

MIT Open Access Articles

Smart recovery decision-making of used industrial equipment for sustainable manufacturing: belt lifter case study

The MIT Faculty has made this article openly available. **Please share** how this access benefits you. Your story matters.

As Published: <https://doi.org/10.1007/s10845-018-1439-2>

Publisher: Springer US

Persistent URL: <https://hdl.handle.net/1721.1/131527>

Version: Author's final manuscript: final author's manuscript post peer review, without publisher's formatting or copy editing

Terms of Use: Article is made available in accordance with the publisher's policy and may be subject to US copyright law. Please refer to the publisher's site for terms of use.



**Smart Recovery Decision-making of Used Industrial Equipment for Sustainable
Manufacturing: Belt Lifter Case Study**

Kai Meng ^a

Email: kmeng17@mit.edu

^aDepartment of Mechanical Engineering,
Massachusetts Institute of Technology, Cambridge, Massachusetts, USA

Xiaoming Qian ^{b,c *}

Email: drqian@nuaa.edu.cn

^bCollege of Mechanical and Electrical Engineering,
Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, China
^c Jiangsu Key Laboratory of Precision and Micro-Manufacturing Technology,
Nanjing, Jiangsu, China

Peihuang Lou ^{b,c}

Email: mecphlou@nuaa.edu.cn

^bCollege of Mechanical and Electrical Engineering,
Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu, China
^c Jiangsu Key Laboratory of Precision and Micro-Manufacturing Technology,
Nanjing, Jiangsu, China

Jiong Zhang ^d

Email: john1225cn@126.com

^dMiracle Automation Engineering Co., LTD
Wuxi, Jiangsu, China

* Corresponding author

Smart Recovery Decision-making of Used Industrial Equipment for Sustainable Manufacturing: Belt Lifter Case Study

Abstract

End-Of-Life (EOL) product recovery is proved to be an attractive way to achieve sustainable manufacturing while extending the producer's responsibility to closed-loop product service. However, it is still a challenge to provide flexible and smart recovery plans for industrial equipment at different periods of product service. In this paper, we investigate the smart recovery decision-making problem. We propose a system framework for the implementation of smart EOL management based on product condition monitoring. Different product-level EOL business strategies and component-level recovery options are suggested in this recovery decision support system. Then, multi-objective optimization models are formulated to identify the age-dependent recovery roadmap that best matches the product condition and meets the business goals. In order to achieve environmentally friendly recovery, both recovery profits and energy performances are optimized in our models. We conduct a case study of belt lifter used in the automobile assembly line. The Non-dominated Sorting Genetic Algorithm II is used to solve the proposed model. Numerical experiments validate our models and provide practical insights into flexible recovery business.

Keywords: Sustainable manufacturing; Product recovery; End-of-life management; Smart manufacturing; Multi-objective optimization.

Highlights:

- We aim to achieve flexible recovery planning while ensuring economic and environmental sustainability.
- We propose an implementation framework for smart EOL management to enable age-based recovery decision-making.
- We build multi-objective optimization models to identify the best EOL solution at both product- and component-level.
- A case study of industrial lifter is elaborated to validate our model.

Abbreviations

AHP	Analytic Hierarchy Process
BCD	Buy-back and Component Dismantling
BOM	Bill of Material
BOR	Buy-back and Overall Remanufacturing
EOL	End-of-Life
ERM	Early Retirement Mode
IoT	Internet of Things
OEM	Original Equipment Manufacturer
PLM	Product Life-cycle Management
MACBETH	Measuring Attractiveness by a Categorical Based Evaluation Technique
MOIP	Multi-Objective Integer Programming
MCDM	Multi-Criteria Decision-Making
NRM	Normal Retirement Mode
NSGA	Non-dominated Sorting Genetic Algorithm
POS	Pareto Optimal Set
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
RCS	Refurnishing for Clunkers Service
RUL	Remaining Useful Life
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

Introduction

Emerging changes in service-oriented sustainable manufacturing shift the managerial focus of the Original Equipment Manufacturers (OEMs) to sustainable business operation (Tao et al., 2011; Ovchinnikov et al., 2014; Wang et al., 2014; Kuik et al., 2016; Ding et al., 2017). Sustainable operation requires a green Product Life-cycle Management (PLM) (Jayal et al., 2010; Dekker et al., 2012). To cope with this challenge, the OEMs need to extend the producer responsibilities to the End-of-Life (EOL) stage of their products. Accordingly, used products are supposed to be properly collected and recovered to exploit the remaining values and provide a new service-life in an environmentally friendly way (Shokohyar et al., 2014). Such EOL business is driven by not only the incentive of cost recovery but also the increasing demand for smart PLM.

In order to enable successful EOL business, recovery decision-making plays a crucial role. An efficient and effective recovery decision can avoid profit losses while achieving

sustainability. Different from the electronic products such as cellphone and computer, an industrial equipment has a long life-span and a large-scale structure with high added-value. Commonly, it consists of a number of mechanical and electrical components such as shafts, motors, gearboxes, and other structure parts. Although the whole equipment may have failed when faced with retirement, its component might be still functional or even have a good quality (Go et al., 2012; Zhang et al., 2013). There are two common ways to extend its service life and enhance its residual useful value. One is to remanufacture the overall equipment to restore it into a nearly brand-new condition. The other strategy is to disassemble, refurbish and reuse its components (Guo et al., 2014; Johnson and McCarthy, 2014). EOL business practitioners need to identify the best recovery plan from a variety of alternatives to meet both economic and environmental goals.

However, it has always been a challenge to handle this task due to the uncertainties associated with the equipment condition. Age-dependent degradation need to be considered to figure out the optimal recovery plan according to the real status of the used equipment (Ondemir and Gupta, 2014; Ng and Song, 2015). To this end, the OEMs need to gather more information throughout the product lifecycle to support recovery decision-making. Advanced smart technologies such as Internet of Things (IoT) and intelligent sensors have offered potential solutions by enhancing the information tracking, gathering and serving (Cao et al., 2011; Yoon et al., 2012; Wang et al., 2014; Fang et al., 2015; Chen et al., 2017). Sensor-embedded products can alleviate the uncertainties through product status sensing, which leads to a more efficient disassembly and recovery (Huang et al., 2008; Parlikad and McFarlane, 2010; Ilgin and Gupta, 2011; Ondemir et al., 2012; Kumar et al., 2013; Kumar et al., 2015; Dulman and Gupta, 2018). Further, a green closed-loop management can be implemented based on their own data platform (Li et al., 2015; Iijima and Takata, 2016).

In such a context, recovery decision-making has increasingly gained attention. After a thorough literature review (as summarized in Table 1), we can find that most studies focus on the product-level or component-level decision-making, separately. Johnson and McCarthy (2014) investigated the tradeoff between remanufacturing and de-manufacturing. Component recovery decisions were also considered. However, environmental performances are not fully examined in their profit-maximization model. Also, few of the previous researches considered

different business strategies and recovery plans for EOL products with different service ages. Product service age was mostly qualitatively considered rather than quantitatively incorporated into the decision model. Actually, the potential recovery value can be quite different at different service ages. It's critical and feasible to draw an age-based recovery roadmap with the help of smart sensing and analysis techniques. However, there is still a lack of decision-making model to provide such flexible recovery plans for used industrial equipment.

The purpose of this paper is to fill these gaps while exemplifying a case study of industrial belt lifter. The contributions lie in the following aspects: first, a condition-based EOL management framework was proposed to provide an overall concept model for smart recovery decision-making; Second, we developed multi-objective optimization models to identify the age-based recovery decisions at both product- and component-level. Also, economic and environmental performances were balanced to ensure sustainability. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was applied to solve the models and thus obtain the Pareto optimal solutions. In addition, we suggested different recovery business strategies according to different service/retirement periods.

The remainder of this article is organized as follows. Section 2 reviews the related studies. A framework of smart EOL management is built in Section 3. Then, Section 4 presents the recovery decision-making optimization model and approach. Case study and scenario experiments are discussed in Section 5. Finally, Section 6 concludes our work and discusses the future work.

