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The ‘Internet of Things’ enabled real-time scheduling for remanufacturing of automobile engines

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Abstract: Typical challenges that managers of remanufacturing face are composed of the lack of timely, accurate, and consistent information of remanufacturing resources. Therefore, it is difficult to implement real-time production scheduling for the shop floor. To address this problem, the authors applied the concept of the ‘Internet of Things’ to the remanufacturing of automobile engines to form an Internet of Manufacturing Things environment. Under the Internet of Manufacturing Things, an identification technology for disassembled engine parts was designed, and the real-time status of the remanufacturable resources can be monitored. Based on the captured remanufacturing information, a real-time production scheduling method was developed, and a mathematical model was developed to achieve cost reduction, dynamic management of remanufacturable resources, and energy consumption decrease. To obtain an optimal solution, a Pareto-based optimization method was used. Finally, a case study was performed to analyze the effectivity of the proposed method. The results showed that the remanufacturing cost and energy consumption were reduced by 34% and 34% respectively, and the worker load rate was more balanced. These improvements can contribute to more sustainable development and greener production within the remanufacturing industry, especially for remanufacturing of automobile engines.

Keywords: Remanufacturing; Internet of Things; Production optimization; Real-time scheduling

1. Introduction

Currently, the manufacturing industry is facing ever growing challenges imposed by the highly demanding constraints ranging from the sustainable development policies related to the end-of-use products to the real-time production scheduling of manufacturing resources, as well as cleaner production and green manufacturing. Remanufacturing greatly contributes to optimizing the use of materials, reducing resource and energy consumption, lowering production costs, and alleviating environmental pollution. It is an effective way to make progress towards sustainable development and cleaner production, which is beneficial to improve the energy efficiency and to reduce environmental impacts.

Remanufacturing has the capability to transform worn components into “like-new” remanufactured products back into services, thus retaining much of the embedded energy and material value of the initial products. Robert Lund, one of the first researchers in this area, provided remanufacturing visionary leadership in the field of remanufacturers in the late 1970s and early 1980s (Lund and Denny, 1977; Lund and Skeels, 1983).

The remanufacturing process begins with the collection of the used parts. It includes the following steps: complete or partial disassembly of products, parts cleaning, inspection and storage of parts, reconditioning and replacement of parts, and reassembly of products, further producing “like-new” products even better than new products in quality and performance. The latest statistical data of remanufacturing industry from the website reported that the remanufacturing industry, expected by 2030 in EU, attains an annual value of €70bn and €100bn with the associated employment of 450,000 and almost 600,000 respectively (Parker et al., 2016). Remanufacturing is a promising option to improve sustainable competitive advantages under today’s global economic recession (Liu, 2013; Liu and Liang, 2015).

The automobile industry is one of the largest industries in remanufacturing, with 70% of all remanufacturing companies operating in the automobile sectors (Kumar et al., 2007; Steinhilper et al., 2011; Zhang et al., 2011). It is a fact that China is the “global manufacturing factory” and one of the largest automobile producers and markets (Amighini, 2012). The continuous and rapid increase of vehicles intensified the interest in remanufacturing and its related policies based on extended product responsibility (Xiang and Ming, 2011). Tian et al. (2014) established an

1 integrated structural diagram of the technological system for the development of China's
2 automobile component remanufacturing industry, to ensure the quality of remanufactured products.
3 Wang et al. (2014) also introduced a new enabling technology-cloud manufacturing into waste
4 electrical and electronic equipment remanufacturing, and designed a novel cloud-based
5 service-oriented remanufacturing platform for manufacturing enterprises. However, how to deal
6 with end-of-life vehicles (ELVs) and parts in a more sustainable manner will be an increasingly
7 urgent challenge in the coming years as a result of the growing number of new vehicles.

8 An overview of used-product remanufacturing was developed, which documented the key
9 motivating factors, sources, markets, characteristics, and remanufacturing processes
10 (Andrew-Munot et al., 2015). The increasing amount of automobile export and the management of
11 ELVs provided automobile engine (AE) manufacturers with significant advantages on
12 remanufacturing of automobile engines (AER) and opportunities for further research on
13 production scheduling methods. It is clear that remanufacturing retains most of the embedded
14 value of materials, achieves the added value during product remanufacturing, and provides good
15 opportunities for companies to increase productivity and profitability (Giuntini and Gaudette,
16 2003). Moreover, the remanufacturing activities, which contribute to environmental and economic
17 benefits under the integrated product service offering, include design, recycling, remanufacturing,
18 reuse, maintenance, holistic planning, and operations (Lindahl et al., 2014). Then, based on the
19 present situation of the engine remanufacturing industry and the government policy, Zhang and
20 Chen (2015) analyzed the characteristics and development trend of the engine remanufacturing
21 industry. Although AER is undergoing profound changes by using the 'Internet of things' (IoT),
22 real-time scheduling for AER is still facing the following challenges:

- 23 (1) There are many deficiencies in the remanufacturing processes such as the lack of timely,
24 accurate, and consistent information of manufacturing resources. Therefore,
25 implementing the real-time production scheduling for AER is difficult. Then, how to
26 sense and capture the real-time information of manufacturing resources through
27 constructing the Internet of Manufacturing Things (IoMT) environment?
- 28 (2) The following characteristics of remanufacturing seriously complicate AER: (i) the
29 uncertain materials recovered from the used AE such as different models and degrees of
30 damage; (ii) the complexity in planning, execution, and control of remanufacturing

operation, etc. These characteristics can be grouped into two major categories: the availability of timely and high-quality key parts and the remanufacturability of key parts (Flapper et al., 2002).

(3) Production scheduling issues in the remanufacturing shop floor are more complex than that in the manufacturing shop floor and require significant modifications compared to traditional production scheduling. The effect of that on cost, energy consumption (electricity), and worker load is a vital restriction factor to implement universal remanufacturing. Therefore, how to structure a real-time data-driven optimization for production scheduling based on the real-time information of manufacturing resources is the key to achieving efficient control over AER process and multi-objective optimization of production scheduling for AER.

The lack of real-time and accurate information of remanufacturing resources, production exceptions, machine breakdown, frequent changes of production planning, and tardiness of finished parts lead to frequent rescheduling in the shop floor. These problems were widely recognized by scholars such as Baker and Scudder (1990), Frantzen et al. (2011), Chen et al. (2015), and Zhang et al. (2017a, b). As a result, there is a significant increase in the cost, energy consumption, and delivery tardiness, and this makes it difficult to achieve the optimal scheduling for AER. To address these problems, the IoT-enabled real-time scheduling is proposed for the dynamic decision-making of multi-objective real-time scheduling of AER. Real-time information of manufacturing resources is sensed and captured based on the constructed IoMT environment. When abnormal events occur, they can be sensed and the production plan is re-scheduled, which is named real-time scheduling. This method can achieve the quick response to abnormal events, and minimize the loss of cost, energy, and delivery tardiness.

