Environmental Science and Pollution Research
https://doi.org/10.1007/s11356-021-13438-z

SUSTAINABLE SUPPLY CHAIN NETWORK DESIGN

An energy and time prediction model for remanufacturing process using graphical evaluation and review technique (GERT) with multivariant uncertainties

Jiali Zhao[1] · Zheng Xue[2] · Tao Li[2] · Jinfeng Ping[3] · Shitong Peng[3]

Received: 29 December 2020 / Accepted: 9 March 2021

Abstract

The rising energy price and stringent energy efficiency-related legislations encourage decision makers to concern more about energy efficiency in current manufacturing competition. In this regard, a quick and accurate prediction of the energy consumption and makespan in the manufacturing process has been a prerequisite for energy optimization. Given the various types of uncertainties in the remanufacturing system such as stochastic, fuzzy, and grey factors, the present study developed a prediction model that forecasts the energy consumption, completion time, and probability of processing routes. It adopted the graphical evaluation and review technique (GERT) to convert remanufacturing process into an uncertain network, considering multivariant uncertainties instead of merely stochastic uncertainty in prior works. We provided a generic seven steps to implement this approach. The energy consumption and completion time of remanufacturing process were determined in conjunction with Mason's rule and chance-constrained programming. Connecting rod reprocessing was presented as a numerical example. Based on the GERT network, we conducted an Arena simulation to validate the feasibility and effectiveness of this approach. In addition, we adopted the concept of criticality index to conduct sensitivity analysis and examine the predominant factors affecting the concerned indicators. This study would enable remanufacturers to perform a quick prediction of energy use and makespan in remanufacturing process.

Keywords GERT · Remanufacturing · Energy modeling · Uncertainty · Connecting rod

Introduction

The modern substantial production enables a higher standard of living worldwide. However, dramatic consumptions have exerted huge environmental and economic burdens and fostered sustainable manufacturing concerns primarily the energy and material conservation in original equipment manufacturers. For example, the National Bureau of Statistics of China indicated that the vehicle population in 2018 was 232.3 million (State Statistics Bureau n.d.) and the quantity of scrapped vehicles was expected to be 99.5 million in 2020 (Xiang and Ming 2011), which necessitate innovative end-of-life disposal approaches. Amongst the various solutions to scrapped products, remanufacturing is widely recognized as an effective paradigm to significantly reuse the embodied raw materials and energy by fully extending the life cycle of a product (Jin et al. 2013). More specifically, the engine remanufacturing would restore the decommissioned engines back to its original condition and has been an important part of the circular economy (Jiang et al. 2016). As highlighted in the 13th Five-Year Plan promulgated by the central government of China, the overall energy intensity per GDP is required to reduce by 15% from 2015 to 2020 (Central People's Government of China 2017). The *industrial green development planning* reported by the Ministry of Industry and Information Technology of China (2016) stated that energy and water consumption per unit industrial added value should be reduced by 28 and 35%, respectively. Legislative pressure

Responsible Editor: Philippe Garrigues

✉ Shitong Peng
shtpeng@stu.edu.cn

[1] School of Mechanical & Electronical Engineering, Lanzhou University of Technology, Lanzhou 730050, China

[2] Institute of Sustainable Design and Manufacturing, Dalian University of Technology, Dalian 116024, China

[3] Department of Mechanical Engineering, College of Engineering, Shantou University, Shantou 515063, China

Published online: 13 April 2021

and market competition would facilitate the remanufacturers to incorporate the energy concerns in their production process.

Compared with conventional manufacturing, remanufacturing exhibits high levels of inherent uncertainty because it regards the returned cores as workblanks. These two types of manufacturing paradigms differ in the following aspects: (1) stochastic returned production in time and quantity, (2) varying qualities and compositions of returned products, and (3) unfixed processing routes and time. The review studies by Tang and Li (2012) and Guide (2000) have comprehensively summarized the uncertainties in remanufacturing, such as the uncertainty of remanufacturing rate, lead time, disassembly of components, returned products, and imbalance between demand and recycling, etc. Amongst these uncertainties, the quality variation of used products is one of the primary sources of uncertainty in remanufacturing as it directly brings a high level of imbalanced processing routes and stochastic processing time. Additionally, the quantity, quality, and timing of returned cores are beyond the direct control of remanufacturers (Jin et al. 2011). It is generally believed that operation planning, control, and management in remanufacturing is more complex than that in conventional manufacturing (Guide et al. 1997; Tian et al. 2019). Therefore, remanufacturing operation management has proved to be challenging. As a prerequisite of systematic energy conservation, predicting the energy and time consumption of remanufacturing system under various uncertainties is more complex compared with conventional manufacturing system.

Generally, there are roughly two types of prediction methods: qualitative and quantitative. The former mainly rests on subjective inference particularly when historical data are unavailable, while the latter includes a wide range of methods. Some commonly used approaches for the quantitative forecast are time series methods (e.g., moving average, autoregressive moving average, and autoregressive integrated moving average), artificial intelligent methods (e.g., data mining, machine learning, and artificial neural networks), judgmental methods (e.g., statistical survey and Delphi method), and so forth (Zhou et al. 2016). As the remanufacturing system possesses many uncertain factors, this would be a fundamental barrier to apply conventional prediction methods, and relevant studies on the prediction of energy consumption in remanufacturing are still scarce. The simulation was proved to be a promising method to analyze and predict the behaviors of complex processes or systems (Zheng et al. 2005). Nevertheless, the stochastic simulation tools might have limited accuracy and high computational or structural complexity particularly for complex systems full of uncertain conditions. The importance of forecasting is appreciable in remanufacturing operations. Remanufacturing cost, environmental burden, and enterprise profile are partially influenced by energy consumption (Zhao et al. 2020). Prior studies on energy consumption in manufacturing systems considering multivariant uncertainties are still scarce. How to forecast energy use has been identified as one of the research gaps in the field of energy benchmark (Liu et al. 2015; Cai et al. 2020). To this end, the prediction of manufacturing power consumption necessitates an easier modeling approach without compromising the accuracy of energy quantification.

As the uncertainty propagation across the remanufacturing system will cause significant impacts on energy consumption and the completion time, an insight into the holistic remanufacturing processes will benefit robust decision makings on improving the energy-saving potential. In this paper, we developed a GERT-based prediction modeling of energy use in the remanufacturing process considering multivariant uncertainties mainly including grey branch possibility, stochastic, and fuzzy processing time. This mathematical model in conjunction with the chance-constrained programming (CCP) model was applied to quantify the energy use during the remanufacturing process of the decommissioned engine crankshaft. Further, we applied the Arena simulation to validate the effectiveness of this GERT model. The concept of criticality index (CI) was adopted to analyze the predominant factors affecting energy consumption and completion time. This study can contribute an effective analytical approach for uncertainty propagation and would benefit the engine remanufacturing management.

The rest of this paper is organized as follows. "Literature review" summarized the relevant works facing the present study. "GERT with multivariant uncertainties" presented the detailed procedure of GERT with multivariant uncertainties. "Case study of connecting rod remanufacturing" provided the numerical example of the connecting rod reprocessing. The final conclusions were given in the "Conclusions" section.

Literature review

The literature that is most relevant to the present study includes energy prediction of manufacturing system and the GERT approach and its application. The state of the art of these two aspects are reviewed as follows.

