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Task-driven data fusion for additive manufacturing: Framework, approaches, and case studies

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ABSTRACT

Additive manufacturing (AM) has been envisioned as a critical technology for the next industrial revolution. Due to the advances in data sensing and collection technologies, a large amount of data, generated from multiple sources in AM production, becomes available for relevant analytics to improve process reliability, repeatability, and part quality. However, AM processes occur over a wide range of spatial and temporal scales where the data generally involves different types, dimensions and structures, leading to difficulties when integrating and then analysing. Hence, in what way and how to integrate the heterogeneous data or merge the spatial and temporal information lead to significant challenges in data analytics for AM systems. This paper proposed a task-driven data fusion framework that enables the integration of heterogeneous data from different sources and modalities based on tasks to support decision-making activities. In this framework, the data analytics activities involved in the task are identified in the first place. Then, the data required for the task is identified, collected, and characterised. Finally, data fusion techniques are employed and applied based on the characteristics of the data for integration to support data analytics. The fusion techniques that best fit the task requirements are selected as the final fusion approach. Case studies on different research directions of AM, including AM energy consumption prediction, mechanical properties prediction of additively manufactured lattice structures, and investigation of remelting process on part density, were carried out to demonstrate the feasibility and effectiveness of the proposed framework and approaches.

1. Introduction

Additive manufacturing (AM) is a manufacturing paradigm that produces physical objects directly from computer-aided design (CAD) models by successively adding materials [1]. It has been recognised as one of the crucial technologies for the era of Industry 4.0 since it has great potential to provide mass customization, efficient supply chains, and decentralized and flexible production. Based on different process features (e.g., working principals, material supplies, state of fusion, etc.), AM processes are currently categorised into seven categories by ASTM standards [2], including powder bed fusion (PBF), material jetting (MJ), binder jetting (BJ), material extrusion (ME), sheet lamination (SL), directed energy deposition (DED), and vat photopolymerization (VP). However, limited material choices, low repeatability and reliability, and lack of standards for design and qualification [3] are the major drawbacks that prevent the widespread adoption of AM technologies in industries. The difficulties in understanding fundamental mechanisms and identifying the latent factors that influence AM processes build up barriers to in-depth research in AM. Therefore, improving decision-making activities for the enhancement of AM process performances and product quality becomes critical challenges.

The integration of advanced data sensing and collection technologies in AM systems has enabled exponential growth of data, providing unprecedented opportunities for understanding the nature of AM processes and uncovering hidden knowledge [4]. In recent years, with the rapid development of advanced data analytics tools (e.g., machine learning technologies), data-driven methods have increasingly played important

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roles in decision support for solving AM issues. Nonetheless, the majority of existing studies focus on the performance of using different data analytics models for tackling a few typical AM issues while what data to be considered in the models and how to deal with the data have not been extensively discussed and explored. This urges in-depth investigations of the guidelines for AM data management, integration, and analytics, especially in the increasingly data-rich environment of AM industries. In general, a typical AM process normally includes six phases, AM design generation, process planning (e.g., determining orientation, adding support structure, etc.), process parameter setting (e.g., slice, scan patterns, etc.), part building, post-process treatment, and part qualification. The data generated during each phase can contain crucial information related to the process stability and part quality. It's essential to take the data from multiple sources or modalities into consideration. However, this multi-source data is normally heterogeneous (e.g., signals, images, geometries), multi-dimensional, and multi-hierarchical, leading to difficulties in integration, especially when high-speed and high-dimensional data is presented [5,6]. Realizing the full potential of data analytics for digging out critical knowledge from massive volumes of AM data with various modalities will significantly improve the process stability, repeatability, and product quality, and ultimately facilitate the development of AM industries [7,8].

This paper proposes a task-driven data fusion framework that provides guidelines when integrating heterogeneous data from various sources or modalities to support decision-making for AM. The contributions of this work are highlighted as follows.

- This study proposes a systematic way to identify, collect, characterise, and fuse the data to support data analytics for AM tasks.
- Based on the levels (layer-level and build level) of the target value to be obtained, guidelines were introduced for integrating data with different sources, dimensions, and modalities.
- Based on the framework, different fusion approaches were proposed to tackle challenging AM issues.

The remaining of this paper is organised as follows. Section 2 reviews the categories of AM data, studies of data analytics for AM tasks, and applications of data fusion techniques in AM. Section 3 introduces the proposed task-driven data fusion framework where 3 critical steps are included, i.e., (1) identifying analytics activities of tasks; (2) data acquisition and characterization; and (3) leveraging data fusion techniques based on task requirements and data characteristics. In Section 4, three case studies that focus on different research directions were carried out to demonstrate the feasibility and effectiveness of the proposed framework and approaches.

2. Related works

2.1. Categories of AM data

The advancement of sensing and storage technologies has led to the data-intensive environment of AM systems where a large amount of production information can be captured, stored, and leveraged. Normally, AM data is continuously generated from the part design phase to the final part validation phase, the attributes of which involve various types, structures and dimensions. Sayyeda et al., [9] characterised AM data from different perspectives, including volume, velocity, and variety. From the volume perspective, terabytes (TB) size of monitoring data and computed tomography (CT) scan data can be generated for each build. The velocity of data depends on the sampling rates of sensors and machine log frequencies. For the variety aspect, various data types are generated per build, such as sensor signals, machine logs, images, CAD models, CT scan data, thermal videos, etc. Hyunseop et al., [10] defined 6 types of AM data, including material properties, design parameters, process parameters, process signatures, part properties, and product performance. For example, in material properties, information on material chemistry and powder size distribution is included. To systematically manage and analyse the data generated from design to final product, the end-to-end digital spectrum of AM was categorized by Duck Bong et al., [11] into 8 phases. The first phase is the part geometry which deals with the information created during part design. Materials are also selected in phase 1. The second phase and third phases are defined as tessellated data and tessellated 3D models respectively where usable geometries are created from raw data. Followed by the fourth phase build file, the fifth phase machine data, the sixth phase fabricated part, seventh phase finished part, and eighth phase validated part. Information of post-processing and mechanical testing on the fabricated parts are included in phases 7 and 8 respectively. Particularly targeted at the metal powder bed fusion process, the study [12] also mentioned data categories which are separated into 3 subsections, feedstock materials, and in-situ and ex-situ measurements.

Previous studies have categorized AM data from different perspectives with different focuses, however, most of them aim for the ease of data storage and management. To be closely linked to data analytics, this paper classifies AM data into three major categories, process-input data, process-generated data, and validation data, based on the sequence of the stages (from part design to final part validation) in an AM process. Each category involves several stages of the whole process.

1) Process-input data: process-input data represents the data and information that are generated before the manufacturing process begins, including design data, process planning data, and parameter setting data. Examples of each sub-category are listed as follows.
   - Design data: part geometries and material information (e.g., material chemistry, particle size distribution, etc.) are included.
   - Process planning data: path planning, part orientation, location, etc.
   - Parameter setting data: scan speed, voltage, scan width, etc.
2) Process-generated data: process-generated data consists of two parts, the data generated during the manufacturing process, and the data generated during the post-process treatment. During the manufacturing process, sensing and measuring technologies (e.g., multiple sensors, high-speed cameras, etc.) are employed for capturing in-process signatures (e.g., melt pool state, temperature, etc.).
   - Process monitoring data: voltage, current, temperature, gas rate, acoustic signals, optical emission, multi-sensor signals, melt pool images, etc.
   - Post-process data: near-net-shape (NNS) part properties, heat treatment, milling, etc.
3) Validation data: the produced products are validated by various testing methods where testing data is generated (e.g., CT scan data, tensile strength, hardness, fatigue life, etc.). Besides, information such as material waste, time cost, and energy consumption, is collected.

2.2. Machine learning & advanced data analytics for AM tasks

Data analytics is increasingly crucial to help engineers or technicians make decisions for tackling critical issues such as energy efficiency improvement, product quality enhancement, and waste reduction, in manufacturing industries. To achieve specific objectives for AM production, it is essential to identify what tasks are involved and then what data analytics activities should be required. These steps are normally done by experienced AM engineers and data scientists [13]. For example, to reduce the porosity of the manufactured parts, tasks such as process parameter optimisation or in-situ monitoring can be involved. In this case, the goal of data analytics is to infer where the porosities possibly form based on the collected information (e.g., process parameters, sensor signals, etc.) and provide actionable insights for decision-makers. Identifying data analytics activities for tackling AM tasks is hard as it lacks systematic methods specifically for AM. Some researchers have made efforts to explore this. Hyunseop et al., [10] introduced a five-tier taxonomy, i.e., "Value Tier", "Decision-Making Tier", "Data Analytics Tier", "Data Tier", and "Data-Source Tier", to identify and prioritize data analytics opportunities in AM. In this classification, the target values are defined in the "Value Tier" in terms of quality, cost, and delivery. The decision-making activities for data analytics are obtained from the "Decision-Making Tier" by using the integration definition for function modelling (IDEF0) [14] where the activities are defined by function models or ICOMs (input (I), control (C), output (O), mechanism (M)). Based on the predefined values and decision-making activities, the decision-making objectives can be represented by using the statement "Improving + [value] + when + [decision-making activity]". Accordingly, the potential data analytics problems corresponding to the objectives are identified in "Data Analytics Tier". As an extension of this study, a data analytics opportunity knowledge (DOKB) base was developed in [13] where AM activity-specific data analytics tasks were defined by experts.

Typically, data analytics problems are classified into 4 types [15,16], descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Each type of analytics answers different types of questions. Descriptive analytics answers the questions of what happened. Diagnostic analytics is for answering why it happened. Predictive analytics is to figure out what and when will happen. Prescriptive analytics aims to answer the question of what strategies should be applied. The explosive availability of data in AM industries has motivated the transformation from traditional analysis methods to advanced data analytics for decision-making. The past decade has witnessed the rise of the adoption of machine learning (ML) technologies for smart manufacturing. As powerful data analytics tools for processing, interpreting, and leveraging data, ML technologies have played a central role in supporting decision-making for tackling AM issues in recent years [17–19]. Statistical learning approaches such as principal component analysis (PCA), and partial least squares (PLSs) have been primarily adopted for handling small-sample problems [20]. With the emergence of deep learning techniques (e.g., convolutional neural network (CNN)), massive data can be effectively processed and leveraged for handling a variety of AM tasks. Hence, data analytics has been extensively applied to AM research for knowledge discovery and decision support, including

Table 1
Studies of applying ML and advanced data analytics for tackling AM tasks in recent 5 years.

Existing studies	Publication year	AM process	AM task	Algorithms	Type of data analytics
DeCost, et al. [22]	2017	Metal AM	Autonomous characterisation of powder feedstocks	PCA, *k*-means, support vector machine (SVM)	Descriptive analytics
Akbari, et al. [23]	2022	Metal AM	Predicting melt pool characteristics for metal AM	Gaussian process model, SVM, linear regression, artificial neural network (ANN), gradient boosting trees	Predictive analytics
Vrábel, et al. [24]	2019	PBF	Material classification	PCA, SVM	Predictive analytics
Fathizadan, et al. [25]	2021	PBF	Real-time melt pool states defect detection	Convolutional auto-encoder (CAE), agglomerative clustering, statistics	Predictive analytics
Bugatti, et al. [26]	2021	PBF	Defect detection for local overheating phenomena	*k*-means, SVM, ANN	Predictive analytics
Ye, et al. [27]	2018	PBF	In-situ monitoring for melt pool state recognition	Deep belief network	Predictive analytics
Montazeri, et al. [28]	2020	PBF	Monitoring of porosity using optical emission spectroscopy	PCA, *k*-nearest neighbours (*k*-NN), SVM, etc	Predictive analytics
Kusano, et al. [29]	2020	PBF	Tensile properties prediction	Random forests (RFs), multiple linear regression	Predictive analytics
Scime, et al. [30]	2018	PBF	Autonomous spreading anomalies detection and classification	CNN	Predictive analytics
Meng and Zhang. [31]	2020	PBF	Prediction of the remelted depth of single tracks to assist the process design and optimization in the laser PBF (LPBF) process	Gaussian process-based model	Predictive analytics
Xin, et al. [32]	2020	PBF	Detecting imprinted internal porosity of AM stainless steel based on thermal tomography	*k*-means singular value decomposition (*k*-SVD)	Predictive analytics
Fischer, et al. [33]	2022	PBF	Detecting and classifying the powder bed inhomogeneities	CNN	Predictive analytics
Andy, et al. [34]	2022	PBF	Image synthesis for dynamic X-Ray radiography of in-situ selective laser melting (SLM) process	Conditional generative adversarial networks (GAN)	Predictive analytics
Gong, et al. [35]	2022	PBF	Building process-structure-property linkages for machining behaviour of Ti-6Al-4V	Extreme gradient boosting (XGBoost), linear regression	Predictive analytics
Liu, et al. [36]	2022	PBF	Online predicting the layer-wise 3D surface morphology in AM	CNN	Predictive analytics
Yao, et al. [37]	2017	PBF	Design feature recommendation during the conceptual design phase	Agglomerative clustering, SVM	Prescriptive analytics
Ko, et al. [38]	2021	PBF	AM design rule construction	Decision tree	Prescriptive analytics
Roy, et al. [39]	2020	ME	Modelling of thermal profiles	ANN	Predictive analytics
Alejandrino, et al. [40]	2020	ME	Design of lattice infill pattern for increasing material efficiency	ANN	Prescriptive analytics
Wang, et al. [41]	2018	MJ	In-situ droplet inspection and closed-loop control	ANN	Prescriptive analytics
Nguyen, et al. [42]	2020	DED	Tool path planning strategy for rib-web structures	ANN	Prescriptive analytics
Li, et al. [43]	2023	DED	Automatic real-time defect detection for the wire arc AM (WAAM) process	You only look once, version 4 (YOLOv4)	Predictive analytics
Huang, et al. [44]	2019	General AM	Support structure detection	CNN	Prescriptive analytics
Hertlein, et al. [45]	2021	General AM	Topology Optimization for early-design stage	Conditional GAN	Prescriptive analytics