The remainder of this paper is organized as follows. Section 2 presents the literature review. The overall architecture of IoT-enabled real-time shop floor management is developed in Section 3. Section 4 establishes a multi-objective real-time optimization model of production scheduling, and Section 5 describes a Pareto approach for particle swarm optimization (PSO)-based real-time production scheduling. A case study is used to demonstrate the proposed method in Section 6. Finally, conclusions and future work are given in Section 7.

2. Literature review

Three streams of literature are relevant to this research. They are the application of advanced technologies in remanufacturing, the optimization methods in multi-objective scheduling, and maintenance scheduling and reassembly scheduling.

2.1. The application of advanced technologies in remanufacturing

Advanced technologies and management methods should be applied to optimize remanufacturing production and make remanufacturing more intelligent (Fang et al., 2013; Ferrern et al., 2011; Zhang et al., 2017c, d). IoT technology, especially radio frequency identification technology (RFID), has been widely used in supporting the production and scheduling management of manufacturing shop floor. For example, manufacturing resources equipped with RFID tags are converted into smart manufacturing objects that are able to sense and interact, and IoT technology is used to create a ubiquitous IoMT environment. This provides an available approach for the acquisition of real-time information of manufacturing resources. Then, Qu et al. (2014) described the configuration of the IoMT environment, both qualitatively and quantitatively. Under the real-time information capturing and integration framework of IoMT, the real-time information of manufacturing resources can be sensed and captured (Zhang et al., 2014). After capturing the dynamic information of AE parts, instead of directly entering the optimization stage, adaptive controlling mechanisms are entailed to achieve the added value and management of real-time information (Qu et al., 2012, and 2015). Based on value-added multi-source manufacturing data, Zhong et al. (2013) proposed an RFID-enabled real-time manufacturing execution system for a typical mass-customization production company, where RFID devices were deployed in the shop floor. Thus, the tracking and traceability of manufacturing resources can be achieved. However, the abnormal events such as changes of production planning, machine breakdown, and production exception, are frequent in the manufacturing shop floor and cause the increase in the cost and energy consumption. To address these abnormal events efficiently, the IoT-enabled real-time production performance analysis and exception diagnosis model based on hierarchical-timed-colored Petri net was developed to identify the causes of exception (Zhang et al., 2016). In addition, with the complexity of manufacturing pattern increasing, the integration of cloud computing (CC) and IoT, such as CC-and IoT-based cloud manufacturing service system,

was applied to deal with production scheduling problems (Tao et al., 2014). Further, Zhong et al. (2015a, b) established a real-time advanced production planning and scheduling model for RFID-enabled ubiquitous manufacturing and introduced a Big Data approach for mining the trajectory knowledge from enormous RFID-enabled logistics data. The real application of these advanced techniques is a strong support in the construction of sensing networks in the physical manufacturing layer from the perspective of framework and strategy.

2.2. The optimization methods in multi-objective scheduling

The optimization method of production scheduling is also a key part of achieving IoT-enabled real-time scheduling for AER, which is a multi-objective scheduling optimization problem. Some state-of-the-art literature conducted on multi-objective scheduling optimization problems. Many optimization algorithms, for example, ant colony optimization algorithm (ACO), genetic algorithm (GA), tabu search algorithm (TS), and their evolved algorithms (Loukil et al., 2005; Li et al., 2010; Marichelvam et al., 2014; Xing et al., 2009; Yagmahan et al., 2010), were developed to solve multi-objective job shop or flow shop scheduling problems. The search space of multi-objective scheduling problems is huge, and reducing the search space of obtaining initial optimal solutions for multi-objective scheduling problems contributes to improving the decision-making of production managers. The local/global search approaches such as PSO, and meta-heuristic algorithms were developed to solve the search space and find the near-optimal candidate results for multi-objective optimization problems (Hecker et al., 2014; Moslehi and Mahnamn, 2011; Zhang et al., 2009). In fact, these initial solutions are the optimal solution sets of scheduling problems rather than the final optimal solutions. Therefore, it is difficult for managers or scheduling planners to choose an appropriate solution. It is also almost impossible to obtain a single solution that is the optimal one of all objectives because of the conflicts among multiple objectives. To address this problem, Pareto optimization that is to achieve the optimal status of each objective was used to optimize multi-objective problems in research such as Gao et al. (2014), Moslehi and Mahnamn (2011), Taboada and Coit (2008), Tavakkoli-Moghaddam et al. (2011), and Sun et al. (2017). Moreover, Pareto optimal solutions for multi-objective problems can achieve the balance of multiple objectives.

2.3. Maintenance scheduling and reassembly scheduling

Real-time production scheduling for AER in this paper involved the maintenance scheduling and reassembly scheduling. A decision-making architecture of the maintenance and production scheduling policies based on the condition-monitoring information was presented to improve the system performance in terms of the expected average profits and the total maintenance costs (Lee and Ni, 2013). GA is a commonly used meta-heuristic technique for production scheduling problems (Wong et al., 2012; Go et al., 2012; Hecker et al., 2014). A significant paper for GA-based production scheduling was published by Go et al. (2012), in which the disassembly sequence of the engine block was optimized to ensure a cost-effective recovery of the ELV assembly. A big data analytics architecture for maintenance processes of complex products was also developed to provide better support for the decision-making of coordination and optimization on the product lifecycle management and the whole production process (Zhang et al., 2017e). However, most research about the shop floor scheduling either focused on the maintenance scheduling or reassembly scheduling. Currently, the main research on maintenance scheduling was the preventive and opportunistic maintenance (Vergin and Scriabin, 1977; Yao et al., 2004; Doostparast et al., 2014). The focus of this paper is not the preventive and opportunistic maintenance scheduling, but it is based on demands of reassembly for AEs in real time. The progress of research on methods of maintenance scheduling and reassembly scheduling was significant, but studies on production scheduling in real time were few. Although Bajestani et al. (2014) addressed the problem of maintenance and production scheduling in a deteriorating multi-machine production system, the interdependence between maintenance scheduling and reassembly scheduling was ignored, which was quite important to describe the mathematical-physical relation between them clearly. Lambert and Gupta (2016) explored the disassembly modeling for assembly, maintenance, reuse, and recycling through real-world case examples, and this provided a new channel to study the mathematical-physical interdependence to some extent. In addition, the production process, namely AER, contains the maintenance (parts) and reassembly process (assembly) of AEs. However, the real production process significantly deviated from the results of the planning process (Zhang et al., 2016), and this was one of the key factors to lead to the rescheduling. These shortages and problems existing in the production scheduling are worth studying.