Energy prediction modeling of manufacturing system

Understanding and characterizing the dynamic variation of energy consumption from the perspectives of the production process, task, and control would support the exploration of energy reduction in manufacturing systems. The energy cascade of manufacturing system can be roughly organized into five levels: unit process, multi-machine system, facility, multi-factory, and global supply chain (Duflou et al. 2012), while the current studies primarily focus on the prior three levels. The unit process typically refers to the individual machine tool as a smallest production unit. At this level, some current studies (Kara and Li 2011; Xie et al. 2016; Shang et al. 2019) built empirical formulas of energy consumption based on amounts of experiments and energy measurements. Their main objectives were to obtain a predictive energy consumption model in a unit process, and a test dataset was usually employed to validate the effectiveness of the formulas. Energy consumption of a multi-machine level can be regarded as cumulative energy profiles of all involved technical equipment. The energy modeling at this level would cope with varying products and machines. He et al. (2012) proposed a task-oriented energy consumption prediction model for machining manufacturing system. They employed the event graph methodology to select the more energy-efficient scheme in two alternatives. Wang et al. (2016) adopted the discrete event system specification formalism and input–output model to simulate hybrid manufacturing and remanufacturing system for lean energy. This model had integrated with the energy flow, material flow, and information flow. Hu et al. (2017) characterized the machining process and minimized the energy consumption by sequencing the features of parts. The energy consumption model at factory level requires a holistic understanding of manufacturing involving technical building services (TBS), production equipment, and production management including planning and scheduling, etc. Alvandi et al. (2015) developed a hierarchical modeling of energy flow at an aluminum recycling and rolled sheet production facility to forecast energy use and identify energy hotspot. Herrmann and Thiede (2009) presented a predictive model of a production plant containing three subsystems: TBS, building shell, and the production system itself. The integrated simulation and evaluation of the production system enabled the improvement of energy efficiency. Mayr et al. (2019) introduced an energy-related plant simulation that enabled tracking load and temperature profiles through the whole process chains.

Since the flexible manufacturing system (FMS) is a discrete event dynamic system, typical energy modeling methods for FMS have been extensively investigated in prior studies mainly including the Petri net (PN) model and its derivatives (e.g., stochastic PN, colored time PN, and hybrid PN) (Cao and Li 2014; Wang et al. 2014; Peng et al. 2019), Markov models and its derivatives (e.g., hidden Markov chain and semi-Markov chain) (Cai et al. 2018; Zhao et al. 2019), queuing theory (Zavanella et al. 2015), activity cycle diagram (ACD) (Choi et al. 2014), and perturbation analysis (PA) (Wardi et al. 2018). Although many uncertainties in remanufacturing conform to specific random distributions, uncertainties such as return time, quality, and quantity of used products have considerable impacts on the production, modeling, and optimization, as stated by Zhou et al. (2016). And conventional FMS modeling method to make a prediction is difficult to handle uncertainties in each process without coupling with stochastic simulation, for instance, the Monte Carlo Simulation method.

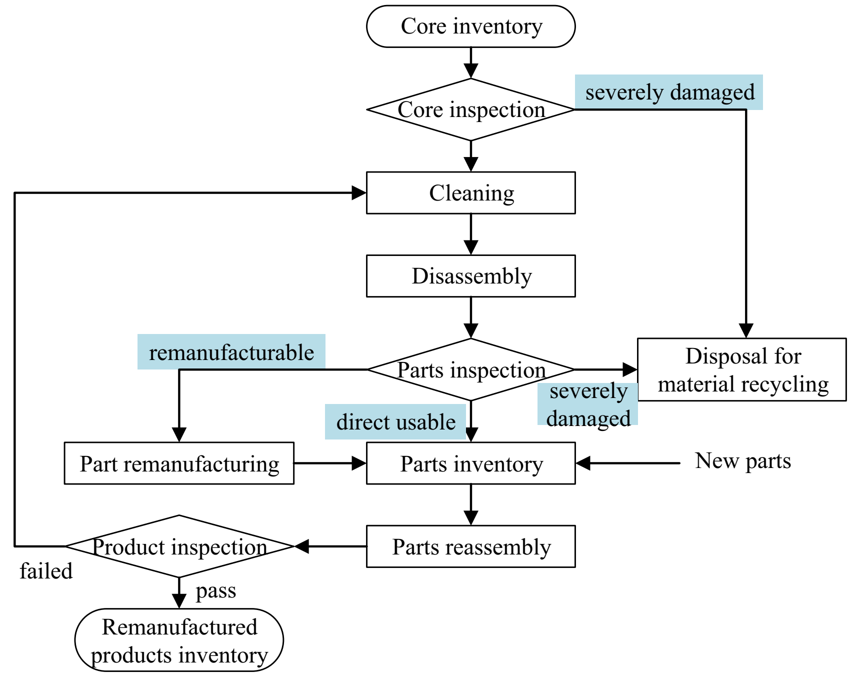
In system engineering, the stochastic network modeling technique could analyze events with branches of probability, uncertain operations, and closed loops. Typically, the GERT approach can directly capture the dynamic process of remanufacturing under uncertain conditions and determine the numerical solutions to the time, energy consumption, and corresponding probability.

The GERT applications

GERT proposed by Pritsker and Happ (1966) was originally developed for managing the Apollo project. One typical application of GERT is undertaking the R&D projects, for example, projects regarding polymer electrolyte fuel cell (Hayashi et al. 2005), CO_2 capture technologies (Kosugi et al. 2004), and selective laser sintering industry (Olivier et al. 2019). Their objectives are to determine project makespan, the cost-effectiveness of investment, or success probability. Since its inception, the GERT method has been widely extended to diverse research domains such as mechanized wheat production (Abdi et al. 2010), repairable reliability (Lin et al. 2011a), risk analysis (Tao et al. 2017), and semiconductor manufacturing (Lin et al. 2011b). Specifically, the GERT also has been utilized in the remanufacturing process for prediction, evaluation, and optimization.

The returned cores in the remanufacturing inspection are generally classified into three types, i.e., direct reusable component, remanufacturable component, and severely damaged component for material recovery. The quality variation of used components seriously affects the processing time and route, resulting in high stochastic energy use. The development of an analytical evaluation for remanufacturing is exceptionally important to realize effective and efficient remanufacturing. As reflected in Fig. 1, the remanufacturing is featured with occurrence probability, stochastic processing consumption, and network structure. These characteristics make GERT an appropriate tool to manage uncertainties in remanufacturing. Wang and Chen (2013) adopted the GERT in the remanufacturing automotive electronic control components to calculate the success rate and remanufacturing time. Apart from the numerical experiments, they revealed the relationship between influencing factors and remanufacturing time and further proposed key process optimization to reduce total time. Zhou et al. (2016) skillfully developed a generic forecasting model for remanufacturing considering the first- and second-hand markets. Their GERT model predicted the returns and remanufacturing quantity, time, and probability of used printers. Li et al. (2011) applied the GERT model to the lathe spindle remanufacturing for uncertain management, particularly the time and probability

Fig. 1 A general remanufacturing process



estimation of each remanufacturing process route. However, the models in these mentioned works are all about the classic GERT. Deviation frequently occurs in the recognition and judgment towards the real-world remanufacturing, and accurate estimations of parameters are sometimes difficult. Thus, incorporating these additional uncertainties, for example, the grey characteristic of branch probability, will make the model more consistent with remanufacturing practice. In addition, the network parameters obtained by the inversion theorem in classic GERT fail to consider the constraints, which may limit the applications of the classic GERT model.

Although there is a growing body of literature addressing the GERT applications in various areas, the studies of the GERT approach addressing remanufacturing issues are limited. Additionally, previous studies mainly utilized the GERT model to address stochastic or fuzzy uncertainty separately instead of a comprehensive consideration of stochastic, fuzzy, and grey uncertainties. Here, we developed a GERT model with multivariant uncertainties for energy and time quantification in the remanufacturing practice and identified the influential factors using the sensitiveness index. This study will contribute to the literature on GERT application in remanufacturing.

GERT with multivariant uncertainties

Basics of classic GERT

Classic GERT enables the analysis of stochastic network with directed branches and logic nodes. Activities in a stochastic network usually have two features: occurrence with probability and stochastic performing time. More specifically, the occurrence of any activity (branches in the network) has a constant probability associated with it, and time (or other attributes) to perform an activity is a random value subject to certain distribution. As elucidated in Fig. 2 (Wang and Chen 2013), any directed branch is connected by two logical nodes (states) and includes two important parameters, i.e., the possibility (p_{ij}) and estimated time period (T_{ij}) from node i to node j. The parameter T_{ij} here can be extended but not limited to cost (C_{ij}), energy (E_{ij}), or material consumption (M_{ij}) in light of specific cases.