material characterisation, classification and selection, design for AM (DfAM), monitoring and defect detection, process modelling and control, and sustainability [8,21]. The following Table 1 has summarized typical studies of applying advanced data analytics and ML techniques for tackling different AM tasks in the recent 5 years. As shown in Table 1, in recent years, most studies have been focusing on process monitoring and defect detection tasks in AM where predictive and prescriptive analytics are the major data analytics types involved.

2.3. Data fusion techniques in AM

Data fusion has different definitions and architectures as it is a multidisciplinary field that involves a wide range of domains. Therefore, data fusion techniques can be classified into different categories based on the relations between data sources, the abstraction level of data, the nature of input and output data, and the architecture types of the fusion system [46]. In general, data fusion is defined as a framework that combines data from several different sources and related information from associated databases to obtain improved accuracy and more reliable inferences than individual ones could achieve [47,48]. In recent years, benefiting from advanced sensing and Internet of Things (IoT) technologies, data fusion techniques have been increasingly applied in manufacturing industries, such as the aerospace industry, automotive industry, and additive manufacturing industry [49–51]. It is common for real-world manufacturing data to be massive, heterogeneous, and contain noise, which makes it difficult to combine data from multiple sources for joint analysis. In AM, researchers have explored using data fusion strategies and techniques for regression and classification tasks, such as process monitoring and defect detection, mechanical property prediction, and surface roughness prediction, which obtained considerable performances [52–56].

Due to the diversity and complexity of interactions during the AM process, process monitoring and defect detection are the most common application scenario of data fusion techniques. A fault diagnosis approach for fused deposition modelling (FDM) process states by using sensor data fusion was proposed by Kim et al. [52]. In this work, to classify process states, accelerometer and acoustic emission signals were collected in real-time from healthy and faulty states where features were extracted from raw signals. Then these features were used as inputs in the SVM model for process state classification. Zhang et al. [57] introduced a registering and fusion method for in-situ monitoring of the LPBF process based on sensor data. The signatures of melt pools were obtained from a coaxial high-speed camera and the spatial information of melt pools was collected by an off-axis camera system. Through perspective transformation and multi-thresholding filtering, the processed images were analysed by CNN where the spatial distribution of melt pools was retrieved and finally registered in both global and local coordinates systems. A long short-term memory (LSTM) neural network was used to fuse the melt pool signatures for predicting layer surface topography. Gaikwad et al. [58] also adopted data fusion strategies for flaw detection in the LPBF process where multiple process phenomena of melt pools were captured by video cameras and a temperature field imaging system. Key signatures of melt pools were extracted and used as inputs in ML models for detecting laser defocusing and predicting porosity levels. Deep learning algorithms are prevailing approaches for fusing data to obtain desired outputs and have been increasingly applied in AM systems, such as CNN and long-term recurrent convolutional networks (LRCN) for in-situ porosity detection based on multiple sensor data from melt pools [59], LSTM for tensile strength prediction based on in-process signatures and static factors [60], and CNN-LSTM for energy consumption prediction based on CAD models and process parameters [56]. In the study [60], the tensile strength of the parts manufactured by the FDM process was predicted based on the in-process signatures and static factors. Multiple sensors were employed to capture in-process signatures and interactions between layers. These signatures were then fused with static factors (e.g., material properties) for tensile strength prediction based on the LSTM model. In addition to the strategies of fusing features in models for obtaining desired outputs, decision fusion is also considered in AM studies. For example, Li et al. [55] introduced an approach for surface roughness prediction of the products produced by the FDM process based on ensemble learning. In this work, real-time sensor signals were collected from different sensors, including accelerometers, thermocouples, and infrared sensors. Time and frequency-domain features were extracted from sensor signals and used as inputs in different ML algorithms for training. An ensemble learning model was introduced to fuse the decision outputs from those base ML models for final surface roughness prediction. The experimental results show that the developed ensemble model outperformed the individual base models. Apart from multi-sensor signal fusion, fusion strategies and techniques are considered significant when dealing with heterogeneous data. Data with different dimensions, such as images and geometries, is commonly generated in AM systems but is difficult to be analysed precisely and integrated properly. Chen et al. [61] used in-situ point clouds to represent the geometries of the surface for defect identification in the DED process. In this work, the point cloud data was clustered by the density-based spatial clustering of applications with noise (DBSCAN) algorithm for separating the regions that potentially have defects (4 surface classes were obtained). Then the key features of the clustered point cloud were extracted and used as input into different ML algorithms for defect classification. Differently, Ma et al. [62] calculated the entropy of geometries to represent the solid and empty information of complex lattice structures. The entropy was fused with other parameters in the SVM model for final mechanical property prediction. To fuse multi-dimensional data for the DED process control [63], Vandone et al. proposed a data-driven approach for process modelling where the data collected from online and offline, including machine parameter settings, images of melt pools, sensor signals, 3D scan of geometries, were combined to estimate the performance of the developed process model. Data fusion techniques are also applied to refine data and improve the quality of data in AM research. For example, to enhance the quality of the reconstructed surface topography of the parts produced by the DED process, Zou et al. [64] proposed two data fusion methods, competitive data fusion and cooperative data integration. The confocal laser scanning microscopy (CLSM) and focus variation microscopy (FV) were used to acquire surface topography data. The CLSM was good at retaining the large shape features while FV was better in resolving small features. Therefore, the competitive data fusion method was used to integrate the advantages of CLSM and FV while cooperative data integration was aiming at including both the global and local details in a representation.

Based on previous studies above, data fusion technologies are beneficial in reducing dimensionality, refining data, and improving model performance, especially when dealing with multi-source and multi-dimensional data. Studies that adopted data fusion techniques for tackling AM issues in recent 5 years are summarised in Table 2. It can be seen from Table 2 that most studies employed ML-based techniques for data fusion to obtain desired outputs, especially in classification and regression tasks. In addition, considering the nature of collected data, LSTM algorithms are frequently employed for tackling sensor signals and CNN-based algorithms are typically adopted for processing image data. Clustering techniques are used in some studies when dealing with the feature or data refinement task, such as [61,65]. A few studies [64,66] dealt with the data scale and spatial issues in AM.

Owing to the advancement of data collecting and analysis technologies, data-driven methods and ML techniques have been increasingly employed to tackle AM issues. However, it lacks a systematic approach to identify what data should be collected for data analytics to support decision-making activities. This collected data is normally from different sources and has different dimensions, modalities, and structures, which is difficult to be jointly analysed. In addition, in what way to effectively uncover the hidden knowledge inside the data remains a challenging issue.

Table 2
The studies of applying data fusion for solving AM issues in recent 5 years.

Existing studies	Publication year	AM process	AM tasks	Data used in the study	Data fusion method
Kim et al., [52]	2018	ME	In-situ process state diagnosis	Multi-sensor signals	SVM
Li et al., [55]	2019	ME	Surface roughness prediction	Multi-sensor signals, surface roughness	SVM, RFs, ANN, Ridge regression
Zhang et al., [60]	2019	ME	Tensile strength prediction	Material properties, process parameters, sensor signals	LSTM
Zhang et al., [67]	2019	ME	Dynamic condition monitoring for 3D printer states	Multi-sensor signals	Sparse auto-encoders (SAE), LSTM
Lin et al., [66]	2019	ME	Online monitoring of overfill and underfill defects in the ME process	3D CAD models, 3D point cloud data	Scale-invariant feature transform
Xu, et al., [68]	2022	ME	Real-time in situ process defect detection	Acoustic emission, 3D point cloud data	SVM, Naïve Bayes, decision tree
Vandone et al., [63]	2018	DED	Process control for improving part quality	Sensor signals, melt pool images, 3D geometries, process parameters	Statistical process models
Chen et al., [61]	2021	DED	Automatic rapid surface defect detection	3D surface shapes	DBSCAN, *k*-NN
Grasso et al., [69]	2018	DED	Automatic process monitoring	Multi-sensor signals	Support vector data description (SVDD)
Zou et al., [64]	2022	DED	Improving the quality of the reconstructed surface tomography	3D surface tomographic data	Cooperative fusion, competitive fusion
Qin et al., [65]	2018	PBF	Energy consumption prediction for the selective laser sintering (SLS) process	3D CAD models, Multi-sensor signals, process parameters	*k*-means, ANN
Tian et al., [59]	2021	PBF	In situ porosity detection	Thermal images, pyrometer images, 3D X-ray CT scan data,	CNN, LRCN
Gaikwad et al., [58]	2022	PBF	Process monitoring for porosity-related flaws	Melt pool images, thermal signals, 3D X-ray CT scan data	*k*-means, CNN
Harbig et al., [70]	2022	PBF	Determine melt pool anomalies in Metal PBF process	Multi-sensor signals	Threshold filters

3. Framework and approaches of task-driven data fusion for AM

Challenges in the multi-source and heterogeneous data integration for data analytics in AM urge the development of systematic methods for guidance in terms of what data should be included and how to integrate it. This section introduces a task-driven data fusion approach that consists of 3 steps, including identification of task-driven data analytics, data required for tasks, acquisition, and characterization, and task-driven data fusion. The three-step approach provides guidelines for (1) the identification of data analytics activities and required data for the tasks, and (2) the fusion of multi-source data in data analytics for tackling different AM tasks. Fig. 1 illustrates the proposed framework. In the framework, the general AM process falls into 4 main stages, part design, process planning and setting, part building and post-treatment, and part qualification, which constitutes the x-axis of the figure. The y-axis is constituted by different categories of AM data. As described in Section 2.1, the general AM data (i.e., design data, process planning data, process parameter setting data, process monitoring data, post-

