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Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries

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ABSTRACT

The circular economy plays an important role in energy-intensive industries, aiming to contribute to ethical sustainable societal development. Energy demand response is a key actor for cleaner production and circular economy strategy. In the Industry 4.0 context, the advanced technologies (e.g. cloud computing, Internet of things, cyber-physical system, digital twin and big data analytics) provide numerous opportunities for the implementation of a cleaner production strategy and the development of intelligent manufacturing. This paper presented a framework of data-driven sustainable intelligent/smart manufacturing based on demand response for energy-intensive industries. The technological architecture was designed to implement the proposed framework, and multi-level demand response models were developed based on machine, shop-floor and factory to save energy cost. Finally, an application of ball mills in a slurry shop-floor of a partner company was presented to demonstrate the proposed framework and models. Results showed that the energy efficiency of ball mills can be greatly improved. The energy cost of the slurry shop-floor saved approximately 19.33% by considering electricity demand response using particle swarm optimisation. This study provides a practical approach to make effective and energy-efficient decisions for energy-intensive manufacturing enterprises.

1. Introduction

In the sustainable production and consumption context, the circular economy (CE) plays an important role in manufacturing industries, which maximises the recycling of resources, materials and energy (de Sousa Jabbour et al., 2018b). CE can benefit the economy, environment and society and achieve a great balance and harmony amongst them. However, most studies aim at explaining a balanced relationship between environmental and economic systems and ignore the ethical sustainable societal development (Ghisellini et al., 2016). It is unclear how the concept of CE will lead to greater social equality, in terms of inter- and intra-generational equity, gender, racial and religious equality and other diversity, financial equality, or in terms of equality of social opportunity. These are important moral and ethical issues which are missing from the construct (Murray et al., 2017). The operationalization of the CE has often been criticised as a sustainability model for its neglect of social and ethical issues and the socio-ethical foundations of the CE need to be strengthened based on the lessons from responsible research and innovation (Inigo and Blok, 2019). Thus, an ethical criterion is always very important for CE (Matallín-Sáez et al., 2019). Cleaner production (CP) is an effective way to achieve CE strategy (Sousa-Zomer et al., 2018). CP aims for sustainable development through energy conservation, emission reduction, and improved production efficiency (Hens et al., 2018). In the

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Abbreviations

CAPP	Computer-aided process planning
CE	Circular economy
CP	Cleaner production
CPS	Cyber-physical system
DR	Demand response
EIIs	Energy-intensive industries
ERP	Enterprise resource planning
IoT	Internet of things
MES	Manufacturing execution system
MRP	Material requirements planning
PDM	Product data management
PSO	Particle swarm optimization
TOU	Time of use
RFID	Radio-frequency identification
RS-232	Recommended Standard 232
RS-485	Recommended Standard 485

Industry 4.0 context, CP and intelligent manufacturing provide numerous opportunities for ethical sustainable societal development (Inigo and Blok, 2019). This work aims to provide a real-life case for the integration of the increasingly popular and largely separate topics of CP, intelligent manufacturing, CE, and business ethics.

CP is becoming increasingly important in manufacturing industries, specifically in energy-intensive industries (EIIs), such as pulp and paper (Posch et al., 2015), cement (Wang et al., 2018), glass (Du et al., 2018), ceramics (Ros-Dosdá et al., 2018), steel (Sun et al., 2019a, 2019b) and nonferrous metals (Lin and Tan, 2016). EIIs account for over half of the energy consumption in China (Zhang et al., 2018). The continuous improvement of sustainability is crucial for the EIIs and also improves their competitiveness. EIIs have discrete and continuous flows during the entire manufacturing processes. The interaction and coupling of these two flows lead to dynamic uncertainties and complexities in modelling and evaluating energy consumption (Li et al., 2018). Consequently, EIIs cause high energy costs and environmental pollution, and therefore, the energy consumption, carbon emission and costs for EIIs must be reduced.

In the background of Industry 4.0, the advanced technologies (e.g. cloud computing, Internet of things (IoT), cyber-physical system (CPS), digital twin and big data analytics) provide numerous opportunities not only for the implementation of CP strategy (Y.Liu et al., 2020) but also for the development of intelligent manufacturing (Zhong et al., 2017; Tao et al., 2018). The integration of CP and intelligent manufacturing has formed a new discipline, which can be regarded as sustainable intelligent manufacturing (Ren et al., 2019). These advanced technologies theoretically provide approaches, tools, rules and principles for data acquisition, processing, mining and application during the entire manufacturing processes.

However, these theoretical studies lack implementation details, which will hinder CP in the actual production process and affect the implementation of sustainable intelligent manufacturing. Thus, this study investigated several energy-intensive manufacturing companies and summarised actual and common problems encountered in companies to solve the problems faced in practice. For example:

- **Energy leakage cannot be detected in time**: e.g. water, natural gas, compressed air and heat.
- **Energy waste due to improper operation**: e.g. high-power equipment is idling or over-running.
- **No consideration for demand response (DR)**: e.g. failure to optimise costs based on real-time energy prices.

In practice, sustainable intelligent manufacturing faces challenges in a variety of and complex manufacturing processes (Shrouf and Miragliotta, 2015). Manufacturing process generates massive amounts of energy data from operation management, production process and process equipment at unprecedented speed. The data are a mixture of structured (e.g. energy consumption data including time, spatial and energy dimension), semistructured (e.g. data exchanged between smart energy management platforms) and unstructured data (e.g. ethical constraints data). Such multi-source heterogeneous data are characterised by high volume, high variety and high value due to the dynamic uncertainty and complexity of energy-intensive manufacturing process. Mining these data even with advanced technologies is sometimes challenging. A new way to mine complex data and find the hidden mechanisms and root causes is through the data-driven method (Tao et al., 2018). Therefore, establishing a data-driven architecture is essential to process and mine these data. Data-driven manufacturing can be regarded as a necessary condition for intelligent manufacturing. For EIIs, DR is a very important indicator to save manufacturing cost and improve sustainability. Thus, a data-driven framework based on DR is suitable for implementing sustainable intelligent manufacturing.

In the Industry 4.0 context, this study proposed a framework of data-driven sustainable intelligent manufacturing based on DR to achieve CE strategy for EIIs, aiming to contribute to ethical sustainable societal development. A new kind of infrastructure is provided to make efficient and energy-efficient decisions for implementing sustainable intelligent manufacturing. In detail, data collection, process and mining were designed in the framework. This framework can provide theoretical and practical insights into the academic and industrial field, which may benefit the environment, manufacturers and society. The technical architecture of the proposed framework was explained in detail to greatly implement the proposed management strategy in practice. Furthermore, multi-level DR models were developed based on machine, shop-floor and factory to save energy costs and improve enterprises' competitiveness. Then, an optimisation strategy based on particle swarm optimisation (PSO) was used to maximise the saving costs. Finally, the authors summarised managerial implications from the policy-related, theoretical and practical perspectives of the current study. Considering the characteristics of energy-intensive manufacturing processes, the following research questions are of our particular interest.

1. How to establish a framework of data-driven sustainable intelligent manufacturing based on DR for EIIs with a systemic and integrated method to achieve CE strategy?
2. How to establish a technological architecture for implementing the proposed framework that can be used as an enterprise portal of energy efficiency optimisation analysis considering CE?
3. How to develop multi-level DR models based on machine, shop-floor and factory considering the characteristics of energy-intensive manufacturing processes?

The remainder of this paper is organised as follows. A literature review is conducted in Section 2. The overall architecture of data-driven sustainable intelligent manufacturing based on DR for EIIs is proposed in Section 3. The implementation of the architecture is designed in Section 4. Multi-level DR models are developed in Section 5. Then, a case study is shown in Section 6. Finally, the discussion and conclusions are given in Sections 7 and 8.

2. Literature review

This section reviews related research which is categorised into two dimensions: (1) CE and business ethics in Industry 4.0 and (2) CP and sustainable intelligent manufacturing based on DR for EIIs. The knowledge gaps are identified and summarised at the end of the section.

2.1. CE and business ethics in industry 4.0

The concept of CE originates in the inability of linear production models to reconcile current levels of production and consumption with the limited availability of resources (Bradley et al., 2018). The CE is a production and consumption system that aims to keep products, components, materials and energy in circulation to continue adding, recreating and maintaining their value over a long period (de Sousa Jabbour et al., 2019). In the last few years, CE is receiving increasing attention worldwide as a way to overcome the current production and consumption model based on continuous increasing resources and energy (Ghisellini et al., 2016). CE is perceived as a new business model that is expected to achieve a balance and harmony amongst economy, economy and society but lacks consideration of socio-ethical issues (Inigo and Blok, 2019).

