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A Service-Oriented Remanufacturing Framework With Recovery Timing Prediction Based on Remote Condition Monitoring

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ABSTRACT Remanufacturing is generally regarded as a key technology to implement cleaner production. However, in traditional remanufacturing, scrap products are recycled and remanufactured after their performance declines sharply. This passive approach easily arises many problems such as increases of remanufacturing cost, unstable product quality, and unsatisfactory customer demand, which brought great challenges to the remanufacturing industry. To address these challenges, a novel framework, namely service-oriented remanufacturing (SORM), is proposed to improve the overall efficiency of remanufacturing. Contrast to the traditional mode, SORM actively recovers in-service products at the optimal recovery time based on their real-time performance obtained by remote monitoring. The operational logic and implementation path of SORM is firstly discussed. Then the recovery timing prediction (RTP) model, as the core issue of the SORM, is presented to figure out the optimal recovery time of in-service products. Moreover, a comprehensive method combining a two-parameter Weibull distribution (TPWD) and gene expression programming (GEP) is developed to solve the model. The example of excavator remanufacturing illustrates the feasibility of the SORM. Finally, the key findings and managerial implications from application results and discussion are summarized, which provides the theoretical guidance and technical support for better sustainable development.

INDEX TERMS Service-oriented remanufacturing, recovery timing prediction, remote condition monitoring, Weibull distribution, gene expression programming.

I. INTRODUCTION

The rapid development of society has created huge material wealth, but environmental pollution and resource crises are becoming increasingly serious. As a sustainable green development mode, remanufacturing is generally considered a primary way to solve these issues. In recent years, it has attracted wide attention and received support from many governments [1]–[4].

The United States has taken the global lead in remanufacturing, with tens of thousands of companies engaged in remanufacturing [5]. Germany has great advantages in the field of automobile parts remanufacturing, while with the rapid updating of electronic products, remanufacturing of the waste electrical and electronic equipment (WEEE) has attracted much attention in recent years in Germany [6]. Japan is short of resources, so it pays more attention to remanufacturing. Particularly impressive is the high acceptance of remanufactured products by Japanese [7]. China's remanufacturing industry dates back to the end of the last century. The National Development and Reform Commission lists the green remanufacturing industry as a key area for vigorously developing a circular economy, and a number of enterprises are identified as the first pilot units for remanufacturing. Subsequently, the application of remanufacturing technologies extends to the fields of high value-added mechanical and

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electrical products such as construction machinery, machine tools, automobiles, and agricultural machinery. China's Circular Economy Promotion Plan, issued in 2015, accelerates the construction of a demonstration base in the remanufacturing industry and promotes the movement of China's remanufacturing industry toward clustering and agglomeration.

The remanufacturing industry is developing rapidly around the world. The problem of effective implementation of remanufacturing has attracted increasing attention [1], [8]–[10]. Currently, there are three main remanufacturing modes: original equipment manufacturer (OEM), independent remanufacturer (IR), and contracted remanufacturer (CR) [1], [11], [12]. These modes are all aimed at scrap products. Moreover, most research on remanufacturing has thus far focused on scrap products [13]–[16]. However, recycling and remanufacturing scrap products can entail many problems. First, when a product is scrapped, its performance has been seriously degraded, which greatly increases the technical difficulty and remanufacturing cost [4]. Second, scrap products have various forms and degrees of failure, which results in many uncertainties in remanufacturing production system, such as in quality, repair time, and process. Finally, random recycling and remanufacturing of scrap products in the market can easily lead to unpredictability in the supply as well as in customer demand [17]. These issues obviously pose great challenges to remanufacturing management [2], [18]–[20]. To overcome these challenges, SORM is proposed. SORM is a kind of remanufacturing production activity that proactively recycles the products before their performance deteriorates sharply to achieve the minimum unit service cost and better remanufacturability. OEM has ownership of products and only sells service to customers. In the entire process, OEM first sells service with new products to customers. The functionality of products will decrease after being used for a period. Then the OEM proactively recycles in-service products at optimal timing point, and improves the function of returns through remanufacturing, afterwards resells new service with remanufactured products to the same customers with functions as that of news. So, customers actually buy services that correspond to functions of products. Therefore, the kind of remanufacturing is regarded as SORM. As OEM is the owner of products, it can recycle and remanufacture products at the optimal time, so as to ensure the minimum cost of unit service time and maximize profits.

Strictly speaking, SORM is not a breakthrough in specific remanufacturing technology, but an innovation in remanufacturing conception or in remanufacturing business mode. Essentially, SORM is the proactive remanufacturing of in-service equipment, while traditional remanufacturing is passive remanufacturing for completely scrapped products. The fundamental division brings about a global change throughout remanufacturing process. Compared with the traditional remanufacturing mode, SORM has many differences such as product design for disassembly, pre-sale agreement, price-deposit mechanism, RTP strategy based on in-service status, construction of forward and reverse logistics network, and coordinating operation of a hybrid manufacturing-remanufacturing system. Among which, RTP is the core content of SORM, which determines the effectiveness of SORM [21]. Too early a recovery time will not give full play to a product's value, and the shorter service time will increase the unit service cost. Otherwise, if the recovery time is set too late, a product's performance will deteriorate sharply, which greatly increases the maintenance cost as well as the remanufacturing cost, and the corresponding unit service cost will also increase. Therefore, accurate prediction of recovery time is the key to SORM. Unfortunately, scant literature has so far been devoted to this issue.

In this paper, we first discuss the basic operating logic and implementation path of SORM. Then we propose a framework for condition-monitoring-based RTP. Moreover, we develop a recovery timing prediction model and propose a solution method for it. Finally, through a case study of excavator remanufacturing, the validity and feasibility of SORM are verified.

The rest of this paper is organized as follows. Section 2 reviews related literature. Section 3 presents the operating logic and implementation path of SORM. Section 4 addresses the framework and modeling of RTP, and presents a solution. Section 5 studies a case to verify the feasibility of SORM. The results are discussed in section 6. Managerial implications and conclusions are presented in sections 7 and 8, respectively.