Each node in the stochastic network is symbolized by a different icon. The input side (left side) of a node in GERT has three logical relations: AND, OR (Inclusive-OR), and XOR (Exclusive-OR), while the output side (right side) has two types: deterministic and probabilistic. For notational convenience, Table 1 integrates the input and output symbols to indicate six types of nodes. As the XOR logic can be more easily processed in analytical method, computation in the GERT network requires the transfer of all the input logical relations into XOR. The topological structure of the network has three basic structures including series, parallel, and self-loop. To simplify the GERT network, these structures have their equivalent representations, and the detailed equivalencies see (Wang and Chen 2013).

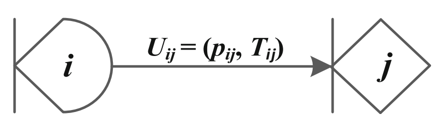


Fig. 2 The basic unit of the GERT network

Table 1 Six types of logic nodes for GERT

Output side	Input side		
	XOR	OR	AND
Deterministic			
Probabilistic			

Description of GERT with multivariant uncertainties: a generic procedure

The classic GERT primarily involves stochastic uncertainty. While in real-world practice, a manufacturing system generally has stochastic, fuzzy, and grey uncertainties. GERT with multivariant uncertainties allows an accurate description for such system.

For uncertain systems with partial known information, particularly the small samples and poor data availability, the uncertain parameters could be expressed by grey numbers (Liu and Lin 2010). In applications, a grey number is regarded as an indeterminate number whose value locates within an interval or a general set of numbers. It is generally written with the symbol "⊗." Liu and Lin (2010) summarized the types of grey numbers and illustrated the arithmetic operations. This study used the interval grey number that has both an upper bound $\overline{a}$ and a lower bound $\underline{a}$, written as $\otimes\in[\underline{a},\overline{a}]$. Therefore, if there is a grey parameter in the GERT network, the value of the output variable must be also within an interval.

Fuzzy uncertainty also frequently occurs in manufacturing system. Fuzzy parameters are commonly represented by a triangular fuzzy number (TFN) and a trapezoidal fuzzy number. The present study adopted the TFNs to show the fuzzy parameters. Three numbers in TFN $t=(t_1, t_2, t_3)$ refer to the lower bound, most feasible, and upper bound situation. In order to conduct the stochastic simulation, the membership function $\mu_t(x)$ (Eq. (1)) of TFN should be transformed into probability distribution function $f_t(x)$ (Eq. (2)).

$$\mu_t(x) = \begin{cases} (x-t_1)/(t_2-t_1), & t_1 \le x \le t_3 \\ (x-t_1)/(t_2-t_1), & t_1 \le x \le t_3 \\ 0, & x < t_1 \ or \ x > t_3 \end{cases} \tag{1}$$

$$f_t(x) = \begin{cases} 2(x-t_1)/[(t_2-t_1)(t_3-t_1)], & t_1 \le x \le t_3 \\ 2(x-t_1)/[(t_2-t_1)(t_3-t_1)], & t_1 \le x \le t_3 \\ 0, & x < t_1 \ or \ x > t_3 \end{cases} \tag{2}$$

The methodology of GERT with multivariant uncertainties can be generalized into the following steps:

Step 1: Mapping the investigated process/system to derive a causal flow diagram or network.

Step 2: Converting input sides of all the nodes into the form of XOR.

Step 3: Collecting necessary data on each activity, for example, the branch possibility and completion time in the form of grey number, probability density function, or membership function.

Step 4: Utilizing the parameters associated with each branch (from node i to node j) to determine the branch's transfer function $w_{ij}(s)$ and the activity's moment generating function (MGF) $M_{ij}(s)$ by Eqs. (3) and (4).

$$w_{ij}(s) = p_{ij} M_{ij}(s) \tag{3}$$

$$M_{ij}(s) = E(e^{t_i s}) = \begin{cases} \int_{-\infty}^{+\infty} e^{t_i s} f(t_i) dt_i & t_i \text{ is continuous variable} \\ \sum e^{t_i s} p(t_i) & t_i \text{ is discrete variable} \end{cases} \tag{4}$$

where t_i is the random variable in branch or activity (i, j); $f(t_i)$ and $p(t_i)$ are the probability distribution function for continuous variable and probability mass function for the discrete variable, respectively.

Step 5: Computing the equivalence transfer function $W_{ij}(s)$ of the concerned route, i.e., from node i to node j using a theory of signal flow graphs, particularly Mason's rules (Mason 1956), as shown in Eq.(5).

$$W_{ij}(s) = \frac{1}{\Delta} \sum_{k=1}^{n} G_k \Delta_k \tag{5}$$

where n is the total amount of forward routes from input node i to output node j; G_k is the gain of kth forward route from node i to j; "gain" in control theory indicates the loop or path's transfer function; Δ is the graph's determinant calculated by Eq. (6):

$$\Delta = 1 - \sum L_x + \sum L_x L_y - \sum L_x L_y L_z \ldots + (-1)^k \sum \ldots + \ldots \tag{6}$$

where $\sum L_x$ is the sum of transfer functions for different loops; $\sum L_x L_y$ is the sum of transfer functions for any two non-touching loops; $\sum L_x L_y L_z$ is the sum of transfer functions for any three non-touching loops; $(-1)^k \sum \ldots$ is the sum of transfer functions for any k non-touching loops; while Δ_k refers the value of Δ for that part of the graph not touching kth forward route.

Step 6: According to the properties of MGF, two equations can be deduced (Li et al. 2011): (1) the equivalent probability from node i to j equals the transfer function at s=0, as shown in Eq. (7); and (2) n order origin moment of the variable equals the nth derivative of MGF at s=0, as reflected in Eq. (8):

$$W_{ij}(0) = p_{ij} M_{ij}(0) = p_{ij}^e \tag{7}$$

$$\left[\frac{\partial^n}{\partial s^n} M_{ij}(s)\right]\bigg|_{s=0} = E\left[T_{ij}^n\right] = f_n(\xi_1, \xi_2, \ldots, \xi_m) \tag{8}$$

where $\xi_1, \xi_2 \ldots \xi_m$ are the stochastic, fuzzy, or grey parameters as the network involved in multivariant uncertainties.

Step 7: Computing the analytical and numerical solutions of concerned variables in the network based on chance-constrained programming (CCP) and simulation. Since the analytical solution contains multiple types of uncertain parameters and manufacturing practices have many processing constraints, the numerical solution requires further CCP and simulations. The simulation method utilized in this study is the traditional Monte Carlo Simulation (MCS) considering its high flexibility and easy application. For detailed elaboration on the theory of uncertain programming, see (Liu 2002). CCP is usually applied to uncertain decision systems with the assumption that constraint will hold at a certain confidence level regarded as an appropriate safety margin by decision maker. The CCP model that minimizes the optimistic return with given confidences can be simply expressed as follows:

$$\begin{cases} \min \ \overline{f} \\ s.t. Cr\left\{f(x,\xi) \geq \overline{f}\right\} \geq \beta \\ Cr\{g_i(x,\xi) \leq 0\} \geq \alpha, j = 1, 2, \cdots, p \end{cases} \tag{9}$$

where α and β are the given confidence levels; $\overline{f}$ is the β-optimistic return; x is a decision vector; ξ is an uncertain vector, usually a stochastic vector; and $f(x, \xi)$ is a return function.

Sensitivity analysis

A sensitivity analysis is conducted to measure the extent that final results would be affected by uncertain factors. This helps identify the most energy- or time-sensitive operations. In this study, we adopted the concept of criticality index (CI) as an indicator for each activity's relative importance. CI had been widely utilized in the studies of Programming Evaluation Review Technique (PERT) (Cho and Yum 1997) and is defined as follows:

$$CI_{ij} = \Delta T / \delta_{ij} \tag{10}$$

where CI_{ij} is the criticality index of activity (i, j) from node i to j; ΔT is the relative change of the value of output variable; δ_{ij} is the relative change of the value of input variable in an activity (i, j). CI can explicitly display the change rates of concerned output variables caused by a unit variation of parameters in an activity. Such index enables decision makers to enhance efficiency more targetedly.