3. IoT-enabled real-time shop floor management

The architecture of the IoT-enabled real-time shop floor management for AER based on IoMT is developed in Fig. 1. It aims to apply the IoT concept to remanufacturing and build a real-time information capturing and integration framework to implement the real-time data-driven production scheduling for the shop floor.

Fig. 1. IoT-enabled scheduling model for AER

Under this architecture, the IoMT environment for AER is constructed, and the important parameters such as the remanufacturability of components and real-time status of manufacturing resources can be timely sensed. The real-time tracking and tracing of each available manufacturing resource can also be achieved. Then, the whole remanufacturing process, namely the disassembly-maintenance-reassembly process, can be dynamically monitored. It can provide supervisors or processors with real-time information to achieve the optimization of production

scheduling. The proposed architecture comprises four sub-modules from the bottom to the top, namely the configuration of the IoMT environment, parts identification, real-time maintenance and reassembly scheduling, and the real-time material handling. They are described as follows:

(1) The configuration of the IoMT environment

The configuration of the IoMT environment is responsible for establishing a low-cost and high-reliability sensing IoMT environment, which is used to capture real-time manufacturing information. It consists of four steps. Firstly, a configuration model of sensing networks within various sensors is constructed to measure different parameters, and describe or label the manufacturing resources such as operators, pallets, machines, key components, and sensors. Then, based on the constructed IoMT environment, the real-time information of these manufacturing resources during AER process can be easily sensed and captured. For instance, when a cylinder head attached with RFID tags comes to a sensing area, this event can be sensed by the registered sensors. Through the transmission protocol, data of the manufacturing resources can be captured by sensors and transmitted to the upper handling mechanism. Finally, adaptive controlling mechanisms process insignificant information to form meaningful data (Qu et al., 2012, and 2015; Zhang et al., 2017f; Cai et al., 2014).

(2) Parts identification

Parts identification is used to define and encode AE parts used for remanufacturing. Some AE parts may have different degrees of wear and tear, even cracks as a result of the long-term mechanical movement and extreme working condition. Therefore, the remanufacturability of engine parts is classified into three situations: (i) non-destructive, involving no part demolition (loosening of screws, detachment, etc.); (ii) partially destructive, with demolition of cheap parts (removal of joints, torch cutting, high-pressure water cutting, laser cutting, etc.); (iii) completely destructive, with uncontrolled destruction of the product structure (crack, milling, shredding, etc.). For better understanding, engine parts corresponding to above-mentioned situations are defined as the directly reused parts, the remanufacturable parts, and the scrapped parts respectively. Then, an advanced identification technology for the disassembled engine parts is designed. The identification information of parts is integrated into different label forms orienting to various properties under the IoMT environment.

AE part is a primary research object of real-time production scheduling (RTPS) method for AER based on IoMT. As a result, AE parts identification technique is an essential and key link of constructing the engine remanufacturing chain. The framework of engine parts identification program is presented as Fig. 2. Three core sub-modules are designed, namely the classification of parts, identification of parts, and management of tags from the top to the bottom. Classification of parts is responsible for identifying and sorting the attributes of different engine parts. Firstly, the engines of ELVs are disassembled into parts. Secondly, due to the potential damage of the parts caused by some factors, the engine parts should be examined after cleaned. Thirdly, the examined results are input into the evaluation systems, and then the remanufacturability of the engine parts is analyzed and evaluated, which is defined as non-destructive, partially destructive, or completely destructive parts. Finally, the identification plans of three classification results are created.

For the remanufacturable engine parts, an RFID-enabled identification technology for engine parts is designed. It is a technology that incorporates the use of electromagnetic or electrostatic coupling in the radio frequency portion of the electromagnetic spectrum to uniquely identify objectives, and comprises three parts: reader, tag, and antenna. Various forms of tags are attached to resources in the IoMT environment such as human and parts with the different properties. These resources can, therefore, be identified by readers automatically without human intervention.

Management of tags involves usage, recycle, and reuse of tags. RFID tags can be immediately identified to capture the dynamic information of parts through web service. As the manufacturing resources attached with tags reach the coverage area of radio frequency, the real-time status can be read and transmitted to the intelligent terminal directly. Supervisors can monitor the real-time process. After completing a cycle of operation, previous storing content of tags is cleared automatically, and tags are recycled and reused in the next cycle.

Fig. 2. The framework of engine part identification program

(3) Real-time maintenance and reassembly scheduling

Real-time maintenance and reassembly scheduling is the key of real-time production scheduling. The change of production plan and production lag increase the complexity of optimization scheduling for AER. Therefore, real-time data-driven optimization is essential to overcome the above-mentioned issues, and a real-time data-driven method of engine parts maintenance and reassembly scheduling based on IoMT is proposed. Introducing a navigation technique (Zhang et al., 2015) for the engine parts based on process sensing can facilitate AER process to achieve the optimization of maintenance and reassembly scheduling accurately.

(4) Real-time material handling

Real-time material handling is responsible for processing insignificant data to form value-added information of remanufacturing resources. Simultaneously, it is also used to manage and monitor the accurate distribution of materials. For example, on the remanufacturable level, real-time location and standard process time can be shown on the intelligent terminal by scanning the tags attached within the engine block groups in the AER shop floor.

The multi-objective real-time optimization model of production scheduling for AER based on Pareto theory is established, considering the total remanufacturing cost, the labor intensity and capacity of workers, and the total energy consumption. RTPS has the following new characteristics such as sensibility and accessibility of manufacturing resources, active sensing and monitoring of manufacturing process, transmission of value-added multi-source manufacturing

information, and real-time dynamic optimization for production scheduling. In this research, we mainly focus on the real-time scheduling method of maintenance and reassembly for AER.

4. Multi-objective real-time optimization model of production scheduling

For the optimization of production scheduling, bi-objective problems that minimize the total energy consumption and the total weighted tardiness in the shop floor were investigated (Liu et al., 2014). Single objective or bi-objective optimization of production scheduling cannot be directly used to handle the real-time optimization of production scheduling for current AER due to the complexity and solution space of problems. Therefore, the multi-objective real-time production scheduling optimization method for AER based on IoMT is proposed.

