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A big data-driven framework for sustainable and smart additive manufacturing

Arfan Majeed[a], Yingfeng Zhang[a,g,*], Shan Ren[a,b], Jingxiang Lv[c], Tao Peng[d], Saad Waqar[e], Enhuai Yin[f]

[a] *Key Laboratory of Industrial Engineering and Intelligent Manufacturing, Ministry of Industry and Information Technology, Northwestern Polytechnical University, Shaanxi 710072, PR China*
[b] *School of Modern Post, Xi'an University of Posts and Telecommunications, Shaanxi 710061, PR China*
[c] *Key Laboratory of Road Construction Technology and Equipment, Ministry of Education, School of Construction Machinery, Chang'an University, Xi'an 710064, Shaanxi, China*
[d] *Department Key Laboratory of 3D Printing Process and Equipment of Zhejiang Province, Institute of Industrial Engineering, School of Mechanical Engineering, Zhejiang University, Hangzhou 310027, China*
[e] *School of Mechanical Engineering, Shandong University, Jinan 250061, China*
[f] *Xi'an Research Institute of Navigation Technology, China Electronics Technology Group Corporation, Xi'an 710068, China*
[g] *School of Mechanical Engineering, Shaanxi University of Technology, Shaanxi 723001, PR China*

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ABSTRACT

From the last decade, additive manufacturing (AM) has been evolving speedily and has revealed the great potential for energy-saving and cleaner environmental production due to a reduction in material and resource consumption and other tooling requirements. In this modern era, with the advancements in manufacturing technologies, academia and industry have been given more interest in smart manufacturing for taking benefits for making their production more sustainable and effective. In the present study, the significant techniques of smart manufacturing, sustainable manufacturing, and additive manufacturing are combined to make a unified term of sustainable and smart additive manufacturing (SSAM). The paper aims to develop framework by combining big data analytics, additive manufacturing, and sustainable smart manufacturing technologies which is beneficial to the additive manufacturing enterprises. So, a framework of big data-driven sustainable and smart additive manufacturing (BD-SSAM) is proposed which helped AM industry leaders to make better decisions for the beginning of life (BOL) stage of product life cycle. Finally, an application scenario of the additive manufacturing industry was presented to demonstrate the proposed framework. The proposed framework is implemented on the BOL stage of product lifecycle due to limitation of available resources and for fabrication of AlSi10Mg alloy components by using selective laser melting (SLM) technique of AM. The results indicate that energy consumption and quality of the product are adequately controlled which is helpful for smart sustainable manufacturing, emission reduction, and cleaner production.

1. Introduction

Nowadays, sustainable manufacturing is a more competitive approach for manufacturing enterprises as its execution can support producers to accomplish complete development plans, decrease resource consumption and pollution along the entire lifecycle [1]. In this advanced production era, the industry and academia have been discussing and focusing on the implementation of smart manufacturing in their arena of research and manufacturing. The recent improvements in the smart enabling technologies, such as Internet of Things (IoT) [2], Artificial Intelligence (AI), Cyber-Physical System (CPS) [3], Big Data Analytics (BDA) [4], Cloud computing and manufacturing [5], Digital Twin (DT) [6], 5G [7], etc. [8] have significantly strengthened the progress of smart manufacturing. Smart manufacturing can make the industry more sustainable, productive, and profitable [9].

Additive manufacturing (AM) is an evolving technology for today's manufacturing enterprises [10], [11]. AM is categorized according to various material states, which include liquid, powder, wire and fused material [12], [13]. When categorized by considering materials, a variety of polymers [14], ceramics [15], metals and alloys [16], airy

* Corresponding author.
E-mail address: zhangyf@nwpu.edu.cn (Y. Zhang).