Case study of connecting rod remanufacturing

Connecting rod remanufacturing process

The engine remanufacturing mainly engages in seven components: gearbox, cylinder head, cylinder block, flywheel, flywheel housing, crankshaft, and connecting rod. The investigated connecting rod (Fig. 3) is from the WD615-87 diesel engine. Although the remanufacturing process generally has disassembly, inspection, cleaning, reprocessing, and reassembly, this study solely concerns the reprocessing stage because it is higher technically and more energy demanding than other stages. As an important kinetic part of the engine, the connecting rod would cause various types of damage including abrasion, deformation, fatigue crack, and even fracture. Fig. 4 presents the reprocessing routes of the waste connecting rod. Remanufacturing finally classified the returned connecting rods into three categories, i.e., direct reusable part, direct disposal part (material recovery), and remanufacturable part. Even though the damage type and degree vary significantly amongst the used connecting rods, there are roughly two reprocessing routes, namely, route 1→3→10 and 1→2→10 for slightly damaged parts and severely damaged parts, respectively. Clearly, compared with the slightly damaged part, the severely damaged part just has an additional operation of brush electroplating. After the inspection phase, the used connecting rods with dimensional tolerance over 0.09 mm were disposed directly for material recovery, while the parts with the abrasion between 0.03 and 0.09 mm required brush electroplating operation. Remanufacturable connecting rods were reprocessed into technically qualified components through honing, bushing, milling, and so forth as shown in Fig. 4. The flaw detection determined whether components after cleaning were qualified or defective. For the used connecting rods with little abrasion, they were collected as direct reuse parts.

Fig. 3 Connecting rod in WD615-87 diesel engine

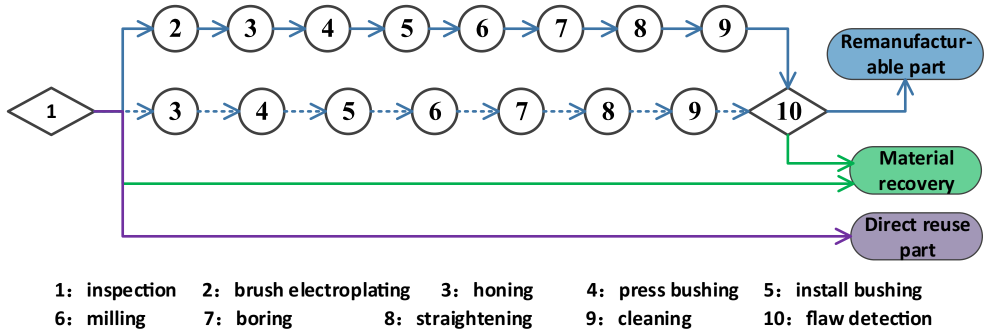


Fig. 4 Reprocessing routes of the used connecting rod

High variation of the used components' damage types and degrees would lead to the uncertainties of processing routes and operation time. An effective representation and analysis of the connecting rod remanufacturing process by GERT will contribute to the decision making associated with energy consumption and completion time.

Data collection

According to the reprocessing routes of connecting rod, we established the corresponding GERT model by mapping the 10 operations in Fig. 4 to the branches or activities as shown in Fig. 5. This model has three underlying assumptions: (1) operations in the reprocessing system are independent and stable; (2) components with identical damage type and degree consume the same amount of energy and operation time; and (3) except for the milling lathe in the 6th operation ($O6$), other equipment will not be breakdown and personnel will not be absent in long enough time.

Based on the onsite survey at SINOTRUK, Jinan Fuqiang Power Corp. Ltd., a large engine remanufacturer in China, Table 2 lists the basic information on each operation of connecting rod reprocessing including the possibility, time distribution, MGF, and transfer function of each branch (activity). The bench inspection ($O1$) classified the used parts into four different states. Due to the limited samples and incomplete information, the possibilities of these states are fuzzy numbers. Notably, the sum of such possibilities equals 1. Time consumption of the bench inspection obeys the triangular distribution in which the parameter ρ obeys the normal distribution. With the time distribution of each operation, the MGF and transfer function could be determined by Eqs. (3) and (4). Admittedly, given that obtaining accurate distributions is not easy and requires substantial amounts of samples, we consulted with onsite engineers who have over 5 years of working experience to get time distributions in Table 2.

Considering the difficulty of monitoring the accurate energy consumption of each operation, the energy use of each operation was determined by the product of rated power of each equipment (Table 3) and its operation time. Even though the computation method is simple and inaccurate, it is commonly applied in the rough estimation of energy consumption in manufacturing system (Zhao et al. 2020). Likewise, the energy-related information is determined using Eqs. (3) and (4), as presented in Table 4.

Time and energy consumption analysis

The connecting rod remanufacturing process has multiple uncertainties as indicated in Tables 2 and 4. Here, we mainly analyzed the expectation of time and energy use for direct reuse parts, remanufacturable parts, and disposed parts.