In the Industry 4.0 context, advance and digital manufacturing technologies (e.g. cloud computing, IoT, CPS, digital twin and big data analytics) can unlock the circularity of resources and energy during the manufacturing processes (Ren et al., 2019). Industry 4.0 technologies can underpin CE which focuses on maximising the circularity of energy and resources with production systems (de Sousa Jabbour et al., 2018b). Industry 4.0 is also known as intelligent manufacturing, which is based on manufacturing systems driven by information technology (Zhong et al., 2017). Environmentally sustainable and intelligent manufacturing provides detailed insights on CE, which can provide economic, environmental, and social benefits (de Sousa Jabbour et al., 2018a).

Industrial managers and scholars require results of rigorous research to show the benefits of adoption of Industry 4.0 concepts and approaches for helping them to be economically, ecologically and ethically responsible corporate players in the needed changes to achieve truly sustainable societies locally, regionally and globally (Luthra et al., 2020). However, the operationalization of the CE has often been criticised as a sustainability model for its neglect of social and ethical issues, focusing on the environmental and economic pillars of sustainability (Kirchherr et al., 2017). The concept of the CE is still evolving, and many conceptualisations and framework to implement the CE in practice have not considered social and ethical dimensions (Murray et al., 2017). The CE frameworks, methodologies and tools need to strengthen its social and ethical dimensions (Pla-Julián and Guevara, 2019) and the socio-ethical foundations of the CE need to be strengthened based on the lessons from responsible research and innovation (Inigo and Blok, 2019).

2.2. CP and sustainable intelligent manufacturing based on DR for EIIs

CP, as defined by the United Nations Environment Program, is a business strategy, aiming to contribute to sustainable development through improved production efficiency, environmental management, and sustainable societal development (Hens et al., 2018). CP is considered as one of the most important means to realise sustainable production and improve the competitiveness for manufacturing enterprises (Zhang et al., 2017), especially for EIIs. With the emergence of new information and communication technologies, EIIs promote the implementation of CP strategy by applying these advance information technologies (Ma et al., 2020). For example, based on IoT technology, real-time energy data can be collected and analysed to achieve CP strategy, which lacks control during the entire manufacturing processes. Thanks to CPS technology, the workshop in the physical layer can be controlled in the cyber layer to implement CP strategy (Ma et al., 2019). Big data analytics offers new opportunities for the implementation of the CP strategy due to the increasing data generated in energy-intensive manufacturing industries (Zhang et al., 2018).

In the Industry 4.0 context, most scholars study CP together with intelligent manufacturing, forming discipline of sustainable intelligent manufacturing (Ren et al., 2019). Giret et al. (2017) have proposed an engineering method that helps the researcher to design sustainable intelligent manufacturing systems. He and Bai (2020) have reviewed digital twin-driven sustainable intelligent manufacturing, which summarised the intelligent manufacturing from a sustainable perspective. Under the background of sustainable intelligent manufacturing, sustainability and intelligence can be achieved by updating equipment and optimising production scheduling. However, updating the equipment is difficult for medium- and small-sized enterprises due to the high cost.

DR is an important way for companies to save costs by optimising the production schedule without adding or updating equipment. The EIIs are the industrial and active consumers of power (Voropai et al., 2016), and DR is an important approach to address temporal mismatches between the demand and supply of power systems (Dababneh and Li, 2019; Wang and Li, 2016). The electricity demand can be shifted from on-peak to off-peak periods through DR. DR can improve the stability of the energy management system and reduce the energy consumption costs during the manufacturing processes (Bego et al., 2014; Wang and Li, 2013). DR is a key factor for CP to achieve CE strategy (Canals Casals et al., 2019). Therefore, increasing enterprises are considering DR to promote sustainable intelligent manufacturing and improve their competitiveness.

2.3. Knowledge gaps

From this review, although the significant process has been made in the two research dimensions mentioned above, some gaps still need to be filled in.

- In terms of CE and business ethics, most studies aim at explaining a balanced interplay of economy, economy and society in theory. In the Industry 4.0 context, in practice, little effort has been devoted to the integrated framework and model of sustainable intelligent manufacturing, CE and business ethics.
- In terms of CP and sustainable intelligent manufacturing based on DR for EIIs, most applications of sustainable intelligent manufacturing only focus on manufacturing industries, and the characteristics of energy-intensive manufacturing processes are not considered. In EIIs, sustainable intelligent manufacturing based on DR is seldom investigated.

3. Data-driven sustainable intelligent manufacturing based on DR for EIIs

In this section, a data-driven sustainable intelligent manufacturing architecture for EIIs is proposed on a cloud platform through real-time monitoring of energy consumption, assessment management of energy efficiency and optimisation analysis of energy efficiency. The proposed framework can improve the energy efficiency of enterprises and reduce the energy costs of the enterprise by considering DR.

3.1. Perception layer

The perception layer of Fig. 1 shows that the IoT devices (e.g. radio-frequency identification (RFID) tags, RFID reader, smart meters and smart sensors) are configured in the factory, shop-floor, production line and equipment levels to capture the energy-related data, respectively. Smart meters are used to collect energy data on fuel gas, electricity, coal and water during the entire manufacturing processes. Recommended Standard 232 (RS-232) is the standard originally introduced for serial communication transmission of data (Wikipedia, 2020a) and Recommended Standard 485 (RS-485) is the standard defining the electrical characteristics of drivers and receivers for use in serial communication systems (Wikipedia, 2020b). Thanks to their past ubiquity and simplicity, RS-232 and RS-485 interfaces are still specifically used in a wide range of computer and automation systems where point-to-point, short-range and wired data communications are entirely adequate. RS-485, RS-232 and TCP are communication protocols, and WiFi, Bluetooth and Cable are transmission modes (W.Liu et al., 2020). The collected energy-related data are transferred to enterprise databases for further management through advanced technologies of communication protocols and transmission modes.

3.2. Management layer

In the management layer, the captured energy data including non-real-time and real-time ones are monitored, which will timely detect the phenomena of energy leakage, equipment idling and over-running. The energy efficiency assessment of the product can accurately obtain the unit energy consumption through product specifications and provide a basis for accurate assessment of product cost. A team is a group of operators and managers, where the knowledge and skills of each member are utilised to work together in solving problems and achieving common goals. The total and unit energy consumption can be calculated for the reward and punishment of each member based on the energy efficiency assessment of the team. The energy efficiency assessment of equipment consists of the assessment of the shop-floor, production line or equipment, which can find the difference in energy efficiency amongst the production equipment. After the energy efficiency assessment, the optimisation analysis of energy efficiency can be provided for enterprise applications.

3.3. Application layer

In the application layer of Fig. 1, the energy efficiency optimisation can be provided on a cloud platform (Xu, 2012) and can be used as the top-level services of the energy management system. Currently, the application services (e.g. running analysis of equipment, energy warning, DR and parameter optimisation) are designed in the data-driven management framework based on DR for the development of sustainable intelligent manufacturing. For example, the running analysis of equipment can automatically identify the status of running, idling, standby and shutdown and will count the duration of each state and the number of starts and stops.

4. Implementation of the proposed framework

Technological architecture can be used as an enterprise portal of energy efficiency optimisation analysis considering CE to implement the proposed framework, as shown in Fig. 2. The external and internal interfaces are designed on the right side of Fig. 2. The energy policy can be formulated by the government department and the various forms of energy can be provided by the energy supply department, which is the external interface. The internal interface, such as product data management (PDM), material requirements planning (MRP), enterprise resource planning (ERP), manufacturing

