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Performance Assessment of a Closed Loop Repair Process in the Circular Economy Context

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Abstract: It is well known that the dependability of equipment on a production site is strongly linked to the quality of maintenance operations. This paper focuses on repair shops dedicated to the overhaul of defective equipment from several sites, via circular economy strategies. The literature provides analytical and numerical models that allow the performance of a repair shop to be evaluated under certain conditions. However, the majority of studies do not highlight the impact of component degradation after each equipment overhaul. We propose to study the life cycle of components throughout a repair process. Each component begins a cycle with a discrete failure rate that increases with the number of operations undergone. At the end of their life, components undergo an operation that allows them to have a second life. The novelty of this paper lies in the evaluation of the impact of the component life cycle on the performance of a repair shop. We propose a closed-loop model with which we were able to carry out a case study in the railway sector. The results show that considering several levels of component degradation in the repair shop has an impact on maintenance costs.

Keywords: discrete event modeling and simulation; manufacturing and service systems; repair shop; life cycle assessment; queuing systems and performance model.

1. INTRODUCTION

The facilities used to produce goods and services are becoming increasingly complex due to a wave of technological transformation (Cloud Computing, Internet Of Things, Big Data, etc...) resulting from Industry 4.0 (Shukla et al. 2019). The increase in the complexity of a system logically leads to an increase in the sensitivity of its correct operation. As a result, maintenance is becoming increasingly important in companies that want to guarantee the optimal functioning of equipment (Cárcel-Carrasco et al. 2021).

Repair shops contribute to maintenance by being places where faulty equipment can be restored. They are quite similar to job shops, but the aim of the operators and the machines is to replace defective components of the equipment with spare parts. The main objective of the repair shops is to restore equipment from several production sites at low cost (Turan et al. 2020). In general, production equipment is manufactured and installed by OEMs (Original Equipment Manufacturers) who guarantee a negligible number of breakdowns at the beginning of their life and spare parts to repair shops in case of failure.

In a repair shop, the process consists of diagnosing the faults, disassembling the equipment, replacing the faulty components and reassembling the equipment. Faulty components are then repaired to produce other spare parts which are kept in stock with those of the OEM. After successive repairs over time, components eventually deteriorate completely and reach the

end of their life. Repair shops then use circular economy strategies to give a second life to certain components.

Industrial applications of repair shops with circular economy strategies are found in the aircraft, railway and oil & gas industries. As shown in Figure 1, equipment is typically transported from production sites to the repair shop where it is overhauled. Subsequently, the failed components are replaced by spare parts available in stock. A spare part comes either from a purchase from the OEM as mentioned above, or from the transformation of a failed component via an on-site repair or other circular economy operations carried out by the OEM

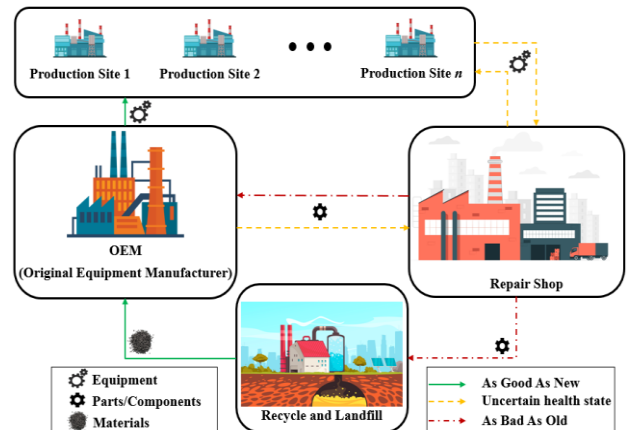


Fig. 1. The ecosystem of a repair shop.

(refurbishment, reconditioning, remanufacturing, etc.). If a component cannot undergo any of the above operations, it is either recycled as a manufacturing material or landfilled.

The literature provides several studies on repair shops (Djeunang Mezafack et al. 2021). A first performance evaluation model was proposed as early as 1984 and 1985 by Scudder to determine the optimal amount of spare parts to stock and the best strategy to maximise the throughput of a repair shop (Scudder 1984; 1985). Analytical approaches and discrete event simulations have been developed over time (Spanjers, van Ommeren and Zijm 2005; Li et al. 2013).