(1) Direct reuse parts

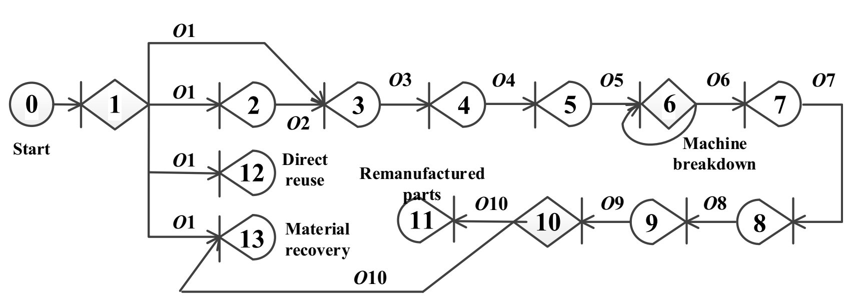


Fig. 5 The GERT network of connecting rod reprocessing

Table 2 Probability parameters and time-related functions on each activity

Operation	Branch	Possibility	Time distribution (min)	MGF	Transfer function
1	1→3	$p_{1,3}(\otimes)$=[0.6, 0.7]	$t_{1,3} \sim Tri(\rho{-}4, \rho, \rho{+}4)$ $\rho \sim N(50, 6)$	$e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$	$p_{1,3}e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$
1	1→2	$p_{1,2}(\otimes)$=[0.1, 0.2]	$t_{1,2} \sim Tri(\rho{-}4, \rho, \rho{+}4)$ $\rho \sim N(50, 6)$	$e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$	$p_{1,2}e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$
1	1→12	$p_{1,12}(\otimes)$=[0.05, 0.1]	$t_{1,12} \sim Tri(\rho{-}4, \rho, \rho{+}4)$ $\rho \sim N(50, 6)$	$e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$	$p_{1,12}e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$
1	1→13	$p_{1,13}(\otimes)=1\text{-}p_{1,3}\text{-}p_{1,2}\text{-}p_{1,12}$	$t_{1,13} \sim Tri(\rho{-}4, \rho, \rho{+}4)$ $\rho \sim N(50, 6)$	$e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$	$p_{1,13}e^{(\rho+4)}\ s + e^{(\rho-4)}\ \frac{s-2e^{\rho s}}{16s^2}$
2	2→3	$p_{2,3} = 1$	$t_{2,3} \sim N(5, 0.8)$	$e^{5s+0.4s2}$	$p_{2,3}e^{5s+0.4s2}$
3	3→4	$p_{3,4} = 1$	$t_{3,4} \sim U(1.5, 3)$	$(e^{3s}-e^{1.5s})/1.5s$	$p_{3,4}(e^{3s}-e^{1.5s})/1.5s$
4	4→5	$p_{4,5} = 1$	$t_{4,5} \sim U(0.6, 1.3)$	$(e^{1.3s}-e^{0.6s})/0.7s$	$p_{4,5}(e^{1.3s}-e^{0.6s})/0.7s$
5	5→6	$p_{5,6} = 1$	$t_{5,6} \sim U(0.7, 1.2)$	$(e^{1.2s}-e^{0.7s})/0.5s$	$p_{5,6}(e^{1.2s}-e^{0.7s})/0.5s$
6	6→7	$p_{6,7} = 0.97$	$t_{6,7} \sim Exp(1)$	$1/(1-s)$	$p_{6,7}/(1-s)$
6	6→6	$p_{6,6} = 0.03$	$t_{6,6} \sim Exp(1/180)$	$1/(1-180s)$	$p_{6,6}/(1-180s)$
7	7→8	$p_{7,8} = 1$	$t_{7,8} \sim N(2, 0.08)$	$e^{2s+0.04s2}$	$p_{7,8}e^{2s+0.04s2}$
8	8→9	$p_{8,9} = 1$	$t_{8,9} \sim U(0.5, 1.2)$	$(e^{1.2s}-e^{0.5s})/0.7s$	$p_{8,9}(e^{1.2s}-e^{0.5s})/0.7s$
9	9→10	$p_{9,10} = 1$	$t_{9,10} \sim U(0.5, 1.5)$	$(e^{1.5s}-e^{0.5s})/s$	$p_{9,10}(e^{1.5s}-e^{0.5s})/s$
10	10→11	$p_{10,11} = 0.92$	$t_{10,11} \sim Exp(1)$	$1/(1-s)$	$p_{10,11}/(1-s)$
10	10→13	$p_{10,13} = 0.08$	$t_{10,13} \sim Exp(1)$	$1/(1-s)$	$p_{10,13}/(1-s)$

Note: *N* is normal distribution; *Exp* is exponential distribution; *U* is uniform distribution; *Tri* is triangular distribution

The bench inspection would select the used parts with little abrasion that would be directly disassembled in remanufactured engines. The equivalent transfer function is as follows:

$$W_{1,12}(s) = w_{1,12}(s) = p_{1,12}\frac{e^{(\rho+4)s} + e^{(\rho-4)s} - 2e^{\rho s}}{16s^2} \tag{11}$$

As the inspection is manipulated manually without energy consumption, the energy and time expectation are 0 kWh and ρ min.

(2) Remanufacturable parts

The GERT network shows two forward routes for remanufacturable parts: node 1→2→3→……→11 and node 1→3→……→11. Both of these two routes have a loop. The relevant terms in Eqs. (5) and (6) and the transfer function associated with time are

$$\begin{cases} G_1 = w_{1,2}(s)w_{2,3}(s)w_{3,4}(s)w_{4,5}(s)w_{5,6}(s)w_{6,7}(s)w_{7,8}(s)w_{8,9}(s)w_{9,10}(s)w_{10,11}(s) \\ G_2 = w_{1,3}(s)w_{3,4}(s)w_{4,5}(s)w_{5,6}(s)w_{6,7}(s)w_{7,8}(s)w_{8,9}(s)w_{9,10}(s)w_{10,11}(s) \\ \Delta = 1 - L_a = 1 - w_{6,6} \\ \Delta_1 = 1 \\ \Delta_2 = 1 \end{cases} \tag{12}$$

$$\begin{aligned} W_{t1,11}(s) &= \frac{(w_{3,4}(s)w_{4,5}(s)w_{5,6}(s)w_{6,7}(s)w_{7,8}(s)w_{8,9}(s)w_{9,10}(s)w_{10,11}(s))}{1-w_{6,6}} \\ &\cdot (w_{1,2}(s)w_{2,3}(s) + w_{1,3}(s)) \\ &= 2.4283\frac{(e^{3s}-e^{1.5s})(e^{1.3s}-e^{0.6s})(e^{1.2s}-e^{0.7s})(e^{1.2s}-e^{0.5s})(e^{1.5s}-e^{0.5s})}{(1-s)^2s^5} \\ &\cdot \left(\frac{e^{2s+0.04s^2}}{1-0.03/(1-180s)}\right)\left(\frac{e^{(\rho+4)s}+e^{(\rho-4)s}-2e^{\rho s}}{16s^2}\right)\left(p_{1,2}e^{2s+0.04s^2}+p_{1,3}\right) \end{aligned} \tag{13}$$

According to Eq. (7), the equivalent possibility of remanufacturable part is

$$\begin{aligned} p_{1,11} &= W_{t1,11}(s)\big|_{s=0} \\ &= 0.0575(p_{1,2}+p_{1,3})\left[\left(\frac{\rho}{2}-2\right)(\rho-4) + \left(\frac{\rho}{2}+2\right)(\rho+4) - \rho^2\right] \end{aligned} \tag{14}$$

It is apparent that the $p_{1,11}$ above contains two grey numbers ($p_{1,2}$ and $p_{1,3}$) and one stochastic number (ρ). When ρ is fixed at its mean value 50, then $p_{1,11}(\otimes)$=[0.644, 0.828]. The completion time of remanufacturable part $t_{1,11}$ is determined by Eq. (8) as follows:

Table 3 Rated power of equipment at each operation

Operation	1	2	3	4	5	6	7	8	9	10
Rated power (kW)	0	21.8	1.5	2.2	2.2	14.12	1.4	2.2	10.69	6

Table 4 Energy-related functions of each operation

Operation	Branch	Energy distribution (kW*min)	MGF	Transfer function
1	1→3	$t_{1,3}$ ~ *Constant* (0)	1	$p_{1,3}$
1	1→2	$t_{1,2}$ ~ *Constant* (0)	1	$p_{1,2}$
1	1→12	$t_{1,12}$ ~ *Constant* (0)	1	$p_{1,12}$
1	1→13	$t_{1,13}$ ~ *Constant* (0)	1	$p_{1,13}$
2	2→3	$t_{2,3}$ ~ N (109, 380.2)	$e^{109s+190.1s2}$	$p_{2,3}e^{109s+190.1s2}$
3	3→4	$t_{3,4}$ ~ U (2.25, 4.5)	$(e^{4.5s}-e^{2.25s})/2.25s$	$p_{3,4}(e^{4.5s}-e^{2.25s})/2.25s$
4	4→5	$t_{4,5}$ ~ U (1.32, 2.86)	$(e^{2.86s}-e^{1.32s})/1.54s$	$p_{4,5}(e^{2.86s}-e^{1.32s})/1.54s$
5	5→6	$t_{5,6}$ ~ U (1.54, 2.64)	$(e^{2.64s}-e^{1.54s})/1.1s$	$p_{5,6}(e^{2.64s}-e^{1.54s})/1.1s$
6	6→7	$t_{6,7}$ ~ *Exp* (1/14.12)	$1/(1-14.12s)$	$p_{6,7}/(1-14.12s)$
6	6→6	$t_{6,6}$ ~ *Constant* (0)	1	$p_{6,6}$
7	7→8	$t_{7,8}$ ~ N (2.8, 0.157)	$e^{2.8s+0.0784s2}$	$p_{7,8}e^{2.8s+0.0784s2}$
8	8→9	$t_{8,9}$ ~ U (1.1, 2.64)	$(e^{2.64s}-e^{1.1s})/1.54s$	$p_{8,9}(e^{2.64s}-e^{1.1s})/1.54s$
9	9→10	$t_{9,10}$ ~ U (5.35, 16.04)	$(e^{16.04s}-e^{5.35s})/10.69s$	$p_{9,10}(e^{16.04s}-e^{5.35s})/10.69s$
10	10→11	$t_{10,11}$ ~ *Exp* (1/6)	$1/(1-6s)$	$p_{10,11}/(1-6s)$
10	10→13	$t_{10,13}$ ~ *Exp* (1/6)	$1/(1-6s)$	$p_{10,13}/(1-6s)$