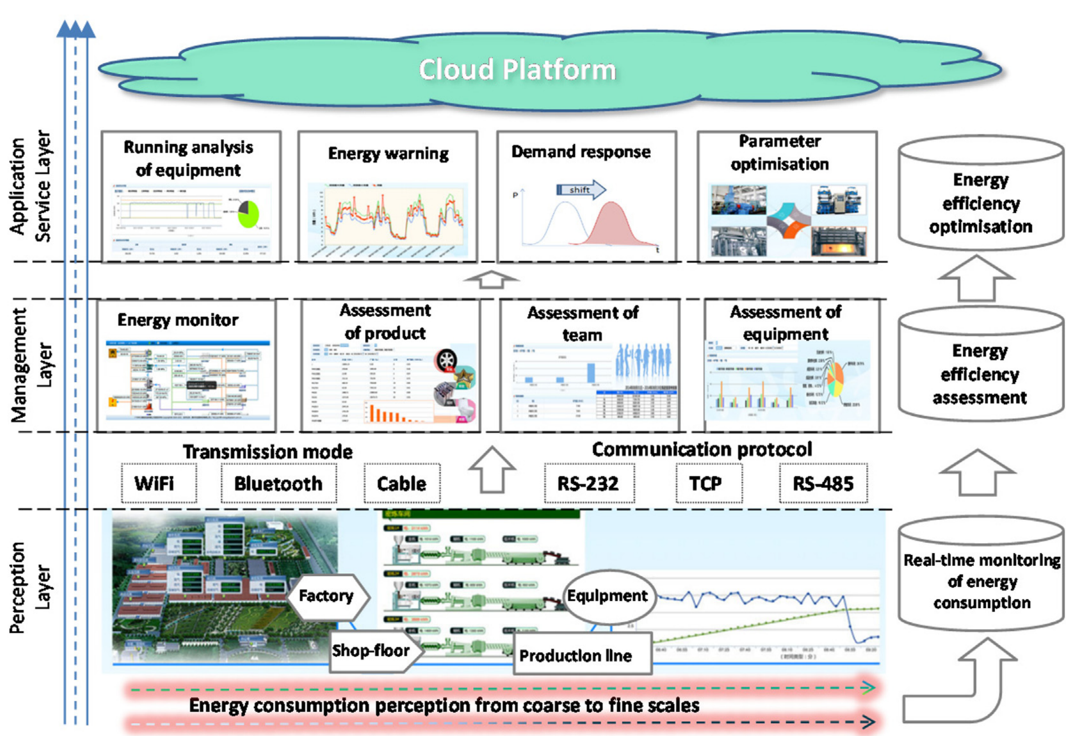

Fig. 1. Data-driven sustainable intelligent manufacturing based on DR for EIIs.

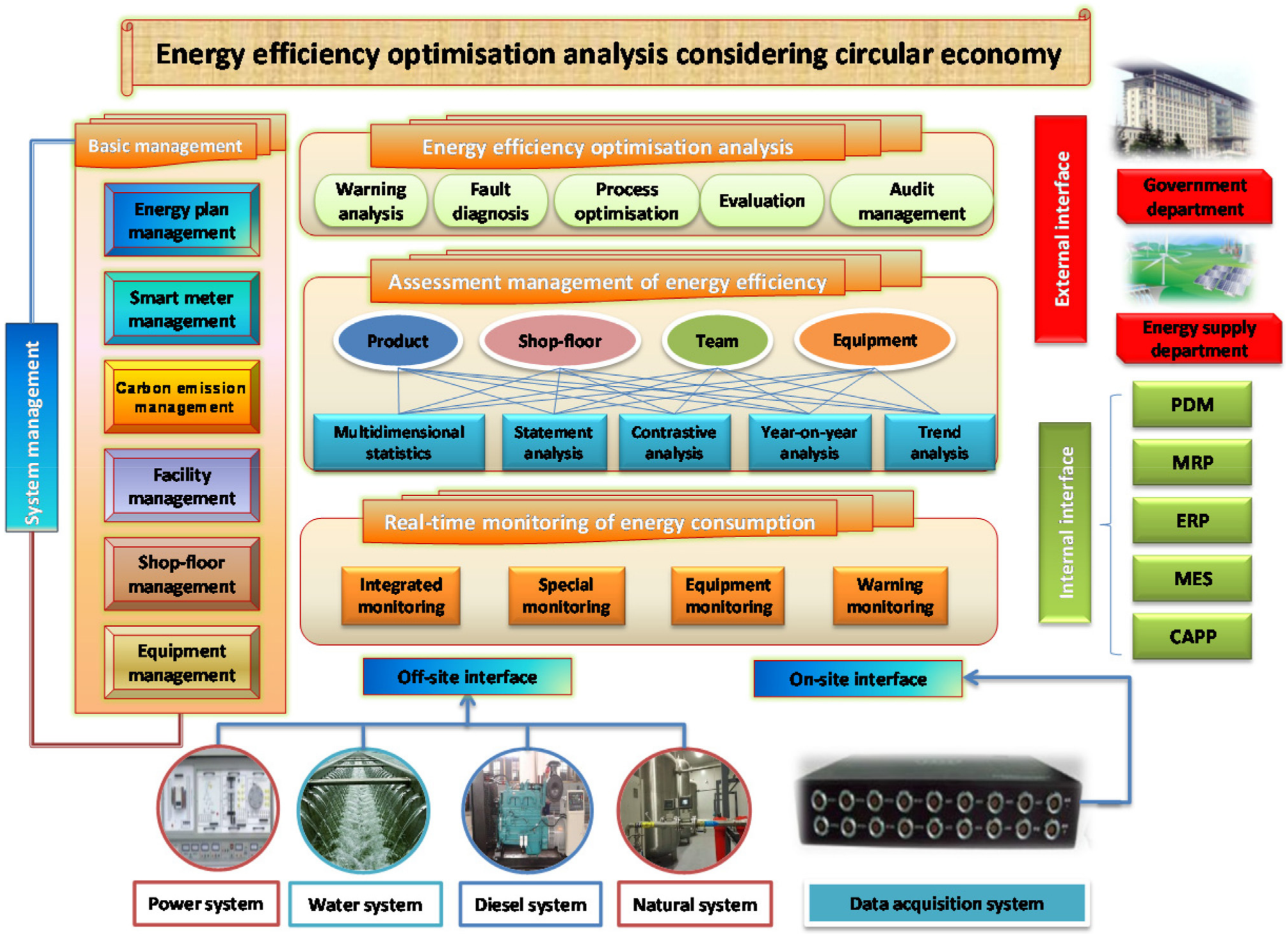

Fig. 2. Technological architecture for implementing the proposed framework.

execution system (MES) and computer-aided process planning (CAPP), can be integrated with the prototype system.

As shown on the left side of Fig. 2, system management can be used as basis management, which includes energy plan, smart meter, carbon emission, facility, shop-floor and equipment management. Products can be manufactured effectively and energy-efficiently during the entire production process through basic management. At the bottom of Fig. 2, off-site and on-site interfaces are used to obtain the energy data. The former includes the power, water, diesel, natural and data acquisition systems, which were used as an on-site interface to collect real-time energy data.

In the middle of Fig. 2, energy consumption can be monitored in real-time, including integrated, special, equipment and warning monitoring. Multidimensional statistics, statement analysis, contrastive analysis, year-on-year analysis and trend analysis of product, shop-floor, team and equipment are designed for assessment management of energy efficiency. After the assessment management, the goals of energy-efficiency optimisation analysis are achieved in terms of warning analysis, fault diagnosis, process optimisation, evaluation and audit management.

5. Multi-level DR models based on machine, shop-floor and factory

Sustainable intelligent manufacturing can be achieved through the implementation of the proposed framework. In general, the two ways to improve the sustainability of intensive-intensive manufacturing industries are energy-efficient machine and energy-efficient production scheduling (Wang et al., 2017). From the perspective of the former, new and smart machines are updated to reduce the energy demands of machine components. Unfortunately, most enterprises, specifically for those small- and medium-sized enterprises, cannot update their equipment because of the high cost. From the perspective of the latter, DR is an effective method to save cost without adding or updating machines.

Companies care mostly on costs and profits. Based on energy DR, production schedule can be optimised according to the electricity prices of the peak, flat and valley periods. With the development of EIIs, the tight supply of electricity due to the extremely high peak load that is very different from the valley load is an increasingly important problem. To address this problem, electrical energy peak load shifting is designed through considering DR. The electricity demand can be shifted from peak to valley periods by optimising the distribution of power resources (Sun et al., 2014, 2016).

Fig. 3 shows a typical serial production line with n shop-floors and n-1 infinite buffers with n shop-floors, each of which is inside the dotted box. Each shop-floor has some machines and an infinite buffer. The authors use circles and rectangles to represent the machines and infinite buffers, respectively. The arrows in the graph indicate the flow of working parts within the line (Yan et al., 2020). The multi-level models of electrical energy peak load shifting are developed based on machine, shop-floor and factory as shown in Fig. 3.

