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Deep Fusion for Energy Consumption Prediction in Additive Manufacturing

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Abstract

Owing to the increasing trend of additive manufacturing (AM) technologies being employed in the manufacturing industry, the issue of AM energy consumption attracts attention in both industry and academia. The energy consumption of AM systems is affected by various factors. These factors involve features with different dimensions and structures which are hard to tackle in the analysis. In this work, a data fusion approach is proposed for energy consumption prediction based on CNN-LSTM (convolutional neural network and long short-term memory) model. A case study was conducted on an SLS system by using the proposed methodology, achieving the RMSE of 8.143 Wh/g in prediction.

Keywords: Additive Manufacturing; Data Fusion; Energy Consumption; Machine Learning; Convolutional Neural Network

1. Introduction

Additive manufacturing (AM), also known as 3D printing, is a new manufacturing paradigm that fabricates components layer by layer [1]. This unique production paradigm has overcome several limitations of conventional manufacturing processes, being capable of creating near-net-shape physical objects with highly complex geometries. Therefore, AM technologies have been increasingly employed in the medical, automotive, and aerospace industries [2]. Typically, AM processes are classified into seven categories, including powder bed fusion, direct energy deposition (DED), material jetting, material extrusion, vat photopolymerization, binder jetting, and sheet lamination [3]. For each AM process, different technologies have been developed to meet the increasing demand of the printing capability in terms of material, structure, and efficiency. As the increasing number of commercial AM systems are employed in industries, energy management issues become crucial for manufacturing sustainability [4]. However, an AM system is considered complex as it normally contains several subsystems with different sub-processes, leading to challenges when analyzing and estimating its energy consumption. Strategies for improving energy efficiency can be made if the power consumption of the system can be predicted before the process begins. Therefore, it is crucial to uncover energy-related knowledge and build accurate prediction models for better energy management in AM industry.

The energy efficiency of manufacturing processes is considered not only closely related to process parameters, but also other factors (e.g., processing time., material attributes, and auxiliary processes states) [5]. For AM systems, existing studies [6-8] has shown that the energy usage has large variations due to different working principles and material types in different AM technologies. Various approaches have been developed in previous researches for modelling power usage. However, each of these methods has advantages and limitations. With the facilitation of Internet of things (IoT)

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technologies and machine learning (ML) techniques, data-driven approaches have shown their merits and been increasingly used for modelling complex systems, as well as uncovering hidden knowledge in digital manufacturing systems (e.g., AM systems). Typically, in AM production, data is generated from the part design stage (i.e., computer-aided design (CAD) models) to the post-treatment stage. This data is heterogeneous that contains different formats, structures, and dimensions. It is rarely independent and hard to be jointly analyzed. Moreover, the CAD models normally contain highly complex geometries that are difficult to be described by simple hand-crafted features. Therefore, it is crucial to capture the information of part geometries more effectively and integrate the data collected from different sources for modelling AM energy consumption.

This paper proposed a data fusion method based on the CNN-LSTM model for AM energy consumption prediction. In section 2, the existing studies on AM energy consumption modelling, the applications of CNN for image and geometry analysis in AM, and the researches of applying data fusion strategies in the manufacturing industry are reviewed. In section 3, the proposed methodology is demonstrated, where layer-wise geometry characteristics are captured and fused with process parameters data in LSTM neural networks. Section 4 presents a case study on a selective laser sintering (SLS) system for validating the proposed method. Finally, the benefits and restrictions of the method are concluded in section 5.