Queueing networks and Petri nets based on Markov chains (Seatzu et al. 2013) are the most widely used approaches to study the stochastic effect of failures. However, most works consider a linear repair shop where the repair successions of a given component are independent from each other. But in reality, the health state of a component remains degraded to a certain level after each repair. Some authors address this problem by considering a closed-loop repair shop (Assadi et al. 2019; Akbari Haghighi et al. 2021). The idea is to vary the health state of a component once it has been repaired and allow it to return to the repair shop at the next failure, until its end of life.

Although current models allow for the study of a closed loop repair shop, they assume that once a component reaches the end of its life, it is remanufactured anyway and considered "As Good As New". However, there is a wider range of circular economy operations that can give a component a second life. As shown in Figure 2, the possible operations vary according to time, cost and the final health state of the transformed component. Indeed, between the "As Good As New" components provided by remanufacturing and the "As Bad As Old" components provided by repair, there are other possible states of health related to other circular economy strategies (reuse, reconditioning, refurbishment, recycling, etc.).

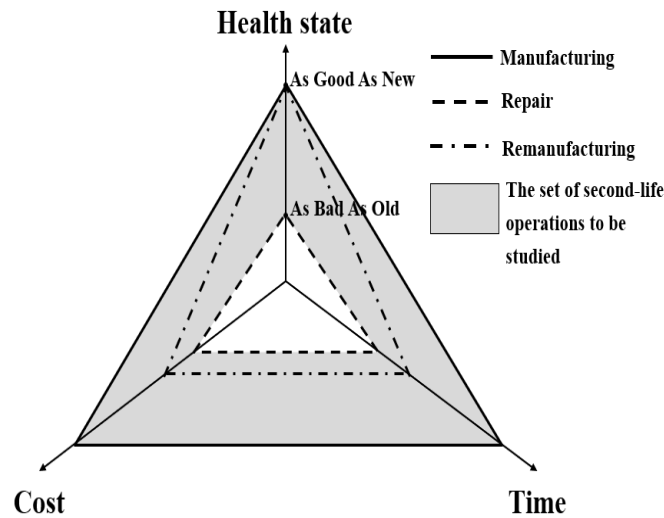


Fig. 2. All life extension strategies

All of these circular economy strategies also differ in the cost and time required for interventions. For example,

remanufacturing takes longer than repair, which takes longer than simple reconditioning. In this study, we consider that repair shops should choose the circular economy strategy that will allow them to achieve the best performance i.e. low cost of operations. Therefore, the novelty of this paper lies in the assessment of the impact of second-life components on the costs of a repair shop. Thus, the questions that arise are the following:

1. How to model a closed-loop repair process considering various circular economy strategies?
2. What is the impact of second-life components on the performance of a repair shop?

To answer these questions, after this first introductory section, this paper is structured as follows: section 2 is dedicated to the modelling of the problem, section 3 describes the experiments carried out, section 4 concerns the analysis and discussion of the results, the last section is allocated to the conclusion and perspectives.

2. PROBLEM DESCRIPTION AND MODELLING

2.1 Component life cycle

Let's consider a set of production sites (*PS*) where *N* new equipment are installed, subject to uncertain failures during their lifetime. If a piece of equipment fails, it is sent to the repair shop for overhaul. After being repaired by replacing the failed component, the piece of equipment is reinstalled in the production site. The objective of this paper is to develop a model for such a closed-loop repair shop that can be used to assess the impact of component life cycle on performance. The main assumptions required for this study are as follows:

1. All equipment are identical and consist of two parts: one that can fail according to a Poisson distribution with a rate λ , and another that is robust enough to be considered as never failing.
2. The life cycle of a piece of equipment is assimilated to the life cycle of its sensitive component whose health state is fully described by its failure rate λ .
3. At its failure *i*, the component has a probability ξ_i of being repaired inversely proportional to *i*.
4. Repairs are imperfect, i.e. they do not restore the components to their pre-failure state.
5. After the i_{max} repair, the component undergoes a second-life operation, *sl*, which returns its failure rate to one of the previous values denoted by $i_{sl} \in [0; i_{max}]$. $i_{sl} = 0$ means that the component is returned "As good As New" and $i_{sl} = i_{max}$ means that the component is returned "As Bad As Old".
6. After a first and second life $l \in \{1,2\}$, the component is automatically recycled.
7. As illustrated in Figure 3, the life cycle of a component starts with its manufacture or purchase from the OEM and