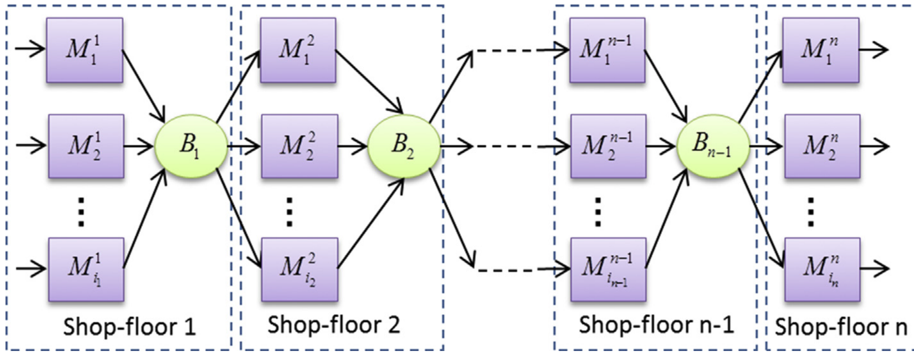

Fig. 3. Typical serial production line with *n* shop-floors and *n-1* infinite buffers.

5.1. Definitions

The notations are defined as follows.

AC_j^i: The cost of *j-th* power consumption after the peak load shifting in *i-th* shop-floor.
AC^i: The total cost of power consumption after the peak load shifting in *i-th* shop-floor.
AC: The total cost of power consumption after the peak load shifting in the factory.
B_j^i: The *j-th* buffer in *i-th* shop-floor.
BC_j^i: The cost of *j-th* power consumption before the peak load shifting in *i-th* shop-floor.
BC^i: The total cost of power consumption before the peak load shifting in *i-th* shop-floor.
BC: The total cost of power consumption before the peak load shifting in the factory.
ΔC_j^i: The saving cost of *j-th* power consumption after the peak load shifting in *i-th* shop-floor.
ΔC^i: The saving cost of total power consumption after the peak load shifting in *i-th* shop-floor.
ΔC: The saving cost of total power consumption after the peak load shifting in the factory.
M_j^i: The *j-th* machine in *i-th* shop-floor.
$P_j^i(t)$: The power of *j-th* machine at the time t in *i-th* shop-floor.
$P^i(t)$: The total power at the time t in *i-th* shop-floor.
$P(t)$: The total power at the time t in the factory.
$p(t)$: The daily electricity price at the time t
r_j^i: The saving cost of *j-th* machine in *i-th* shop-floor.
r^i: The saving cost of *i-th* shop-floor.
r: The saving cost of the factory.
ΔT_k: The time of use (TOU) of electricity price.
t_0: The time of peak load shifting. For example, if $t_0 = -1$, then the total power $P(t)$ will be shifted 1 h to the back.
w_k: The weighted electricity prices of ΔT_k in a day.

5.2. Models of electrical energy peak load shifting based on machine

The cost of M_j^i before the peak load shifting is

$$BC_j^i = \int_{\Delta T_k} P_j^i(t)p(t)dt = \sum_k w_k \int_{\Delta T_k} P_j^i(t)dt. \tag{1}$$

The cost of $P_j^i(t)$ after shifting t_0 is

$$AC_j^i(t_0) = \int_{\Delta T_k} P_j^i(t+t_0)p(t)dt = \sum_k w_k \int_{\Delta T_k} P_j^i(t+t_0)dt. \tag{2}$$

The saving cost after shifting t_0 is

$$\begin{aligned}\Delta C_j^i(t_0) = BC_j^i - AC_j^i(t_0) &= \sum_k w_k \int_{\Delta T_k} P_j^i(t)dt - \sum_k w_k \int_{\Delta T_k} P_j^i(t+t_0)dt \\ &= \sum_k w_k \int_{\Delta T_k} \left[P_j^i(t) - P_j^i(t+t_0)\right]dt.\end{aligned} \tag{3}$$

The saving rate of M_j^i is

$$r_j^i(t_0) = \Delta C_j^i(t_0) \Big/ BC_j^i. \tag{4}$$

Eqs. (1)–(4) show that the saving cost and saving rate are strongly associated with t_0. The saving cost will be obtained by adjusting t_0. The objective of the model is to find t_0 to minimise the cost AC_j^i or maximise the saving cost ΔC_j^i and the saving rate r_j^i.

5.3. Models of electrical energy peak load shifting based on shop-floor

The cost of total power consumption before the peak load shifting in i-th shop-floor is

$$BC^i = \int_{\Delta T_k} P^i(t)p(t)dt = \sum_k w_k \int_{\Delta T_j} P^i(t)dt = \sum_{k,j} w_k \int_{\Delta T_j} P_j^i(t)dt. \tag{5}$$

The cost of $P^i(t)$ after shifting t_0 is

$$\begin{aligned}AC^i(t_0) = \int_{\Delta T_k} P^i(t+t_0)p(t)dt &= \sum_k w_k \int_{\Delta T_k} P^i(t+t_0)dt \\ &= \sum_{k,j} w_k \int_{\Delta T_k} P_j^i(t+t_0)dt.\end{aligned} \tag{6}$$

The saving cost after shifting t_0 is

$$\Delta C^i(t_0)=BC^i-AC^i(t_0)=\sum_k w_k\int_{\Delta T_k}P^i(t)dt-\sum_k w_k\int_{\Delta T_k}P^i(t+t_0)dt$$
$$=\sum_k w_k\int_{\Delta T_k}\left[P^i(t)-P^i(t+t_0)\right]dt=\sum_{k,j} w_k\int_{\Delta T_k}\left[P^i_j(t)-P^i_j(t+t_0)\right]dt. \tag{7}$$

The saving rate in *i-th* shop-floor is

$$r^i(t_0)=\Delta C^i(t_0)\Big/BC^i. \tag{8}$$

Eqs. (5)–(8) show that the saving cost and saving rate are strongly associated with t_0. The saving cost will be obtained by adjusting t_0. The objective of the model is to find t_0 to minimise the cost AC^i or maximise the saving cost ΔC^i and the saving rate r^i.

5.4. Models of electrical energy peak load shifting based on factory

The cost of total power consumption before the peak load shifting in the factory is

$$BC=\int_{\Delta T_k}P(t)p(t)dt=\sum_i\int_{\Delta T_k}P^i(t)p(t)dt=\sum_{k,i}w_k\int_{\Delta T_k}P^i(t)dt$$
$$=\sum_{k,i,j}w_k\int_{\Delta T_k}P^i_j(t)dt. \tag{9}$$

The cost of power consumption after shifting t_0 is

$$AC(t_0)=\int_{\Delta T_k}P(t+t_0)p(t)dt=\sum_i\int_{\Delta T_k}P^i(t+t_0)p(t)dt$$
$$=\sum_{k,i}w_k\int_{\Delta T_k}P^i(t+t_0)dt=\sum_{k,i,j}w_k\int_{\Delta T_k}P^i_j(t+t_0)dt. \tag{10}$$

The saving cost after shifting t_0 is

$$\Delta C(t_0)=BC-AC(t_0)=\int_{\Delta T_k}P(t)p(t)dt-\int_{\Delta T_k}P(t+t_0)p(t)dt$$
$$=\sum_{k,i}w_k\int_{\Delta T_k}P^i(t)dt-\sum_{k,i}w_k\int_{\Delta T_k}P^i(t+t_0)dt$$
$$=\sum_{k,i}w_k\int_{\Delta T_k}\left[P^i(t)-P^i(t+t_0)\right]dt$$
$$=\sum_{k,i,j}w_k\int_{\Delta T_k}\left[P^i_j(t)-P^i_j(t+t_0)\right]dt. \tag{11}$$

The saving rate in the factory is

$$r(t_0)=\Delta C(t_0)/BC. \tag{12}$$

Eqs. (9)–(12) show that the saving cost and saving rate strongly associated with t_0. The saving cost will be obtained by adjusting t_0. The objective of the model is to find t_0 to minimise the cost $AC(t_0)$ or maximise the saving cost $\Delta C(t_0)$ and the saving rate $r(t_0)$.

5.5. Solution technique

In the PSO algorithm, each particle in the swarm is considered a possible solution (Wang and Li, 2014). N_P denotes the number of particles in the swarm, and V and L denote the velocity vector and position vector of the particles (Ge and Li, 2018). Based on Eqs. (13) and (14), the velocity and location are updated after each iteration (or flight) of each particle,

$$V(s+1)=\alpha V(s)+c_1w_1(L_{PB}-L(s))+c_2w_2(L_{GB}-L(s)),\ s=1,2,\dots,N_s, \tag{13}$$

$$L(s+1)=L(s)+V(s+1),\ s=1,2,\dots,N_s, \tag{14}$$

where $V(s)$ and $L(s)$ denote the particle's velocity and the location at iteration s, respectively. In detail, α is the inertia weight, N_s is the maximum number of iterations, c_1 and c_2 are learning factors, ω_1 and ω_2 are random numbers between 0 and 1, L_{PB} is the best solution of the particle and L_{GB} is the swarm's global best solution. The algorithm terminates when the number of iteration reaches N_s. Fig. 4 shows the solution procedures of the DR model using PSO.

