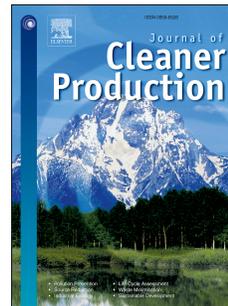


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**An active preventive maintenance approach of complex equipment based on a novel product-service system  
operation mode**

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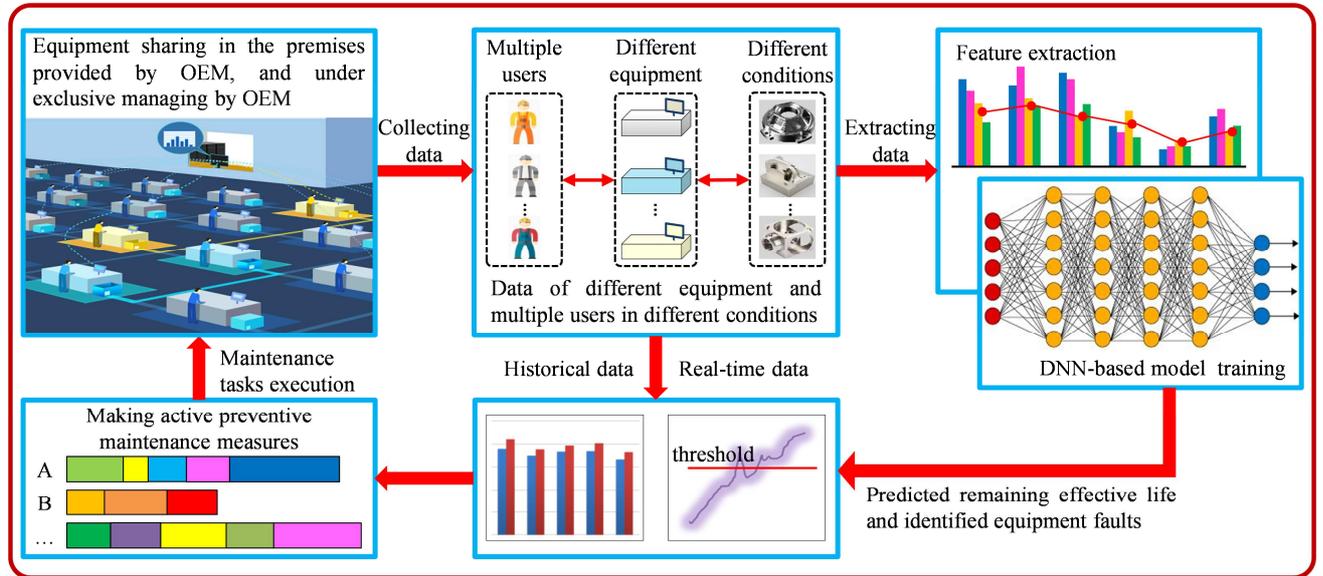
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### Research Highlights

- A novel PSS-based operation mode for equipment sharing was outlined.
- An active preventive maintenance approach based on PSS was proposed.
- The feasibility of the proposed method was verified in a case study.
- The advantages of the proposed method were discussed and summarized.

### Graphical Abstract



**An active preventive maintenance approach of complex equipment based on a novel product-service system operation mode**

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**Abstract:** The product-service system (PSS) business model has received increasing attention in equipment maintenance studies, as it has the potential to provide high value-added services for equipment users and construct ethical principles for equipment providers to support the implementation of circular economy. However, the PSS providers in equipment industry are facing many challenges when implementing Industry 4.0 technologies. One important challenge is how to fully collect and analyse the operational data of different equipment and diverse users in widely varied conditions to make the PSS providers create innovative equipment management services for their customers. To address this challenge, an active preventive maintenance approach for complex equipment is proposed. Firstly, a novel PSS operation mode was developed, where complex equipment is offered as a part of PSS and under exclusive control by the providers. Then, a solution of equipment preventive maintenance based on the operation mode was designed. A deep neural network was trained to predict the remaining effective life of the key components and thereby, it can pre-emptively assess the health status of equipment. Finally, a real-world industrial case of a leading CNC machine provider was developed to illustrate the feasibility and effectiveness of the proposed approach. Higher accuracy for predicting the remaining effective life was achieved, which resulted in predictive identification of the fault features, proactive implementation of the preventive maintenance, and reduction of the PSS providers' maintenance costs and resource consumption. Consequently, the result shows that it can help PSS providers move towards more ethical and sustainable directions.

**Keywords:** product-service system; ethical; sustainable; preventive maintenance; sharing; remaining effective life

**Abbreviations**

|     |                    |     |                                  |
|-----|--------------------|-----|----------------------------------|
| AE  | Autoencoder        | MP  | Machining parameters             |
| BDA | Big data analytics | MRO | Maintenance, repair and overhaul |

|          |   |        |                                     |
|----------|---|--------|-------------------------------------|
| CE       | Circular economy                          | MS-SQL | Microsoft structured query language |
| CP       | Cleaner production                        | NC     | Numerical control                   |
| CPS      | Cyber-physical system                     | OEM    | Original equipment manufacturer     |
| DNC      | Distributed numerical control             | PSS    | Product-service system              |
| DNN      | Deep neural network                       | R&D    | Research and development            |
| DNN-ELPM | DNN-based effective life prediction model | REL    | Remaining effective life            |
| EOL      | End of life                               | RJ45   | Registered jack 45                  |
| FC       | Flat-end cutters                          | RS-232 | Recommended standard 232            |
| IIoT     | Industrial internet of things             | SMEs   | Small and medium-sized enterprises  |
| MOL      | Middle of life                            | WIP    | Work-in-process                     |

## 1. Introduction

With the increasing pressure from global competition and environmental protection, many manufacturing enterprises are making efforts to explore and employ a more sustainable business model aligned with the developing ethical principles of enterprise social responsibility and multi-generational equity for sustainable societies (Luthra and Mangla, 2018; Man and Strandhagen, 2017; Nemoto et al., 2015). The purpose is to provide high value-added services in addition to the traditional design and manufacturing businesses (Zheng et al., 2020), and to promote the implementation of cleaner production (CP) and circular economy (CE) for ethical and sustainable business development (Lopes de Sousa Jabbour et al., 2018; Yadav et al., 2020). In this context, various concepts, features and advantages of the product-service system (PSS) have been studied by researchers (Beuren et al., 2013; Meier et al., 2010; Yang and Evans, 2019; Zheng et al., 2020). Recently, Halstenberg and Stark (2019) developed a PSS architecture for realizing CE. A systemic design approach for integrating PSS and CE in the context of business model innovation was investigated by Fernandes et al. (2020).

Currently, the Industry 4.0 paradigm has become more popular because of recent advancements in big data analytics (BDA), cyber-physical system (CPS) and industrial internet of things (IIoT) (Liu et al., 2020; Ren et al., 2019; Wan et al., 2017). In the Industry 4.0 paradigm, CP strategies and advanced information technologies provide opportunities for ethical sustainable societal development (Inigo and Blok, 2019). As pointed by Zheng et al. (2018), the combination of PSS, CPS and Industry 4.0 can enable innovative applications of products and services. Meanwhile, as an enabler for sustainable development, exploring the potentials of Industry 4.0 in CP to construct an ethical criterion has become one of the hottest topics for CE (Matallín-Sáez et al., 2019; Stock et al., 2018). For instance, Jensen and Remmen (2017) analysed different product stewardship means (e.g. data management, extended PSS) in Industry 4.0 for enabling CE from a manufacturer's perspective, and Blunck and Werthmann (2017) discussed the potential of Industry 4.0 applications to realize sustainable production and to create CE. The key components of industrial symbiosis practices,

and the research gaps combined Industry 4.0, CE and big data were investigated by Tseng et al. (2018). A product and service design approach for CP and smart production was developed by Lin (2018) to empower Industry 4.0 in the CE of a glass recycling industry. Moreover, Halse and Jæger (2019) analysed the barriers that manufacturing industry adopts Industry 4.0 to achieve CE, Rosa et al. (2020) assessed the relations between CE and Industry 4.0, and Dev et al. (2020) proposed a model for sustainable supply chain by the integration of Industry 4.0 principles and CE approaches to carry out CP strategy. These research achievements provide insights for practitioners to integration of Industry 4.0 and CP as well as CE to develop more sustainable business models, and to extend enterprise social responsibility and business ethics.

Equipment maintenance provides numerous opportunities for reducing usage cost, decreasing influence of product service lifecycle on natural environment and more efficient resource utilization. Therefore, maintenance service can benefit to establish a balance among economic, social, and environmental goals (Behzad et al., 2019; Franciosi et al., 2018). In the complex equipment industry (e.g. CNC machine centre, aero-engine, etc.), maintenance and repair services are normally provided during the use stage. By providing an ethical and sustainable PSS which has the potential to benefit all stakeholders—the complex equipment industry is in a uniquely positive position to catalyse changes towards sustainable enterprises. Additionally, considering that complex equipment is usually a durable product with a lifespan of over 10 to 30 years (Zhu et al., 2012), the opportunities for application of PSS in equipment maintenance to develop and implement ethical and sustainable business models are tremendous. Therefore, in the Industry 4.0 context, the potential benefits of integrating PSS with maintenance services have attracted many researchers' attention.

For example, Goncalves and Kokkolaras (2017) developed a collaborative PSS between original equipment manufacturers (OEM) and maintenance, repair and overhaul (MRO) companies. Such cooperation can benefit all stakeholders (i.e. OEM, MRO companies, operators and end-users), to promote the development of CE and to accelerate the transition to sustainable business models. Exner et al. (2017) reviewed the existing maintenance approaches and analysed how maintenance services can be connected to the PSS to enhance machine availability, while reducing environmental concerns by reducing energy consumption and costs of maintenance procedures. D. Mourtzis et al. (2018) implemented an assistance application for the unscheduled maintenance of manufacturing equipment following the PSS approach. Recent research achievements, such as lease-oriented opportunistic maintenance for multi-unit systems (Xia et al., 2017), cloud-based augmented reality remote maintenance (Mourtzis et al., 2017), maintenance strategies planning and decision-making for aero-engines (Thomsen et al., 2015), and service-oriented multi-player maintenance grouping strategy (Chang et al., 2019), etc., have provided a solid foundation to enable design and development of PSS-based maintenance approaches for complex equipment. These studies provided opportunities for industrial practitioners to

apply environmental ethics during the implementation of sustainable production and CE within the Industry 4.0 paradigm (Keitsch, 2018; Mangla et al., 2017; Tunn et al., 2019).