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Abbreviations

3D	three dimensional
5G	5th generation technology
3DP	3D printing
AA	artificial aging
AB	as-built
AI	artificial intelligence
AM	additive manufacturing
ANN	artificial neural networks
ASTM	American Society of Testing and materials
BDA	big data analytics
CAD	computer aided design
CAE	computer aided engineering
CAM	computer aided manufacturing
CAPP	computer-aided process planning
CC	cloud computing
CM	conventional manufacturing
CP	cleaner production
CPS	cyber-physical systems
DM	data mining
DMLS	direct metal laser sintering
DSS	decision support systems
DT	digital Twin
EISs	enterprise information systems
EOL	end of life
ERP	enterprise resource management
FDM	fused Deposition Modeling
GA	genetic Algorithm
IIoT	industrial internet of things
IoT	internet of things
MES	manufacturing execution systems
MOL	middle of life
OM	optical microscope/ microscopic
PDKM	product data & knowledge management
PDM	product data management
RFID	radio frequency identification
SAM	sustainability of additive manufacturing
SCM	supply chain management
SEC	specific energy consumption
SEM	scanning Electron Microscope
SHT	solution heat treatment
SL/SLA	stereolithography
SLM	selective Laser Melting
SLS	selective laser sintering
SM	smart manufacturing
SSAM	sustainable and smart additive manufacturing
SSM	sustainable smart manufacturing
SVM	support vector machine
UHF	ultra-high frequency
WIP	work in process

structures [17], composites [18], functionally-graded materials [19] and multi-phase materials [20] are used for various type of AM processes. With a growing emphasis on sustainability and cleaner production, AM proposes a significant worth in relation to decrease buy-to-fly ratios. AM can be applied anywhere in the product lifecycle [21]. AM is claimed as green technology which holds a lot of potential in enhancing effectiveness of materials, dropping life cycle effects, and permitting better engineering functionality correlated to traditional

