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A Framework of Energy Consumption Modelling for Additive Manufacturing using Internet of Things

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Abstract

The topic of 'Industry 4.0' has become increasingly popular in manufacturing and academia since it was first published. Under this trending topic, researchers and manufacturing companies have pointed out many related capabilities required by current manufacturing systems, such as automation, interoperability, consciousness, and intelligence. Additive manufacturing (AM) is one of the most popular applications of Industry 4.0. Although AM systems tend to become increasingly automated, the issue of energy consumption still attracts attention, even in the Industry 4.0 era, and is related to many processing factors depending on different types of AM system. Therefore, defining the energy consumption behaviour and discovering more efficient usage methods in AM processes is established as being one of the most important research targets. In this paper, an Internet of Things (IoT) framework is designed for understanding and reducing the energy consumption of AM processes. A huge number and variety of real-time raw data are collected from the manufacturing system; this data is analysed by data analytical technologies, combining the material attributes parameter and design information. It is uploaded to the cloud where more data will be integrated for discovering the energy consumption knowledge of AM systems. In addition, a case study is also presented in this paper, which the typical AM system is focused on the target system (EOS P700). The raw data is collected and analysed from this process. Then, based on the IoT framework, a novel energy consumption analysis proposal is proposed for this system specifically.

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Keywords: Energy Consumption, Additive Manufacturing, Internet of Things Framework

1. Introduction

Nowadays, Industry 4.0 is not only a research and development slogan but is also an industrial and academic activities. Many industrial companies and research organizations have begun working on this far-sighted topic including various aspects [1; 2]. With more and more related publication of technologies, principles, and concepts, the achievement criteria of Industry 4.0 has become much clearer and more specific. A qualified Industry 4.0 manufacturing system needs necessary capabilities, like interoperability and consciousness. To achieve these capabilities, data is considered as being vitally important. It is the connecting media of the integration between different manufacturing objects and activities. Enabling technologies are included in manufacturing such as; the Internet of Things (IoT), Data Mining (DM), and Big Data (BD) [3]. With the development of digital manufacturing, the current manufacturing is settled in the big data environment. It is summarized as the great volume, various modalities, high velocity, and huge value data environment [4]. This big data is generated by both production processing and other manufacturing events such as product design, production planning, energy supply, marketing, and customers' reviews [5]. In an industry 4.0 factory, the data is collected and tabulated, and valuable information can be extracted and used to improve processes.

Although Industry 4.0 manufacturing is integrated, automated, predictive, and intelligent it has to be sustainable and renewable [6]. At present, industrial production activities use about 35% of the entire global electricity supply, which produces approximately 20% of total carbon emissions. In the last 20 years, there has been an increase of more than 50% in greenhouse gas emission is released by the top five manufacturing countries. The manufacturing sustainability has

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never escaped industry's attention, and is also an indispensable research topic in the age of Industry 4.0. It is known that the energy efficiency of production process is normally below 30% [7]. Therefore, much industrial research has been paying close attention to energy consumption and its environmental and financial impact. Highly efficient energy usage can not only reduce production costs, and expand profit margins, but also solve associated environmental and social problems. In most manufacturing systems, energy consumption is part of essential standards to measure the benefits [8]. Additionally, during the past two decades, additive manufacturing (AM) machines are increasingly being employed, due to their digitalization, automation, flexibility, and customization, which are also becoming a popular production system in the modern industry. Comparing with the traditional manufacturing processing, the AM processing is a low energy efficiency system with a high production yield, especially selective laser sintering (SLS) and selective laser melting (SLM) [9]. The energy consumption of AM processing is influenced by many factors, and according to the Life Cycle Analysis (LCA) of SLS processing the energy consumption is the most important factor affecting environmental impact [10]. Reducing energy consumption of AM process is one of the necessary research targets for the manufacturing sustainability in the age of Industry 4.0.

This paper tries to solve the industrial sustainability problems in the Industry 4.0 era, specifically, working out the energy consumption problem of AM processes by using IoT technology. In this research, current AM energy consumption analysis models and optimization methods will be discussed and refined in section 2. Section 3 presents an integrated IoT framework for AM energy consumption analysis including various layers and components. This method follows the Service Oriented Architecture (SOA) approach. It assists people in understanding the energy consumption behaviour, to predict the trends in energy usage and guides people to use energy efficiently. Section 4 deliveries a case study of the SLS system (EOS P700). The raw data is collected from process parameters and the data log files. After analysis of the correlation between the process environment and energy consumption, a particular IoT proposal of energy consumption will be proposed at the end of this section. Section 5 discusses the main function and future work of this research.

2. Literature review of AM processes energy consumption

Additive manufacturing processing is known as a complex system because of complicated material parameters, highly automated levels, and various types of processing technologies. Different processing technologies show different energy consumption performances. Table 1 shows the energy consumption comparison of three additive manufacturing technologies including SLS, SLM, and electron beam melting (EBM) in experimental measurement [11; 12; 13].

From these experimental measurements, it is clear that the energy consumption has a large range. Even when testing on the same machine and with the same material, the results show a large variation in every experiment. That means the energy consumption of AM processing is challenging to analyse and optimise. Many researchers have shown that energy consumption of AM processing is caused by many different components and impacted by numerous attributes.

Table 1. Energy consumption comparison between different AM processes.

AM Technology	Energy consumption rate	Experiment material	Experiment machine
EBM [11]	61.20 to 176.67 MJ/kg	Ti-6Al-4V	Arcam A1
SLM [12]	96.82to 139.50 MJ/kg	SAE 316L	MMT SLM250 / EOSINT P760
SLS [13]	52.20 to 129.73 MJ/kg	Polyamide	HiQ+HS / EOSINT P390

Fig.1 displays a schematic layout of the SLS process which is one of the most important and commercial AM processes currently in use. In Fig.1, it is seen that the system consists of many different types of power usage [10; 13]. There are several energy consumers in each power usage, which are also demonstrated in Fig.1. The heating system, consisting of frame heating, platform heating, and process chamber heating, is responsible for the major of energy consumed in this process. In addition, the laser units, scanner, and laser cooling system are three main power components in the laser system, with the laser cooling system consuming the most of energy in this subsystem. The main energy usages of the build platform system are driving the motors. Feed and recycle system includes the material and inert gas feed and recycle process. There are controllers, electrical elements, and sensors supporting the system controlling and monitoring functions in such an SLS system, which are also a main part of energy consumers [12].