Despite the progress on PSS-based equipment maintenance studies, major limitations still exist:

1) the existing literature has been primarily focused on maintenance decision based on the operational data of smaller cluster equipment (e.g. the data of smaller cluster equipment and smaller cluster users in specific conditions), which have resulted in low efficiency and accuracy of fault diagnosis as well as wastage of resources during maintenance procedures;

2) many studies on PSS-based equipment maintenance were only focused on the breakdown maintenance, which is a passive equipment management style. This approach has led to a suspension in some production processes, and cause increased production costs and energy consumption.

These limitations have had many negative impacts on reducing resource consumption and pollutant emission in manufacturing processes thereby violating the 3R (reduction, reuse and recycling) principle of CE (Lieder and Rashid, 2016). As pointed by Inigo and Blok (2019), the ethical issues should be integrated into the initial planning phases of implementation of CE, to make more effective progress toward sustainable business operations. However, this perspective has usually been neglected in the existing research. From these limitations, the research questions related to this paper arise are:

1) how can industrial practitioners fully use the multi-source operational data of equipment in different conditions to improve the management and control capability of equipment during operation stage, and to implement synergies among CP, CE and business ethics in the context of Industry 4.0?

2) how can implementation of a procedural approach for achieving real-time and off-line data analysis to evaluate the health status of equipment and to work out proactive maintenance planning, so as to establish a balance amongst economy, environment and society in the context of ethical business development?

As previously mentioned, Industry 4.0 has catalysed integration of information and communication technologies into all aspects of manufacturing, and can enhance the ability to communicate and cooperate among all lifecycle stakeholders. As a result, the operations status data of all PSS offerings in different conditions can be captured. These operational data are valuable assets to produce innovative applications, such as energy consumption process optimization, production planning optimization, sustainable supply chain management and active preventive maintenance. However, active preventive maintenance for complex equipment in the context of Industry 4.0 must address these significant challenges:

1) how to develop a PSS-based operation mode to collect the operations status data of different equipment and multiple users in different conditions, to create means to inter-connect equipment, end-users and ethics to reduce waste and improve production efficiency;

2) how to design a solution to identify faults earlier and implement active preventive maintenance for better management of complex equipment, to enhance utilization and to reduce material mobility throughout the whole society based upon ethically sound principles.

To address these challenges, an active preventive maintenance approach for complex equipment based on PSS was developed by the authors of this paper. It integrates three important characteristics. The first is a novel PSS-based operation mode for equipment leasing and sharing to collect the operational data of all equipment in different conditions. The second is smart equipment with the capability of active sensing and dynamic interaction. The third is a method of predicting the remaining effective life (REL) for complex equipment to reduce the deviations between maintenance planning and implementation of maintenance activities. The proposed approach can become a new paradigm for complex equipment industries to implement real-time and early decision-making of equipment maintenance. Additionally, it has the potential to promote the implementation of CP and CE among corporately, socially responsible business chains designed to reduce resource and energy consumption, and to improve worker health and safety in utilization of equipment and provision of customer services.

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature. Section 3 outlines the novel PSS-based operation mode for active preventive maintenance and compares it with the traditional maintenance approach. In Section 4, the conceptual architecture was outlined as a solution for active preventive maintenance for complex equipment based on the proposed operation mode. In Section 5, a case study is used to illustrate the feasibility and effectiveness of the proposed solution. In Section 6, the conclusions and future works are summarized.

## **2. Literature review**

Maintenance plays an important role in ensuring continuous production and improving equipment utilization. To achieve these goals, leasing or sharing complex equipment by multiple users combined with the PSS has become a promising way (Exner et al., 2017; Meier et al., 2010; Zhu et al., 2012). This section briefly reviews related studies in two aspects: (1) the PSS paradigm, and (2) PSS-based equipment maintenance. Current limitations on PSS-based equipment maintenance identified from the review are summarized at the end of Section 2.

### *2.1 Product-service system paradigm*

As a promising business model for improving the competitive advantage and revenue of manufacturers (Zhang et al., 2017b), enhancing the environmental sustainability and resource utilization ratios of societies (Tukker, 2015; J. Wang et al., 2019; Zheng et al., 2019), academic and industrial interests in PSS have increased significantly in recent years.

The concept of PSS was first proposed by Goedkoop et al. (1999), who defined it as “a system of products, services, networks of players and supporting infrastructures that continuously strive to be competitive, to satisfy customer needs and to have lower environmental impacts than traditional business models”. Manzini and Vezzoli (2003) emphasized that PSS shifts the business focus from only designing (and selling) physical products, to designing (and selling) a system of products and services. Similar concepts were discussed in the literature (Beuren et al., 2013; Yang et al., 2018). The classification of PSS has been explored by (Gao et al., 2011; Tukker, 2004). These authors highlighted that the PSS can be mainly divided into three categories: i.e. product-oriented PSS, use-oriented PSS and result-oriented PSS. Based on the methodologies of product lifecycle modelling, a framework for designing an application-oriented PSS was proposed by Yang et al. (2010). By integrating costs and resource consumption as well as the product status, the primary input & output parameters can be built upon for the service process modelling.

Recently, the key success factors and issues that require special attention during implementation of PSS in organizations were explored by (Tukker, 2015). The opportunities from combined usage of big data and service-oriented business strategies were investigated by (Opresnik and Taisch, 2015), who emphasised that the value of big data depends on an adopted business model including an operational mode and a way to quantify value capture. A systematic overview of PSS together with its different methods, tactics, benefits and barriers were discussed by Annarelli et al. (2016). To use the PSS's lifecycle data and to improve PSS attributes as well as to expand the related activities, a PSS lifecycle model was proposed by Cavalcante and Gzara (2018). A PSS evolution method, which includes a quantitative PSS classification architecture and transformation processes were developed by Chiu et al. (2019) to build the core competence of enterprises. Recent investigations show that the PSS is being utilized by an increasing number of manufacturers and could provide manufacturers with the capability of better control and management of their products, thereby provide numerous opportunities for manufacturers to implement CP and CE. Through a dynamics simulation model, the effects of combining multiple product design and PSS strategies for slowing and closing resource loops in a CE was analysed by Franco (2019). Inspired by the outcome-driven innovation approach, a mixed-method for increasing consumer participation in CE-linked PSS was studied by Hankammer et al. (2019) to strengthen the competitive advantage of organizations. Through a set of interviews with experts belonging to the waste from electrical and electronic equipment sector, Rosa et al. (2019) established the links between CE benefits and the PSS-based circular business models. Finally, the authors utilized four use cases to illustrate how to link PSS with CE benefits. The key elements of PSS that contribute to closed-loop resource flows and CE were explored by Zeeuw van der Laan and Aurisicchio, (2020). The authors categorized the PSS elements and their contributions to closed-loop by six architectural levels, i.e. services, resources, stakeholders, contract, value delivery, systems and tools. By using a case study in the electronics manufacturing industry,

Werning and Spinler (2020) identified and analysed the potential barriers to achieve the transition from PSS to a CE. The authors recommended that the findings of their research allowed practitioners to map barriers to managerial responsibilities, thus improving the organizational transition process.

## 2.2 PSS-based equipment maintenance

Appropriately timed maintenance directly influences the lifetime of equipment and its productivity, especially for complex equipment working in various conditions and harsh environments (Tao et al., 2018; Wan et al., 2017). Meanwhile, through gathering and analysing relevant operational data, the reliability of equipment for the entire PSS system can be improved.

The cutting-edge information technologies are being integrated into all aspects of manufacturing, which is accelerating the generation of industrial big data (Thoben et al., 2017). These data can be analysed to provide useful knowledge for product innovation design (Manyika et al., 2011), production process and energy consumption optimization (Zhang et al., 2015; Zhou et al., 2016), and intelligent fault diagnosis and maintenance service (Jia et al., 2016; Kumar et al., 2018). As reported by the McKinsey Global Institute, analyses of operation big data and provision of maintenance services can reduce operational costs by 10%-25%, and can potentially increase production by 5% or more (Manyika et al., 2011). Studies such as O'Donovan et al. (2015) and Lee et al. (2015) investigated the requirements, challenges and opportunities of industrial big data for equipment manufacturing and maintenance applications.

Generally, an innovative business strategy or operational model can be used to improve the maintenance service of products (Kuo and Wang, 2012). Since the advantages of the PSS for reducing product defects and maintenance costs (Zhang et al., 2017b), as well as for improving the accuracy and efficiency of maintenance tasks (Tao et al., 2018), research on combining maintenance and PSS is attracting more scholars' interests. For example, to integrate product development with maintenance service, a web-based PSS was developed and tested by Zhu et al. (2012). Focussing upon the MRO services in the aerospace industry, they developed a model for improving the PSS. In the context of PSS, a methodology for acquiring reusable knowledge from vast amounts of operational data for guiding maintenance decision-making was developed by Xiao et al. (2016). The advantages of PSS-based maintenance service for enhancing competitiveness and supporting sustainability as well as for decreasing energy consumption in the steel industry were evaluated by Marchi et al. (2016). The effectiveness of their proposed methodology was verified in the maintenance decision-making of an agricultural equipment manufacturing enterprise. The relationships between OEM and MRO enterprises were analysed to develop a collaborative PSS between them (Goncalves and Kokkolaras, 2017). The author recommended that the proposed cooperation method can benefit all stakeholders, thereby provided new tools and insights

to make the PSS system more effective and make the PSS providers more socially responsible. Mourtzis et al. (2017) proposed a cloud-based PSS platform for condition-based maintenance to detect the machine tool failures before they occur. The authors found that the proposed platform can increase the production efficient and reduce the resource consumption of manufacturers by performing accurate and quick maintenance. Following the PSS approach, an assistance application for the preventive and unscheduled maintenance of equipment was introduced by Mourtzis et al. (2018). The proposed method can lead to time and cost reduction during maintenance procedures. Based on the leasing business of PSS, an improved opportunistic maintenance for a manufacturing system was investigated by Guo et al. (2018) to decide whether to execute early preventive maintenance. The authors found that one machine's preventive maintenance can create a maintenance opportunity for others due to the structural dependencies of the manufacturing system. Therefore, the manufacturing system can be made more effective and sustainable. A smart PSS-based multi-player maintenance grouping strategy for a complex system was proposed by Chang et al. (2019) to determine the optimal grouping service time for each service provider. The interaction relations among OEM and multiple service providers were modelled and analysed by the authors. Through a numerical example from a wind turbine, the authors found that the proposed method can provide an effective maintenance grouping strategy for service providers to make the enterprise more ethical and sustainable, and to support the implementation of CE.