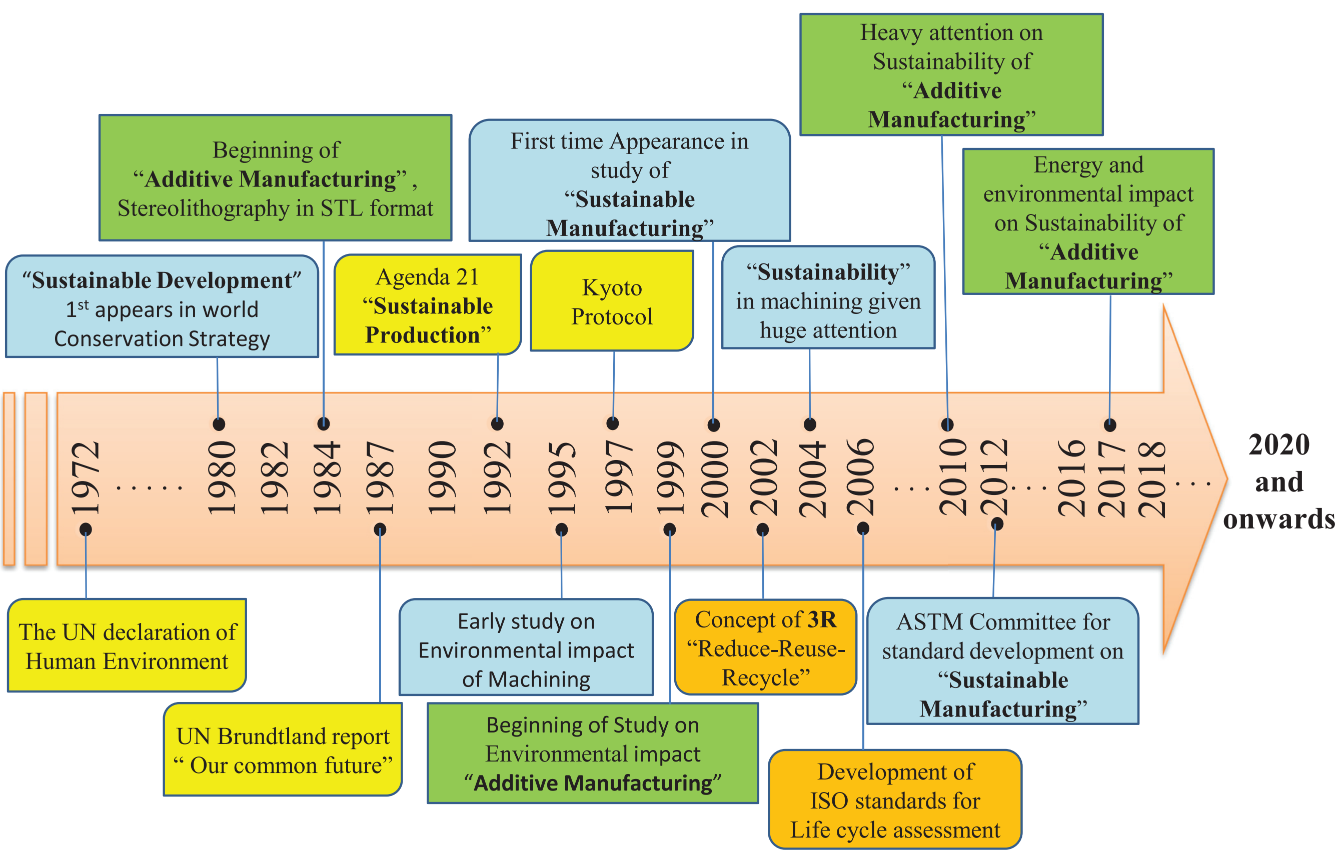


Fig. 1. A route map of sustainable manufacturing milestones [10].

approaches, with a minimum requirement of specialized tooling in the fabrication of a product, quick tooling manufacture, and material wastage is also reduced [22]. Furthermore, AM has reduced cost and processing time for customized and low-volume components production.

Smart manufacturing (SM) is an innovative, service-oriented, and networked manufacturing model, which progressed from, but extends beyond, conventional manufacturing (CM) and service methods, and integrates various cutting-edge technologies such as IIoT, AI, BDA, CPS, CC and DM [23]. In the SM environment, there are lots of monitoring and control points organize along entire manufacturing processes, like from delivery of raw materials to shop-floor to final delivery and packaging of the products [1].

Consequently, a vast amount of manufacture data is produced and collected. Producers can investigate these data by using BDA to enhance the performance of manufacturing and management of the whole production processes for complex products, such as optimizing process parameters, reducing process flaws, improving product quality and productivity, etc. Such managerial improvement and optimization may significantly contribute to reducing energy consumption, material waste, carbon emission, and environmental impact [24–27]. Currently, theories and applications of the innovative ways of manufacturing can be further studied and analyzed for better resource efficiency, e.g., collaborative manufacturing, AM, green supply chain, etc.

The product lifecycle management (PLM) comprises three stages, which are beginning of life (BOL), middle of life (MOL), and end of life (EOL). Majeed, et al. [28] proposed a BDA framework for process analysis and optimization of AM and implemented it on the BOL phase of AM. Brundage, et al. [29] analyzed environmental sustainability calculation approaches to enable more precise decisions earlier in design phase of product life cycle. As previously discussed, AM and big data both dealt separately in the manufacturing enterprises. There is minimal work done in the combined form. SM and sustainable manufacturing are also a niche for AM industries. The sustainability in the manufacturing enterprises was started about four decades ago, and the route of sustainability for the subtractive and additive manufacturing is shown in Fig. 1 [10].

It can be seen that manufacturing enterprises identify the sustainability issue after a century of industrialization. After recognition, many researchers have worked on sustainable manufacturing. With the development in the AM technology, the efforts on the implementation and adoption of sustainability of additive manufacturing (SAM) in AM enterprises have also been expedited. So, the AM leaders are interested in benefiting their companies by effectively using SAM.

In the present paper, big data analytics, additive manufacturing, and sustainable smart manufacturing (SSM) have combined to form a new interdisciplinary research area, namely big data-driven sustainable and smart additive manufacturing (BD-SSAM), as shown in Fig. 2. Therefore, a framework of big data-driven sustainable and smart additive manufacturing (BD-SSAM) is proposed, which is an initial step for the development of smart manufacturing environment in the additive manufacturing enterprises. This framework is applied for the BOL phase of whole product life cycle of AM process. Also, very supportive of AM enterprises and produces products with energy-efficient and working on cleaner production strategies for the environment.

The paper structure is mentioned as follows. In Section 2, a detailed literature survey is conducted for BDA, AM, and SSM. In Section 3, the overall framework of BD-SSAM is established. Section 4 describes the key enabling technologies of SSAM. In Section 5, the benefits of the framework are briefly mentioned. In Section 6, an application scenario of the additive manufacturing industry is presented. Section 7 explains the results and discussions of the case study. The managerial implications of the framework are presented in Section 8, and in Section 9, conclusions with future research direction are explained.

2. Literature review

There are five subsections which are categorized as follow:

- Additive manufacturing and its qualification.
- Sustainability of additive manufacturing.
- Smart manufacturing and its key enabling technologies.
- Big data and its architecture in smart manufacturing.
- Research Gaps.

