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Industrial Internet of Things enabled supply-side energy modelling for refined energy management in aluminium extrusions manufacturing

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A B S T R A C T

To improve industrial sustainability performance in manufacturing, energy management and optimisation are key levers. This is particularly true for aluminium extrusions manufacturing —an energy-intensive production system with considerable environmental impacts. Many energy management and optimisation approaches have been studied to relieve such negative impact. However, the effectiveness of these approaches is compromised without the support of refined supply-side energy consumption information. Industrial internet of things provides opportunities to acquire refined energy consumption information in its data-rich environment but also poses a range of difficulties in implementation. The existing sensors cannot directly obtain the energy consumption at the granularity of a specific job. To acquire that refined energy consumption information, a supply-side energy modelling method based on existing industrial internet of things devices for energy-intensive production systems is proposed in this paper. First, the job-specified production event concept is proposed, and the layout of the data acquisition network is designed to obtain the event elements. Second, the mathematical models are developed to calculate the energy consumption of the production event in three process modes. Third, the energy consumption information of multiple manufacturing element dimensions can be derived from the mathematical models, and therefore, the energy consumption information on multiple dimensions is easily scaled. Finally, a case of refined energy cost accounting is studied to demonstrate the feasibility of the proposed models.

1. Introduction

Cleaner production is crucial to global resource consumption, atmospheric pollution, climate change, human health, and other issues that jeopardise the sustainability of the current economic system (Hens et al., 2018; Khalili et al., 2015). With the increasing awareness of sustainability (Bocken et al., 2016; Geissdoerfer et al., 2017; Rashid et al., 2013), sustainable and cleaner production has been recognised as a national development strategy in many countries (Cai et al., 2016). Meanwhile, as an important link to achieving sustainability, energy-saving has become a competitive advantage for a company (Kramer and Porter, 2011).

Manufacturing, especially energy-intensive manufacturing (Lin and Tan, 2017; Zhang et al., 2018), introduces severe carbon emissions and other pollution. Meanwhile, manufacturing energy supply should meet but often exceed the energy demand (Ma et al., 2020; Summerbell et al., 2016). Energy demand indicates the minimum required processing energy, which is determined by the process mechanism and processing parameters. To find the energy-saving potentials and to support energy optimisation decisions, such as energy-awareness scheduling (Gahm et al., 2016) and parameter optimisation (Li et al., 2017), energy consumption information is essentially obtained to figure out energy footprint (Henao-Hernández et al., 2019), while the effectiveness of those decisions would be compromised without refined supply-side

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Abbreviation

EDP	energy discrete process
ECP	energy continuous process
IIoT	industrial internet of things
MMS	mixed manufacturing system
MBOM	manufacturing bill of material
PLC	programmable logic controller
RECI	refined energy consumption information
RFID	radio frequency identification
WIP	work in process

Nomenclature

$A_{S(\varepsilon_\zeta)}$	the energy meter value at the starting moment of a production event
$A_{C(\varepsilon_\zeta)}$	the energy meter value at the completion moment of a production event
B^w_{ilqp}	the set of jobs whose processing time frame has an intersection with J^w_{ilqp}'s
$C^e(\varepsilon_\zeta)$	energy consumption amount of $P_{Event}(\varepsilon_\zeta)$
$\mathrm{C}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$	the completion moment of J^w_{ilqp} on M^w_{kj} on process T^w_{kb}
$\mathrm{C}(\varepsilon_\zeta)$	the completion moment of $P_{Event}(\varepsilon_\zeta)$
D	the number of manufacturing element dimensions
F_{map}	an energy information filter model
F_E	energy category filter
G	the total amount of jobs on the M^w_{kj}
$\{h_\delta\}$	an extensible amount of manufacturing elements set
$h_j, h_p, h_t, h_o, h_r, h_m, h_u, h_{ws}$	job element, product element, production task element, order element, process element, machine element, machine group element, workshop element
$H^\delta(h_\delta)$	the value of each dimension h_δ
J^w_{ilqp}	the p-th job of product Pr_{ilq} in workshop w
K_E	energy category
$K_E(\varepsilon_\zeta)$	energy category of $P_{Event}(\varepsilon_\zeta)$
m^w_{ilqp}	the weight of J^w_{ilqp}
M^w_{kj}	the j-th machine of the k-th machine group in workshop w
M_{space}	an extensive mapping coordinate space
$mo(\beta)$	the moment of jobs' arrival or leaving in $\mathrm{Mo}(M^w_{kj})$
$\mathrm{Mo}(M^w_{kj})$	a moment sequence of the start and completion moment of each job on the M^w_{kj}
O_i	the i-th order
$P_{Event}(\varepsilon_\zeta)$	the production event of ε_ζ
P^N_{Event}	a production events domain
Pr_{ilq}	the q-th product of Ta_{il}
$\{R_{\mathrm{oto}}\}$	the process set where a machine has a one-to-one relationship with the processed job
$\mathrm{Sch}(M^w_{kj})$, $\mathrm{Sch}(w)$	a scheduling scheme on M^w_{kj} and in workshop w, respectively
$\mathrm{S}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$	starting moment of J^w_{ilqp} on machine M^w_{kj} on process T^w_{kb}
$\mathrm{S}(\varepsilon_\zeta)$	the starting moment of $P_{Event}(\varepsilon_\zeta)$
t^w_r	the initial value of release time for the scheduling scheme for workshop w
t^w_0	the starting moment of production moment in workshop w
T^w_{kb}	the b-th process of the k-th machine type in workshop w
Ta_{il}	the l-th production task of order O_i
$V(h_\delta)$	information content of the element h_δ
W_w	the w-th workshop
$\mathscr{B}$	the times of job's arrival and leaving during $(\mathrm{S}(J^w_{ilqp}, M^w_{kj}), \mathrm{C}(J^w_{ilqp}, M^w_{kj})]$
ε_ζ	the tuple to express the assignment of a job processed a process on a machine
ω^w_{ilqp}	the job-specified energy consumption coefficient of J^w_{ilqp}
$\phi(J^w_{ilq\gamma}, t)$ $\psi(J^w_{ilq\gamma}, t)$	the state function of $J^w_{ilq\gamma}$ in mode B and mode C, respectively
$\Omega_j, \Omega_{ws}, \Omega_u, \Omega_m$ and Ω_r	the universal set of job, workshop, machine unit, machine and process
γ_{K_E}	the average unit price of K_E

energy consumption information.

For supply-side energy data collection, existing energy management of manufacturing systems is largely limited to energy measurement and estimation at an industry level (Goto et al., 2014), factory level (Shrouf et al., 2014) or machine level (Vijayaraghavan and Dornfeld, 2010; Yilmaz et al., 2015). Limited research involves refined energy consumption obtainment of a specific job in a process, especially in an energy-intensive industry. Based on existing methods, job-specified energy consumption is roughly evaluated by apportioning the energy consumption of machines evenly or by a weighted coefficient, causing the information fails to reflect energy differentiation and support energy optimisation. Furthermore, many energy-intensive manufacturing systems are mixed manufacturing system (MMS), where multiple types of processes co-exist in the actual production workshop. Regarding the modes of energy supply, MMS includes energy discrete process (EDP) and energy continuous process (ECP). EDP indicates the process where jobs are processed one by one; otherwise, it is ECP. ECP is subdivided into two modes: ECP with jobs synchronously processed and ECP with jobs non-synchronously processed. In ECP, the energy consumption of each job cannot be directly obtained since an energy meter can only measure the aggregated energy consumption of all the jobs. Industrial internet of things (IIoT) approaches pave the way to the data acquisition of energy flow (de Sousa Jabbour et al., 2018; Liu et al., 2020). Refined energy consumption information (RECI) acquired by IIoT has been studied in some research (Hu et al., 2017; Park et al., 2020), while the processes are regarded as EDP and these methods cannot be applied in MMS. Two research questions remain to be solved for obtaining RECI in MMS. 1) How to generate RECI based on energy data and other production data? 2) How to measure the energy supply for specific jobs in a batch in ECP? Meanwhile, diversified customised products increase the difficulties in RECI acquisition.