### *2.3 Limitations on PSS-based equipment maintenance*

This sub-section summarises the limitations on PSS-based equipment maintenance identified from the literature.

- The cutting-edge information technology makes it possible to access and acquire the whole lifecycle data of PSS delivery processes. Therefore, the opportunities arising from combined the maintenance service and the PSS have attracted many researchers' attention. As highlighted by Cavalcante and Gzara (2018), a promising application in PSS data management is the use of its lifecycle data to improve PSS values in related activities (e.g. preventive maintenance, prediction of need for spare parts, etc.). However, this research is still in its infancy as documented via our literature review. Therefore, we highlight an important challenge: how to develop a new operation mode to collect the multi-source operational data of the complex equipment under multiple conditions, and to accelerate the synergies among CP, CE and business ethics?
- Most existing studies related to PSS-based equipment maintenance were focused upon passive maintenance, where the operators report faults to maintenance personnel according to the feature parameters of the equipment (Wan et al., 2017). The faults then need to be exactly located and eliminated, which will lead to the shutdown of production equipment and to the reduction of production efficiency. The solution of preventive maintenance for complex

equipment based on PSS was seldom investigated. This resulted in the situation in which PSS providers were unable to assess the functional/operational conditions of complex equipment in a timely manner. Therefore, they were unable to anticipate breakdowns by providing active preventive maintenance, and to revolutionize the way of production and consumption within the context of ethical sustainable business development.

According to the above analysis, under the PSS paradigm, the solution of these two limitations can help PSS providers to monitor multiple operating statuses and to ensure in a timely manner when preventative repairs should be made to help to ensure the healthy and stable operation of the complex equipment. Therefore, maintenance planning that combines the novel PSS operation mode and an active preventive maintenance approach can help equipment users to improve production efficiency, to minimize resource waste and emissions from industrial processing, and to reduce worker health and safety risks. This can also help to facilitate the PSS providers to make progress towards the CP strategy, and to promote the implementation of CE for more sustainable and ethical societal development.

### 3. An overview of a novel PSS operation mode for active preventive maintenance

In this section, a novel PSS operation mode for active preventive maintenance of complex equipment is outlined. The objective of this operation mode is to better integrate the PSS delivery processes with associated maintenance service processes, to achieve early detection and active prevention of breakdowns based on the real-time status of complex equipment. This operation mode can help OEM to extend their ethical and societal responsibilities to the whole lifecycle by providing more value-added services to their traditional product design and manufacturing businesses.

For better understanding, the proposed PSS mode is described with seven characteristics, in comparison to those existing PSS modes in the industry as shown in Table 1. The equipment is located at the OEM's premise, and exclusively controlled and managed by the OEM in a centralized manner. The operator of the equipment may be the OEM or multiple customers. Furthermore, the operation and maintenance data is collected and accessed by the OEM. In the proposed mode, multiple customers lease or share all equipment at a pre-defined location of the OEM, while in the traditional mode each of the customers uses its own equipment at their location individually. This means that the customers do not need to purchase equipment and build plants, let alone shipping equipment to their factories. The customers only need to pay the OEM by the usage time or by the processing quantity. Within the novel leasing/sharing operation mode, in addition to the equipment sharing, the sharing of production orders, processing technologies, and professional production operators and maintenance staffs are all possible.

**Table 1**

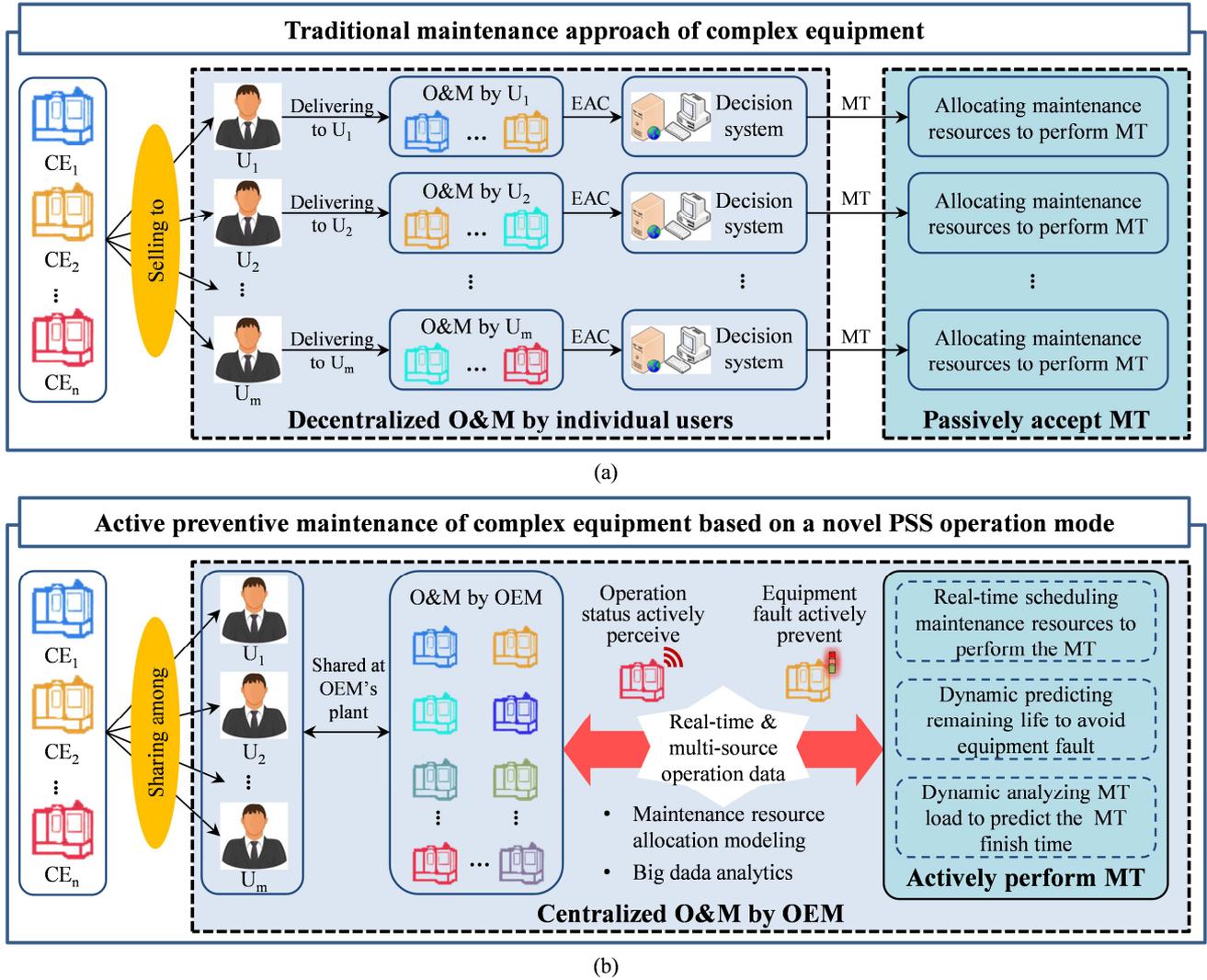
Comparison of the proposed PSS mode with the existing PSS modes.

| Characteristics | Proposed PSS mode | Existing PSS modes |
|-----------------|-------------------|--------------------|
|-----------------|-------------------|--------------------|

|  |                                  |                         |
|--|----------------------------------|-------------------------|
| Equipment location   | In the premises the OEM provided | In the customers' plant |
| Management manner  | Centralized                      | Decentralized           |
| Control and manage by  | OEM                              | Mainly by customers     |
| Operator   | OEM/Multiple customers           | Single customer         |
| Access to data by  | OEM                              | Mainly by customers     |
| Plant build by   | OEM                              | Customers               |
| Sharing of production orders, processing technologies, operators and maintenance | Available                        | Not available           |

Besides, Fig.1 illustrates the comparison of the two types of maintenance approaches. Fig. 1 (a) describes the traditional maintenance approach, and Fig. 1 (b) shows the active preventive maintenance approach of complex equipment based on the novel PSS operation mode, respectively.

For the traditional maintenance approach, OEM's equipment is sold and delivered to users with the additional after-sale services selected according to purchase contracts. Therefore, all equipment is decentralized operation and management by individual users. In this case, the ownership of complex equipment belongs to various users, who are motivated to continuously improve production efficiency and save manufacturing costs through reducing the failure frequency and extending the service life of the complex equipment. Therefore, equipment is operated and managed by individual users at their own shop floors, and equipment maintenance is performed by the users or by third party maintenance service providers. In this context, the owners depend upon abnormal condition system alarms to alert them to 'equipment faults' which need the services of the maintenance staff. Of course, the problems have to be accurately located within the system. Subsequently, maintenance tasks are performed to solve the equipment faults by making maintenance plans and scheduling available maintenance resources. The maintenance decisions are made based on extracted feature parameters and historical label data. As a result, the real-time operations status data of complex equipment has not been considered in the traditional method, which can lead to a prolonged shutdown of equipment, and then affect the normal progress of the production assignment. Meanwhile, deviations between the maintenance plan and task execution have happened due to the unpredictable exceptions. As stated earlier, the implementation of the traditional equipment maintenance method is mainly based on the product-orientated PSS, which is chiefly the breakdown maintenance and is a passive equipment management style. Moreover, due to the constraints of technical skills and investment costs, the operation state data of equipment accumulated by individual users is incomplete, and the data is always deriving from smaller cluster equipment. Thus, decision-making based on the operational data of incomplete and smaller cluster equipment will reduce the accuracy and efficiency of fault diagnosis.



$CE_i$ : the  $i$ th complex equipment;  $U_j$ : the  $j$ th user; O&M: operation and management;

EAC: equipment abnormal condition; MT: maintenance task; OEM: original equipment manufacturers

**Fig.1.** Comparison of two types of maintenance approaches.

For the active preventive maintenance approach based on the novel PSS operation mode, all equipment forms a manufacturing resource pool (Tao et al., 2014). Then, the equipment is leased and shared by various users with an integrated service contract, which is primarily focused on maintenance activities for complex equipment. In situations where the ownership of equipment is retained by the OEM, and all the leased and shared equipment are operated and managed by OEM in the premises they provide in a centralized manner. Therefore, the OEM is motivated to create a PSS to produce more durable equipment and to extend the lifespan as well as to provide high-quality maintenance services for their users. This means that complex equipment is provided as a part of PSS, and under exclusive control and maintenance by the PSS provider. The OEM is supposed to be the best maintainers over the equipment lifecycle, due to the fact that they are most familiar with the assets and operational data. In other words, relying on the rich experience and specialized technical skills, the PSS providers can monitor the equipment's operation state in a timely, comprehensively

and accurately. As a result, the real-time and multi-source operations status data of different equipment and different users in diverse conditions can be collected more easily and comprehensively. These data are valuable assets for the OEM to optimise their daily production processes and equipment management. For example, through analysing the real-time operational data, the knowledge related to real-time and active maintenance can provide decision support for maintenance resource scheduling (e.g. actively allocate maintenance tasks to the idle maintenance resources) and active preventive maintenance (e.g. dynamically predict the completion time of maintenance tasks). Moreover, through integration and analysis of the real-time and historical operational data, the remaining lifespan of equipment can be predicted and evaluated dynamically to provide early detection of faults.