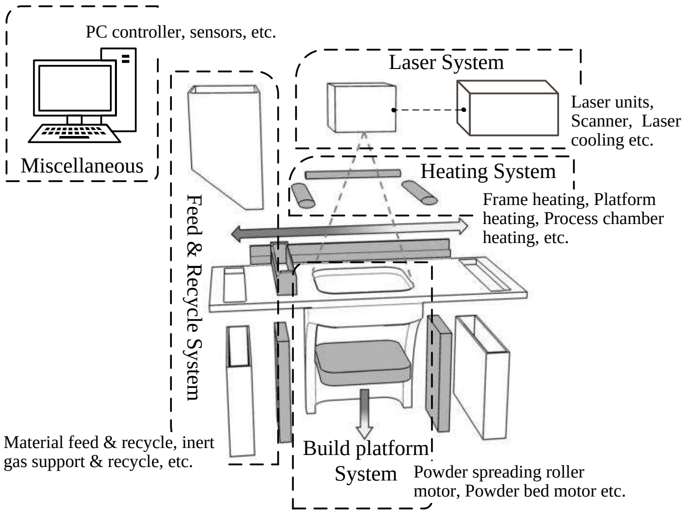

Fig. 1. Main power drains of SLS process adopted from [14].

However, it does not mean these factors related to this system are the only impact elements. Built on the understanding of system and manufacturing experiments, a lot of research indicates relationships between energy consumption and various processing attributes of AM processes. Table 2 presents the processing, design, material attributes relating to the energy consumption of AM processing in literature.

In their works, models are built for predicting energy consumption in AM processes. However, the impact is varied because there are many correlations. It is hard to identify all related attributes of AM process energy consumption from current research. Therefore, energy consumption in AM processes is known as a complicated model to analyse [14]. More data collected from the process, design, material, environment, and any related activities, and factors the more accurate an energy consumption model can be built. Nowadays, the manufacturing is facing the next industrial revolution, it can collect greater amounts of data from the entire manufacturing system [15]. With this valuable data, the behaviour of energy consumption in AM processes is predictable. The efficient energy use decision can be made by intelligent systems. In the next section, an IoT framework for energy consumption is going to be presented for AM processes.

Table 2. Energy consumption related attributes in literature.

Literature	Processing attributes	Design attributes	Material attributes
Sreenivasan and Bourell [13]	Scan speed, laser power rate, build platform size	Nil	Material density
Paul and Anand [9]	Layer thickness, laser beam radius, scan speed, laser power	Part orientation	Absorptivity powder
Watson and Taminger [16]	Feedstock & recycling transported distance, build platform size	Volume of deposited material	Nil
Telenko and Speeperad [17]	Nil	Z-height	Material density
Baumers et al. [11]	Processing procedures, build time	Part geometry, Z-height, capacity utilization	Nil

3. An Internet of Things framework of energy consumption for additive manufacturing system

In the age of Industry 4.0, interoperability is one of the most important and essential capabilities and design principles. To achieve the integrated function, the IoT technology has become one of the best solutions, generate horizontal integration, end-to-end digital integration, and vertical integration in manufacturing systems [5]. In this interoperable manufacturing environment, an AM system is also integrated. The production design, operators, and materials statement are integrated with AM machine to generate a new processing model. In this model, plenty of data is collected, where information and knowledge can be discovered. In addition, it is known that the life-cycle management and energy sustainability management are two basic business services in Industry 4.0, and this integration not only focuses on the improvement of manufacturing production but also engages in the industrial enterprise management [18; 6]. Therefore, the Service Oriented Architecture (SOA) approach is the main design principle for this AM energy consumption analysis modeling. Based on this design principle an IoT framework is designed which is shown in Fig.2 [19].

In this framework, there are four layers, which are: the Process execution layer, the Data integration layer, the Information and Knowledge generation layer, and the Application performance layer. These four layers are linked together closely, and each layer consists of several components.

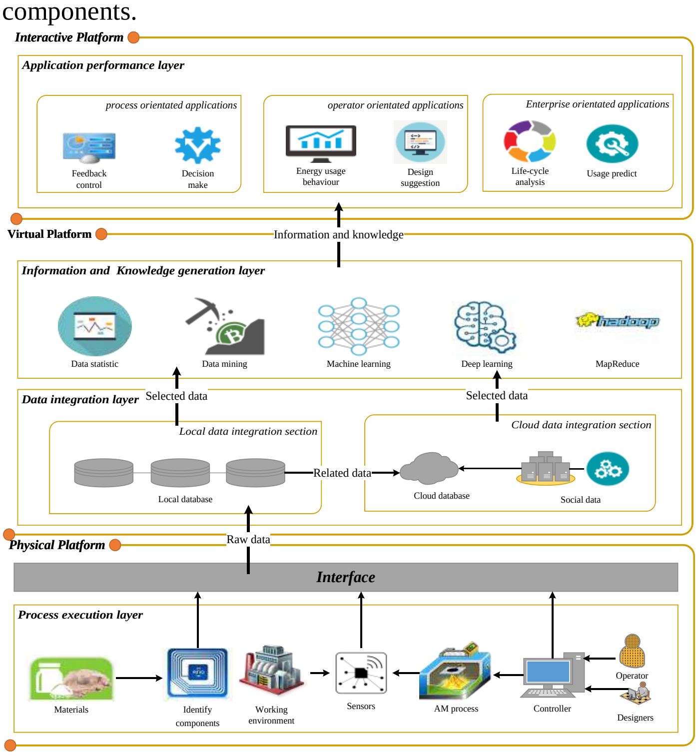

Fig.2. Internet of Things framework of energy consumption analysis

3.1. Process execution layer

The Process execution layer is known as the production status and processing environmental condition where the target AM system, materials, operators, products, and other environmental factors are included. In this layer, the AM system and other associated physical objects carry the most relevant data invisibly. With different sensors and components, these invisible data sets are extracted [20]. However, on this layer, the digital data sets are only created, which means they tend to be unreadable, being represented as massive and meaningless strings of numbers. The AM system is the main object of this research, as the majority of energy is consumed by it. Most current AM systems have embedded sensors in them obtaining various processing data collected during operation. Parts of the data can be related to the system energy consumption. In addition, some factors on this layer may be invisible because integrated sensors are not collecting information associated energy consumption [21]. The selection method is one of the main functions of the Data integration layer, which will be discussed later.

3.2. Data integration layer

Data integration layer is simply divided into two parts, the local integration section, and cloud integration section. In the local data integration section, the data generated from the Process execution layer is collected and stored in the local database. It is known that only a part of the data is related to energy consumption, which means any other data collection would be a waste of resources within the scope of this research. Therefore, selecting the associated attributes data integrating with another data becomes necessary. Fig.3 shows related attributes data selection diagram. When a new attribute is considered to start on a new data set analysis, the example data set should be tested at first, by matching the example data with the total energy consumption. If the result shows a relationship, this attribute data will be marked as the related data. Otherwise, the example data set will be compared with other existing related attributes data. When the new example data set shows an association with existing related data. This additional data type is added to the database. Another part of this layer is the cloud integration section, where the local database uploads the related energy consumption data to the Cloud [22]. In the cloud, data from different machines, systems, and production processing are integrated. The Direct Attached Storage (DAS), Network Attached Storage (NAS), and distributed storage system are considered as the main storage solution models [4].