2.1. Additive manufacturing and its qualification

AM was established about three decades ago, alias as rapid prototyping (RP), additive layer manufacturing, layer-based manufacturing (LBM), stereolithography (SL), 3D printing, etc. [30]. ASTM characterized AM into seven categories as vat photopolymerization, material jetting, binder jetting, powder bed fusion, material extrusion, directed energy deposition and sheet lamination [30], [31].

The quality of AM products is characterized by dimensional and surface quality, mechanical properties, hardness, densification, and residual stress behavior. Numerous research work is done on the qualification of different materials components by applying different kinds of AM technologies as per requirement. Previous researchers' studies have shown that for metal AM processes, appropriate combinations of process parameters such as scan speed, laser power, hatch distance, layer thickness, etc. influence on above-mentioned quality characteristics. Most of the research is focused on the manufacturing of fully dense parts; it means that the relative density is nearly equal to 100%. But it is difficult to achieve almost 100% or above 99% relative density in every material in every AM technique [13]. So, the most commonly used AM technique in which the relative density is higher than 99% is selective laser melting (SLM), which belongs to powder bed fusion (PBF) technology of metal AM.

Mumtaz and Hopkinson [32] investigated that the high scan powers persuaded to reduce surface quality, and comparatively low scanning speed is mostly preferred because of the longtime permits the melt pool to restructure and attain a smooth surface. Islam, et al. [33] presented a comparative experimental study on the dimensional accuracies of fabricated parts of two broadly used AM techniques and the results exposed that in both processes, the primary reason of dimensional dissimilarities was the volumetric changing of the process, and SLA accuracy was better than PBP produced parts. Wang, et al. [34] explained that scanning track characteristics were very critical for attaining a successful surface finish on the SLM products. Relvas, et al.

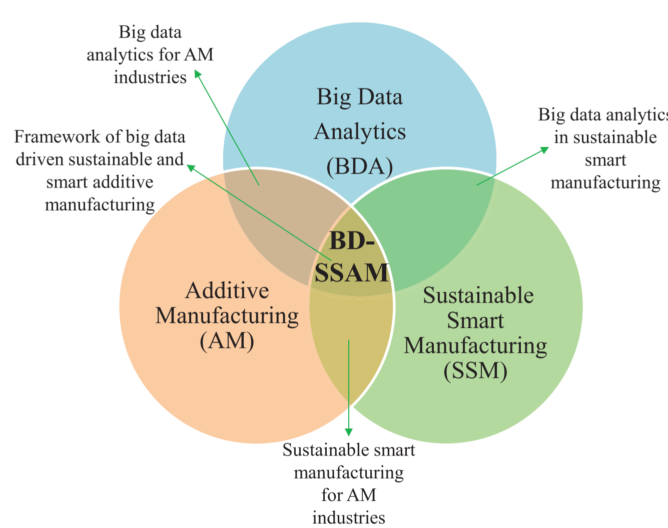


Fig. 2. Combinations of research of BDA, AM, and SSM.

[35] investigated a comparison study on the 4 AM processes SLA, SLS, FDM, and 3DP for the dimensional and geometrical accuracy, and concluded that the worst dimensional performance of all the AM processes was from 3DP, but the geometrical performance of 3DP compared to other processes was in favorable condition.

Calignano, et al. [36] investigated the influence of main process parameters on surface roughness of DMLS, built AlSi10Mg alloy specimens, and analyzed that scan speed had the highest impact on surface roughness, also described that the surface roughness could be minimized by shot peening. Delgado, et al. [37] evaluated DMLS and SLM built parts mechanical properties and resulted that part mechanical performance is inversely proportional to layer thickness.

2.2. Sustainability and additive manufacturing

With the progress in sustainable manufacturing, the sustainable development of the AM industry is also vital, and researchers have influenced the SAM for implementation and adoption in the AM enterprises [10]. The development route of sustainability for subtractive and additive Manufacturing industries is shown in Fig. 1. Previous researchers have correlated the sustainability of AM or other processes with energy consumption and its environmental effects [38]. Jawahir, et al. [39] presented the 6R concept (i.e. reduce, redesign, recover, remanufacture, recycle and reuse) for three main dimensions of sustainability, which are environmental, society and economy as shown in Fig. 3. The environmental effect of AM is further divided into three main aspects which are, resource consumption, management of waste and controlling pollution which are shown in Fig. 3.