Aluminium extrusions manufacturing system is a typical energy-intensive, customised MMS. Plenty of research has been conducted to reduce its energy consumption by equipment upgrading (Ma et al., 2004a), process parameter-optimisation (Ebrahimi et al., 2008), production scheduling (Gravel et al., 2002) and beyond. However, there is a lack of automatic acquired RECI to support the above approaches. Bunse et al. (2011) pointed out that energy balance sheets, new sensor technology, and smart embedded devices could be important tools for energy monitoring to help make a proper manufacturing decision using online data. Nevertheless, IIoT is not capable of acquiring RECI in aluminium extrusions manufacturing, for the production usually goes through a series of EDP and ECP processes, including billet melting and casting, extrusion dies machining, preheating for billet and extrusion die, profile extrusion, and thermal treatments. For example, in the melting process, which is considered as ECP, different aluminium billets are melted together in one furnace. Thus, the smelting energy consumption acquired by an energy meter cannot be directly attributed to each billet.

Motivated by the automatic acquisition of refined energy consumption with IIoT technology in MMS, a supply-side energy modelling approach for three types of processes is proposed. In this approach, a data collection scheme based on sensor devices and production systems in existing software is presented, see Fig. 1 Modules (1) and (2). Three mathematical models are developed for different energy supply modes, see Fig. 1 Module (3). Then, the production event is constructed to establish the relationship between energy and other manufacturing elements, including job element, machine element and process element. Moreover, three mathematical models are applied to derive energy information of the multiple element dimensions, see Fig. 1 Module (4).

The remainder of this paper is organised into five sections. A brief review of related works is presented in Section 2. In Section 3, the framework of this research is elaborated. The concept of production event is demonstrated, and the refined energy models are described in Section 4. In Section 5, a cost refinement accounting of aluminium extrusions manufacturing is studied as a case using the proposed approach. Finally, summary and discussions are given in Section 6.

2. Related works

Aiming at effective data support for energy management and optimisation, a considerable amount of explorations in energy consumption information acquisition for manufacturing can be found (Afkhami et al., 2015; Liu et al., 2012). Related works and their constraints in achieving refined energy management are analysed in this section, and an overview of the existing works is summarised in Table 1.

Energy consumption information has been studied at different levels, such as industry (Posch et al., 2015; Rudberg et al., 2013), factory (Shrouf et al., 2014), and process (Lv et al., 2019; Yilmaz et al., 2015). Different energy information levels can support different managerial decisions. As for the energy saving in a workshop, the data should be refined to the process level. At the process level, many researchers studied energy consumption on the demand-side (Reinhardt et al., 2020) by constructing energy consumption model (Jia et al., 2018; Ma et al., 2004b) or estimating publicly available data (Ciceri et al., 2010). However, the demand-side energy consumption is just a portion and cannot reflect the actual supply-side energy consumption.

A massive amount of data is generated in the production process, which is hard to be collected by the traditional method. The emergence and implementation of IIoT technology have enabled the exploitation of real-time and ubiquitous production data (de Man and Strandhagen, 2017; Lu, 2017), including energy consumption data. Limited but increasing research has been conducted to reframe energy management with IIoT.

In most of the existing IIoT based supply-side energy management at the process level, research was mainly focused on key machines, including supply-side energy consumption of a specific machine or machines in a manufacturing system. For the energy management of a specific machine, Chen et al. (2018) developed a management system to get the energy efficiency of equipment and workshop by calculating the integral of power at each processing stage. Lenz et al. (2017) measured and quantified the energy consumption of the machine tools' auxiliary units using a programmable logic controller (PLC) signals. Abele et al. (2015) designed a standardised energy management function module and a data

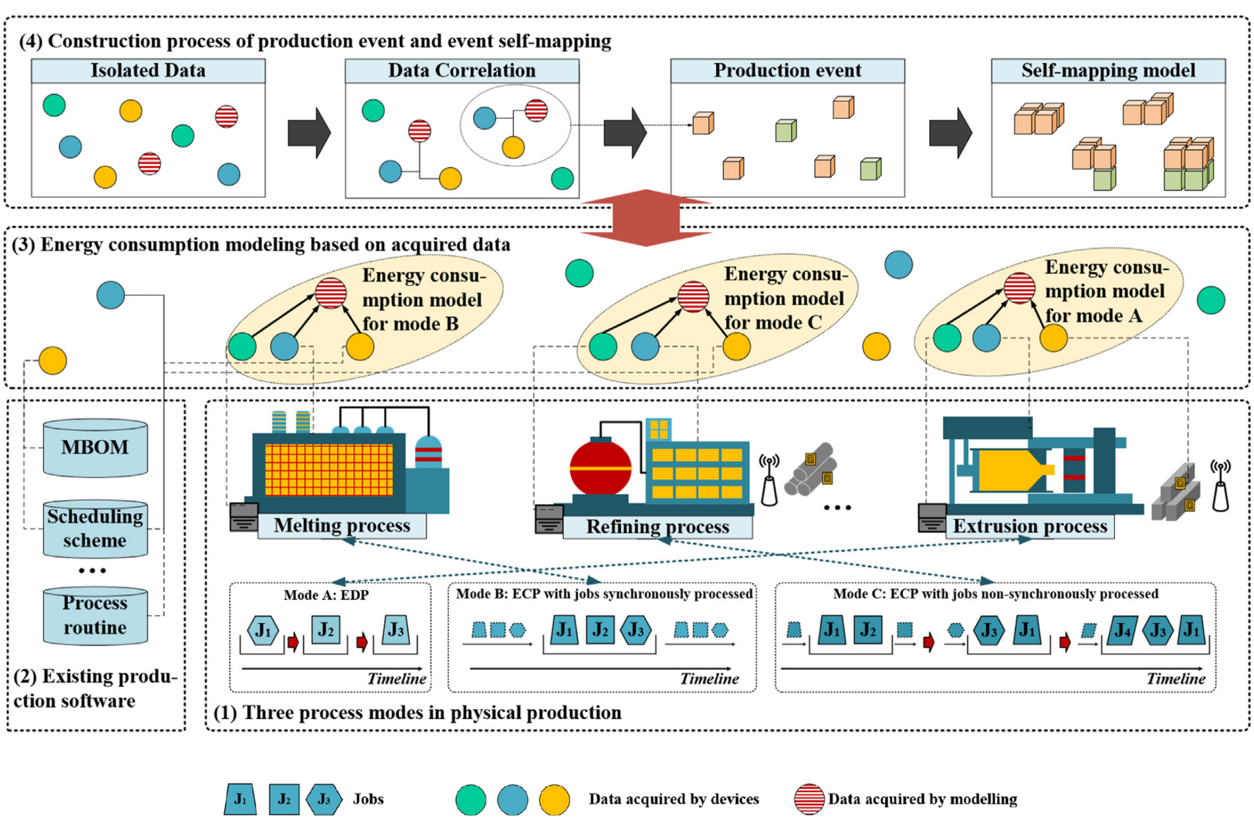

Fig. 1. The deployment of energy management.

Table 1
An overview of the existing works in energy consumption information acquisition.
Ind.: Industry Fac.: Factory Pro.: Process.

Reference	Level			Side		Type of process		Process scale		Job-specified		Acquisition
	Ind.	Fac.	Pro.	Supply	Demand	ECP	EDP	Systematic	Specific	Yes	No	
Afkhami et al. (2015)			✓	✓		✓		✓			✓	Energy meter, Cumulative sum technique
Liu et al. (2012)	✓			✓	✓						✓	Statistical reports, Modelling,
Posch et al. (2015)	✓			✓							✓	Statistical report
Rudberg et al. (2013)	✓			✓							✓	Meetings, Semi-structured interviews, Plant internal documentation
Shrouf et al. (2014)		✓		✓							✓	IIoT
Yilmaz et al. (2015)			✓	✓		✓		✓			✓	Statistical reports
Lv et al. (2019)			✓	✓		✓		✓			✓	Plant internal documentation, Literature
Ma et al. (2004b)			✓		✓		✓		✓		✓	Modelling
Jia et al. (2018)			✓		✓		✓		✓		✓	Modelling, Power acquisition system
Ciceri et al. (2010)			✓		✓		✓		✓		✓	Literature
Chen et al. (2018)			✓	✓			✓		✓		✓	IIoT
Lenz et al. (2017)			✓	✓			✓		✓		✓	Power monitoring PLC module
Abele et al. (2015)			✓	✓			✓		✓		✓	Energy monitoring PLC module
Sihag et al. (2018)			✓	✓			✓		✓		✓	Non-intrusive smart energy sensor
Liu et al. (2018)			✓	✓		✓			✓		✓	IIoT
Summerbell et al. (2016)			✓	✓	✓	✓		✓			✓	Statistical reports, Plant production data
Papetti et al. (2019)			✓	✓	✓	✓		✓			✓	Sensors, Bills, Meters, Interviews
Hu et al. (2017)			✓	✓			✓	✓		✓		RFID, Digital energy meter
He et al. (2012)			✓	✓			✓	✓		✓		Experiment, Historical statistical data
Park et al. (2020)			✓	✓			✓	✓		✓		Cyber physical system, IIoT
Ma et al. (2019)			✓	✓			✓	✓		✓		Cyber physical system, IIoT
This paper			✓	✓		✓	✓	✓		✓		Modelling, IIoT, Production software,