Note: N is normal distribution; *Exp* is exponential distribution; U is uniform distribution

$$t_{1,11} = \frac{1}{p_{1,11}} \frac{\partial W_{t1,11}(s)}{\partial s}\bigg|_{s=0} = 42.2313 \tag{15}$$

$$\left\{ \frac{\partial}{\partial s} \left[\frac{(e^{3s}-e^{1.5s})(e^{1.3s}-e^{0.6s})(e^{1.2s}-e^{0.7s})(e^{1.2s}-e^{0.5s})(e^{1.5s}-e^{0.5s})}{(1-s)^2 s^5 (p_{1,2}+p_{1,3}) \left[\left(\frac{\rho}{2}-2\right)(\rho-4) + \left(\frac{\rho}{2}+2\right)(\rho+4)-\rho^2 \right]} \cdot \left(\frac{e^{2s+0.04s^2}}{1-0.03/(1-180s)} \right) \left(\frac{e^{(\rho+4)s}+e^{(\rho-4)s}-2e^{\rho s}}{16s^2} \right) \left(p_{1,2}e^{2s+0.04s^2}+p_{1,3} \right) \right] \right\} \bigg|_{s=0}$$

As the expression above contains grey and stochastic parameters, the numerical solution of $t_{1,11}$ requires the stochastic simulation method. We adopted the MCS and CCP models to minimize the completion time with the constraint $P\{t_{1,11}(p_{1,2},p_{1,3},\rho)\geq\bar{t}_{1,11}\}\geq\beta$. The simulation was conducted on the Matlab platform. Table 5 displays the completion time under varying confidence levels. Since grey numbers exist in Eq. (15), the results are also presented in the form of grey numbers.

It can be observed from Table 5 that the estimation of completion time increase with the confidence levels. As the confidence level reflects the preference or prudence of decision makers, the higher confidence level suggests decision makers tend to be more prudent. This implies that the production process will schedule more time allowance to make the production scheme more robust. Examination of this table indicates that the completion time by confidence levels 0.7 and 0.9 shows a slight difference. Additionally, the length of completion time interval at each confidence level is short. This suggests the grey possibilities have a very limited impact on the completion time.

Table 5 Completion time of remanufactured part under varying confidence levels

Confidence levels β	Estimation of completion time $t_{1,11}$ (min)
0.9	[69.33, 69.96]
0.8	[68.25, 68.88]
0.7	[67.48, 68.10]

According to the transfer function and MGF of each activity, the transfer function associated with energy $W_{E1,11}(s)$ is as follows:

$$\begin{aligned} W_{E1,11}(s) &= \frac{(w_{3,4}(s)w_{4,5}(s)w_{5,6}(s)w_{6,7}(s)w_{7,8}(s)w_{8,9}(s)w_{9,10}(s)w_{10,11}(s))}{1-w_{6,6}} \\ &\cdot (w_{1,2}(s)w_{2,3}(s)+w_{1,3}(s)) \\ &= 0.01422\left(\frac{p_{1,2}e^{109s+190.1s^2}+p_{1,3}}{0.97}\right)e^{2.8s+0.0784s^2} \\ &\cdot \frac{(e^{4.5s}-e^{2.25s})(e^{2.86s}-e^{1.32s})(e^{2.64s}-e^{1.54s})(e^{2.64s}-e^{1.1s})(e^{16.04s}-e^{5.35s})}{(1-14.12s)(1-6s)s^5} \end{aligned} \tag{16}$$

Similarly, we use Eq. (8) to determine the expectation of energy consumption $E_{1,11}$:

$$E_{1,11} = \frac{1}{60 \times p_{1,11}} \frac{\partial W_{E1,11}(s)}{\partial s}\bigg|_{s=0} = \frac{2.5339 p_{1,2} + 0.7173 p_{1,3}}{p_{1,2} + p_{1,3}} \quad (17)$$

Considering the $p_{1,2}$ and $p_{1,3}$ in the expression of $E_{1,11}$, then grey number $E_{1,11}(\otimes)$ = [0.944, 1.171] kWh. Due to the manual operation of bench inspection, the uncertainty of time in this operation would not affect the total energy consumption.

(3) Disposed parts

The network has three forward routes for the disposed parts: node 1→13, node 1→2→3→……→13, and node 1→3→……→13. Similar to the method earlier for remanufacturable parts, the transfer function for disposed parts is

$$W_{t1,13}(s) = \frac{(w_{3,4}(s)w_{4,5}(s)w_{5,6}(s)w_{6,7}(s)w_{7,8}(s)w_{8,9}(s)w_{9,10}(s)w_{10,13}(s))}{1-w_{6,6}} \quad (18)$$

$$\cdot\,(w_{1,2}(s)w_{2,3}(s) + w_{1,3}(s)) + w_{1,13}(s) = \frac{(e^{3s}-e^{1.5s})(e^{1.3s}-e^{0.6s})(e^{1.2s}-e^{0.7s})(e^{1.2s}-e^{0.5s})(e^{1.5s}-e^{0.5s})}{(1-s)^2 s^5}$$

$$\cdot\,0.211156\left(\frac{p_{1,2}e^{5s+0.4s^2} + p_{1,3}}{1-0.03/(1-180s)}\right)e^{2s+0.04s^2}\frac{e^{(\rho+4)s} + e^{(\rho-4)s}-2e^{\rho s}}{16s^2} + p_{1,13}\frac{e^{(\rho+4)s} + e^{(\rho-4)s}-2e^{\rho s}}{16s^2}$$

According to Eq. (7), the equivalent possibility of disposed part is $p_{e1,\ 13} = W_{t1,\ 13}(s)|_{s=0}$ = [0.072, 0.306]. Similarly, the mathematic expression of completion time also contains grey numbers ($p_{1,2}$ and $p_{1,3}$) and stochastic number (ρ). Its numerical solution with constraint $P\{t_{1,13}(p_{1,2}, p_{1,3}, p_{1,13}, \rho) \geq \bar{t}_{1,13}\} \geq \beta$ is determined by stochastic simulation. The results are presented in Table 6.

As indicated in this table, the completion time also increases with the confidence level. The length of each interval is longer, which implies that grey possibilities of the branches associated with bench inspection exert greater impacts on time expectation of disposed parts. Likewise, we applied Eq. (8) to determine the expectation of energy consumption for disposed part $E_{1,13}(\otimes)$=[0.18, 0.66] kWh.

Validation of the GERT model

In order to validate the effectiveness of the established GERT model, we built a simulation model using the Arena software. In the Arena simulation model (Fig. 6), all grey possibilities were fixed as deterministic numbers, $p_{1,2}$=0.1, $p_{1,3}$=0.6, $p_{1,12}$=0.1, and $p_{1,13}$=0.2. ρ is set as the mean value 50. Hereby, this can be a special form of the GERT model. Arena created 10,000 used connecting rods to simulate the average time and energy consumption of direct reuse parts, remanufacturable parts, and disposed parts. Results comparison of the Arena simulation and GERT model are displayed in Table 7. From this table, it can be seen that all the relative errors are confined to 2%. The results validate the effectiveness and feasibility of the GERT model in quantifying the time and energy consumption of connecting rod reprocessing.

Table 6 Completion time of disposed part under varying confidence levels

Confidence levels β	Estimation of completion time $t_{1,11}$ (min)
0.9	[56.12, 69.82]
0.8	[55.04, 68.74]
0.7	[54.26, 67.96]

Sensitivity analysis

Uncertainties propagate along with the process chain and cause the perturbation of the production indicators such as the completion time and energy consumption. To what extent the uncertain factors affect the production are estimated by the CI concept. This section merely considered the uncertain time in each operation and assumed the grey possibilities are fixed and identical with prior section. We assumed the mean values of time distributions in Table 2 vary −10, −5, +5, and +10% and determined the corresponding four CIs by Eq. (10). The average of these CIs associated with one operation is utilized to measure the impact of the uncertainty in the operation. Table 8 lists the CI of primary activities, namely, the impact of uncertainty on average energy consumption and completion time of remanufacturable parts and disposed parts.