II. LITERATURE REVIEW

A. REMANUFACTURING OPERATION MODES

Relevant research on remanufacturing is carried out under a certain operation mode [13], [14], [18]. Tian *et al.* [1] compared the main operation modes for automotive component remanufacturing in China and concluded that the contracted remanufacturing enterprise is most suitable for Chinese automobile remanufacturing. Li *et al.* [22] proposed an upgraded remanufacturing strategy for OEM, taking into account government subsidies and the donation of remanufactured products. Ma *et al.* [23] established a closed-loop supply chain model for a remanufacturing business and explored the relationship between IRs and OEMs. Lund and Hauser [12] summarized remanufacturing practice in the United States from aspects such as industry structure and scope, patterns in inputs and costs, and forms of organization of remanufacturing enterprises. Some research has proposed new remanufacturing modes. Mont *et al.* [20] took baby carriages as an example to present a new business model considering leasing and remanufacturing. Zhang *et al.* [11] proposed three development modes oriented toward remanufacturing: government incenting, technology driving, and market leading. Wang *et al.* [24], [25] referred to cloud manufacturing and proposed a cloud-based approach for WEEE recovery.

Many studies have investigated how to implement remanufacturing. However, these studies all take scrap products as the object. Few studies have addressed the remanufacturing of in-service products, taking into account the evolutionary law of product performance.

B. THE SORM FIELD

SORM is a novel remanufacturing conception whose enabling technologies include remanufacturing design [26], recovery timing prediction [21], [39], forward and reverse logistics network construction [13], hybrid manufacturing/remanufacturing systems [27], [28], and the contract mechanism between the remanufacturer and customer [29]. SORM requires that disassembly be considered at an early stage of product design. Chiodo and Ijomah [26] studied proactive disassembly technology that unifies product design and disassembly to enable the rapid, non-destructive, self-disassembly of products. Recovery timing prediction is an important method to ensure maximum profit from SORM [21]. Here, traditional reverse logistics theory is difficult to use directly for the logistics network of SORM. Elements such as network structure, site layout, function partition, and node traffic must all be considered in a unified way. Contract mechanisms must be developed to ensure a stable number of returns for a remanufacturing production system as well as predictable market demand [30].

Many existing technologies and theories are related to the SORM concept and enable its implementation.

C. RTP BASED ON REMOTE CONDITION MONITORING

There are two main methods to predict recycling time. One method is to establish a mathematical model to determine the optimal time based on the performance index of parts. Song *et al.* [31] analyzed the evolution law of part performance and concluded that a product has an optimal recycling time domain. Liu *et al.* [21] discussed characteristic indicators of the performance status of waste parts, and considered the optimal remanufacturing recovery time to be a zone whose upper and lower limits were determined respectively by game theory (GT) and an artificial neural network (ANN). Steeneck and Sarin [32] studied the level of durability of parts for leased products under remanufacturing, and analyzed the optimal time to recycle leased products. The other method is to determine the optimal recovery time based on the minimum unit service cost from the perspective of the product life cycle. Liu *et al.* [33] used life substitution theory (LST) to build a mathematical model to obtain the optimal time of crankshaft remanufacturing, considering the environmental impact and service time. Ke *et al.* [34] established a mathematical model to minimize the average energy consumption in the whole life cycle of a product, and analyzed the optimum time to remanufacture a six-cylinder diesel engine.

Previous studies have shown that the operating environment, working conditions, and running time of in-service equipment all vary. The prediction results achieved just from the original product design, cost, or energy consumption may be far from the actual situation. The RPT of SORM must be based on the service state of the in-service equipment.

Remote monitoring can effectively obtain service status. Wired and wireless remote monitoring are two commonly used methods [35]. Wireless remote monitoring is suitable for field equipment such as construction machinery [36]. Truong and Vu [37] developed a remote monitoring machine tool based on a mobile platform. Xie *et al.* [38] addressed a remote monitoring communication method based on a 4G network, which sends collected vehicle data to a remote server in real time, and realizes the functions of synchronous query and monitoring on the client side. Shin *et al.* [35] proposed a dynamic real-time data compression method, aimed at the large amount of data generated by real-time dynamic remote monitoring. The collected data is diverse. Some indicators, such as equipment state, failure rate, energy consumption efficiency, and environmental emissions, will continue to change as the service time increases [39]. All of these states are functions of time t. Therefore, monitoring data are analyzed and fused to determine the changing rules of each indicator [40]. Wang *et al.* [41] thought that an appropriate data processing method should be used to improve the reliability of the results.

There is little literature on RTP. Moreover, no research has been found to predict the recovery time based on remote monitoring data. This is the focus of this paper.

III. OPERATING LOGIC AND IMPLEMENTATION PATH OF SORM

A. OPERATING LOGIC

Previous studies have found that the evolution of product performance obeys the ''bath curve'' during its service period, which can be roughly divided into the three stages of running in, normal working, and frequent failure [29], [31], as shown in Figure 1. The service period enters the later stage, due to the coupling effect of fatigue, wear, corrosion, and other failure forms, the failure frequency of products increases, energy consumption rises, and emissions fall short of standards. As a result, product performance deteriorates gradually. From Figure 1, there is an inflection point in the frequent failure stage, after which product performance declines sharply, until it completely fails. The method that remanufacturing scrap products, usually adopted in traditional remanufacturing, can cause many intractable problems. Therefore, it is necessary to determine an optimal recovery time, rather than the time when the product is completely scrapped, i.e., at the end of product life cycle. This is the logic basis of implementing SORM.

As can be seen from Figure 1, the optimal recovery time is between T_2 and T_3. Here, T_2 is the time corresponding to ''inflection point'' of performance degradation, and T_3 is the minimum q-precentile life.

As mentioned above, SORM mode provides not only the products, but the services coupled with them, i.e., customers buy services, not products. OEM is responsible for products throughout their lifecycles. The customer receives high-quality services, and the remanufacturer receives returned products with high remanufacturability. This kind of service-oriented proactive remanufacturing mode not only alleviates the customer's concerns about the quality of remanufactured

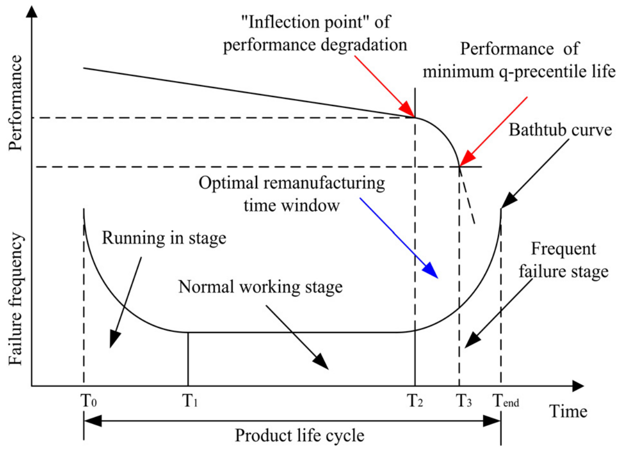

FIGURE 1. Evolution curve of a product's service performance and optimal recovery time.