Material consumption and energy consumption are mainly related to the resource consumption of the AM industry. In comparison to CM, the AM processes material efficiency is better, but the energy consumption is more due to low productivity and other accessories requirements of different AM processes [40]. Peng et al. [10] studied the SAM, and discussed the SAM with the main concentration on energy and environmental effects, and also predicted that the most crucial feature for SAM is resource consumption. By the implementation of AM techniques, there is a considerable saving of material by reducing waste; sometimes it reaches more than 90%. The pollution is also controlled by applying AM technologies because there are no cutting fluids, lubricants, etc. used by AM processes, which make the environment clean and step to green production. From the life cycle perspective of AM products, there is very little work done, and there is a requirement to work on the long-term influence of AM on the environment [41].

Energy consumption is a critical approach to calculate the sustainability of AM technology [42], [43]. Huang et al. [44] calculated the life-cycle energy and greenhouse gas emissions savings possibility of AM techniques for aerospace components. A new methodology of multi-flow consumption of materials, fluids, and energy was investigated by Le Bourhis et al. [45] on a direct laser solid forming (DLSF) technique of AM, and the flow of energy is based on the energy consumption during laser system, cooling system, and motor drives. Ford and Despeisse [46]

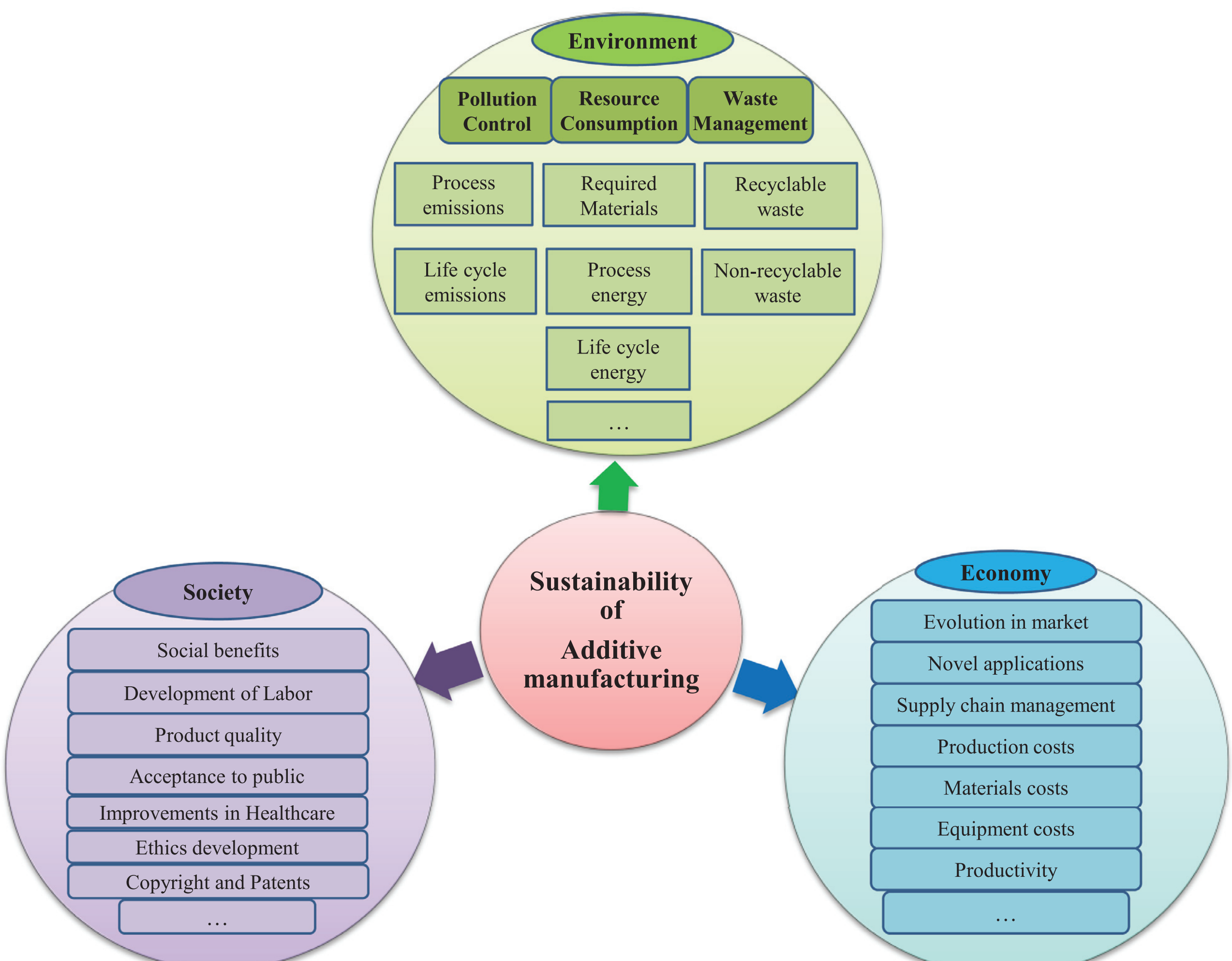


Fig. 3. The three dimensions of SAM [10].

investigated the implementation of AM from the perspective of the life cycle and concluded that sustainability benefited in the redesigning of product, processing of input material, manufacturing of the product, and product reuse by remanufacturing of the AM industry. Gebler et al. [47] analyzed the life cycle perspective of AM and resulted that AM has potential for reduction in costs, energy, and CO2 emissions, and also predicted that cost saving of \$113 ~ \$370 billion till 2025 due to reduction in material consumption with reduction in the supply chains. Mani et al. [48] and Chen et al. [49] defined the potential benefits of sustainability of AM which are reduce wastage during production, optimization of products and creation of lightweight structures, reduction in material and energy consumption, reduction in the supply chain, reduction in inventory management, etc. Wits et al. [21] investigated the sustainability of AM from end-user perspectives and concluded that AM is a more sustainable substitute from maintenance, repair, overhaul (MRO) or replace point of view.

2.3. Smart manufacturing and its key enabling technologies

SM is adopted by different industries and manufactures, and established its significant enabling technologies which are utilized to report data acquisition, storage, communication, processing, analysis, the discovery of knowledge and pattern [1]. The sustainability and proficiency of the SM systems are enhanced with the provision of valuable and reliable data by using these enabling technologies of SM. Some of the key enabling SM technologies are described as follows:

- Abell et al. [50] has defined that BDA is the method of investigative vast and diverse data groups to expose hidden correlations, unknown patterns, customer likings, market trends and further valuable material which can support organizations to enhance sustainability, make more-informed business decisions and to initiative the society on the way to the globular economy and also do sound business decisions. Gunasekaran et al. [51] studied the influence of BDA on sustainable and green SCM for the improvement of organizational performance. Tao et al. [52] designed a fiber channel (FC) switch based on field programmable gate array (FPGA) and applied due to its high speed, low latency, and high-performance transmission capacities. The FC switch higher capacity of communicating and processing big data opens a bright perspective for SM.
- Data Mining (DM) is extensively used in manufacturing and service industries for making decisions on the available data, and it is also applied in a sustainable manufacturing environment. Köksal et al. [53] studied and analyzed the applications of DM for improving the manufacturing and product quality. With the development in DM technologies, it is executed in various phases of the lifecycle, like designing of product, production, maintenance, service, recycling, etc. [54].
- For the advanced sustainable manufacturing and SM, the IoT systems are chiefly employed to monitor energy consumption, emissions-reduction, and improving the efficiency of recycling during the life cycle [55]. Shrouf and Miragliotta [56] established an energy management system on IoT-based and concluded that this system is beneficial to manufacturing company managers for making decisions, and also helpful for sustainable manufacturing and energy management.
- Lee et al. [57] developed a CPS framework in Industry 4.0 system which was utilized in the production line of machine tools for integration of CPS in SM and concluded that CPS could be implemented for improving product quality and reliability of the system, reducing production downtime and optimizing production planning and inventory management. Song and Moon [58] developed an architecture of cyber manufacturing systems (CMS) by using CPS methodology and concluded that CMS has potential sustainability benefits in comparison to conventional manufacturing systems.
- 5G networking is a new emerging technology for the data-driven industries, SM, smart cities and infrastructure management because it will be possible to have many more devices working, reliably, securely and uninterrupted in the similar zone [59]. 5G has several benefits such as higher speeds, less latency, capacity for a larger number of connected devices, less interference and better efficiency [7]. As discussed above, it is very beneficial for the big data and internet of things. For example, with 5G technology, more manufacturing resources and devices can be connected and to carry out large scale communication. This is benefit to promote information and knowledge share among heterogeneous manufacturing resources and thereby to optimize the manufacturing service abilities that involved in the proposed framework. Meanwhile, the advantages of 5G technology on higher reliability and less latency are benefit to improve the real-time operation and control as well as decision-making capabilities of SSAM processes.