Table 1. Comparison of the existing studies on recovery decision-making

Research work	Decision level/depth		Objectives/Criteria		Age Factor
	Product	Component	Economic	Environmental	
Bufardi et al. (2004)	√		√	√	
Chan (2008)	√		√	√	
Xing and Luong (2009)	√		(Product characteristics)		
Du et al. (2012)	√		√	√	
Remery et al. (2012)	√		√	√	√
Goodall et al. (2014)	√		√	√	
Ondemir and Gupta (2014)	√		√	√	√
Ovchinnikov et al. (2014)	√		√	√	
Ziout et al. (2014)	√		√	√	√

Dhouib (2014)	√		√	√	
Ng and Song (2015)	√		√	√	√
Dehghanbaghi et al. (2016)	√		√	√	
Jun et al. (2007)		√	√		
Lee et al. (2010)		√	√		√
Zhou et al. (2012)		√	(Product characteristics)		
Shokohyar et al. (2014)		√	√	√	√
Yang et al. (2015)		√	√	√	√
Ma and Okudan Kremer (2015)		√	√	√	
Johnson and McCarthy (2014)	√	√	√		
Our work	√	√	√	√	√

Literature Review

Most researches focused on the product-level recovery decision problem. A variety of Multi-Criteria Decision-Making (MCDM) approaches have been developed to assess the comprehensive reusability or remanufacturability of EOL products (Bufardi et al., 2004; Chan, 2008; Xing and Luong, 2009; Subramoniam et al., 2010; Du et al., 2012; Zhou et al., 2012; Goodall et al., 2014). Remery et al. (2012) established a multi-criteria evaluation system to select the best recovery option in terms of income, cost, compliance with regulation and environmental performance. A fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was used to incorporate the designer's knowledge. Ziout et al. (2014) provided an AHP (Analytic Hierarchy Process)-based holistic and flexible decision-making model considering all the interests of stakeholders involved in the reverse logistics. Dhouib (2014) developed a fuzzy MACBETH (Measuring Attractiveness by a Categorical Based Evaluation Technique) approach, which is a well-established interactive multi-criteria decision-making technique, to assess and rank the recovery options. Ondemir and Gupta (2014) built a mixed integer goal programming model to determine whether a product need to be remanufactured, disassembled, repaired or recycled to meet different market demands. In their study, remaining useful life was utilized to represent the quality state of an EOL product. Ovchinnikov et al. (2014) presented an analytical model to assess

the economic and environmental performances of product remanufacturing strategies in service-oriented sustainable manufacturing. Ng and Song (2015) proposed a hierarchical multi-criteria recovery decision-making framework based on product condition evaluation and life cycle analysis. Dehghanbaghi et al. (2016) developed a combined approach of fuzzy rule-based reasoning system and fuzzy AHP to determine the best recovery strategy. A two-phase comprehensive evaluation system was established to assess both product properties (i.e. technical, commercial and ecological properties) and process properties (i.e. economic return, simplicity, service and environmental impacts).

Some other studies took component recovery into account. Yang et al. (2015) proposed an EOL decision-making method to assess the remanufacturability of multiple EOL components while balancing economic revenue and environmental impact. An overall index that considered component quality was formulated and used as an indicator of remanufacturability. Ma and Okudan Kremer (2015) designed a fuzzy-logic based assessment framework for recovery decision-making from the perspective of sustainability and designer's preferences. Economic, environmental and societal criteria were considered to recognize the best recovery option. Dulman and Gupta (2018) utilized the discrete event simulation method to evaluate the performances of maintenance and EOL treatment with the purpose of investigating the value of sensor-embedded disassembly system. Mathematical programming models were also widely utilized to deal with the component-level recovery decision-making problem. Jun et al. (2007) proposed a multi-objective mixed integer programming model to address the problem of recovery optimization. A heuristic evolutionary algorithm was designed to solve this problem. Lee et al. (2010) modeled the profit-maximization problem as an integer programming model. A bottom-up decision approach was proposed to handle the hierarchical structure. In each layer, the branch and bound technique was used to search for the best option for each part. Niknejad and Petrovic (2014) proposed a two-phase mixed integer programming model to optimize the integrated reverse logistics network. Two component recovery routes, remanufacturing and repair, were considered in this model. Johnson and McCarthy (2014) presented a 0-1 integer programming model to identify the optimal recovery plan of remanufacturing versus de-manufacturing. To deal with conflicting goals and a vast number of candidate combinational solutions, several studies developed

meta-heuristic algorithms to solve the multi-objective recovery optimization problem. Shokohyar et al. (2014) developed a multi-objective mixed integer non-linear programming model to make a tradeoff between economic and environmental effects. Optimal EOL recovery options were determined by the NSGA-II. Kuik et al. (2016) proposed a profit-maximization model to identify the optimal recovery option under various practical constraints such as manufacturing lead-time, waste proportion and product reliability. They designed a GA to solve their model.

The abovementioned studies provided valuable models and methodologies for recovery decision-making. Nevertheless, few of them can help achieve age-based recovery planning at both product- and component- level while considering economic and environmental effects. To address this problem, this work aims to develop a flexible recovery planning mechanism to assist the practitioners in making efficient EOL decisions at different service-life periods.

Smart EOL management framework

We examine the recovery decision-making problem by a case study on industrial belt lifter used in the automobile assembly line. The belt lifter considered is used as a conveying equipment to transfer the car bodies between the underslung conveying system and the mobile skillet system. It consists of six major components (subassemblies): spindle, bearing, bearing base, motor, gear reducer and main belt, as shown in Fig.1.

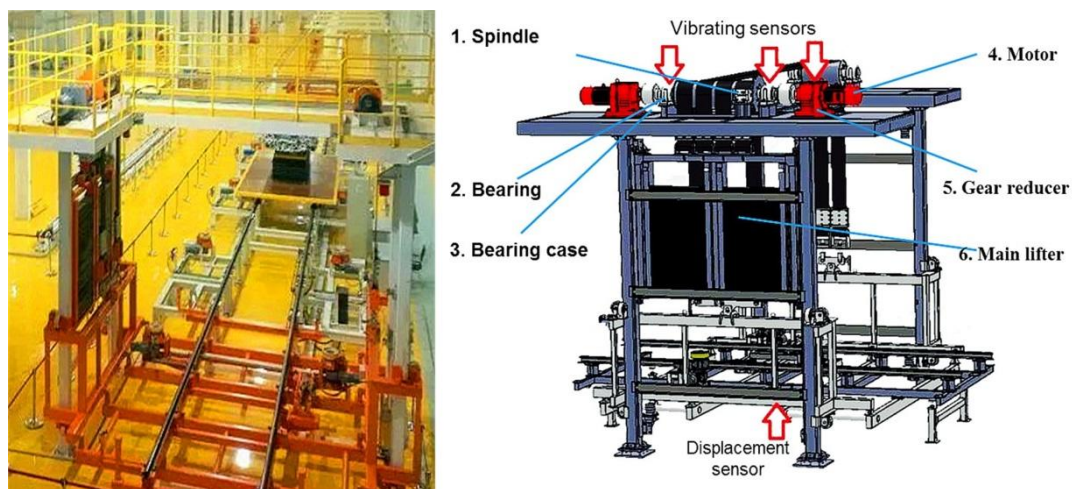


Fig.1 Belt lifter used in the automobile assembly line

In order to achieve closed-loop recovery service, we establish an EOL management

framework to aid the EOL practitioners in understanding a more smart and profitable path to environmentally friendly recovery. The system is built upon an existing remote condition-monitoring platform. Fig.2 depicts the proposed framework. The primary function modules are discussed as below.