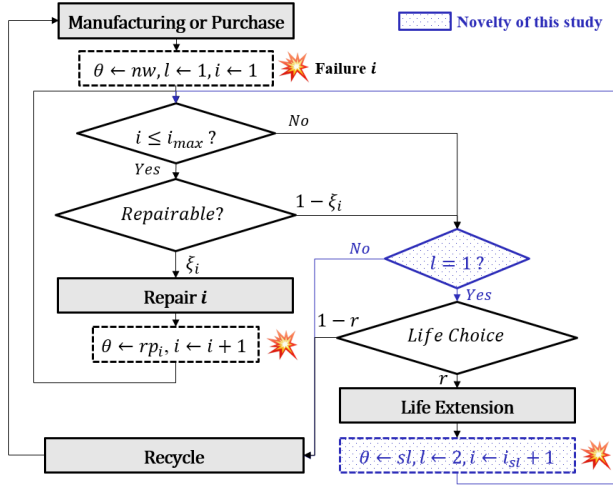


Fig. 3. Life cycle of a component

ends with its recycling. After being purchased/manufactured, the component is repaired each time it fails, up to the maximum number i_{max} of failures. Each repair is represented by the state rp_i with $i = 1, 2, \dots, i_{max}$. When a component can no longer be repaired, it goes through the operation sl which allows it to start its second life. Each operation is associated with a health state of the component. Thus, the set Θ of possible health states θ of a component during its life is considered discrete:

$$\Theta = \{nw, rp_1, rp_2, \dots, rp_{i_{max}}, sl\}.$$

A variable r is defined to represent the proportion of components allowed to have a second life. r is crucial as it determines the quantity of second-life components in the repair loop. The remaining $1 - r$ components are scrapped and replaced with new ones.

In the following, we will model and evaluate the performance of a repair shop considering the life cycle of the components presented above.

2.2 Repair shop modelling

The repair shop consists of service stations, a stock of spare parts and a stock of equipment. The general objective of the structure is to be able to offer ready-to-use equipment in the shortest possible time and at the lowest cost as soon as broken equipment arrives from the production sites (PS).

As shown in Figure 4, the repair shop is modelled as a closed multiclass queuing network. There are five classes corresponding to the different types of components: new (λ_{nw}), repaired (λ_{rp_i}) and those that have just undergone a second-life operation (λ_{sl}). To simplify the representation, we choose a maximum number i_{max} of 3 repairs. The model is quite similar to a classical base stock model (Zijm and Avşar 2003). The novelty lies in the exchange of equipment that takes place between the repair shop and the PS, leading to the multiclass aspect.

Table 1. Repair shop variable and parameters

	Description	Decision variable	Parameters	
			Input	Output
r	Proportion of components allowed to have a second life	•		
i_{sl}	Index indicating the health state of a component after a second-life operation		•	
λ_{nw}	Failure rate of new, repaired or second-life components.		•	
λ_{rp_i}			•	
λ_{sl}			•	
ξ_i	Probability of being repaired at failure i		•	
μ_{ds}	Service rate of disassembly, diagnostic, life choice, life extension, purchase, repair or assembly stations (exponential distribution)		•	
μ_{dg}			•	
μ_{lc}			•	
μ_{sl}			•	
μ_{nw}			•	
μ_{rp_i}			•	
μ_{as}			•	
N_{nw}	Total quantity of components purchased, in second-life or repaired.			•
N_{sl}				•
N_{rp_i}				•

After diagnosis, only the repaired components 3 are taken to the life choice station where they can either be given a second life or recycled and replaced with new components. The remaining components are sent to repair stations according to the probability of being repaired ξ_i . The other variable and parameters are described in Table 1.

In the next section, we will use the proposed model to evaluate the performance of a repair process in the railway domain.

3. EXPERIMENTS

3.1 Case study

Having developed a repair shop model considering the life cycle of components, it is now a question of using it in an application. We chose to adapt a real-life case study proposed by (Li et al. 2013) in the railway domain. It involves the maintenance of train bogies with different components (wheels, dampers, suspensions, etc...) as presented in Figure 5. The wheel is considered the component most likely to fail. This case study considers the train bogies as the only equipment that arrive at the repair shop for overhaul and a wheel as the only failed component. The number of failures over time follows an exponential distribution regardless of the health of the wheel (new, repaired or in second life).