6. Case study

In this section, the proposed architecture and models are demonstrated through a real-life case. The ceramic manufacturing industry consumes considerable energy and results in numerous carbon emissions (Ma et al., 2019) but has a great potential to achieve sustainable intelligent manufacturing, CP and CE. In China, ceramic belongs to manufacture of nonmetallic mineral products that are included in six EIIs (Zhang et al., 2018). Thus, a cooperative ceramic manufacturing company ('Company X') is selected as the case study, which is located in Foshan, China. This company consumes more than 14 million cubic meters of natural gas, 25 million kWh of electricity, 350,000 tons of water and 280 tons of diesel every year (Li et al., 2018). Therefore, it is suitable to validate the proposed architecture and models.

In the proposed framework, data can be collected and monitored in real-time theoretically. However, implementing the framework in most companies is a challenge because real-time data acquisition requires exceptionally advanced technology, which is costly. This cost is higher than that of energy saving. Hence, most companies are reluctant to obtain data in real-time.

In our partner, Company X, various data related to resource and energy can be collected every five seconds to a minute based on smart meters and smart sensors. This collection can be set by the operator according to the needs of the company. In Company X, the parameter in the energy management system is set to monitor data every minute. The minute-level data are sufficient for energy

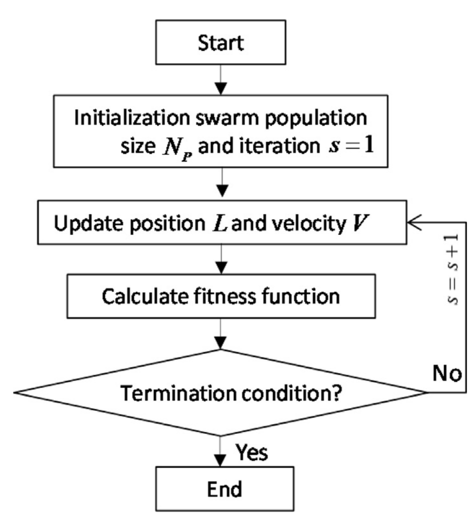

Fig. 4. Flow chart of the DR model using PSO.

conservation and emission reduction in the actual production process. Thus, the case study shows the analysis and comparisons of hourly and minutely electricity consumption. Notably, the data in 2016 shown in this section are representative to keep the confidentiality of their key business.

6.1. Case description

In Company X, the production chain includes grinding, casting, drying, glazing firing and packing (Lv et al., 2019). The grinding process is the largest electrical energy consumption process based on the e-p analysis model (Ma et al., 2020). Thus, the authors will analyse the ball mills in a slurry shop-floor and find out unreasonable energy utilisation problems. Production costs are saved based on the models of electrical energy peak load shifting.

The machine (ball mill) is a type of grinder (Lv et al., 2020b), comprising a horizontal cylindrical rotating device, electric machine, belt and two warehouses. Fig. 5 shows that this machine is used to grind and blend materials of ceramics. The material from the feeding device initially enters into the warehouse. Steel balls have different specifications, such as the grinding media, in the first warehouse. The electric machine generates the power to rotate the cylinder by the belt, and then, the cylinder rotates to produce centrifugal force to the balls, which will reach a certain height. The balls will rotate, and the falling balls will hit and grind the material. The material will have rough grinding in the first warehouse and then enters the second warehouse for further grinding. The powder is discharged through the discharge device to complete the grinding operation.

6.2. Energy data perceptions of ball mills

Slurry shop-floors have two types: old and new. The new slurry shop-floor has six 40-tons ball mills, and the old one has eighteen 8-tons ball mills. The energy consumption of ball mills in the former is more than that in the latter. Thus, the energy-saving space in the new shop-floor is relatively larger than that in the old one. Given that, the new shop-floor is selected as the object of study.

A ball mill is a machine for blending and grinding ceramic materials. The water and materials can be mixed according to a certain proportion. The 24th ball mill is a special ball mill for high-pressure grouting slurry, and the parameters of the other five ball mills, including the feeding volume and formula, are nearly the same. The main motors of the six ball mills are the same at a rated power of 160 kW. All ball mills are in normal use. Based on the actual production data, Table 1 shows the grinding parameters of the six ball mills from 00:00 on March 1st to 00:00 March 21st, 2016.

6.3. Energy data management of ball mills

The following data mining is completed through horizontal and vertical analyses. The former can be mainly used to analyse the power curve from left to right, whereas the latter primarily can be applied to compare the power curves of different ball mills from top to bottom. Fig. 6 depicts that the power consumption curve of a grinding cycle is framed by a green rectangle, and the trend of curves of each ball mill is nearly the same, which indicates that the grinding state is relatively stable. If the curve changes abnormally or an abnormal change in the figure exists, then a problem with the ball mill will probably occur.

The idle time of the ball mill is represented inside a red circle in Fig. 6. Except for the 25th ball mill, the other five ball mills have a long idle time. The 29th ball mill has a high-frequency usage. On the contrary, the 24th ball mill is special for high-pressure grouting slurry and is not used frequently.

6.3.1. Power consumption of six ball mills

The red lines in Fig. 6 show that the hourly power consumption of 23rd, 24th, 29th and 25th ball mill is approximately 50 kWh, and that of 28th and 26th ball mill is approximately 30 and 75 kWh, respectively. From the red lines in Fig. 7, the standard power consumption per minute of the ball mill labelled as the 23rd, 24th, 29th, and 25th is approximately 0.8 kWh, whereas that for 28th and 26th ball mills is roughly 0.4 and 1.2 kWh, respectively. As shown in Fig. 8 with detailed data, the average energy consumption of the 28th and 26th ball mills is the maximum and minimum, respectively, and the difference is approximately two times.

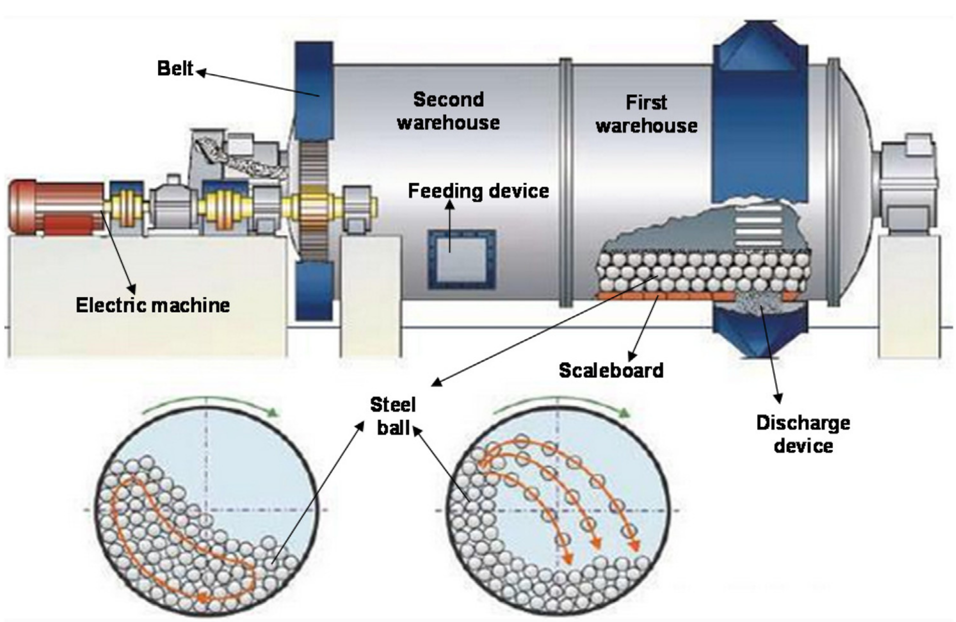

Fig. 5. Schematic graph of a ceramic ball mill.

Table 1
Comparison of the six ball mills.