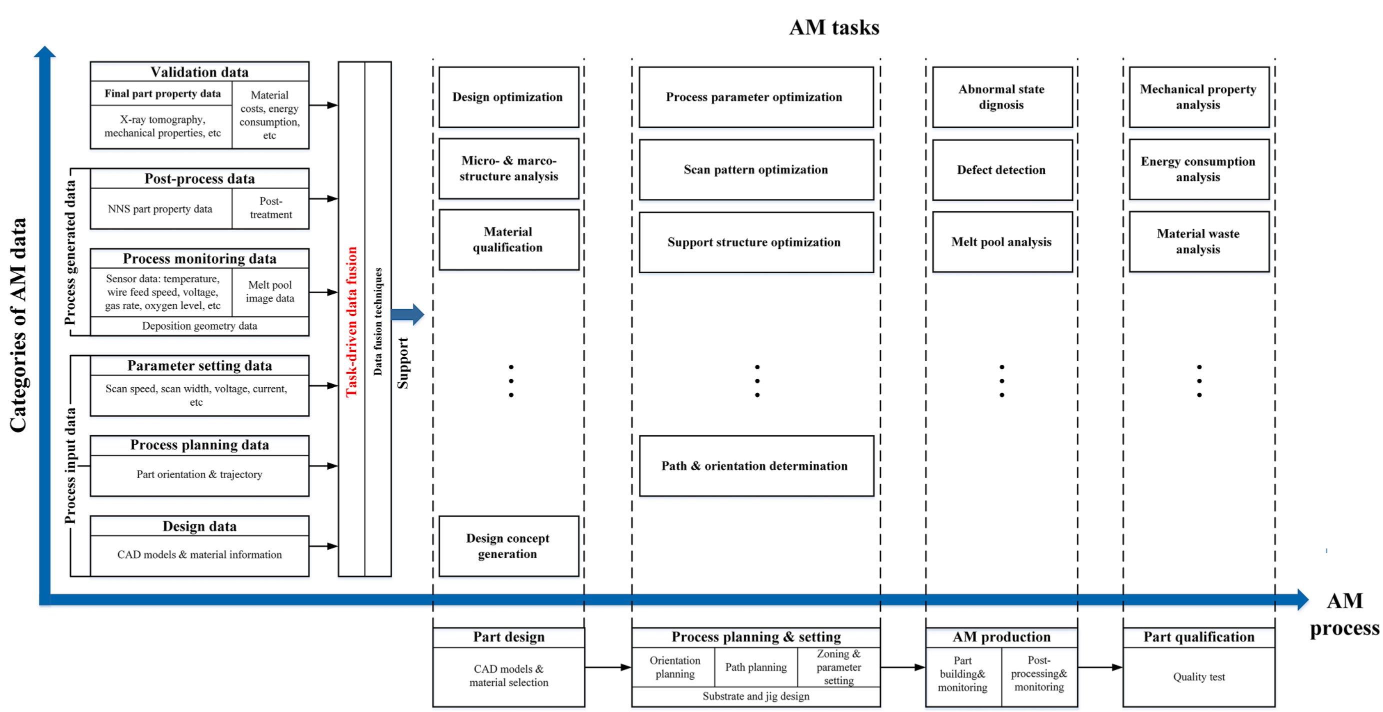

Fig. 1. The proposed task-driven data fusion framework for AM.

process data, and validation data) is classified into 3 main categories, process input data, process-generated data, and validation data. The maturity of the collected data and information increases vertically. Different AM tasks (e.g., design concept generation, defect detection, mechanical property prediction, etc.) are assigned into different blocks (with dashed lines) according to the stages they belong to. With the increase in the maturity of the collected information, the tasks become more diverse. The collected data and information are processed by the task-driven data fusion methodology for data analytics to support the tasks. The detailed demonstrations of the proposed methodology are presented in Fig. 2.

3.1. Identification of task-driven data analytics

In the first step, data analytics activities for AM tasks are identified by employing the method developed in the study [5]. The AM task is firstly defined by AM researchers or engineers and its target value (V) is defined in terms of quality, cost, and delivery or their extensions (e.g., specific indicators of the quality). Decision activities involved in the task can be represented by a set of components using Input (I), Control (C), Output (O), and Mechanism (M) [14]. Data, objects, or materials can be represented by inputs. They are transformed by the activity. Controls are the essential conditions to ensure that correct outputs are produced by the activity. The output is generated through the activity. Mechanisms are tools (e.g., equipment, software) that help execute an activity. Based on the predefined target value (V) and identified decision activities, the decision objective can be stated as "Conducting [decision-making activities] for improving/ maximising [V]". Accordingly, the types of data analytics activities (i.e., descriptive, diagnostic, predictive, and prescriptive analytics) can be identified. The example statements of different types of data analytics are presented as follows.

- Descriptive analytics: characterizing [V], [I], [C], [O], and [M].
- Diagnostic analytics: identifying the relationship between [ICOM] and [V].
- Predictive analytics: predicting [V] based on [ICOM]
- Prescriptive analytics: prescribing [C] for maximising [V]

3.2. Data required for tasks, acquisition, and characterization

3.2.1. Data required for tasks

Once the data analytics activities and corresponding types are identified, the data required for the analytics can be identified, collected and characterized in the second step. The connections between different types of data analytics are illustrated in Fig. 3. As shown in the figure, the lower-level data analytics supports the higher-level analytics while

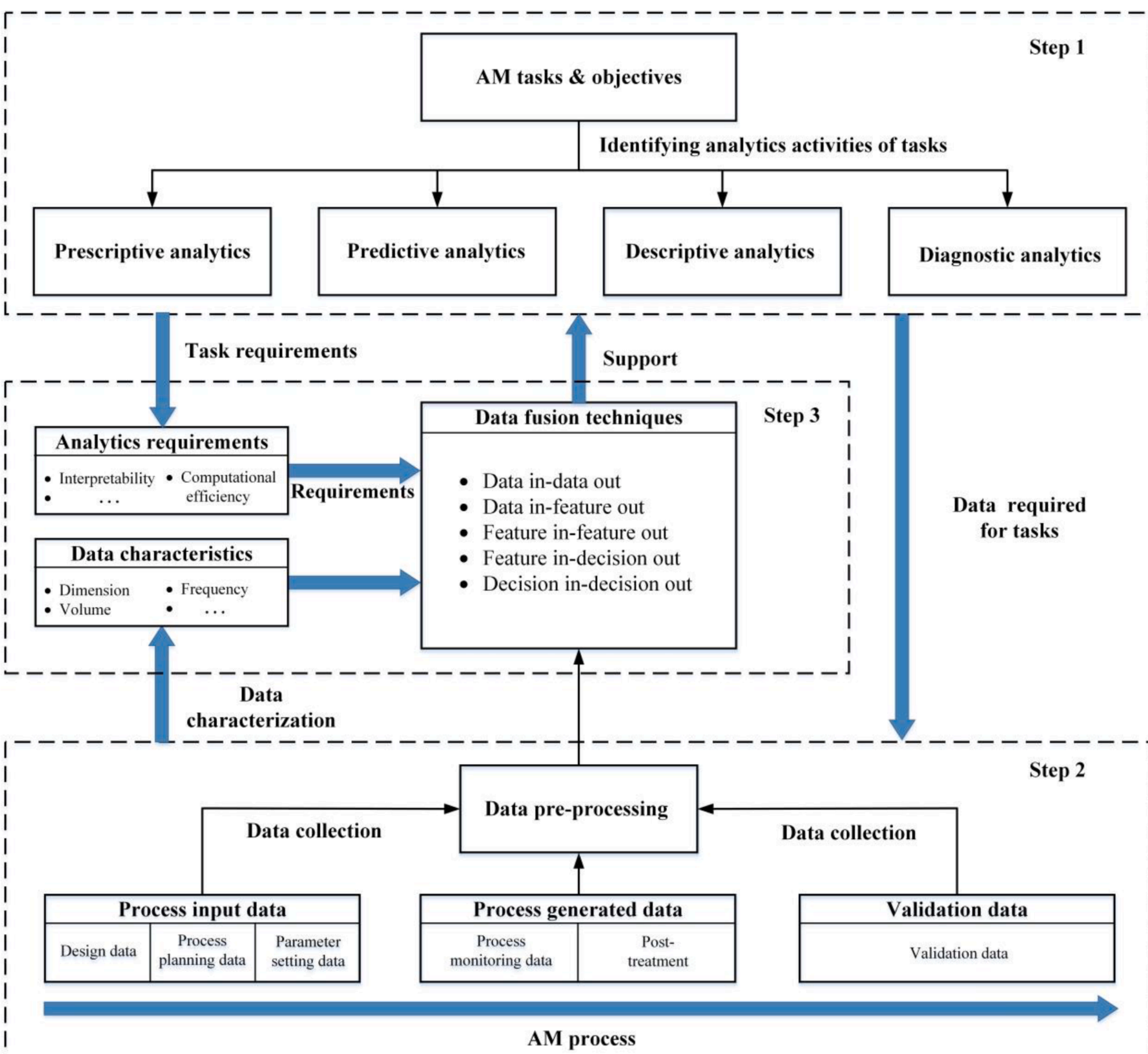

Fig. 2. Illustration of the 3-step approach for identifying, collecting, characterising, and fusing data for AM data analytics.

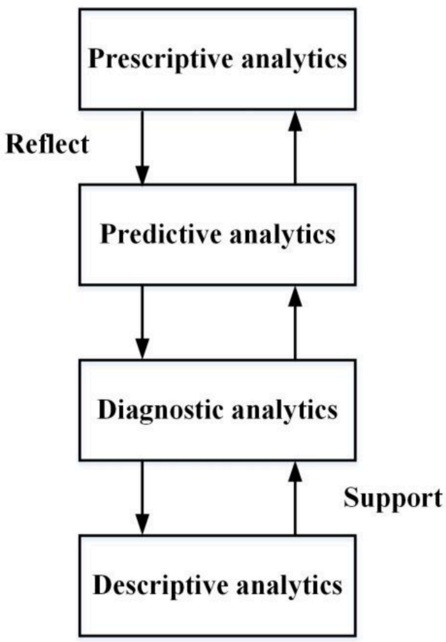

Fig. 3. The connections between different types of data analytics.

the higher-level analytics can reflect the results derived from the lower level. For example, descriptive analytics aims to describe or characterize the ICOM and V of which the analytics results are used to support the diagnostic analytics. Therefore, the data required for descriptive analytics is ICOM- and V-specific. Diagnostic analytics aims to analyse the relationship between ICOM and V, in other words, finding out their correlations or casual relations. Data required for this type of analytics should be the characterization data supported by descriptive analytics. The diagnostic analytics results can reflect whether the characterization data should be extended. The goal of predictive analytics is to accurately predict the target value V to support prescriptive analytics. Hence, supported by the diagnostic analytics, data required for predictive analytics is normally the characterization data of ICOM which has been identified to have correlations with V. Prescriptive analytics focuses on developing strategies or providing possible solutions to achieve the decision-making objectives and is normally supported by the corresponding predictive analytics. The solutions or strategies generated from the prescriptive analytics aim to develop control C to obtain the desired target value V or obtain desired O based on I and M.

3.2.2. Data acquisition and characterisation

Data acquisition is an essential process for data analytics. After the data required for the task is determined, it is crucial to figure out how to obtain the required data and collect it precisely. The data sources for the required data collection can be identified based on 4 main stages of AM process. Data and information are generated during each stage where some of the data is recorded by AM machine automatically while others need to be captured by a specific set of devices. Table 3 presents examples of data generated during an AM process with corresponding process stages, sources, measurement types, data types, and collection devices. In the table, the measurement types and devices are not limited to the information provided. The required data needs to be characterised after it is collected for better understanding and the development of corresponding processing strategies to meet the task requirements. Normally, data is characterised by the “3V” approach [43,44], volume, variety, and velocity, which has been used to characterise AM data in previous studies [4]. The volume represents the amount of data received during AM processes and is to be processed for further analytics where adequate storage capacity and computing power are necessary. Variety in data refers to the different types of data (e.g., sensor signals, images, videos, text, etc.). Due to the heterogeneity, it is usually hard to simply combine the generated data for analytics. Velocity indicates how fast the data is being generated. It is crucial for developing appropriate data processing and analytics strategies for some particular AM tasks, for example, online monitoring.

Table 3
An example of the data generated during an AM process.

Process stage	Data source	Measurement type	Data type	Device for Collection
Design (process stage 1)	Material	Chemistry Properties	Multiple	Test equipment
	Part design	Part geometry	3D geometry	AM design software
Process planning & setting (process stage 2)	Process planning	Support detection & generation	3D geometry	AM software
		Part location & orientation	Multiple	AM software
	Parameter setting	Scan power, space, speed,	Numerical value	Machine log files
Part building & post-process treatment (process stage 3)	Process monitoring	Melt pool images	2D image	High-speed camera, infrared sensor
		Surface morphology	2D image	High-speed camera, spectral sensor
		Acoustic emission	Time-series signal	Acoustic sensor
		Optical emission		Spectral sensor
		Temperature		Infrared sensor
		Vibration		Acceleration sensor
		Chamber conditions or machine conditions		System-embedded sensor
		Power, voltage (laser, machine, etc.)		Power meter
		Material conditions		Multiple sensors
	Post-processing	Post-process type	Nominal information	Text record
		Process monitoring	Multiple	Multiple sensors
Part qualification (process stage 4)	Part test	Porosity	Multiple	X-ray CT scan, acoustic sensor, etc
		Mechanical properties	Multiple	Test equipment
		Surface roughness	3D geometry	X-ray CT scan, profilometer, etc
		Deformation	3D geometry	3D scan

3.3. Task-driven data fusion techniques

Data fusion techniques have different categories due to various criteria in multi-disciplinary areas, such as the classification according to the relations between the data sources, the abstraction levels, and architectures. The data fusion defined in Dasarathy’s architecture [71] is adopted in this framework as it considers the nature of input data and output data that aligns with the framework and approach of this paper. Data fusion techniques in Dasarathy’s architecture fall into 5 categories:

- Data In-Data Out Fusion (DAI-DAO): The purpose of this type of fusion is to improve the accuracy or polish the input data and it is normally used to directly process the raw data captured from devices. The processing of signals and images is one of its typical applications.