processing method for machines' PLCs. Sihag et al. (2018) formulated a non-intrusive energy monitoring technique to monitor energy consumption at the unit process level of machine tools and determine the operational status by the energy data profile. Compared to the energy management of devices in EDP, the research on ECP is limited. Liu et al. (2018) captured the power data and operation data using the power meter and PLC. They evaluated the seven class actions' energy consumption of die casting machines and proposed a set of indicators. To find the potential reduction of carbon emissions, Summerbell et al. (2016) investigated both supply-side and demand-side energy consumption of the processes in the cement industry. Papetti et al. (2019) assessed and monitored energy efficiency with mapping activities and related energy/resource consumptions according to lean philosophy principles (value-added, non-value-added, waste). Above studies concern more on the energy information of devices, which lay a foundation for RECI. However, the collected energy consumption data is isolated from other manufacturing elements, so the energy consumption on the job dimension cannot be obtained.

Several attempts have been made to correlate the energy data with the job element, mainly in EDP. Hu et al. (2017) proposed a radio frequency identification (RFID) enabled energy consumption monitoring for the order fulfilment. In their research, job information can be read by RFID tags, and the logistics information can be acquired by the RFID readers. Based on this information, the energy consumption information in material and machine dimensions can be extracted. In contrast, the management method of a discrete process cannot be directly transferred and applied in MMS. In aluminium extrusions manufacturing, most processes are thermal, so that the RFID tags cannot be attached along with the material. Event stream processing technique is proved to be a feasible tool to establish the relationship between energy flow, material flow and machines (Vijayaraghavan and Dornfeld, 2010). He et al. (2012) investigated the energy consumption in different task schemes based on the event graph. Energy information of a specific job on a machine is finely managed, and job information can be acquired by the task arrangement. The event graph proposed by Schruben is a tool to model the event list logic graphically (Schruben, 1983). However, it can only be applied to a discrete process, not a continuous process. Park et al. (2020) studied the processes in dyeing and finishing shops, which is a continuous manufacturing scenario. They obtained the energy information of lots by merging the energy meter data and ERP database. Ma et al. (2019) proposed a general synergy model among energy flow, material flow and information flow. In the above studies, energy supply modes were considered as EDP. Thus the energy amount acquiring method of a job cannot be adapted in the ECP process of MMS before further refinement. The energy consumption information in ECP is more complicated than in EDP.

Above all, research on RECI for mixed process in MMS is still limited. Most works focus on the energy monitoring of machines without considering other elements. Furthermore, existing research studied little about the energy usage structure on the supply-side. Owing to the development of IIoT (Zhong et al., 2013), the dimension coverage and refinement degree of data acquisition network is enhanced, which contributes to the RECI mining. Current research on the application of IIoT in energy data collection lays a foundation. Therefore, this paper proposes a supply-side modelling approach in three process modes to achieve the target of energy refined management in MMS.

3. Framework of supply-side energy modelling

For energy modelling in aluminium extrusions manufacturing system, three problems are crucial to be solved. First, the material information of work in process (WIP) cannot be obtained directly. In the aluminium production process, the physical state of WIP is under solid-liquid dual conversion, and the liquid WIP may be mixed in some processes. Thus, standard sensor hardware cannot identify the specific WIP and monitor its location. Second, energy consumption acquisition varies in different production modes. There exist both EDP and ECP in aluminium extrusions manufacturing system. In EDP, the main work for energy modelling is bridging the relationship between a job and its related energy consumption data read by digital energy meter. For ECP, such as a metal melting process, heating of a smelter supplies multiple jobs simultaneously. They cannot be referred to each job specifically, which brings difficulty in obtaining job-specified energy consumption. Third, the information integration challenge is brought by diverse energy sources and the multi-source heterogeneous manufacturing elements. Collected energy data is isolated from other manufacturing elements, which cannot support refined management. An automated RECI acquisition method in the aforementioned process modes is required.

To satisfy the RECI acquisition requirement for aluminium extrusions manufacturing system, a bottom-up logical framework is proposed, see Fig. 2. In the physical production layer, where the production data, including energy data, is generated and collected, a feasible data collection layout is required to be designed. The data that cannot be acquired from the production site, such as the BOM data and schedule scheme data, should be obtained from a database shared by other systems. In the information layer, production data and energy data are integrated and transformed into energy information, where the energy consumption mathematical models of three process modes are established. To assign physical meaning to energy data, a production event is created to express when the energy is consumed, by which job, and in what process. This operation correlates material and energy consumption. To obtain the energy consumption information on different manufacturing element dimensions, the physical relationship among the manufacturing elements is exploited, and the results of energy usage on multiple element dimensions are illustrated in an information module.

4. Energy modelling for refined management

In this section, three steps of energy modelling for refined management are outlined. First, the job-specified production event is constructed as the finest energy information unit. Second, supply-side energy consumption models of a production event on three process modes are constructed, including EDP, ECP with synchronously processed jobs and ECP with non-synchronously processed jobs. Third, the energy information on the required manufacturing element dimensions is derived from energy consumption models. The assumptions are as follows:

(1) The production follows the schedule;
(2) All the data collected via IIoT are reliable;
(3) The time of entrancing or existing a machine is accounted into processing time;
(4) For the jobs processed in the same batch, the material loss rate is the same.

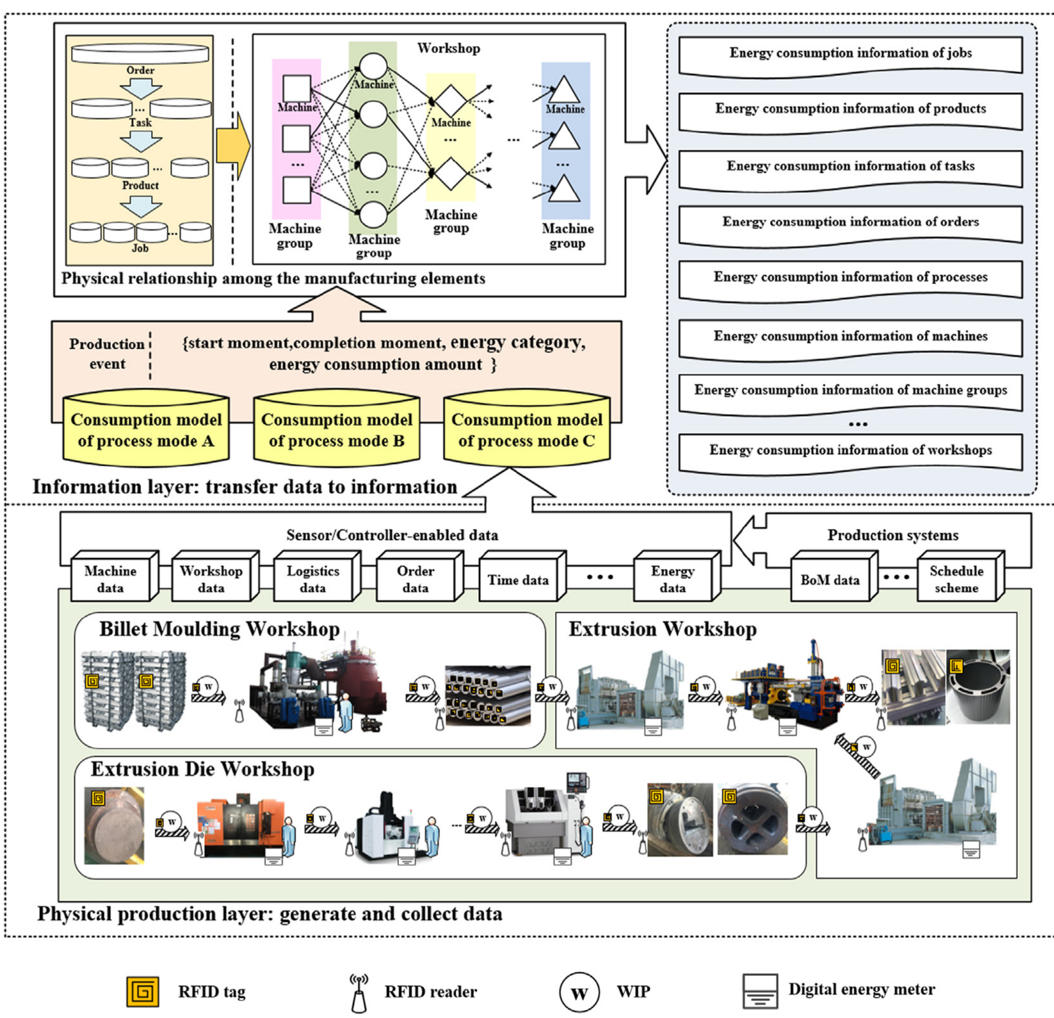

Fig. 2. The framework of the supply-side energy modelling.