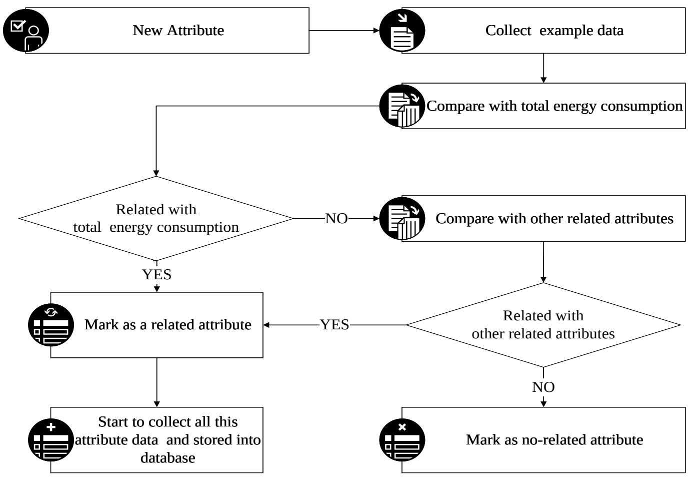

Fig.3. Related attributes data selection

3.3. Information and Knowledge generation layer

Due to the different data resources, local database and the cloud, there are two types of information and knowledge generated from this layer. With local data resources, the relationship between system energy consumption and related attributes can be found. The energy usage behaviour is discovered depending on various situations. The trend line of energy consumption is also depicted, which delivers the energy usage prediction of the AM system. This information is integrated together with the generation of local processing knowledge. It can assist people in predicting energy usage of the system, and making the decisions. The application will be discussed later in the Application performance layer. With the data from the cloud, theoretically, information and knowledge are more diverse and accurate. In addition, the information and knowledge can be shared on the cloud which contributes to all people using the cloud. On this layer, various data analytics technologies are used. For local information and knowledge generation, data mining is the core technology; it is used to discover information and knowledge for future processes storage. Prior knowledge is working with some machine learning algorithms makes raw local data present its valuable potential. The cloud information and knowledge generation come under the big data environment. The main methods of big data analysis are bloom filter, hashing, index, trial and parallel computing, of which the MapReduce is one of the most popular parallel computing methods [23].

3.4. Application performance layer

On the Application performance layer, the information, and knowledge, discovered from Information and Knowledge generation layer, are displayed as different implementations. The performance can be divided into three sections: the Process orientated applications, the Operator orientated applications, and the Enterprise orientated applications based on differently oriented objects. In the section of process orientated applications, AM processing receives the feedback controlling signals, which then changes the settings of the relevant parameters for reducing the energy consumption. These decisions change parameter are made by the IoT framework relying on the information and knowledge that analysed from the preceding layer. Operators are able to obtain the system energy consumption behaviour from the production energy recorded, and by predicting the future energy use. The information will be presented to them virtually and graphically; which can guide operators to utilize the system economically. In addition, they can also receive production design suggestion for improving the design. The enterprise manager is more interested in the system life-cycle analysis and energy sustainability analysis which can also be delivered to this layer.

This IoT framework focuses on AM process energy consumption which creates a new method of energy consumption analysis in the age of Industry 4.0. This framework involves numerous related factors which integrate different attributes within the data and cloud-based database. Benefits from the data mining and big data analysis technology. Valuable information and knowledge about AM process energy consumption are generated and presented to people intelligently and some decisions are made by framework and control system automatically. This IoT framework is able to match Industry 4.0 required capabilities, which is regarded as an application of Industry 4.0 [3].

4. Case study

Recently, the SLS processing has become a mainstream AM processes, in which the powdered material is sintered by laser. EOS P700 is one of the popular ongoing SLS machines, which has a maximum build envelope size for 740* 400* 590mm (x, y, and z). This machine consists of two 50W CO_2 lasers which sinter the material of PA2200 and PA3200GF. The PA2200 is the original polyamide-12 without any fillers, and the PA 3200GF contains 40% glass beads for enhancing stiffness. According to the discussion in section 2, this machine includes several main energy consumers built as different power parameters such as; the chamber heating built by four heaters on four sides (2*1.65kw and 2*0.8kw), four heaters of frame heating (2*1.22kw and 2*630kw), platform heater (1*1.5kw), cooling system (1*1.3kw), and so on [24].

In the production processing of this machine, some parameters are pre-set and monitored. Part of the data can be seen from the machine data log. Table 3a shows the process parameters setting for the EOS P700 system which normally is fixed for one production process. Table 3b shows part of the monitoring data log received from the machine sensors in real time. However, other data is generated by embedded sensors in this machine. This data can be viewed with the process software (EOS PSW 3.1), which is not collected in the data log [25].

Table 3a. EOS P700 process parameters setting.

Process parameters	Values
Material	PA2200
Layer thickness	0.15 (mm)
Scan spacing	0.3 (mm)
Scan speed	3000 (mm/s)
Laser power	2*50(W)
Build bed heater power	5000 (W)
Build bed heater power limitation	70 (%)
Build bed temperature set point	176.5 (°C)

Table 3b. Part of the process log file.

Layer Number	Platform temperature (°C)	Heat power (W)	Hold power (W)	Last exposure duration (s)
560	173.2	1420	700	34.2
561	173.2	1440	700	34.2
562	173.0	1445	720	34.2
563	173.0	1470	725	34.7
564	173.0	1420	725	34.5
565	173.0	1445	720	35.0
566	173.2	1410	710	35.2
567	173.2	1425	720	35.4

From table 3a and 3b, the varieties of data which is capable of being collected from EOS P700 are clear. Being Compared to Table 2, it is obvious that the collected data attributes from the EOS P700 data log files are less than the energy consumption related attributes in literature. Therefore, to analyse the energy consumption, in this case, various related attributes need to be collected. The Fig.3 shows correlations between the process environment and energy consumption.

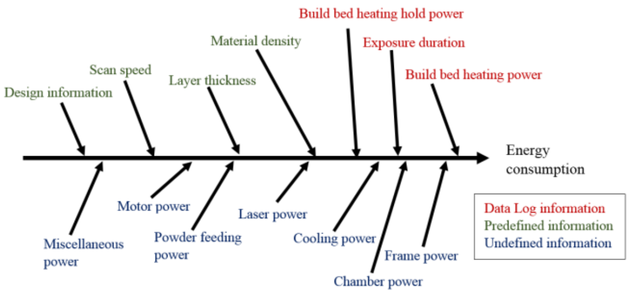

Fig. 3. Correlations between process environment and energy consumption.