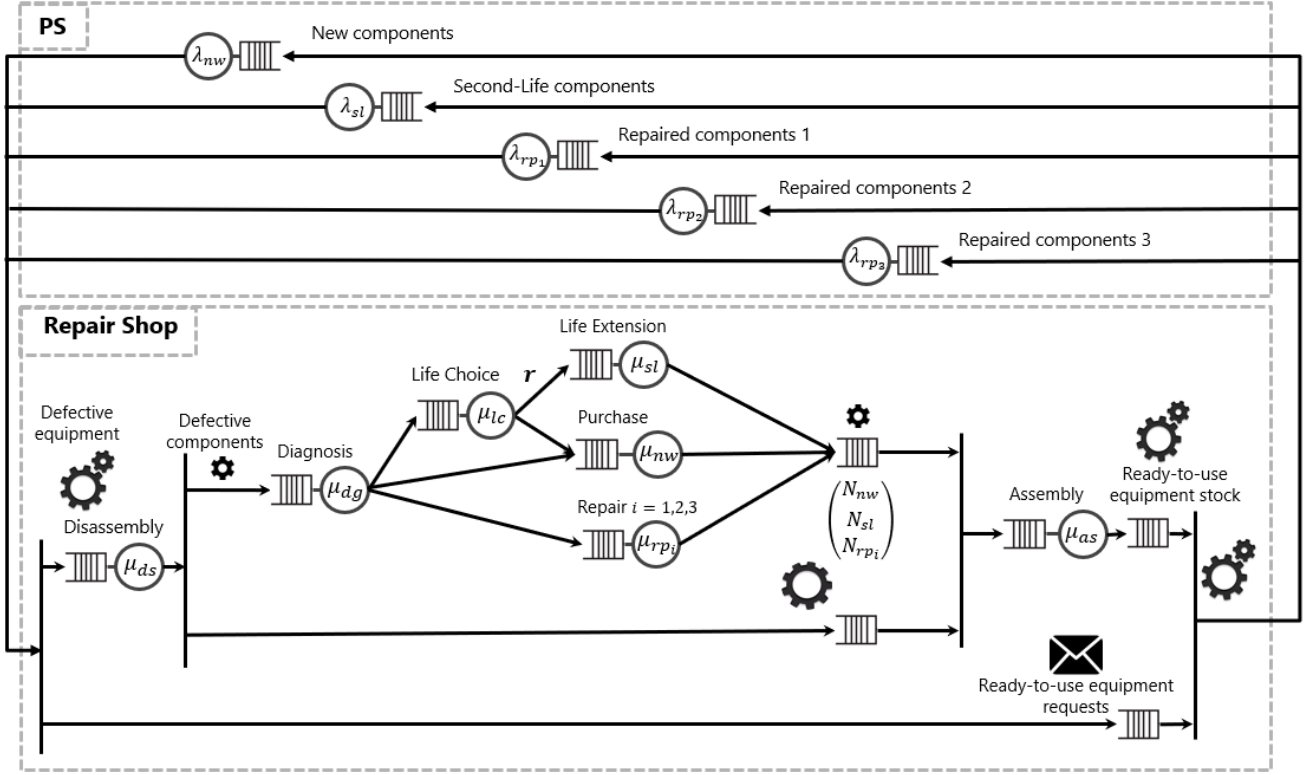


Fig. 4. Proposed queuing network model for a repair shop

- A new wheel is considered to be faulty after an average of 714 days (~ 2 years): $\lambda_{nw} = 0.0014$
- A wheel repaired for the first time is considered to be faulty after 244 days on average (~ 9 months): $\lambda_{rp_1} = 0.0041$
- A wheel repaired for the second time is considered to be faulty after 81 days on average (~ 3 months): $\lambda_{rp_2} = 0.0123$
- A wheel repaired for the third time is considered to be faulty after 27 days on average (~ 1 month): $\lambda_{rp_3} = 0.0370$
- 9 out of 10 new wheels can be repaired, 7 wheels repaired the first time can be repaired a second time and 5 out of 10 wheels can be repaired a third time: $(\xi_1, \xi_2, \xi_3) = (0.9, 0.7, 0.5)$
- If a wheel has already been repaired three times and fails, it undergoes a final operation that returns it to one of the following states: as if it had been repaired once, twice or three times (λ_{sl}). In this case, the repair shop must choose the least expensive state ($sl = 0, 1, 2$ or 3 ?).