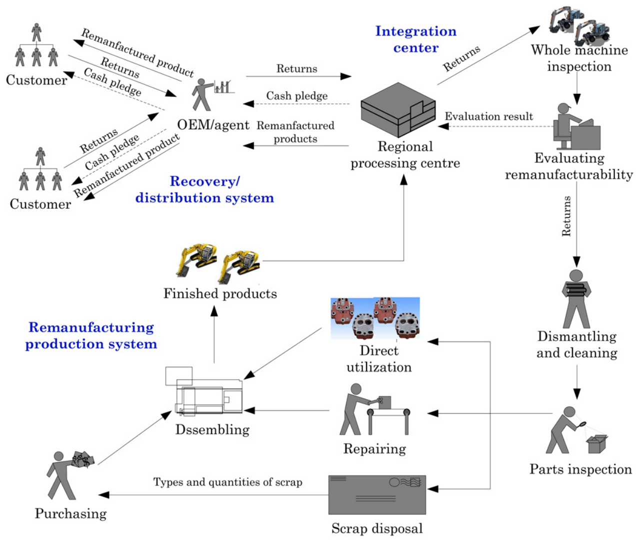

FIGURE 2. Implementation path of SORM.

TABLE 1. Comparison between SORM and TR.

	Index	Mode	
		TR	SORM
Strategy	Production type	Multi-variety and small batch	Stable varieties and large batch
	Focus	Product	Service
	Control mode	Partial control	Integrated control
Mechanism	Operation mode	Passive remanufacturing	Proactive remanufacturing
	Operating mechanism	Technology integration	Resource and technology integration
	Technical support	Surface repair technology leading	Organizational change and human factor exertion
	Guiding ideology	Extended producer responsibility	Service-oriented life cycle management
	Implementation difficulties	Changing consumption concept	Improvement of service system
Attribute	Topological structure	Ring structure	Closed-loop network
	Information dissemination	Information island	Information sharing
	Client property	Passive acceptance by customers	Customer initiative
	Prediction level	Production based on forecast of consumption and demand	Regular production based on customer contract

products but reduces the impact on remanufacturing production of uncertainties in the source. The economic value of this process has been proved in the literature [42]. The SORM mode saves resources and achieves sustainable development.

SORM is significantly different from traditional remanufacturing in guiding ideology, operational mechanism, and mode attributes. Table 1 summarizes the differences between the SORM mode and the traditional remanufacturing (TR) mode.

The ''Made in China 2025'' plan explicitly mentions the vigorous development of the remanufacturing industry and its implementation in high-end remanufacturing, intelligent remanufacturing, and in-service remanufacturing. The main idea of in-service remanufacturing is the same as SORM, which differs from traditional remanufacturing engineering, based on the theory of monitoring and diagnosis of equipment health, and proactive large-scale remanufacturing of obsolete in-service equipment [43]. SORM will have a significant impact on the development of the remanufacturing industry.

B. IMPLEMENTATION PATH

Implementation path of SORM is as follows and shown in Figure 2.

Step 1: The OEM signs agreements with customers through a contract coordination mechanism.

Step 2: The OEM sells service with new products to customers for less than the market price. The lower part than the market price can be used as a deposit to ensure that customers return the products.

Step 3: The products begin their first life cycle. OEM monitors in-service equipment in real time through the remote monitoring platform and delivers maintenance and recovery suggestions.

Step 4: After used by customers for a service period, the products should be returned to the OEM at the optimal recovery time.

Step 5: The remanufacturability of the returns is evaluated in integration center. Based on the evaluation, the OEM returns all or part of the deposit to the customers.

Step 6: Returns are sent to the remanufacturing workshop. After disassembly, cleaning, testing, repair, and assembly, the performance of the products is restored to the same level as that of the new products.

Step 7: The new service are resold with remanufactured products for less than the original price through the supply chain, and the products start a new life cycle.

Several key points in implementation path of SORM are summarized:

(1) OEM needs to sign pre-sale agreements with customers before selling service to ensure that products can be

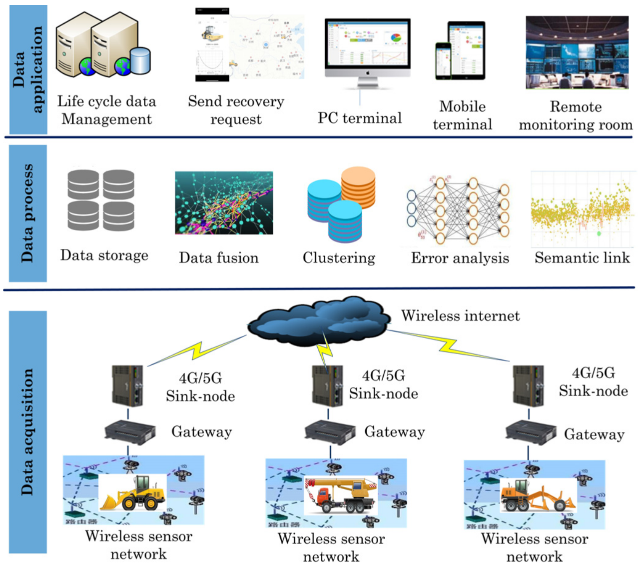

FIGURE 3. Recovery timing prediction framework model.

returned at the optimal time, and also needs to formulate a reasonable price mechanism to ensure the competitiveness of SORM.

(2) The reasonable forward and reverse logistics network needs to set up to deal with recycled products, including regional processing center and remanufacturing evaluation department.

(3) A remote monitoring platform should be developed to monitor the running status of equipment in real time, so as to give suggestions of maintenance and recovery in time.

IV. RTP PROBLEM

RTP is the core issue of SORM. In this section, we conduct an in-depth study of this issue. We first describe the RTP framework based on remote condition monitoring, and then we establish a prediction model and propose a solution method combining TPWD and GEP.