Grinding parameters	23rd ball mill	24th ball mill	28th ball mill	29th ball mill	25th ball mill	26th ball mill
Main motor power (kW)	160	160	160	160	160	160
Pressure type of grouting slurry	Low	High	Low	Low	Low	Low
Grinding times (times)	15	14	16	18	16	17
Hourly power consumption (kWh)	50	50	30	50	50	75
Minutely power consumption (kWh)	0.8	0.8	0.4	0.8	0.8	1.2

As shown in Fig. 8, the daily and total power consumption of six ball mills, including the percentage of total energy consumption, were obtained and compared through the horizontal analysis. The energy consumption and its daily comparison of each ball mill were obtained and compared from 1 March to 21 March through the vertical analysis. The 26th ball mill consumes the most energy with 15,871.290 kWh, accounting for 25.79% of the total power consumption of ball mills. However, the energy consumption of the 28th ball mill is the minimum, with only 5728.070 kWh, accounting for 9.31% of the total power consumption. The power consumption of the 26th ball mill is approximately three times than that of the 28th ball mill.

The authors went to the scene to investigate the running operation of ball mills. The grinding speed of six ball mills was measured and almost no difference was observed amongst them, with approximately 50 s every 10 turns. In 21 days, the number of grinding materials is almost the same each time. Moreover, according to the actual observation, the running speeds of six balls are almost the same, and the time for turning 10 turns is roughly 50 s. Notably, six ball mills have different power consumption although the motor, the grinding ball, the speed and the feed amount are almost the same. The 28th and 26th ball mills have different data from others, which may be due to problems with the operation of ball grinding. For example, the particle size ratio and the proportion of grinding may be unreasonable.

According to the system data and shop-floor records, the grinding cycle of each ball is approximately 16–18 h. Assuming that the physical properties of the slurry after grinding meet the production requirements, the overall efficiency of the 28th ball mill is the best. The effects of reducing energy consumption and saving costs can be achieved as long as the state of the 28th ball mill is specifically analysed and extended to the other five ball mills.

6.3.2. Analysis of the 25th and 26th ball mills

Through analysing the power consumption of the 25th and 26th ball mills from March 14 to March 17, 2016, Fig. 9 shows that the two ball mills run approximately three working cycles, and the peak-to-valley control of the 26th ball mill is better than that of the 25th ball mill. The 25th ball mill mainly uses electricity during peak periods but not during valley periods. On the contrary, the 26th ball mill frequently stops during the peak periods, taking full advantage of electricity of valley and flat periods. Therefore, the average cost of the 26th ball mill must be lower than that of the 25th ball mill.

During three days, the total electricity consumption of the 25th ball mill was 1784.85 kWh, and the cost was 1391.698 CNY. As shown in Table 2, the total electricity consumption of the 26th ball was 2053.29 kWh, and the cost was 1497.272 CNY. Although the power consumption of the 26th ball mill is more than that of the 25th, the extra cost was only 95.574 CNY due to the lower power price during the flat and valley periods. In other words, the average cost of the 25th ball mill is 0.7797 CNY/kWh, which exceeds 0.0505 CNY/kWh compared with that of the 26th ball mill. The rational arrangement of production and full use of electricity has a significant positive effect on reducing production costs. Detailed DR models based on ball mills and the slurry shop-floor are provided in the Appendix.

6.4. Results

The rational use of these six 40-ton ball mills is a key to save energy and cost in the slurry shop-floor. From the preliminary analysis above, some potential for saving energy and reducing consumption in the slurry shop-floor still exists. According to the analysis and comparison, the ball milling efficiency of the 28th ball mill is the highest amongst the six ball mills. Energy and cost savings will be achieved as long as the state of the 28th ball mill is specifically analysed and extended to the other five ball mills. The regulations and rules are also made to improve the daily maintenance. For example, reasonable production arrangements can be fully used through considering DR.

In Company X, various energy data can be monitored and analysed based on the energy management system. The energy network of the entire plant can be used to balance energy supply and demand. The energy efficiency assessment is implemented throughout the plant based on the production data in ERP. Then, the energy consumption of each ball mill can be calculated automatically. Production scheduling can be optimised, and low-efficiency equipment can be timely maintained based on the ranking of energy consumption. CE aims to increase the efficiency of energy and resource use to achieve a balance amongst the economy, environment and society. Industrial managers and operators should pay additional attention to implementing ethical and sustainable business models, such as CP and CE.

DR is a key factor for CP to achieve CE strategy (Canals Casals et al., 2019). The electricity demand for energy-intensive equipment can be shifted from peak to valley periods to reduce energy consumption costs through considering DR. Managers and operators can also effectively make the optimal decision by predictive analytics (Lv et al., 2020a; Sun et al., 2020c). More importantly, the use of cleaner technology can recycle energy and resources (Sun et al., 2020a, 2020b).

7. Discussion

7.1. Results and findings

CP is an increasingly critical part of the planning, design, operation and management in all industrial sectors (Klemeš et al., 2012). CP approaches are key to making progress towards sustainable business models embedded in CE based on sustainable production and consumption (Tunn et al., 2019). In the background of Industry 4.0 (also known as intelligent manufacturing), the integration of CP and intelligent manufacturing forms a new discipline regarded as sustainable intelligent manufacturing, which provides numerous opportunities for managers to develop and implement CE strategies (de Sousa Jabbour et al., 2018b). The CE concept has gained good recognition worldwide for the past decades. CE aims to increase the efficiency of energy and resource use to achieve a balance amongst the economy, environment and society.

In a sustainable intelligent manufacturing context, Nascimento et al. (2019) explored how the rising technologies from Industry 4.0 can be integrated with CE practices to establish a business

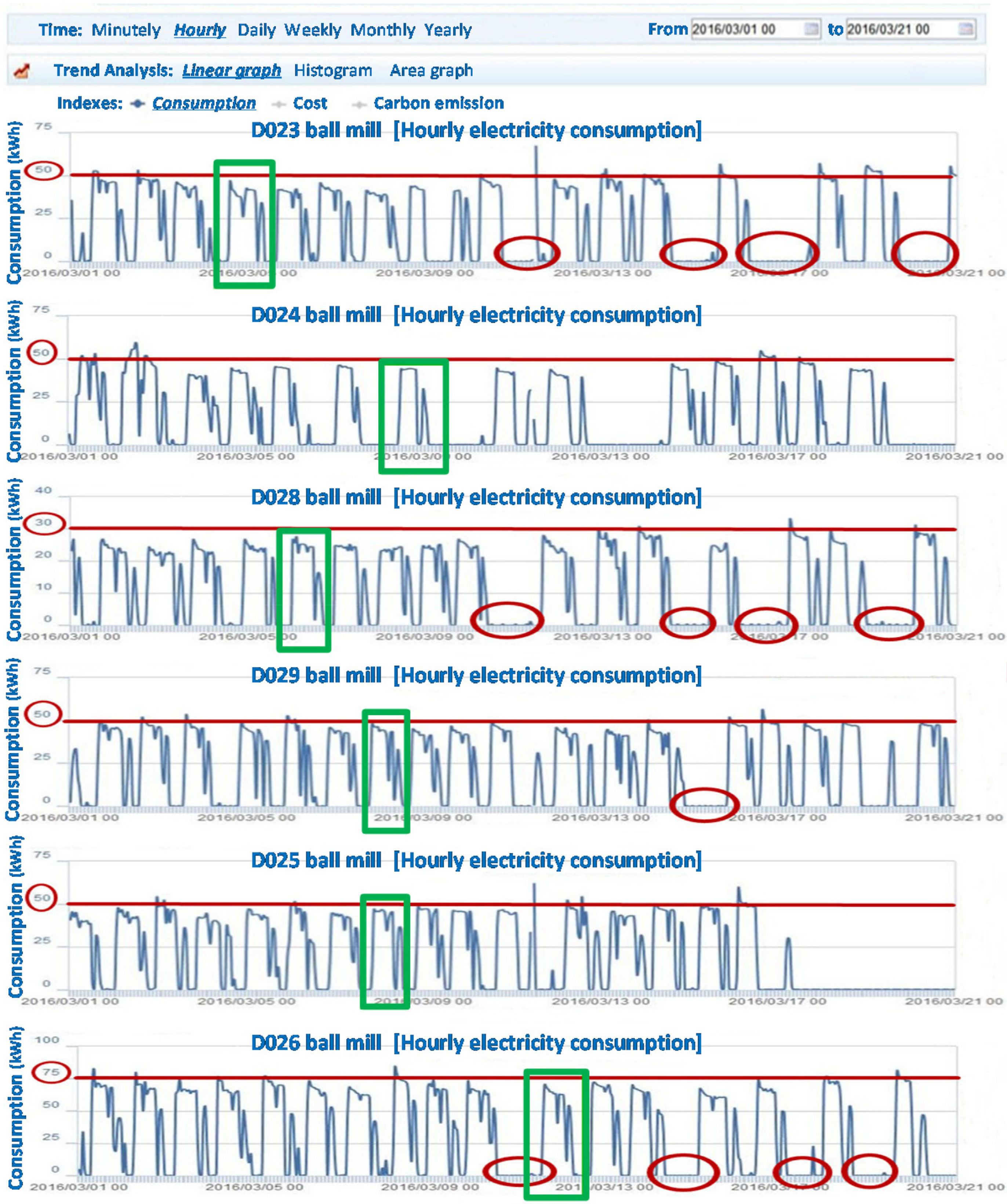

Fig. 6. Hourly power consumption of six ball mills from 00:00 on 1 March to 00:00 on March 21, 2016.