The active preventive maintenance approach proposed in this paper has the following advantages:

Firstly, the PSS provider can provide complete solutions and systematic services for the equipment users, especially for complex equipment (e.g. aero-engine, high-grade CNC machine tools, etc.), thus exempting the users from performing delicate maintenance on complex equipment and carrying large amounts of spare part stocks for their equipment. The users pay only for the provisions of the agreed results, thereby, relieving the equipment users from the high cost and high risk of purchasing complex equipment.

Secondly, the novel PSS operation mode, as described above, is suitable for application-oriented PSS and result-oriented PSS, which can extend the social responsibility and business ethics of OEM to the middle of life (MOL) and end of life (EOL) stages of complex equipment. As a result, the OEM can refurbish, reuse and recycle some parts of complex equipment by specialized maintenance service or recycling service, to promote a closer relationship between the manufacturers and users, and to reduce the environmental impacts.

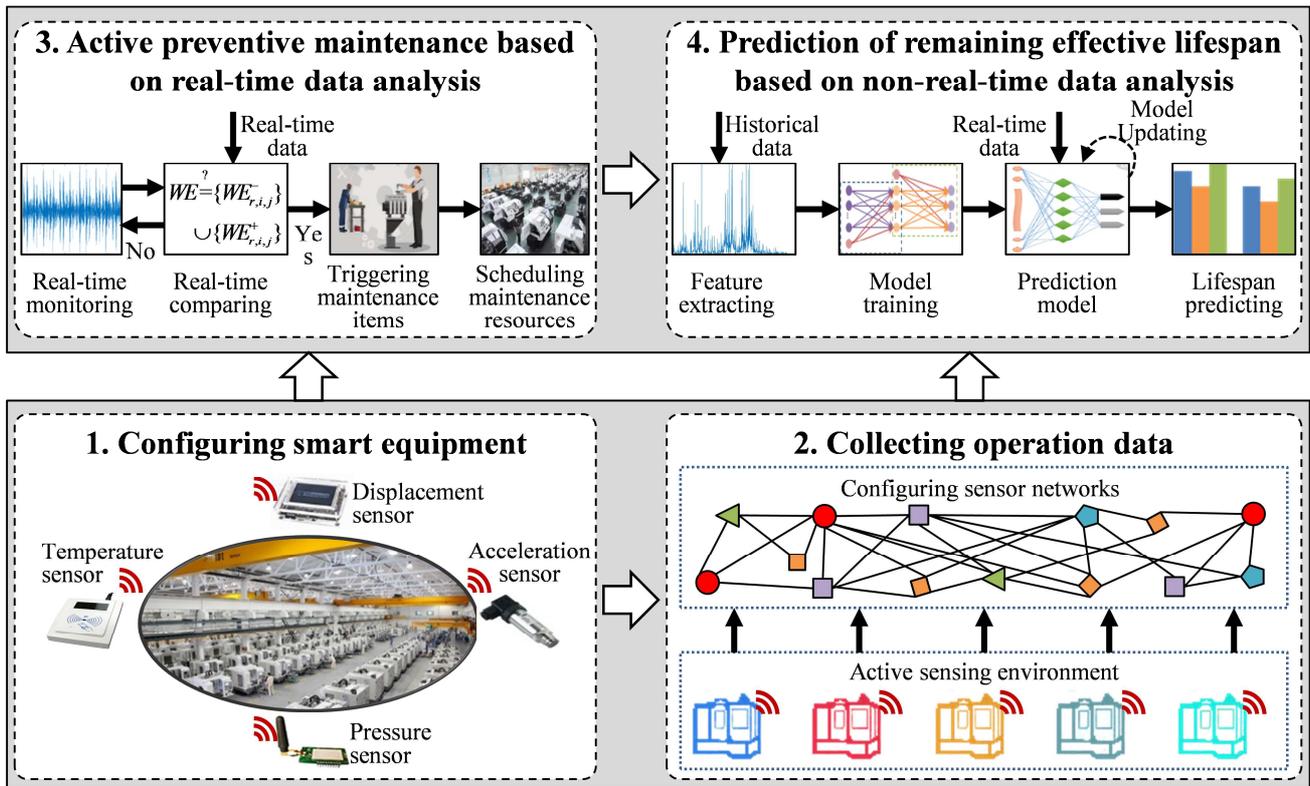
Thirdly, under the novel PSS operation mode, real-time operations status of all equipment (e.g. whether they are working, what task they are processing, how much workload they have, how much power they consume, and which equipment are idling, etc.) can be automatically transmitted and shared to implement the interactive ability among them. As a result, the utilization rate of equipment can be more effectively documented by the PSS provider, which can assist them to optimize the leasing or sharing business. For example, equipment that is underutilized by one user can be leased to other users who urgently need such equipment. Such a type of dynamic leasing or sharing contract is beneficial to improve the equipment utilization rates and to reduce resource wastage as well as to promote the implementation of CE.

Fourthly, within the centralized management format, the multi-source and heterogeneous operations status data of different equipment and different users in different conditions can help PSS providers to improve the accuracy and efficiency of fault diagnosis and fault prediction. Moreover, the complete and abundant data and knowledge accumulated by the PSS provider can provide effective support for proper operation of equipment and can help users to select and

lease the most suitable equipment for their needs. As a result, the proposed approach provides numerous opportunities for practitioners to develop and implement synergies among business ethics, CP and CE in the Industry 4.0 context.

#### 4. The solution of active preventive maintenance approach based on the novel operation mode

Based on the proposed PSS operation mode, a conceptual architecture for active preventive maintenance of complex equipment was developed as depicted in Fig. 2. It includes four main modules, namely (1) configuring smart equipment, (2) collecting operational data, (3) active preventive maintenance based on real-time data analysis, and (4) prediction of REL based on non-real-time data analyses.



**Fig.2.** A conceptual architecture for active preventive maintenance approach of complex equipment based on the novel PSS operation mode.

##### 4.1 Configuring smart equipment

The objective of configuring smart equipment is to enhance the sensing and interacting capability of all kinds of complex equipment in the pre-defined location of the PSS provider. Therefore, before putting the complex equipment into use, numerous sensors should be installed to monitor the parameters of the environment, manufacturing resources and the processing equipment. These sensors are necessary for achieving the proposed novel PSS operation mode and implementing active preventive maintenance. In contrast to other methods for configuring the smart objects in different lifecycle stages (Jun et al., 2009; Zhang et al., 2017a), smart sensors are used to establish smart equipment and to collect

useful data for active preventive maintenance. This is done because with the continuous development and maturity of modern sensor technologies, smart sensors can ensure high data quality and information quality (e.g. high accuracy of data due to mainly numerical values) as well as sufficient data veracity (Matyas et al., 2017). All kinds of complex equipment in the pre-defined location of the PSS provider are made 'smart' by equipping the physical objects with multiple sensors to achieve a certain degree of intelligence. With the support of multiple sensors, the operational status of complex equipment and its operating environment data can be monitored effectively.

From the moment complex equipment is put into use to the moment the complex equipment reaches the end-of-it's-life, the smart sensors deployed on the complex equipment are the most important data gathering source for the business decision-making of the whole product lifecycle. For example, the large quantities of data generated from smart sensors in operation and maintenance as well as in the recovery stages can be used to improve production efficiency, to facilitate the planning and implementation of preventive maintenance, to predict remaining lifespan and to optimize recovery decisions (Ren et al., 2019).

#### *4.2 Collecting operational data*

Based on the configuration of smart equipment, an active sensing environment can be constructed. As a result, a large number of real-time and multi-source operations status data of equipment (e.g. used by different customers, different equipment and different operating conditions) are generated automatically. For active preventive maintenance, all relevant data should be collected, such as alarm events (raw and abnormal information that reflects the operational state of the components), failure protocol, maintenance records, equipment operations status, etc. These data have various structures and features. For instance, alarm events are raw sensor information that needs to be handled and analysed in real-time. Failure protocol and maintenance records often exist in the form of free text with low quality, which can be transferred to the enterprise database periodically. Equipment operations status is usually collected periodically since a reasonable sampling frequency should be selected in designing the real-time monitoring system. Pre-processing of all types of data generated and collected in the equipment operation field is of vital importance to guarantee the effectiveness and efficiency of further data management and data analyses. Therefore, the service-oriented architecture can be used as a solution for implementing the data integration, such as data cleaning, data reduction, data transformation, etc. (Zhang et al., 2017a; Zhong et al., 2015).

Collecting the necessary and comprehensive data required to identify equipment failures and to plan active preventive maintenance activities is difficult due to the diversity and multi-sources of data. Therefore, another important component of data collecting is the management and configuration issues for sensor networks. To make it function properly, a

redundant sensor network considering cost constraints and reliability theory can be designed (Aponte-Luis et al., 2018; Marrón et al., 2005; Morais and Mateus, 2019), which can help to provide effective solutions for improving the comprehensiveness and accuracy of data collection.

#### 4.3 Active preventive maintenance based on real-time data analysis

During the daily production processes, a higher real-time requirement to handle alarm data from different complex equipment is needed. Therefore, in the pre-defined workspace of the PSS provider, the key component of different equipment can be regarded as active preventive maintenance items with a similar priority. According to the features of each maintenance item, the alarm data or operations status of equipment can be encapsulated as the items needing maintenance. The alarm data possess the highest priority in achieving active preventive maintenance. By constantly monitoring the key data of each maintenance item and comparing and evaluating the key data with its normal value range in a real-time manner, the active, preventive maintenance can be accomplished by scheduling maintenance resources dynamically. The main symbols used in this paper are described in Table 2.