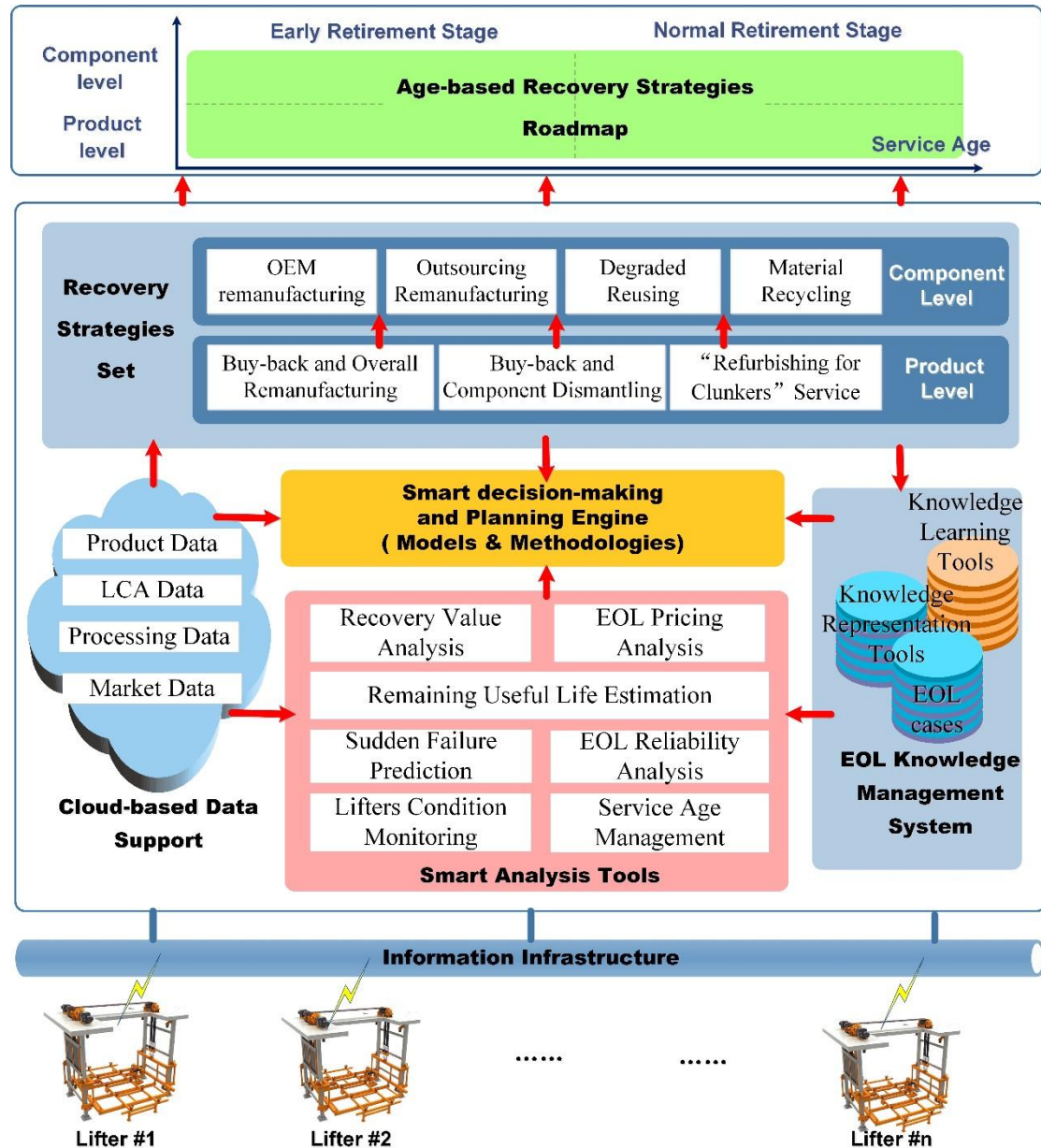


Fig. 2 Smart EOL management framework

(1) **Advanced information infrastructure.** This is the key to enable condition monitoring and information sharing. Real-time condition data of the belt lifters distributed in different factories can be gathered automatically. The condition data includes various I/O data and sensor data acquired from the controllers. Vibrating sensors are used to monitor the status of the spindle, bearings and reducers. Displacement sensors are deployed to detect the

elongation of the main belt.

(2) **Cloud-based data support.** Product life-cycle data is required for EOL decision-making, including but not limited to product BOM (Bill of Material), structure model, life-cycle analysis list, manufacturing/remanufacturing process data, forward/reverse logistics records, and market data. Data collection relies on the information tracking and sharing mechanism among the OEM, suppliers and EOL business partners based on a public or community cloud platform. These data can be considered as decision input for smart analysis. More available information can contribute to a more effective EOL management.

(3) **EOL knowledge management system.** This system aims to exploit the decision rules and EOL knowledge from historical cases to support smart analysis and recovery decision-making, such as providing the empirical operation parameters for algorithms, estimating the priori distribution parameters of mean useful life, improving the model via sample training and learning.

(4) **Smart analysis tools.** Original condition data needs to be processed to extract valuable information to enable subsequent recovery planning. Remaining useful life (RUL) is considered as a measure of product/component quality status in this study. RUL can be estimated by the hybrid analysis of historical condition data, current service age and reliability characteristics (Zhang et al., 2013; Meng et al., 2017a). For tactical recovery planning, RUL is assumed dependent on the natural degradation process. It can be calculated by subtracting current service age from the estimated service life. When implementing real-time planning for individual lifter, RUL can be obtained by competing failure prediction techniques, $RUL = \min(rul_1, rul_2)$, where rul_1 and rul_2 are the RUL estimations based on natural deterioration process and sudden failure probability, respectively. Then, age-based component recovery value and cost can be assessed and further an appropriate pricing strategy can be determined for each reused or refurbished component.

(5) **Recovery strategies set.** Both product- and component- level recovery strategies are suggested in this system. For component recovery, according to the OEM's recovery capabilities, different recovery options are recommended as follows. a) Spindle. It's a high added-value and self-made component. The OEM intends to renovate it unless it completely and physically fails. If the spindle is still in a good quality, it can be directly reused as a spare

component or resold for degraded usage. However, if a complete failure occurs, the spindle is supposed to be recycled to reclaim the materials. b) Bearing. This purchased component has relatively low replacement cost. We consider material recycling for its recovery. c) Bearing base. The OEM will remanufacture, reuse or recycle this self-made component according to its service age and EOL status. d) Motor. It's a purchased component with a long service-life. Reusing and recycling are considered in this study. e) Gear reducer. It has a high replacement cost but also a high recovery value. The OEM plans to implement a remanufacturing outsource strategy by cooperating with a third-party reducer remanufacturer. f) Main belt. This is a high-value purchased component but hard to remanufacture. Reusing and recycling are suggested according to its service age and performance status.

Two different retirement modes are considered for product-level recovery strategies. One is the Early Retirement Mode (ERM), referring to the lifters that are still in a normal condition but retired due to some special circumstances such as production line updating. Otherwise, Normal Retirement Mode (NRM) is considered to deal with the EOL lifters. System degradation and RUL can be recognized by the smart analysis tools. Here, an empirical critical retirement age based on the maintenance history, 10000 hours, is suggested by the OEM for tactical recovery planning. For the ERM, the OEM intends to choose one of the following strategies: Buy-back and Overall Remanufacturing (BOR) or Buy-back and Component Dismantling (BCD). BOR means remanufacturing the whole equipment while BCD suggests to disassemble the equipment into components for reusing or recycling. For the NRM, the OEM offers Refurnishing for Clunkers Service (RCS) to the customers. The used lifter can be refurnished to a quality "as good as new" for their original user.

(6) **Smart decision-making and planning engine.** This module provides the decision-making models and methodologies to find the best recovery solutions. We will elaborate the details of this aspect in the next section.

Recovery decision-making model and approach

Economic profits and energy performance are considered as two optimization goals in the decision-making model. Energy performance, including the energy consumptions and savings,

is a good measure of environmental effects. It is also considered as an indirect indicator of cost saving when recovering a used lifter instead of fabricating a new one. In addition, we suppose that the used lifter should be completely disassembled in all the three strategies. To simplify our models, all the common cost items. i.e. disassembly cost, cleaning cost, test cost, management cost, etc., are included in the miscellaneous cost. The nomenclatures used in our models are as follows.

Indexes

- i Index for component, $i=1, 2, \dots, 6$
- o Index for component recovery option, 1 for remanufacturing, 2 for reusing, 3 for material recycling
- s Index for equipment recovery strategy, 1 for BOR, 2 for BCD, 3 for RCS

Parameters

- N_s Net profits gained by implementing recovery strategy s
- E_s Energy savings gained by implementing recovery strategy s
- I_{io} Recovery income of component i if recovery option o is assigned
- C_{io} Recovery cost of component i if recovery option o is assigned
- C_{iu} Maximum remanufacturing cost of component i
- C_{il} Minimum remanufacturing cost of component i
- C_{os} Other miscellaneous cost when implementing recovery strategy s
- α_i Reuse depreciation factor of component i
- ε_{io} Shape factor of the cost or revenue curves for component i with recovery option o
- P_r Suggested price for the remanufactured lifter
- P_b Buy-back price of the used lifter
- P_i Procurement/replacement cost of component i
- ES_{io} Energy saving of component i with recovery option o
- EC_{io} Energy consumption of component i with recovery option o
- EC_{iu} Maximum energy consumption for remanufacturing component i
- EC_{il} Minimum energy consumption for remanufacturing component i
- t_i Actual service age of component i
- $rul_i(t_i)$ Remaining useful life of component i at service age t_i

U_i Minimal requirement on the remaining useful life for reusing component i

Decision variable

$r_{s,io}$ Decision variable for component recovery option, 1 if component i is assigned with recovery option o in strategy s , otherwise 0