A. RTP FRAMEWORK

Without global status monitoring of in-service equipment, RTP will become "an unachievable plan." Therefore, perceiving, acquiring, and analyzing the status of in-service equipment is the foundation of RTP. Thus it is essential to establish a remote monitoring system for RTP.

We take the remote monitoring of construction machinery as an example. The system can monitor the running status of equipment in real time, analyze the collected data, and send recovery requests to customers to enable the accurate prediction of recovery time. Therefore, the framework model should consist of three layers, for data acquisition, data analysis, and data application, as shown in Figure 3. The RTP framework is supported by basic theories and methods such as construction operation, automatic monitoring, data transmission, database management, web services and statistics, industrial big data, and remanufacturing.

- **Data-acquisition layer** The remote data-acquisition system based on the 4G/5G wireless transmission mode usually has a sensor module, processor module, wireless communication module, and power module. The sensor module collects the status information of the equipment and converts the data to a standard format, i.e., it converts the original analog signals to digital signals or converts AC signals to DC signals for the next module to use. The processor module is divided into processor and memory parts, which are responsible for node control and data storage, respectively. The wireless communication module is responsible for communication between nodes. Data are transmitted through the network layer to the data link layer, and then to the transceiver, which converts data to binary objects. Afterwards, the signal is sent to the medium access control (MAC) layer, and finally transmitted to the server via the 4G/5G wireless internet. The power module provides energy for sensor nodes, generally using the micro-battery power supply. The data acquired by remote monitoring system can be divided into two categories. One is the indicators directly reflecting equipment performance, which are called direct indicators, such as noise, vibration, fuel consumption, water temperature, engine speed, power and hydraulic pressure. These indicators are directly acquired by sensors installed on the equipment, and displayed on the remote monitoring platform and user interface. The other is the indicators indirectly reflecting the equipment performance, which is called indirect indicator. Here, indirect indicator is the failure number that usually manually input by customers through monitoring platform.
- **Data processing layer** For direct indicators, data processing has four aspects. First, the operating environment of construction machinery is often relatively harsh, which may cause errors in the monitoring data. It is necessary to construct models to analyze these errors. Second, these monitoring data are heterogeneous. Therefore, the data storage structure should be set up based on the data format and protocol, and a hierarchical relationship model of monitoring data also need to be built to ensure accurate data and efficient access. Third, there may be redundancy in the monitoring data. Therefore, it should be clustered, fused, extracted, and analyzed. Finally, the mapping relationship between these indicators and recovery time is established by principal component analysis and neural network. For indirect indicator, i.e., failure number, data processing layer can obtain failure probability density function and reliability function based on the relationship between failure number and operation time, and then calculates the optimal recovery time according to the mathematical model compiled by the program. In the follow-up case study of this paper, the latter method is adopted, that is, to obtain the optimal recovery time through indirect indicator.

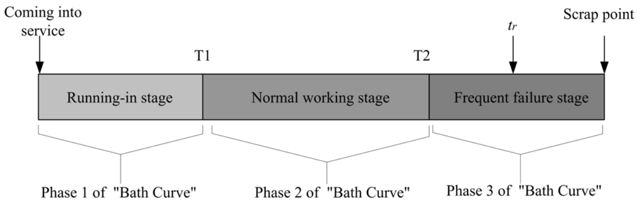

FIGURE 4. Three stages of product life cycle operation.

- **Data application layer** In the data application layer, first, according to the collected data, the terminal can present the location, working time, status of key components, failure rate, and other information. More importantly, according to the processed data, mapping relationship between monitoring data and recovery time, the reliability function, probability density function, and remanufacturing cost function of the equipment should be fitted separately. Then, by constructing a prediction model, the best time for equipment maintenance and recovery can be predicted, and maintenance or recovery requests can be sent to customers in advance. As construction machinery often works in the field, customers can log on to a mobile app to view the equipment information and OEM recommendations.

B. PREDICTION MODEL

1) PROBLEM DESCRIPTION

The life cycle of a product can be divided into three stages, as shown in Figure 4. In the early stage of service, when a failure occurs, a maintenance strategy is often used for functional recovery. However, in the later stage of service, i.e., the third stage of the "bath curve," product performance declines sharply. As a result, the use cost, marginal cost, maintenance time, and maintenance cost of a product are all rising. Moreover, the remanufacturing cost also increases over time. If the maintenance strategy is always adopted, the economy will gradually decrease. Therefore, it is necessary to establish a mathematical model based on the monitoring data to predict the optimal recovery time and to minimize the unit time cost.

2) MATHEMATICAL MODEL

It is easy to recover the product in the first and second stages, and the corresponding maintenance cost is low. The decision model neglects the maintenance cost of the first two stages and considers the maintenance cost of a product from the third stage. Therefore, the total cost includes the original purchase cost of service with a product, the maintenance cost during the service period, and the remanufacturing cost. The model's objective is to minimize the cost per unit time, which can be described as

$$\min UTC(t_r) = \frac{C_o + C_p(t_r)R(t_r) + C_m F(t_r)}{t_r R(t_r) + M(t_r)F(t_r)}, \tag{1}$$

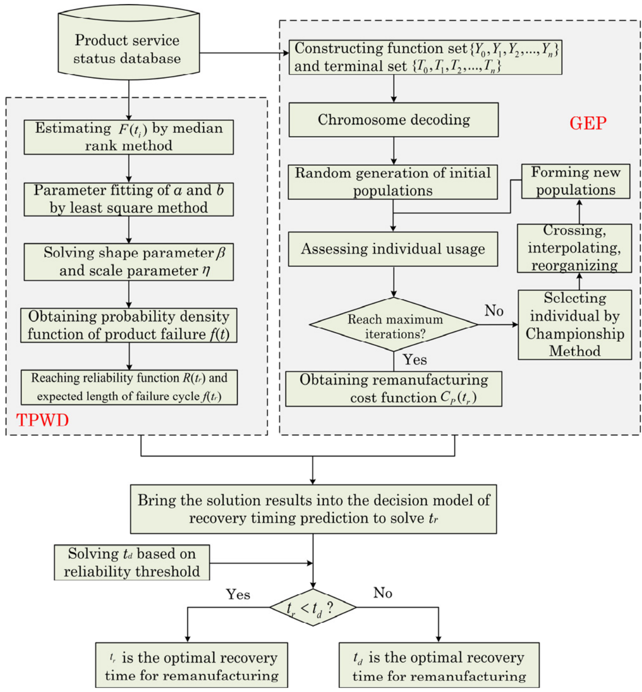

FIGURE 5. Flowchart of the solution method.