The real-time production scheduling method for AER based on IoMT is a joint production scheduling of the reassembly scheduling (AS) and the maintenance scheduling (MS). AS and MS of AE parts are combined together to discuss in terms of the remanufacturing production criteria as below.

Assumptions: (i) each working process and production time of each product are known before planning; (ii) products are produced in sequence and the same production sequences are processed at the same workstation; (iii) batch products arrive at the same time in a cycle; (iv) a workstation can only deal with a product at the same time and the different working processes of a product cannot be dealt with simultaneously; (v) corresponding products can be processed right away when the needed equipment is ready or becomes idle; (vi) different products with similar production characteristics are produced on the assembly line which has a finite number of workstations; (vii) travel time of workers is ignored.

Notations used in AS model are as follows.

F finite AE set $\{f_i\}_{i=1}^n$

i serial number of engines $1 \leq i \leq n$

j serial number of assembly lines $\{m_j\}_{j=1}^2$

p_i tardiness penalty parameter per unit time of engine i

d_i delivery date of engine i

W finite assembly worker set $\{w_k\}_{k=1}^h$

a serial number of assembly workers $1 \leq a \leq h$

l assembly line stations $1 \leq l \leq k$

e_j energy consumption per unit time of assembly line j

c_j running cost per unit time of assembly line j

s_{ija}^l starting time of engine i processed by worker a at the l-th station of assembly line j

t_{ija}^l processing time of engine i processed by worker a at the l-th station of assembly line j

t_{ij} needed assembly time of engine i on assembly line j

c_i assembly completion time of engine i

1 Decision variable:

x_{ij} $x_{ij} = 1$ if engine i is assembled on assembly line j, 0 otherwise

x_{ija}^l $x_{ija}^l = 1$ if the l-th station of assembly line j of engine i is worker a, 0 otherwise

2 The objective of real-time production assembly scheduling optimization (RTPAS) comprises

3 the total energy consumption (E_A), the total reassembly cost (C_A), the loading rate of workers (μ),

4 and the tardiness delivery rate (η).

$$5 \quad E_A = \sum_{j=1}^2 \sum_{i=1}^n x_{ij} e_j t_{ij}, t_{ij} = \sum_{l=1}^k t_{ija}^l \quad (1)$$

$$6 \quad C_A = \sum_{j=1}^2 \sum_{i=1}^n [x_{ij} c_j t_{ij} + p_i (c_i - d_i)] \quad (2)$$

$$7 \quad \mu = \sum_{a=1}^h (T_a - T/h)^2 \quad (3)$$

$$8 \quad \eta = [\sum_{i=1}^n f(d_i - c_i)]/n, \begin{cases} f(x) = 1 (x < 0) \\ f(x) = 0 (x \geq 0) \end{cases} \quad (4)$$

9 Where

$$10 \quad p_i = \begin{cases} a_i t_i, t_i < t \\ b_i t_i - (b_i - a_i) t, t_i \geq t \end{cases} \quad (5)$$

$$11 \quad T = \sum_{i=1}^n \sum_{j=1}^2 \sum_{a=1}^h \sum_{l=1}^k x_{ija}^l t_{ija}^l \quad (6)$$

$$12 \quad T_a = \sum_{i=1}^n \sum_{j=1}^2 \sum_{l=1}^k x_{ija}^l t_{ija}^l \quad (7)$$

13 For Eq. (2), the assembly and maintenance of AER is a push-and-pull production strategy, so

14 if $c_i - d_i \leq 0$, it is assigned 0. $f(x)$ is a piecewise linear function in Eq. (4). Eq. (5) is a piecewise

15 linear function of tardiness penalty parameter, a_i and b_i ($a_i < b_i$) are different tardiness penalty

16 coefficients per unit time for engine i. t_i is the total time of tardiness delivery for engine i, and t

17 represents the piecewise boundary value for t_i . Eq. (6) and Eq. (7) indicate the total operation

18 time of all workers and worker-a respectively.

19 RTPAS aims to reduce the energy consumption, minimize the tardiness penalty and the total

assembly cost, and balance the worker load rate based on real-time information. Consequently, the objective function with the above-mentioned four optimization variables is proposed in Eq. (8), and minimizing the objective function implements the global optimization and obtains Pareto optimal solutions.

$$\text{Minimize } (E_A, C_A, \mu, \eta) = \min H \quad (8)$$

Where four optimization variables in Eq. (8) have different physical dimensions, they should be converted to unified dimensionless variables by using the dimensionless method. The weighted objective function (H) is presented as Eq. (9), and the larger the weight (λ), the more important the corresponding variable is.

$$\begin{aligned} H &= h(E_A, C_A, \mu, \eta) \\ &= \lambda_1 E_A / E_A^* + \lambda_2 C_A / C_A^* + \lambda_3 \mu / \mu^* + \lambda_4 \eta / \eta^* \\ &= \sum_{i=1}^4 \lambda_i V_i \end{aligned} \quad (9)$$

Where $(E_A^*, C_A^*, \mu^*, \eta^*) = (\max\{E_A\}, \max\{C_A\}, \max\{\mu\}, \max\{\eta\})$, $(V_1, V_2, V_3, V_4) = (E_A / E_A^*, C_A / C_A^*, \mu / \mu^*, \eta / \eta^*)$, $\sum_{i=1}^4 \lambda_i = 1$, and λ_i is not all equal.

Notations used in MS model are as follows.

P finite part maintenance set $P = \{p_i\}_{i=1}^n$

i serial number of parts $1 \leq i \leq n$

p_{ij} the j -th operation of part i $1 \leq j \leq q_i$

J operation set of parts $p_{ij} \in J$

M maintenance station set $M = \{m_k\}_{k=1}^r$

W maintenance worker set $W = \{w_a\}_{a=1}^h$

c_k running cost per unit time of maintenance station k

e_k energy consumption per unit time of maintenance station k

s_{ika}^j starting time of the j -th operation of part i on machine k maintained by worker a

t_{ika}^j maintenance time of the j -th operation of part i on machine k maintained by worker a

c_{ika}^j completion time of the j -th operation of part i on machine k maintained by worker a

d_i delivery date of part i

c_i completion time of part i

Decision variable:

x_{ika}^j $x_{ika}^j = 1$ if the j -th operation of part i on machine k is maintained by worker a , 0

otherwise

The model is subject to the following constraints for ensuring its integrity during MS.