The models for BOR, BCD and RCS are formulated respectively. In the BOR strategy, recovery revenues come from reselling the remanufactured product and its recovered components. The costs for BOR mainly involves buy-back, remanufacturing, component replacement, and other miscellaneous costs. the net-profit is defined as below:

$$N_1 = P_r + \sum_{i=1}^6 \sum_{o=2}^3 r_{1,io} (R_{io} - C_{io} - P_i) - P_b - \sum_{i=1}^6 r_{1,i1} C_{i1} - C_{o1} \quad (1)$$

Energy effects refer to the energy saving via component recovery compared to component fabrication. However, recovery processing also needs energy consumption. The energy consumption associated with component replacement is supposed to be as same as the energy required for fabricating a new one. Net energy saving is calculated by formula (2).

$$E_1 = \sum_{i=1}^6 \sum_{o=2}^3 r_{1,io} (ES_{io} - EC_{io}) - \sum_{i=1}^6 \sum_{o=2}^3 r_{1,io} ES_{i1} \quad (2)$$

For the BCD strategy, all the revenues are obtained by component recovery. No component needs to be replaced. The calculations of recovery revenue and energy savings are given below:

$$N_2 = \sum_{i=1}^6 \sum_{o=1}^3 r_{2,io} (N_{io} - C_{io}) - P_b - C_{o2} \quad (3)$$

$$E_2 = \sum_{i=1}^6 \sum_{o=1}^3 r_{2,io} (ES_{io} - EC_{io}) \quad (4)$$

The RCS strategy is similar with the BOR strategy whilst RCS remanufactures the used lifter for its original user rather than resells it. Thus, the buy-back cost is no longer considered:

$$N_3 = P_r + \sum_{i=1}^6 \sum_{o=2}^3 r_{3,io} (R_{io} - C_{io} - P_i) - \sum_{i=1}^6 r_{3,i1} C_{i1} - C_{o3} \quad (5)$$

$$E_3 = \sum_{i=1}^6 \sum_{o=2}^3 r_{3,io} (ES_{io} - EC_{io}) - \sum_{i=1}^6 \sum_{o=2}^3 r_{3,io} ES_{i1} \quad (6)$$

Both remanufacturing costs and reusing revenues depend on the quality state of the used component. By using the RUL indicator, service-age dependent economic functions are constructed in the formula (7)-(9). Here, remanufacturing cost is empirically estimated based on its service age and RUL (Ferguson et al., 2009). Different from the other components, remanufacturing cost of the gear reducer (C_{5l}) depends on the negotiated price for remanufacturing outsourcing service, given in formula (8). Reuse value is determined by its age-based resale revenue (formula (9)). In addition, it should be noted that component service-age is not absolutely as same as system service-age due to the maintenance and replacement operations.

$$C_{i1}(t_i) = C_{iu} - (C_{iu} - C_{il}) \left(\frac{rul_i(t_i)}{t_i + rul_i(t_i)} \right)^{\varepsilon_{i1}} \quad \forall i = 1, 3 \quad (7)$$

$$C_{51}(t_5) = C_{5u} \left(\frac{t_5}{t_5 + rul_5(t_5)} \right)^{\varepsilon_{51}} \quad (8)$$

$$R_{i2}(t_i) = \alpha_i P_i \left(\frac{rul_i(t_i)}{t_i + rul_i(t_i)} \right)^{\varepsilon_{i2}} \quad (9)$$

Then, we can formulize the optimization problem for the ERM and NRM decisions as below:

$$\text{ERM: } \max(\max(N_1, E_1), \max(N_2, E_2)) \quad (10)$$

$$\text{NRM: } \max(N_3, E_3) \quad (11)$$

$$\text{s.t. } \sum_{o=1}^3 r_{s,io} = 1 \quad \forall s, i \quad (12)$$

$$r_{s,i2} U_i \leq rul_i \quad \forall s, i \quad (13)$$

$$r_{s,io} \in \{0, 1\} \quad (14)$$

Where, constraint (12) ensures that each component is assigned only one recovery option in each strategy, constraint (13) describes the minimal RUL requirement for component reusing, and constraint (14) refers to the decision variable attributes.

The proposed models (formula (1)-(11)) include three different Multi-Objective Integer Programming (MOIP) problems. They are also typical multi-objective discrete combinational optimization problems. Exact enumeration method can be applicable for handling simple cases. However, in order to make our approach capable of efficiently dealing with various complex scenarios, a meta-heuristic algorithm is suggested to be incorporated into our decision-making engine. Since Pareto optimal solutions can aid the decision-makers in better understanding and evaluating the solutions on multi-objective performances, we choose the classic NSGA-II to solve the proposed models. The NSGA-II has been proved to be an efficient tool for obtaining the Pareto Optimal Set (POS) (Deb et al., 2000; Chaube et al., 2012; Shokohyar et al., 2014; Zhou et al., 2016; Torabi et al., 2017; Zhou et al., 2017).

In this study, each chromosome individual has six genes to represent the recovery options for the corresponding six components. Integer coding is adopted to represent the options, where 1 for remanufacturing, 2 for reusing and 0 for material recycling. The non-dominated sorting technique is used to rank the individuals by comparing their economic and energy performances (formula (1)-(4) or (5)-(6)). One-point crossover and gene swap operations are applied respectively to generate child individuals and maintain the population diversity. In each iteration, the parent and child populations are combined and sorted to form a new population by truncation. Also, the individuals with no dominators, termed as Pareto optimal solutions, are recorded and updated. For more operational details, please refer to (Deb et al., 2000; Shokohyar et al., 2014; Meng et al., 2017b). Finally, the decision maker can select the best solution from the limited number of Pareto optimal solutions by making the tradeoffs between recovery profits and energy savings. Since there are finite solutions in the final optimization frontier, a lot of conventional MCDM techniques can be used, such as AHP, TOPSIS and Preference ranking organization method for enrichment evaluation (PROMETHEE). Here, a simple weight-based aggregate method suggested by Shokohyar et al. (2014) is utilized for our case, as shown in equation (15). Noted that various MCDM tools can be offered in the decision-making engine from which the decision-makers can choose their preferred approach.

$$B_s = \arg \min \left(\frac{\omega_N (\max N^s - N^s)}{\max N^s} + \frac{\omega_E (\max E^s - E^s)}{\max E^s} \right) \quad (15)$$

where N^s and E^s are recovery net-profits and energy savings of the S^{th} Pareto solution, ω_N and ω_E are the preference weights, and B_s is the best solution obtained by minimizing the weighted sum of objective value deviations.

In summary, the major procedures of our approach are described as shown in Fig. 3.

Step 1: Obtain various product life-cycle information from the cloud-based EOL management platform.

Step 2: Select the decision-making model according to the system service-age and degradation condition. If the lifter is at the stage of ERM, model (10) is applied for subsequent recovery planning. Otherwise, model (11) is suggested.

Step 3: Model solving. The NSGA-II is utilized to search for the POS. For the ERM, both BOR and BCD models need to be solved for the subsequent comparison analysis while only RCS model needs to be addressed for the NRM.

Step 4: Recovery decision-making to meet the economic and environmental criteria. For the NRM, the Pareto optimal solutions of BOR and BCD are combined and then they are sorted to generate a new POS. For the NRM, RCS is the unique recovery strategy. Afterwards, a final decision is made by applying the formula (15) into the obtained POS to identify both product-level recovery strategy and component-level recovery options.