$$F(t_r) = \int_0^{t_r} f(t)dt, \tag{2}$$

$$M(t_r) = \int_0^{t_r} tf(t)dt / F(t_r), \tag{3}$$

$$R(t_r) + F(t_r) = 1, \tag{4}$$

where $UTC(t_r)$ is the optimization objective; C_o is the original value of the product, i.e., the purchase cost; $C_P(t_r)$ is the remanufacturing cost; C_m is the expected value of the maintenance cost; $f(t)$ is the failure probability density function; $F(t_r)$ is the cumulative failure distribution function; $R(t_r)$ is the reliability function; $M(t_r)$ is the expected length of the failure cycle; and t_r is the decision variable that recovery time. Both $F(t_r)$ and $R(t_r)$ are related to $f(t)$ of a product. Note that $C_P(t_r)$ is also a function of time t.

C. SOLUTION METHOD

The key to solving the model is to find the reliability function $R(t_r)$ and the remanufacturing cost function $C_P(t_r)$. The Weibull distribution has been proved effective for reliability analysis of mechanical and electrical products. The key of Weibull distribution lies in the estimation of shape and scale parameters, which can be deduced by using failure probability. In SORM, failure probability is easily obtained by remote monitoring system. Therefore, TPWD is selected to solve $R(t_r)$. GEP is a new adaptive evolutionary algorithm based on the structure and function of biological genes. It is very suitable for solving classification and mining complex function relations. So GEP is adopted to solve $C_P(t_r)$. The solution process is shown in Figure 5.

1) FITTING RELIABILITY FUNCTION

According to the collected data of in-service equipment status, the effective failure data is selected and the reliability function is fitted by TPWD theory. The reliability function expression of TPWD is

$$R(t) = \exp(-\frac{t}{\eta})^{\beta}, \tag{5}$$

where β is the shape parameter and η is the scale parameter.

The failure probability density function and the cumulative failure distribution function of TPWD are

$$f(t) = \frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1} \exp\left[(-\frac{t}{\eta})^{\beta}\right] \tag{6}$$

$$F(t) = 1 - \exp\left[(-\frac{t}{\eta})^{\beta}\right]. \tag{7}$$

To obtain formula (5), the next step is fitting the parameters of the Weibull distribution by the least square method. Because of the randomness and fuzziness of failure data, $F(t)$ is calculated from fault time series by the empirical analysis method, whose steps are as follows. First, the ordered fault time series $(t_1, t_2, \ldots, t_n)$ is obtained by arranging the fault data from small to large. Then the estimation value of the cumulative failure distribution function $F(t_i)$ is calculated by the median rank method:

$$F(t_i) = \frac{i - 0.3}{n + 0.4}, \tag{8}$$

where i is the failure order and n is the sample size.

We introduce $R(t) = 1 - F(t)$ in formula (5), and take the reciprocal on both sides to obtain

$$\frac{1}{1 - F(t)} = \exp(\frac{t}{\eta})^{\beta}. \tag{9}$$

Take logarithms on both sides of the equation:

$$\ln \frac{1}{1 - F(t)} = (\frac{t}{\eta})^{\beta}, \tag{10}$$

and continue to take logarithms:

$$\ln \ln \frac{1}{1 - F(t)} = \beta \ln t - \beta \ln \eta \tag{11}$$

$$\begin{cases} y = \ln \ln \left[\dfrac{1}{1 - F(t)}\right] \\ x = \ln t \\ a = \beta \\ b = -\beta \ln \eta. \end{cases} \tag{12}$$

From formula (12), the TPWD function can be translated to $y = ax + b$. The core idea of parameter estimation by the least square method is to minimize the sum of squares of errors between the fitting function values and actual data values. Parameters a and b are estimated as

$$a = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n \sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \tag{13}$$

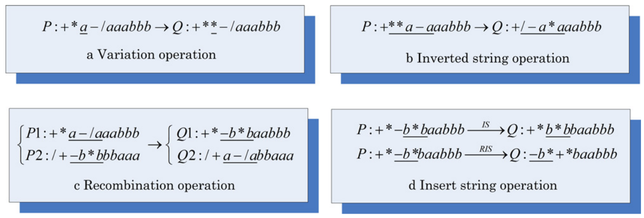

FIGURE 6. Operator of GEP.

$$b = \frac{1}{n} \sum_{i=1}^{n} y_i - \frac{a}{n} \sum_{i=1}^{n} x_i. \tag{14}$$

By introducing a and b in formula (12), the two parameters β and η of the Weibull distribution can be determined. Thus, $R(t), f(t)$ and $F(t)$ are all available.

2) SOLVING REMANUFACTURING COST FUNCTION

As shown in Figure 5, the GEP algorithm is solved as follows. First, aiming at the RTP problem, the input and output components and the control parameters are determined. Second, the population is initialized and the fitness values are calculated to determine whether the termination conditions are satisfied. If not, then various genetic operations are carried out to realize the evolution of the population. If the termination condition is satisfied, then the optimal individual is output. Finally, $C_P(t)$ is decoded. Operator of GEP is shown in Figure 6.

- **Establishing the functional relation between remanufacturing cost and time** GEP is a heuristic algorithm based on evolutionary theory, with the characteristics of explicit expression and easy parsing. Absent prior knowledge, GEP can use mutation, interpolation, reorganization, and other operations to find more accurate functional expressions that match the problem attributes. Based on GEP, the remanufacturing cost function is studied to explore the relationship between remanufacturing cost and equipment service time. The involved monitoring data include remanufacturing costs $\{Y_0, Y_1, Y_2, \ldots, Y_n\}$ and equipment service times $\{T_0, T_1, T_2, \ldots, T_n\}$. The relationship between Y and T can be expressed as

$$Y = C_p(T). \tag{15}$$

- **Fitness function** Since the final result is a functional expression of the remanufacturing cost and service time, the fitness function is mainly used to evaluate the consistency between the real data and the results from the prediction function. Therefore, the fitness function is chosen based on the mean absolute percentage error (MAPE). The function can reflect the deviation between the predicted value and the real value and has high portability. It is expressed as

$$f = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_i(T) - \hat{Y}_i(T)}{Y_i(T)} \right| \times 100\%, \tag{16}$$

where n is the number of sample points, $Y_i(T)$ is the real value of the remanufacturing cost, and $\hat{Y}_i(T)$ is the predictive value of individual function expressions.