**Table 2**

Main symbols used in the paper.

| Symbols                  | Description  |
|--------------------------|--|
| $R$                      | The number of equipment  |
| $Q$                      | The number of components that each equipment should be monitored   |
| $rt_{r,i,j}$             | The $j$ th real-time operations status parameters of the $i$ th components for the $r$ th equipment  |
| $S_i$                    | The total number of operations status parameters that $i$ th components need to be monitored in real-time  |
| $nr_{r,i,j}^-$           | The lower limit of normal value of the $j$ th operations status parameters of the $i$ th components for the $r$ th equipment                                       |
| $nr_{r,i,j}^+$           | The upper limit of normal value of the $j$ th operations status parameters of the $i$ th components for the $r$ th equipment                                       |
| $K$                      | The number of selected components of $R$ equipment   |
| $t_p$                    | The pre-set data extraction cycle  |
| $\mathbf{P}_{rs}$        | The real-time operations status data set of $K$ components of $R$ equipment at the time $t_p$  |
| $\mathbf{P}_{se}$        | The allowed range value set of $K$ components of $R$ equipment at the time $t_p$   |
| $WE$                     | The set of alarm events for the $K$ components of $R$ equipment  |
| $WE_{r,i,j}^-$           | The alarm events when the $j$ th real-time operations status of the $i$ th component of $r$ th equipment is lower than the lower limit of its allowed range value  |
| $WE_{r,i,j}^+$           | The alarm events when the $j$ th real-time operations status of the $i$ th component of $r$ th equipment is higher than the upper limit of its allowed range value |
| $\eta$                   | The total relative lifespan loss rate of key components  |
| $t_i$                    | The service time of key components under the $i$ th operating condition  |
| $T_i$                    | The effective life of key components under the $i$ th operating condition  |
| $\rho$                   | The empirical threshold of relative lifespan loss rate   |
| $\varepsilon_i$          | The proportion of service time of key components under the $i$ th operating condition in the actual lifespan based on a statistical analysis of historical data    |
| $\sum \varepsilon_i T_i$ | The predicted value of effective life under different operating conditions   |
| $\bar{T}$                | The expectancy-value of remaining lifespan based on a statistical analysis of historical data  |
| $\alpha$                 | The weights (empirical parameters) of $\sum \varepsilon_i T_i$   |
| $\beta$                  | The weights (empirical parameters) of $\bar{T}$  |

The implementation steps of active, preventive maintenance based on real-time data analysis are as follows:

**Step 1: Monitoring and establishing initial active preventive maintenance items.**

Suppose there is  $R$  equipment, which constitutes a complex equipment group, and each piece of equipment has  $Q$  components that are monitored in real-time. Therefore, a total of  $R \times Q$  components are monitored, which constitute the  $R \times Q$  initial active preventive maintenance items. Given a data set of real-time operations status parameters  $RT$  for  $R \times Q$  components in Eq. (1):

$$RT = \{rt_{r,i,j} \mid 1 \leq r \leq R, 1 \leq i \leq Q, 1 \leq j \leq S_i\} \quad (1)$$

Meanwhile, given a set of allowed range values  $NR$  for each component under normal operations status in Eq. (2):

$$NR = \{(nr_{r,i,j}^-, nr_{r,i,j}^+) \mid 1 \leq r \leq R, 1 \leq i \leq Q, 1 \leq j \leq S_i\} \quad (2)$$

**Step 2: Extracting real-time operations status data of components and determining maintenance items.**

For  $K$  ( $K \leq Q$ ) components of  $R$  equipment, the real-time operations status data and allowed range value was extracted from  $RT$  and  $NR$ , respectively. Then make Eq. (3) and Eq. (4) be:

$$\mathbf{P}_{\text{rts}} = \{rt_{r,i,j} \mid 1 \leq r \leq R, 1 \leq i \leq K, 1 \leq j \leq S_i\} \quad (3)$$

$$\mathbf{P}_{\text{sc}} = \{(nr_{r,i,j}^-, nr_{r,i,j}^+) \mid 1 \leq r \leq R, 1 \leq i \leq K, 1 \leq j \leq S_i\} \quad (4)$$

**Step 3: Comparing the operations status data with the allowed range value in real-time.**

Through comparing and evaluating the real-time operations status data of components with the allowed range value of each component under normal operations status, a set of alarm events for the components can be obtained. Then the preventive maintenance items that correspond to each alarm event can be determined. The set of alarm events for the components of equipment can be represented as  $WE$  in Eq. (5):

$$WE = \{WE_{r,i,j}^- \mid rt_{r,i,j} < nr_{r,i,j}^-\} \cup \{WE_{r,i,j}^+ \mid rt_{r,i,j} > nr_{r,i,j}^+\} \quad (5)$$

**Step 4: Triggering maintenance items and scheduling maintenance resources to carry out maintenance tasks.**

If the above-mentioned alarm events occurred, it can be considered that abnormality or degradation has happened on the corresponding components. Moreover, with the continuous accumulation of abnormality or degradation, these components will eventually breakdown. Therefore, the maintenance resources should be scheduled dynamically to trigger the maintenance items and to deal with the alarm events in real-time.

The maintenance resource scheduling models for different optimization objectives, such as minimization of the completion time for all maintenance activities (Yang and Yang, 2010) or aim to minimize the total production loss during the process of performing all maintenance activities (Kovács et al., 2011), can be established to achieve real-time and

active maintenance.

Meanwhile, through statistical analyses of the maintenance activities, the load of each maintenance resource can be calculated. On this basis, by tracking and analysing the real-time progress of the maintenance activities performed by each maintenance resource, the complete time of the maintenance activities can be predicted dynamically, which can provide decision-making support for optimal scheduling of maintenance.

#### 4.4 Prediction of REL based on non-real-time data analysis

The objective of the REL prediction is to enhance the accuracy and efficiency of maintenance activities. By integrating real-time operation status data with historical data stored in enterprise database, the REL of the key components of complex equipment can be predicted. The traditional methods for assessment of equipment lifespan are generally based on the experience of maintenance staff (e.g. the accumulated service time or historical lifespan record), or wait for an occurred fault of the key components. The experience-based approach takes the using safety of complex equipment and the operational fluency of production into consideration. However, the experience-based method is commonly conservative, and results in wastage of maintenance resources and spare parts. Although the fault-based approach can make the best of the lifespan that the components have, the lack of emergency measures for dealing with sudden failures (e.g. whether the maintenance resources are available or not, and whether there is a safe inventory of spare parts, etc.) will result in increased maintenance time and to shutdowns in the normal production processes.

In the practical production and operation process, the actual lifespan of the key components of complex equipment is different under different operating conditions. Therefore, large deviations exist while relying on the accumulated service time or the historical lifespan record of key components in various operating conditions to decide whether to execute maintenance activities. These deviations will lead to conservative or excessive usage of the key components, and further lead to serious production exceptions or equipment faults.

To solve these highlighted problems, the relative lifespan loss rate (Wan et al., 2017) was introduced to comprehensively measure and evaluate the REL of the key components under different operating conditions. The total relative lifespan loss rate of key components can be represented as  $\eta$  in Eq. (6):

$$\eta = \sum \frac{t_i}{T_i} \quad (6)$$

Here, a deep neural network (DNN) model is established based on autoencoder (AE) to predict and estimate the effective life of a key component under a specific operating condition  $T_i$ . Then, based on  $\eta$  and  $T_i$  obtained by DNN model, and historical and real-time operation data, the REL of a key component can be predicted. The procedures of REL

prediction are described as the following steps.

**Step 1: Extracting the effective life characteristics of key components.**

An AE is one type of unsupervised neural network that includes three layers: input layer, hidden layer and output layer. The AE can be used to extract the key information that represents the characteristics of the input layer data and to reduce the dimensions of the input layer data. For example, during the numerically controlled machining processes, the three typical elements (spindle speed, feed speed and cutting depth) can be used as the input data of AE, to extract and reflect the lifespan characteristics of cutting tools under specific operating conditions. The encoding, decoding, and the model training based on minimizing reconstruction errors are performed in AE to realize the above objectives.

In the encoding process, the data of the input layer are transformed into hidden layer data by Eq. (7):

$$\mathbf{h}_m = f(\mathbf{w}\mathbf{x}_m + \mathbf{b}) \quad (7)$$

where input vector  $\mathbf{x}_m$  of sample  $m$  contains the parameters that affecting the remaining lifespan of key components;  $\mathbf{h}_m$  is the encoding vector of sample  $m$  that contains the main characteristics of the input layer data;  $\mathbf{w}$  and  $\mathbf{b}$  are weight matrix and bias vector, respectively;  $f(\square)$  is the encoding function.

In the decoding process, the data of the input layer are reconstructed from the corresponding hidden layer by Eq. (8):

$$\hat{\mathbf{x}}_m = \hat{f}(\hat{\mathbf{w}}\mathbf{h}_m + \hat{\mathbf{b}}) \quad (8)$$

where  $\hat{\mathbf{x}}_m$  is the reconstruction vector of the input data;  $\hat{\mathbf{w}}$  and  $\hat{\mathbf{b}}$  are weight matrix and bias vector, respectively;  $\hat{f}(\square)$  is the decoding function.

In the training processes, the AE is constructed through the back-propagation method to minimize the reconstruction errors  $\varphi(\mathbf{x}, \hat{\mathbf{x}})$  (by Eq. (7)), and to achieve better performance of feature extraction:

$$\varphi(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{M} \sum_{m=1}^M \|\mathbf{x}_m - \hat{\mathbf{x}}_m\|^2 = \frac{1}{M} \sum_{m=1}^M \|\mathbf{x}_m - \hat{f}(\hat{\mathbf{w}}f(\mathbf{w}\mathbf{x}_m + \mathbf{b}) + \hat{\mathbf{b}})\|^2 \quad (9)$$

where the  $M$  is the total number of samples.

**Step 2: Establishing DNN-based effective life prediction model (DNN-ELPM) of key components under a specific operating condition.**

Given the strong coupling of different parameters and the diversity of input data (such as operating state, temperature, humidity, vibration, etc.), the DNN with deep architectures can be established to extract valuable information from raw data and approximate complex non-linear fitting and to carry out more accurate and efficient lifespan prediction. The inputs of DNN-ELPM are the operating state parameters and the operating environment parameters of key components under a specific operating condition. The output of DNN-ELPM is the prediction value of the effective life of key

components under this condition. Here, two processes, i.e. pre-training and fine-tuning are included in the DNN-ELPM establishment.

In the pre-training process, the above-mentioned AE is used to initialize the parameters of  $n$  hidden layers, as shown in Fig. 3. Firstly, the original  $AE_1$  is constructed by the above-mentioned encoding, decoding and model training processes, and the  $(\mathbf{w}^1, \mathbf{b}^1)$  of  $AE_1$  encoding process is used to construct the initial mapping relationship between the input layer and the first hidden layer of the DNN-ELPM (Huang et al., 2019). Secondly, the above process is repeated until the mapping parameters (weight metrics  $\mathbf{w}$  and bias vectors  $\mathbf{b}$ ) of all hidden layers are pre-trained.