From Fig. 3, the undefined information shows attributes of data which have not been collected due to embedded sensor limitation. In the current state, it is hard to accurately analyse the energy consumption of this process. However, based on the IoT framework, a more completed energy consumption analysis proposal can be generated; following steps for the EOS P700 process;

- **Steps 1. Expand necessary hardware components.** In this research, the energy monitoring component is the intuitive equipment. A communicable digital power meter is going to be used for monitoring the EOS P700 total energy consumption. Relying on the user manual, the supply voltage of this machine is 3*400V, and the maximum power is about 12kw [24]. The power meter is chosen due to these parameters. This equipment is understood to be one of the essential monitoring components for this research, it is not necessary to add the additional components for every power using system of the process. In addition, for combining the material data, the RFID system is another necessary component in this research, which includes tags and readers [26]. Considering this particular process with the IoT platform, there is plenty of data generated from the process execution layer. Currently, most of the data has not been applied to any functional analysis, and becomes a waste resource.
- **Step 2. Integrate related data.** In this step, the collected data is selected by the related attributes selection method as mentioned in section 2. All monitoring data of EOS P700 is displayed on the EOS PSW 3.1 software, such as the hatching data, laser data, and so on. Only part of this data is printed in the data log, and valuable data has not been collected for analysis. All this data will be collected and stored in the local database which includes materials and order data, product design data, predefined process data, and real-time monitoring data. These selected data ranges will be uploaded to the cloud database, combining with public data and data from other SLS machines for later analysis.
- **Step 3. Discover research information.** Energy consumption associated information is discovered from the integrated data in data analysis methods and algorithms. The selection of methods and algorithms is based on the features of the integrated data. In the case of EOS P700, for the basic data statistical analysis is applied as the pre-investigation for finding out the data features. Then, data mining technology is used for local data analysis as the fundamental data analysis method, WEKA 3.8 is used as the main data mining software. Meanwhile, cloud computing technologies are applied for cloud data analysis on IBM Cloud.
- **Step 4. Delivery and presenting the results.** Without a graphical or visual display, the results produced by data statistics analysis, data mining and cloud computing will rarely be used by operators or designers. Three displaying modes are applied in this case. Firstly, the energy consumption status, behaviour, and prediction information are displayed as real-time figures showing on the screen for the machine operators. The product design suggestions

which can reduce process energy consumption are presented to designers directly when they design similar products. Secondly, the machine life cycle information and energy consumption knowledge is sent to the system managers for improving enterprise cost and sustainability management. Finally, the defined energy reduction control signals are set as the input to processing control system. A selection of pre-defined algorithms will process the information to produce and optimise each build; the power reducing element will be the primary position in the algorithms.

These four steps will apply the EOS P700 into the IoT platform, which not only obtains the energy consumption analysis of the process but also achieves the requirements of Industry 4.0.

5. Discussion and closing remarks

Using this IoT framework, energy consumption of AM process is going to be identified and predicted, which assists AM engineers, researchers and enterprise managers in solving the energy problem of the process. In the era of Industry 4.0, AM processes are necessary for the whole manufacturing production industry. With the huge volume of production, energy consumption is an unavoidable issue for this process. It is an indispensable component of the power source reduction, environment protection, and process life cycle analysis. Current AM energy consumption analysis methods are reviewed in section 2. These methods, hardly obtain accurate results because the energy consumption problem is a multi-attribute convergence problem. The Industry 4.0 solution is designed for solving this type of problem. This paper generates a service orientated IoT framework focusing on the energy consumption in the AM process for reducing the power usage during production. This IoT framework collects, integrates, and analyse data from the entire production environment, and the discovered information, knowledge, and analysed results are shown intelligently to different processing participants dependent upon their roles in the system; which is proposed as an Industry 4.0 solution. The EOS P700 is applied to the IoT framework as a case study for proving that the current AM processes lack sufficient energy consumption analysis. It means that much-related works need to be planned and finished in future. A feasible proposal, building the EOS P700 energy consumption IoT framework, outlines the method which will be done. Most results have not been received yet in this research, which the proposal will be acted following the plan. As the final target of this research, it is going to achieve the requirement of Industry 4.0 when the proposal is finished.

References

[1] F. Gruber, Industry 4.0: A Best Practice Project of the Automotive Industry, in: G. Kovács, D. Kochan (Eds.), Digital Product and Process Development Systems, Springer Berlin Heidelberg, 2013, pp. 36-40.

[2] H. Lasi, P. Fettke, H.-g. Kemper, T. Feld, M. Hoffmann, Industry 4.0. Business & Information Systems Engineering 6 (2014) 239-242.

[3] J. Qin, Y. Liu, R. Grosvenor, A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. Procedia CIRP 52 (2016) 173-178.

[4] M. Chen, S. Mao, Y. Liu, Big data: a survey. Mobile Networks and Applications 19 (2014) 171-209.

[5] H. Kagermann, J. Helbig, A. Hellinger, W. Wahlster, Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0: Securing the Future of German Manufacturing Industry; Final Report of the Industrie 4.0 Working Group, Forschungsunion, 2013.

[6] T. Stock, G. Seliger, Opportunities of Sustainable Manufacturing in Industry 4.0. Procedia CIRP 40 (2016) 536-541.

[7] A. Dietmair, A. Verl, A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing. International Journal of Sustainable Engineering 2 (2009) 123-133.

[8] C.-W. Park, K.-S. Kwon, W.-B. Kim, B.-K. Min, S.-J. Park, I.-H. Sung, Y.S. Yoon, K.-S. Lee, J.-H. Lee, J. Seok, Energy consumption reduction technology in manufacturing—A selective review of policies, standards, and research. International Journal of Precision Engineering and Manufacturing 10 (2009) 151-173.

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

[10] K. Kellens, E. Yasa, R. Renaldi, W. Dewulf, J.-P. Kruth, J. Duflou, Energy and Resource Efficiency of SLS/SLM Processes (Keynote Paper), SFF Symposium 2011, 2011, pp. 1-16.

[11] M. Baumers, C. Tuck, R. Wildman, I. Ashcroft, R. Hague, Energy inputs to additive manufacturing: does capacity utilization matter? EOS 1000 30-40.

[12] K. Kellens, E. Yasa, W. Dewulf, J. Duflou, Environmental assessment of selective laser melting and selective laser sintering. Going Green—Care Innovation: From Legal Compliance to Energy-efficient Products and Services, Paper (2010) 5.

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

[14] 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) 2228-2239.

[15] 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, Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on, 2014, pp. 697-701.

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

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

[18] D.L. Bourell, M.C. Leu, D.W. Rosen, Roadmap for additive manufacturing: identifying the future of freeform processing. The University of Texas at Austin, Austin, TX (2009).

[19] L. Atzori, A. Iera, G. Morabito, The internet of things: A survey. Computer networks 54 (2010) 2787-2805.

[20] D.D. Gajski, F. Vahid, S. Narayan, J. Gong, Specification and design of embedded systems, Prentice Hall Englewood Cliffs, 1994.

[21] S. Madakam, R. Ramaswamy, S. Tripathi, Internet of Things (IoT): A literature review. Journal of Computer and Communications 3 (2015) 164.