- Data In-Feature Out Fusion (DAI-FEO): the raw data is integrated and extracted into a certain level of abstract information in this DAI-FEO fusion.
- Feature In-Feature Out Fusion (FEI-FEO): The majority of feature fusion algorithms fall into this category, which incorporates both feature inputs and feature outputs. Compared with raw data inputs, feature inputs are normally refined and have initially extracted characteristics.
- Feature In-Decision Out Fusion (FEI-DEO): Most fusion models or algorithms are classified in this fusion type and they are typically used for classification or regression tasks to support predictive analytics. Decisions are acquired through FEI-DEO fusion based on feature inputs (e.g., pattern recognition, target identification, state estimation, etc.).
- Decision In-Decision Out Fusion (DEI-DEO): DEI-DEO fusion involves the transfer of certain local or low-level decisions to a global decision, considering the information from the local or low-level decision-making nodes.

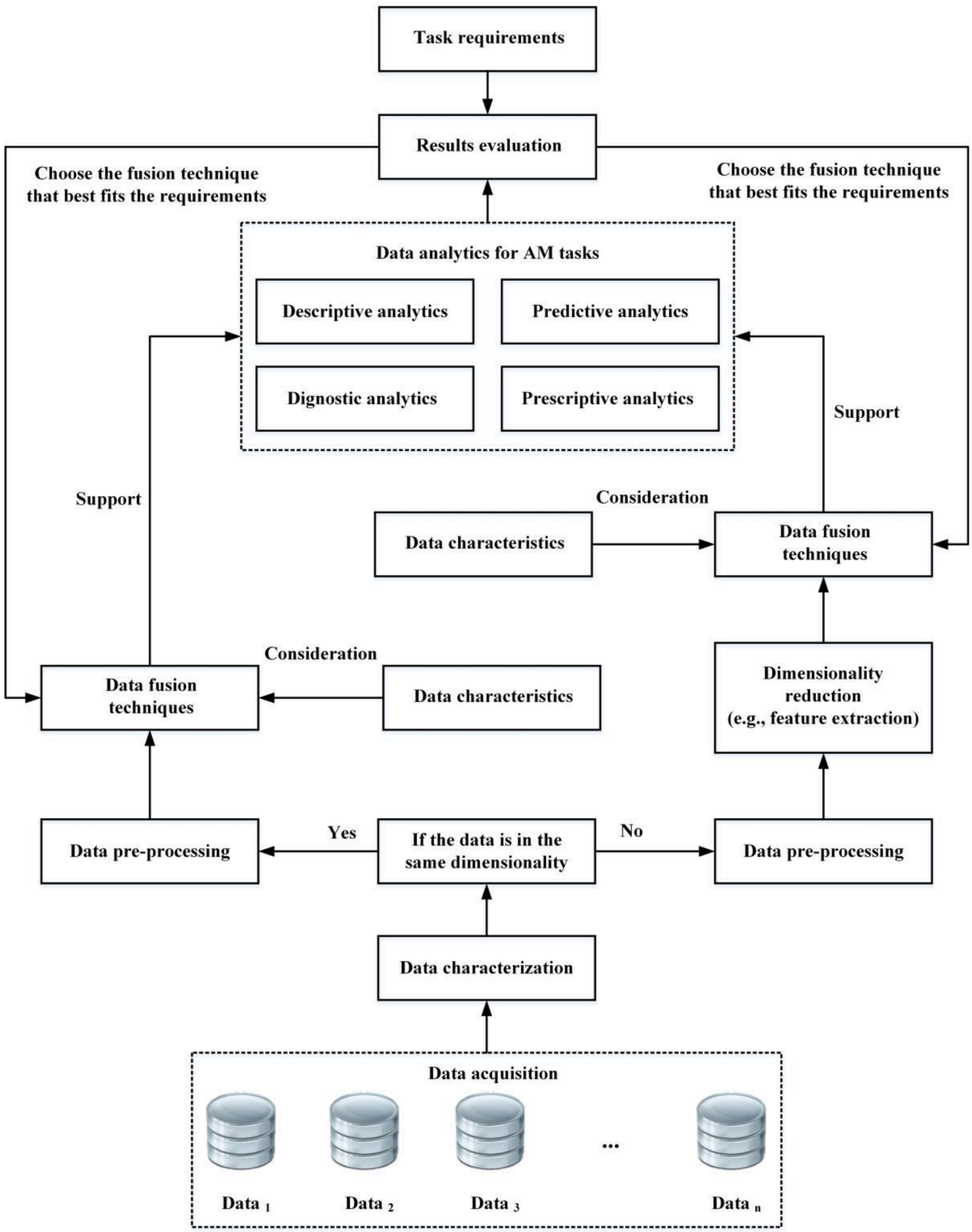

Fig. 4. The flowchart of the task-driven data fusion.

Fig. 4 presents the flowchart of task-driven data fusion. The data required for AM tasks is first collected and characterized. Then the obtained data is judged if it is in the same dimensionality. If yes, the obtained data is pre-processed (e.g., dealing with missing data, abnormal data) and processed through data fusion techniques by considering data characteristics to support data analytics. The evaluation process is conducted based on the task requirements to evaluate the analytics results and finally choose the fusion technique that best meets the requirements. If the obtained data is not in the same dimensionality, a dimensionality reduction process (e.g., feature extraction) is required to process the high dimensional data before using the data fusion techniques. The strategy for data fusion techniques follows Dasarathy's architecture. For example, Data In-Data out techniques are typically employed for processing in-process sensor signals.

Typically, researchers and engineers focus on two levels of data and information collected from AM production for data analytics, layer level and build level. Layer-level data represents the data collected during the manufacturing process (e.g., sensor signals) and contains the information for each printed layer. The build-level data represents the information for the whole build. This data is normally obtained before the start of the process (e.g., CAD models, process parameters) or after the part is finished (e.g., part test). The target value of the data fusion driven by the AM task can be represented by the following Eq. (1).

$$V = F\left\{f_{li}[x_{li}(t), x_{li}(t-1), \ldots, x_{li}(t-k)], f_{bj}\left(x_{bj}\right)\right\}, (i,j,k = 1, \ldots, n) \tag{1}$$

In Eq. (1), t is the discrete-time, $x_{li}(t)$ represents the i^{th} time-series measurement data at layer-level that is required by the task at time t, k represents the previous k^{th} discrete time, x_{bj} represents the j^{th} build-level data, V is the target value, f_{li} and f_{bj} are the techniques used for processing the i^{th} layer-level data and the j^{th} build-level data (e.g., feature extraction, data refinement techniques) respectively, and F represents the data fusion techniques. The data fusion techniques follow Dasarathy's architecture and consider the characteristics of $x_{li}(t)$ and x_{bj}. The $f_{li}[x_{li}(t), x_{li}(t-1), \ldots, x_{li}(t-k)]$ and $f_{bj}(x_{bj})$ should be processed to the same dimension for fusion. Specifically, for the target value to be obtained at layer-level (e.g., real-time defect detection), the target value of the next moment can be estimated based on the data collected at the current moment and previous measurement data. It can be represented by the following Eq. (2).

$$V_l(t+1) = F\left\{f_{li}[x_{li}(t), x_{li}(t-1), \ldots, x_{li}(t-k)], f_{bj}\left(x_{bj}\right)\right\}, (i,j,k = 1, \ldots, n) \tag{2}$$

In Eq. (2), V_l $(t + 1)$ represent the estimated target value at $(t + 1)$ discrete time. For the target value to be obtained at the build-level (e.g., mechanical properties prediction of printed parts), the layer-level data required by the task should be packed to the build-level and the fusion can be represented by the Eq. (3).

$$V_b = F\left\{f_{li}[x_{li}(t), x_{li}(t-1), \ldots, x_{li}(1)], f_{bj}\left(x_{bj}\right)\right\}, (i,j = 1, \ldots, n) \tag{3}$$

In Eq. (3), $f_{li}[x_{li}(t), x_{li}(t-1), \ldots, x_{li}(1)]$ represents the time-series measurement data during the whole build, and V_b is the target value at the build-level. A typical f_{li} method is to extract time and frequency domain features.

This section introduces the proposed framework and approaches of task-driven data fusion for data analytics in AM. In the next section, case studies are presented to demonstrate the feasibility and effectiveness of the approach.

4. Case studies

To demonstrate the feasibility and effectiveness of the proposed task-driven data fusion framework, three case studies on different AM tasks were carried out, including AM unit energy consumption prediction, mechanical property prediction of additively manufactured lattice structures (LS), and investigation of the effect of the remelting process on part density. (1) In case study 1, in the first step, the AM task is unit energy consumption prediction of printed objects, and the prediction is required to be made before the AM process begins. Hence, this task is identified as predictive analytics and involves prediction activities based on energy consumption-related information. In the second step, for predictive analytics, the information or data used for prediction should be identified correlated with unit energy consumption, such as material information, part geometries, machine parameter settings, etc. The part geometry data and material information are generated and collected during the part design stage (process stage 1). The machine setting and process planning data (e.g., laser power, scan speed, etc.) are generated and collected during the process planning and setting stage (process stage 2). A power meter is used to measure and collect power consumption data during the AM production (process stage 3). After data collection, the data is characterized and used for training the prediction model in the third step where the fusion technique should consider the time-series patterns and complexity of 3D geometry features. The accuracy of the energy consumption prediction model is used for evaluating the fusion performances. (2) In case study 2, the task is to predict the mechanical properties of AM-produced LS with the requirement that the prediction model can apply to different materials. Considering the requirement, the data and information to be collected should be relevant to the mechanical properties of AM-produced parts, such as the used material density, LS types, process parameter settings, etc. The mechanical property data of printed LS need to be collected from the part qualification stage (process stage 4) by using specific test equipment. As the LS is complex, the fusion strategies should consider the complexity of LS for the prediction model. (3) In case study 3, the AM task aims to investigate the joint effect of different remelting process parameters on printed part density. Hence, it is diagnostic analytics involving statistical correlation analysis. As predictive analytics can provide reflections to its corresponding diagnostic analytics, predictive analytics is also adopted in this case study. Data required for the task is different combinations of remelting process parameters and corresponding part densities of printed parts. Combined with statistical analysis, the importance of each remelting process parameter is analysed based on the predictive model for density prediction. Table 4 presents the details of applying the proposed task-driven data fusion framework for the case studies. The specific fusion techniques adopted for the case studies are demonstrated in the following sub-sections.

4.1. *Case study of AM energy consumption prediction*

4.1.1. *Data description*

The target system in this experimental study is an SLS machine (EOS P700). The collected datasets include data and information from more than a hundred production processes with thousands of produced parts. The produced products were designed by different AM designers and had a variety of shapes and geometries. The information of process parameters, 6 attributes, was recorded in machine log files for each build, including hatch speed, hatch space, hatch power, recoater speed, and the values of the dispenser. The material used is polyamide PA2200. The unit energy consumption E_u (Wh/g) is used to evaluate the consumed energy level and calculated by the following equation.

$$E_u = \frac{E_t}{M_l} \tag{4}$$

In Eq. (4), E_t is the total energy consumed for each printed layer, and M_l represents the weight of each layer. After calculation, the unit energy consumption of printed layers ranges from 3.37 to 301.63 Wh/g, with a mean value of 14.45 Wh/g.

4.1.2. *Data fusion for energy consumption prediction based on CNN-LSTM model*

To implement the predictive analytics, different fusion strategies, including (1) FEI-DEO, and (2) FEI-FEO combined with FEI-DEO, are considered that directly use feature inputs for predicting the target

Table 4
The details of applying the proposed task-driven data fusion framework for the case studies.

