzienz. (2021)
16. K. Wang and Li. A genetic simulated annealing algorithm for parallel partial disassembly line balancing problem. Appl. Soft Comput. **107**(11) 107404. (2021), ISSN: 15684946
17. WWF. EU overshoot day living beyond nature's limits, World Wide Fund for Nature. 2019. url: https://www.wwf.at/de/view/les/download/showDownload/?tool=&feld=&sprac_hconnect=3371