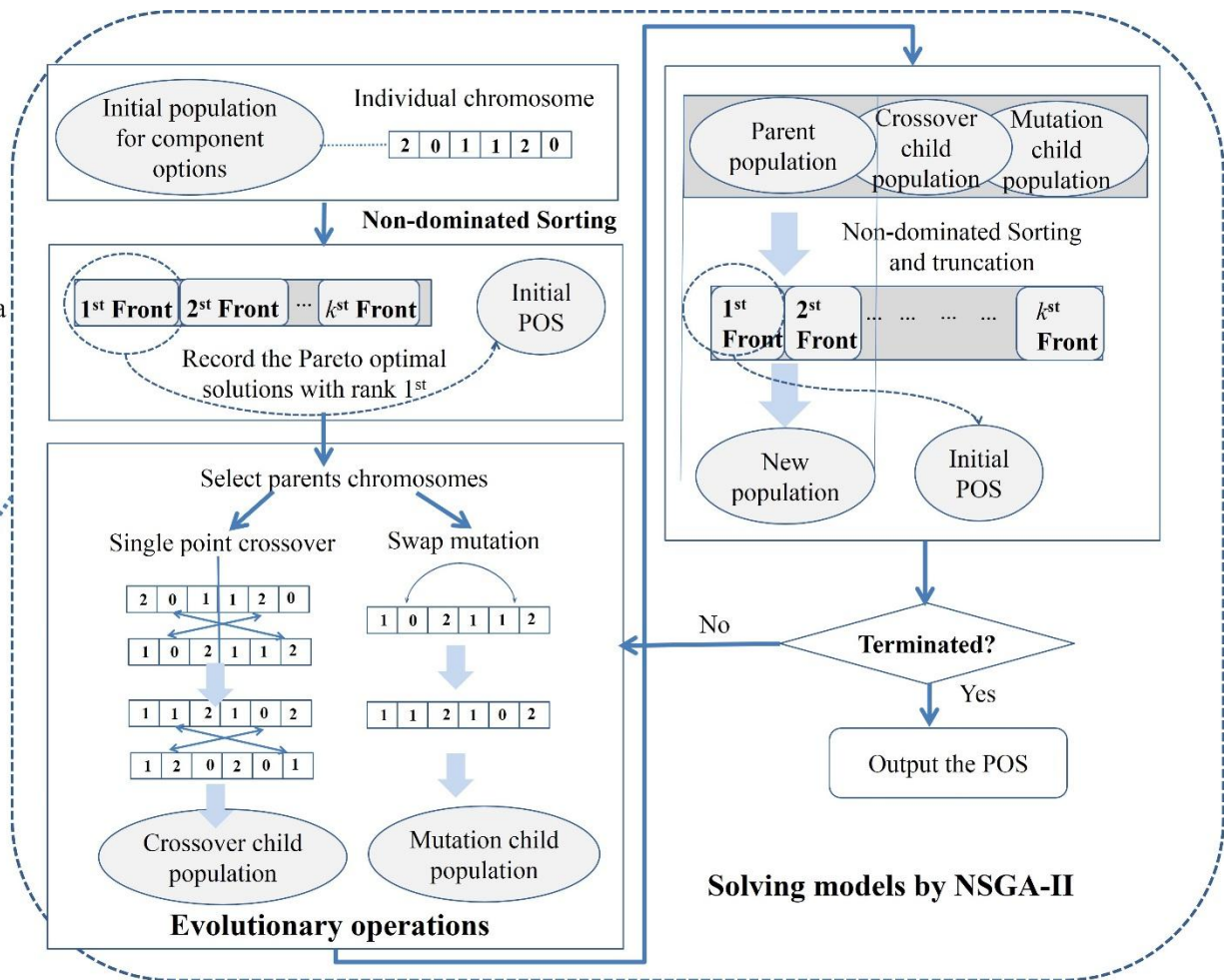
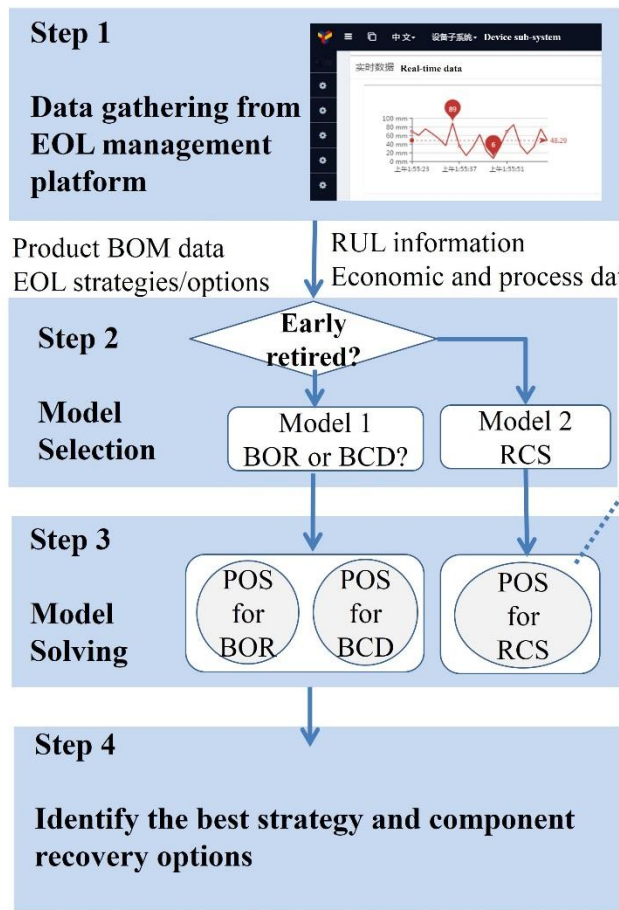


Fig. 3. Major procedures of smart recovery decision-making

Tactical recovery planning and discussion

A tactical recovery planning is performed to attain a recovery roadmap for both ERM and NRM. The range of service-age is from 2000 hours to 24000 hours. An empirical threshold (10000h) is considered as a critical age between ERM and NRM. All the basic information of the lifter and its estimated economic and energy performances are listed in Table 1, where the mean life of each component is estimated by the OEM based on the failure event records. For tactical decision-making, we suppose that the RUL of a component is the difference between the mean life and its actual service age. According to the failure records provided by the condition monitoring platform, sudden failure occasionally occurs to the spindle. Taking this situation into account, we consider two operation circumstances: one, all the components run under the normal maintenance operations. No component except the main belt needs to be replaced until the whole system fails. The main belt is supposed to be replaced at every 7530 hours. In the other circumstance, a sudden failure of the spindle occurs at the age of 9000h. Thus, there are two components that need to be replaced during the service life. In practice, a more exact estimation of the sudden failure can be obtained through online conditional RUL prediction based on the smart EOL management platform.

In order to examine the impacts of decision preferences on the tactical decisions, we consider two types of decision weights for the two objectives, profit-maximization weights (1, 0) and balanced weights (0.5, 0.5). Therefore, four decision scenarios are studied in this case: (1) normal operation and profit-maximization preference, (2) normal operation and balanced preference, (3) sudden failure and profit-maximization preference, and (4) sudden failure and balanced preference.

Table 2. Basic information of the lifter used in the automobile assembly line

Component	Spindle	Bearing	Bearing case	Motor	Gear reducer	Main belt
Mass /kg	45.0	6.9	12.5	189.0	111.0	29.3
Material	Alloy steel	Bearing steel	Cast steel	Cast steel, alloy steel, carbon steel, silicon steel, copper	alloy steel, carbon steel	High-strength steel wire composite polyurethane
$R_{i1}/10^4$ RMB	1.25	N/A	0.8	N/A	2	N/A
$R_{i2}/10^4$ RMB	$R_{12} = 0.8 \cdot (1 - \frac{t_1}{25100})^4$	N/A	$R_{32} = 0.48 \cdot (1 - \frac{t_3}{25100})^4$	$R_{42} = 0.9 \cdot (1 - \frac{t_4}{50200})^4$	$R_{52} = 2.5 \cdot (1 - \frac{t_5}{25100})^4$	$R_{62} = 3 \cdot (1 - \frac{t_6}{7530})^4$
$R_{i3}/10^4$ RMB	0.3060	0.0020	0.0016	0.1366	0.0311	0.0498
$C_{i1}/10^4$ RMB	$C_{11} = 1 - 0.8 \cdot (1 - \frac{t_1}{25100})^4$	N/A	$C_{31} = 0.6 - 0.5 \cdot (1 - \frac{t_3}{25100})^4$	N/A	$C_{51} = 2 \cdot (\frac{t_5}{25100})^{0.5}$	N/A
$P_i/10^4$ RMB	1.5	0.3	0.8	1.5	4.0	4.8
$ES_{i(i2)}/MJ$	3555	541.15	711.25	10593.45	5938.5	3398.8
ES_{i3}/MJ	2295.0	349.4	361.3	5301.5	2830.5	2900.7
EC_{iu}/MJ	315.0	48.0	87.5	1323.0	777.0	117.2
EC_{i1}/MJ	25.2	3.8	7.0	105.8	62.2	9.4
EC_{i3}/MJ	113.4	17.3	31.5	476.3	279.7	73.8
$U_i/hour$	12850	N/A	12850	12550	10040	2510

Through applying the proposed approach, a recovery roadmap for the four scenarios are obtained as given in Appendix 1. The NSGA-II is coded by MATLAB R2017b. It should be noted that the algorithm parameter setting should be adjusted according to the product complexity. Considering there are only 6 components in the lifter, a small population is sufficient and efficient to achieve global combinational optimization for such simple case. Accordingly, we set the size of the population as same as the number of components $N=6$. A relatively high crossover rate (0.5) and a low mutation rate (0.2) are adopted to maintain the population diversity without any damage to the convergence process. Numerical experiments show that the NSGA-II performs a good convergence for this case. Fig.4(a)~4(d) give several examples of the convergence curves in the BCD optimization at the service-age of 4000h and 8000h. The corresponding Pareto optimal solutions are also shown in Fig.4(e)~(f). It can be found that the solutions are relatively uniformly distributed on the Pareto frontier. Moreover, Fig.5 depicts how the optimal recovery net-profits and energy savings change as the system service-age increases in different decision scenarios.