4.1. Construction process of a production event

To construct the model of a production event, energy-related production data should be acquired and integrated. There are two main accesses for data acquisition, one is from the existing system, and the other is from the sensors. For the first mode, data can be obtained directly through the corresponding communication protocol. For the rest of the data obtained from the field workshop, it is necessary to reasonably layout the data collection points based on process characteristics. The data acquisition process is demonstrated as follows.

First: For a particular production stage, according to the manufacturing bill of material (MBOM), orders $\{O_i\}$ are disassembled into processing jobs $\{J^w_{ilqp}\}$ to dispatch to the relevant workshop W_w. In this process, each job J^w_{ilqp} establishes the mapping relationship with products, tasks and orders. J^w_{ilqp} indicates the p-th job of the q-th product Pr_{ilq} in the l-th task Ta_{il} of the i-th order O_i in workshop w. Meanwhile, the job-product-task-order information is generated and loaded to the tag of the raw material of the product. It should be mentioned that the notation J^w_{ilqp} is ambiguous in the assembling process, such as extrusion. Thus, here is a special note about J^w_{ilqp}: the input and output jobs in a process are equivalent according to the MBOM. For example, one billet job J^1_{1111} is transferred to extrusion workshop W_3 from moulding workshop W_1, if the billet job extrude to three extrusions jobs J^3_{1111}, J^3_{1112}, J^3_{1113}, the billet job J^1_{1111} equals the sum of J^3_{1111}, $J^3_{1112}$and J^3_{1113}. An example of MBOM is illustrated in Fig. 3.

Second: Jobs are scheduled, and the release time t^w_r is regarded as zero. Based on the scheduling schemes Sch(w) in corresponding workshop w, the starting moment $\mathrm{S}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$ and completion moment $\mathrm{C}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$ of J^w_{ilqp} on machine M^w_{kj} on process T^w_{kb} are given.

Third: Raw material's arrival triggered the production. The RFID reader at the entry of the processing zone acquires the raw material information in the tag and record the starting moment in this workshop t^w_0. If the tag information matches the scheduling scheme, processing continues. Otherwise, the correct material is reselected, and this step is repeated. This aims to ensure the actual processing is correctly performed following the schedule.

Fourth: The release time t^w_r is updated to t^w_0. The starting moment $\mathrm{S}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$ and completion moment $\mathrm{C}(J^w_{ilqp}, M^w_{kj}, T^w_{kb})$ delay t^w_0 consequently.

Fifth: As production proceeds, the energy category and the energy meter value are read at the updated starting and completion moments of each job. A whole process assignment of a job on a machine can be regarded as a tuple ε_ζ in equation (1).

$$\varepsilon_\zeta = \left\{J^w_{ilqp}, M^w_{kj}, T^w_{kb}\right\} \tag{1}$$

The production event of ε_ζ is indicated as $P_{Event}(\varepsilon_\zeta)$, which is composed of the elements including starting moment $\mathrm{S}(\varepsilon_\zeta)$, completion moment $\mathrm{C}(\varepsilon_\zeta)$, energy category $K_E(\varepsilon_\zeta)$ and energy consumption amount of this event $C^e(\varepsilon_\zeta)$, which is represented as equation (2).

$$P_{Event}(\varepsilon_\zeta) = \{\mathrm{S}(\varepsilon_\zeta), \mathrm{C}(\varepsilon_\zeta), K_E(\varepsilon_\zeta), C^e(\varepsilon_\zeta)\} \tag{2}$$

where $C^e(\varepsilon_\zeta)$ cannot be acquired directly but calculated. The mathematical model of $C^e(\varepsilon_\zeta)$ varies by the type of T^w_{kb}.

Sixth: Once a job is detected to be unqualified, production would be rescheduled. The starting moments and completion moments of the rescheduled jobs are updated. New energy information is updated as step five, and the current energy information remains.

4.2. Energy modelling of production event

In an aluminium extrusions manufacturing system, there exist three mathematical models of $C^e(\varepsilon_\zeta)$ classified by the energy supply modes of process. Detailed modelling methods of process modes A, B and C are developed as follows.

4.2.1. Mode A: EDP

When $T^w_{kb} \in \{R_{\mathrm{oto}}\}, \{R_{\mathrm{oto}}\}$ indicates the process set where a machine has a one-to-one relationship with the processed job, such as machining, wire cutting, extrusion. This type of process is regarded as EDP, and the energy supply of the processing machine supports only one job at a time. To obtain the $C^e_{ModeA}(\varepsilon_\zeta)$ of energy $K_E(\varepsilon_\zeta)$ in EDP, the value of energy meter $A_{\mathrm{S}(\varepsilon_\zeta)}$ and $A_{\mathrm{C}(\varepsilon_\zeta)}$at the starting moment $\mathrm{S}(\varepsilon_\zeta)$ and the completion moment $\mathrm{C}(\varepsilon_\zeta)$ are required to be recorded, respectively. The energy consumption $C^e_{ModeA}(\varepsilon_\zeta)$ in process mode A consumed by the job J^w_{ilqp} on machine M^w_{kj} on process T^w_{kb} can be calculated as equation (3), which is the difference between $A_{\mathrm{C}(\varepsilon_\zeta)}$ and $A_{\mathrm{S}(\varepsilon_\zeta)}$.

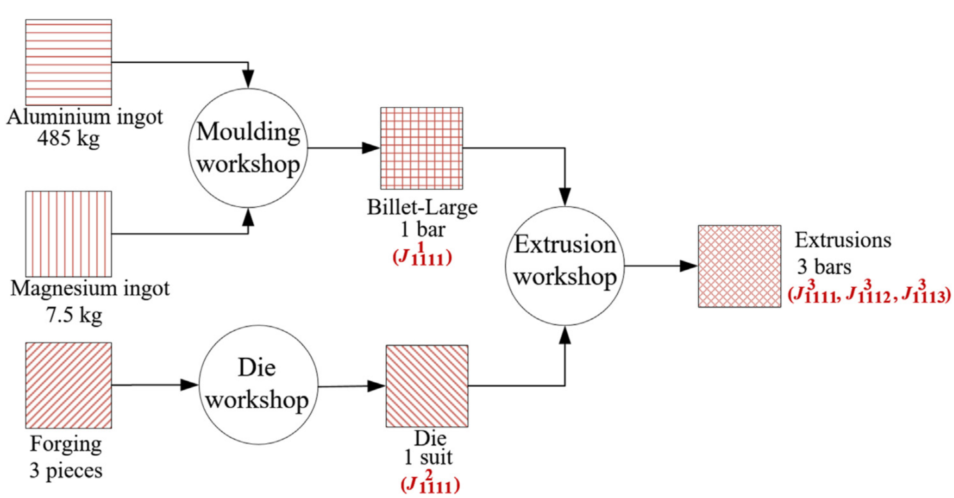

Fig. 3. An example of a manufacturing bill of material.

$$C^{e}_{ModeA}(\varepsilon_\zeta) = A_{C(\varepsilon_\zeta)} - A_{S(\varepsilon_\zeta)} \tag{3}$$

4.2.2. Mode B: ECP with jobs synchronously processed

When $T^{w}_{kb} \notin \{R_{oto}\}$, it means that the relationship between machines and the processed job is one-to-many, such as metal refining and thermal treatment. This type of process is considered as ECP, and the energy supply of the processing machine supports only multiple jobs at a time. Furthermore, the ECP is classified into two modes by the relationship among the start and completion moments of processed jobs.