[22] 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) 206-215.

[23] M. Minelli, M. Chambers, A. Dhiraj, Big data technology. Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today's Businesses (2013) 61-88.

[24] EOS, EOSINT P700 Operation User Manual. (2004).

[25] S.P. Soe, Quantitative analysis on SLS part curling using EOS P700 machine. Journal of Materials Processing Technology 212 (2012) 2433-2442.

[26] H. Kopetz, Internet of Things, Real-Time Systems: Design Principles for Distributed Embedded Applications, Springer US, Boston, MA, 2011, pp. 307-323.

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Abstract

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Keywords: Energy Consumption, Additive Manufacturing, Internet of Things Framework

1. Introduction

Nowadays, Industry 4.0 is not only a research and development slogan but is also an industrial and academic activities. Many industrial companies and research organizations have begun working on this far-sighted topic including various aspects [1; 2]. With more and more related publication of technologies, principles, and concepts, the achievement criteria of Industry 4.0 has become much clearer and more specific. A qualified Industry 4.0 manufacturing system needs necessary capabilities, like interoperability and consciousness. To achieve these capabilities, data is considered as being vitally important. It is the connecting media of the integration between different manufacturing objects and activities. Enabling technologies are included in manufacturing such as; the Internet of Things (IoT), Data Mining (DM), and Big Data (BD) [3]. With the development of digital manufacturing, the current manufacturing is settled in the big data environment. It is summarized as the great volume, various modalities, high velocity, and huge value data environment [4]. This big data is generated by both production processing and other manufacturing events such as product design, production planning, energy supply, marketing, and customers' reviews [5]. In an industry 4.0 factory, the data is collected and tabulated, and valuable information can be extracted and used to improve processes.

Although Industry 4.0 manufacturing is integrated, automated, predictive, and intelligent it has to be sustainable and renewable [6]. At present, industrial production activities use about 35% of the entire global electricity supply, which produces approximately 20% of total carbon emissions. In the last 20 years, there has been an increase of more than 50% in greenhouse gas emission is released by the top five manufacturing countries. The manufacturing sustainability has

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never escaped industry's attention, and is also an indispensable research topic in the age of Industry 4.0. It is known that the energy efficiency of production process is normally below 30% [7]. Therefore, much industrial research has been paying close attention to energy consumption and its environmental and financial impact. Highly efficient energy usage can not only reduce production costs, and expand profit margins, but also solve associated environmental and social problems. In most manufacturing systems, energy consumption is part of essential standards to measure the benefits [8]. Additionally, during the past two decades, additive manufacturing (AM) machines are increasingly being employed, due to their digitalization, automation, flexibility, and customization, which are also becoming a popular production system in the modern industry. Comparing with the traditional manufacturing processing, the AM processing is a low energy efficiency system with a high production yield, especially selective laser sintering (SLS) and selective laser melting (SLM) [9]. The energy consumption of AM processing is influenced by many factors, and according to the Life Cycle Analysis (LCA) of SLS processing the energy consumption is the most important factor affecting environmental impact [10]. Reducing energy consumption of AM process is one of the necessary research targets for the manufacturing sustainability in the age of Industry 4.0.

This paper tries to solve the industrial sustainability problems in the Industry 4.0 era, specifically, working out the energy consumption problem of AM processes by using IoT technology. In this research, current AM energy consumption analysis models and optimization methods will be discussed and refined in section 2. Section 3 presents an integrated IoT framework for AM energy consumption analysis including various layers and components. This method follows the Service Oriented Architecture (SOA) approach. It assists people in understanding the energy consumption behaviour, to predict the trends in energy usage and guides people to use energy efficiently. Section 4 deliveries a case study of the SLS system (EOS P700). The raw data is collected from process parameters and the data log files. After analysis of the correlation between the process environment and energy consumption, a particular IoT proposal of energy consumption will be proposed at the end of this section. Section 5 discusses the main function and future work of this research.

2. Literature review of AM processes energy consumption

Additive manufacturing processing is known as a complex system because of complicated material parameters, highly automated levels, and various types of processing technologies. Different processing technologies show different energy consumption performances. Table 1 shows the energy consumption comparison of three additive manufacturing technologies including SLS, SLM, and electron beam melting (EBM) in experimental measurement [11; 12; 13].

From these experimental measurements, it is clear that the energy consumption has a large range. Even when testing on the same machine and with the same material, the results show a large variation in every experiment. That means the energy consumption of AM processing is challenging to analyse and optimise. Many researchers have shown that energy consumption of AM processing is caused by many different components and impacted by numerous attributes.

Table 1. Energy consumption comparison between different AM processes.

AM Technology	Energy consumption rate	Experiment material	Experiment machine
EBM [11]	61.20 to 176.67 MJ/kg	Ti-6Al-4V	Arcam A1
SLM [12]	96.82to 139.50 MJ/kg	SAE 316L	MMT SLM250 / EOSINT P760
SLS [13]	52.20 to 129.73 MJ/kg	Polyamide	HiQ+HS / EOSINT P390

Fig.1 displays a schematic layout of the SLS process which is one of the most important and commercial AM processes currently in use. In Fig.1, it is seen that the system consists of many different types of power usage [10; 13]. There are several energy consumers in each power usage, which are also demonstrated in Fig.1. The heating system, consisting of frame heating, platform heating, and process chamber heating, is responsible for the major of energy consumed in this process. In addition, the laser units, scanner, and laser cooling system are three main power components in the laser system, with the laser cooling system consuming the most of energy in this subsystem. The main energy usages of the build platform system are driving the motors. Feed and recycle system includes the material and inert gas feed and recycle process. There are controllers, electrical elements, and sensors supporting the system controlling and monitoring functions in such an SLS system, which are also a main part of energy consumers [12].

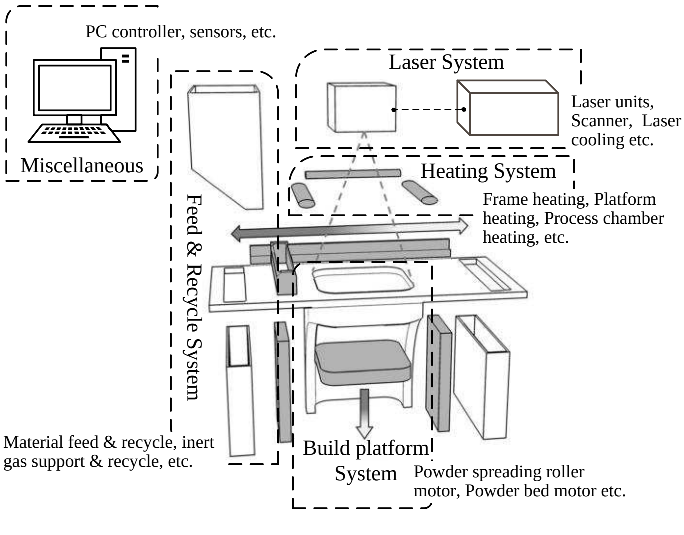

Fig. 1. Main power drains of SLS process adopted from [14].