$$c_{i+1} - c_i \geq \sum_{j=1}^{q_i} t_{ika}^j, 1 \leq i < i+1 \leq n, \forall m_k \in M, \forall w_a \in W, 1 \leq k \leq r, 1 \leq a \leq h \quad (10)$$

$$s_{ika}^{j+1} - c_{ika}^j \geq 0, 1 \leq i \leq n, 1 \leq j < j+1 \leq q_i, \forall m_k \in M, \forall w_a \in W, 1 \leq k \leq r, 1 \leq a \leq h \quad (11)$$

$$c_{ika}^{j+1} - c_{ika}^j \geq t_{ika}^j, 1 \leq i \leq n, 1 \leq j < j+1 \leq q_i, \forall m_k \in M, \forall w_a \in W, 1 \leq k \leq r, 1 \leq a \leq h \quad (12)$$

$$\sum_{k=1}^r \sum_{a=1}^h x_{ika}^j = 1, 1 \leq i \leq n, 1 \leq j \leq q_i \quad (13)$$

Where

$$s_{ika}^j \geq 0, c_{ika}^j \geq 0, \forall j \in J, \forall m_k \in M, \forall w_a \in W \quad (14)$$

Eq. (10) and Eq. (11) ensure that the precedence relationship between the operations of a part is not violated, i.e. the (j+1)-th operation cannot start before the j-th operation is completed and no operation can be processed on more than one machine each time. Eq. (12) indicates that no machine can process more than one operation each time. Eq. (13) denotes that each station has a worker who maintains parts. Eq. (14) denotes the constraints of the starting and completion time of part maintenance.

Real-time production maintenance scheduling (RTPMS) for AER based on IoMT consists of three MS variables, namely the total energy consumption of maintenance (E_M), the total maintenance cost (C_M), and the loading rate of workers (v).

$$E_M = \sum_{i=1}^n \sum_{j=1}^{q_i} \sum_{k=1}^r e_k t_{ika}^j x_{ika}^j \quad (15)$$

$$C_M = \sum_{i=1}^n \sum_{j=1}^{q_i} \sum_{k=1}^r c_k t_{ika}^j x_{ika}^j \quad (16)$$

$$v = \sum_{a=1}^h (T_a - T/h)^2 \quad (17)$$

Where

$$T = \sum_{a=1}^h \sum_{i=1}^n \sum_{j=1}^{q_i} \sum_{k=1}^r x_{ika}^j t_{ika}^j \quad (18)$$

$$T_a = \sum_{i=1}^n \sum_{j=1}^{q_i} \sum_{k=1}^r x_{ika}^j t_{ika}^j \quad (19)$$

Meeting the constraints (11)-(14), the objective function of RTPMS (G) is

$$\text{Minimize } (E_M, C_M, v) = \min G \quad (20)$$

$$G = g(E_M, C_M, v) = \sigma_1 E_M / E_M' + \sigma_2 C_M / C_M' + \sigma_3 v / v' = \sum_{j=1}^3 \sigma_j U_j \quad (21)$$

Where $(E_M', C_M', v') = (\max\{E_M\}, \max\{C_M\}, \max\{v\})$, $(U_1, U_2, U_3) = (E_M / E_M', C_M / C_M', v / v')$,

$\sum_{j=1}^3 \sigma_j = 1$, σ_j is the weight and not all equal.

5. A Pareto approach for PSO-based real-time production scheduling

Multi-objective real-time production scheduling problem (MRTPS) is one of the most complex multi-objective optimization problems with multiple conflicting objectives. If objectives are combined into a weighted scale function, the difficulty is to assign the weight for each objective; if all objectives are optimized simultaneously, the problem is to design the effective search algorithm for the extra steps and considerable increment of the computational complexity.

5.1 The pre-optimized Pareto candidate solutions method based on PSO

PSO is used to pre-optimize MRTPS and generate candidate solutions in this section. The objective is to minimize the total energy consumption, the total cost, and the total tardiness delivery rate, and balance the worker load rate reasonably. The optimization procedure can be divided into two parts. First is to generate and evaluate candidate solutions by using PSO (Fu, 2002). Then, a Pareto optimization model is proposed to implement the optimization of maintenance and reassembly scheduling for AER.

PSO has been proved to be an efficient evolutionary computation technique inspired by birds' flight and communication behavior. The multi-objective PSO is applied to the RTPS based on priority. Members of the swarm in PSO can be seen as the agent searching through the solution space. Each solution is like a "bird" in the D-dimension search space, called "particle". All particles have fitness values which are evaluated by the fitness function, and velocities which direct the flight of particles. Firstly, PSO comprises a randomly produced population and velocity in the user's domain. The swarm size is problem-dependent, within the sizes of 20-50 as the most common sizes (Hu et al., 2004). Then, the velocity is dynamically adjusted at each step according to the experience by itself and its colleagues as given in Eq. (22). The first part on the right side of Eq. (22) indicates the inertia of the previous velocity. The second is the 'cognition' part, denoting individual thinking, and the third is the 'social' awareness, representing cooperation among the particles. A new particle position is found by adding a new velocity to the current position according to Eq. (23):

$$V_{i,t+1} = wV_{i,t} + \xi C_1 (P_i - X_{i,t}) + \zeta C_2 (P_g - X_{i,t}) \quad (22)$$

$$X_{i,t+1} = X_{i,t} + \gamma V_{i,t+1} \quad (23)$$

$$w = w_{\max} - (w_{\max} - w_{\min}) / \text{iter}_{\max} \times \text{iter} \quad (24)$$

Where i is the i -th particle; $X_{i,t}$ and $V_{i,t}$ are the position and velocity of particle i at the t -th iteration respectively; P_i is the best previous position of particle i so far, named $pbest$ (memorized by every particle); and P_g is the best previous position among all particles, named $gbest$ (memorized in a common repository). w is an inertial weight and its function is to balance global and local exploitations of the swarm. One of the most widely used methods of inertia weight is the linear decreasing, which is determined by Eq. (24) (Zhang et al., 2009). $w_{\max}$ and $w_{\min}$ are the inertial and final values of weighting coefficients respectively; $\text{iter}_{\max}$ is the maximum number of iterations; iter is the number of the current iteration. C_1 and C_2 are two learning factors which control the influence of $pbest$ and $gbest$ on the search process, and the most common values for them are $C_1 = C_2 = 2$. ξ and ς are two random numbers within the range of $[0, 1]$, and the constraint factor γ is equal to 1.

The procedure for standard PSO is summarized as follows:

Step 1: Initialize a population of particles with random positions and velocities in the D -dimensional problem space.

Step 2: Evaluate the objective values of all particles, let $pbest$ of each particle equal to its current position, and let $gbest$ equal to the position of the best initial particle.