The first mode is ECP with jobs synchronously processed, where processed jobs start and complete processing simultaneously. In this mode, each job's energy consumption can be specified based on the processing mechanism model. For aluminium extrusions manufacturing, this mode mainly exists in thermal treatments of the moulding workshop and extrusion workshop. According to the specific heat capacity formula, the job-specified energy consumption coefficient ω^{w}_{ilqp} is proportional to the weight of jobs. Thus, energy consumption$C^{e}_{ModeB}(\varepsilon_\zeta)$ in process mode B can be calculated as equation (4).

$$C^{e}_{ModeB}(\varepsilon_\zeta) = \omega^{w}_{ilqp}\left(A_{C(\varepsilon_\zeta)} - A_{S(\varepsilon_\zeta)}\right) \tag{4}$$

where the job-specified energy consumption coefficient ω^{w}_{ilqp} is defined as equation (5).

$$\omega^{w}_{ilqp} = m^{w}_{ilqp} \Big/ \sum_{J^{w}_{ilq\gamma} \in B^{w}_{ilqp}} \phi\left(J^{w}_{ilq\gamma}, t\right) m^{w}_{ilq\gamma} \tag{5}$$

where the state function $\phi(J^{w}_{ilq\gamma}, t)$ in equation (5) is constructed as equation (6). The B^{w}_{ilqp} indicates the set of jobs whose processing time frame has an intersection with J^{w}_{ilqp}'s, and m^{w}_{ilqp} denotes the weight of J^{w}_{ilqp}. $J^{w}_{ilq\gamma} \in B^{w}_{ilqp}$ in equation (5) denotes the job $J^{w}_{ilq\gamma}$ belongs to the set B^{w}_{ilqp}, defined as equation (7).

$$\phi\left(J^{w}_{ilq\gamma}, t\right) = \begin{cases} 1, if\ t \in (S(\varepsilon_\zeta),\ C(\varepsilon_\zeta)] \\ 0, \quad otherwise \end{cases} \tag{6}$$

$$\begin{aligned}&\left\{J^{w}_{ilq\gamma} \in B^{w}_{ilqp} \middle| \left(S\left(J^{w}_{ilq\gamma}, M^{w}_{kj}, T^{w}_{kb}\right), C\left(J^{w}_{ilq\gamma}, M^{w}_{kj}, T^{w}_{kb}\right)\right] \right. \\ &\left. \cap (S(\varepsilon_\zeta), C(\varepsilon_\zeta)] \neq \varnothing \right\}\end{aligned} \tag{7}$$

4.2.3. Mode C: ECP with jobs non-synchronously processed

Another mode is ECP with jobs non-synchronously processed, where processed jobs have different start and complete moments, see Fig. 4. For aluminium extrusions manufacturing, this mode mainly exists in semi-continuous melting and billet preheating process, etc.

In this mode, it is hard to obtain each job's energy consumption because the batch varies during the processing of J^{w}_{ilqp}. The job-specified energy consumption coefficient ω^{w}_{ilqp} is also proportional to the weight of jobs. Thus, energy accounting requires to be discussed in periods.

For a scheduling scheme $Sch(M^{w}_{kj})$ on M^{w}_{kj}, the arrival and departure of jobs are determined. The start and completion moment of each job can be determined based on $Sch(M^{w}_{kj})$, and they are arranged in a moment sequence $Mo(M^{w}_{kj})$.

To obtain the energy consumption of J^{w}_{ilqp}, the moment $mo(\beta)$ of jobs' arrival or departure during J^{w}_{ilqp}'s processing is required to be read. The domain definition of $mo(\beta)$ can be represented as equation (8).

$$\left\{mo\left(\beta\right) \middle| mo(\beta) \subseteq (S(\varepsilon_\zeta), C(\varepsilon_\zeta)], mo\left(\beta\right) \in Mo\left(M^{w}_{kj}\right)\right\} \tag{8}$$

The energy consumption value is $A_{mo(\beta)}$ on related moment $mo(\beta)$. Thus, energy consumption $C^{e}_{ModeC}(\varepsilon_\zeta)$ of J^{w}_{ilqp} in process mode C can be calculated as equation (9).

$$C^{e}_{ModeC}(\varepsilon_\zeta) = \sum_{\beta=1}^{\beta=\mathscr{B}} \omega^{w}_{ilqp}\left(A_{mo(\beta)} - A_{mo(\beta-1)}\right) \tag{9}$$

where $\mathscr{B}$ indicates the times of job's arrival and departure during $(S(\varepsilon_\zeta),\ C(\varepsilon_\zeta)]$ and $mo(0)$ equals $S(\varepsilon_\zeta)$. The job-specified energy consumption coefficient ω^{w}_{ilqp} of $C^{e}_{ModeC}(\varepsilon_\zeta)$ can be calculated as equation (10).

$$\omega^{w}_{ilqp} = m^{w}_{ilqp} \Big/ \sum_{J^{w}_{ilq\gamma} \in B^{w}_{ilqp}} \psi\left(J^{w}_{ilq\gamma}, t\right) m^{w}_{ilq\gamma} \tag{10}$$

where the state function $\psi(J^{w}_{ilq\gamma}, t)$ is defined as equation (11).

$$\psi\left(J^{w}_{ilq\gamma}, t\right) = \begin{cases} 1, if\ t \in [mo(\beta-1), mo(\beta)] \\ 0,\ otherwise \end{cases} \tag{11}$$

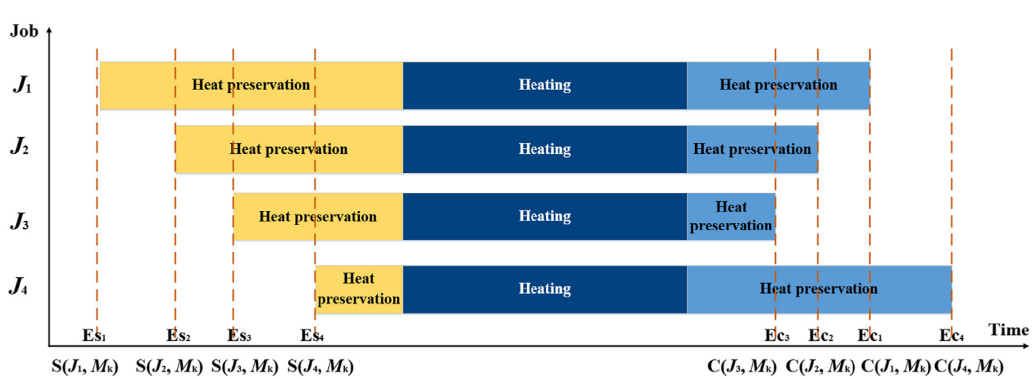

Fig. 4. An example of ECP with jobs non-synchronously processed.

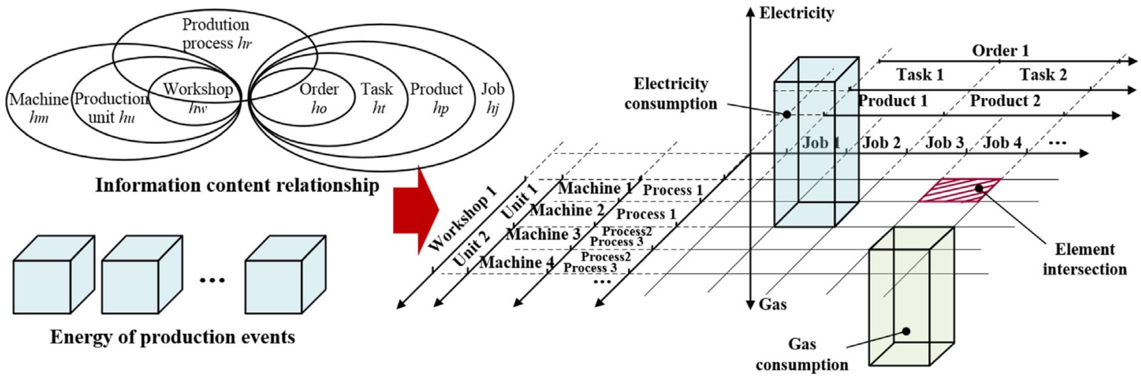

Fig. 5. Energy consumption information mapping.