However, it does not mean these factors related to this system are the only impact elements. Built on the understanding of system and manufacturing experiments, a lot of research indicates relationships between energy consumption and various processing attributes of AM processes. Table 2 presents the processing, design, material attributes relating to the energy consumption of AM processing in literature.

In their works, models are built for predicting energy consumption in AM processes. However, the impact is varied because there are many correlations. It is hard to identify all related attributes of AM process energy consumption from current research. Therefore, energy consumption in AM processes is known as a complicated model to analyse [14]. More data collected from the process, design, material, environment, and any related activities, and factors the more accurate an energy consumption model can be built. Nowadays, the manufacturing is facing the next industrial revolution, it can collect greater amounts of data from the entire manufacturing system [15]. With this valuable data, the behaviour of energy consumption in AM processes is predictable. The efficient energy use decision can be made by intelligent systems. In the next section, an IoT framework for energy consumption is going to be presented for AM processes.

Table 2. Energy consumption related attributes in literature.

Literature	Processing attributes	Design attributes	Material attributes
Sreenivasan and Bourell [13]	Scan speed, laser power rate, build platform size	Nil	Material density
Paul and Anand [9]	Layer thickness, laser beam radius, scan speed, laser power	Part orientation	Absorptivity powder
Watson and Taminger [16]	Feedstock & recycling transported distance, build platform size	Volume of deposited material	Nil
Telenko and Speeperad [17]	Nil	Z-height	Material density
Baumers et al. [11]	Processing procedures, build time	Part geometry, Z-height, capacity utilization	Nil

3. An Internet of Things framework of energy consumption for additive manufacturing system

In the age of Industry 4.0, interoperability is one of the most important and essential capabilities and design principles. To achieve the integrated function, the IoT technology has become one of the best solutions, generate horizontal integration, end-to-end digital integration, and vertical integration in manufacturing systems [5]. In this interoperable manufacturing environment, an AM system is also integrated. The production design, operators, and materials statement are integrated with AM machine to generate a new processing model. In this model, plenty of data is collected, where information and knowledge can be discovered. In addition, it is known that the life-cycle management and energy sustainability management are two basic business services in Industry 4.0, and this integration not only focuses on the improvement of manufacturing production but also engages in the industrial enterprise management [18; 6]. Therefore, the Service Oriented Architecture (SOA) approach is the main design principle for this AM energy consumption analysis modeling. Based on this design principle an IoT framework is designed which is shown in Fig.2 [19].

In this framework, there are four layers, which are: the Process execution layer, the Data integration layer, the Information and Knowledge generation layer, and the Application performance layer. These four layers are linked together closely, and each layer consists of several components.

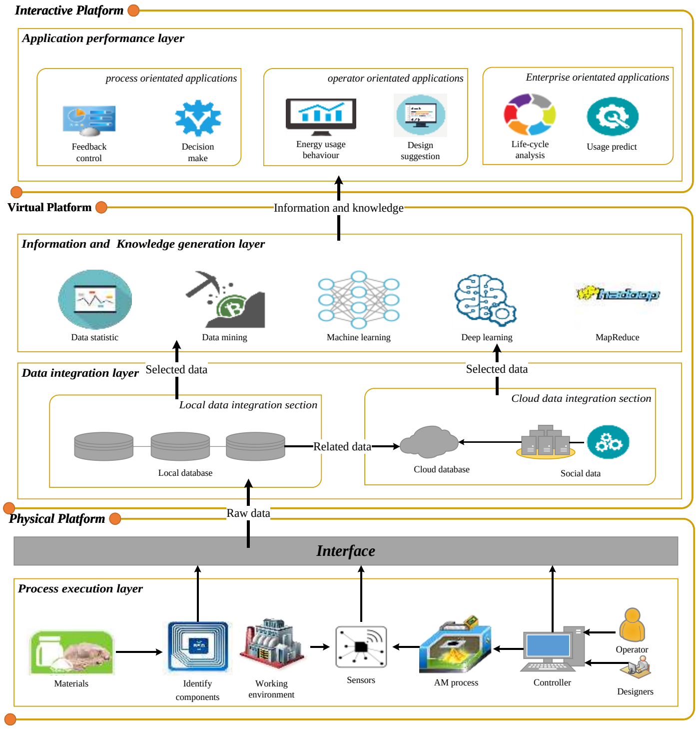

Fig.2. Internet of Things framework of energy consumption analysis

3.1. Process execution layer

The Process execution layer is known as the production status and processing environmental condition where the target AM system, materials, operators, products, and other environmental factors are included. In this layer, the AM system and other associated physical objects carry the most relevant data invisibly. With different sensors and components, these invisible data sets are extracted [20]. However, on this layer, the digital data sets are only created, which means they tend to be unreadable, being represented as massive and meaningless strings of numbers. The AM system is the main object of this research, as the majority of energy is consumed by it. Most current AM systems have embedded sensors in them obtaining various processing data collected during operation. Parts of the data can be related to the system energy consumption. In addition, some factors on this layer may be invisible because integrated sensors are not collecting information associated energy consumption [21]. The selection method is one of the main functions of the Data integration layer, which will be discussed later.

3.2. Data integration layer

Data integration layer is simply divided into two parts, the local integration section, and cloud integration section. In the local data integration section, the data generated from the Process execution layer is collected and stored in the local database. It is known that only a part of the data is related to energy consumption, which means any other data collection would be a waste of resources within the scope of this research.

Therefore, selecting the associated attributes data integrating with another data becomes necessary. Fig.3 shows related attributes data selection diagram. When a new attribute is considered to start on a new data set analysis, the example data set should be tested at first, by matching the example data with the total energy consumption. If the result shows a relationship, this attribute data will be marked as the related data. Otherwise, the example data set will be compared with other existing related attributes data. When the new example data set shows an association with existing related data. This additional data type is added to the database. Another part of this layer is the cloud integration section, where the local database uploads the related energy consumption data to the Cloud [22]. In the cloud, data from different machines, systems, and production processing are integrated. The Direct Attached Storage (DAS), Network Attached Storage (NAS), and distributed storage system are considered as the main storage solution models [4].