- **Gene structure and coding pattern** GEP individuals consist of one or more equal-length gene sequences. Gene coding consists of a head and tail. The head gene is composed of a function set and terminal set, and its length is determined by the actual needs. The tail gene contains only the terminal set, and its length is determined by

$$t = h * (n - 1) + 1, \tag{17}$$

where n is the maximum number of operations of a function set. Considering the nonlinear relationship between the remanufacturing cost and operation time, the function set is set as $F = \{+, -, *, /, \sqrt{}, \sin, \cos, \exp\}$ and the terminal set is set to $T = \{x\}$. When the length of the gene head is set to 5, the length of the gene tail is equal to 6 by formula (17), and the total length of the gene is 11.

- **Genetic operation** GEP's genetic operation is similar to the genetic algorithm. It has special interpolation operators in addition to the conventional selection, mutation, and recombination operators. GEP can ensure that the good gene fragments of the father generation are inherited by the offspring, thus having global convergence characteristics. Figure 6 shows the operator of GEP.

V. CASE STUDY

This section takes the scenario of construction machinery remanufacturing as an example. A proof-of-concept application scenario is described to demonstrate how to implement SORM. Construction machinery works in large quantities with a wide scope, which is very suitable for remanufacturing [44]. Based on the SORM concept, we choose an excavator working in Luoyang, China, for which to predict the recovery time. The type of the excavator is SY155W, of which working weight is 13500 kg, and the rated power is 120kw. This excavator is owned by a leasing company, often rented to different users with no fixed construction site. Therefore, the working environment of the excavator is composite working medium.

The solution was implemented using MATLAB 2016a software. The running environment was a 3.3 GHz CPU with 8 GB memory.

A. RESULTS

1) RELIABILITY FUNCTION

Table 2 shows the data collected remotely from the excavator in 11 time periods. Based on the proposed TPWD method, a $= 7.5351$ and b $= -71.9415$. The values of a and b are brought into formula (12) to obtain the shape parameter β and scale parameter η, with values $\beta = a = 7.5351$ and $\eta = \exp^{(-\frac{b}{\beta})} = 14009.4$. Thus the reliability function of the excavator can be described as

$$R(t) = \exp(-\frac{t}{14009.4})^{7.5351}. \tag{18}$$

TABLE 2. Failure data of an excavator working in Luo Yang.

Period	Service time (t/h)	$F(t_i)$	x	y
1	9,816	0.0614	9.1918	-2.7588
2	10,922	0.1491	9.2985	-1.8233
3	11,564	0.2368	9.3557	-1.3083
4	12,028	0.3246	9.3950	-0.9355
5	13,282	0.4123	9.4942	-0.6320
6	13,594	0.5000	9.5174	-0.3665
7	14,122	0.5877	9.5555	-0.1210
8	14,529	0.6754	9.5839	0.1180
9	14,854	0.7632	9.6060	0.3649
10	15,028	0.8509	9.6177	0.6434
11	15,336	0.9386	9.6380	1.0261

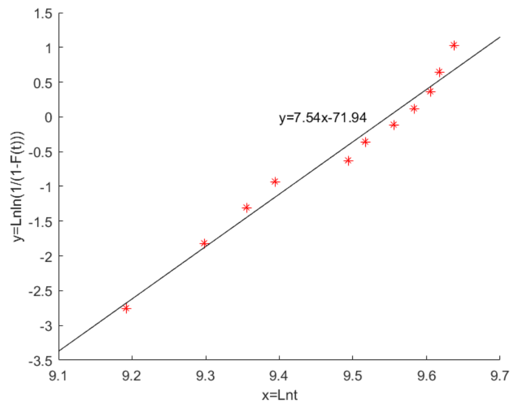

FIGURE 7. Least square fitting graph.

TABLE 3. Algorithm parameters.

Parameters	Values	Parameters	Values
Population size	50	Gene number	3
Maximum iterations	2,000	Head length	5
Competition scale	3	Mutation probability	0.1
Insertion probability	0.2	Recombining probability	0.3

The correlation coefficient R^2 between x and y is 0.972, which is close to 1, indicating a high correlation between x and y. Figure 7 shows a line fitted by the least square method. From the fitting results, most points are concentrated near the line. The fitting is ideal.

2) REMANUFACTURING COST FUNCTION

Table 3 shows the parameters of the GEP algorithm.

The expression of the remanufacturing cost function $C_p(t)$ in composite working medium is obtained as

$$C_p(t) = e^t + t + e^{\sin(2t+\sin t)} + e^{\sin[\cos(\cos t+t)]}. \tag{19}$$

The difference between the prediction value and the actual value is expressed by MAPE. MAPE is used to evaluate the prediction accuracy, as shown in formula (16). Its value in

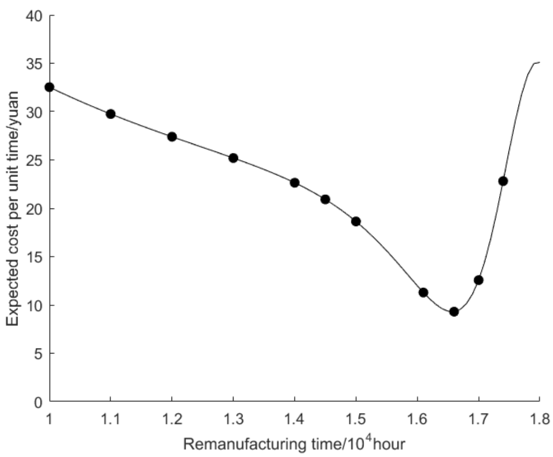

FIGURE 8. Optimal remanufacturing time of the excavator.

this experiment is 0.485%, which shows that the predictive accuracy of the function expression is high.