Step	Sub-items		Case study 1	Case study 2	Case study 3
Step 1	AM task		AM unit energy consumption prediction	Mechanical property prediction of LS	Investigation of the joint effect of remelting processes on part density
	Task requirements		Predicting before the process begins	Applicable to different materials	Identifying the relationship between remelt process and part density
	Type of the target value		Cost	Quality	Quality
	Involved decision-making activities		Predicting unit energy consumption based on process-input data	Predicting mechanical properties of LS manufactured by using different materials	Predicting part density
	Type of data analytics		Predictive analytics	Predictive analytics	Diagnostic analytics
Step 2	Data required for the task		Design CAD models, material information, process planning data, parameters setting data, energy consumed during the process	Design CAD models, material information, parameter setting data, the mechanical property of final printed parts	Parameter setting data, remelting strategy, the density of final printed parts
	Data acquisition	Process stage 1	AM design software, material test equipment	AM design software, material test equipment	N/A
		Process stage 2	Machine log file	Machine log file	Machine log file, manual records
		Process stage 3	Power meter	N/A	N/A
		Process stage 4	N/A	Mechanical property test equipment	Density test equipment
	Data characterization		Volume 2GB (total) Velocity Time-series: 1HZ Variety 3D models, 1D numerical data, time-series sensor data	Volume 5 MB (total) Velocity N/A Variety 3D models, 1D numerical data	Volume >1GB (total) Velocity N/A Variety 1D numerical data (porosity is calculated based on the 3D reconstruction)
Step 3	Data dimensionality		Multi-dimensional data	Multi-dimensional data	Data in the same dimension
	Data fusion strategy		(1) FEI-DEO (2) FEI-FEO + FEI-DEO	FEI-DEO	FEI-DEO
	Data fusion techniques consideration		The fusion technique should consider the time-series patterns and complexity of 3D geometry features.	The fusion technique should consider the complexity of 3D geometry features	Combined with statistical analysis, leveraging feature importance ranking based on information entropy in predictive models for density prediction
	Evaluation method		Prediction accuracy	Prediction accuracy	Prediction accuracy

energy consumption values. For the FEI-DEO fusion strategy, it is common for the 3D models of the products to have different shapes and geometries some of which are difficult to be described by hand-crafted features due to their complexity. In conventional feature extraction methods, such as statistical features or envelopes of geometries, the inner structures are inevitably neglected while the general information about geometries is extracted. 3D models in AM systems are sliced into layer-wise models with predefined layer thicknesses for layer-by-layer construction of physical objects. This facilitates the analysis of 3D geometries by transforming the sliced models into layer-wise images (shown in Fig. 5), which is consistent with the nature of AM processes.

CNN, a type of deep learning algorithm, consists of multiple convolutional layers and pooling layers for automatically extracting and learning highly represented features that are used for regression or classification tasks in the fully connected layers. The highly representative features are extracted from images by convolution operations and max pooling operations which are defined by the following equations.

$$Y(i,j) = \sum_m \sum_n K(i-m, j-n)^* X(m,n) \tag{5}$$

$$y_n(i,j) = max(Y_n\{i,j\}) \tag{6}$$

Eq. (5) represents the convolution operation where Y (i, j) is the output feature map of the next layer, (i, j) denotes the position of the output pixel, X is the input image, K is the kernel, (m, n) is the position of the kernel element, and * represents the convolution operation. Eq. (6) represents the max pooling operation used to reduce the dimensionality of the output feature map from the convolution operation. $Y_n\{i,j\}$ are the elements in the neighbourhood of (i, j) in the extracted feature map at the n^{th} layer and$y_n(i,j)$ is the output through the max pooling operation. The max pooling operation aims to replace the sub-region of feature maps with the maximum value in the region. Fig. 6 illustrates the convolutional feature extracting process. The final extracted features of the layer-wise images are flattened into 1D feature vectors and fused with process parameter data in the LSTM neural network for time-series energy consumption prediction. The LSTM algorithm is a type of recurrent neural network (RNN) and is composed of several cells that retain the temporal information of the previous cells. It is typically used for learning the sequential patterns within data. Finally, the CNN-LSTM model fuses the geometric features with process parameter data for

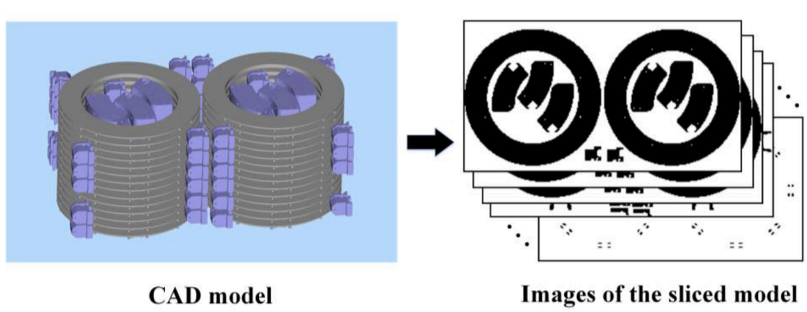

Fig. 5. An example of transforming the CAD model to sliced layer-wise images for analysis.

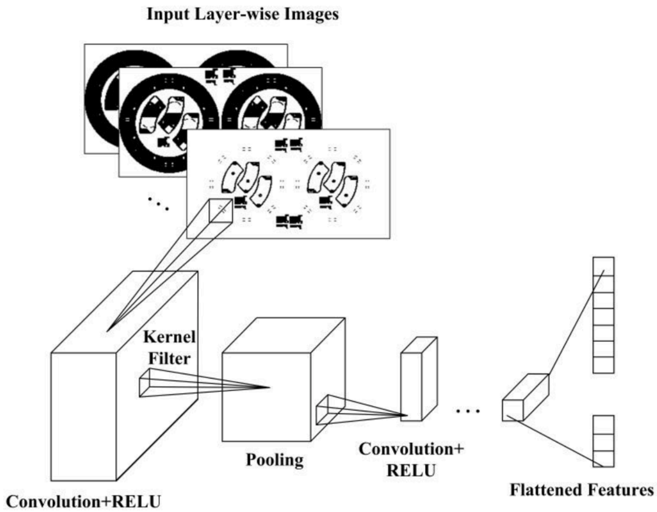

Fig. 6. The illustration of the feature extraction process of layer-wise images of sliced CAD models.

predicting the unit energy consumption of each printed layer. For comparison, different ML models, including light gradient boosting machine (LGBM), XGBoost, RFs, and ANN are adopted for energy consumption prediction where convolutional features from CNN are used as inputs.

For the FEI-FEO combined with the FEI-DEO fusion strategy, as the features (over thousands of feature vectors) learned from layer-wise images through convolution operations are sparse and contain redundant features, the learned features are refined by typical fusion techniques before being used as inputs for FEI-DEO fusion in the LSTM model. PCA, kernel PCA (KPCA), locally linear embedding (LLE), and locality preserving projections (LPP) fusion techniques are applied to refine the features while simultaneously retaining essential information. The proposed approach is illustrated in Fig. 7.

4.1.3. Prediction results

By using AM analysis software (Autodesk Netafbb), the geometry information of different products was obtained from CAD models. The layer-wise images were obtained from sliced models and saved in BMP format. The evaluation metrics for the fusion models are the root mean squared error (RMSE) and the coefficient of determination (R^2). The evaluation metrics are calculated by the following equations.

$$RMSE = \sqrt{\frac{1}{s}\sum_{i=1}^{s}(y_i - \hat{y}_i)^2} \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{s}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{s}(\bar{y}_i - y_i)^2} \tag{8}$$

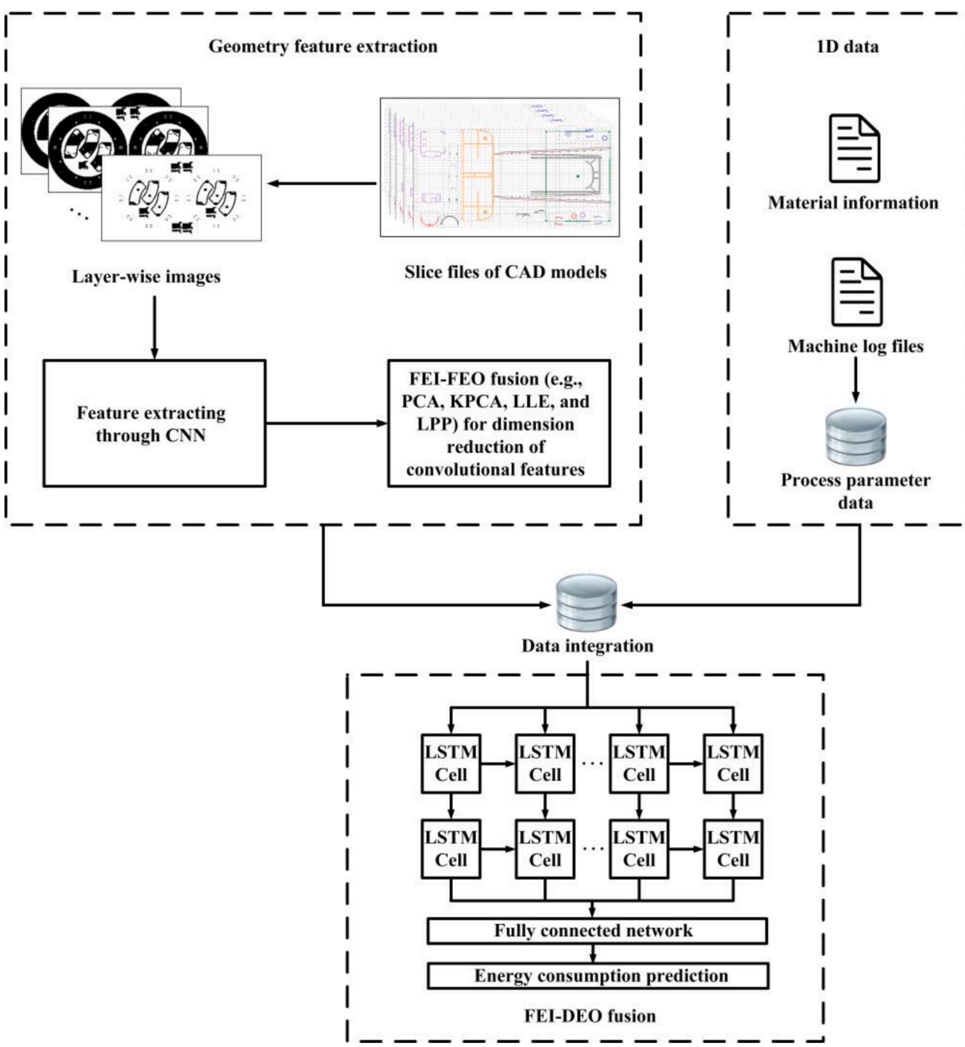

Fig. 7. The proposed approach for energy consumption prediction based on the CNN-LSTM model.

In Eqs. (7) and (8), s represents the number of samples, y_i, $\hat{y}_i$, and $\bar{y}$ denotes the actual, predicted, and mean value of the outputs, respectively. There were more than 10,000 layer-wise images used for model training and more than 3000 samples used for validation. In the first FEI-DEO fusion strategy, the performances of different models are shown in Fig. 8. In the figure, the proposed CNN-LSTM model had the best result with an RMSE of 7.04 while RFs performed the worst with an RMSE of 12.35. Fig. 9 shows the comparisons of the performances between the original CNN-LSTM model and the models with different fusion techniques. The CNN-LSTM model combined with the LLE fusion algorithm obtained the best results in terms of RMSE (5.38) and R^2 (0.72) while the CNN-PCA-LSTM had the largest error with an RMSE of 8.79. The CNN-KPCA-LSTM had the worst performance in R^2 (0.44). Obviously, after applying FEI-FEO strategies, the performances of most prediction models are improved. Information loss could occur during the FEI-FEO process. However, the fused features are normally more informative and less likely to lead to underfitting problems when the number of training samples is limited.

4.2. Case study of predicting mechanical properties of LS

4.2.1. Data description

The AM data used in this experimental study, including 57 samples, is collected from the 3D printing research group at Chongqing University [62]. The parts were fabricated by SLM machines using Ti6Al4 V and 316 L stainless steel powders. Different LS, strut structures and strut-based and sheet-based TPMS structures, are included in the samples. The final printed parts are composed of LS units. The examples of LS are shown in Fig. 10. The mechanical properties of produced LS were tested and indicated by the elastic modulus and yield strength. The tested elastic modulus of the final printed LS ranges from 37.5 to 9309 MPa, with a mean value of 3299 MPa. The tested yield strength of the final LS ranges from 1.9 MPa to 590.3 MPa, with a mean value of 154.88 MPa.