Table 2
Details of a given order.

h_o	h_t	h_p		h_j		h_{ws}
Order ID	Task ID	Product	Quantity	Job type	Quantity	Workshop
O_1(2769096)	Ta_{11}(GT201)	Pr_{111}(JCA203)	9	Billet-L-01	3	W_1 (Moulding)
				Die-JCA203	1	W_2 (Extrusion die)
				Profile-JCA203	9	W_3 (Extrusion)
	Ta_{12}(GT206)	Pr_{121}(DTG301)	20	Billet-S-06	5	W_1 (Moulding)
				Die-DDG307	2	W_2 (Extrusion die)
				Profile-DDG307	20	W_3 (Extrusion)
		Pr_{122}(JCB012)	12	Billet-S-06	4	W_1 (Moulding)
				Die- JCB012	2	W_2 (Extrusion die)
				Profile- JCB012	12	W_3 (Extrusion)
O_2(2769097)	Ta_{21}(HD307)	Pr_{211}(JCA206)	9	Billet-S-01	3	W_1 (Moulding)
				Die-JCA206	1	W_2 (Extrusion die)
				Profile-JCA206	9	W_3 (Extrusion)
		Pr_{212}(JCA203)	9	Billet-L-01	3	W_1 (Moulding)
				Die-JCA203	1	W_2 (Extrusion die)
				Profile-JCA203	9	W_3 (Extrusion)
	Ta_{22}(HD603)	Pr_{221}(GZL603)	15	Billet-L-01	5	W_1 (Moulding)
				Die-GZL603	2	W_2 (Extrusion die)
				Profile-GZL603	15	W_3 (Extrusion)

Table 3
Process in the aluminium extrusions manufacturing system.

Process		Type	Machine group		Energy category	Workshop	
Furnace preparation	T^1_{11}	A	Furnace	M^1_1	Gas	Billet moulding	W_1
Melting	T^1_{12}	B	Furnace	M^1_1	Gas	Billet moulding	W_1
Refining	T^1_{21}	C	Finery	M^1_2	Electricity	Billet moulding	W_1
Casting	T^1_{31}	A	Moulding chamber	M^1_3	Electricity	Billet moulding	W_1
Homogenisation	T^1_{41}	B	Homogenising furnace	M^1_4	Electricity	Billet moulding	W_1
Machining	T^2_{11}	A	Machine tool	M^2_1	Electricity	Die machining	W_2
Wire cutting	T^2_{21}	A	Linear cutting machine	M^2_2	Electricity	Die machining	W_2
Thermal treatment	T^2_{31}	B	Ageing oven	M^2_3	Electricity	Die machining	W_2
Billet preheating	T^3_{11}	C	Billet heating furnace	M^3_1	Gas	Extrusion	W_3
Die preheating	T^3_{21}	C	Die heating furnace	M^3_2	Electricity	Extrusion	W_3
Cut & extrusion	T^3_{31}	A	Extrusion machine	M^3_3	Electricity	Extrusion	W_3

Table 4
Jobs of product Pr_{111} (2769096- GT201- JCA203).

Job type	Job
Billet-L-01	$J^1_{1111}, J^1_{1112}, J^1_{1113}$
Die-JCA203	J^2_{1111}
Profile-JCA203	$J^3_{1111}, J^3_{1112}, J^3_{1113}, J^3_{1114}, J^3_{1115}, J^3_{1116}, J^3_{1117}, J^3_{1118}, J^3_{1119}$

4.3. Energy informatisation on manufacturing element dimensions

To monitor energy usage information of each element, an energy model is required to map the energy consumption data to each manufacturing element dimensions. In aluminium extrusions manufacturing system, an extensible amount of manufacturing elements set $\{h_\delta\}$ includes: job element h_j, product element h_p, production task element h_t, order element h_o, process element h_r, machine element h_m, the machine group element h_u, workshop element h_{ws}. The relationship between the information content $V(h_\delta)$ of these elements are: $V(h_o) \subseteq V(h_t) \subseteq V(h_p) \subseteq V(h_j)$, $V(h_{ws}) \subseteq V(h_u) \subseteq V(h_m)$.

M_{space} is considered as an extensive mapping coordinate space, which is given as equation (12).

$$M_{space} = diag(h_1, h_2, \ldots, h_\delta, \ldots, h_D) \tag{12}$$

where *diag* denotes diagonal matrix and h_δ indicates a manufacturing element. D is the number of dimensions. To map the energy consumption, an energy information filter model F_{map} is expressed as equation (13).

$$F_{map} = \left[H^1(h_1), H^2(h_2), \ldots, H^\delta(h_\delta) \ldots, H^D(h_D)\right] M_{space} \tag{13}$$

where $H^\delta(h_\delta)$ is the value of each dimension h_δ.

In an aluminium extrusions manufacturing system, M_{space} contains eight dimensions, represented as equation (14).

$$M_{space} = diag(h_o, h_t, h_p, h_j, h_{ws}, h_u, h_m, h_r) \tag{14}$$

Based on the relationship of manufacturing elements, ε_ζ and $P_{Event}(\varepsilon_\zeta)$ are equivalently transformed as equation (15) (16) and (17).

$$\varepsilon_\zeta = \left\{J^w_{ilqp}, M^w_{kj}, T^w_{kb}\right\} \Leftrightarrow \left\{O_i, Ta_{il}, Pr_{ilp}, J^w_{ilqp}, W_w, M^w_k, M^w_{kj}, T^w_{kb}\right\} \tag{15}$$

$$\varepsilon_\zeta = \left\{J^w_{ilqp}, M^w_{kj}, T^w_{kb}\right\} \Leftrightarrow [i, l, p, q, w, k, j, b] M_{space} \tag{16}$$

$$\begin{aligned} & P_{Event}(\varepsilon_\zeta) \Leftrightarrow P_{Event}([i, l, p, q, w, k, j, b] M_{space}) \\ & = \{S(\varepsilon_\zeta), C(\varepsilon_\zeta), K_E(\varepsilon_\zeta), C^e(\varepsilon_\zeta)\} \end{aligned} \tag{17}$$

F_{map} is represented as equation (18).

$$F_{map} = \left[H^1(h_o), H^2(h_t), H^3(h_p), H^4(h_j), H^5(h_{ws}), H^6(h_u), H^7(h_m), H^8(h_r)\right] M_{space} \tag{18}$$

define all the production events belong to a domain P^N_{Event}. The total consumption $C^e(t_1 \sim t_2, F_{map}, F_E)$ of the energy category filter F_E for an energy information filter model F_{map} in a certain period $t_1 \sim t_2$ is calculated as equation (19). The constraint condition can be expressed as equation sets (20).

$$C^e(t_t \sim t_2,\ F_{map},\ F_E) = \sum_{P_{Event(\varepsilon_\zeta)} \in P^N_{Event}} C^e(\varepsilon_\zeta) \tag{19}$$

$$\text{Subject to}[S(\varepsilon_\zeta),\ C(\varepsilon_\zeta)] \subseteq [t_1, t_2], K_E(\varepsilon_\zeta) = F_E, [i, l, p, q, w, k, j, b] \subseteq \left\{\left[H^1(h_o), H^2(h_t), H^3(h_p), H^4(h_j), H^5(h_{ws}), H^6(h_u), H^7(h_m), H^8(h_r)\right]\right\} \tag{20}$$

Fig. 5 is illustrated the self-mapping process of energy consumption information on multiple manufacturing element dimensions.

5. Case study: application in refined energy cost accounting

To demonstrate the application of the proposed supply-side energy modelling, we adopted it for energy cost accounting in an aluminium extrusions workshop of a company in Guangdong Province, China. It has an urgent need for refined energy cost accounting. In the current method, energy cost is apportioned evenly on each order, while the specific energy consumption can be a big difference for various shapes of products (Ajiboye and Adeyemi, 2007). Following the requirements of the company, the data has been adjusted due to confidential and sensitivity concerns.

1) Order and task arrangement.

At 9:30, 9th Sep 2019, aluminium profile orders are released. The production tasks for each workshop of an order are issued based on the MBOM, as shown in Table 2. In this process, product information h_p establishes the mapping relationship with production task information h_t and order information h_o. The h_j-h_p-h_t-h_o relationship information is then created.