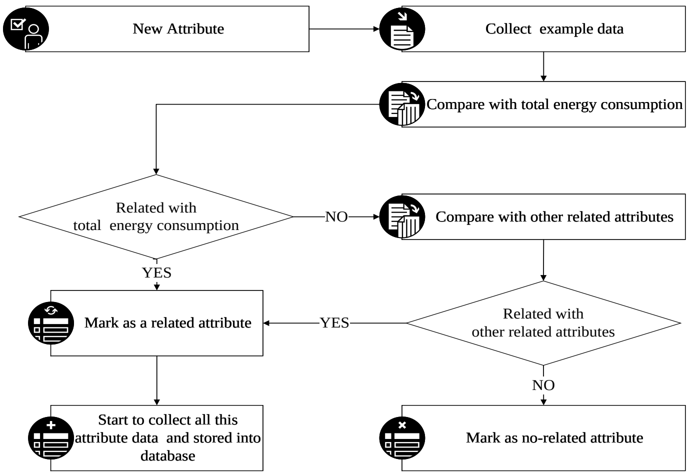

Fig.3. Related attributes data selection

3.3. Information and Knowledge generation layer

Due to the different data resources, local database and the cloud, there are two types of information and knowledge generated from this layer. With local data resources, the relationship between system energy consumption and related attributes can be found. The energy usage behaviour is discovered depending on various situations. The trend line of energy consumption is also depicted, which delivers the energy usage prediction of the AM system. This information is integrated together with the generation of local processing knowledge. It can assist people in predicting energy usage of the system, and making the decisions. The application will be discussed later in the Application performance layer. With the data from the cloud, theoretically, information and knowledge are more diverse and accurate. In addition, the information and knowledge can be shared on the cloud which contributes to all people using the cloud. On this layer, various data analytics technologies are used. For local information and knowledge generation, data mining is the core technology; it is used to discover information and knowledge for future processes storage. Prior knowledge is working with some machine learning algorithms makes raw local data present its valuable potential. The cloud information and knowledge generation come under the big data environment. The main methods of big data analysis are bloom filter, hashing, index, trial and parallel computing, of which the MapReduce is one of the most popular parallel computing methods [23].

3.4. Application performance layer

On the Application performance layer, the information, and knowledge, discovered from Information and Knowledge generation layer, are displayed as different implementations. The performance can be divided into three sections: the Process orientated applications, the Operator orientated applications, and the Enterprise orientated applications based on differently oriented objects. In the section of process orientated applications, AM processing receives the feedback controlling signals, which then changes the settings of the relevant parameters for reducing the energy consumption. These decisions change parameter are made by the IoT framework relying on the information and knowledge that analysed from the preceding layer. Operators are able to obtain the system energy consumption behaviour from the production energy recorded, and by predicting the future energy use. The information will be presented to them virtually and graphically; which can guide operators to utilize the system economically. In addition, they can also receive production design suggestion for improving the design. The enterprise manager is more interested in the system life-cycle analysis and energy sustainability analysis which can also be delivered to this layer.

This IoT framework focuses on AM process energy consumption which creates a new method of energy consumption analysis in the age of Industry 4.0. This framework involves numerous related factors which integrate different attributes within the data and cloud-based database. Benefits from the data mining and big data analysis technology. Valuable information and knowledge about AM process energy consumption are generated and presented to people intelligently and some decisions are made by framework and control system automatically. This IoT framework is able to match Industry 4.0 required capabilities, which is regarded as an application of Industry 4.0 [3].

4. Case study

Recently, the SLS processing has become a mainstream AM processes, in which the powdered material is sintered by laser. EOS P700 is one of the popular ongoing SLS machines, which has a maximum build envelope size for 740* 400* 590mm (x, y, and z). This machine consists of two 50W CO_2 lasers which sinter the material of PA2200 and PA3200GF. The PA2200 is the original polyamide-12 without any fillers, and the PA 3200GF contains 40% glass beads for enhancing stiffness. According to the discussion in section 2, this machine includes several main energy consumers built as different power parameters such as; the chamber heating built by four heaters on four sides (2*1.65kw and 2*0.8kw), four heaters of frame heating (2*1.22kw and 2*630kw), platform heater (1*1.5kw), cooling system (1*1.3kw), and so on [24].

In the production processing of this machine, some parameters are pre-set and monitored. Part of the data can be seen from the machine data log. Table 3a shows the process parameters setting for the EOS P700 system which normally is fixed for one production process. Table 3b shows part of the monitoring data log received from the machine sensors in real time. However, other data is generated by embedded sensors in this machine. This data can be viewed with the process software (EOS PSW 3.1), which is not collected in the data log [25].

Table 3a. EOS P700 process parameters setting.

Process parameters	Values
Material	PA2200
Layer thickness	0.15 (mm)
Scan spacing	0.3 (mm)
Scan speed	3000 (mm/s)
Laser power	2*50(W)
Build bed heater power	5000 (W)
Build bed heater power limitation	70 (%)
Build bed temperature set point	176.5 (°C)

Table 3b. Part of the process log file.

Layer Number	Platform temperature (°C)	Heat power (W)	Hold power (W)	Last exposure duration (s)
560	173.2	1420	700	34.2
561	173.2	1440	700	34.2
562	173.0	1445	720	34.2
563	173.0	1470	725	34.7
564	173.0	1420	725	34.5
565	173.0	1445	720	35.0
566	173.2	1410	710	35.2
567	173.2	1425	720	35.4

From table 3a and 3b, the varieties of data which is capable of being collected from EOS P700 are clear. Being Compared to Table 2, it is obvious that the collected data attributes from the EOS P700 data log files are less than the energy consumption related attributes in literature. Therefore, to analyse the energy consumption, in this case, various related attributes need to be collected. The Fig.3 shows correlations between the process environment and energy consumption.

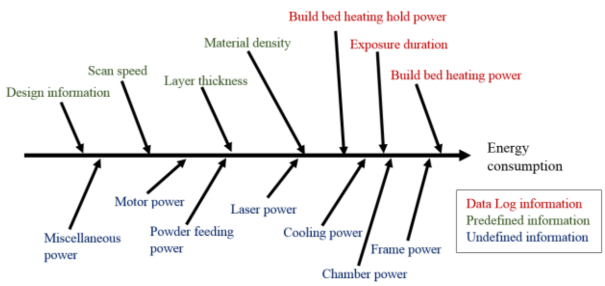

Fig. 3. Correlations between process environment and energy consumption.