4.2.2. Data fusion for mechanical properties prediction based on ML models

LS produced by AM has been increasingly adopted in industries, such as the aerospace industry, due to their adjustable mechanical properties and light weights. LS are normally complex and their geometric features are hard to be extracted and analysed. Methods such as point clouds and feature curves are typically employed for analysing LS geometries. However, there are also drawbacks when applying these methods, such as too much data generated through point clouds, and hard to represent the internal shapes and structures of LS. Therefore, considering the mechanical properties of printed parted are correlated with the solid proportion of LS units, the geometric features of LS can be extracted and represented by the entropy of their voxelized 3D models [62]. By voxelizing a 3D model, a new model consisting of pixels of a specified size is created and positioned in a space with an R^3 resolution. This space contains empty and solid pixels to represent the geometries of LS. In this experiment, $100 \times 100 \times 100$ resolution was used. The LS units were first voxelized into 3D voxels of which the porosities were calculated. Following are the equations Eqs. (9) and ((10)) used to calculate entropy [72]. In the equations, P_1 and P_2 represent the proportions of solid and empty voxels respectively.

$$E = -P_1 \log_2 P_1 - P_2 \log_2 P_2 \tag{9}$$

$$P_1 + P_2 = 1 \tag{10}$$

Since it is hard to distinguish different LS unit models with the same entropy but have different geometries, the units were divided into 20 subspaces and the entropy of each subspace was calculated, illustrated in Fig. 11. The direction for dividing aligns with the fabrication direction Z-axis. Then the entropy of an LS unit is represented by the entropy vector that includes the entropy of 20 subspaces.

Hence, the geometric features of LS can be represented by the entropy vector of the unit, the unit length, and the porosity of the unit. The density and elastic modulus of used materials and the machine process parameters are closely related to the mechanical properties of the final printed parts. These data and information are taken into consideration for mechanical property prediction. FEI-DEO fusion is adopted where the ML algorithms are used to fuse the features for predicting mechanical properties. Fig. 12 shows the developed fusion approach for the mechanical properties prediction of LS.

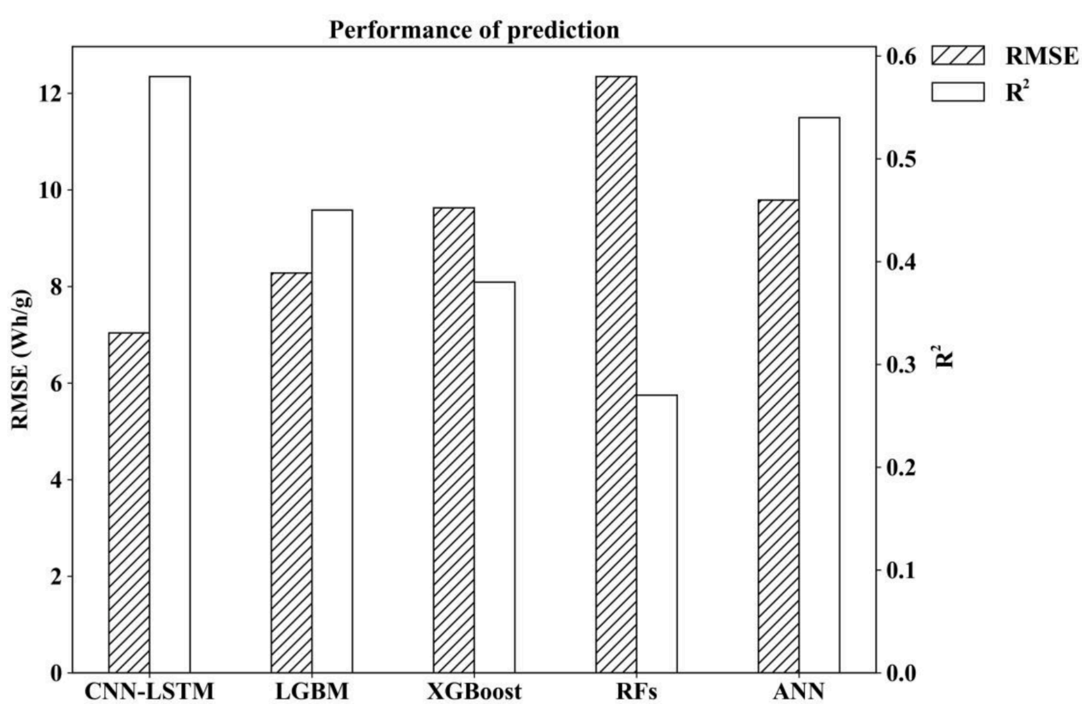

Fig. 8. The performances of different prediction models.

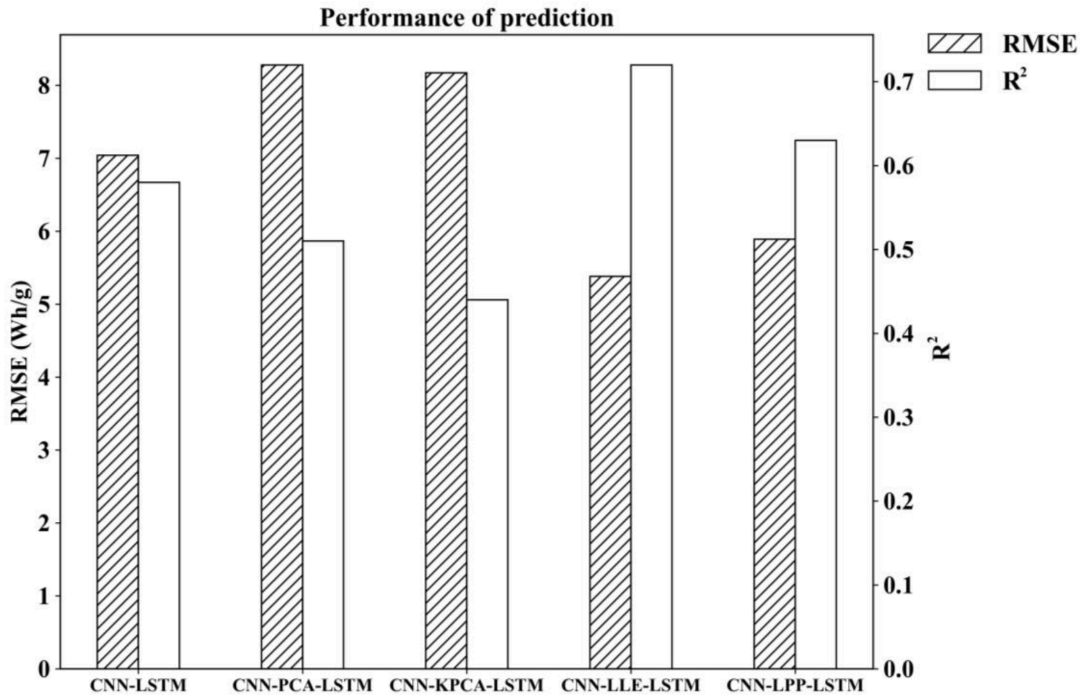

Fig. 9. The comparisons of performances between different fusion techniques.

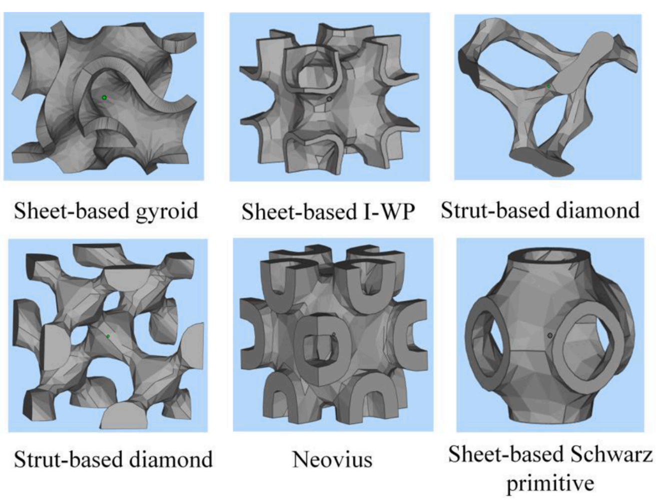

Fig. 10. The examples of LS in the experimental study.

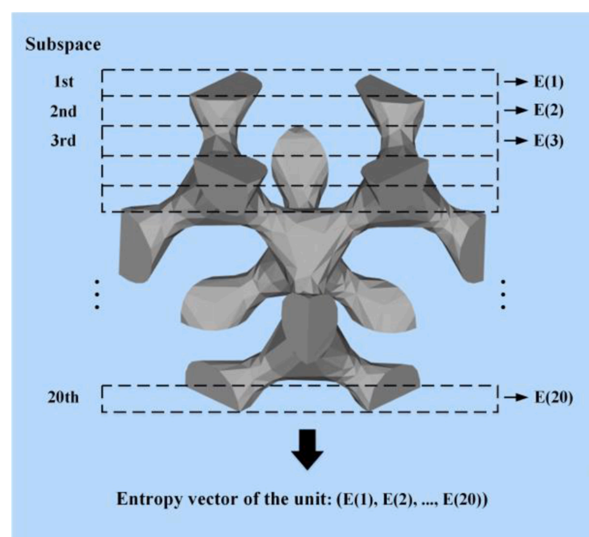

Fig. 11. Obtaining the entropy vector of LS units based on the entropy of subspaces.

4.2.3. Prediction results

The elastic modulus and yield strength are used as indicators of part mechanical properties. Figs. 13 and 14 show the prediction results for elastic modulus and yield strength respectively. The RMSE and R^2 were used to evaluate the model's accuracy. As shown in the figures, the RFs achieved the best results in RMSE (556.80 MPa) for elastic modulus prediction with an R^2 of 0.76. Also, it had an RMSE of 28.28 MPa with an R^2 of 0.78 for yield strength prediction. The *k*-NN algorithm had the worst performance with an RMSE of 1417.96 MPa for elastic modulus prediction and an RMSE of 81.31 MPa for yield strength prediction. The SVM had the best performance in R^2 (0.91) for elastic modulus prediction while ANN had the best performance in R^2 (0.96) for yield strength prediction.

4.3. Case study of investigating the effect of the remelting process on part density

4.3.1. Data description

In this experimental study, both AM and remelting processes were conducted on an SLM machine (EP-M250) where the used material was 18Ni-300 maraging steel [73]. The schematic diagram of the remelting process is shown in Fig. 15 where the arrows in red represent the remelt scan paths. The remelt angle in Fig. 15 is 90° Different process parameters combined with remelting strategies were used to investigate the relationship between remelting process and part density. The parts were manufactured in a cube shape with dimensions of $8 \times 8 \times 8$ mm^3.

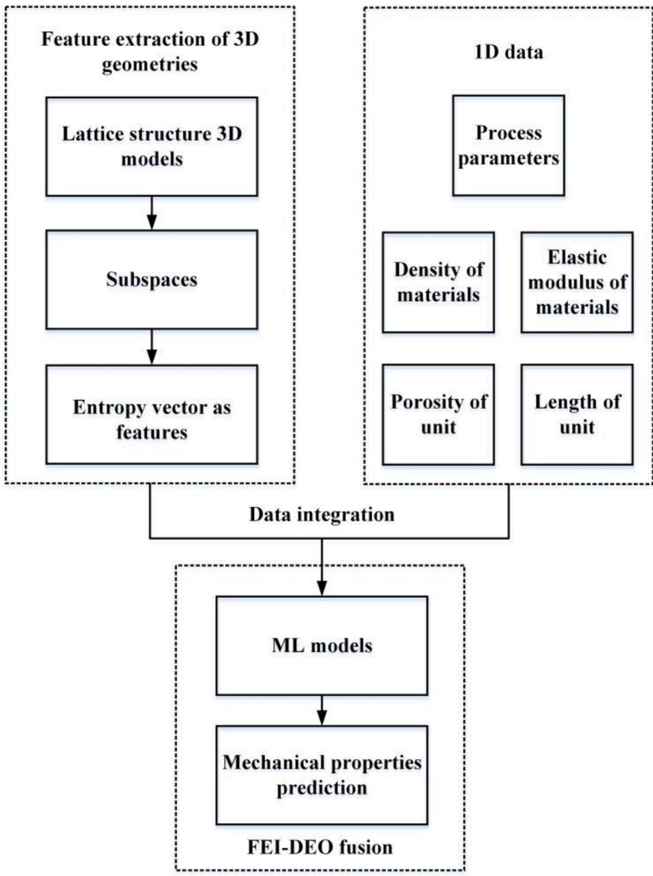

Fig. 12. The proposed fusion approach for mechanical properties prediction of LS parts.