In addition, 12 days, 3 days and about 1 day are successively needed to buy, repair and assemble/disassemble 2 train bogies. The time ($1/\mu_{sl}$) and cost (c_{sl}) required to give the wheels a second life depends on the state chosen after this operation (sl)

We chose to use discrete event simulation via Arena software to implement the repair shop model. At the beginning of the experiment, 50 new train bogies are installed at the production sites for a period of use of 10 years. The repair shop stations are considered empty at the beginning and the inventory consists of 5 wheels and 2 train bogies (these two values have been set to maximise the throughput of the repair shop). We are mainly interested in the number of operations of each type (purchase, repair and second-life) performed in the repair shop after 10 years, denoted by the following variables: N_{nw}, N_{rpi} and N_{sl} .

3.2 Key performance indicator and decision variable

The quantities of purchased, repaired and second-life wheels are used to calculate the cost of repair shop operations. Using a simple linear combination, the following equation is obtained:

$$Maintenance_{Cost} = \sum_{k \in \Theta} c_k \cdot N_k$$

$$\text{Where } \Theta = \{nw, rp_1, rp_2, \dots, rp_{i_{max}}, sl\}$$

And $c_k \in [0; 1]$ are relative weights in relation to the purchase of a wheel ($c_{nw} = 1$).

The aim is to minimise this cost over 10 years of bogies operations by determining the best rate of wheels allowed to have a second life $r \in [0; 1]$, based on different scenarios of second-life wheels denoted by the triplet $(i_{sl}, \mu_{sl}, c_{sl})$. 40

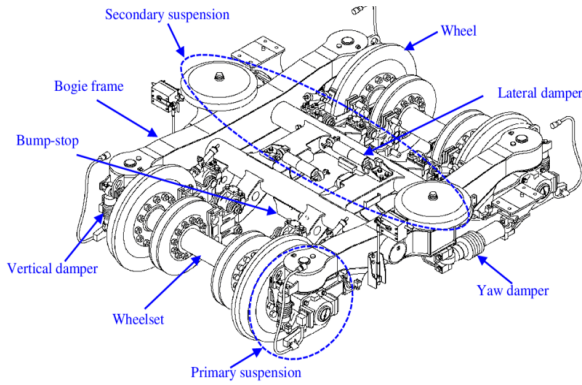


Fig. 5. Bogie of a high-speed train (Ling et al.)

replications of the simulation, each lasting 10 years, provide a 95% confidence interval of the results.

4. RESULTS

As illustrated above, a second-life wheel is characterised by the duration and cost of the operation that brings it into second life and its state of health. The triplet $(i_{sl}, \mu_{sl}, c_{sl})$ thus allows the construction of the different possible second-life operations to be considered, with $\mu_{sl} \in [\mu_{rp_i}; \mu_{nw}]$ and $c_{sl} \in [c_{rp_i}; c_{nw}]$. The simulation is used to vary these parameters in order to determine the maintenance cost as a function of r for each case. There are thus 1760 different possible configurations.

4.1 Quantitative analysis

Figure 6 shows the distribution of results for all simulated repair shop scenarios. For each value of r , the minimum and maximum values of maintenance costs were selected. The results obtained are therefore distributed between 111 and 363 i.e. a ratio of 3.27 comparing the minimum maintenance cost of the worst scenario to the best scenario. The mean is 217 with a standard deviation of 41 due to the variation in the life cycle parameters of wheels, compared to a mean of 200 with a standard deviation of 0 obtained without taking the life cycle into account. This comparison highlights the wide dispersion

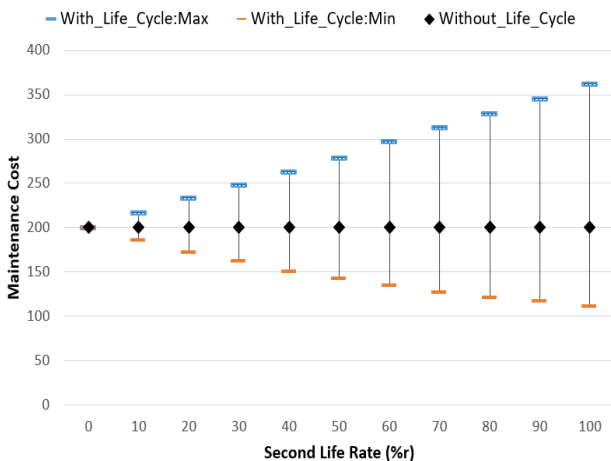


Fig. 6. Distribution of maintenance costs

of costs according to the life cycle scenarios of wheels, indicated by the triplet $(i_{sl}, \mu_{sl}, c_{sl})$. From a cost perspective, there are favourable scenarios for second-life, where costs are reduced by the choice of r , and unfavourable scenarios, where costs increase. The higher the proportion of second-life wheels, the greater the difference between the minimum and maximum costs. We will now examine the influence of each parameter of the triplet $(i_{sl}, \mu_{sl}, c_{sl})$.