From Fig. 3, the undefined information shows attributes of data which have not been collected due to embedded sensor limitation. In the current state, it is hard to accurately analyse the energy consumption of this process. However, based on the IoT framework, a more completed energy consumption analysis proposal can be generated; following steps for the EOS P700 process;

- **Steps 1. Expand necessary hardware components.** In this research, the energy monitoring component is the intuitive equipment. A communicable digital power meter is going to be used for monitoring the EOS P700 total energy consumption. Relying on the user manual, the supply voltage of this machine is 3*400V, and the maximum power is about 12kw [24]. The power meter is chosen due to these parameters. This equipment is understood to be one of the essential monitoring components for this research, it is not necessary to add the additional components for every power using system of the process. In addition, for combining the material data, the RFID system is another necessary component in this research, which includes tags and readers [26]. Considering this particular process with the IoT platform, there is plenty of data generated from the process execution layer. Currently, most of the data has not been applied to any functional analysis, and becomes a waste resource.
- **Step 2. Integrate related data.** In this step, the collected data is selected by the related attributes selection method as mentioned in section 2. All monitoring data of EOS P700 is displayed on the EOS PSW 3.1 software, such as the hatching data, laser data, and so on. Only part of this data is printed in the data log, and valuable data has not been collected for analysis. All this data will be collected and stored in the local database which includes materials and order data, product design data, predefined process data, and real-time monitoring data. These selected data ranges will be uploaded to the cloud database, combining with public data and data from other SLS machines for later analysis.
- **Step 3. Discover research information.** Energy consumption associated information is discovered from the integrated data in data analysis methods and algorithms. The selection of methods and algorithms is based on the features of the integrated data. In the case of EOS P700, for the basic data statistical analysis is applied as the pre-investigation for finding out the data features. Then, data mining technology is used for local data analysis as the fundamental data analysis method, WEKA 3.8 is used as the main data mining software. Meanwhile, cloud computing technologies are applied for cloud data analysis on IBM Cloud.
- **Step 4. Delivery and presenting the results.** Without a graphical or visual display, the results produced by data statistics analysis, data mining and cloud computing will rarely be used by operators or designers. Three displaying modes are applied in this case. Firstly, the energy consumption status, behaviour, and prediction information are displayed as real-time figures showing on the screen for the machine operators. The product design suggestions which can reduce process energy consumption are presented to designers directly when they design similar products. Secondly, the machine life cycle information and energy consumption knowledge is sent to the system managers for improving enterprise cost and sustainability management. Finally, the defined energy reduction control signals are set as the input to processing control system. A selection of pre-defined algorithms will process the information to produce

and optimise each build; the power reducing element will be the primary position in the algorithms.

These four steps will apply the EOS P700 into the IoT platform, which not only obtains the energy consumption analysis of the process but also achieves the requirements of Industry 4.0.

5. Discussion and closing remarks

Using this IoT framework, energy consumption of AM process is going to be identified and predicted, which assists AM engineers, researchers and enterprise managers in solving the energy problem of the process. In the era of Industry 4.0, AM processes are necessary for the whole manufacturing production industry. With the huge volume of production, energy consumption is an unavoidable issue for this process. It is an indispensable component of the power source reduction, environment protection, and process life cycle analysis. Current AM energy consumption analysis methods are reviewed in section 2. These methods, hardly obtain accurate results because the energy consumption problem is a multi-attribute convergence problem. The Industry 4.0 solution is designed for solving this type of problem. This paper generates a service orientated IoT framework focusing on the energy consumption in the AM process for reducing the power usage during production. This IoT framework collects, integrates, and analyse data from the entire production environment, and the discovered information, knowledge, and analysed results are shown intelligently to different processing participants dependent upon their roles in the system; which is proposed as an Industry 4.0 solution. The EOS P700 is applied to the IoT framework as a case study for proving that the current AM processes lack sufficient energy consumption analysis. It means that much-related works need to be planned and finished in future. A feasible proposal, building the EOS P700 energy consumption IoT framework, outlines the method which will be done. Most results have not been received yet in this research, which the proposal will be acted following the plan. As the final target of this research, it is going to achieve the requirement of Industry 4.0 when the proposal is finished.

References

[1] F. Gruber, Industry 4.0: A Best Practice Project of the Automotive Industry, in: G. Kovács, D. Kochan (Eds.), Digital Product and Process Development Systems, Springer Berlin Heidelberg, 2013, pp. 36-40.

[2] H. Lasi, P. Fettke, H.-g. Kemper, T. Feld, M. Hoffmann, Industry 4.0. Business & Information Systems Engineering 6 (2014) 239-242.

[3] J. Qin, Y. Liu, R. Grosvenor, A Categorical Framework of Manufacturing for Industry 4.0 and Beyond. Procedia CIRP 52 (2016) 173-178.

[4] M. Chen, S. Mao, Y. Liu, Big data: a survey. Mobile Networks and Applications 19 (2014) 171-209.

[5] H. Kagermann, J. Helbig, A. Hellinger, W. Wahlster, Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0: Securing the Future of German Manufacturing Industry; Final Report of the Industrie 4.0 Working Group, Forschungsunion, 2013.

[6] T. Stock, G. Seliger, Opportunities of Sustainable Manufacturing in Industry 4.0. Procedia CIRP 40 (2016) 536-541.

[7] A. Dietmair, A. Verl, A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing. International Journal of Sustainable Engineering 2 (2009) 123-133.

[8] C.-W. Park, K.-S. Kwon, W.-B. Kim, B.-K. Min, S.-J. Park, I.-H. Sung, Y.S. Yoon, K.-S. Lee, J.-H. Lee, J. Seok, Energy consumption reduction technology in manufacturing—A selective review of policies, standards, and research. International Journal of Precision Engineering and Manufacturing 10 (2009) 151-173.

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

[10] K. Kellens, E. Yasa, R. Renaldi, W. Dewulf, J.-P. Kruth, J. Duflou, Energy and Resource Efficiency of SLS/SLM Processes (Keynote Paper), SFF Symposium 2011, 2011, pp. 1-16.

[11] M. Baumers, C. Tuck, R. Wildman, I. Ashcroft, R. Hague, Energy inputs to additive manufacturing: does capacity utilization matter? EOS 1000 30-40.

[12] K. Kellens, E. Yasa, W. Dewulf, J. Duflou, Environmental assessment of selective laser melting and selective laser sintering. Going Green—Care Innovation: From Legal Compliance to Energy-efficient Products and Services, Paper (2010) 5.

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

[14] 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) 2228-2239.

[15] 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, Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on, 2014, pp. 697-701.

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

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

[18] D.L. Bourell, M.C. Leu, D.W. Rosen, Roadmap for additive manufacturing: identifying the future of freeform processing. The University of Texas at Austin, Austin, TX (2009).

[19] L. Atzori, A. Iera, G. Morabito, The internet of things: A survey. Computer networks 54 (2010) 2787-2805.

[20] D.D. Gajski, F. Vahid, S. Narayan, J. Gong, Specification and design of embedded systems, Prentice Hall Englewood Cliffs, 1994.

[21] S. Madakam, R. Ramaswamy, S. Tripathi, Internet of Things (IoT): A literature review. Journal of Computer and Communications 3 (2015) 164.

[22] 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) 206-215.

[23] M. Minelli, M. Chambers, A. Dhiraj, Big data technology. Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today's Businesses (2013) 61-88.

[24] EOS, EOSINT P700 Operation User Manual. (2004).

[25] S.P. Soe, Quantitative analysis on SLS part curling using EOS P700 machine. Journal of Materials Processing Technology 212 (2012) 2433-2442.

[26] H. Kopetz, Internet of Things, Real-Time Systems: Design Principles for Distributed Embedded Applications, Springer US, Boston, MA, 2011, pp. 307-323.