It can be observed from this table that bench inspection has a noticeable impact on the completion time of

Table 7 Comparison of numerical solutions in GERT network and the simulation results

Categories	Completion time (min)			Energy consumption (kWh)		
	Numerical solution	Simulation result	Relative error	Numerical solution	Simulation result	Relative error
Direct reuse parts	50	49.9223	0.16%	0	0	0%
Remanufacturable parts	66.2813	67.2166	1.4%	0.9768	0.9752	0.16%
Disposed parts	53.5615	53.7202	0.30%	0.2137	0.2170	1.5%

remanufacturable and disposed parts. The impacts of other operations on the completion time are similar and much smaller. Since the bench inspection would not consume energy, it would not influence the energy use. The brush electroplating and milling operation have greater impacts on energy consumption, while the impact of others is quite limited. Therefore, improvements on the dominant operations would significantly enhance the overall energy and efficiency performance of remanufacturing.

Conclusions

This study developed a GERT model with multivariant uncertainties to predict the energy consumption and completion time of connecting rod remanufacturing process. The generic procedure of this model has seven steps involving process mapping, network establishment, theory of signal flow graph, and equivalent transfer function of each operation or the system. Different from previous works that merely concern stochastic uncertainty, this model captured the various uncertain features of the system including the grey, stochastic, and fuzzy factors. The Arena simulation was conducted to validate the feasibility and effectiveness of the GERT model. We utilized the concept of CI to perform a sensitivity analysis and identify the dominant operations that affect the energy consumption and completion time of the reprocessing system, which would facilitate remanufacturers to take more targeted actions to improve energy efficiency. This approach enables the simultaneous evaluation of equivalent probabilities and production indicators like completion time and energy consumption. In addition, it can be directly extended to other remanufactured components in general.

Considering the multivariant uncertainties in the remanufacturing system, the GERT model in the present study could handle different types of uncertainties and predict the values of production indicators. However, some limitations are worth noting. Data on the processing time of each operation were primarily based on the limited samples and onsite engineers' experience. Efforts should be made to collect data on large amounts of samples, which would make the results more accurate and convincing. In the future study, a computation tool integrating the GERT with multivariant uncertainties could be developed for fast and automatic evaluation of production indicators, not limiting to energy use. Aforementioned, this approach can be also applied to other

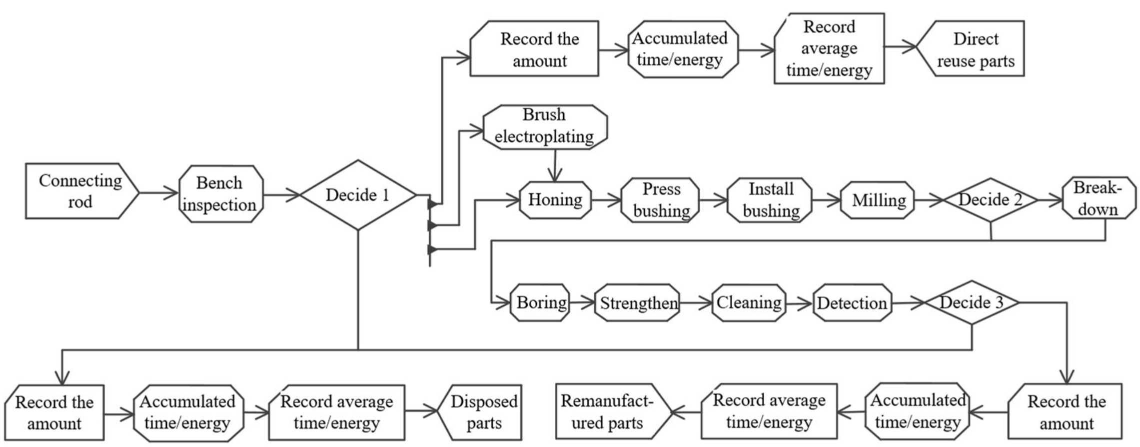


Fig. 6 Simulation model of Arena

Table 8 Average CI of the primary activities in connecting rod reprocessing

Operations	Remanufacturable parts		Disposed parts	
	Average energy	Average time	Average energy	Average time
Bench inspection	/	0.7544	/	0.9335
Strengthen	0.0317	0.0128	0.0328	0.0035
Flaw detection	0.1024	0.0151	0.1029	0.0041
Brush electroplating	0.2659	0.0108	0.2656	0.0029
Honing	0.0576	0.0339	0.0573	0.0092
Milling	0.2408	0.0151	0.2398	0.0041
Boring	0.0479	0.0302	0.0480	0.0082

products. Thus, follow-up research on enhancing the reconfigurability and adaptability of this computation tool would be desirable for a more universal application.

Author contribution Jiali Zhao: writing the original draft, visualization, formal analysis, investigation, writing–reviewing, and editing. Zheng Xue: conceptualization, methodology, software, and data curation. Tao Li: supervision and project administration. Jinfeng Ping: methodology, software, validation, and investigation. Shitong Peng: supervision, project administration, and conceptualization.

Funding Financial support and sponsorship from the Natural Science Foundation of China under Grant number 51775086 and STU Scientific Research Foundation for Talents (NTF20019).

Data availability The datasets used or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Abdi R, Ghasemzadeh HR, Abdollahpour S, Sabzeparvar M, Nasab ADM (2010) Modeling and analysis of mechanization projects of wheat production by GERT networks. Agric Sci China 9:1078–1083. https://doi.org/10.1016/S1671-2927(09)60193-0

Alvandi S, Bienert G, Li W, Kara S (2015) Hierarchical modelling of complex material and energy flow in manufacturing systems. Procedia CIRP 29:92–97. https://doi.org/10.1016/j.procir.2015.01.023

Cai Y, Shi X, Shao H, Wang R, Liao S (2018) Energy efficiency state identification in milling processes based on information reasoning and Hidden Markov model. J Clean Prod 193:397–413. https://doi.org/10.1016/j.jclepro.2018.04.265

Cai W, Li L, Jia S, Liu C, Xie J, Hu L (2020) Task-oriented energy benchmark of machining systems for energy-efficient production. Int J Precis Eng Manuf - Green Technol 7:205–218. https://doi.org/10.1007/s40684-019-00137-x

Cao H, Li H (2014) Simulation-based approach to modeling the carbon emissions dynamic characteristics of manufacturing system considering disturbances. J Clean Prod 64:572–580. https://doi.org/10.1016/j.jclepro.2013.10.002

Central People's Government of China (2017) Notification of energy conservation and emission reduction strategy for "13th Five-Year Plan" delivered by the State Council. http://www.gov.cn/zhengce/content/2017-01/05/content_5156789.htm. Accessed 20 Apr 2018

Cho JG, Yum BJ (1997) An uncertainty importance measure of activities in pert networks. Int J Prod Res 35:2737–2758

Choi BK, Kim H, Kang D, Jamjoom AA (2014) Parameterized ACD modeling of flexible manufacturing systems. IEEE Trans Autom Sci Eng 11:637–642. https://doi.org/10.1109/TASE.2013.2296570

Duflou JR, Sutherland JW, Dornfeld D, Herrmann C, Jeswiet J, Kara S, Hauschild M, Kellens K (2012) Towards energy and resource efficient manufacturing: a processes and systems approach. CIRP Ann - Manuf Technol 61:587–609. https://doi.org/10.1016/j.cirp.2012.05.002

Guide VDR (2000) Production planning and control for remanufacturing: industry practice and research needs. J Oper Manag 18:467–483

Guide VDR, Srivastava R, Kraus RE (1997) Product structure complexity and scheduling of operations in recoverable manufacturing. Int J Prod Res 35:3179–3199