3) OPTIMAL RECOVERY TIMING PREDICTION

The excavator working in Luoyang is taken for further analysis. Its purchase cost is 2.5×10^5 yuan. The expected value of the average maintenance cost is 1.2×10^4 yuan one time. Bringing formulas (18) and (19) into previous mathematical model, the trend of the expected cost per unit time over recovery time is obtained by MATLAB, as shown in Figure 8. The optimal remanufacturing time is at about 16,602 hours, and the expected total cost per unit time is about 9.30 yuan. Because an excavator is a complex piece of equipment consisting of thousands of parts, the reliability of the whole excavator is very low in the later period of service. Therefore, the minimum q-precentile life requirement is not considered here.

B. REMOTE MONITORING PLATFORM

Construction machinery usually works in the field. The WebAPP platform can be accessed by mobile phones, as shown in Figure 9, which is convenient in such a case. The platform can remotely monitor the location, and direct parameters such as noise, vibration, fuel consumption, water temperature, oil pressure, and engine speed. After analyzing these monitoring data, the platform compares these parameters with maintenance standards, and sends out maintenance recommendations to customers. The platform can also monitor the number of failures and the service time of the equipment. Based on the model and solution method in this paper, the platform calculates the optimal recovery time and sends a reminder to customers in advance. Next the customer returns the excavator to the regional processing center on time. The remanufacturing evaluation department evaluates the remanufacturability of the excavator and returns all or part of the deposit to the customer. Then the excavator is sent to the remanufacturing factory. Three months later, the customer will receive a remanufactured excavator as new one, and a new service cycle begins.

FIGURE 9. Snapshots of WebAPP platform for SORM providers.

VI. DISCUSSION

A. RELEVANT FACTORS OF RTP

The total cost of equipment in a complete life cycle consists of the purchase cost, remanufacturing cost, and maintenance cost, as shown in formula (1) and Figure 10. The purchase cost is determined by the market price of the product. The remanufacturing cost depends on the remanufacturability [45], which is highly correlated with the product failure rate. Product failure has two main reasons. One is aging failure, which occurs over a long period of time. The other is wear failure, which appears in the service process of a product. Obviously, due to the continuous effect of stress, wear failure is highly related to the operating environment. Maintenance cost is the product of the expected maintenance cost and maintenance frequency, and the maintenance frequency is also related to the failure rate of a product. Through the above analysis, it is found that the service time and operating environment are two key factors affecting the total cost.

Therefore, we mainly consider the above two aspects in the solving model parameters. However, in the process of service, many factors affect the life of equipment, such as equipment lubrication, operator proficiency, and unexpected accidents. So, it is necessary to improve the monitoring status database based on the big data theory and establish the mapping model of multi-factors and recovery time, so as to more accurately forecast the remanufacturing recovery time.

B. RELATIONSHIP BETWEEN SERVICE TIME AND REMANUFACTURING COST

In practice, a remote monitoring platform collects a large amount of data on the equipment service time and

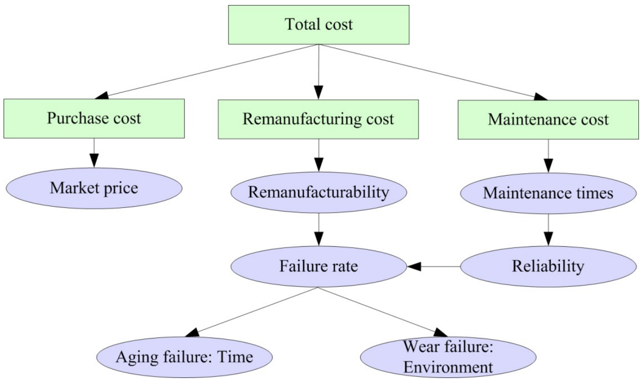

FIGURE 10. Analysis of factors affecting the cost.

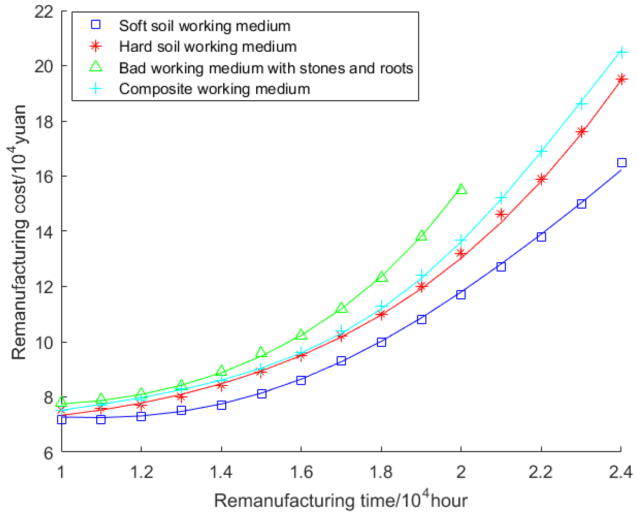

FIGURE 11. Relationship between remanufacturing cost and service time.

remanufacturing cost. Statistical analysis shows no obvious relationship between them. This is because the remanufacturing cost is related to not only the service time but to the operating environment. For example, one excavator always takes rocks and roots as the operating object, and another may often excavate soft soil or sand. In the same working time, the damage situations of the two devices are obviously quite different. Thus, to explore the relationship between remanufacturing cost and operation time, it is necessary to clarify the operating environment of equipment. Therefore, the working medium of excavators is classified into four categories: soft soil working medium, hard soil working medium, bad working medium with stones and roots, and composite working medium that excavators work randomly in above three environments. The functional relationship between excavator service time and remanufacturing cost is solved for these four types of working medium, using the GEP algorithm, as shown in formulas (19), (20), (21), and (22), with results as shown in Figure 11.

Soft soil working medium:

$$C_p(t) = e^t + t + e^{\sin(2t+\sin t)} + e^{\sin[\cos(\cos t+t)]}. \tag{20}$$

Hard soil working medium:

$$C_p(t) = 2e^t + \cos(\cos t - t) - t + 2. \tag{21}$$

Bad working medium with stones and roots:

$$C_p(t) = e^t + \frac{t^2+1}{\sin t} + e^{\cos[(\sin t)^2]}. \tag{22}$$

The curves in Figure 11 are fitted according to a large amount of data collected from the SORM platform. The data in each working medium are divided into 15 groups according to the service time. The average value of the data in each group is marked by a point in the graph. The curve of the bad working medium with stones and roots has only 11 points because excavators always working in a harsher environment rarely serve more than 20,000 hours, in other words, by the time point, the excavators is scrapped. Eastern areas of China are mainly plains, and the working medium of construction machinery in these areas is primarily soft soil. There are many hills and mountains in the central and western areas, and monitoring data show that the operating environment of construction machinery is relatively poor. Note that more than 50 percent of construction machinery does not have a fixed construction site, and to characterize their operating environment is complex, such as for the excavator in Luoyang taken as an example in this paper.