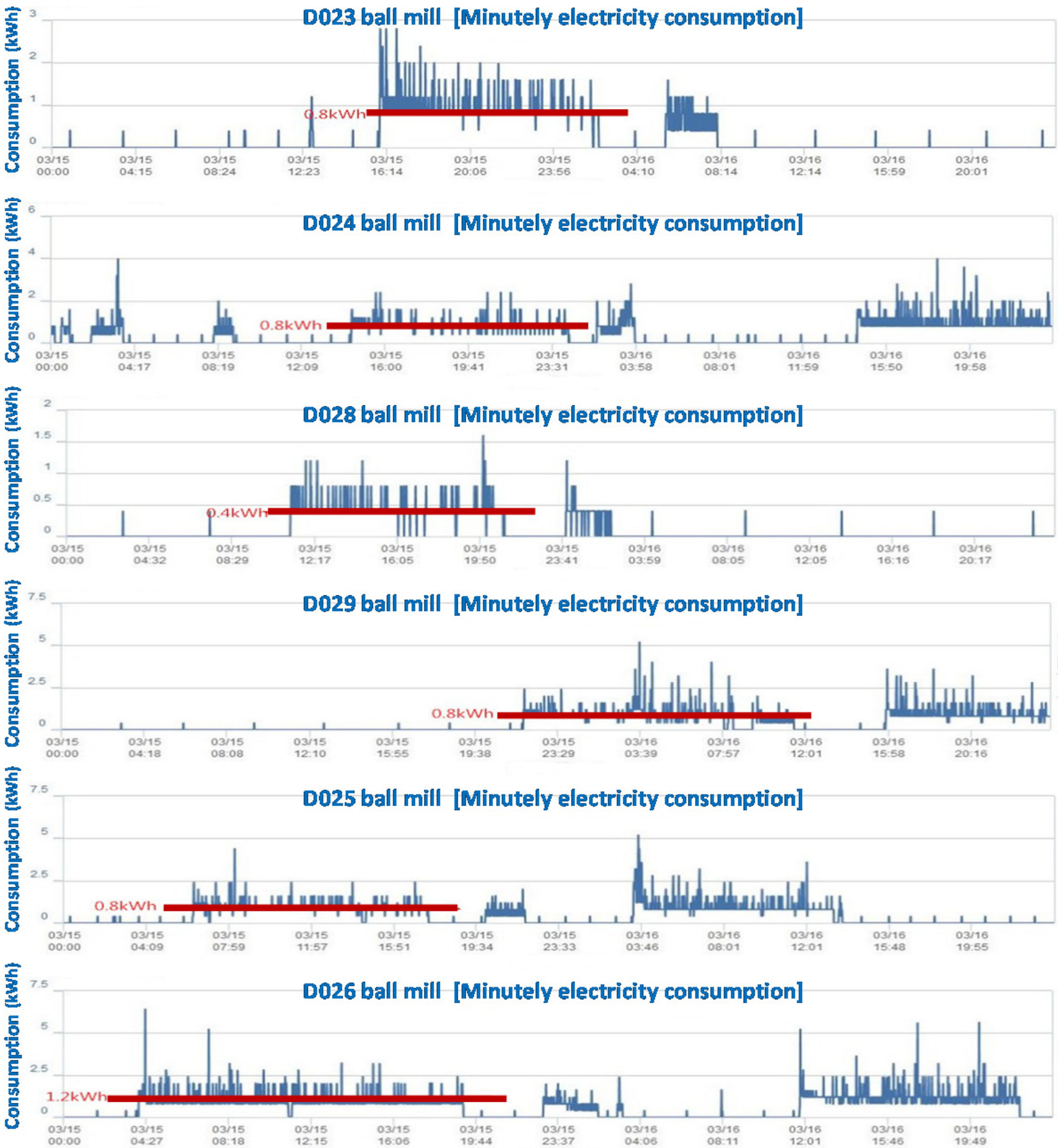

Fig. 7. Minutely power consumption of six ball mills from 00:00 on 15 March to 00:00 on March 17, 2016.

model that reuses and recycles wasted material. As one of the most important technologies for intelligent manufacturing, big data analytics can uncover hidden knowledge, unknown correlations, market trends, customer preferences and other useful information to improve sustainability with CE (Ren et al., 2019). CE is often cited as one of the best solutions to support sustainable development (Ngan et al., 2019). The sustainability with CE can be assessed from environmental, economic and social dimensions, and the social-ethical foundations and social implications of CE must be strengthened (Inigo and Blok, 2019).

Lieder and Rashid (2016) proposed a framework to be used as a CE implementation strategy, especially keeping the manufacturing industry in mind. In China, CE is promoted as a top-down national political objective, whereas in other developed areas and countries

Time	Consumption (kWh)					
	D023 ball mill	D024 ball mill	D025 ball mill	D026 ball mill	D028 ball mill	D029 ball mill
2016/03/01	654.800	668.020	564.410	1024.400	299.600	515.190
2016/03/02	718.810	873.990	694.410	982.420	329.600	760.800
2016/03/03	700.000	383.990	698.830	940.010	380.410	645.610
2016/03/04	419.990	600.010	506.010	974.380	236.390	311.220
2016/03/05	617.210	595.630	688.410	960.440	274.000	588.790
2016/03/06	650.430	111.620	612.400	900.010	374.800	574.820
2016/03/07	552.400	484.020	641.990	929.640	347.600	614.810
2016/03/08	597.990	424.430	619.610	875.610	387.200	673.220
2016/03/09	264.820	79.220	819.990	1037.620	436.810	702.390
2016/03/10	562.820	367.220	552.810	701.210	181.210	657.590
2016/03/11	186.420	324.820	272.410	611.230	209.590	124.030
2016/03/12	577.990	396.020	643.210	795.600	231.220	610.800
2016/03/13	712.420	8.840	678.390	1066.030	403.590	604.790
2016/03/14	565.180	423.230	642.000	280.430	294.400	640.800
2016/03/15	425.230	580.810	605.210	987.610	243.990	112.420
2016/03/16	181.220	608.790	537.240	784.840	40.810	883.990
2016/03/17	128.430	615.200	87.630	146.040	352.020	576.410
2016/03/18	528.820	437.220	7.640	851.620	309.590	608.800
2016/03/19	571.610	280.430	8.040	639.250	3.210	98.420
2016/03/20	169.210	8.430	7.640	191.640	383.220	633.210
2016/03/21	495.590	336.820	6.030	191.260	8.810	208.810
Total	10281.390	8608.760	9894.310	15871.290	5728.070	11146.920
Percentage	16.71%	13.99%	16.08%	25.79%	9.31%	18.12%

Fig. 8. Daily power consumption of six ball mills from 1 March to March 21, 2016.

(e.g. European Union, Japan and the USA), CE is a tool to design bottom-up environmental and waste management policies (Ghisellini et al., 2016). Numerous studies concern the implementation of CE in China. This country seems to be strongly committed and attracted to CE due to the considerable environmental, human health and social problems considering its very rapid and continuous economic development pattern (Ghisellini et al., 2016).

Products manufactured in developing nations are being sent to developed nations for mass consumption (Mangla et al., 2018a). Substantial energy is consumed, and many pollutants are emitted during the manufacturing processes. Therefore, developing CE strategy in developing countries has additional barriers. A comprehensive review of the CE concept was provided for developing countries (Ngan et al., 2019). For example, barriers to CE and circular supply chain management implementation were identified and analysed in the context of developing countries, specifically in India (Mangla et al., 2018a). In China, barriers to smart waste management for CE were explored based on interviews with experienced practitioners (Zhang et al., 2019). In Indonesia, a sustainable CE approach for smart waste management system was proposed to implement sustainable development goals.

7.2. Managerial implications

This section presents the policy, theoretical and practical implications of the current study for various stakeholders, such as academicians and decision-makers at different levels.