From the results, we can obtain several interesting observations and provide practical insights into recovery decisions of the industrial lifter.

First, decision preference plays a critical role in the selection of product-level recovery strategy for the early retired lifter (ERM) before 8000 hours. If the firm pursues profit-maximization, remanufacturing the whole lifter (BOR) is the absolute dominating strategy (Scenario 1). In contrast, the BCD strategy appears better if balanced sustainable performances are expected (Scenario 2). The reason for why the BCD strategy brings more environmental benefits than the BOR strategy in the ERM lies in the facts that no component needs to be replaced in the BCD strategy as well as components with good quality require less refurbishment efforts and thus less energy consumptions. However, the situation changes when the system service-age reaches 10000 hours under the normal maintenance operations. The best strategy in Scenario 2 turns into the BOR strategy. This is mainly because the increasing deterioration of EOL components causes more cost and energy consumption in the BCD strategy compared to BOR. This observation can also be partially proved by the results of Scenario 4. In addition, if the spindle is replaced due to sudden failure, BCD is the first choice for all the ERM lifters.

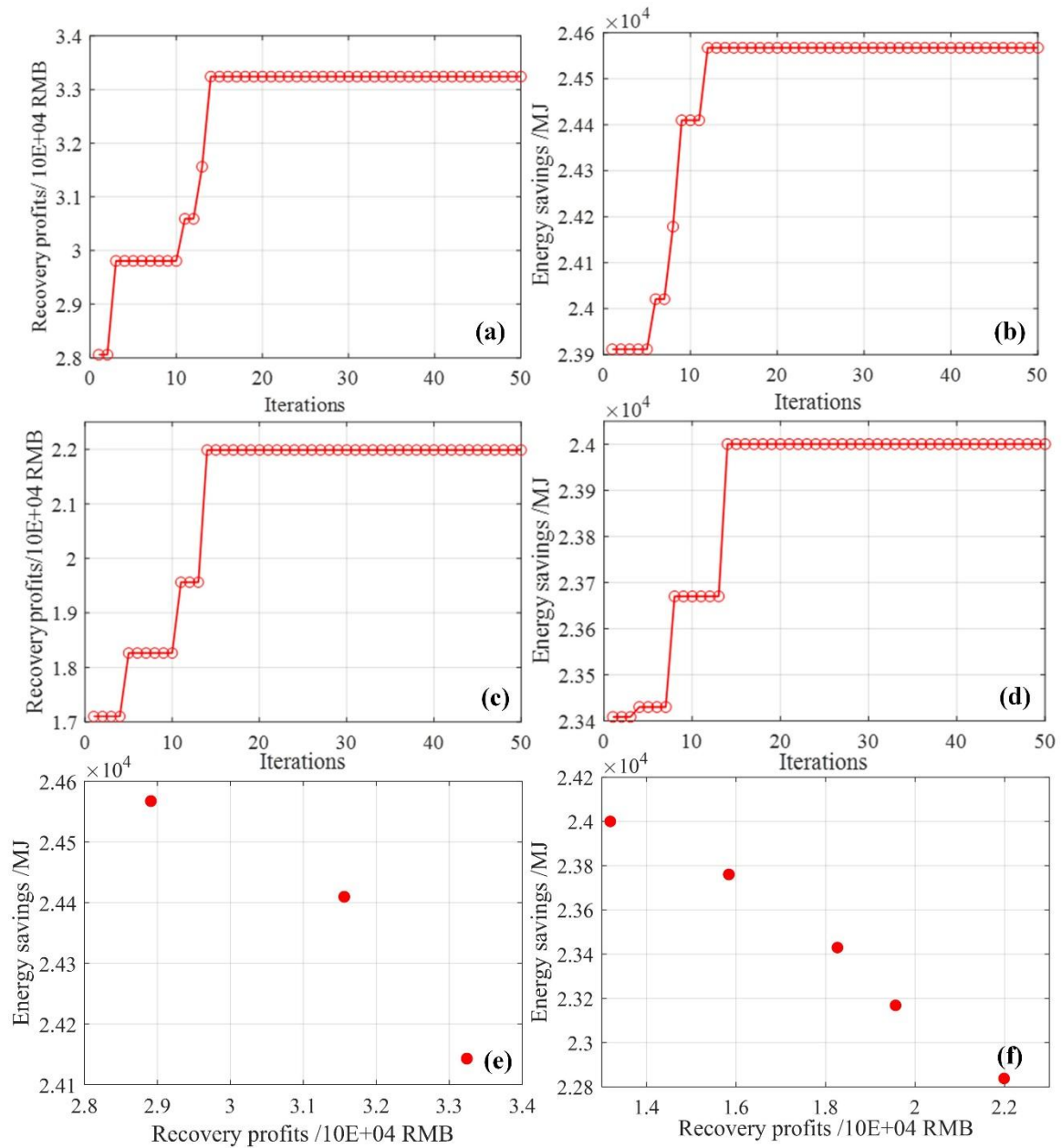
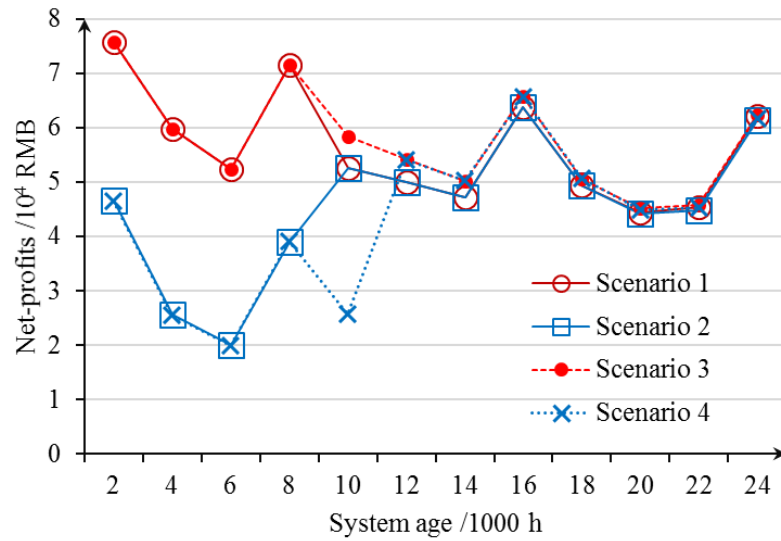


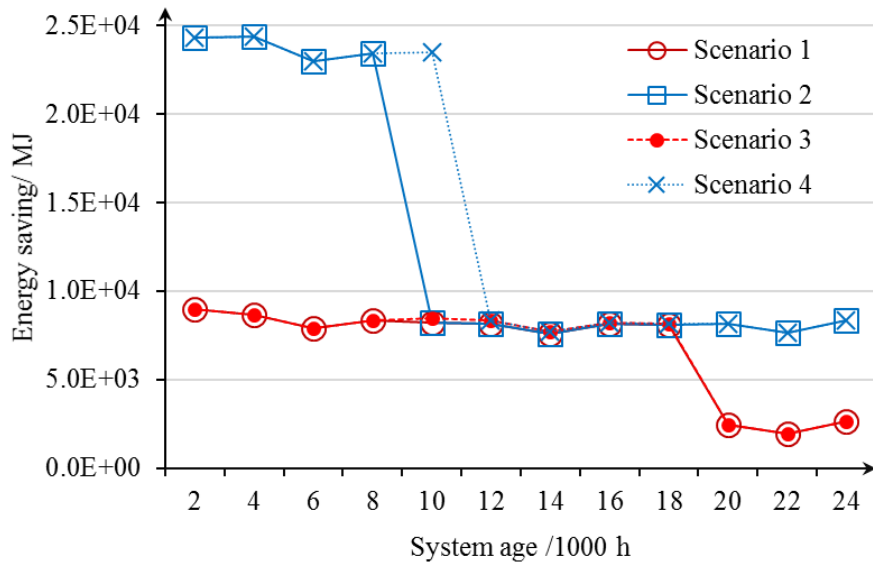
Fig. 4 Convergence curves and Pareto solutions (BCD strategy at 4000h (a, b, e) and 8000h (c, d, f))

Second, an interesting finding for the normal retired lifters is that component recovery options, except for the motor, appear to be insensitive to either product-level strategy or decision preference in all the four scenarios. This is good news for the lifter OEM since it can support more stable designs for recovery processing schemes, routes and facilities. For the motors over 20000h, recycling is the most profitable choice. However, it can be found from Fig.5(b) that motor recycling leads to a significant drop of energy savings compared to reusing. Therefore, direct or degraded reusing is still suggested if the working efficiency of

the motor is acceptable for the customer.