C. ADVANTAGES OF SORM

SORM theoretically performs remanufacturing before the performance of in-service equipment drops sharply, which saves remanufacturing costs, reduces unit service costs, and lessens the impact of uncertainty on remanufacturing production. In practice, based on abundant collected data, the curve of the relationship between service time and cost is fitted. This shows that in the early stage of service, the remanufacturing cost does not change significantly with service time, but in the frequent-failure stage, it increases rapidly, as seen in Figure 11. This also indicates that traditional remanufacturing, taking scrap product as product objects, may not be the most rational operation mode. Figure 8 illustrates the same problem. The products are recycled to remanufacture at the optimal recovery time, and the expected total cost per unit time is about 9.30 yuan, while that of traditional remanufacturing is about 20.3% higher at 11.67 yuan.

Based on the concept of SORM, a remote monitoring platform is developed to master the equipment operation and give timely help and guidance to customers. Moreover, the SORM mode shifts the focus of customers' attention from products to services, and dispels their doubts about the quality of remanufactured products (the contract guarantees that products can perform complete services). Moreover, this closed-loop whole-process control mode, to a certain extent, reduces the impact of many uncertainties on the remanufacturing system and ensures its smooth operation. In addition, the enterprise fulfills the extended producer responsibility (EPR) and achieves sustainable development. In summary, all stakeholders benefit from SORM.

VII. MANAGERIAL IMPLICATIONS

A. SUPPORT POLICY FROM GOVERNMENT

The concept of remanufacturing has existed for a long time. Nevertheless, few enterprises are engaged in remanufacturing, and the development of the remanufacturing industry has not reached expectations. Without losing generality, both automotive components and construction machinery are taken as an example. These are the most typical fields of remanufacturing in China [1], [11]. We have investigated some domestic companies, such as Sany Heavy Industry Co., Ltd., Xuzhou Construction Machinery Group Co., Ltd., and Dongfeng Motor Co., Ltd. They all have been trying to remanufacture their own products, but the ratio of remanufacturing to manufacturing is extremely small. There are three main reasons for this. First, remanufactured products are still not easily accepted by the public in China, and the market demand for remanufactured products is relatively small. Second, remanufacturing management is more complex than that of traditional manufacturing, and there are insufficient human resources to support remanufacturing. Third, OEMs are reluctant to remanufacture in the current situation of overcapacity.

To some extent, SORM can handle these challenges well. The government should create a better environment, especially introducing more active fiscal and taxation policies, to support enterprises to better develop SORM, and to encourage them to take the road of sustainable development.

B. INTEGRATION OF FORWARD AND REVERSE LOGISTICS NETWORK

A supply chain logistics network has nodes and routes through which new products go from manufacturing systems to customers, and returns from customers to remanufacturing systems. Constructing a perfect logistics network is the foundation of SORM operation. The logistics network of SORM is significantly different from conventional logistics networks, which is mainly embodied in facilities integration, function division, transportation integration, uncertain return quantities, and a random remanufacturing rate. Issues such as network structures, facility locations, and traffic allocation all require further study.

C. UNIFIED MANAGEMENT OF A HYBRID MANUFACTURING–REMANUFACTURING SYSTEM

In SORM mode, the production plan, material requirement plan, and capability requirement plan of a hybrid manufacturing–remanufacturing system should be considered in a unified way. Although SORM reduces many uncertainties, the addition of remanufacturing still brings management complexity to OEMs. In the initial design stage, the problem of production balance should be considered first. The production capacity of remanufacturing, disassembly, repair, and assembly stations should be simulated to ensure that there is no bottleneck in the process. Moreover, the task allocation of manufacturing and remanufacturing should be well coordinated, which can be achieved through production scheduling. Traditional production control theory cannot be directly applied to a hybrid system. Many factors, such as disassembling order, time and quantity, process route of waste parts, and repair time, as well as quantities of various types of parts required for assembly, must be highly coordinated to achieve smooth operation of this hybrid system.

VIII. CONCLUSIONS

This paper introduces a new mode called SORM, which is quite different from previous remanufacturing operation modes. By remotely monitoring the status of in-service equipment, SORM can recover and remanufacture equipment before its performance drops sharply. The operation logic and implementation path of SORM were discussed in this paper. Subsequently, we focused on RTP that the core problem of SORM. An RTP framework based on remote monitoring data was given. The prediction model was established with the goal of minimum operating cost per unit. Then a method combined with TPWD and GEP was proposed to solve the model. Finally, the feasibility of SORM was illustrated by an excavator remanufacturing example. Additionally, we discussed the managerial implications of key findings and observations on SORM.

Several conclusions were drawn from the above research. First, the SORM mode avoids the rapid deterioration of equipment performance in the later period of service. Second, SORM is a new business model of remanufacturing, which brings about the overall change of the whole remanufacturing industry chain. Third, the relationship between service time and remanufacturing cost of construction machinery is closely related to the working medium. Therefore, before analyzing and processing monitoring data, it must be clustered according to the operating environment. Fourth, technologies such as big data, the internet of things, and RFID are developing rapidly, and will provide much support for SORM. Our example of remote monitoring proved this.

The present study can be extended as follows. SORM depends on product performance. The failure probability was used to reflect product performance in this paper. While failure probability is the indirect manifestation of product performance. In practice, before the product loses efficacy, its performance changes are first reflected in noise, vibration, water temperature, hydraulic pressure, fuel consumption and so on. Future research should use these direct indicators to judge product performance and predict recovery time, rather than waiting for product failure. In addition, the time period involved in the proposed model is from the beginning of service to remanufacturing. After remanufacturing, the product will have a new life cycle. Another interesting research direction is taking the original life cycle and the new life cycle into account.

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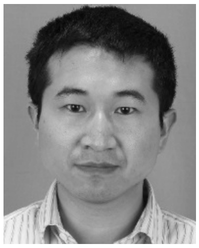

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