7.2.1. Policy implications

The government plays a very crucial role in defining sustainability objectives in sustainable intelligent manufacturing within CE and can work with the Ministry of Education to further integrate CE into the education of the younger generations. For example, the educational institutions may teach students and companies at the academic level and design courses to develop product-service systems for contributing to CE. The government must urgently develop and implement policies to improve materials and energy use efficiency and reduce toxicity and fossil carbon footprint. Having adequate funds and resources is important for an organisation to develop sustainability orientation (Mangla et al., 2018b). Top managers should allocate sufficient resources and funds to invest in research and development activities to promote sustainability.

7.2.2. Theoretical implications

The integration of Industry 4.0 and sustainability is in its very initial stages (de Sousa Jabbour et al., 2018a). This work provides a theoretical basis to understand the potential challenges to Industry 4.0 to develop sustainable intelligent manufacturing and CE. Knowing challenges can assist process engineers and industrial managers to focus on the design, manufacturing, operation,

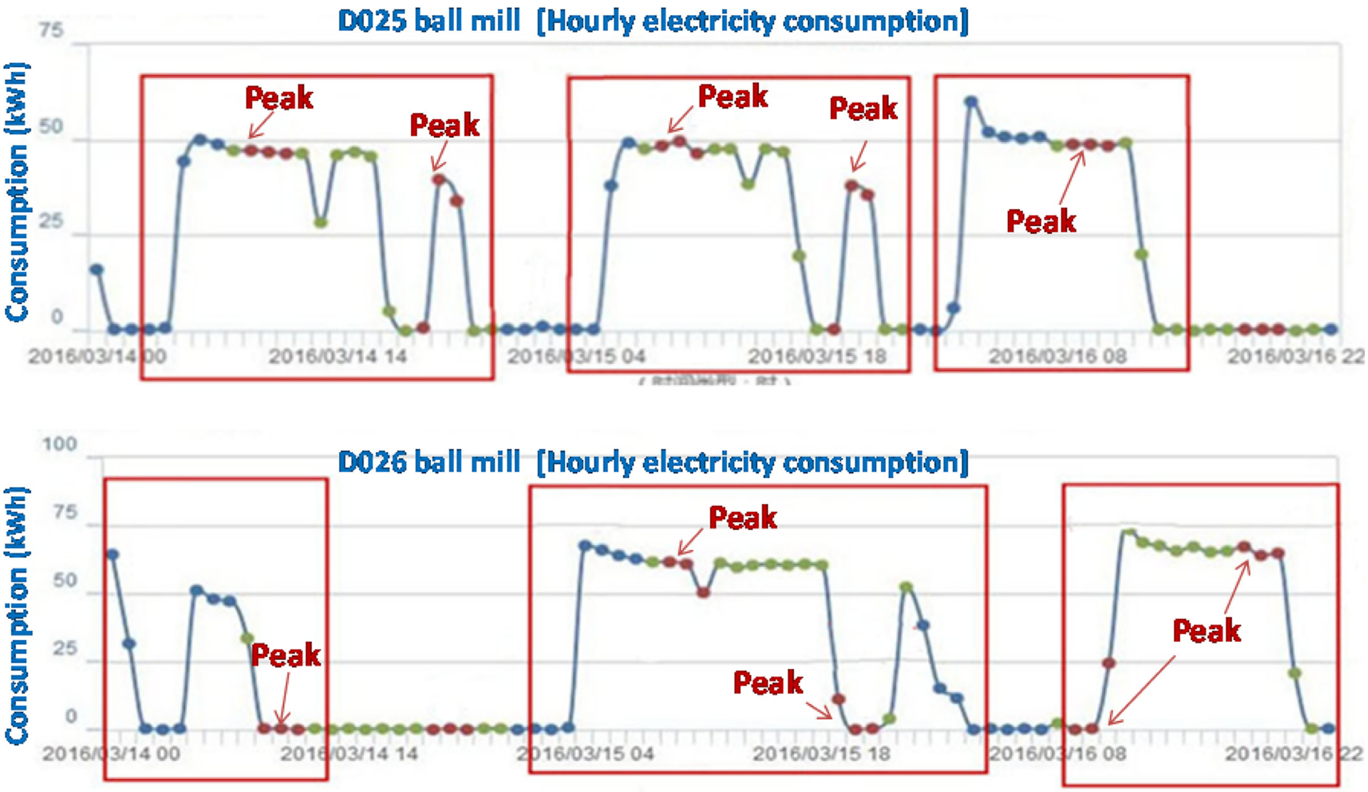

Fig. 9. Comparison of power consumption of the 25th and 26th ball mills from 14 March to March 17, 2016.

Table 2
Comparison of the 25th and 26th ball mills.

Parameters	Peak radio	Flat radio	Valley radio	Power consumption (kWh)	Cost (CNY)	Average cost (CNY/kWh)
25th ball mill	32.5%	38.2%	29.3%	1784.850	1391.698	0.7797
26th ball mill	19.8%	52.4%	27.8%	2053.290	1497.272	0.7292

maintenance, recycle and remanufacturing of products. The information technology network plays an important role in enhancing the sustainability of CE. Managers need to consider sustainability aspects while adopting advanced technologies, such as cloud computing, IoT, CPS, digital twin and big data analytics. This input can stimulate the development of new technologies in manufacturing new products (Zheng et al., 2019). Besides, smart waste management should involve smart resource management based on the technical, biological, ecological, economical and ethical attributed to resources (Zhang et al., 2019).

7.2.3. Practical implications

Sustainable intelligent manufacturing provides detailed insights into the execution of Industry 4.0. The critical success factors can be explored to implement green supply chain management towards sustainability taking into account energy-intensive manufacturing industries (Luthra et al., 2016; Luthra and Mangla, 2018). The sustainability in energy management system must be assessed to meet the requirements of energy with an enhanced economic, ecological and social performance from a national context (Mangla et al., 2020). Implementation of lean manufacturing practices can provide competitive advantages, such as improvements in product quality, productivity, worker health and safety and customer satisfaction, which is beneficial for company leaders and researchers working to improve environmental, economic and societal health (Yadav et al., 2020).

8. Conclusions

In the Industry 4.0 context, CE plays an important role in improving the sustainability in manufacturing industries, specifically in EIIs. The integration of Industry 4.0 and sustainability is in its very initial stages. CP is an effective way to improve the sustainability base on DR models. Therefore, this research aimed to present data-driven sustainable intelligent manufacturing based on DR for EIIs, which provided a new kind of infrastructure to make efficient and energy-efficient decisions for implementing sustainable intelligent manufacturing and contribute to ethical sustainable societal development.

This study has four major contributions. Firstly, the framework of data-driven sustainable intelligent manufacturing based on DR can provide theoretical and practical insights into the academic and industrial field. Secondly, the technological architecture for implementing the proposed framework can be used as an enterprise portal of energy efficiency optimisation analysis considering CE. Thirdly, the multi-level DR models based on machine, shopfloor and factory were developed to save the energy cost and improve sustainability. Fourthly, managerial implications from the policy-related, theoretical, and practical perspectives of the current study were summarised for various stakeholders, such as academicians and decision-makers at different levels.

The proposed framework and models have been applied in energy-intensive manufacturing companies that achieve CP, CE and sustainable intelligent manufacturing through energy management systems. The environment, manufacturers and society can benefit from the framework given that improving energy efficiency in manufacturing industries can not only relieve environmental pressure but also save costs for manufacturers and improve their competitiveness. Furthermore, the threat to human health will be reduced continually due to the reduction of pollutants.

This research has its limitations. The proposed framework of sustainable intelligent manufacturing only considers the manufacturing stage of the product lifecycle, ignoring other stages, such as design, operation, maintenance, recycle and remanufacturing. Moreover, the proposed framework and models lack a detailed description of the relationship among Industry 4.0, CE and CP.

Future research will integrate the latest advanced technologies and sustainable intelligent manufacturing to achieve CE strategy. For example, Digital Twin- or Blockchain-driven frameworks and models through product lifecycle can be established to support sustainable intelligent manufacturing. Furthermore, synergies amongst Industry 4.0, CP and CE would be developed and implemented in the context of ethical sustainable societal development.

CRediT authorship contribution statement

Shuaiyin Ma: Writing - original draft, Methodology, Software. **Yingfeng Zhang:** Supervision, Validation, Writing - review & editing. **Yang Liu:** Supervision, Validation, Writing - review & editing. **Haidong Yang:** Data curation. **Jingxiang Lv:** Conceptualization. **Shan Ren:** Software.

Declaration of competing interest

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.123155.

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