(a) Recovery net-profit



(b) Energy saving

Fig.5 Economic and energy performance

Further, the best component-level recovery options are suggested as follows: if technically feasible, remanufacturing is recommended for the spindle no matter which product-level strategy is chosen. From the perspective of balanced sustainable benefits, the bearing case can be reused when its age is less than 4000h, otherwise, remanufacturing is a better option. It would be better to reuse the motors in most scenarios as mentioned above. As for the main belt, the results suggest it to be recycled when its service-age is over 6000h. In

addition, material recycling is recommended for the bearings and the severely degraded motors.

The last but not the least, an obvious periodic fluctuation in the total net-profits can be observed as illustrated in Fig. 5(a). The profit fluctuation over time is primarily caused by the periodic replacement of the main belt, which is a high-value critical component. Fortunately, the deterioration progress of the main belt elongation presents a good approximate linearity. Nevertheless, considering its significant impacts on recovery profits, an online RUL estimation is expected to be more helpful to avoid profit loss. Based on the availability of the real-time estimation, our model can help achieve a more exact decision-making.

Conclusion

This work focused on the recovery decision-making problem for EOL industrial equipment, aiming to help the OEMs to make an age-dependent recovery plan at both product- and component-level. With the help of cloud-based service platform and advanced condition monitoring, we proposed a framework for smart EOL management to enable flexible recovery planning. Different product-level EOL businesses strategies and component-level recovery process options were considered. In order to identify the best recovery solution, we built multi-objective optimization models to take both economic and environmental sustainability into account. We used the NSGA-II to get the Pareto optimal solutions of the proposed models and investigated the impacts of decision preference on the final decisions. A case of industrial belt lifter was studied to validate our model.

Numerical experiments show that our approach performs as an effective decision support tool for recovery decision-making under various scenarios. However, when putting the proposed framework and approach into large-scale practices, two potential limitations need to be further addressed: one, reliable and creditable condition monitoring is the footstone on which the proposed framework is established. Data unavailability or condition misestimation can lead to wrong recovery decisions. The other limit lies in the fact that the parameter setting of metaheuristic algorithm is scenario-sensitive. In order to search for the global optima, the

algorithm parameters need to be finely adjusted for different scenarios, especially when handling complicated industrial products. More intelligent rules or interactive optimization mechanisms can be expected to solve this problem.

In addition to the aforementioned challenges, there are several other interesting directions for the future research: first, online real-time recovery decision-making can be further studied. Online RUL prediction models need to be designed. Condition monitoring platform can provide strong data basis for using information fusion and machine learning to address this problem. However, it remains challenging to extract useful information from the “big data” of equipment condition and then make precise estimation for degradation progress, especially for those non-linear degradation processes. Second, more market-related factors, i.e. customer perceived value, price fluctuation of the recycled items, and policy subsidies, can be incorporated in the model to better describe the relationship between recovery economic performance and second-hand market. Finally, the joint decision-making of predictive maintenance service and product recovery can be studied to extend the equipment service life and determine the best time point for recovery without any sacrifice of sustainability.

Acknowledgement

This work was supported by the Fundamental Research Funds for the Central Universities in China [NO. NS2017028].

References

- Bufardi, A., R. Gheorghe, D. Kiritsis & P. Xirouchakis (2004). Multicriteria decision-aid approach for product end-of-life alternative selection. *International Journal of Production Research*, 42 (16), 3139-3157.
- Cao, H., P. Folan, D. Potter & J. Browne (2011). Knowledge-enriched shop floor control in end-of-life business. *Production Planning & Control*, 22 (2), 174-193.
- Chan, J. W. K. (2008). Product end-of-life options selection: grey relational analysis approach.

International Journal of Production Research, 46 (11), 2889-2912.

Chen, S., J. Yi, X. Zhu, H. Jiang & W. Ju (2017). RFID-based integrated method for electromechanical products disassembly decision-making. *International Journal of Computer Integrated Manufacturing*, 30 (2-3), 229-254.

Chaube, A., L. Benyoucef, & M. K. Tiwari (2012). An adapted NSGA-2 algorithm based dynamic process plan generation for a reconfigurable manufacturing system. *Journal of Intelligent Manufacturing*, 23(4), 1141-1155.

Deb, K., S. Agrawal, A. Pratap & T. Meyarivan (2000). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. International Conference on Parallel Problem Solving from Nature, Springer Berlin Heidelberg, 849-858.

Dehghanbaghi, M., H. Hosseini nasab & A. Sadeghieh (2016). A hybrid approach to support recovery strategies (A case study). *Journal of Cleaner Production*, 113, 717-729.

Dekker, R., J. Bloemhof & I. Mallidis (2012). Operations Research for green logistics – An overview of aspects, issues, contributions and challenges. *European Journal of Operational Research*, 219 (3), 671-679.

Dhouib, D. (2014). An extension of MACBETH method for a fuzzy environment to analyze alternatives in reverse logistics for automobile tire wastes. *Omega*, 42 (1), 25-32.

Ding, K., P. Jiang & M. Zheng (2017). Environmental and economic sustainability-aware resource service scheduling for industrial product service systems. *Journal of Intelligent Manufacturing*, 28 (6), 1303 – 1316.

Du, Y., H. Cao, F. Liu, C. Li & X. Chen (2012). An integrated method for evaluating the remanufacturability of used machine tool. *Journal of Cleaner Production*, 20 (1), 82-91.

Dulman, M. T. & S. M. Gupta (2018). Evaluation of Maintenance and EOL Operation Performance of Sensor-Embedded Laptops. *Logistics*, 2 (1), 3.

Fang, H. C., S. K. Ong & A. Y. C. Nee (2015). Use of Embedded Smart Sensors in Products to Facilitate Remanufacturing. *Handbook of Manufacturing Engineering And Technology*. London, Springer London, 3265-3290.

Ferguson, M., V. D. Guide, E. Koca & G. C. Souza (2009). The Value of Quality Grading in Remanufacturing. *Production and Operations Management*, 18 (3), 300-314.

Go, T. F., D. A. Wahab, M. N. A. Rahman, R. Ramli & A. Hussain (2012). Genetically

- optimised disassembly sequence for automotive component reuse. *Expert Systems with Applications*, 39 (5), 5409-5417.
- Goodall, P., E. Rosamond & J. Harding (2014). A review of the state of the art in tools and techniques used to evaluate remanufacturing feasibility. *Journal of Cleaner Production*, 81, 1-15.
- Guo, S., G. Aydin & G. C. Souza (2014). Dismantle or remanufacture? *European Journal of Operational Research*, 233(3), 580 - 583.
- Huang, G. Q., Y. F. Zhang, X. Chen & S. T. Newman (2008). RFID-enabled real-time wireless manufacturing for adaptive assembly planning and control. *Journal of Intelligent Manufacturing*, 19 (6), 701-713.
- Iijima, H. & S. Takata (2016). Condition based renewal and maintenance integrated planning. *CIRP Annals - Manufacturing Technology*, 65 (1), 37-40.
- Ilgin, M. A. & S. M. Gupta (2011). Performance improvement potential of sensor embedded products in environmental supply chains. *Resources, Conservation and Recycling*, 55 (6), 580-592.
- Jayal, A. D., F. Badurdeen, O. W. Dillon & I. S. Jawahir (2010). Sustainable manufacturing: Modeling and optimization challenges at the product, process and system levels. *CIRP Journal of Manufacturing Science and Technology*, 2 (3), 144-152.
- Johnson, M. R. & I. P. McCarthy (2014). Product recovery decisions within the context of Extended Producer Responsibility. *Journal of Engineering and Technology Management*, 34, 9-28.
- Jun, H. B., M. Cusin, D. Kiritsis & P. Xirouchakis (2007). A multi-objective evolutionary algorithm for EOL product recovery optimization: turbocharger case study. *International Journal of Production Research*, 45 (18-19), 4573-4594.
- Kuik, S. S., T. Kaihara & N. Fujii (2016). Product Recovery Configuration Decisions for Achieving Sustainable Manufacturing. *Procedia CIRP*, 41, 258-263.
- Kumar, V. V., F. W. Liou, S. N. Balakrishnan & V. Kumar (2015). Economical impact of RFID implementation in remanufacturing: a Chaos-based Interactive Artificial Bee Colony approach. *Journal of Intelligent Manufacturing*, 26(4), 815-830.
- Lee, H. B., N. W. Cho & Y. S. Hong (2010). A hierarchical end-of-life decision model for