4.2 Qualitative analysis

We considered a repair shop where the stock of spare parts and the bogies were initially optimised for maximum throughput without considering the life cycle of the wheels. Considering a second life of the wheels, Table 2 shows that the service rate of the second-life station has very little influence on the maintenance costs. Indeed, by selecting the minimum costs obtained according to r , for each of the values of μ_{sl} (i_{sl} and c_{sl} various for each value), similar results are obtained whatever the value of μ_{sl} considered. Thus, for each value of r , the standard deviation is less than or equal to 2, indicating that the second-life service rate has little influence on the minimisation of maintenance costs.

This time we want to highlight the impact of the cost of a second-life operation c_{sl} on the variation of the cost of maintenance as a function of r . Compared to the results in Table 2, the influence is more pronounced with a standard deviation of up to 38 compared to 2 in the previous table, as shown in Table 3.

The state of health of wheels brought into second-life remains the most important factor in determining which operation is the most cost effective. Indeed, Table 4 shows a standard deviation of more than 43 compared to the previous 38 and 2. If the second-life operation guarantees “As Good As New” wheels, maintenance costs are reduced from 200 to 111. Otherwise, depending on the level of degradation of the

Table 2. Influence of the second-life service rate (μ_{sl}) on minimum costs

μ_{sl} (comp/day)	<i>Maintenance</i> _{Cost}				Standard deviation
	0.67 ^a	0.33	0.22	0.17 ^b	
r (%)					
0	200	200	200	200	0
10	188	188	186	185	1
20	175	176	172	174	2
30	163	163	163	162	0
40	154	153	153	151	1
50	143	143	143	144	0
60	136	134	137	138	2
70	127	129	128	132	2
80	121	123	123	123	1
90	117	117	118	117	0
100	112	112	112	111	0

^a $\mu_{sl} = \mu_{rp_i}$; ^b $\mu_{sl} = \mu_{nw}$

Table 3. Influence of the second-life operation cost (c_{sl}) on the minimum costs

c_{sl}	<i>Maintenance</i> _{cost}				Standard deviation
	0.1 ^a	0.4	0.7	1 ^b	
r (%)					
0	200	200	200	200	0
10	185	190	195	199	6
20	172	180	189	198	11
30	162	175	187	200	16
40	151	166	181	197	20
50	143	161	180	198	24
60	134	156	177	198	27
70	127	150	173	196	30
80	121	146	171	196	33
90	117	145	172	199	35
100	111	141	170	200	38

^a $c_{sl} = c_{rpi}$; ^b $c_{sl} = c_{nw}$

Table 4. Influence of the second-life health state (i_{sl}) on the minimum costs

i_{sl}	<i>Maintenance</i> _{cost}				Standard deviation
	0 ^a	1	2	3 ^b	
r (%)					
0	200	200	200	200	0
10	185	197	200	200	7
20	172	192	199	201	13
30	162	189	199	201	18
40	151	184	199	202	23
50	143	182	199	202	28
60	134	180	200	204	32
70	127	174	200	206	36
80	121	171	200	208	39
90	117	172	201	207	41
100	111	170	198	208	43

^a "As Good As New"; ^b "As Bad As Old"

second-life wheels, costs can be reduced ($i_{sl} = 1$ or 2) or not ($i_{sl} = 3$).

5. CONCLUSION

The objective of this paper was to propose a model of a closed-loop repair shop and to evaluate the impact of the component life cycle in such a structure. It was found that the cost and quality of second-life operations can be critical to the performance of a repair shop in the long term. Considering the complete life cycle of components allows to consider all the operations that a component could undergo at the end of its life, sometimes profitable and sometimes not. The model and the results obtained could be used as a decision support tool for company managers to choose the proportion of components put into second life that is profitable in the long term.

For the further development of this study, it would be interesting to propose a continuous life cycle instead of the

proposed discrete one. In this case, the degradation could follow a more realistic law such as the Weibull distribution which models the degradation of equipment throughout their life cycle. In addition to the railway domain, a case study in other domains could allow to generalise the results.

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