Step 3: Update the velocity and position of particles according to Eq. (22) and (23).

Step 4: Evaluate the objective values of all particles.

Step 5: For each particle, compare its current objective value with its $pbest$ value. If the current value is better, then update $pbest$ with the current position and objective value.

Step 6: Determine the best particle of the current whole population with the best objective value. If the objective value is better than that of $gbest$, then update $gbest$ with the current best particle.

Step 7: If a stopping criterion is met, then output $gbest$ and its objective value; otherwise, go back to Step 3.

5.2. Pruning Pareto optimal sets

The pruning process is used to prune Pareto optimal sets and obtain a set of desirable optimal solutions (pruned solutions) so that production planners can easily choose an appropriate solution.

The non-numerical objective function ranking preference method, proposed by Taboada and Coit (2008), is adopted to implement the pruning process based on an iterative simulation process. Solutions obtained by the pruning process are the final Pareto optimal ones. For simplicity, it is assumed that the assembly and maintenance lines discussed are empty initially.

6. Case study

RTPS is simulated by a case of reassembly and maintenance of AER. Compared with industrial solutions, the effectiveness of proposed RTPS is verified.

6.1 Experiment 1: remanufacturing reassembly optimization scheduling

Reassembly orders of five engines are allocated to the remanufacturing shop floor. The information of each engine can be seen in Table 1 in Appendix.

The reassembly information of five AEs is shown in Table 2 (Appendix), including engine number, assembly worker, assembly line, and assembly station.

There are five assembly workers at four assembly stations on different assembly lines in Table 2, and the values in the 3rd - 10th columns of each row show the operation time of each worker for assembling engines at different stations. For example, value (20, 1, 1, 1, 2) = (operation time, engine number, assembly station, assembly line, assembly worker) denotes that the operation time of worker 2 who assembles engine f1 at assembly station 1 on assembly line 1 is 20 minutes. Operation time ∞ indicates that the worker at this station does not have the assembly skill.

The man-hour of workers assembling engines at each assembly station can be calculated based on real-time information of AEs. Then, the results are submitted to workers to confirm. Workers can adjust the man-hour in terms of self-conditions, and transmit it to the system and recheck. Finally, the man-hour of each worker at different assembly stations can be verified.

Matrix M represents the real-time information of assembly lines.

$$M = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} = \begin{bmatrix} 50 & 145 \\ 60 & 132 \end{bmatrix}$$

The row indicates the different assembly lines, and the first row denotes assembly line 1. The first column and the second indicate the energy consumption per unit time (kWh) and running cost per unit time (CNY/h) respectively.

1 The experimental results generated by RTPS are presented as follows. The pre-optimized
 2 candidate solutions for five AEs generated by PSO in MATLAB are shown in Fig. 3(a) in a
 3 3-dimensional space, including 300 solutions in total. Compared with the initial search space with
 4 a total of 240^5 points (solutions), it is obvious that it can reduce the complexity and the search
 5 space of the RTPAS problem, and generate candidate solutions quickly and efficiently. Then, the
 6 final Pareto optimal solutions can be acquired by using the Pareto method based on the
 7 pre-optimized solutions. Fig. 3(a) also shows that all points obviously converge to three different
 8 domains, namely worker load domain, energy domain, and cost domain, and this is due to the
 9 priority of three objectives. For example, if cost is the most important among them, solutions
 10 converging to the opposite direction of the cost axis are selected as a final Pareto optimal set. In
 11 addition, the maintenance and reassembly of AEs during AER is a push-and-pull scheduling
 12 strategy. Before assembling parts of AEs based on real-time information of manufacturing
 13 resources, the maintenance strategy for these engines is given. Once these engines start to be
 14 assembled, the maintenance for them has been completed.

(a)

Fig. 3, (a) The pre-optimized candidate solutions for five AEs based on PSO; (b) The Pareto optimal solutions of AE assembly in a 3-dimensional space; (c) The Pareto optimal sets of AE f3

It is a fact that the current process of engine assembly affects the next one, and is also affected by the previous one, shown as constraints in Section 4. Therefore, certain correlations exist among them. Pre-optimized solutions based on PSO are still a large solution set and difficult for production planners to choose an appropriate solution for real-time production. Thus, five AEs should be optimized as the whole to achieve the global optimization based on the multi-objective function. Pareto optimal solutions for the global optimization scheduling generated by RTPAS are shown in Fig. 3(b).

A total of 65 Pareto optimal solutions are obtained in Fig. 3(b). Based on these solutions, the pruning procedure generates 4 pruned solutions marked by red $\bigcirc$ and Δ respectively. Solutions locating at the right, the center, and the left marked by $\bigcirc$ in Fig. 3(b) denote the minimum cost, the most balanced worker load, and the minimum energy consumption respectively.

To illustrate the procedure from local optimization to global optimization, engine f3 is taken to demonstrate Pareto local optimization process as shown in Fig. 3(c). It can be seen that points are an approximately uniform distribution of being discrete in Fig. 3(c). 65 points are chosen to make a simulation and form a Pareto optimal set, and 3 pruned solutions marked by $\bigcirc$ are taken as the final optimal results.

To formulate the effect of different Pareto optimal solutions on the worker load rate for assembling f3, the distribution diagram of that is shown in Fig. 4. The change of worker load rate

of all solutions is shown clearly, and it can be found that the worker load rate of the 35-th solution is minimum, while that of the 41-th is maximum. The worker load rate indicates the labor intensity and capacity of workers. The smaller the value of the worker load rate, the more balanced labor intensity and capacity of workers is.

Fig. 4. The distribution of worker load rate for assembling AE f3

Based on alternative optimal solutions, 14 pruned solutions are chosen to guide the real production in Table 3. From Table 3, it can be easily found that the number of pruned solutions is much less than that of the original Pareto optimal solutions. It is assumed that the priority of cost is the highest among all the variables, the cost of solution 1 is minimum in Table 3, which is 1234.9. Nevertheless, it is an abnormal state that workers of solution 1 are always 1, 3, 4, 5, and worker 2 is idle all the time. Therefore, solution 2 is the best one. Meanwhile, due to worker 2 does not have the skills at station 4 and 8 in solution 2, the labor intensity and capacity of worker 2 is lower than that of others. In addition, to explain the pruned solutions clearly in Fig. 3(b), the worker load of solution 10 is minimum, and the total energy consumption of solution 14 is minimal. They are 0.089437 and 526.5 respectively. In Table 3, $[No.:l_1:s_1]=[1:1:1345]$ represents that the four operations of solution 1 for engine f1 (from the first operation to the fourth) are reassembled by worker 1, 3, 4, 5 on assembly line 1 respectively. The others in Table 3 are candidate solutions in case of the failure of the selected one. To make the table more readable, a Gantt diagram of solution 1 for assembling five AEs in Table 3 is shown in Fig. 5. It is noted that this Gantt diagram describes a cycle of assembly planning for five AEs so that there is much idle time, and worker 2 is always idle because of its inability at certain stations.