2. Literature review

2.1. Energy consumption modelling for AM

The energy consumption of an AM system is difficult to model as it is affected by various factors during the complex manufacturing process. The influences of these factors are normally inconsistent due to different machines, processes, and materials. Thus, it is rather difficult to uncover and analyze all the energy-related factors from a single study or experiment. The identified energy-related attributes with their energy consumption model in existing studies are summarized in table 1. For example, considering the quality of the produced parts, a linear regression model was developed by Tian et al. [10] to investigate the relationship between process parameters, part quality and energy usage of the fused filament fabrication (FFF) process. This work provides a solution for reducing energy usage while simultaneously ensure the geometry-related quality of produced parts. Yang et al. [11] developed a mathematical model for estimating energy consumption of the Stereolithography (SLA) system by calculating the power consumed from three sub-consumers. The authors analyzed the influences of orientation, layer thickness, and the curing time of stable layers and transition rates on the power usage. Lv et al. [12] also introduced a physical-based prediction approach for estimating the energy consumed by a selective laser melting (SLM) system based on the machine subsystems, subprocesses, and working status. In this study, the power consumption of each subsystem was firstly calculated. Then, the temporal models for the subprocesses, including warming up, building, and cooling down, were developed by taking machine setting, product design, and process parameters as input parameters. This work provides solid physical insights that mainly focus on the investigation of the impacts of process parameters on energy consumption.

Besides focusing on processing attributes and material-relevant information for power consumption modelling, the geometry characteristics of the products are also found significant influences on the energy usage in several studies, such as build height [6] and part envelop volume [8]. Considering the influences of the geometry features, Qin, et al [13] introduced a data-driven modelling method to predict the power consumption of an SLS system. In this paper, the authors collected the data generated from multiple sources, including CAD models, material types, process parameters, and working conditions, during the whole AM production. In specific, geometry-related features were extracted manually from CAD models and taken as inputs with the data collected from other sources in the artificial neural network (ANN). Differently, Yang et al. [15] used the characteristics of layer-wise geometry for estimating the energy consumption of a mask image projection SLA system. The layer-wise geometry-related indexes were extracted from CAD models and processed with three feature selection methods, including sensitivity analysis, principal component analysis (PCA), and stacked autoencoders (SAE). These selected features were then fed into different ML models for energy consumption prediction. However, when considering the impacts of geometry characteristics, it is always hard to extract representative features based on hand-

Table 1. AM energy consumption related attributes in literature

Previous Studies	AM System	Identified Energy Consumption Related Attributes	Energy Consumption Model
Sreenivasan et al. [7]	SLS	The scan speed, layer thickness, laser power rate; road width size, material density	N/A
Watson et al. [8]	Mental AM	Deposited material volume, part envelope volume, the transported distance of feedstock and recycling, build platform size	Mathematical model
Baumers et al. [9]	SLS	Manufacturing procedures, capacity utilization, Z-height, part geometry, build time	N/A
Tian et al. [10]	FFF	Process parameters (e.g., printing resolution, printing speed, nozzle temperature)	Linear regression
Yang et al. [11]	SLA	Part orientation, layer thickness, the curing time for stable layers, curing time transition rate	Mathematical model
Lv et al. [12]	SLM	Different machine subsystems, subprocesses, and working status	Physical-based model
Qin et al. [13]	SLS	Part geometry, process parameters (e.g., hatch width, hatch speed, hatch power, dispenser), in situ temperature, material conditions (e.g., temperature, humidity)	ANN
Yang et al. [14]	SLA	Part geometry	ML-based model
Li et al. [15]	SLS	Part geometry, process parameters (e.g., hatch width, hatch speed, hatch power, recoater speed), in situ temperature, material types	ML-based model

crafted methods, especially for highly complex shapes and geometries. From the existing studies above, there are only a few studies that have explored to predict energy consumption based on geometry characteristics. Additionally, these studies either focus on build-level information or layer-wise information, which inevitably lose some critical information from both sides. Hence, it is crucial to explore the method to extract informative geometry features and capture multi-sourced information for energy consumption prediction. In the next section, the applications of CNN in AM are reviewed.

2.2. *CNN for image and geometry analysis in AM*

Convolutional neural network (CNN) is a type of deep learning (DL) technique to deal with the data with grid patterns (e.g., image). It is able to automatically learn the spatial hierarchies of features by several building blocks [16], including convolution layers, pooling layers, and fully connected layers. In the vision of computers, an image is treated as an array of numbers. In a typical CNN architecture, convolutional layers aim to extract and learn the highly representative features from input images. A kernel is applied across the input image matrix where an element-wise product between each element of the kernel and the input matrix is calculated to obtain the output feature map, shown in Fig.1. In this figure, the kernel size is 3×3 and the stride value is 1. After convolution operation, the output is passed through a nonlinear activation function to the pooling layer for dimensionality reduction.

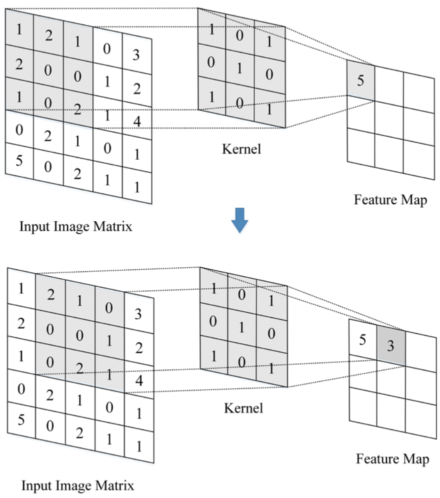

Fig. 1. An example convolution operation in CNN

Due to the superiority of CNN in learning hidden patterns, it is increasingly applied in various domains, especially in AM systems for defect detection and geometry analysis. Patel et al. [17] developed a CNN-based method for recognizing dross based on the cross-section images that are captured from each printed layer of the build in the laser powder bed fusion (L-PBF) system. In their experiments, the dross was bounded by a specific coordinate system and the images taken from the bounded area were used for training CNN to identify the dross. For real-time monitoring, Li et al. [18] proposed an analytical model where a deep CNN was used to extract features and classify thermal images that were collected from the DED process. The raw image data were shrunk and extracted in a proper size in this work for computational efficiency and noise reduction. Another study on real-time classification of melt pool images based on CNN was demonstrated in [19], where CNN was used to distinguish melt pool changes for close loop control.

Some researchers have also tried to analyze 3-dimensional (3D) data through convolution operation in AM systems. In addition to the recognition and classification of 2D images, CNN is able to extract 3D geometric features. Ghadai et al. [20] proposed a local feature identification framework to determine the drilled holes of manufactured products. The augmented voxel data was trained in a 3D-CNN to support the design for manufacturability. The 3D-CNN was able to recognize 3D objects and learn hidden patterns directly from the voxel-based models. This framework can also be applied in other manufacturing processes (e.g., milling). Adding support structure plays a vital role in fabricating overhanging structure in 3D printing [21]. However, traditional techniques (e.g., normal-based techniques) are hard to generate accurate support positions due to the loss of topology. Therefore, a CNN-based support detection method was proposed [22], which used the surface elements defined by the layered depth-normal images. The input images represented the local topological information of the entity in the CNN model. This research pointed out that the proposed CNN-based method was superior in accuracy and robustness. Through existing studies above, CNN-based methods have been demonstrated effective in AM for images processing and analysis, which normally superior to conventional methods. In the next section, the studies on applying data fusion technologies and strategies in the AM industry are reviewed and discussed.

2.3. *Data fusion in the AM industry*

Data fusion is a framework [23], fit by an ensemble of tools, for integrating and analyzing the data from multiple sources or modalities to produce more reliable results and uncover hidden information. Generally, depending on the stage where fusion is implemented, data fusion strategies are categorized as data level, feature level, and decision level. In recent year, deep learning has been demonstrated effective in wide applications as it has strong capabilities of learning hidden patterns within big data automatically. Strategies of using deep learning-based algorithms to fuse data are also referred to as deep fusion. Many researchers have applied this fusion method and obtained considerable performances for regression and classification tasks [24-26].

In AM, some researchers have made efforts to apply data fusion strategies for detecting defects and monitoring [27-29]. Kim et al. [28] introduced a data-driven method for fault diagnosis of FDM process states. Accelerometer and acoustic emission sensors were used to obtain real-time signals under healthy and faulty process states. Features were extracted from raw signal data and then fed into a support vector machine (SVM) model for state classification. To improve the surface integrity of the products produced by the FFF process, Li et al. [30] proposed a decision-level data fusion approach that used an ensemble learning algorithm to fuse the prediction results from six different ML algorithms for surface roughness prediction. In this paper, time and frequency-domain features that were extracted from real-time multi-sensor signals were selected based on the feature importance ranking. According to the experimental results, the ensemble model outperforms the individual base ML models.

Apart from the fusion of multi-sensor signals, fusion is also considered significant when dealing with data that has different types, dimensions, and structures. The data collected from real-world manufacturing scenario is normally massive, heterogeneous, and noisy, building up barriers for joint analysis. For the DED process modelling and control, Vandone et al. [31] introduced a data-driven method that fused the features extracted from online and offline data, including sensor signals, melt pool images, 3D scan geometries, and machine parameter settings. Similarly, Zhang, et al. [32] also took into account the in-process signatures and static factors for tensile strength prediction of the parts manufactured by the FDM process. In this work, the in-process variation and layer-wise interaction were captured by multi-sensors. A long short-term memory (LSTM) network was used to process the in-process data and then fused with other factors (e.g., material properties) for final prediction.

It can be seen from the previous studies that data fusion technologies show their advantages in dimensionality reduction, uncovering hidden information, and improving model performance, especially in dealing with multi-source data. In the next section, a data fusion strategy based on deep learning models is proposed for energy consumption prediction in AM.

3. Methodology

3.1. Data sensing and collection

Typically, the data generated from AM production is mainly from 4 sources [13], including product, process, working conditions, and material. The collected raw data is heterogeneous and is categorized as different levels, layer-level, and build-level. For example, the process control parameters are categorized as build-level as they are set before the AM process starts and not changed during one build. The information of working conditions is considered layer-level as it normally keeps changing during each layer. In order to predict the energy consumption before the process begins, the information of part geometries and process parameters are taken into account in this study. The process parameter settings (e.g., hatch power, hatch speed, hatch width) are collected from machine log files. Layer-wise images of the products, considered as the layer-level data, are generated, and obtained from the sliced CAD models in AM software. After data collection, the layer-wise images are firstly analyzed by CNN, where geometry characteristics of each layer can be obtained. Then these layer-level geometry features are fused with the data of process parameters in the LSTM neural networks for energy consumption prediction. The diagram of the introduced methodology is presented in Fig. 2.

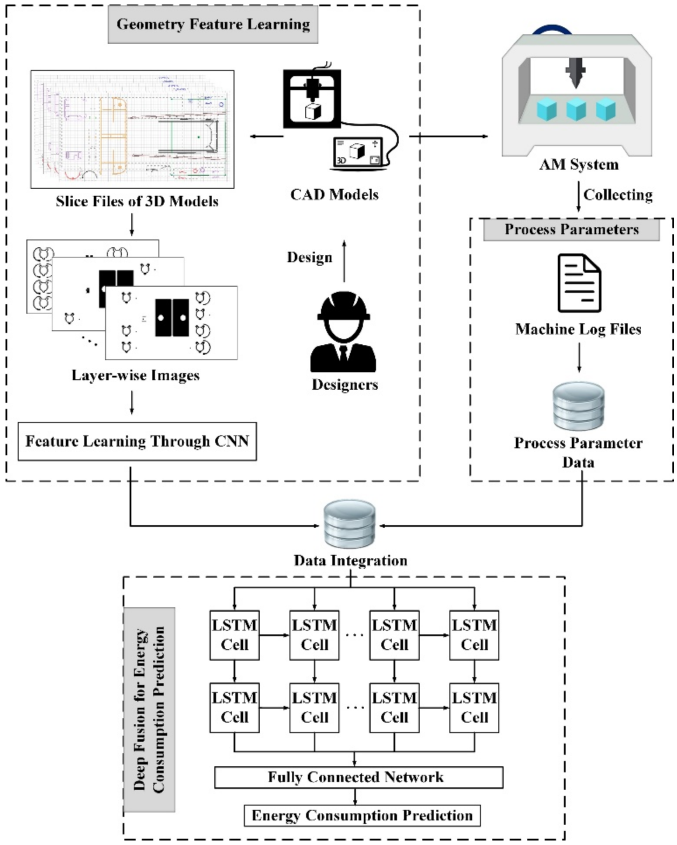

Fig. 2. Diagram of the proposed methodology

3.2. Deep fusion for energy consumption prediction based on CNN-LSTM

As described previously, it is essential to integrate the multi-sourced data for AM energy consumption prediction. However, due to the hierarchies of the collected raw data, it is hard to integrate this data simply and directly for analysis. Therefore, to capture both the layer-wise geometry information and build-level processing information, a data fusion method based on CNN-LSTM is developed to fuse the data collected from CAD models and process parameters. The 3D models of the products normally have various shapes and geometries. Some of these geometries are highly complicated that is hard to describe by hand-crafted features. Conventional feature extraction methods, such as extracting statistical features, are capable of extracting general information of the geometries while some detailed information of the inner structures is inevitably neglected. In AM, 3D models are sliced into layer-wise models with predefined layer thickness for producing physical objects layer by layer. This enables the analysis of 3D geometries by transforming the sliced models into layer-wise images. Researchers have explored and demonstrated the feasibility of using CNN to analyze the sliced geometries in AM [22]. In convolution operations, kernels are used as feature detectors that slide over the input image to form output feature maps. The convolution operation is used for extracting high-level features from images and is defined as,

$$X_n = f(X_{n-1}W_n + B_n) \tag{1}$$

Where n represents the layer number, X_n and X_{n-1} denote the outputs of the n^{th} and $(n-1)^{th}$ layers, f represents a nonlinear activation function, W_n and B_n are the weights and bias term of the n^{th} layer respectively. Pooling operation is used for reducing the dimensionality of feature maps while still retains significant information. Max pooling is a typical pooling function in CNN structure that replaces the sub-region of feature maps by the maximum value in the region,

$$x_{n+1}(i,j) = \max(x_{n+1}\{i,j\}) \tag{2}$$

Where x_n $\{i, j\}$ represents the elements in the neighbourhood of (i, j) on the feature map at the n^{th} layer, $x_{n+1}(i, j)$ is the output at (i, j) of the $(n+1)^{th}$ layer. The illustration of the convolutional feature learning process of the layer-wise images is presented in Fig.3.

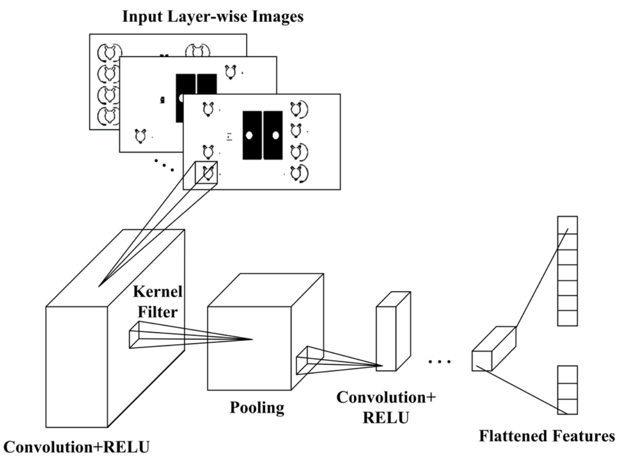

Fig. 3. Illustration of convolution feature learning process

After obtaining the flattened feature maps of each layer-wise image, LSTM is adopted to treat the flattened features as time series data and fused with process parameters. LSTM is a type of recurrent neural networks (RNNs) that consists of a number of cells that capture the temporal information of previous cells. It is widely used for learning the sequential patterns within data. In the LSTM model, there are three gates, including the input gate, forget gate, and output gate, that are used to control memory in each cell. The basic RNNs model is expressed as,

$$c_n = \phi(W_v v_n + W_h c_{n-1} + b) \tag{3}$$

In equation (3), v_n is the n^{th} input, c_n and c_{n-1} are the outputs of the n^{th} and the $(n-1)^{th}$ recurrent neuron layers, respectively. W_v and W_h are weight matrices, b is the bias term, and ϕ is the activation function. Finally, the developed CNN-LSTM model is trained for AM energy consumption prediction.

3.3. Validation of the predictive model

As is known, the energy usage of an AM system largely depends on manufacturing. Hence, the unit energy consumption E_u (Wh/g) is adopted for the evaluation of the energy consumption level and expressed as,

$$E_U = \frac{E_p}{M_p} \tag{4}$$

In equation (4), The E_p and M_p denote the energy consumed for printing the objects and the weight of the printed objects, respectively. Root Mean Square Error (RMSE) is used as an evaluation metric that calculates the error between predicted and actual values. RMSE is calculated as,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - T_i)^2} \tag{5}$$

Where n denotes the number of samples, P_i and T_i are the i^{th} predicted value and true value, respectively.

4. Case study

In the case study, an SLS machine (EOS P700) was employed as the target system where the data was collected for over 2 years. The datasets include different formats of data and information of more than a hundred production processes with thousands of manufactured products. The produced products were designed by different commercial companies, containing various geometries and structures for different applications.

4.1. Data collection and pre-processing

The data was collected from an SLS system, including thousands of layer-level information and more than a hundred of build-level information. By using AM analysis software (Autodesk Netafbb), the geometry information of different products was obtained from CAD models. The layer-wise images (more than 10000 layer-wise images in total) were obtained from sliced models and saved in BMP format. The dataset of process parameters recorded information of 6 attributes, including hatch speed, hatch space, hatch power, recoater speed, and the values of the dispenser. The actual energy consumed by the SLS system was measured by a power meter. In the dataset, the unit energy consumption for printing each layer ranges from 4 ~ 200 (Wh/g) due to different geometry characteristics and process parameters.

4.2. Results and discussion

The experimental study aims to validate the proposed methodology for energy consumption prediction in AM. After training, the model was validated on 3129 samples, shown in Fig. 4. In the figure, the red line represents the actual energy consumption of the SLS system for each printed layer. The blue line represents the predicted values by the trained CNN-LSTM model. Overall, it can be seen from the figure that the model

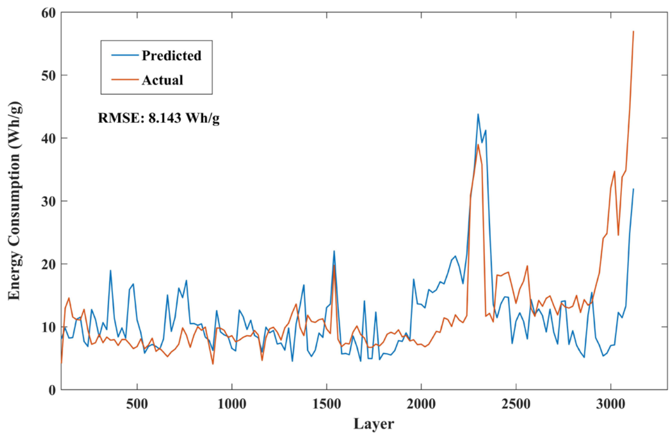

Fig. 4. The comparison between predicted values and actual values

is effective in predicting the energy consumed by the SLS system based on the proposed deep fusion strategy, with an RMSE of 8.143 Wh/g. The predictions made by the developed model can generally follow the changes of the actual values. However, when the actual unit energy consumption values reached a relatively high level, the CNN-LSTM model was hard to predict the value accurately. This is possibly due to the low-capacity utilization rate of the working platform (i.e., the sliced images are less informative), leading to considerable information loss during the convolution feature extraction process. Moreover, working conditions and material conditions will also affect energy efficiency. Further exploration will be made to optimize the feature extraction process especially dealing with the images that have less geometric information.

5. Conclusions

In this paper, a data fusion method based on the CNN-LSTM model is introduced to fuse data from CAD models and process parameters for AM energy consumption prediction before the manufacturing process begins. The CNN model can effectively learn the hidden patterns from the layer-wise images of the sliced models and make relatively accurate predictions through the LSTM neural networks. Additionally, this work provides a strategy for fusing data from different sources with different dimensions in AM energy consumption modelling. For future work, optimization for a more effective convolution feature extraction process will be explored. Additionally, computational efficiency will be considered for a more efficient energy prediction model.

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