2) Each part, as well as its WIP, is regarded as a job. All the jobs are scheduled by existing algorithms, and the related Gantt charts are generated. In this process, the elements of P_{Event} except for energy consumption amount C^e can be acquired, including the starting and completion moments of jobs, the choice of machines for jobs, the current process, and the energy category.
3) The three process modes A (EDP), B (ECP with jobs synchronously processed), and C (ECP with jobs non-synchronously processed), are listed in Table 3.
4) To calculate the energy cost of an order, the energy cost of the product should be first calculated. Take the product Pr_{111} (2769096- GT201- JCA203) as an example, three units Pr_{111} need to be processed. Based on the MBOM, three units of Billet-L-01,

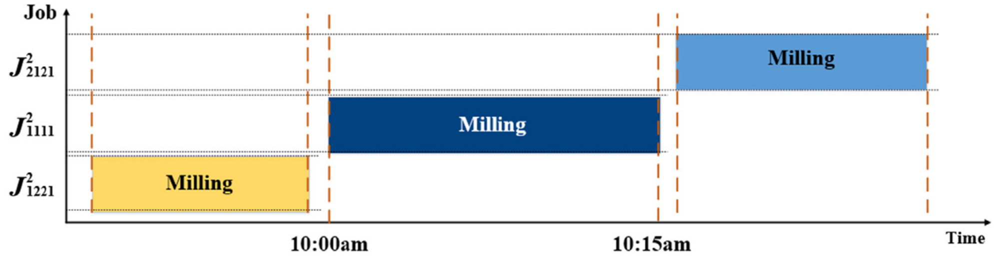

Fig. 6. The Gantt chart of M^2_{12}

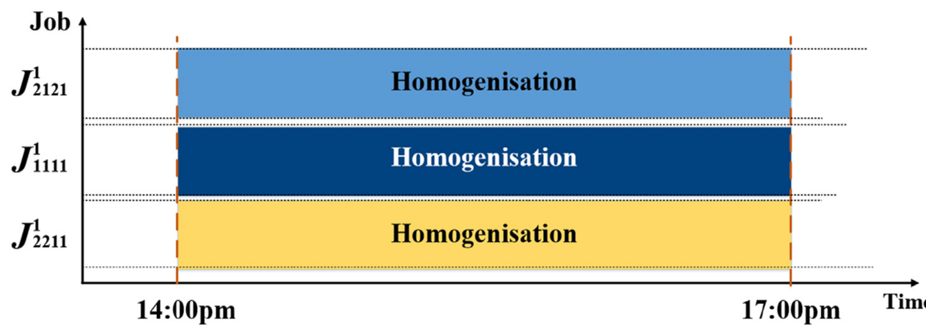

Fig. 7. The Gantt chart of M^1_{41}

one unit of Die-JCA203 and three units of Profile-JCA203 are assigned as jobs, see Table 4.

Choose feasible C^e mathematical models for each job on the related process. Calculation example is demonstrated for three process modes under a given scheduling scheme.

1 For J^2_{1111}'s machining process on M^2_{12} in die machining workshop, the Gantt chart is illustrated as Fig. 6.

Jobs on a machine tool are processed one by one, and the energy consumption model is $C^e_{ModeA}(\varepsilon_\zeta)$. The starting moment and completion moment are at 10:00, 9th Sep 2019 and 10:15, 9th Sep 2019, respectively. Energy values on the electricity meter of M^2_{12} at 10:00 is 325.6 kW•h and 328.8 kW•h. The energy consumption consumed by the job J^2_{1111} on machine M^2_{12} is 3.2 kW•h, and the production event can be presented as equation (21).

$$P_{Event}\left(J^2_{1111}, M^2_{12}, T^2_{11}\right) = \{10{:}00, 9\ \text{Sep}\ 2019,\ 10{:}15, 9\ \text{Sep}\ 2019,\ \text{Electricity}, 3.2\} \tag{21}$$

2 For the homogenisation process of J^1_{1111}'s on M^1_{41} in billet moulding workshop, the Gantt chart is illustrated as Fig. 7.

Three jobs are homogenised at the same time, and the energy consumption model is $C^e_{ModeB}(\varepsilon_\zeta)$. The starting moment and completion moment are at 14:00, 9th Sep 2019 and 17:00, 9th Sep 2019, respectively. Energy values on the electricity meter of M^1_{41} at 14:00 and 17:00 is 11829.3 kW•h and 12653.7 kW•h. The weight ratio of J^1_{2211}, J^1_{1111} and J^1_{2121} is 1:2:1, the energy consumption consumed by the job J^1_{1111} on machine M^1_{41} is 412.2 kW•h and the

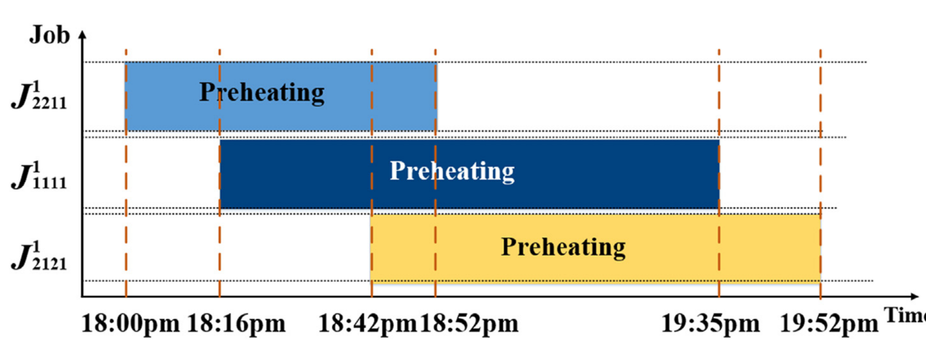

Fig. 8. The Gantt chart of M^3_{12}

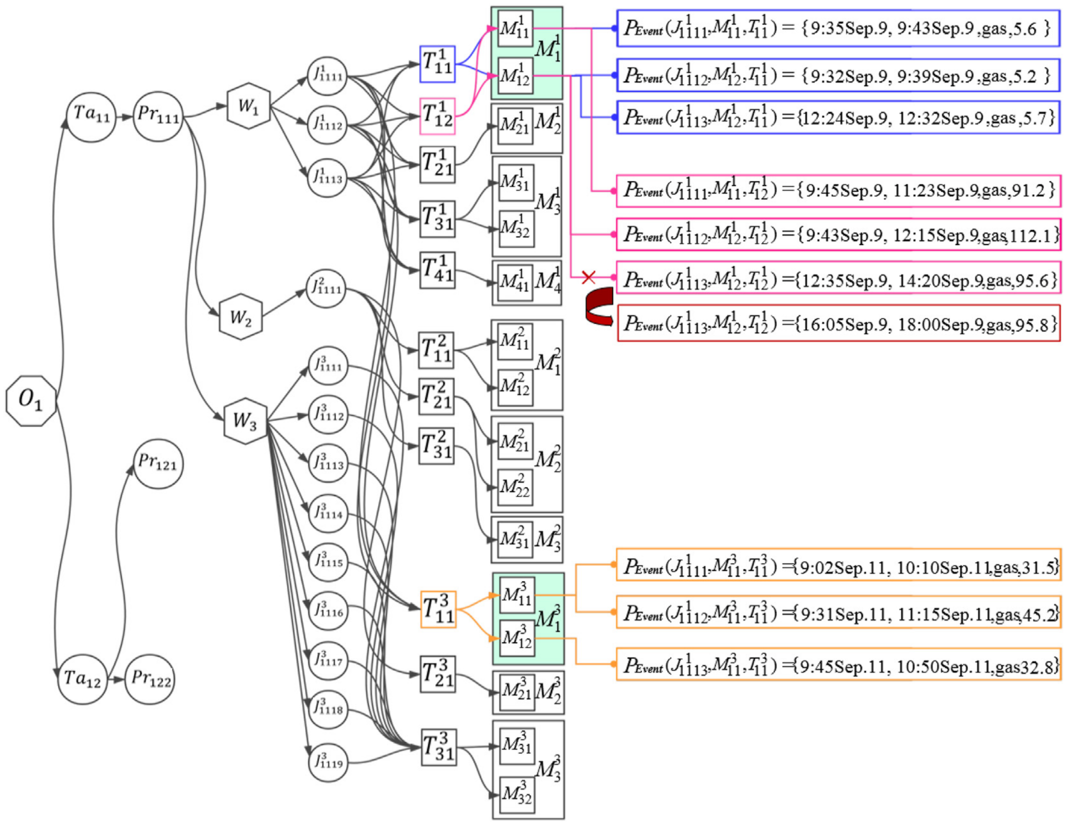

Fig. 9. The generation process of production events and the selection of gas energy event for Pr_{111}

production event can be presented as equation (22).

$$P_{\text{Event}}\left(J^1_{1111}, M^1_{41}, T^1_{41}\right) = \{14{:}00, 9\ \text{Sep}\ 2019, 17{:}00, 9\ \text{Sep}\ 2019, \text{Electricity}, 412.2\} \tag{22}$$

③ For J^1_{1111}'s billet preheating process on M^3_{12} in extrusion workshop, the Gantt chart is illustrated as Fig. 8.