1

Table 3 Pareto optimal solutions for five AEs assembly scheduling

Solution No.	Solutions of AE assembly										Value of objective function		
	f1		f2		f3		f4		f5		Objective 1: cost	Objective 2: energy	Objective 3: load rate
	s ₁	l ₁	s ₂	l ₂	s ₃	l ₃	s ₄	l ₄	s ₅	l ₅			
1	1345	1	3145	1	5143	1	1354	2	3154	2	1234.9	569.3	0.121364
2	1345	1	1345	1	5143	1	1354	2	2153	2	1235.4	569.1	0.119293
3	1354	1	1345	1	2143	2	1354	1	3154	2	1281.8	544.6	0.116924
4	1345	1	1345	1	2145	1	1354	2	3154	2	1284.7	547.4	0.108833
5	1345	1	1345	1	5143	2	1345	1	3154	2	1286.2	546.8	0.098929
6	1345	2	3145	1	2145	1	1354	2	2153	1	1288.4	547.9	0.099212
7	1354	1	1345	2	5143	2	1354	1	3154	1	1288.9	547.7	0.096608
8	1345	1	3145	1	2145	1	1354	2	2153	2	1289.6	549.4	0.105938
9	1345	2	2153	1	5143	2	1354	1	3154	1	1289.9	547.3	0.090588
10	1345	1	1345	1	5143	2	3154	2	3154	1	1290.1	549.2	0.089437
11	1354	1	1345	1	5143	2	1345	1	3154	1	1290.6	549	0.096843
12	1345	1	1345	1	2153	2	1345	1	3154	2	1291.1	548.8	0.099176
13	1345	1	2153	2	2145	1	1354	2	3145	1	1292.8	550.1	0.109915
14	1345	2	3145	1	2145	1	1354	1	3154	1	1341.9	526.5	0.104229

2

3

Fig. 5. The Gantt diagram of Solution 1 for five AEs assembly in Table 3

4

6.2 Experiment 2: remanufacturing maintenance optimization scheduling

5

Table 4 (Appendix) represents the parameter information of AE maintenance, where the 1st - 3rd

6

rows indicate AE number, cost per unit time, and energy consumption per unit time for engine

7

maintenance. Table 5 (Appendix) shows the maintenance information of AEs. Values in the 3rd -

8

7th columns of each row denote the operation time of workers maintaining engines at different

9

stations and others are similar to Table 2.

10

A total of 120 Pareto optimal solutions of AE maintenance generated by the proposed model

11

are obtained. Based on these solutions, the pruning process generates 10 pruned solutions as

12

shown in Table 6. For simplicity, 3-dimensional figures of Pareto optimal solutions for AE

13

maintenance are not shown. It can be found that the total cost and the total energy consumption of

solution 1, 3, 4, 5 are minimal in Table 6, which are 354.2 and 381.01. The worker load of solution 2 is minimum (0.03488). If the delivery time is urgent, solution 3 is the best one because the total assembly time of that is minimum. In Table 6, [No.:f1]=[1:13254] represents that the first operation to the fifth operation of solution 1 for engine f1 are maintained by worker 1, 3, 2, 5, 4 respectively. Other solutions offer alternative strategies for production planners to choose from.

Table 6 Pareto optimal solutions for AE maintenance scheduling

Solution No.	Solutions of AE maintenance					Value of objective function			Total Time
	f1	f2	f3	f4	f5	Objective1	Objective2	Objective3	
1	13254	12345	13245	14253	15234	354.2	381.01	0.041513	268
2	25413	42315	42315	41253	25341	402.7	433.23	0.03488	292
3	15243	15342	14253	13452	14352	354.2	381.01	0.044431	244
4	15243	15342	14253	13452	15234	354.2	381.01	0.042926	251
5	13254	12345	13245	14253	14352	354.2	381.01	0.43018	261
6	13254	15342	14253	13452	25341	357.2	384.43	0.041222	254
7	15243	12345	13245	14253	24153	357.2	384.43	0.04249	262
8	25413	12345	13245	14253	14352	359.6	387.13	0.41797	266
9	25413	15342	14253	13452	25341	362.6	390.55	0.040001	259
10	35412	32415	23145	31254	35241	435.1	468.63	0.035327	289

Solutions from industrial practices are called industrial solutions (Wong et al., 2014). Due to the complexity of RTPS problem and a large number of reassembly and maintenance tasks, it is difficult for production planners to obtain optimal or near-optimal solutions that meet the objectives in Section 4. Table 7 describes the industrial solutions for five AEs. For Experiment 2, there is only one maintenance line, so $l_i=1$.

Table 7 Industrial solutions for five AEs

Experiment No.	f1		f2		f3		f4		f5		Value of objective function		
	s_1	l_1	s_2	l_2	s_3	l_3	s_4	l_4	s_5	l_5	Objective1	Objective2	Objective3
1	3254	2	4135	1	2453	2	1524	2	3451	1	1570.5	595.5	0.11024
2	54321	1	54231	1	54312	1	52341	1	54213	1	536.8	577.2	0.047347

By comparing pruned solutions in Table 3 and 6 with solutions in Table 7, it is clear that the obtained solutions are better than the industrial ones giving whatever the priority of objectives is. For example, in Experiment 2, if Objective 1 has a higher importance than other two, solution 1-10 are superior to industrial solutions, and solution 1, 3-5 are the most appropriate solutions. If the total processing time has a high priority, solution 1, 3-9 are superior to industrial solutions, and solution 3, 4, 6 are the most suitable solutions among them.

In Experiment 2, compared with industrial solutions, the total cost, the total energy

consumption, and the worker load rate of solution 3 in Table 6 are decreased from 536.8, 577.2, and 0.047347 to 354.2, 381.01, and 0.044431 (-34%, -34%, and -6%) respectively. The total of the processing time of solution 3 is decreased by 31, compared with that of the industrial solution which is 275. It can be seen from the experimental results that important parameters influencing the efficiency of AER could be significantly improved by using advanced IoT technologies and optimization methods. In turn, these improvements contribute to sustainable development of remanufacturing industry, especially for AER. The production and management performance can be greatly improved based on the simulation results in which the real-time response is within the order of minutes, well satisfying the real-time demand of AER. RTPS can handle the investigated production scheduling problem for AER by generating Pareto optimal solutions, and this demonstrates the effectiveness of the presented model. The results also indicate that the proposed PSO pre-optimized method and pruning operators are efficient in searching optimal solutions.