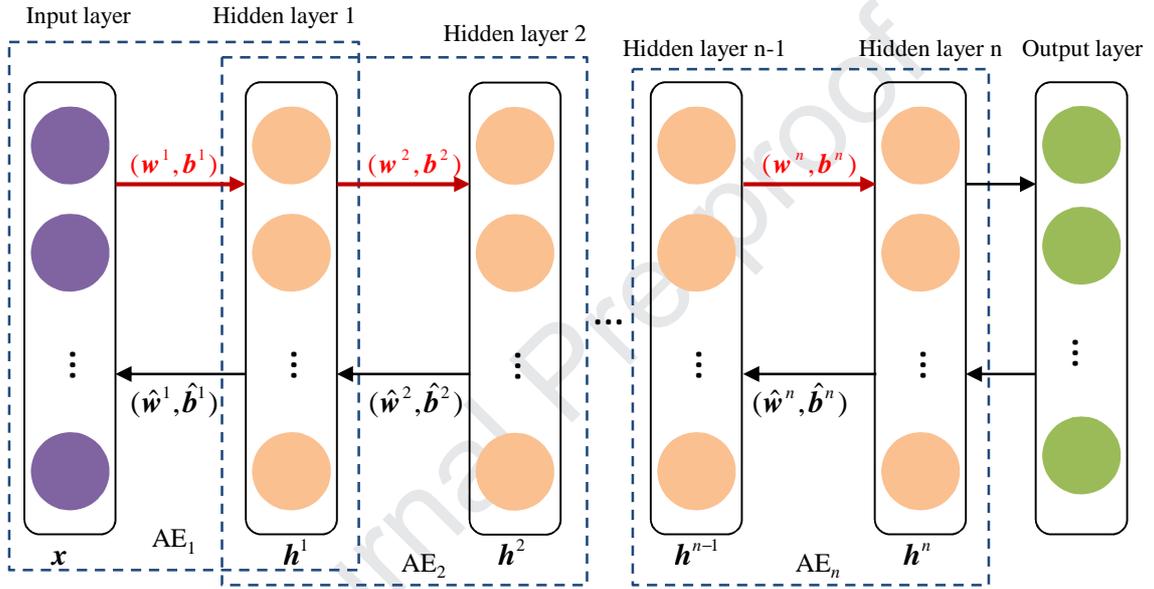


Fig. 3. The pre-training processes of DNN-based effective life prediction model

After the DNN-ELPM is pre-trained, the fine-tuning operation is performed to improve the performance of model fitting. Firstly, relations between the output layer and the  $n$  th hidden layer are established by Eq. (10):

$$\mathbf{y}_m^* = f^{n+1}(\mathbf{w}^{n+1} \mathbf{h}_m^n + \mathbf{b}^{n+1}) \quad (10)$$

where  $\mathbf{y}^* = \{\mathbf{y}_m^*\}_{m=1}^M$  is the actual output data of the DNN-ELPM;  $\mathbf{h}^n = \{\mathbf{h}_m^n\}_{m=1}^M$  is the  $n$  th hidden layer data;  $\mathbf{w}^{n+1}$  and  $\mathbf{b}^{n+1}$  are weight matrix and bias vector from the  $n$  th hidden layer to the output layer, respectively;  $f^{n+1}(\cdot)$  is the activation function of the  $n$  th hidden layer to the output layer.

Secondly, the error function of the DNN-ELPM is constructed by Eq. (11):

$$\varphi_{DNN}(\mathbf{y}, \mathbf{y}^*) = \frac{1}{M} \sum_{i=1}^M \|\mathbf{y}_m - \mathbf{y}_m^*\|^2 \quad (11)$$

where  $\mathbf{y} = \{\mathbf{y}_m\}_{m=1}^M$  is the expected output of the DNN-ELPM. By using the back-propagation process (Jia et al., 2016), the error function of the DNN-ELPM is minimized, to obtain the effective life prediction model of key components under a

specific operating condition.

After training the model, when transferring operating state parameters and operating environment parameters into the DNN-ELPM, the effective life of key components under a specific operating condition can be calculated and predicted.

### **Step 3: Predicting the REL of key components under different operating conditions.**

As previously mentioned, the operating conditions of key components are dynamic changing in the practical production and operation processes. Therefore, the predicted value of effective life for key components under specific operating conditions cannot accurately reflect their actual REL. Therefore, the Eq. (6) is used to provide a comprehensive evaluation of relative lifespan loss rate of the key components under different operating conditions.

Given an empirical threshold  $\rho$  of relative lifespan loss rate, when the calculated  $\eta$  is much less than threshold  $\rho$ , it indicates that the key components still have a long REL, and it is not necessary to predict the REL. When  $\eta$  reaches the empirical threshold  $\rho$ , it indicates that the key components have reached the critical point of their REL. Therefore, it is necessary to predict the REL and to implement preventive maintenance activities according to the predicted results.

When the calculated relative life loss rate  $\eta$  of key components reaches the empirical threshold  $\rho$ , the REL  $RL$  can be predicted by Eq. (12):

$$\begin{aligned}
 RL &= \alpha(1-\eta)\sum \varepsilon_i T_i + \beta(1-\eta)\bar{T} \\
 \alpha &> 0, \beta > 0, \alpha + \beta = 1 \\
 \varepsilon_i &> 0, \sum \varepsilon_i = 1
 \end{aligned} \tag{12}$$

Here, when the REL of key components is sensitive to the operating condition, the  $\alpha$  might be bigger. On the contrary, if the key components are stable enough, the expectancy-value of remaining lifespan based on historical data should be taken into more consideration, so  $\beta$  might be bigger.

## **5. Case study**

The proposed mode was tested in a case study of an industrial partner company. The main objectives of the case study were to test how the equipment maintenance approach could be changed by the proposed operation mode, as well as what improvements were made by using active preventive maintenance.

In this section, firstly, an overview of the case company was provided. Then, the configuration methods of the smart machine and the data collection methods of the case study were introduced. Thirdly, the prediction processes of the REL of cutting tools for CNC machine were elaborated. Finally, the advantages of the proposed novel PSS operation mode and the active preventive maintenance approach of complex equipment were analysed and discussed.

### 5.1 Overview of the case company

The case company is a high-tech enterprise in China, which focuses on the research and development (R&D), manufacturing, sales and service support of CNC machines. The company has developed more than 300 types of high-precision CNC machines. These machines are used by over 100 key customers to process nearly 200 kinds of precision and high-end products, such as precision moulds, precision electrodes and specular machining. Because of the case company's CNC machines are mainly used in the precision processing industry, it is of utmost importance for the company to prevent faults and to ensure the machining precision and processing quality.

In the past, all CNC machines were placed in a different geographical area and used by a specific customer. Restrained by the development of information and communication technologies, the operational data of the different machines and different customers in diverse conditions and areas could not be acquired accurately and completely. As a result, the accuracy and efficiency of fault diagnosis and lifespan prediction for machines based on incomplete and inaccurate operational data under a specific condition were lower, which have directly affected the service life of machines and their production efficiency. Meanwhile, the hidden factors that affect the machine fault and service life are difficult to be discovered, which makes prevention and prediction of faults extremely difficult to realize. They also cause reductions in processing precision and increases in production costs.

Therefore, it is important to determine how to improve the accuracy and efficiency of fault diagnosis and lifespan prediction for CNC machines, to enhance the processing precision, which was the main challenge the case company faced for a long period. Recently, with the digitization of the industry and the advancement of information technologies, the case company sought a new way to achieve the potential of sensing and applying the operational data of different machines and different customers in different conditions for fault diagnosis and lifespan prediction, and they therefore, tested the novel operation mode according to Section 3.

### 5.2 Configuration of the smart CNC machine and data sources

For simplicity of understanding but without losing generality of principle, a certain type of CNC machines (named VT and used throughout this section) were selected to illustrate the solution of configuring smart machines and collecting operational data that were adopted by the case company. For example, multiple types of smart sensors are used to configure the smart VT machines and to collect the multi-source operational data and environmental data of different customers in different operational conditions. Due to the limited space, parts of the configuration information of the smart sensors for VT machines are shown in Table 3.

**Table 3**

Example of the configuration information of the smart sensors for VT machine.

| <b>Sensor types</b>                   | <b>Locations</b>                        | <b>Measuring parameters</b>   |
|---------------------------------------|---|---|
| Refractometer                         | Cutting fluid cooling tank              | The concentration of cutting fluid  |
| Liquid level sensor                   | Cutting fluid cooling tank              | Cutting fluid level   |
|                                       | Machine lubrication pump                | Lubricant oil level   |
| Temperature sensor                    | Spindle end                             | Spindle temperature   |
|                                       | Cutting fluid cooling tank              | Spindle coolant temperature   |
| Temperature and humidity sensor       | Around the CNC machine                  | Temperature and humidity of machine surrounding                                 |
| Humidity sensor                       | The compressed air inlet of the machine | The humidity of compressed air  |
| Displacement sensor                   | Spindle bearing                         | Spindle vibration   |
| Acceleration sensor                   | Around the CNC machine                  | The vibration of the machine surrounding  |
| Photoelectric touch probe             | Spindle                                 | Geometric errors of work-in-process (WIP)                                       |
| Laser displacement sensor             | WIP                                     | WIP quality   |
| Pressure sensor                       | The compressed air outlet of machine    | The pressure of compressed air for changing the cutters                         |
| Machine numerical control (NC) system | —                                       | Spindle motor current and load torque, spindle speed, feed speed, cutting depth |

The gateway of local area network adopted in the production field can support multiple types of communication interfaces, such as Registered Jack 45(RJ45), Recommended Standard 232 (RS-232) and wireless, thus the communication among heterogeneous sensors can be realized. To achieve the data collection, uploading and handling, the smart sensors were connected to the NC system of VT machines, and were incorporated into a data collection and communication system based on Microsoft Structured Query Language (MS-SQL) Server. As a result, the data gathered by MS-SQL Server can be added to a Distributed Numerical Control (DNC) system, and then the visual information (e.g. processing records, machine alarms, tool wear, etc.) can be provided for operators or managers.

The proposed operation mode described in Section 3 was implemented in the case company. That is, these VT machines were leased and shared in the pre-defined location of the case company by multiple customers, such as 3C small hardware industry, precision mode, precision electrodes, hard-cutting materials and medical industry. Therefore, the operation state data and operation environment data of different machines and different customers in different processing conditions were acquired accurately and timely. These multi-source data were useful for the analyses and prediction of the REL of key components for the VT machine.