- determining the economic levels of remanufacturing and disassembly under environmental regulations. *Journal of Cleaner Production*, 18 (13), 1276-1283.
- Li, J., F. Tao, Y. Cheng & L. Zhao (2015). Big Data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology*, 81 (1-4), 667-684.
- Ma, J. & G. E. Okudan Kremer (2015). A fuzzy logic-based approach to determine product component end-of-life option from the views of sustainability and designer's perception. *Journal of Cleaner Production*, 108, 289-300.
- Meng, K., P. Lou, X. Peng & V. Prybutok (2017a). Quality-driven recovery decisions for used components in reverse logistics. *International Journal of Production Research*, 55 (16), 4712-4728.
- Meng, K., P. Lou, X. Peng & V. Prybutok (2017b). Multi-objective optimization decision-making of quality dependent product recovery for sustainability. *International Journal of Production Economics*, 188, 72-85.
- Ng, Y. T. & B. Song (2015). Product Characteristic Based Method for End-of-Life Product Recovery. *Handbook of Manufacturing Engineering and Technology*, Springer London, 3377-3403.
- Niknejad, A. & D. Petrovic (2014). Optimisation of integrated reverse logistics networks with different product recovery routes. *European Journal of Operational Research*, 238 (1), 143-154.
- Ondemir, O., M. A. Ilgin & S. M. Gupta (2012). Optimal End-of-Life Management in Closed-Loop Supply Chains Using RFID and Sensors. *IEEE Transactions on Industrial Informatics*, 8 (3), 719-728.
- Ondemir, O. & S. M. Gupta (2014). Quality management in product recovery using the Internet of Things: An optimization approach. *Computers in Industry*, 65 (3), 491-504.
- Ovchinnikov, A., V. Blass & G. Raz (2014). Economic and Environmental Assessment of Remanufacturing Strategies for Product + Service Firms. *Production and Operations Management*, 23 (5), 744-761.
- Parlikad, A. K. & D. McFarlane (2010). Quantifying the impact of AIDC technologies for vehicle component recovery. *Computers & Industrial Engineering*, 59 (2), 296-307.
- Remery, M., C. Mascle & B. Agard (2012). A new method for evaluating the best product

- end-of-life strategy during the early design phase. *Journal of Engineering Design*, 23 (6), 419-441.
- Shokohyar, S., S. Mansour & B. Karimi (2014). A model for integrating services and product EOL management in sustainable product service system (S-PSS). *Journal of Intelligent Manufacturing*, 25 (3), 427-440.
- Subramoniam, R., D. Huisinigh & R. B. Chinnam (2010). Aftermarket remanufacturing strategic planning decision-making framework: theory & practice. *Journal of Cleaner Production*, 18 (16-17), 1575-1586.
- Tao, F., L. Zhang, V. C. Venkatesh, Y. Luo & Y. Cheng (2011). Cloud manufacturing: a computing and service-oriented manufacturing model. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 225 (10), 1969-1976.
- Torabi, S. H. R., S. Alibabaei, B. B. Bonab, M. H. Sadeghi, & G. Faraji (2017). Design and optimization of turbine blade preform forging using RSM and NSGA II. *Journal of Intelligent Manufacturing*, 28(6), 1409-1419.
- Wang, L., X. V. Wang, L. Gao & J. Váncza (2014). A cloud-based approach for WEEE remanufacturing. *CIRP Annals - Manufacturing Technology*, 63 (1), 409-412.
- Xing, K. & L. Luong (2009). Modelling and evaluation of product fitness for service life extension. *Journal of Engineering Design*, 20 (3), 243-263.
- Yang, S. S., S. K. Ong & A. Y. C. Nee (2015). EOL strategy planning for components of returned products. *The International Journal of Advanced Manufacturing Technology*, 77 (5-8), 991-1003.
- Yoon, J., S. Shin & S. Suh (2012). A conceptual framework for the ubiquitous factory. *International Journal of Production Research*, 50 (8), 2174-2189.
- Zhang, X. G., H. Zhang, Z. G. Jiang & Y. H. Wang (2016). A decision-making approach for end-of-life strategies selection of used parts. *The International Journal of Advanced Manufacturing Technology*, 87(5-8), 1457-1464.
- Zhou, J., P. Huang, Y. Zhu & J. Deng (2012). A quality evaluation model of reuse parts and its management system development for end-of-life wheel loaders. *Journal of Cleaner Production*, 35, 239-249.

Zhou, Q., Y. Rong, X. Shao, P. Jiang, Z. Gao, & L. Cao (2016). Optimization of laser brazing onto galvanized steel based on ensemble of metamodels. *Journal of Intelligent Manufacturing*. <https://doi.org/10.1007/s10845-015-1187-5>. (online)

Zhou, Q., Y. Yang, P. Jiang, X. Shao, L. Cao, J. Hu, Z. Gao, & C. Wang (2017). A multi-fidelity information fusion metamodeling assisted laser beam welding process parameter optimization approach. *Advances in Engineering Software*, 110, 85-97.

Ziout, A., A. Azab & M. Atwan (2014). A holistic approach for decision on selection of end-of-life products recovery options. *Journal of Cleaner Production*, 65, 497-516.

Appendix 1.

Recovery roadmap of the lifter used in the automobile assembly line*

Scenario	Decision level	System age	Early Retirement Stage					Normal Retirement Stage							
			2000	4000	6000	8000	10000	12000	14000	16000	18000	20000	22000	24000	
Scenario 1	Product Level	BOR	✓	✓	✓	✓	✓								
		BCD													
		RCS						✓	✓	✓	✓	✓	✓	✓	✓
	Component Level	1	●	●	●	●	●	●	●	●	●	●	●	●	●
		2	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇
		3	●	●	●	●	●	●	●	●	●	●	●	●	●
		4	■	■	■	■	■	■	■	■	■	◇	◇	◇	◇
5		●	●	●	●	●	●	●	●	●	●	●	●	●	
6		■	■	◇	■	■	■	■	◇	■	■	■	◇	■	
Scenario 2	Product Level	BOR					✓								
		BCD	✓	✓	✓	✓									
		RCS						✓	✓	✓	✓	✓	✓	✓	✓
	Component Level	1	●	●	●	●	●	●	●	●	●	●	●	●	●
		2	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇
		3	●	●	●	●	●	●	●	●	●	●	●	●	●
		4	■	■	■	■	■	■	■	■	■	■	■	■	■
5		■	■	●	●	●	●	●	●	●	●	●	●	●	
6		■	■	◇	■	■	■	■	◇	■	■	■	◇	■	
Scenario 3	Product Level	BOR	✓	✓	✓	✓	✓								
		BCD													
		RCS						✓	✓	✓	✓	✓	✓	✓	✓
	Component Level	1	●	●	●	●	●	●	●	●	●	●	●	●	●
		2	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇
		3	●	●	●	●	●	●	●	●	●	●	●	●	●
		4	■	■	■	■	■	■	■	■	■	■	◇	◇	◇
5		●	●	●	●	●	●	●	●	●	●	●	●	●	
6		■	■	◇	■	■	■	■	◇	■	■	■	◇	■	
Scenario 4	Product Level	BOR													
		BCD	✓	✓	✓	✓	✓								
		RCS						✓	✓	✓	✓	✓	✓	✓	✓
	Component Level	1	●	●	●	●	●	●	●	●	●	●	●	●	●
		2	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇	◇
		3	●	●	●	●	●	●	●	●	●	●	●	●	●
		4	■	■	■	■	■	■	■	■	■	■	■	■	■
5		■	■	●	●	●	●	●	●	●	●	●	●	●	
6		■	■	◇	■	■	■	■	◇	■	■	■	◇	■	

*The symbol ● denotes remanufacturing, ■ for reusing, and ◇ for recycling.