There are two main differences between the real-time scheduling and the traditional rescheduling. Firstly, before scheduling, IoT is applied to the real-time scheduling, and under the constructed IoMT environment, the real-time status of machines such as the real-time load of machines can be sensed and captured. For the traditional scheduling, tasks are only assigned based on the processing capacity of machines, but the current processing load of these machines is unknown. Therefore, it is common for the traditional scheduling that the over-load status of machines and the block of tasks etc. occur. Change of production planning results in frequent rescheduling, and the increase in cost, energy consumption, makespan, and tardiness of manufacturing tasks. Secondly, for IoT-enabled real-time scheduling, each exception event triggers a new scheduling, and this is the real-time information-driven rescheduling. These exception events can be handled in real time once sensed and captured. For traditional scheduling, if the period of scheduling is too long, many exception events would aggregate and form a huge production exception. This increases the complexity and difficulty for manufacturing system in handling these exception events, and further results in the breakdown of machines.

7. Conclusions

This paper focuses on AER based on IoMT and RTPS in the remanufacturing shop floor. Currently,

remanufacturing of AEs is facing challenges imposed by the highly demanding constraints from the lack of real-time, accurate, and consistent manufacturing information, to the uncertainty of materials recovered and complexity of production scheduling. This paper applies IoT to AER to construct the IoMT environment. Under the IoMT environment, advanced identification technology is used to sense and capture the real-time status of different manufacturing resources through the Internet, and this provides very important production information for real-time production scheduling through the whole remanufacturing system.

Three main contributions of this paper are concluded. The first is using IoT in the remanufacturing workshop to capture and monitor data of remanufacturing resources such as operators, machines, pallets, and key components. The availability and remanufacturability of key AE parts can be identified, and exception events in the process of AER can be also sensed in real time. The second is presenting a real-time production scheduling method for AER based on IoMT, which is used for dynamic decision-making of multi-objective real-time scheduling of AER. PSO method is used to obtain pre-optimized candidate solutions of multi-objective real-time scheduling problems based on the initial Pareto optimal sets. The initial search space with a large number of points (solutions) is efficiently decreased to form the pre-optimized candidate solution sets with a total of 300 points. Based on the pre-optimized solutions, the pruning process is adopted to prune Pareto optimal solution sets of reassembly and maintenance scheduling, and the pruned solutions can minimize the total cost of AER, decrease the total energy consumption, and better balance the labor intensity and capacity of workers, compared with industrial solutions. The third is that Pareto optimal solutions provide production planners with an appropriate solution in real production scheduling. Solution 3 of the Pareto optimal solution set of MS reduces 34% of the total cost and 34% of the total energy consumption, and greatly balances the worker load. These improvements can contribute to sustainable development and cleaner production of the remanufacturing industry, especially for AER. Pareto optimal solutions for maintenance and assembly scheduling of AEs help production planners and managers for better decision-making.

Future research is proposed to focus on the mathematical-physical interdependence between the models of AS and MS, and the improvement of the methodology to solve RTPS problem with more objectives and practical constraints.

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Appendix

Table 1 Information of AERs

Information of engines		Time: 11:45:26,3/11/2014	
Engine model	Engine No.	Delivery date(d/h:m)	Delay penalty (CNY/h)
YC4D120-21	f1	07/12:20	90
YC4E135-21	f2	08/14:50	80
YC4D120-20	f3	07/13:30	100
YC4D130-20	f4	09/06:45	45
YC4E135-20	f5	09/08:34	60

Table 2 Reassembly information of five AEs

Engine No.	Worker No.	Assembly line 1(l_1)				Assembly line 2			
		Station1(s_1)	Station2	Station3	Station4	Station1	Station2	Station3	Station4
f1	1	13	25	34	45	26	34	32	50
	2	20	34	41	∞	32	38	40	∞
	3	17	26	43	36	21	34	32	45
	4	23	35	39	40	21	35	34	58

	5	12	30	32	32	18	31	30	43
	1	12	23	34	45	25	33	32	49
	2	18	32	41	∞	31	37	40	∞
f2	3	16	26	43	36	20	34	32	43
	4	22	34	38	39	21	35	34	57
	5	13	29	32	32	18	31	30	42
	1	13	22	35	44	25	33	31	46
	2	17	33	40	∞	30	36	38	∞
f3	3	19	27	42	36	20	34	32	42
	4	20	33	37	38	22	33	33	56
	5	12	28	33	31	18	32	29	41
	1	10	24	33	42	23	31	32	45
	2	19	31	41	∞	31	37	38	∞
f4	3	15	27	42	35	20	34	31	43
	4	24	33	36	38	21	35	34	56
	5	15	30	29	32	18	31	32	46
	1	14	23	34	45	25	33	31	47
	2	17	35	41	∞	29	36	38	∞
f5	3	15	27	46	36	20	31	33	42
	4	24	34	38	37	23	35	32	56
	5	14	29	32	32	18	31	30	41

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Table 4 Parameter information of AE maintenance

Engine No.	f1	f2	f3	f4	f5
Cost/CNY	1.2	1.4	1.5	1.7	2
Energy/kWh	0.13	0.12	0.14	0.1	0.09

3

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Table 5 Maintenance information of five AEs

Engine No.	Worker No.	Station 1	Station 2	Station 3	Station 4	Station 5
	1	8	10	10	12	11
	2	12	13	11	9	11
f1	3	13	12	14	12	12
	4	11	10	13	11	13
	5	15	14	16	14	17
	1	10	12	11	13	9
	2	13	13	12	14	11
f2	3	15	11	14	15	13
	4	13	12	12	13	15
	5	15	16	17	18	19
	1	9	12	12	0	10
	2	14	15	14	0	12
f3	3	12	14	14	0	12
	4	14	10	11	0	13
	5	15	14	18	0	17

	1	7	12	9	0	9
	2	10	13	12	0	12
f4	3	11	12	13	0	14
	4	12	9	10	0	15
	5	14	13	16	0	16
	1	8	11	11	0	12
	2	11	12	11	0	11
f5	3	12	13	12	0	12
	4	13	8	14	0	15
	5	15	12	15	0	18

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