### 5.3 Prediction of the REL of cutting tool for CNC machine

In this section, the method of prediction of the REL was verified by using the cutting tools of VT machine. Through the typical milling processes, the empirical estimation value of REL was compared with the calculated value obtained by

the proposed method in this paper.

During the machining processes, different processing materials and machining parameters and cutting tool materials were used. In this case study, the specific information and parameters for the REL prediction of cutting tools are shown in Table 4. The flat-end cutters (FC-1) with tungsten carbide were used in the milling processes. The machined material was 6063-T6 aluminium alloy. Three different groups of machining parameters (MP) were tested. Therefore, the data used to predict the REL were collected from these different machining processes. It is important to note that machine tool vibration has a direct effect on tool wear, durability, machining accuracy and quality of the machined surfaces. When the calculation of REL of cutting tools, the spindle vibration signal collected from Section 5.2 was regarded as the main factor, and as an essential input of the DNN-ELPM.

**Table 4**

Parameters and information used for the REL prediction of cutting tools.

| MP number       | Spindle speed (r/min) | Feed speed (m/min) | Cutting depth (mm) | Tool type              | Tool material    | Machined material       | Processing type |
|-----------------|-----------------------|--------------------|--------------------|------------------------|------------------|-------------------------|-----------------|
| MP <sub>1</sub> | 8000                  | 5                  | 0.4                | Flat-end cutter (FC-1) | Tungsten carbide | 6063-T6 aluminium alloy | Milling process |
| MP <sub>2</sub> | 9000                  | 5                  | 0.1                |                        |                  |                         |                 |
| MP <sub>3</sub> | 9000                  | 5                  | 0.2                |                        |                  |                         |                 |

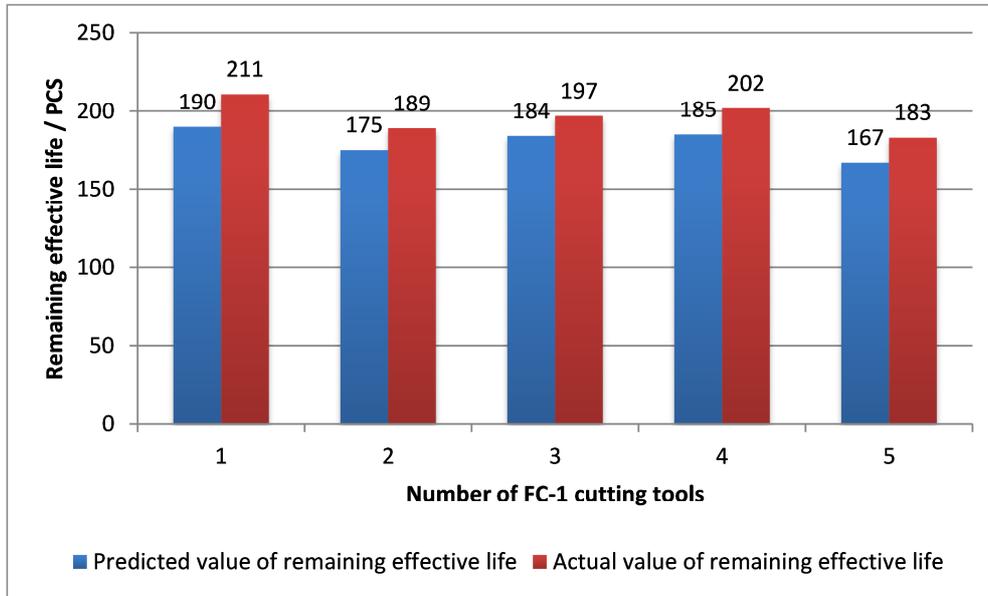
According to the method proposed in Section 4.4, the processes of prediction of REL for FC-1 cutting tools are carried as follows.

Firstly, the data of 6063-T6 material machined by FC-1 cutting tool were extracted from the MS-SQL Server system of the case company. These data including the vibration data of the FC-1 cutting tool under the specific operating condition of MP<sub>1</sub>, MP<sub>2</sub> and MP<sub>3</sub>, and the actual lifespan of FC-1 (that statistic by the case company). A total of 120 samples of FC-1 under a specific operating condition were extracted to establish the effective life prediction model of FC-1. At the same time, to predict the REL of the FC-1 cutting tool under different operating conditions, the data of five FC-1 cutting tools, under the three operating conditions (i.e. MP<sub>1</sub>, MP<sub>2</sub> and MP<sub>3</sub>) were documented. The data included: the service time, vibration data, and actual lifespan of each cutting tool under the specified operating conditions.

Secondly, a 1-input 1-output 2-hidden 4-layer DNN was designed to predict the effective life of FC-1 under a specific operating condition. The input layer parameters of the DNN were the spindle speed, feed speed, cutting depth and vibration signals under specific operating conditions (MP<sub>1</sub>, MP<sub>2</sub> and MP<sub>3</sub>), and the output layer parameters were the actual lifespan of FC-1 under the corresponding operating conditions. In particular, the first 1200 data points in the frequency domain of the vibration signal were selected as the input parameters of the DNN. Therefore, the input layer of the DNN had a total of 1203 neuron nodes. Based on experience settings, the structure of DNN-ELPM is designed as

[1203, 300, 64, 1], which means the established network contains 1-input layer (1203 neurons), 2-hidden layer (300 and 64 neurons, respectively) and 1-output layer (1 neuron). These input parameters were randomly divided into training data, test data and validation data, among which training data accounted for 70%, test data and validation data accounted for 15% respectively. In the pre-training process, two AEs are used to initialize the weights and thresholds of hidden layers, and the maximum iteration number of AE is set as 100. In the fine-tuning process, the maximum iteration number of the whole DNN-ELPM is set as 300. As a result of these settings, the effective life prediction model of FC-1 under a specific operating condition was established, which can provide a reference for the prediction of REL of the five FC-1 cutting tools. The tests were performed on a workstation (Intel(R) Core (TM) i7-7700K CPU @ 4.20GHz) with 32G of RAM, Windows 10 Enterprise Edition operation system with 64-bit, and Matlab 2017a was used to train the DNN. In this case study, the computational time of DNN model mainly includes three parts: 1) the parameters mapping time from the input layer to the first hidden layer based on  $AE_1$  (45.33s); 2) the parameters mapping time from the first hidden layer to the second hidden layer based on  $AE_2$  (2.38s); and 3) the fine-tuning time for the whole DNN-ELPM (9.22s). Therefore, the total time for the establishment of DNN-ELPM is 56.93s. Compared with the DNN-ELPM training process, the calculation time of the final REL based on Eq. (12) could be nearly ignored. This is because of the main parameters (i.e.  $\eta$  and  $T_i$ ) of REL prediction for cutting tools that in Eq. (12) have already been obtained through the DNN model when the final REL prediction is conducted.

Thirdly, the empirical threshold of relative lifespan loss rate  $\rho$  was set to 0.7, and the weights  $\alpha$  and  $\beta$  were set to 0.6 and 0.4 respectively. The prediction value of effective life for each FC-1 cutting tool under a specific operating condition ( $MP_1$ ,  $MP_2$  and  $MP_3$ ) was obtained from the second step. Using the cutting tool and machined material and machining parameter designated in this case study, while the relative lifespan loss rate reached the pre-defined threshold (i.e. 0.7), the REL prediction is triggered. At the moment of triggering the REL prediction, the relative lifespan loss rate of 5 FC-1 cutting tools can be calculated based on the service time of them under the above stated three operating conditions. The actual REL of the 5 FC-1 cutting tools can be expressed by the differences between the actual lifespans of each FC-1 obtained from the case company and the service time of the tools when predicting effective life. Comparisons between the predicted and actual REL of the 5 FC-1 cutting tools are shown in Fig. 4. In this case study, the REL is expressed by the quantity unit “pieces (PCS)”, where 1-PCS means that the FC-1 cutting tool can be used to machine one 6063-T6 aluminium alloy product. It can be seen from Fig. 4 that the predicted REL of the 5 FC-1 cutting tools was less than the actual value. The results have guidance value for maintenance personnel and on-site operation personnel for making timely repairs and re-grinding and replacing the tools, which is helpful to avoid the WIP damaging when the cutting tools reach end-of-their-lifespan.



**Fig.4.** Comparison of the predicted and actual REL of the 5 FC-1 cutting tools.

#### 5.4 Analysis and discussions

In this part, the historical data and experiment data of VT maintenance in the case company were used to test the validity of the proposed method, and the findings were also discussed.

The safe range for REL of five FC-1 cutting tools released by the REL predicted value is analysed. The deviations between the predicted and actual REL of the five FC-1 cutting tools is calculated (seen in Table 5 and Table 6).

**Table 5**

Deviations between the predicted and actual REL of the five FC-1 cutting tools.

| Number of FC-1 cutting tool | 1    | 2    | 3    | 4    | 5    |
|-----------------------------|------|------|------|------|------|
| Deviations (%)              | 9.95 | 7.40 | 6.60 | 8.42 | 8.74 |

**Table 6**

Deviation analysis of the predicted and actual REL of the five FC-1 cutting tools.

| Maximum deviation (%) | Minimum deviation (%) | Mean deviation (%) | Standard deviation (%) |
|-----------------------|-----------------------|--------------------|------------------------|
| 9.95                  | 6.60                  | 8.22               | 1.15                   |

As shown in Table 5, for the five FC-1 cutting tools, the maximum deviation between the predicted and actual REL was 9.95%, and the minimum deviation was 6.6%. According to the semi-structured interviews with managers of the case company, in the actual production processes, the safe range of deviation for the cutting tools is usually pre-set to be 10%. Therefore, the deviations of REL for all the five FC-1 cutting tools are within the allowable and safe range. The results showed that the REL predicted by the proposed method did not result in a conservative or excessive use of the tools. On the one hand, the problems of low tool utilization and production cost increase caused by the conservative estimation of REL can be avoided. On the other hand, the problems of high cutting temperatures, low machining accuracy, tool breakage and spindle shaft break caused by the excessive use of the tools can also be avoided by using the

proposed approach.

Similarly, through the integrated and comprehensive analysis of the deviations between the predicted and actual REL of the five FC-1 cutting tools, the mean deviation (8.22%) and the standard deviation (1.15%) are both at a lower level (as seen in Table 6). This indicates that the proposed method has high robustness in predicting the REL of cutting tools under different operating conditions. Therefore, in the complex operating and machining conditions (e.g. the above-mentioned different processing materials, machining parameters, cutting tool materials, etc.), the proposed method can predict the REL of components accurately and effectively.