4.3.2. Data fusion for identifying the relationship between remelt process and part density

To investigate the effect of the remelting process on part density, the statistical correlation between remelt process settings and relative density was first analysed based on the Pearson correlation coefficient (PCC). The PCC is calculated by the following Eqs. (11) where r_{XY} is the PCC between variables X and Y, $\overline{X}$and $\overline{Y}$represent the mean values of X and Y respectively.

$$r_{XY} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}} \tag{11}$$

PCC analysis only measures the linear relationship between variables, therefore, feature importance ranking based on the information gain is employed for further investigation. Information gain measures the reduction in uncertainty about the target variable after splitting the dataset on a particular feature. The information gain of the tree-based algorithms is calculated by the following equations.

$$H(D) = \sum_{k=1}^{K} -p_i \log_2 p_i \tag{12}$$

$$H(D|A) = \sum_{i=1}^{n} \frac{|D_i|}{|D|} H(D_i) \tag{13}$$

$$Gain(D, A) = H(D) - H(D|A) \tag{14}$$

In Eqs. (12) - (14), $H(D)$ is the entropy of dataset D relative to the K-wise classification, p_i denotes the proportion of D that belongs to class i. D_i denotes the subset of dataset D where feature A takes the value i. $|D_i|$ is the number of instances in D_i, and $|D|$ is the total number of instances in D. $H(D \mid A)$ represents the entropy of D conditional on feature A, and $Gain(D, A)$ represents the information gain of feature A relative to the dataset D. For the quality of the part density, the samples were classified into 3 quality levels: low, medium, and high. The FEI-DEO fusion strategy is adopted where the remelting process setting data is used for part density level prediction. Based on the prediction result, the importance of features is analysed through information gain. The

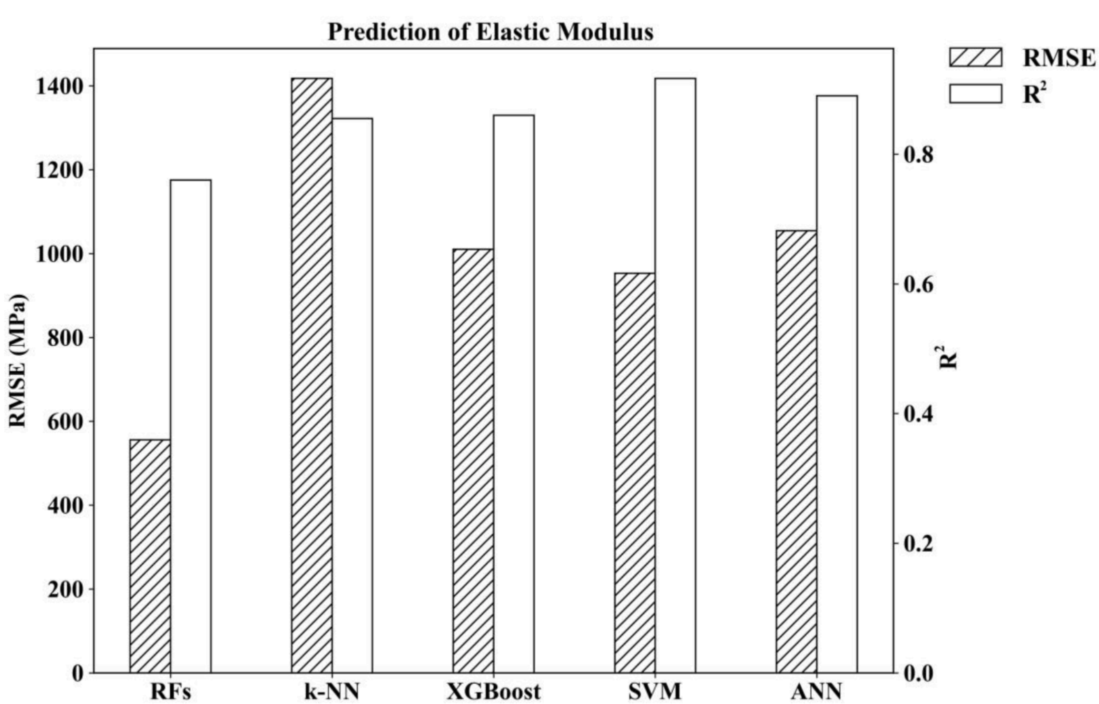

Fig. 13. The performances of different prediction models for elastic modulus prediction.

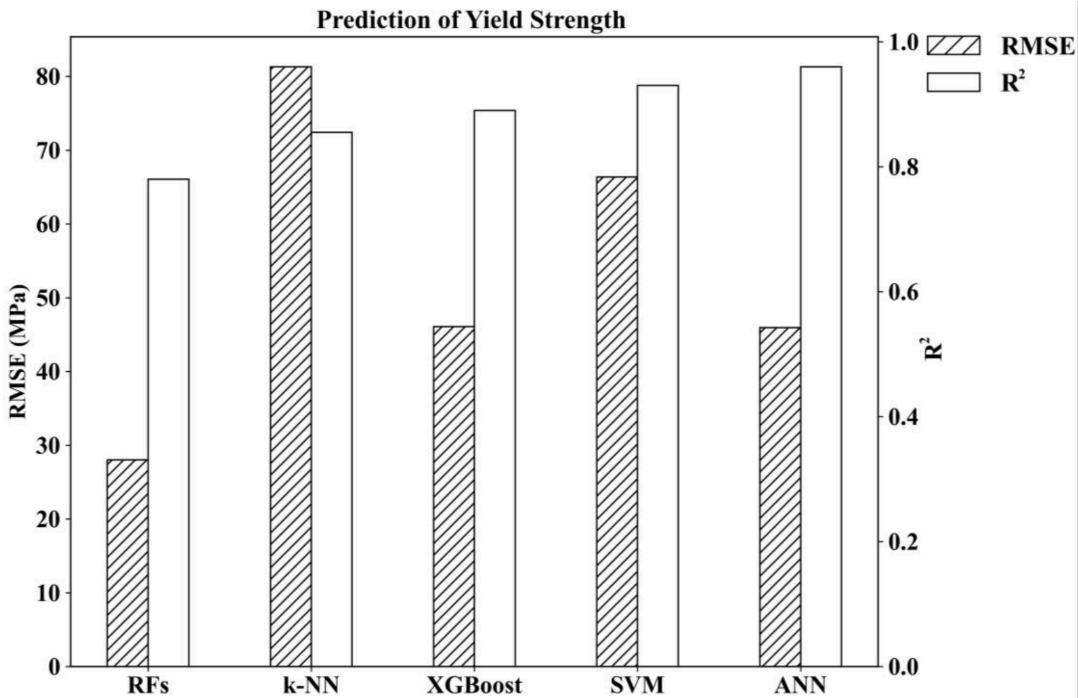

Fig. 14. The performances of different prediction models for yield strength prediction.

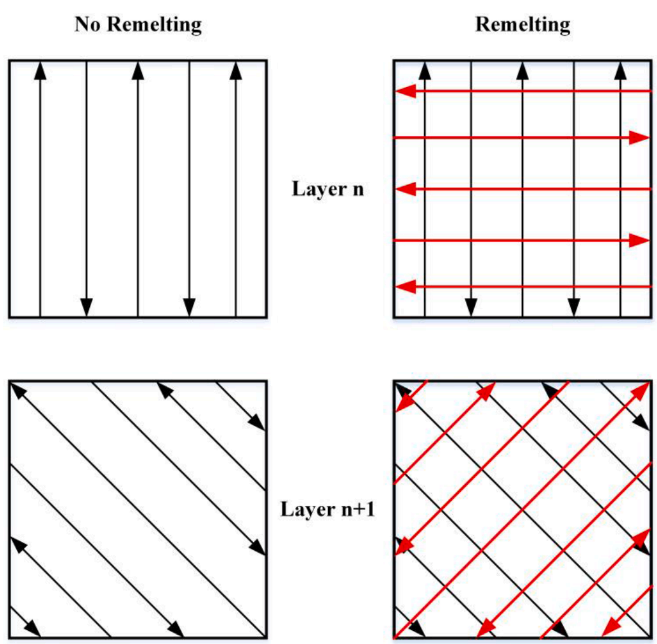

Fig. 15. Schematic diagram of the remelting process.

approach is illustrated in Fig. 16.

The prediction model used in this case study is XGBoost which is an ensemble learning algorithm of decision trees. It provides a parallel tree boosting for classification, regression, and ranking tasks.

4.3.3. Analytics results

As shown in Fig. 17, the PCC between each feature is calculated and presented. From the results, the laser power and scan speed tend to have negative correlations with part density while the remelt angle and hatch space tend to have positive correlations. However, there is no strong linear relationship between the remelting process parameters and part density that has been observed.

For further investigation, the feature importance ranking through predictive analytics was conducted. Different tree-based algorithms, RFs, XGBoost, LGBM, and Adaptive Boosting (AdaBoost), were trained for part density level classification based on the given remelting process parameters. Besides tree-based algorithms, *k*-NN was also adopted for comparison. The evaluation metric for evaluating the classification is accuracy which is calculated by the following equation.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

In Eq. (15), *TP* represents the number of correctly predicted positive samples, *FP* represents the number of incorrectly predicted positive samples, *TN* is the number of correctly predicted negative samples, and *FN* is the number of incorrectly predicted negative samples. The performances of different models are shown in Fig. 18. XGBoost achieved the best classification accuracy (77.8%) while the *k*-NN had the worst accuracy (60.7%). Based on the XGBoost model, the feature importance ranking of remelting process parameters on part density level is shown in Fig. 19 by calculating the information gain. It can be seen from the results that the scan speed has the most significant impact on part density level, followed by the hatch space. However, there is no strong relationship observed between laser power and part density level. The information gain of layer thickness on the prediction model is zero as the value of layer thickness in this experimental study keeps the same. More experiments need to be carried out for further investigation.

5. Discussion

5.1. Advantages and limitations of the proposed approach

The proposed task-driven data fusion framework and approach provide guidelines for data analytics to support decision-making activities in AM when dealing with heterogenous and multi-source AM data and information. In the increasingly data-intensive environment of AM industry, the issues of what data and information should be collected and how to leverage them to support AM production becomes crucial. Additionally, the data involved in AM systems vary not only in time

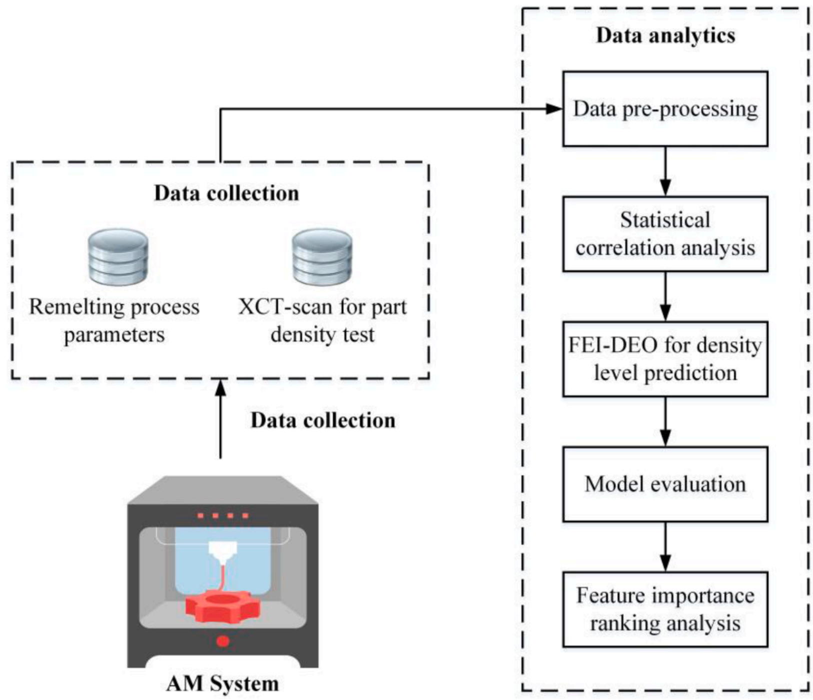

Fig. 16. Data fusion for identifying the relationship between the remelting process and part density.

