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# Data-driven decision process for robust scheduling of remanufacturing systems

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**Abstract:** Robust scheduling problem is a major decision problem that is addressed in the literature, especially for remanufacturing systems; this problem is complex because of the high uncertainty and complex constraints involved. Generally, the existing approaches are dedicated to specific processes and do not enable the quick and efficient generation and evaluation of schedules. With the emergence of the Industry 4.0 paradigm, data availability is now considered an opportunity to facilitate the decision-making process. In this study, a data-driven decision-making process is proposed to treat the robust scheduling problem of remanufacturing systems in uncertain environments. In particular, this process generates simulation models based on a data-driven modeling approach. A robustness evaluation approach is proposed to answer several decision questions. An application of the decision process in an industrial case of a remanufacturing system is presented herein, illustrating the impact of robustness evaluation results on real-life decisions.



*Keywords:* data-driven modeling, simulation, decision making, remanufacturing, scheduling, robustness evaluation

## 1. INTRODUCTION

In the era of Industry 4.0, a high level of connectivity and intelligence through the adoption of ubiquitous information and communication technologies is required for the manufacturing industry. These capabilities could help address the current challenges faced by remanufacturing systems (Yang et al., 2018). In addition to recycling and reuse strategies, remanufacturing is an end-of-life strategy that enables sustainability in the context of a circular economy. Remanufacturing involves the restoration of end-of-life products to their original working condition (Yang et al., 2018). This process is marked by complete disassembly, processing and reassembly of the products. The challenges faced in the remanufacturing process generally center on high uncertainty regarding the physical conditions of the products. The routing and processing times are unknown before the disassembly and inspection of the product. Accordingly, these unknown properties are determined through stochastic analyses. In this study, we considered a robust proactive scheduling strategy for the remanufacturing process, aiming to generate predictive schedules that satisfy the performance threshold. To address the operational challenge of process scheduling under uncertainty, we propose a hybrid approach integrating data-driven modeling with Industry 4.0 capabilities and decision-making support through a robust evaluation of scheduling scenarios.

Currently, Different static and dynamic tools are available and can be used to propose schedules. Discrete-event simulation (DES) is a dynamic simulation approach, which allows the generation of schedules via simulation models. A limitation of this simulation approach is the need for valid simulation models. Model building and validation are time-consuming processes that require expertise in a variety of technical areas. Data-driven modeling is employed for the generation of valid simulation models from the data. These models can be used for experiments to provide schedules for robustness evaluation. Therefore, production data are required for modeling, which are assumed to be available from the workshop in the Industry 4.0 framework. To advance a working hypothesis in this paper, the production data were assumed to be available.

This paper is organized as follows. The following section presents the state-of-the-art scheduling problems in the context of remanufacturing. Section 3 presents a modeling and evaluation approach that addresses the aforementioned limitations as well as those listed in the state of the art. An application of the remanufacturing process is provided in Section 4. Further work and perspectives are described in the previous section.


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## 2. STATE OF THE ART

### *2.1 Scheduling in stochastic environment*

The scheduling problem in stochastic environments has been widely treated as a decision problem in the field of optimization. Generally, existing approaches are used to generate predictive schedules that satisfy the performance thresholds. This method is referred to as robust proactive scheduling. Scheduling remanufacturing processes in this context is a considerably challenging task. Unlike job- and flow-shops, remanufacturing processes generally comprise a three-stage process (Guide et al., 2000). In the disassembly stage, the returned products are dismantled into construction groups and materials. In the processing stage, the materials are repaired, and in the reassembly stage, the restored product is reassembled using the materials and construction groups. This process is subject to a high level of uncertainty, which should be considered when scheduling remanufacturing activities. Several approaches have been reported to address this issue (Morgan and Gagnon, 2013). Considering the stochastic environment of workshops, a common concern in all these approaches is the performance evaluation of the proposed schedules (Renke et al., 2021).
Robustness is a property that is typically used as a performance indicator to evaluate schedules in a stochastic environment. (Himmiche et al., 2021) proposed a robustness framework to facilitate decision-making in the scheduling context, in which the robustness serves as a measure of the service level. Their definition of robustness was used to evaluate the robustness of remanufacturing schedules. In particular, robustness evaluation requires valid production schedules. Owing to the high uncertainty stemming from the condition of returned products, the scope of traditional operation management technologies is severely limited (Ilgin and Gupta, 2010). The routing and time required for processing are not always known upon the arrival of the product; these parameters are determined after the disassembly and inspection of the product. Moreover, the complexity of the scheduling problem increases when the possible disturbances in the workshop are considered. To address this issues, (Guo et al., 2021) proposed the use of stochastic models for dynamic scheduling.

### *2.2 Simulation-based scheduling*

Simulation allows the representation of real-world systems through digital models and the analyses of possible scenarios, and currently, different simulation technologies are available for use. (Okorie et al., 2020) analyzed a remanufacturing system using simulation tools for system dynamics, agent-based modeling, and DES. They exploited the properties of DES to perform an exact micro-level analysis of flow elements exhibiting stochastic behavior. DES is a widely employed tool in production scheduling. (Mohan et al., 2019) identified simulation as one of the most popular tools for modeling manufacturing systems in the context of dynamic job-shop scheduling problems. In addition to modeling scheduling problems, simulation is also used to evaluate the robustness of schedules under the uncertainties of the workshop (Vieira et al., 2017). Several examples of DES usage for scheduling in the field of remanufacturing have been provided by (Guide et al., 2000).

### *2.3 Data-driven modeling of remanufacturing systems*

The simulation approach is severely limited by the considerable time and effort involved as well as the expertise of the modeler. To address these shortcomings, (Hubl et al., 2011) presented a data-driven modeling approach for flow- and job-shop production systems based on the Manufacturing Resource Planning (commonly known as MRP II) data. Such data-driven approaches enable users to generate simulation models of manufacturing systems using the data and provide valid production schedules within seconds. An overview of data-driven modeling approaches has been provided by (Reinhardt et al., 2019). For the generation of simulation models, data-driven approaches for modeling and simulation use data typically stored in enterprise resource planning, management execution, and production planning systems and provided via technical interfaces such as spreadsheets and databases. In the simulation environment, the algorithms create simulation objects according to the data retrieved from the database. The algorithm further runs simulation experiments in the generated model and records the simulation results in a database. To the best of our knowledge, automated modeling and simulation approaches capable of generating valid production schedules for remanufacturing systems via simulation, which uses data featuring stochastic behavior, are currently unavailable. To this end, a complete decision process was developed, as detailed in the next section.

## 3. DECISION PROCESS DESCRIPTION

In Industry 4.0, the comprehension of the generated data and considerations regarding the data represents major operational challenges. The cross-industry standard process for data mining (CRISP) was reported by (Schröer et al., 2021) and derived for data mining applications, and this standard is generally used in the manufacturing industry to define machine learning processes. In this study, this standard was adapted to the context of the dynamic robust scheduling problem for remanufacturing systems, as illustrated in the sequencing diagram (Fig. 1). The first phase of this process involves gathering an insight into the business and data aspects; it focuses on interpreting the robustness objectives from the data available in the workshop. From the available data, the decision-maker develops decision scenarios and formulates the questions to be answered. The primary aim of the data preparation phase is the collection of simulation data for the database. The modeling phase is categorized into multiple subphases. The DES-Simulator pulls data from the database and generates a simulation model in the digital factory. During experimentation, the DES-Simulator parameterizes the digital factory for each experiment, simulates the scenario, and finally obtains the results. Following the modeling phase, the DES-Simulator records the results of all experiments in the database. The evaluation phase involves the evaluation of simulated schedules, determination of robustness, and preparation of key performance indicators (KPIs) for the decision-maker. This phase consists of extracting data from the database, evaluating the robustness, and pushing the evaluation results. In the deployment phase, the decision-maker interprets the KPIs and applies the optimal scenarios to the physical system. The CRISP is a circular process that loops back with a new business and data understanding. In this study, we focused on the modeling and evaluation phases. As previously stated, the data were considered available.

### 3.1 Understanding of business and data phase

In the business understanding phase, the decision-maker formulates the requirements and goals of the study. To this end, the decision-maker analyzes the business and available data, which can be retrieved from the factory, and defines the KPIs to be analyzed.

### 3.2 Data preparation phase

In the data preparation phase, the decision-maker provides relevant data for the analysis, modeling, and simulation stages. The relevant data to analyze remanufacturing processes include the workshop characteristics and its capacities, remanufacturing processes, and planning of product returns. In this study, the simulation was performed to facilitate scheduling under uncertainty for a robustness assessment. Accordingly, adequate simulation models are required for this purpose. Owing to the size and complexity of such systems, as well as the alternating simulation experiments, manual modeling is not appropriate for the simulation process. Data-driven modeling was chosen to generate valid simulation models, run simulation experiments, and provide schedules for robustness analysis in an automated manner. Consequently, data describing the entire remanufacturing system are stored in a database. The database contains static data describing the products to be remanufactured, shop floor resources, remanufacturing process, and shift schedules, as well as dynamic experimental data describing variable order schedules and stochastic patterns of machine disturbance and cycle times.

### 3.3 Data-driven-modeling phase

In the modeling phase, the simulation data are initially extracted from the database. To set up the simulation model, referred to as the digital factory, the algorithm uses manually predefined and reusable standard elements for the remanufacturing processes and resources. The digital factory is created based on these elements and the static data pulled from the database. The elements of the process include the logic of disassembly, processing, and reassembly of products and parts, as well as the prioritization and material routing through the system. The elements of resources include the logic of the physical system and mirror the remanufacturing capacities by adhering to the shift plans and business rules of the shop floor. For each experiment, the simulation model was parameterized using dynamic data, and a simulation was subsequently performed. The simulation results, which include the scheduling of tasks, were captured. To provide simulation results to the decision-maker, the simulation results were processed by the algorithm. The outputs for the modeling phase are the production schedules and all measures of KPIs. Following the modeling phase, all the experimental results were pushed to the database.

### 3.4 Robustness evaluation phase

In the robustness evaluation phase, the simulated schedules were first extracted from the database. Generally, robustness is defined as the capacity of a schedule to assimilate the impact of perturbations. A schedule is considered to be robust if it exhibits low sensitivity to uncertainty. In this definition of robustness, the notion of schedule sensitivity is subjective. To overcome this subjectivity, (Himmiche et al., 2021) proposed that the robustness be measured as a probability measure. In this study, we used this measure and defined the robustness for the probability that the KPI measure of a schedule $s_i$ under uncertainties, $U$, is less than or equal to a KPI limit defined by the decision-maker (Equation 1).

$$RL(s_i, U, KPI_{lim}) = Pr(KPI(s_i, U) \leq KPI_{lim}) \quad (1)$$

In the second step of the robustness evaluation phase, a statistical analysis was performed for the simulation results to obtain the robustness level of each schedule and for each KPI. In the third step, the evaluation results are pushed to the database and made readily available to the decision-maker. The results of the evaluation are used by the decision-maker to obtain indications of the schedule performance.

### 3.5 Interpretation and deployment phase

The interpretation of the evaluation results depended on the questions defined in the data preparation phase. For example, two interpretations are possible. For the same schedule, $s_i$, the robustness levels of different KPIs were compared to interpret the performance of this schedule. For a set of schedules $S$ with $s_i \in S$, the comparison of their robustness levels for the same KPI allows for the determination of the schedule with the higher robustness, which can be considered robust.

After interpreting the results, the decision-maker can select the optimal scenario and related actions to deploy the scenario in the workshop. The deployment phase allows for the execution of a robust schedule by the decision-maker. If the obtained results are unable to address the decision-maker's expectations, the decision process can be repeated with specific data adjustments. This process can also be repeated with the new data from the workshop. The new data may concern the configuration of the remanufacturing workshop (workshop reconfiguration); it can also concern the decision-maker's requirements that may change according to the factory's strategy.

## 4. ILLUSTRATION ON TRAIN REMANUFACTURING SYSTEM

The decision process described herein was applied to the remanufacturing process of trains. All trains arrive at the workshop following a predefined order. In the workshop, train cars are decoupled in the disassembly process. These cars are subjected to individual processes through a remanufacturing system that may include additional disassembly processes as well. After the maintenance of parts is complete, reassembly is performed to complete the remanufacturing of trains.

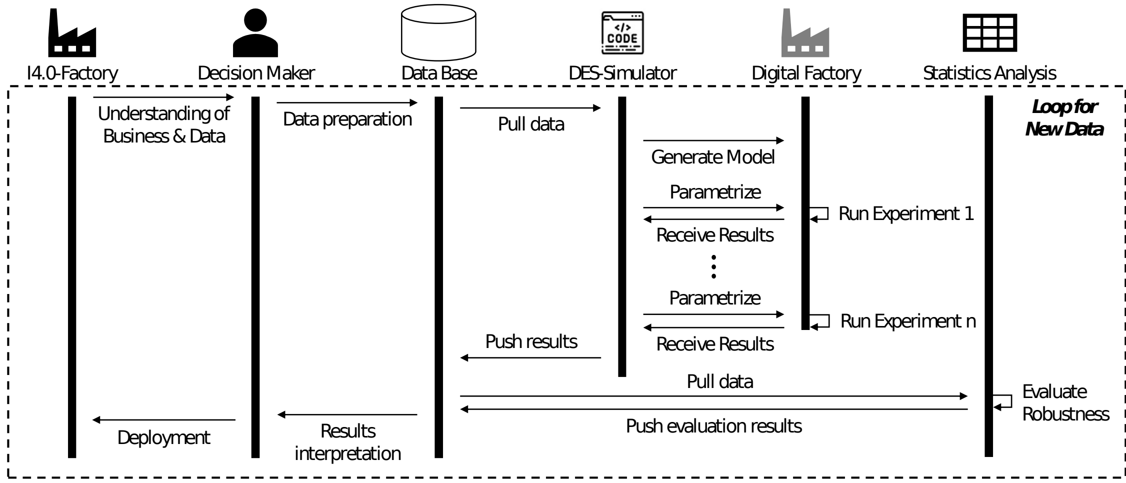


Fig. 1. Data-Driven decision process

### *4.1 Understanding of business and data phase*

The entire remanufacturing process of one train contains more than 400 processes, which are defined by the predecessor and successor relations, precedence rules, and cycle times. Additionally, more than 3000 subprocesses exist per train, which were not considered in this step; however, data-driven modeling is inevitable for future analysis. The processes and operations were conducted in a workshop using 50 different resources. These resources were assigned to two- and three-shift systems. For the modeling approach, infinite buffers were used, and the spatial restrictions of the workshop were not considered. A business rule was established wherein no more than five trains were allowed at the same time.
In the described system, decision-makers focus on two KPIs: the makespan of trains ($C_{max}$) and the productivity ($p$) calculated using Equations 2 and 3, respectively. In Equation 2, the makespan, $C_{max}(s_i, tr_j)$, of the train $tr_j$ belonging to the schedule $s_i$ represents the difference between the departure and arrival times of this train, considering a set $T$ of trains $tr_j$ with $j \in 1...NbT$ and $NbT$ denote the total numbers of trains. In Equation 3, the productivity, $p(s_i)$, for a given schedule, $s_i$, is expressed as the difference between the departure time of the last train and the arrival time of the first train divided by the number of trains, $NbT$.

$$C_{max}(s_i, tr_j) = t_{dep}(s_i, tr_j) - t_{arr}(s_i, tr_j) \tag{2}$$

$$p(s_i) = (t_{dep}(s_i, tr_{NbT}) - t_{arr}(s_i, tr_1))/NbT \tag{3}$$

For the analysis, the steady-state of the system was investigated. The makespan describes the duration of remanufacturing for a single train. To decrease the total train tardiness experienced by customers, the train makespan must be reduced. The productivity represents the number of trains that the system can remanufacture in a given time, and it should be enhanced. Based on these KPIs for analysis and improvement, the following two questions were formulated: How do the scheduling strategies influence productivity and makespan? How does the uncertainty impact the robustness of the schedules?

### *4.2 Data preparation phase*

Using the obtained data, the decision-maker can describe the workshop characteristics with the uncertainties to be considered and the KPIs to be measured. In particular, the entrance data considered for scheduling describe the arrival of the 20 trains to be scheduled. The duration between train arrivals was defined in terms of the number of weeks. The uncertainties considered in the workshop are as follows. Deviations of the cycle times (ST) were modeled using a normal distribution with a standard deviation of 10% around the mean. Machine failures (MF) were modeled to represent an average availability of 97%, 98%, and 99% of the available time with a mean repair time of 2 h. The chosen parameters were the Erlang distribution with means of $66.6, 100$, and 200 h and deviations of 11.5, 14.1, and 20 h as well as the NegExp distribution with a mean of 2 h.
The decision-maker defined the following thresholds for makespan and productivity: $C_{maxlim} = 190$ days and $p_{lim} = 39$ days/train. These data were pulled from the database to initiate the generation of the simulation models.

### *4.3 Data-driven-modeling phase*

The modeling of the aforementioned problem depends on the understanding of the remanufacturing process and the description of the experimental scenarios. The description of the workshop and its parameters allow for the generation of simulation models using a discrete-event simulator (Witness 23.1a). These scenarios were defined using two parameters. First, the scheduling strategy was evaluated for six values of the duration between train arrivals ($s_1, ..., s_6 \in S$). The second parameter is uncertainty, which must be considered. For each scheduling strategy, the deterministic case (no uncertainty) as well as the stochastic time cycles (ST), MF, and combined (ST+MF) uncertainties are treated, which led to the analysis of 24 scenarios. The number of simulation replications for each scenario was fixed at 100. From these simulation results, a robustness evaluation of the different KPIs can be executed. The outputs of the modeling phase are the simulated production schedules, productivity KPIs, and makespan of trains.

### *4.4 Robustness evaluation phase*

To address the first question, a comparison of schedules was performed, considering the worst-case scenario of perturbations (MF+ST). The robustness evaluation is employed to distinguish the impact of changing the scheduling strategy on the productivity and the makespan of trains. The robustness levels were measured according to the definition given in (Equation 1). For instance, the robustness level for productivity KPI is expressed using (Equation 4).

$$RL(s_i, U, 39) = Pr(p(s_i, U) \leq 39) \quad (4)$$

The robustness evaluation results for the makespan and productivity are illustrated in Figs. 2 and 3, respectively. Using these figures, comparisons can be drawn between the robustness levels of different scheduling strategies, $s_1$ to $s_6$. The thresholds defined by the decision-maker are depicted in red.

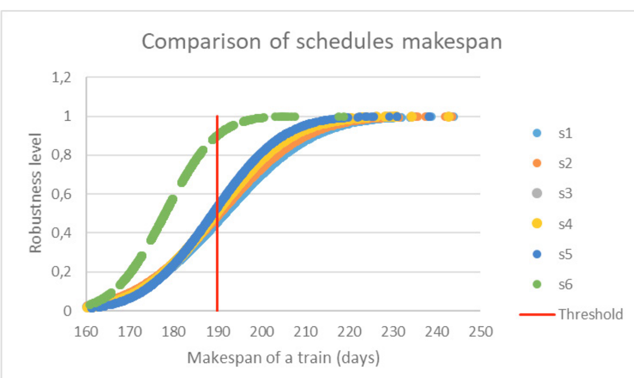


Fig. 2. Impact of scheduling strategy on train makespans

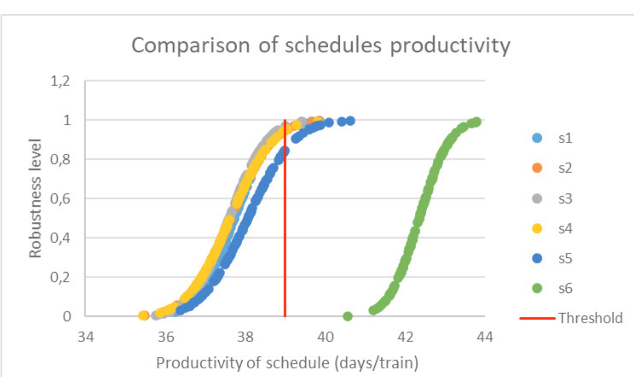


Fig. 3. Impact of scheduling strategy on schedule productivity

To answer the second question, a robustness evaluation was performed for each scenario of uncertainty for each schedule. Results of the evaluation are presented for the first schedule, $s_1$, to analyze the impact of uncertainties on the makespan (Fig. 4) and the impact of resource availability on productivity (Fig. 5).

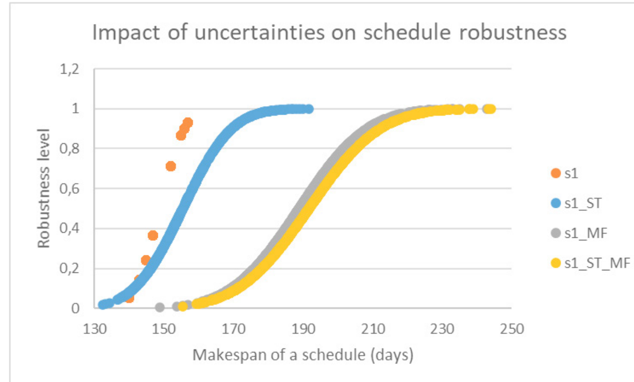


Fig. 4. Impact of uncertainties on schedule robustness

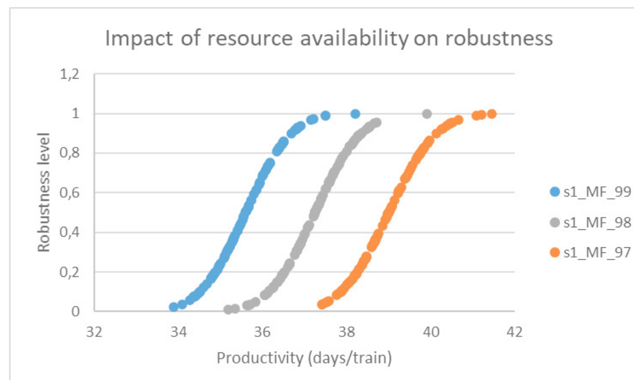


Fig. 5. Impact of resource availability on schedule robustness

### *4.5 Interpretation and deployment phase*

Owing to the different results obtained from the evaluation phase, the decision-maker possesses a holistic view for answering the decision questions. First, according to the analysis results concerning the impact of scheduling strategies on the robustness (Fig.2) and (Fig.3), the worst-performing strategy, s6, exhibited the highest robustness level of 91%, which met the threshold of 190 days. However, the same strategy notably decreased the robustness level of productivity to 0%. To emulate these results, the decision-maker should consider a compromise between these two KPI values. In this case, the optimal compromise comprises s4 with $RL(s_4, U, 190) = 51\%$ and $RL(s_4, U, 39) = 97\%$.
By adopting this strategy, the decision-maker will surely meet the threshold values that were defined with a minimum probability of 50%. A comparative study of (Fig.2) and (Fig.3) reveals a conflict between the makespan and productivity KPIs. Scenarios featuring satisfactory makespan provide poor productivity and vice versa. This behavior is observed, especially, in examples $s_5$ and $s_6$. To overcome this conflict and improve the makespan and productivity, decision-makers can redesign the system. The starting point for system redesign constitutes changes in the physical workshop or the organization of work. For instance, decision-makers can enhance the workshop capacities or improve the organization of work by changing the priority and dispatching rules.
To address the second question, the decision-maker can measure the impact of uncertainties on the robustness level

of a schedule, as illustrated in Fig. 4. For the makespan, the degradation of the robustness is clearly observed. In fact, when the uncertainties in the scheduling scenario increase, the robustness level gradually decreases. The decision-maker can note that the deviation from the deterministic values is minimal when considering only the ST scenario, but it decreases upon the introduction of the MF scenario. This trend demonstrates the manner in which different types of uncertainties impact productivity and makespan. The results plotted in (Fig. 5) clearly indicate that increasing the availability of resources may increase the robustness level of a schedule and the system KPIs, implying that resource unavailability negatively impacts the schedules. The impact of uncertainties on the makespan and productivity is evident in (Figs. 4 and 5), respectively. The decision-makers should note from (Fig. 4) the manner in which the uncertainty negatively impacts the system efficiency and from (Fig. 5) the manner in which minute changes in availability impact the KPIs. Further uncertainties can occur owing to missing materials and workforce. To improve the system, new maintenance strategies such as predictive maintenance can be implemented to improve resource availability. Notably, analogous strategies are required to reduce material and workforce unavailabilities. In addition, general pricing practices and scheduling processes can be considered for making strategies to mitigate the uncertainties. Reduction of the risk of delays could also be considered for the pricing strategy and realized in workshops by prioritizing critical trains

## 5. CONCLUSIONS AND PERSPECTIVES

In this study, we presented a performance analysis process for remanufacturing systems based on data-driven dynamic modeling and simulation. This technique facilitates the implementation of simulation studies on complex and parameter-intensive systems. Its implementation benefits from the availability of a standardized remanufacturing process (i.e., a general model is available). This approach can also be used for decision-making in medium- or short-term planning if the modeling and simulation tools are linked to a digital twin of the production and system. Moreover, to consider the uncertainties inherent to remanufacturing systems, the presented approach involves the study of the influence of scheduling strategies on performance measures (KPIs) via the concept of scheduling robustness. The presented example illustrates the feasibility and scope of the process in real-world problems involving resources, processes, and products. This example was limited to a comparative study of the performance of the production system as a consequence of disturbances and scheduling scenarios to choose a scheduling strategy. In future work, we will reveal the manner in which the information richness of the employed simulation and scheduling models can be leveraged to guide changes in the remanufacturing and/or scheduling systems and achieve performances that dominate, in the Pareto sense, those obtained with the approach presented herein.

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