The case study provides strong empirical evidence that the proposed method is valid and feasible, which indicates that it has the potential to be applied in industry for equipment preventive maintenance. Compared with other research (Cheng et al., 2020; Wan et al., 2017; X. Wang et al., 2019; Xia et al., 2017; Zhu et al., 2012), the major difference is the novel leasing/sharing mode together with the possibility of achieving more comprehensive data collection and the advantage of providing higher quality services for their customers. The proposed novel PSS operation mode makes it possible to track and access the operational state data of non-key components (namely auxiliary devices or accessories). For example, geometric errors of WIP, concentration and the fluid level of cutting fluid, the temperature of spindle coolant, the humidity of compressed air, temperature and humidity and vibration of the machining environment, and so on. These data create effective means to inter-connect equipment, end-users and ethics. For example, the collected data can be analysed to better control and management of machine tools, the product that is produced is of a better quality, and therefore will work better for the user of the 'turned' product. This would be a potential and an illustrative ethical parameter.

The proposed active preventive maintenance approach along with the collected real-time and multi-source operations status data (e.g. different equipment and different users in different conditions) allows the PSS providers to find more hidden, common fault features in a shorter time. This will help PSS providers to reduce resource waste and improve production efficiency. Therefore, the operation mode and data and active preventive maintenance approach are three pillars that are critically important to exploit the potential of the operations status data for complex equipment. These three elements provide insights to PSS providers to develop and implement sustainable business models in line with the evolving ethical principles of enterprise social responsibility. For instance, within the proposed operation mode, the operational data of different equipment and diverse users in varied conditions can be collected to perform active preventive maintenance at the proper time. As a result, worker's health and safety risks which caused by a sudden equipment failure may be reduced and avoid, which is consistent with the ethical dimensions of the CE.

According to the semi-structured interviews with the manager of the case company, in the past, even though all MP of

the CNC machines were set in an appropriate range, the final turned product was not always of the expected quality or precision. By applying the novel operation mode and method with real-time and multi-source data, more hidden fault features were pre-emptively found and detected, thereby active preventive maintenance can be performed to eliminate the faults earlier and to ensure the fluency of production processes. This can move the PSS providers from planned corrective maintenance to proactive and smart maintenance planning (Matyas et al., 2017), and can reduce the PSS providers' maintenance costs and customers' use costs while substantially reducing material's and production time wastage.

Although a substantial amount of cost and effort is needed to invest in the novel operation mode, the benefits outweigh the investment. It should also be noted that the collected real-time and multi-source operations status data can bring additional benefits for the PSS providers. For example, the results of statistical analysis of frequent faults for different machine tools in different operational conditions can provide new ideas and insights for research and development of the next generation of the machine tool. Moreover, other potential benefits of the novel PSS operation mode such as the usage rate of CNC machines can be increased because of the shared usage. Therefore, resource efficiency can be achieved by implementing the CP strategy while improving worker health and safety, and by ethically and responsibly ensuring that the turned products are uniformly of top quality. As a result, catalysing the PSS providers can make progress in transitioning their company's business to performing corporately, socially and environmentally responsibly. At the same time, the PSS providers will improve their competitive advantage by expanding their visions and plans to continue to innovate in their PSS so their products are designed to be re-used as inputs to CE in the context of the 17 Sustainable Development Goals and in co-working to achieve the targets of the Paris Climate Change Accords.

The major disadvantage of the proposed operation mode is the risk of a customer's sensitive information (e.g. what products are produced by the machine tools) being exposed to the PSS provider. This is currently a limitation to the wide application of the proposed operation mode, but this concern can be resolved in the future. For example, the encrypted data protocol can be used in the PSS delivery processes to protect the customer privacy. At the moment, as stated at the beginning of Section 5.1, most of the customers have long-term cooperation with the case company and highly trust them, therefore, this concern is minor compared to the benefits they can gain.

## **6. Conclusions**

Many manufacturing companies have transformed their businesses towards PSS business models, to integrate product development with relevant operation and maintenance services as part of CE and which helps to accelerate the societal transition to equitable, sustainable, livable, post-fossil carbon societies. Thereby they are increasingly working to help to fulfil the Paris Climate Change Accords and to implement the 17 Sustainable development goals. However, with the

permeation and application of the smart enabling technologies in all aspects of the manufacturing industry, the PSS providers are facing many challenges. For example, how to collect and analyse the operational data of different equipment and users in different conditions in a timely fashion, to perform maintenance pre-emptively and to reduce resource consumption during maintenance procedures.

In order to address the challenges, in this paper, an active predictive maintenance approach for complex equipment based on a novel PSS operation mode was proposed. The main purposes were: 1) to integrate the PSS delivery processes with associated operation and maintenance services and to create the capability for PSS providers to better control and management of their products; 2) to create means to inter-connect equipment end-users and ethics to reduce natural resource consumption and to improve equipment utilization by using leasing and sharing mode.

The proposed approach was motivated by the massive and multi-source operational data of complex equipment and employs DNN to train a model for prediction of the REL of key components. As a result, the health status of equipment was monitored in a real-time. A case study from a leading CNC machine provider was used to verify the feasibility and effectiveness of the proposed solution. Through the typical milling process, the empirical estimation value of REL for cutting tools was compared with the predicted value obtained by the proposed method. Results from the comparisons shown the superiority of the proposed approach. The main contribution lies in scientific and practical knowledge for how the novel PSS operation mode can provide value-added services for equipment users and provide opportunities for PSS providers to explore and develop more sustainable business models aligned with the evolving ethical principles of enterprise social responsibility. The unique contributions, implications and limitations of this paper were summarized and elaborated as follows.

### *6.1 Unique contributions*

The deployment of a more ethical and sustainable business model using Industry 4.0 to achieve CP and CE remains to be difficult for industrial practitioners and managers (Nascimento et al., 2019). Given this challenge, the purpose of this paper is to explore how emerging technologies from Industry 4.0 can be integrated with the PSS paradigm to establish a novel operation mode that can help enterprises and governments carry out more efficient and sustainable production and consumption. The proposition is proposed from the perspective of maintenance service for complex industrial equipment. Consequently, supporting the implementation of CP and CE, and accelerating the transition to more ethical and sustainable societies. The following contributions were made by the authors of this paper:

Firstly, by combining the key technologies of Industry 4.0 with the PSS paradigm, a novel leasing/sharing mode for complex industrial equipment was proposed. Under the operation mode, all leased/shared equipment is independently

controlled and managed by the OEM in the premises they provide and in a centralized manner. Therefore, the operational data of different equipment and multiple users in varied conditions can be collected and analysed by the OEM. As a result, more professional operation and maintenance services can be provided for the end-users. Moreover, the professional production operators and maintenance staffs of OEM can also be shared to reduce the failure rate and to improve the product quality and resource utilization. These advantages can help OEM to construction of the corporate social responsibility and to integration of CP, CE and business ethics.

Secondly, from the perspective of efficient usage of complex equipment under the proposed leasing/sharing operation mode, conceptual architecture and solution for active preventive maintenance were developed. In contrast to the existing approaches, the novelty of the proposed solution for active preventive maintenance is the integration of these approaches based on historical data combined with real-time operational data as well as design parameters of key components. This integration is important for the novelty of the solution, the REL and faults of key components are predicted more precisely, and preventive maintenance measures are planned pre-emptively. As a result, resources and energy consumption can be reduced while improving worker health and safety. This is benefit to achieve a balance and harmony among environment, society and socio-ethical issues.

## 6.2 Implications

The PSS has the potential to facilitate sustainable production and consumption and to support a transition towards a CP and CE. For this study, the research implications could be illustrated from the following perspectives.

Firstly, it was found that the utilization rate of equipment can be improved and the circulation of equipment can be reduced by using the proposed leasing or sharing mode. Thus, it can help practitioners minimize resource consumption and negative environmental impacts. Furthermore, it can promote the resource integration of the entire manufacturing industry and can reduce the threat to ecosystems. Consequently, numerous opportunities for PSS providers to develop sustainable business models, to carry out CP and CE strategies, and to extend ethical principles of enterprise social responsibility can be provided.

Secondly, under the proposed PSS operation mode, all equipment is leased/shared in the premises the OEM provided, and exclusive controlled and managed by the OEM. This is the biggest difference between traditional PSS. The small and medium-sized enterprises (SMEs) can significantly reduce equipment purchase costs and plant building costs by leasing/sharing mode. Meanwhile, due to the SMEs do not have to consider the problem of idle equipment disposal when their production and finance fall into crisis, the operational risk can be reduced. Furthermore, enterprises' normal production can be ensured when the orders changed dynamically and reached a peak, yet without the need to purchase

additional equipment. Therefore, rational and efficient usage of social resources can be achieved. This can promote the implementation of a more efficient CP practice and the development of a more ethical and sustainable business.

Thirdly, since the costs for leasing/sharing equipment is much lower than owning one (especially for high-value and high-end production machines), the proposed new PSS mode reduces the capital requirements of practitioners' entrepreneurship. Therefore, more entrepreneurs can enjoy the benefits of the leasing or sharing mode, thus driving the enthusiasm of entrepreneurs. As a result, the implementation of the proposed PSS operation mode enables the development of local business networks that generate more jobs as well as improve economic performance. The operation mode also promotes a culture of CP and CE and motivates the transition to more ethical and sustainable societies through the use of Industry 4.0 paradigm.

### *6.3 Limitations*

The limitations of this paper are summarized as follows. Firstly, in the case study, only one machined material and processing type (see Table 4) were used to test the effectiveness of the proposed approach. To strengthen the robustness and accuracy of the proposed approach in REL prediction, the machining process accompanied by different processing materials and processing types as well as processing parameters should be considered and tested comprehensively. Secondly, the data security of the customers was not considered. In the proposed operation mode, the customers' sensitive information may be leaked to the PSS providers. To solve this problem, new technology such as Blockchain (Bechini et al., 2008; Feng et al., 2020; Hawlitschek et al., 2018) should be used to establish a trust mechanism between the customers and the PSS providers.

Future works should be focused on the following three aspects. Firstly, with the continuous accumulation of equipment operational data, more advanced models and algorithms should be taken into consideration to improve the accuracy of fault features for detection and lifespan predicting. Secondly, the mechanisms and approaches for dynamic allocation of production resources within the novel PSS operation mode should be investigated to maximize the utilization rate of these resources (as stated in Section 3) and to reduce the PSS providers' production and operation cost. Thirdly, under the proposed PSS operation mode, new strategies and propositions for supporting enterprises and society to cope with the negative effects of workers' unemployment caused by technological innovation and improvement should be taken into account.

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**Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: