Multi-Source Data Analytics for AM Energy Consumption Prediction

Jian Qin[a], Ying Liu[a]*, and Roger Grosvenor[a]

[a] *Institute of Mechanical and Manufacturing Engineering, Cardiff University, Cardiff, UK, CF24 3AA*

* *Corresponding author. Tel: +44(0) 29208 74696; E-mail address: Liuy81@Cardiff.ac.uk*

ABSTRACT:

The issue of Additive Manufacturing (AM) system energy consumption attracts increasing attention when many AM systems are applied in digital manufacturing systems. Prediction and reduction of the AM energy consumption have been established as one of the most crucial research targets. However, the energy consumption is related to many attributes in different components of an AM system, which are represented as multiple source data. These multi-source data are difficult to integrate and to model for AM energy consumption due to its complexity. The purpose of this study is to establish an energy value predictive model through a data-driven approach. Owing to the fact that multi-source data of AM system involves nested hierarchy, a hybrid approach is proposed to tackle the issue. This hybrid approach incorporates clustering techniques and deep learning to integrate the multi-source data that is collected using the Internet of Things (IoT), and then to build the energy consumption prediction model for AM systems. This study aims to optimise the AM system by exploiting energy consumption information. An experimental study using the energy consumption data of a real AM system shows the merits of the proposed approach. Results derived using this hybrid approach reveal that it outperforms pre-existing approaches.

Keywords:

Additive Manufacturing; Energy Consumption Prediction; Clustering; Deep Learning; Internet of Things.

1. INTRODUCTION

In the last decade, the number of AM systems in the world has increased approximately six times [1]. Funded by a number of leading industrial enterprises and governments, many factories and companies were constructed to house hundreds of AM machines which work together to generate thousands of products simultaneously [2]. Due to the large amount of machines and production yield, the AM process is defined as a low energy efficient process [3]. Also, according to the Life Cycle Analysis (LCA), the energy consumption of AM systems tends to have a significant effect on the environment [4]. Hence, based on the current situation, understanding and reducing the AM system energy consumption has become an essential topic in the manufacturing industry.

The AM process is widely known as a complex system including various technologies, such as electron beam melting (EBM), selective laser melting (SLM), and selective laser sintering (SLS) [5]. Different processing technologies show different energy consumption rates due to various impact factors [6]. These factors are identified from the entire AM process. Generally, a typical AM process includes six stages (Convert, Locate and orient, Adding support structure, Slice, Build, and Post-process). In this standard process, process and environmental attributes, including evident and hidden energy consumption related factors, can be digitalised and connected in a virtual world [7] using IoT techniques [8]. Depending on the different data sources, this data is defined as the multi-source data [9], which are often used to build data mining models for ascertaining the AM system relevant information and knowledge [10]. Unfortunately, multi-source data are generally collected by different methods from various data sources [11]. This data involves various features and dimensions, which tend to be nested as a multiple hierarchical structure. The features of this data structure are rarely independent [12]. This data is difficult to integrate using typical data integration methods, such as the extract, transform, and load (ETL) technique [13]. Under this comprehensive data environment, it is very challenging to integrate the multi-source data which include the multiple hierarchical structure for building the prediction model [14]. Integrating and modelling this multi-source data of AM system to predict energy consumption becomes a crucial research question for AM development.

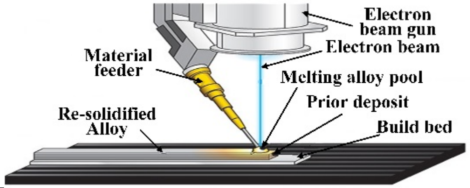
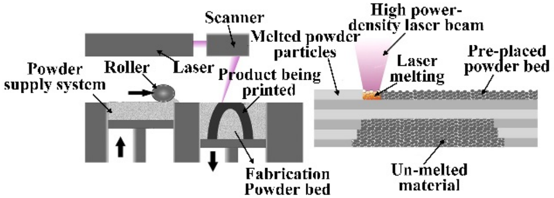
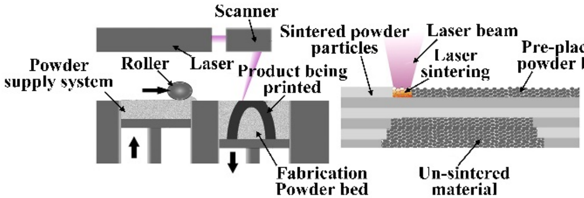
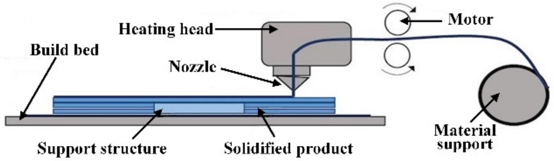
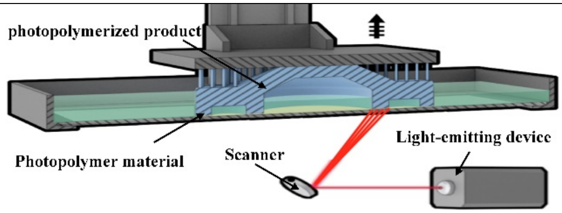
This paper proposes a hybrid multi-source data analytic approach based on IoT, clustering, and deep learning techniques, which addresses the energy consumption prediction problems in the AM system. Section 2 reviews the studies of the energy consumption analysis and data generation process in AM systems. This section also discusses multi-source data integration methods in the manufacturing. In section 3, a hybrid approach is proposed, where the multi-source data is sensed and collected by IoT technique. Then, this data is integrated and modelled by a clustering based deep learning approach to predict the AM energy consumption. In Section 4, a case study is introduced to predict the energy consumption of an AM system. Results are compared and discussed to reveal the performance of the proposed approach. In Section 5, the benefits and the limitations of the proposed approach are concluded.

2. RELATED WORKS

2.1. Energy Consumption Analysis of AM Systems

The AM system shows different energy consumption performances due to the various technical principles with different material supplies. Table 1 shows a comparison of the energy consumption of typical AM technologies including electron beam melting (EBM) [15], selective laser melting (SLM) [16], selective laser sintering (SLS) [15, 17], fused deposition modelling (FDM) [18], and STereoLithography (SLA) [18]. Based on different working principles, AM techniques have been applied to a number of different systems with various material supplies, which are also shown as schematics in Table 1. It is interesting that the energy consumption has shown a large difference.

Table 1
Comparison of the energy consumption of different AM techniques.

AM Techniques	Schematics of AM process adopted from [19-21]	Basic working principles	Main material	Energy consumption rates (W*h/g)
EBM		Using a concentrated beam of electrons to melt metal powder or filament material to build products.	Ti-6Al-4V, 316L stainless steel, etc. (Type: Beam or powder)	17.0 to 49.1
SLM		Using high power-density laser power to the melt metal powder material to build products.	Ti-6Al-4V, 316L stainless steel, etc. (Type: Powder)	26.9 to 38.75
SLS		Using laser to sinter powder material (typically, non-metallic) to build products.	Polyamide, nylon, etc. (Type: Powder)	14.5 to 36.0
FDM		Fusing thermoplastic filament material by heating printer extruder head's nozzle to build products.	Acrylonitrile butadiene styrene (ABS), Polycarbonate (PC), etc. (Type: Beam)	23.01 to 346.4
SLA		Using photopolymerization converts liquid materials (Photopolymer) into a solid form.	Poly1500, TuskXC2700T, etc. (Type: Liquid)	20.7 to 41.4

For instance, EBM and SLM both use similar materials. But, their energy consumption rates are different due to their different working principles. EBM utilises the concentrated beam of electrons to melt metal powder or filament material in order to build products, while SLM utilises the high power-density laser to melt metal powder material to build products. Moreover, SLM and SLS apply a similar technique. However, their energy consumption level shows large difference caused by different material usages. Comparing SLA and SLM, although the working principles and materials are different entirely the energy consumption rates are similar. Furthermore, even using the same technology and the same materials to conduct tests, the changes incurred in terms of energy consumption. Thus, it highlights the difficulty in analysing and optimising the energy consumption of AM systems [15-18]. Table 2 has shown the differences in the rates of AM energy consumption caused by many different components and impacted by numerous attributes. Based on the system understanding and manufacturing experience, research has found correlations between energy consumption and various processing attributes of AM processes, such as processing, product design, and material attributes.

Table 2
Energy consumption related attributes of AM systems in literature.

Literature	**Processing attributes**	**Product design attributes**	**Material attributes**
Sreenivasan and Bourell [15]	Scan speed; Laser power rate; Build platform size	N/A	Material powder density
Gross et al. [16]	Layer thickness; Laser beam radius; Scan speed; Laser power	Part orientation	Material powder absorption
Watson and Taminger [17]	Feedstock and recycling transported distance; Build platform size	Volume of deposited material	N/A
Telenko and Speeperad [18]	N/A	Z-height	Material powder density
Baumers et al. [19]	Processing procedures; Build time	Part geometry; Z-height; Capacity utilisation	N/A

In Table 2, authors showed various models for examining energy consumption in AM systems. However, the impacts are inconsistent because many correlations exist. Thus, it is difficult to identify all related attributes of AM process energy consumption from a single study or experiment. Specifically, Sreenivasan and Bourell [15] applied a basic energy consumption function, where the voltage and the current are the main inputs. In their study, system power is calculated from 1000 watts to 2500 watts, and the heater system is highlighted as the largest energy consumer. Furthermore, this article shows that scan speed, laser power rates, build platform size, and material density impact the energy consumption in the targeted AM system. However, energy consumption modelling was not established in this paper. Watson and Taminger [17] built an energy consumption model by considering the impact of the process and product design attributes, such as the feedstock and recycling transported distance, build platform size, and the volume of deposited material. But, in this paper, the energy consumption model was suggested without any experimental validation. In another paper, Telenko and Speeperad [18] compared the differences in energy consumption between SLS and injection moulding (IM). They also revealed the correlations between energy consumption and build height and material density, which were obtained from the experimental results. A Similar methodology had been also applied by Baumers et al. [19]. In this paper, the energy consumptions of two SLS machines was compared. They defined an AM process as 3 phases of energy consumption, which are warm-up, building, and cooling down. Furthermore, the authors indicate that product geometry could have an essential impact on energy consumption in the AM system. From these studies, some researchers consider processing attributes are more closely related to energy usage. They contain scan speed, layer thickness and building time. While, product design attributes and material attributes, such as part orientation, the products of height, material density, and absorption powder, are also defined as critical energy-relevant factors in AM systems. However, only with part of attributes consideration, it is hard to model the energy consumption of AM systems accurately [22].

The manufacturing industry is currently moving into the next industrial revolution, which allows the production equipment to sense and collect more data from AM systems using IoT technology [23]. With more data being sensed and collection, the behaviour of energy consumption in AM systems tends to be predictive. In the next section, the details of data generation and data analytics in AM systems will be reviewed and discussed.

2.2. Multi-Source Data Generation and Analytics of the AM Process

AM process is a data generation process starting from the initial order to the product delivery. As mentioned in the Introduction, this process includes six stages [24]. In the first stage (Convert), All of CAD (Computer-aided design) models, created by any design software, are converted into a particular format, such as STL (Standard Tessellation Language) format. Then, these models are sent to system operators [25]. In the next stage (Locate and orient), system operators decide orientations and positions of each part in every production [26]. The location and layout rotation of each product in the building bed depends on the operators' knowledge and experiences. Furthermore, AM system software helps operators to add a supporting structure if it is necessary, which is the Support structure stage. These two stages (Locate and orient, and Support structure) generate information about products orientation, position and supporting structure. Once these three information is generated, AM aided software creates slice files (Slice) for the system to organise the processing paths of each layer [16]. During the production process (Build), sensors generate sensing data to represent the working and environment information. Before shipping to the customer, the products need to be cleaned and checked. Unfused powders and support structures are removed, which is the last stage, Post-process. In this stage, data of the material usage and product accuracy is obtained. Consequently, the whole data generation process creates a considerable volume of data from multiple data sources, up to one trillion voxels information and dozens of attributes [27], which includes four primary data:

- Process operation data [28, 29], e.g., scan speed, scan power, laser power rate, etc.
- Working environment data [29-31], e.g., environment temperature, chamber temperature, etc.
- Product design data [25, 32, 33], e.g., part orientation, part height, part geometry, etc.
- Material condition data [34, 35], e.g., material density, material humility, material melting point, etc.

The four primary data has mainly constituted a multi-source database of the AM system. Using this database, data analytics becomes one of the most powerful solution to solve many problems in the current AM context. Unfortunately, current related research only uses a part of the data in this multi-source database, which is mostly collected from the process operation and the working environment.

Steed et al. [28] pointed out that it was essential to analyse process data to understand AM process. Thus, a software, called Falcon, was developed for a better exploratory visual analysis of the large, irregular and multivariate time-series data that are generated from AM process. Falcon software displayed data from system monitoring files with a clear visualisation. It allows users to check the data across multiple views and provides users with basic data analysis results, including the mean, quartile, and variance. Falcon software also showed product imagery to users helping people to understand the building condition of every single layer. However, their research focused on a single AM process which failed to reveal general knowledge of AM systems. O'Regan et al. [30] proved some correlations between building environment and product voids and residual stress after summarising critical process parameters and data in an SLM system. They found that most attributes that impacted the product voids and residual stress were represented and displayed as different types of data in system monitoring files by the target system. However, they did not establish any data analytical model in this paper, which was indicated as a future work. Uhlmann et al. [29] introduced a data analytical method for assessing SLM process. They collected data generated by monitoring sensors, which included 16 different features, such as platform temperature, chamber temperature, layering time and process pressure. In their paper, the working and environmental data was used to build a data mining model to predict the idle time of the system. They also believed that more system behaviour knowledge could be discovered when more related data was collected and used, and data analytical methods could be optimised by expanding input data.

Current data analytics research of AM system is rare to integrate the multi-source data of an entire AM process. It is challenging due to complexity of multi-source data. It is evident that the data collected from these four data sources varies in types and formats. This data is also categorised into different levels depending on the collection methods and forms. For example, usually the product design data are collected once for each build, and working environment data are collected once for each layer or every second [24]. This issue makes problems more complicated. In the next section, data integration methods in manufacturing are reviewed and discussed for helping to clear the issue of data integration.

2.3. Data Integration in Manufacturing

Data integration is defined as combining multi-source data to discover hidden information and knowledge [36]. Commonly, data collected from different sources needs a three-stages process to integrate, which is Extracting, Transforming, and Loading (ETL). Firstly, data is extracted from different resources, which may use different format files, like XML files, JSON files or standard flat format files. Then, a number of rules and functions are applied to this data for specific purposes, such as selecting the necessary features, translating the coded values, and joining data from different sources. The last stage is loading this transferred data into a database, so-called data warehouse [37]. Presently, many researchers are looking for many other data integration approaches to improve data analytics models or obtain better results. Zhan et al. [38] introduced a hybrid approach which not only integrates different types of data (image data and sensor data) but also integrates different recognition models to identify items in smart refrigerators. In their paper, data was collected from two data sources, the camera, and the weight sensor. Firstly, three pre-trained single shot multi-box detectors (SSD), ResNet, VGG16, VGG19, were used to identify the images that were taken by the camera. By using a neural network, three outputs were combined to obtain another output. This output was integrated to the data collected from weight sensors to receive the final output. In their case study, 20,000 images were used for training the model, and 5000 images were to test the model. The recognition accuracy was 0.97 which was about 5 % higher than any separated model.

Moreover, in the context of digital manufacturing, the IoT is considered as one of the best techniques to collect and integrate data. Typically, data is collected in real time through a wire or wireless communication by sensors, Auto-ID integration, and other electronic or mechatronic devices [39-41]. By integrating the data collected by IoT application, industrial production can be improved by decreasing unscheduled machine downtime and energy costs with other significant benefits [42]. Lee and Bagheri proposed [43] a method of industrial robot health monitoring. In their project, a health monitoring prediction model was generated by using the IoT technique for 30 industrial robots. A multi-regime prognostic clustering approach was used in this case within an IoT framework. Two main parameters: torque, and speed of these robots were detected and integrated as a condition dataset. The condition data was then uploaded to a local database. Moreover, the database also obtained other types of data from other systems and data sources to predict the production processing, pressure calibrations, or gear and load ratio. Meanwhile, all this multi-source data was uploaded to a cloud database. In the cloud database, clustering data mining methods were used to analyse the health condition of robots. This information was presented to the user and supported to other systems through the network. In this project, the multi-source data were integrated twice in the local and in the cloud database. Contrastively, the integration in the cloud database is much more difficult than the integration in the local due to the complex of data, while it was rarely introduced in this paper.

Besides, the multi-source data tends to become more irregular, massive, and hard to combine directly. The features and observations of this data is rarely independent, which is nested as a multiple hierarchical structure, called multi-level data [12]. Rajeswaran et al. [12] believed that the traditional analysis methods assumed measurements (attributes or features) are independent. However, in many real situations, features were nested, which tends to be correlated at various levels. There was much more valuable information hiding in these levels. In their articles, the patient data collected from surgery were levelled as several structures with different levels. With these multi-level structures, it was much easier to discover the information and knowledge hidden using this massive data. Furthermore, Frazzon et al. [44] proposed a comprehensive data-driven production control platform that includes most parts of the entire manufacturing process, such as a terminal, workers, material, customer, and suppliers. In their platform, there was many data collected from the process, such as machine status data, job processing data, personal data, customer order data, and procurement order data. The platform tended to combine all this multi-source data to improve the production control. This paper rarely introduced specific multi-level data integration methods although they were necessary. The reason why this data is hard to combine them directly in reality because the data were on different levels. It is necessary to consider the multi-level data structure for this multi-source data platform.

According to the previous research and paper of multi-source data integration, there are many methods to deal with this issue, and IoT techniques are designed to solve it mainly. Generally, the IoT collected data includes different data sources with various dimensions. This advanced technique is considered to solve the problem of combining the entire objects among thousands of items and used in many fields in manufacturing. However, due to the complicated data structure, it is hard to integrate the multi-source and multi-level data only applying the IoT and other common data integration techniques.

Consequently, AM process is a complicated data generation process. In the current AM process data environment, the number and types of impact features have become increasingly significant. Thus, to address specific problems, more and more impact factors must be considered together to obtain accurate results. To build an accurate energy consumption prediction model, data from the entire process needs to be collected and integrated. In the next section, a multi-source data analytics approach is revealed, which focuses on integrating various levelled multi-source data in an AM system. This cutting-edge approach incorporates the techniques of IoT, clustering, and deep learning.

3. RESEARCH METHODOLOGY

In order to integrate the multi-source data and predict energy consumption for AM systems, a hybrid approach is proposed in this study. Firstly, an IoT application is utilised to sense and collect the multi-source data from several relevant data sources of an AM system, such as production process operation, product design, working environment and materials condition. Secondly, the collected data is categorised into two levelled datasets (layer-level dataset and build-level dataset) as mentioned in section 2.3. Then, this multi-source and multi-level data is integrated and modelled to predict the energy consumption by fusing clustering and deep learning techniques.

3.1. Multi-source Data Sensing and Collecting

The first task to analyse the energy consumption of an AM process is to sense and collect the data from four primary sources: production operation, working environment, product design and materials. In the context of IoT, there are three main data collection methods, such as system monitoring files, design CAD models, and IoT application, to collect data from these four data sources in an AM process.

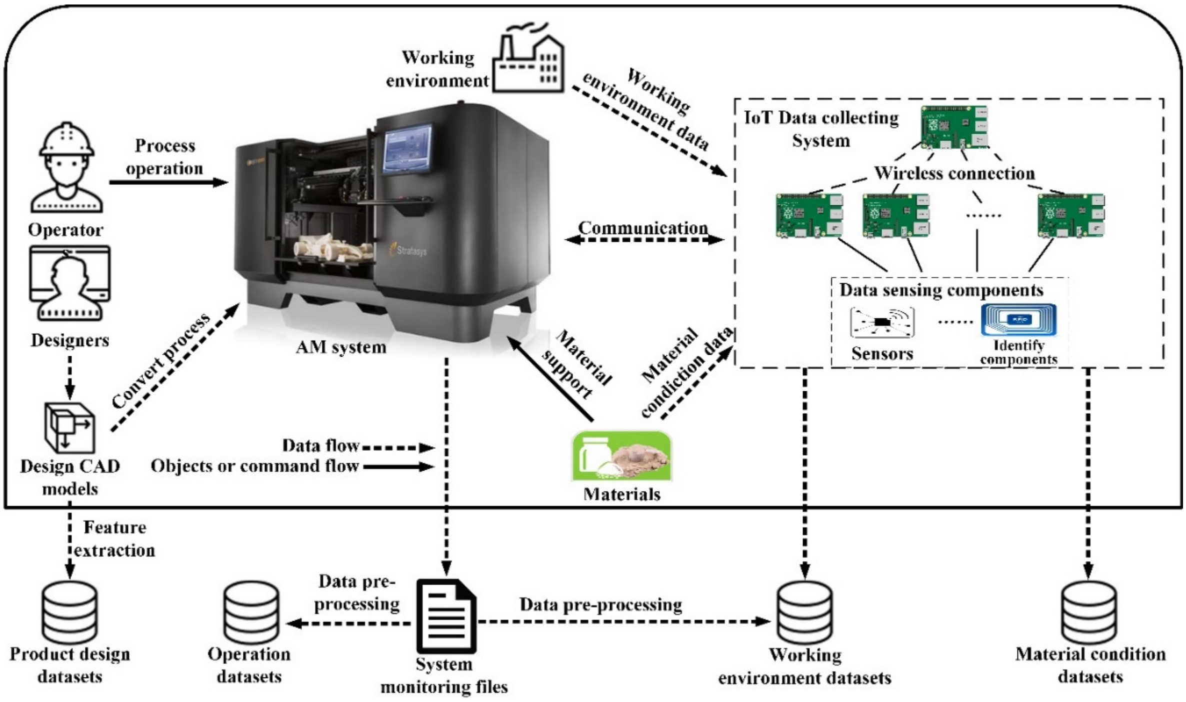


Fig. 1. Multi-source data sensing and collection using IoT for an AM process.

In Fig. 1, system operation data and working environment data are collected from the machine embedded sensors, which are represented as a series of numbers in the system monitoring files. These numbers can be temperature, voltage, current, and gas concentration, etc., where data pre-processing is necessary before model building. Furthermore, the data collected from system monitoring files is not enough to present the comprehensive aspects of a working environment [45]. In this research, extra working environment data is sensed and collected using an IoT data collecting platform. This IoT platform is structured on single-board computers, such as Raspberry Pi and MBed devices, to connect sensors [46-48], and the target AM system. This connection builds a wireless data sensing and collection network [49, 50]. Besides, product design CAD models can be shown as various formats depending on CAD design software and saving templates [32, 33]. By converting process, these design CAD models are converted to STL format, which has mentioned in section 2.2. To obtain design feature information, such as geometric information, spatial location information, spatial proportion information, these design CAD models need to be analysed by software, such as SolidWorks, Autodesk CAD, or AM software [51, 52].

3.2. Multi-Source Data Integrating and Modelling Approach

After the data is collected from the monitoring files, product design models, and the IoT data collecting system. Four main types of data, process operation data, working environment data, product design data, and material condition data, are created. In an AM process, it is obvious to realise that these four multi-source data are presented as two levelled datasets, build-level and layer-level data. Specifically, during each build, process parameter settings are constant. The relevant data is collected once at each build. This data is classified into the build-level dataset. Also, work environment, and material condition may keep changing all the time during a working process. This type of relevant data is collected many times during a build, specifically several times or once per layer, which is categorised into the build-level dataset. To integrate the multi-source data and build an energy consumption prediction model, this paper proposes a hybrid approach shown in Fig. 2.

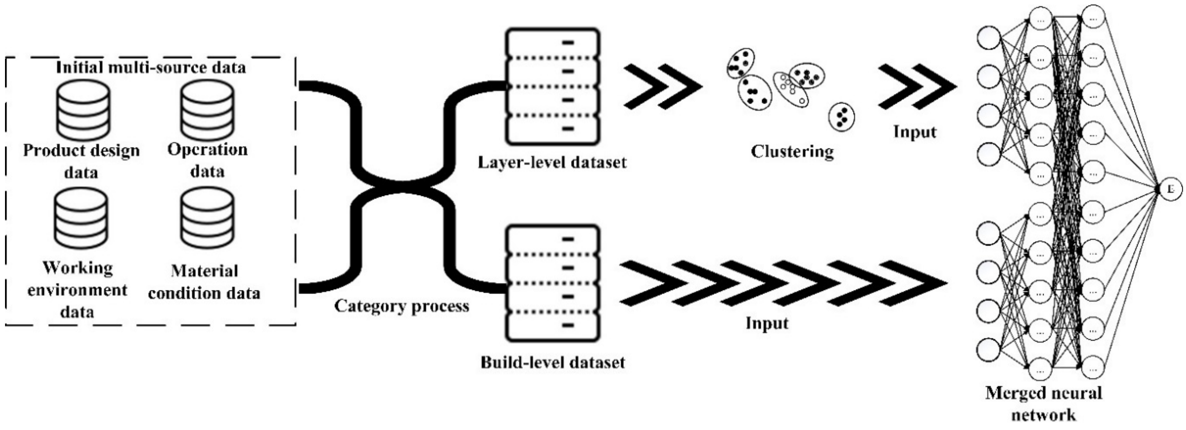


Fig. 2. Multi-source data integrating and modelling process.

It is evident that each build contains layers in different number, which depends on the height of the products. Therefore, the size of each layer-level dataset is various. Hence, keeping the same format for every dataset is necessary. In this paper, the clustering method is introduced to unify layer-level database format.

The $\boldsymbol{L_{ni}^{j}}$ is a raw layer-level dataset for each build, where $\boldsymbol{j}$ is the $\boldsymbol{j^{th}}$ build ($\boldsymbol{j}$ is between 0 to $\boldsymbol{J}$, which $\boldsymbol{J}$ is the total number of builds). $\boldsymbol{n}$ is the number of layers for each build, $\boldsymbol{i}$ is the number of features collected for layer data. Because every build includes various layer number depending on the height of build, n is different between different $\boldsymbol{j}$. For every $\boldsymbol{L_{ni}^{j}}$:

$$\boldsymbol{CL_{ci}^{j}} = \boldsymbol{f_{C}}(\boldsymbol{L_{ni}^{j}}) \qquad (1).$$

$\boldsymbol{f_C}$ is the clustering function to discover the number of $\boldsymbol{C}$ centre points ($\boldsymbol{CL_{ci}^{j}}$). In each build, the layer-level raw dataset ($\boldsymbol{L_{ni}^{j}}$) represents a dataset with the number of $\boldsymbol{n}$ indexes and the number of $\boldsymbol{i}$ features. With the algorithm, each $\boldsymbol{L_{ni}^{j}}$ will be clustered into $\boldsymbol{C}$ clusters, and, minimize the total Euclidean distance, between cluster centre and each point. So, in each build, a centre points dataset ($\boldsymbol{CL_{ci}^{j}}$) can represent an original layer-level dataset. Then, combining all the $\boldsymbol{CL_{ci}^{j}}$ into a resided dataset, representing as $\boldsymbol{L_{ic}^{J}}$. The $\boldsymbol{L_{ic}^{J}}$ is one input part of the merged neural network that is structured as Fig. 3. The $\boldsymbol{B_{k}^{J}}$ is a build-level database which is the other input part of the merged neural network, which $\boldsymbol{k}$ is the number of features in the build-level database.

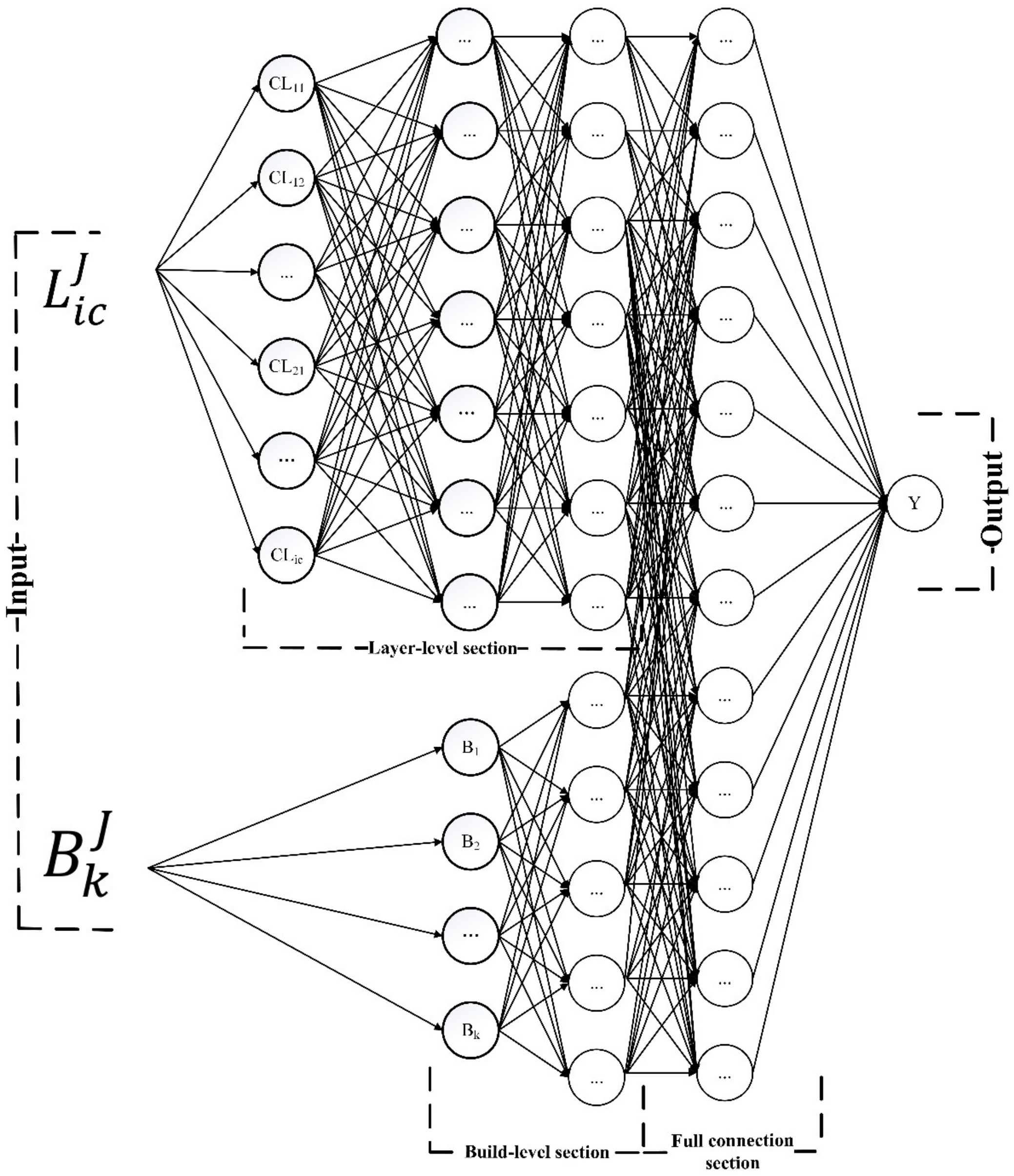


Fig. 3. Merged neural network structure.

This merged neural network (MNN) includes three sections, layer-level section, build-level section and full-connected section. The $\boldsymbol{L_{ic}^{J}}$ is the input of the layer-level section and the $\boldsymbol{B_{k}^{J}}$ is the input of the build-level section. The full-connected section is connected to the layer-level and build-level sections.

Specifically, the neurons of a layer-level section are described using the following equations:

$$\boldsymbol{u_L} = \sum_{\boldsymbol{1}}^{\boldsymbol{l}} \boldsymbol{w_{Lic}CL_{ic}}\,, \boldsymbol{y_L} = \boldsymbol{f_l}(\boldsymbol{u_L} + \Delta\boldsymbol{b_l}) \quad (2),$$

$\boldsymbol{w_{Lic}}$ is the weight of each neuron on each layer-level section, $\boldsymbol{l}$ is the number of neurons on each layer-level section, $\boldsymbol{y_L}$ is the output of each neuron, which is the input of next layer, $\boldsymbol{f_l}$ is the activation function of a layer-level section, and $\Delta\boldsymbol{b_l}$ is the bias.

The neurons of a build-level section are denoted as a set of following equations:

$$\boldsymbol{u_B} = \sum_1^{\boldsymbol{b}} \boldsymbol{w_B B_k}\,, \boldsymbol{y_B} = \boldsymbol{f_b}(\boldsymbol{u_B} + \Delta\boldsymbol{b_b}) \qquad (3),$$

$\boldsymbol{w_B}$ is the weight of each neuron on each build-level section, $\boldsymbol{b}$ is the number of neurons on each build-level section, $\boldsymbol{y_B}$ is the output of each neuron, which is the input of next layer, $\boldsymbol{f_b}$ is the activation function, and $\Delta\boldsymbol{b_b}$ is the bias.

With the full connection layer, neurons are represented as:

$$\boldsymbol{u_f} = \sum_1^{\boldsymbol{F}} (\boldsymbol{w_{fi} y_l} + \boldsymbol{w_{fi} y_b}), \boldsymbol{y_f} = \boldsymbol{f_f}\left(\boldsymbol{u_f} + \Delta\boldsymbol{b}\right) \qquad (4),$$

$\boldsymbol{w_{fi}}$ is the weight of each neuron on each full connection section, $\boldsymbol{F}$ is the number of neurons, which $\boldsymbol{F} = \sum \boldsymbol{fi}$, $\boldsymbol{y_f}$ is the output of each neurons, which is the input of next layer, $\boldsymbol{f_f}$ is the activation function of, and $\Delta\boldsymbol{b}$ is the bias of full connection section.

This hybrid approach fuses clustering and deep learning techniques, the levelled multi-source data is integrated and modelling to predict target values. In next section, the target values, which is the energy consumption of AM systems, are introduced. Additionally, the validation methods are presented.

3.3. Model Validation

The total energy consumption of each AM process is measured. However, the AM process is a time-consuming process which means with the longer production time the energy consumption is increasing obviously. The total energy consumption strongly depends on the process time. Therefore, the unit energy consumption of each build is considered as the target values that is denoted as following [15]:

$$\boldsymbol{E_U} = \frac{\boldsymbol{E_T}}{\boldsymbol{M_T}} \tag{5),}$$

$\boldsymbol{M_T}$ is the product weight of a total build. $\boldsymbol{E_T}$ represents the total energy consumption, which is denoted as following, where $\boldsymbol{e}$ is the number of energy consumers, such as heating system, layer system, and feed and recycle system [6], in the system, $\boldsymbol{t}$ is the total time of each process.

$$\boldsymbol{E_T} = \sum_{\boldsymbol{e}}(\int_{\boldsymbol{0}}^{\boldsymbol{t}} \boldsymbol{E_e}) \tag{6).}$$

In this article, two evaluation methods, Model Correlation Coefficient (MCC) and Root Mean Square Error (RMSE), are used to verify the accuracy of the energy consumption prediction. MCC is doneted as:

$$\boldsymbol{MCC} = \frac{\boldsymbol{S_{PA}}}{\sqrt{\boldsymbol{S_P S_A}}} \tag{7),}$$

$$\boldsymbol{S_{PA}} = \frac{\sum_i(\boldsymbol{p_i}-\overline{\boldsymbol{p}})(\boldsymbol{a_i}-\overline{\boldsymbol{a}})}{\boldsymbol{n-1}};\ \boldsymbol{S_P} = \frac{\sum_i(\boldsymbol{p_i}-\overline{\boldsymbol{p}})^2}{\boldsymbol{n-1}};\ \boldsymbol{S_A} = \frac{\sum_i(\boldsymbol{a_i}-\overline{\boldsymbol{a}})^2}{\boldsymbol{n-1}} \tag{8).}$$

In the above equations, $\boldsymbol{p_i}$ is the prediction data, $\overline{\boldsymbol{p}}$ is the average value of the prediction data, $\boldsymbol{a_i}$ is the actual data and the $\overline{\boldsymbol{a}}$ is the average value of the entire data. Also, the RMSE ($\mathbf{e}_{\boldsymbol{RMSE}}$) is shown as:

$$\boldsymbol{e_{RMSE}} = \sqrt{\frac{\sum_{i=1}^{n}\left(\boldsymbol{p_{1,i}}-\boldsymbol{a_{1,i}}\right)^2}{\boldsymbol{n}}} \tag{9),}$$

where $\boldsymbol{p_i}$ is the prediction data, $\overline{\boldsymbol{p}}$ is the average value of the prediction data, $\boldsymbol{a_i}$ is the actual data, and $\overline{\boldsymbol{a}}$ is the average value of the entire actual data [53].

This proposed prediction approach has integrated levelled multi-source data that is collected from an entire AM process and then, predicts AM process energy consumption. A case study using a real AM system has been designed to reveal the performance of the proposed approach in the next section.

4. CASE STUDY

In the last decade, SLS has become a mainstream AM system. This system sinters powdered material to build products using lasers. In this case study, a SLS machine (EOS P700) is focused as the target system. The EOS P700 has a build envelope, maximum size is 740* 400* 590mm (x, y, and z), with two 50W CO_2 lasers which can sinter nylon materials (PA2200 and PA3200GF). PA2200 is the original polyamide-12 without any fillers, and PA 3200GF contains 40% glass beads for enhancing stiffness.

4.1. Data Collection and Description

In this case study, data was collected from four data sources (production operation, working environment, product design, and material condition) of each build in the target system. This data is collected through three collection methods (system monitoring files, IoT data collecting system, and product design CAD models), which was categorised into two levels (layer-level and build-level). The data description is shown in Table 3.

Table 3

Data description including data sources, categories, and collecting methods.

Data Attributes	Data Description	Data Sources	Data Categories	Collection Methods
DispenserMax	The maximum value of dispenser measured in '%'.	Process operation	Build-levelled data	Machine log
DispenserMin	The minimum value of dispenser measured in '%'.			
RecoaterSpeed	The recoater speed measured in 'mm/m'.			
HatchPower	The power of laser for sintering measured in '%'.			
HatchSpeed	The scan speed of laser for sintering measured in 'mm/s'.			
HatchWidth	The scan space of laser for sintering measured in 'mm'.			
HatchAngle	The scan angle between each layer measured in '°'.			
AverFillingDegSingle	The average filling degree of single part measured in '%'	Product design		Product design model
FillingDegWhole	The filling degree of the whole build measured in '%'.			
AverRateLWSingle	The average rate between length and width of single part measured in '%'.			
AverRateLHSingle	The average rate between length and height of single part measured in '%'.			
AverRateHWSingle	The average rate between height and width of single part measured in '%'.			
AverRateLWWhole	The rate between length and width of the whole build measured in '%'.			
AverRateLHWhole	The rate between length and height of the whole build measured in '%'.			
AverRateHWWhole	The rate between height and width of the whole build measured in '%'.			
BottomArea	The bottom area measured in 'mm^2'.			
HeightBuild	The entire height measured in 'mm'.			
NoPart	The number of printing products.			
HightLayer	The absolute height of current layer.			
AreaLayer	The print area of current layer measured in '%'.			
RateNewRecy	The rate between new and recycle powder, measured in '%'.	Material condition		Wireless IoT platform
TypeMaterial	The type of material.			
TempNewPowder	The new powder temperature measured in '°C'.		Layer-levelled data	
HumNewPowder	The new powder humidity measured in '%'.			
TempRecyPowder	The recycle powder temperature measured in '°C'.			
HumRecyPowder	The recycle powder humidity measured in '%'.			
LabTemperature	The lab temperature measured in '°C'.	Working environment		
ControlTemperature	The control system temperature measured in '°C'.			
ControlHumidity	The control system humidity measured in '%'.			
t_at_BNLA	The time of each production layer measured in 's'.			Machine log
ChamberTemperature	The building chamber temperature measured in '°C'.			
FrameTemperature front	The front-frame temperature measured in '°C'.			
FrameTemperature back	The back-frame temperature measured in '°C'.			
FrameTemperature left	The left-frame temperature measured in '°C'.			
FrameTemperature right	The right-frame temperature measured in '°C'.			
PlatformTemperature	The working platform temperature measured in '°C'.			
ScannerTemperature	The scanner temperature measured in '°C'.			
PyrometerTemperature	The Pyrometer temperature measured in '°C'.			
O_2Level	The oxygen percentage in the working chamber measured in '%'.			
EnergyDeviation	The energy deviation percentage of the system.			

The target system generated two monitoring files in each build automatically. One file, called Job File, recorded parameter settings of each process. These 7 settings were given by system technicians before starting production process, which were not changed during process. However, technicians would change some parameters between builds depending on working condition. This data was categorised into a build-level dataset. Also, during each production process, the system automatically generated another monitoring file, called Report File, which included 13 production process data attributes. This data was collected for every production layer by various sensors that are embedded within the system, such as working time of each layer, laser sintering time and cumulative recoating time, frame temperature, chamber temperature, platform temperature, scanner temperature, and oxygen level. The data size of each Report File was different depending on heights of building products, which meant more layers that were produced, more significant of the data was generated. This data was classified into a layer-level dataset. These monitoring files were formatted as RPT files by the system, which were typical machine report files. In this case study, these RPT format files were converted to standard comma-separated values (CSV) data format which was popular in many data analytics areas. Benefit from completed monitoring system in EOSP700, there was no any missed or abnormal data in the monitoring files.

A part of data cannot be collected from working environment and material condition only via system monitoring files. In this case study, an IoT platform was introduced to sense and collect more data from working environment and material condition. This IoT platform was designed using RPIs, and it connected multiple RPIs and the AM system via a wireless communication by an Ad-Hoc network. The network allowed nodes to be dynamically added and removed from the system. This system is entirely self-sufficient with no external infrastructure required. Notably, three RPIs were connected, and one of them was linked to the EOS P700 controlling system. Several sensors and RFID system were set up on this wireless IoT platform to collect external data and identify the type of used material. With this RPI based IoT platform more working environment and material condition data were sensed and collected, like lab temperature, humidity, controlling system temperature and humidity, material powder temperature and humidity, and proportion between new powder and recycled powder. The categories of this data are explained in Table 3.

Another build-level data was collected from product CAD models, which include product design information. This information highly relies on human's knowledge and experience. The number of parts made in every production was different from one to hundreds. System operators decided products location and rotation in each build without following any specific rules. These decisions only depended on the size of the building platform and their knowledge and experience. Using these CAD model, 13 product design features was recognised from product design CAD models. To recognise these features, an AM analysis software was applied in this case study, called Autodesk Netfabb. These features included average filling degree of a single part, filling degree of a whole build, average rates between three dimensions of a single part, rates between three dimensions of a whole build, and bottom area, and so on.

4.2. Results and Discussion

In this case study, results focused on validation of the proposed method. Several comparisons were raised for verifying performances of the proposed approach. Firstly, this case study introduced three ML methods as benchmarks. In this section, results yielded from three machine learning methods were presented using results from single level datasets and multi-level datasets.

4.2.1. Results of ML algorithms

These three ML algorithms are linear regression (LR), *k*-nearest neighbours (*k*-NN), decision tree (DT), which are popular in academia, industry, and business [53]. LR was the first ML algorithm to predict the energy consumption in this case study. Using this algorithm, outputs were expected to be a linear combination of inputs. The Scikit-learn package, used for applying LR model, chooses and sets parameters automatically. In this project, results from the ordinary least squares regression were taken as the LR results shown in Fig. 4. *k*-NN is one of the most straightforward supervised machine learning, which is applied to both classification and regression [54]. DT is a first classifier structure like a flowchart. Every internal node, branch and leaf node of a DT represents an attribute, a result, or a class label, respectively, and the topmost node is called the root. Depending on attribute values, unknown tuple is classified within each leaf node storing the class information, which contains the classification rules of a DT models[55].

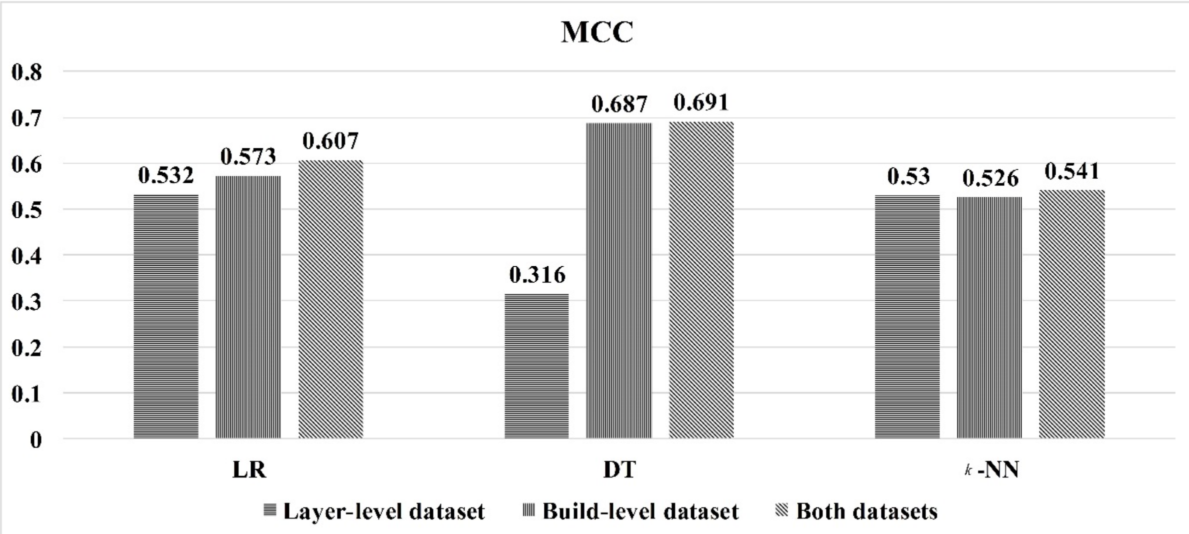


Fig. 4a. MCC of three ML methods.

The Fig. 4a shows the MCCs of three ML methods. When only using the layer-level dataset, the best results appear when the number of clusters is set as one. So, Fig 4 shows results from the layer-level dataset when the number of clusters is set as one. Generally, when both datasets are used as the input dataset MCCs appear the highest number (0.691) by applying all three ML methods. Specifically, DT obtains the best MCC when using the entire dataset, but, this method yields the lowest MCC (0.316) when only using the layer-level dataset. The MCCs of LR and *k*-NN rarely change much when using different input datasets.

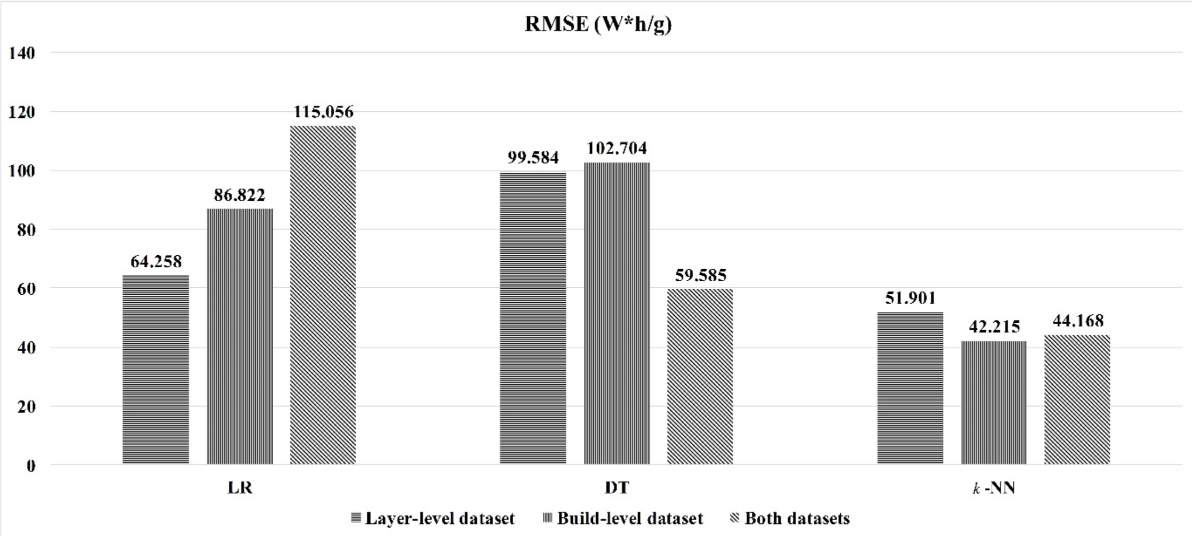


Fig. 4b. RMSE of three ML methods.

In Fig. 4b, RMSEs of three ML methods are illustrated. Different to MCCs, when extending input dataset (from single to multiple), the RMSEs do not always decrease. When LR is used to build the model, with more significant dataset, the RMSE is increased, and the difference between the highest and lowest RMSE is 50.798 W*h/g. Conversely, using DT algorithm, the lower RMSE (59.585 W*h/g) is yielded when both datasets are applied comparing to using the single input dataset. When *k*-NN is applied, the lowest RMSE (42.215 W*h/g) appears at using build-level database. Combining both validations, when collecting and using more data to predict energy consumption the effects of ML methods tends to be fluctuating.

Now, it is interesting to realise results yielded by the proposed approach. To be clear that the data was collected from over a hundred builds including thousands of product design models, and each build contained the different number of layers from 20 to 3500 approximately. It is necessary to find an applicable number of clusters for representing the layer-level dataset of each build for each predictive model.

4.2.2. Results of the proposed approach

Results using the layer-level dataset and considering the number of clusters from 1 to 20 is shown in the Fig. 5. An artificial neural network was applied as the prediction model. Parameter settings of the neural network are highly depended on different training and testing dataset. With a different dataset, neural network structures tended to be different for obtaining the best performance. All neural networks used two types of activation: (1) for the output layer, scaled exponential linear activation was applied, and (2) for the remaining layers, the ReLU activation was used. The mean squared error was used to represent the loss. Supported by a popular Python package, Keras, the Adam optimiser was used [56].

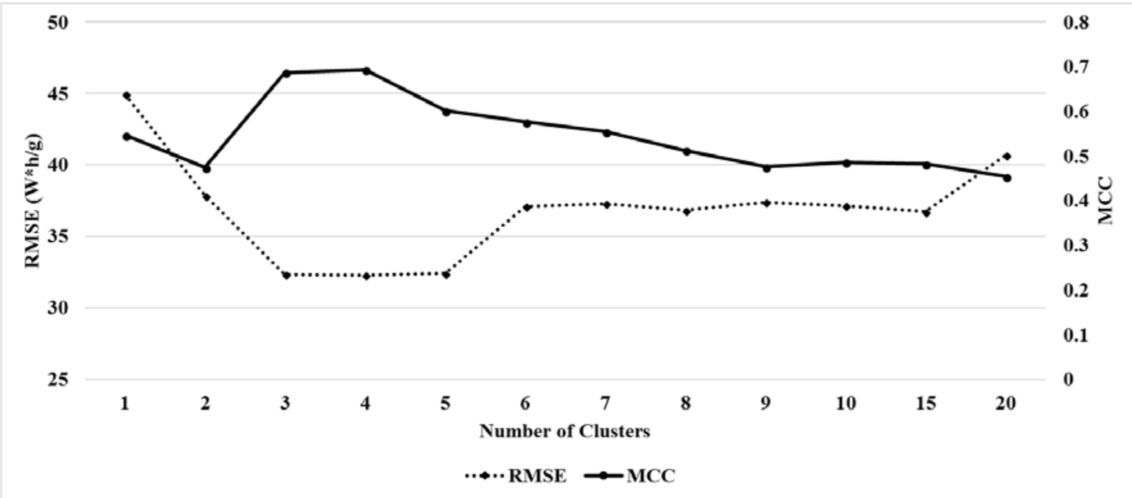


Fig. 5. Results comparison between a different number of the cluster representing layer-level dataset.

With the different number of clusters represents the layer-level dataset, MCCs and RMSEs show an irregular change. The best result appears when choosing 4 clusters with the highest MCC (0.694) and lowest RMSE (32.306 W*h/g). Also, the results of 3 and 5 clusters take the second and third best place. Specifically, with 3 clusters, the MCC is 0.687 and RMSE is 32.353 W*h/g, and, with 5 clusters, the MCC is 0.602 and RMSE is 32.414 W*h/g. It is also needed to be highlighted that the highest RMSE is 44.965 W*h/g with only one cluster. When the number of clusters is increased more than 5, RMSEs start to increase. MCCs is reduced when the number of clusters is more than 4, and the lowest is 0.454 when 20 clusters are chosen. Moreover, when only using build-levelled datasets as input dataset the

MCC is 0.753, and the RMSE is 62.955 W*h/g. It is interesting to know the prediction performance when integrated these two datasets by using the proposed method.

Table 4
Results comparison applying MNN using the build-level dataset and layer-level dataset with different the number of clusters (3 to 5).

Validation	3 Clusters	4 Clusters	5 Clusters
MCC	0.786	0.803	0.685
RMSE (W*h/g)	25.906	25.460	28.406

From Table 4, when to apply 4 clusters representing the layer-level dataset prediction performance is the best. This case study uses 3 to 5 clusters as the layer-level input dataset separately. The results comparison is displayed in Table 4. From this table, when 4 clusters represent the layer-level data and integrating with build-level data is used, the best result is obtained with the highest MCC (0.803), and lowest RMSE (25.460 W*h/g). Comparing with all other results from any above input datasets and prediction models, this result is the best.

4.2.3. Discussion

According to the results from the last section, the energy consumption of the AM process is predicted accurately by using the proposed method. A few of interesting points are necessary to discuss from the results. Firstly, the prediction accuracy varies with a different number of clusters. When layer-level data are clustered as 3 to 5 clusters, the best results are obtained. It is interesting to note that the AM production process can also be divided as 3, 4 or 5 energy phases regarding Baumers et al.'s [22] research. This finding indicate the clustering centre points are able to represent the entire production process. It also proves the correctness of Baumers et al.'s suggestion. Secondly, by using the ML algorithms, it is difficult to show that expanding input datasets can yield better results. With the results obtained by either datasets (layer-level dataset, build-level dataset or both datasets), the deep learning based algorithms, including typical neural networks and proposed clustering based MNN, show merits compared to the results of benchmark algorithms in this case study. The deep learning methods have presented a good performance for building the relationship between the target and high dimension data input. However, with the integrated input datasets, typical ANNs cannot easily be applied to model the target values, while the proposed clustering based MNN structure is able to integrate different levelled datasets and predict AM energy consumption precisely.

5. CONCLUSIONS

In this paper, the focus is on the modelling and prediction of energy consumption given an example of SLS process in the AM system. This approach is based on a review of related research indicating the significant meaning of data-driven methods in industrial sustainability domain. Different from existing effort, a hybrid approach has been proposed fusing IoT, clustering and deep learning techniques. In this paper, the multi-source data generated from an AM process are sensed and collected by IoT techniques. This data includes process operation data, working environment data, material condition data and product design data, which is categorised into two level datasets, layer-level dataset and build-level dataset. By applying a clustering based MNN to integrate this multi-level multi-source data, the AM energy consumption is predicted accurately. A case study is carried out based on real-word SLS process data collected which has shown the merits of the proposed approach. Experimental results have indicated that the proposed approach tends to yield better performance when integrating the multi-level multi-source data. Especially, comparing with other AM energy consumption analysis, this method can predict the energy consumption of each production rather than measure a range of energy usage, which provides an accurate value of energy consumption. In the actual industrial scenario, this can be very helpful to implement data analytics when the multi-source data is collected.

6. REFERENCES

[1] T. Wohlers, Wohlers Report 2011: Additive Manufacturing and 3D Printing, State of the lndustry, Wohlers Associates, Ft, Collins, CO, (2011).

[2] K.V. Wong, A. Hernandez, A review of additive manufacturing, ISRN Mechanical Engineering, (2012).

[3] Q. Han, R. Setchi, S.L. Evans, Synthesis and characterisation of advanced ball-milled Al-Al 2 O 3 nanocomposites for selective laser melting, Powder Technology, 297 (2016), pp. 183-192.

[4] R. Huang, M. Riddle, D. Graziano, J. Warren, S. Das, S. Nimbalkar, J. Cresko, E. Masanet, Energy and emissions saving potential of additive manufacturing: the case of lightweight aircraft components, Journal of Cleaner Production, (2015).

[5] S. Ford, M. Despeisse, Additive manufacturing and sustainability: an exploratory study of the advantages and challenges, Journal of Cleaner Production, 137 (2016), pp. 1573-1587.

[6] J. Qin, Y. Liu, R. Grosvenor, A Framework of Energy Consumption Modelling for Additive Manufacturing Using Internet of Things, Procedia CIRP, 63 (2017), pp. 307-312.

[7] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, Internet of Things (IoT): A vision, architectural elements, and future directions, Future Generation Computer Systems, 29 (2013), pp. 1645-1660.

[8] J. Qin, Liu, Ying and Grosvenor, Roger Data analytics for energy consumption of digital manufacturing systems using Internet of Things method, in: IEEE International Conference on Automation Science and Engineering, Xi'an, China, (2017).

[9] R.R. Yager, A framework for multi-source data fusion, Information Sciences, 163 (2004), pp. 175-200.

[10] H. Boyes, B. Hallaq, J. Cunningham, T. Watson, The industrial internet of things (IIoT): An analysis framework, Computers in Industry, 101 (2018), pp. 1-12.

[11] S.L. Chan, Y. Lu, Y. Wang, Data-driven cost estimation for additive manufacturing in cybermanufacturing, Journal of Manufacturing Systems, 46 (2018), pp. 115-126.

[12] J. Rajeswaran, E.H. Blackstone, multilevel data analysis: What? Why? How?, The Journal of thoracic and cardiovascular surgery, 155 (2018), pp. 210-211.

[13] S. Yin, O. Kaynak, Big data for modern industry: challenges and trends [point of view], Proceedings of the IEEE, 103 (2015), pp. 143-146.

[14] J. Cavalheiro, P. Carreira, A multidimensional data model design for building energy management, Advanced Engineering Informatics, 30 (2016), pp. 619-632.

[15] R. Sreenivasan, D. Bourell, Sustainability Study in Selective Laser Sintering- An Energy Perspective, in, Minerals, Metals and Materials Society/AIME, 420 Commonwealth Dr., P. O. Box 430 Warrendale PA 15086 USA, (2010).

[16] B.C. Gross, J.L. Erkal, S.Y. Lockwood, C. Chen, D.M. Spence, Evaluation of 3D printing and its potential impact on biotechnology and the chemical sciences, in, ACS Publications, (2014).

[17] J. Watson, K. Taminger, A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption, Journal of Cleaner Production, (2015).

[18] C. Telenko, C.C. Seepersad, Assessing energy requirements and material flows of selective laser sintering of Nylon parts, in: Proceedings of the Solid Freeform Fabrication Symposium 2010, (2010), pp. 8-10.08.

[19] W.E. Frazier, Metal Additive Manufacturing: A Review, Journal of Materials Engineering and Performance, 23 (2014), pp. 1917-1928.

[20] F.P. Melchels, J. Feijen, D.W. Grijpma, A review on stereolithography and its applications in biomedical engineering, Biomaterials, 31 (2010), pp. 6121-6130.

[21] R. Paul, S. Anand, Process energy analysis and optimization in selective laser sintering, Journal of Manufacturing Systems, 31 (2012), pp. 429-437.

[22] M. Baumers, C. Tuck, D. Bourell, R. Sreenivasan, R. Hague, Sustainability of additive manufacturing: measuring the energy consumption of the laser sintering process, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 225 (2011) pp.2228-2239.

[23] F. Shrouf, J. Ordieres, G. Miragliotta, Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm, in: Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on, (2014), pp. 697-701.

[24] L. Wang, C.A. Alexander, Additive Manufacturing and Big Data, International Journal of Mathematical, Engineering and Management Sciences, 1 (2016), pp. 107-121.

[25] L.D. Sturm, C.B. Williams, J.A. Camelio, J. White, R. Parker, Cyber-physical vulnerabilities in additive manufacturing systems: A case study attack on the .STL file with human subjects, Journal of Manufacturing Systems, 44 (2017), pp. 154-164.

[26] W. Sealy, Additive manufacturing as a disruptive technology: how to avoid the pitfall, American Journal of Engineering and Technology Research Vol, 11 (2011).

[27] R. Dehoff, In-Situ Process. Monitoring and Big. Data Analysis for Additive. Manufacturing of Ti-6All-4V, Workshop Presentation, (2015), pp. 1-21.

[28] C.A. Steed, W. Halsey, R. Dehoff, S.L. Yoder, V. Paquit, S. Powers, Falcon: Visual analysis of large, irregularly sampled, and multivariate time series data in additive manufacturing, Computers & Graphics, 63 (2017), pp. 50-64.

[29] E. Uhlmann, R.P. Pontes, A. Laghmouchi, A. Bergmann, Intelligent Pattern Recognition of a SLM Machine Process and Sensor Data, Procedia CIRP, 62 (2017), pp. 464-469.

[30] P. O'Regan, P. Prickett, R. Setchi, G. Hankins, N. Jones, Metal based additive layer manufacturing: variations, correlations and process control, Procedia Computer Science, 96 (2016), pp. 216-224.

[31] X. Zhao, D.W. Rosen, A data mining approach in real-time measurement for polymer additive manufacturing process with exposure controlled projection lithography, Journal of Manufacturing Systems, 43 (2017), pp. 271-286.

[32] O. Diegel, S. Singamneni, S. Reay, A. Withell, Tools for sustainable product design: additive manufacturing, (2010).

[33] S. Hällgren, L. Pejryd, J. Ekengren, 3D data export for Additive Manufacturing-improving geometric accuracy, Procedia CIRP, 50 (2016), pp. 518-523.

[34] Q. Han, R. Setchi, B. Karihaloo, Challenges and Opportunities in the Additive Layer Manufacturing of Al-Al2O3 Nanocomposites, (2015).

[35] B. Meredig, Industrial materials informatics: Analyzing large-scale data to solve applied problems in R&D, manufacturing, and supply chain, Current Opinion in Solid State and Materials Science, 21 (2017), pp. 159-166.

[36] M. Lenzerini, Data integration: A theoretical perspective, in: Proceedings of the twenty-first ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems, ACM, (2002), pp. 233-246.

[37] J. Widom, Research problems in data warehousing, in: Proceedings of the fourth international conference on Information and knowledge management, ACM, (1995), pp. 25-30.

[38] W. Zhang, Y. Zhang, J. Zhai, D. Zhao, L. Xu, J. Zhou, Z. Li, S. Yang, Multi-source data fusion using deep learning for smart refrigerators, Computers in Industry, 95 (2018), pp. 15-21.

[39] A.M. Ortiz, D. Hussein, P. Soochang, S.N. Han, N. Crespi, The Cluster Between Internet of Things and Social Networks: Review and Research Challenges, Internet of Things Journal, IEEE, 1 (2014), pp. 206-215.

[40] B. Zhuming, X. Li Da, W. Chengen, Internet of Things for Enterprise Systems of Modern Manufacturing, Industrial Informatics, IEEE Transactions on, 10 (2014), pp. 1537-1546.

[41] M. Thibaud, H. Chi, W. Zhou, S. Piramuthu, Internet of Things (IoT) in high-risk Environment, Health and Safety (EHS) industries: A comprehensive review, Decision Support Systems, 108 (2018), pp. 79-95.

[42] D. Miorandi, S. Sicari, F. De Pellegrini, I. Chlamtac, Internet of things: Vision, applications and research challenges, Ad Hoc Networks, 10 (2012), pp. 1497-1516.

[43] J. Lee, B. Bagheri, Cyber-Physical Systems in Future Maintenance, in: 9th WCEAM Research Papers, Springer, (2015), pp. 299-305.

[44] E.M. Frazzon, M. Kück, M. Freitag, Data-driven production control for complex and dynamic manufacturing systems, CIRP Annals, (2018).

[45] C.-Y. Chong, S.P. Kumar, Sensor networks: evolution, opportunities, and challenges, Proceedings of the IEEE, 91 (2003), pp. 1247-1256.

[46] Z. Min, L. Wenfeng, W. Zhongyun, L. Bin, R. Xia, A RFID-based material tracking information system, in: Automation and Logistics, 2007 IEEE International Conference on, IEEE, (2007), pp. 2922-2926.

[47] W. Zhou, S. Piramuthu, F. Chu, C. Chu, RFID-enabled flexible warehousing, Decision Support Systems, 98 (2017), pp. 99-112.

[48] B.L. Risteska Stojkoska, K.V. Trivodaliev, A review of Internet of Things for smart home: Challenges and solutions, Journal of Cleaner Production, 140 (2017),pp. 1454-1464.

[49] R.I. Pereira, I.M. Dupont, P.C. Carvalho, S.C. Jucá, IoT embedded linux system based on Raspberry Pi applied to real-time cloud monitoring of a decentralized photovoltaic plant, Measurement, 114 (2018), pp. 286-297.

[50] T. Yashiro, S. Kobayashi, N. Koshizuka, K. Sakamura, An Internet of Things (IoT) architecture for embedded appliances, in: Humanitarian Technology Conference (R10-HTC), 2013 IEEE Region 10, IEEE, (2013), pp. 314-319.

[51] J. Han, M. Pratt, W.C. Regli, Manufacturing feature recognition from solid models: a status report, IEEE Transactions on Robotics and Automation, 16 (2000), pp. 782-796.

[52] B. Babic, N. Nesic, Z. Miljkovic, A review of automated feature recognition with rule-based pattern recognition, Computers in Industry, 59 (2008), pp. 321-337.

[53] J. Han, M. Kamber, J. Pei, Data mining: concepts and techniques, Elsevier, (2011).

[54] N.S. Altman, An introduction to kernel and nearest-neighbor nonparametric regression, The American Statistician, 46 (1992), pp. 175-185.

[55] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, Scikit-learn: Machine learning in Python, Journal of Machine Learning Research, 12 (2011), pp. 2825-2830.

[56] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature, 521 (2015), pp. 436-444.