Multiple jobs are preheated on the M^3_{12} and non-synchronously processed, and the energy consumption model is $C^e_{ModeC}(\varepsilon_\zeta)$. During the processing, there are two other jobs J^1_{2121} and J^1_{2211} sharing the machine with J^1_{1111}. The gas meter values are 1250.8 m^3, 1268.6 m^3, 1276.8 m^3, 1306.8 m^3, at 18:16, 18:42, 18:52 and 19:35, 9th Sep 2019. The weight ratio of J^1_{2211}, J^1_{1111} and J^1_{2121} is 1:2:1, the energy consumption consumed by the job J^3_{1111} on machine M^3_{12} is 36.0 m^3, and the production event can be presented as equation (23).

$$P_{Event}\left(J^3_{1111}, M^3_{12}, T^3_{11}\right) = \{18{:}16, 9\ \text{Sep}\ 2019, 19{:}35, 9\ \text{Sep}\ 2019, \text{Gas}, 36.0\} \tag{23}$$

5) The production events of all jobs on each machine and each process are obtained. The unit price of energy can be constant or fluctuant under different energy tariff. In some district, the unit price of energy is time-of-use or gradient pricing. However, it is not logical to consider the specific cost of the job by the above strategies for the unit price. In this case, the unit price of all the energy should be the average unit price γ_{K_E}, where K_E is the category of energy. γ_{gas} is 3.45 CNY per cubic meter and $\gamma_{electricity}$ is 0.72 CNY per kW·h. The cost $Acc(P_{Event}(\varepsilon_\zeta))$ of $P_{Event}(\varepsilon_\zeta)$ can be calculated as equation (24), and $K_E(\varepsilon_\zeta)$ should be the same as K_E.

$$Acc(P_{Event}(\varepsilon_\zeta)) = \gamma_{K_E} * C^e(\varepsilon_\zeta) \tag{24}$$

6) To figure out the energy cost of each manufacturing element dimensions, including product, task and order, the mapping model is required to be applied. Take the gas cost accounting of Pr_{111} from 9th Sep 2019 9:30 to 9th Oct 2019 9:30 as an example, the information filter F_{map1} can be represented as equation (25).

$$F_{map1} = (1, 1, 1, \Omega_j, \Omega_{ws}, \Omega_u, \Omega_m, \Omega_r) M_{space} \tag{25}$$

$\Omega_j, \Omega_{ws}, \Omega_u, \Omega_m$ and Ω_r represent the universal set of job, workshop, machine unit, machine and process. The gas cost of Pr_{111} can be calculated as Acc (F_{map1}). The energy consumption is calculated as equation (26), and the constraint conditions are expressed as equation sets (27).

$$C^e(t_1 \sim t_2, F_{map1}, Gas) = \sum_{P_{Event}(\varepsilon_\zeta) \in P^N_{Event}} C^e(\varepsilon_\zeta) \tag{26}$$

$$\begin{aligned} \textit{Subject to}[\mathrm{S}(\varepsilon_\zeta),\ \mathrm{C}(\varepsilon_\zeta)] \subseteq [&9:30, 9\ \mathrm{Sep}\ 2019,\\ &9:30, 9\ \mathrm{Oct}\ 2019],\\ &K_E(\varepsilon_\zeta) = Gas, [i,l,p,q,w,k,j,b]\\ &\subseteq \{[1,1,1,\ \Omega_j, \Omega_{ws}, \Omega_u, \Omega_m, \Omega_r]\} \end{aligned} \tag{27}$$

The generation process of production events and the selection of gas energy event for Pr_{111} are illustrated in Fig. 9. Three process T^1_{11}, T^1_{12} and T^3_{11} are gas-supplied. J^3_{1111} is processed twice on T^1_{12} for quality reason, and it generated two related production events. Gas consumption of Pr_{111} is the total gas consumption of its related jobs on processes T^1_{11}, T^1_{12} and T^3_{11}. Calculated by equations (26) and (24), the gas consumption of Pr_{111} is 520.7 m^3 and the gas cost is 1796.42 CNY.

6. Conclusions

Supply-side energy is usually larger than theoretical energy demand during the processing of a job with the implication of unnecessary loss. Thus, it is essential to manage supply-side RECI to quantify and optimise the energy-saving potential of jobs. Based on existing methods, job-specified energy is roughly evaluated by apportioning energy consumption of machines evenly or by a weighted coefficient, which cannot reflect differences in real-life practice. Aiming to automatically acquire refined job-specified supply-side RECI, this paper proposes a supply-side energy modelling method for MMS and studies an aluminium extrusions manufacturing system as the case. In this modelling method, a concept of a production event is proposed to describe the energy consumption information. To obtain the energy consumption of each production event in different process modes, three energy consumption models are developed. Then, energy information on multiple manufacturing element dimensions is calculated based on the models. Finally, a case study on refined cost accounting demonstrates the feasibility of the proposed method. The energy cost can be evaluated in the eight manufacturing dimensions. The main contribution of this paper is to support job-specified refined quantification of energy consumption, evaluation of environmental impacts, energy cost accounting, etc. The implications and limitations are further discussed.

6.1. Managerial implications

The proposed method provides a refined data foundation to quantitatively support management. The implications include but are not limited to:

(1) Quantification and optimisation of processing energy-related impact

Based on the RECI, the energy-related cost accounting and environmental impact of each job on each process can be quantified and evaluated. The energy-saving potential of each process can be illustrated clearly by comparing supply-side RECI with theoretical energy demand. Meanwhile, the RECI of jobs on different types of machines is obtained and compared to support machine selection. For example, three types of furnace can be chosen in the melting process, including gas furnace, electric furnace and coal furnace. Diverse energy supply resource brings different environmental impacts and production rates. According to management demand, decision-makers can choose feasible machines based on supply-side energy information. Furthermore, by connecting RECI with other processing data, process strategies and processing parameters can be optimised to meet the production and sustainability targets.

(2) Quantification for cleaner production responsibility of each execution unit

For a company to achieve overall sustainability targets, it is essential to delegate the target to each execution unit. The energy consumption of jobs in each execution unit, such as production cell, workshop, or department, can be quantified. The performance of energy-saving and the environmental impact of each execution unit is evaluated for comparison, contributing to responsibility tracking. It should be noted that it is not reasonable to directly compare the supply-side energy consumption without considering specific jobs since the demand-side energy consumption of jobs is different in each execution unit.

(3) Providing sustainability data in supporting the two-way choice among vendors and customers

The supply-side RECI provides a two-way-choice sustainability data basis for both vendors and customers. For customers, with the detailed quantified energy usage information of each job, the transparency of energy cost is delivered. Meanwhile, the energy cost and environmental impact of the same product can be compared among vendors. Customers hold the opportunity to select favourite vendors whose sustainability performance is more consistent with their brand or business strategy. For vendors, this could incentivise technology development toward reducing specific energy consumption. The proposed model provides a method to assist vendors in evaluating the energy consumption for each of their products.

6.2. Limitations

These developed models for RECI are not limited to aluminium extrusions manufacturing system but can be generalised to workshops with similar process traits, including EDP and ECP where the energy consumption is specified to jobs based on weight proportion. However, when it comes to a process where energy consumption is specified based on other indicators, such as surface area, ECP models are not applicable. Besides, it is noted that the reliability of the proposed approach depends on the timeliness and accuracy of sensor devices. It is also less effective if IIoT infrastructure is not fully in place. In future, more fine-grained energy data will be considered. For example, the energy consumption of each stage in one process can be monitored, which can provide refined data to support stage-wise optimisation.

CRediT authorship contribution statement

Chen Peng: Writing – original draft, Methodology, Conceptualization. **Tao Peng:** Supervision, Validation, Writing – review & editing. **Yang Liu:** Supervision, Validation, Writing – review & editing. **Martin Geissdoerfer:** Writing – review & editing. **Steve Evans:** Writing – review & editing, Conceptualization. **Renzhong Tang:** Project administration, Funding acquisition.

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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