Hayashi A, Kosugi T, Yoshida H (2005) Evaluation of polymer electrolyte fuel cell application technology R & Ds by GERT analysis. Int J Hydrog Energy 30:931–941. https://doi.org/10.1016/j.ijhydene.2004.11.004

He Y, Liu B, Zhang X, Gao H, Liu X (2012) A modeling method of task-oriented energy consumption for machining manufacturing system. J Clean Prod 23:167–174. https://doi.org/10.1016/j.jclepro.2011.10.033

Herrmann C, Thiede S (2009) Process chain simulation to foster energy efficiency in manufacturing. CIRP J Manuf Sci Technol 1:221–229. https://doi.org/10.1016/j.cirpj.2009.06.005

Hu L, Peng C, Evans S, Peng T, Liu Y, Tang R, Tiwari A (2017) Minimising the machining energy consumption of a machine tool by sequencing the features of a part. Energy 121:292–305. https://doi.org/10.1016/j.energy.2017.01.039

Jiang Z, Jiang Y, Wang Y, Zhang H, Cao H, Tian G (2016) A hybrid approach of rough set and case-based reasoning to remanufacturing process planning. J Intell Manuf 30:19–32. https://doi.org/10.1007/s10845-016-1231-0

Jin X, Ni J, Koren Y (2011) Optimal control of reassembly with variable quality returns in a product remanufacturing system. CIRP Ann - Manuf Technol 60:25–28. https://doi.org/10.1016/j.cirp.2011.03.133

Jin X, Hu SJ, Ni J, Xiao G (2013) Assembly strategies for remanufacturing systems with variable quality returns. IEEE Trans Autom Sci Eng 10:76–85. https://doi.org/10.1109/TASE.2012.2217741

Kara S, Li W (2011) Unit process energy consumption models for material removal processes. CIRP Ann - Manuf Technol 60:37–40. https://doi.org/10.1016/j.cirp.2011.03.018

Kosugi T, Hayashi A, Matsumoto T, Akimoto K (2004) Time to realization: evaluation of CO_2 capture technology R & Ds by GERT (graphical evaluation and review technique) analyses. Energy 29: 1297–1308. https://doi.org/10.1016/j.energy.2004.03.088

Li C, Tang Y, Li C (2011) A GERT-based analytical method for remanufacturing process routing. IEEE Int Conf Autom Sci Eng: 462–467. https://doi.org/10.1109/CASE.2011.6042398

Lin K, Wen W, Chou C et al (2011a) Applying fuzzy GERT with approximate fuzzy arithmetic based on the weakest t-norm operations to evaluate repairable reliability. Appl Math Model 35:5314–5325. https://doi.org/10.1016/j.apm.2011.04.022

Lin K, Wu M, Hung K, Kuo Y (2011b) Developing a Tω (the weakest t-norm) fuzzy GERT for evaluating uncertain process reliability in semiconductor manufacturing. Appl Soft Comput J 11:5165–5180. https://doi.org/10.1016/j.asoc.2011.05.043

Liu B (2002) Theory and practice of uncertain programming, 2nd edn. Springer, Heidelberg

Liu S, Lin Y (2010) Grey systems: theory and applications. Springer, Heidelberg

Liu F, Xie J, Liu S (2015) A method for predicting the energy consumption of the main driving system of a machine tool in a machining process. J Clean Prod 105:171–177

Mason SJ (1956) Feedback theory - some properties of signal flow graphs. Proc IRE 44:920–926

Mayr A, Lechler T, Donhauser T, Metzner M, Schäffer E, Fischer E, Franke J (2019) Advances in energy-related plant simulation by considering load and temperature profiles in discrete event simulation. Procedia CIRP 81:1325–1330. https://doi.org/10.1016/j.procir.2019.04.021

Ministry of Industry and Information Technology of China (2016) Industrial green development planning (2016-2020). http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757016/c5143553/content.html. Accessed 8 Jun 2018

Olivier CM, Oosthuizen GA, Sacks N (2019) Improving the R&D process efficiency of the selective laser sintering industry through numerical thermal modeling. Procedia Manuf 33:131–138. https://doi.org/10.1016/j.promfg.2019.04.017

Peng S, Li T, Zhao J, Guo Y, Lv S, Tan GZ, Zhang H (2019) Petri net-based scheduling strategy and energy modeling for the cylinder block remanufacturing under uncertainty. Robot Comput Integr Manuf 58:208–219. https://doi.org/10.1016/j.rcim.2019.03.004

Pritsker AAB, Happ WW (1966) GERT: graphical evaluation and review technique, Part I, foundamental. J Ind Eng 17:267–274

Shang Z, Gao D, Jiang Z, Lu Y (2019) Towards less energy intensive heavy-duty machine tools: power consumption characteristics and energy-saving strategies. Energy 178:263–276. https://doi.org/10.1016/j.energy.2019.04.133

State Statistics Bureau No Title (n.d.) http://www.stats.gov.cn/. Accessed 12 Aug 2020

Tang Y, Li C (2012) Uncertainty management in remanufacturing: a review. IEEE Int Conf Autom Sci Eng:52–57. https://doi.org/10.1109/CoASE.2012.6386365

Tao L, Wu D, Liu S, Lambert JH (2017) Schedule risk analysis for new-product development : the GERT method extended by a characteristic function. Reliab Eng Syst Saf 167:464–473. https://doi.org/10.1016/j.ress.2017.06.010

Tian G, Ren Y, Feng Y, Zhou MC, Zhang H, Tan J (2019) Modeling and planning for dual-objective selective disassembly using AND/OR Graph and discrete artificial bee colony. IEEE Trans Ind Informatics 15:2456–2468

Wang J, Chen M (2013) Remanufacturing process for used automotive electronic control components in China. J Remanufacturing 3:1–17. https://doi.org/10.1186/2210-4690-3-9

Wang Q, Wang X, Yang S (2014) Energy modeling and simulation of flexible manufacturing systems based on colored timed petri nets. J Ind Ecol 18:558–566. https://doi.org/10.1111/jiec.12180

Wang X, Luo W, Zhang H, Dan B, Li F (2016) Energy consumption model and its simulation for manufacturing and remanufacturing systems. Int J Adv Manuf Technol 87:1557–1569. https://doi.org/10.1007/s00170-015-7057-7

Wardi Y, Cassandras CG, Cao XR (2018) Perturbation analysis: a framework for data-driven control and optimization of discrete event and hybrid systems. Annu Rev Control 45:267–280. https://doi.org/10.1016/j.arcontrol.2018.04.003

Xiang W, Ming C (2011) Implementing extended producer responsibility: vehicle remanufacturing in China. J Clean Prod 19:680–686. https://doi.org/10.1016/j.jclepro.2010.11.016

Xie N, Duan M, Babu R et al (2016) An energy modeling and evaluation approach for machine tools using generalized stochastic Petri Nets. J Clean Prod 113:523–531. https://doi.org/10.1016/j.jclepro.2015.09.100

Zavanella L, Zanoni S, Ferretti I, Mazzoldi L (2015) Production economics energy demand in production systems : a queuing theory perspective. Int J Prod Econ 170:393–400. https://doi.org/10.1016/j.ijpe.2015.06.019

Zhao B, Lv C, Hofman T (2019) Driving-cycle-aware energy management of hybrid electric vehicles using a three-dimensional Markov Chain model. Automot Innov 2:146–156. https://doi.org/10.1007/s42154-019-00059-z

Zhao J, Peng S, Li T et al (2020) Energy-aware fuzzy job-shop scheduling for engine remanufacturing at the multi-machine level. Front Mech Eng 14:474–488

Zheng G, Wilmarth T, Jagadishprasad P, Kale LV (2005) Simulation-based performance prediction for large parallel machines. Int J Parallel Program 33:183–207

Zhou L, Xie J, Gu X, Lin Y, Ieromonachou P, Zhang X (2016) Forecasting return of used products for remanufacturing using graphical evaluation and review technique (GERT). Int J Prod Econ 181:315–324. https://doi.org/10.1016/j.ijpe.2016.04.016

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.