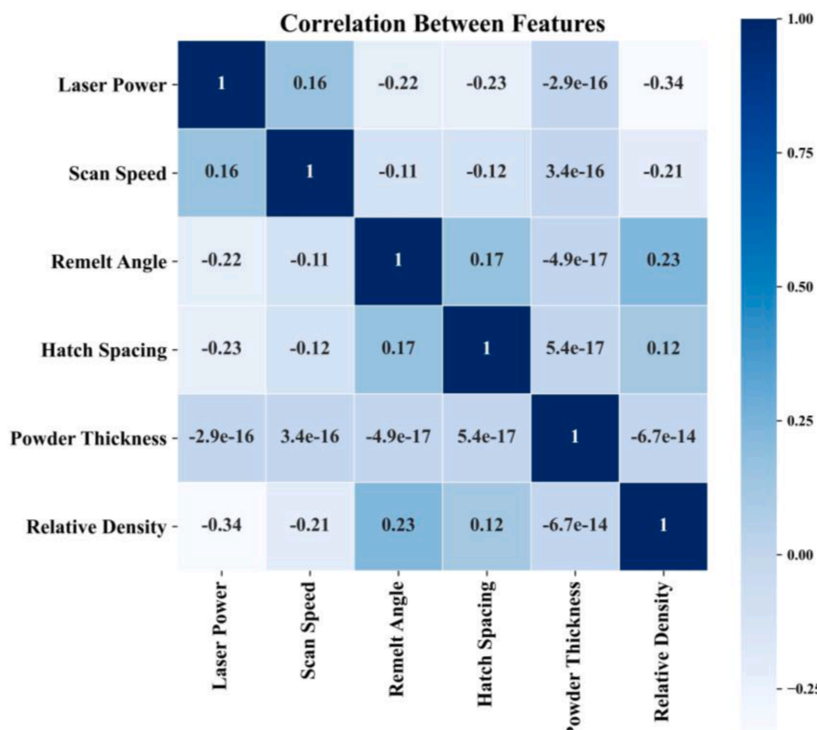

Fig. 17. PCC between remelting process parameters and part density.

scales but spatial scales, which builds up barriers to joint analysis. Driven by AM tasks, the proposed approach helps AM engineers and decision-makers systematically identify the data and information required for tackling the tasks and implement data fusion techniques based on the data characteristics to best fit the task requirements. It provides a methodological way to collect, fuse, analyse, and evaluate the multi-source and multi-dimensional data and information in data analytics for AM. Limited by the type of fusion architecture, the proposed approach focuses on leveraging the AM data for supporting decision-making while the fusion of the distributed AM nodes, networks, and systems is not considered. The fusion for the system level of AM will be explored in future studies. In addition, when adopting data-driven methods to tackle AM issues, the quality of data should be ensured. Sensors must be calibrated and the status of AM machines should be checked regularly to avoid errors when collecting data. However, the performance of developed models will inevitably be affected by

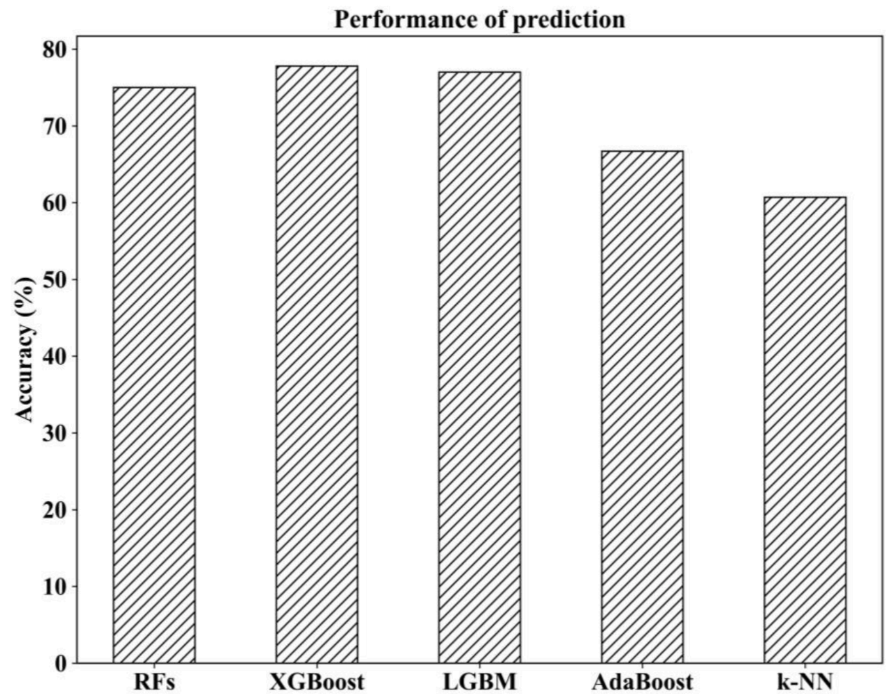

Fig. 18. The accuracy for classifying part density levels of different models.

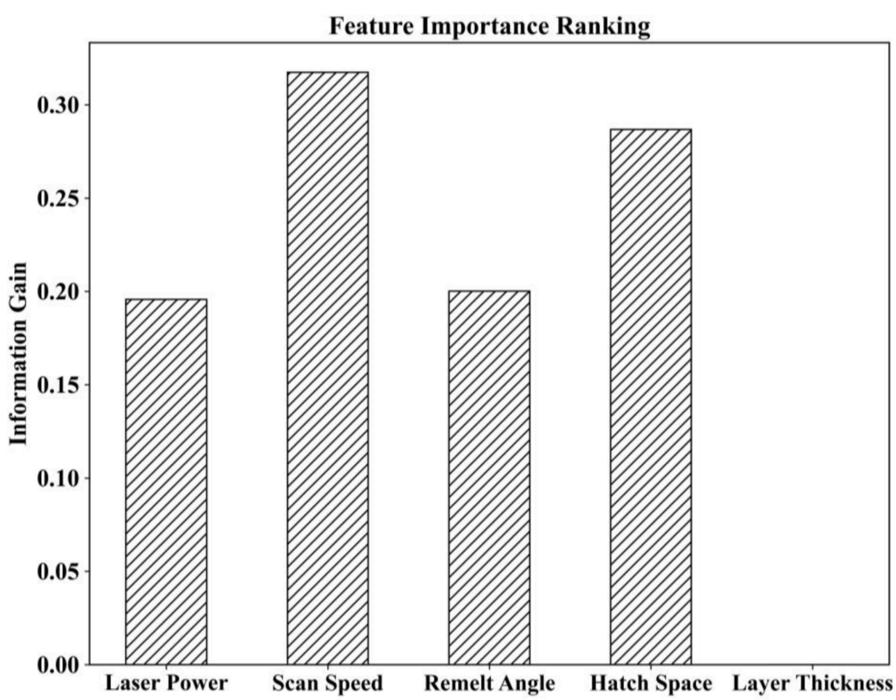

Fig. 19. The feature importance ranking of remelting process parameters.

uncertainties. Process stability and repeatability might also influence the accuracy of predictions. In some cases, environment variations could affect the target value and they should be treated as variables in data analytics.

5.2. Data considered in analytics

AM data used in analytics vary in terms of type, volume, and dimension. The variety and heterogeneity of data lead to challenges when jointly analysed. Given that the characteristics of the generated data normally depend on the nature of AM processes and the collection devices, essential data pre-processing and dimensionality reduction processes are required for data alignment before analysing. During data analytics, the performances of different analytical models vary due to the differences in their capabilities when dealing with different kinds of data. It is crucial to employ the analytical models that best fit the data structures. For example, in case studies 1 and 2, 3D CAD models were both involved in predictive analytics. However, different feature extraction processes and fusion models were considered. The layer-level energy consumption prediction in case study 1 should consider the time-series patterns while case study 2 should consider how the LS of parts can be precisely represented. Also, too many data points generated after feature extraction or data fusion process should be avoided in some cases as it normally requires considerable computational capabilities for further data analytics. In addition, the data consideration in analytics needs to take the task requirements into account. For example, implementing an X-ray CT scan for part density calculation is accurate but fairly time-consuming. Thus, using acoustic emission and Archimedes' principle for density tests are preferable alternatives in some cases.

5.3. With fusion and without fusion

Large amounts of AM data are generated from labs and industries nowadays, offering huge opportunities for data analytics to improve the understanding of AM processes and support decision-making activities. However, some of this data can contain crucial information related to the decision-making activities while some data is redundant. The inclusion of redundant data or irrelevant data for data analytics not only affects the performances of analytical models where conflicts may occur but causing resource inefficiency. Therefore, when comes to data fusion of multi-sourced data, the sources to be included should be the most relevant to the decision-making activities. Additionally, some data fusion techniques provide a refining process of data where noise data, outliers, or redundant data can be reduced. However, the refining process can also lead to considerable information loss that ultimately jeopardizes the performance of data analytical models. Considering this, evaluations are essential for the assessment of fusion processes on whether the data should be included or whether the refining processes are appropriate. Evaluation criteria from different perspectives should be developed in future research. In the case studies, this paper adopted RMSE for evaluating the regression performances of different models, as RMSE is the most effective and widely employed indicator for assessing regressions. With the task requirements becoming more complex and diverse, other evaluation metrics should be employed.

5.4. Optimization between performance and task requirements

When evaluating the performances of analytics models supported by data fusion techniques, the results derived from the analytical models should best fit the AM task requirements. However, in some cases, for example, real-time process monitoring requires the time for inference of the analytical model to be as short as possible. This leads to the pursuit of a fast reaction of models while the data and information to be involved are inevitably reduced. Some essential information may lose during the shrinking or refining process of the data, which ultimately affects the model's performance. In addition, apart from the data and information to be considered, the complexity of the analytical model also needs to be reduced to avoid extra computing time. Therefore, the optimization between model performance and task requirements is critical and challenging. Establishing evaluation models for specific AM tasks to find optimized solutions between analytical model performance and task requirements is a promising strategy.

6. Conclusions

This paper proposed a task-driven data fusion framework that provides guidelines for integrating heterogeneous data from various sources or modalities to support decision-making activities in AM tasks. The proposed framework and approach fill the research gap that lacks a methodological way to identify, collect, and leverage the multi-source and multi-dimensional data for data analytics in AM. In addition, targeted at the characteristics of the collected data and AM task requirements, different data fusion strategies are applied to refine the data and improve the accuracy of the target value. By considering the information from different sources, measurements, and modalities, the performances of the models for obtaining target values are normally improved. However, it is worth noting that evaluations of the fusion are essential as some fusions result in considerable information loss and jeopardize models' performances. Three case studies on different AM tasks were carried out to demonstrate the feasibility and effectiveness of the proposed approaches, including AM energy consumption prediction, mechanical property prediction of additively manufactured LS, and investigation of the joint effect of remelting process on part density. The experimental results show that the applied data fusion strategies and techniques can effectively integrate the data with different dimensions, structures, and types for data analytics to support decision-making activities. Due to the strong capability in learning hidden information within data and modelling complex nonlinear relationships, ML has been widely used for fusing data to obtain desired target values. Therefore, in the FEI-DEO fusion, ML algorithms prevail. Besides, in the case studies, as the task requirement is accurate prediction, RMSE and R^2 were adopted as indicators to evaluate the fusion in regression tasks. Accuracy was used as the indicator for the classification task. The fusion model with the best performance was used to obtain the target value. In different AM tasks, different requirements can be attached, thus, different evaluation methods should be applied. Compared with traditional single-dimensional and single-modality data analytics, the proposed task-driven data fusion framework and approach not only systematically identify and collect the data required for the AM task but effectively leverage the information from multi-sources, measurements, and modalities to support decision-making activities. It has great potential to be applied in AM industry to help improve AM production.

CRediT authorship contribution statement

Fu Hu: Conceptualization, Methodology, Programming, Writing-Original draft preparation and Validation. **Ying Liu:** Conceptualization, Methodology, Writing - Review & Editing and Supervision **Yixin Li:** Methodology, Writing- Original draft preparation, Case Study and Validation. **Shuai Ma:** Case Study and Validation. **Jian Qin:** Case Study and Validation. **Jun Song:** Case Study and Validation. **Xianfang Sun:** Writing - Review & Editing and Validation. **Qian Tang:** Writing - Review & Editing and Validation.

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.

Data availability

Data will be made available on request.

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