2.4. Big data and its architecture in smart manufacturing

Laney [60] has defined the big data on the theory of 3Vs (i.e. Volume, Variety, and Velocity), which means that a great volume of data is generated and collected, the speed of data collection and analysis is high, and various types of semi-structured and unstructured data are received for final processing. Big data is classified according to different life cycle stages, which are BOL, MOL, EOL, on the systematic changing like static and dynamic, and also categorized on a semi-structured, structured, and unstructured basis. Recently, Ren et al. [1] conducted a big data analytics review to support sustainable smart manufacturing for the whole lifecycle and proposed a framework to deal with the future challenges of smart manufacturing. Jiang et al. [61] used big data based neural network to predict the printable bridge length in additive manufacturing for reducing support material waste.

With the developments in the BDA, it has been applied by many companies to improve their production, maintenance, services, etc. Leitão et al. [62] described that challenges of the industrial and manufacturing automation arena would be efficiently handled by applying BDA due to its ability of management of enormous volume of rapidly created data. Siemens [63] implemented big data for remote diagnostics services to investigate the operational behaviors of their power plants from all over the world by taking 100,000 measurements.

2.5. Research gaps

From the literature review, there is significant progress in the field of AM, SM, Sustainable manufacturing, and BDA, but all the fields were discussed or investigated separately. Based on this, there are following research gaps for SSAM which needs to be examined:

- A big data-driven framework in a combined form of additive manufacturing and smart manufacturing is not available or discuss previously, because both fields have been studied in parallel. So, there is a need to develop a framework that jointly works and how to establish a framework for BD-SSAM?
- In the SM environment for AM, an enormous amount of process control and performance of product data is produced, and the most vital is to extract valuable information from the big data, which can be possible by applying BDA in Smart AM environment.

3. Big data analytics framework for sustainable and smart additive manufacturing

With the developments in the information and manufacturing technologies, there is a massive amount of data generated during AM processes, which becomes a substantial challenge for conventional architecture to handle it. With time, the requirement of sustainable and smart additive manufacturing is developing, and there is a need for particular architecture which will help the AM companies' engineers and managers to improve their capability with the growing world standards and to compete with the market demands. Considering the previous literature survey and discussion, the role of BDA is very significant and vital for manufacturing enterprises like additive manufacturing [64] due to its ability of collection and storage of data, preparation, cleaning, reduction, integration and transformation of data and the more vital phase of big data is the data mining. Then, decision making is performed from the extracted knowledge of big data [65].

Based on the presented overview, an overall framework of BD-SSAM is designed, which is shown in Fig. 4. By using the framework, real-time and non-real time data of the BOL stage of product life cycle of AM is determinedly monitored, controlled and captured. By the usage of communication and network technologies, the gathered data can be transferred and stored in databases. Furthermore, reliable and available data after preprocessing is provided for supporting data mining and decision making. There are mainly four phases of the developed framework which work in a closed-loop and interconnected with each other. The details are mentioned in the upcoming subsections.

3.1. Perception and acquisition of big data for SSAM

It is the main layer of the framework, as shown on the top left of Fig. 4. Firstly, the IoT devices such as smart devices, RFID readers, RFID tags, smart sensors, etc. [66] are configured on the whole product manufacturing cycle (i.e. smart design, smart production, smart maintenance and services, smart delivery) of the smart AM environment. Then, the huge heterogeneous and multi-source data of AM such as product planning and design, material and procurement, AM systems, AM production control and status, product qualification, energy consumption, products delivery, and customer feedback, maintenance and services, products recovery, etc. are sensed and captured for further evaluation. The smart sensors and calibration devices are used to control and monitor the AM system working and manufacturing of quality products according to customer requirements. The product quality data is also monitored and collected at each stage of production to the assembly phase. Then, the standard communication procedures (i.e. Modbus, intranet, Internet RS- 485/323, 5G, etc.) [66] are utilized to transfer the large captured data for further processing in the next

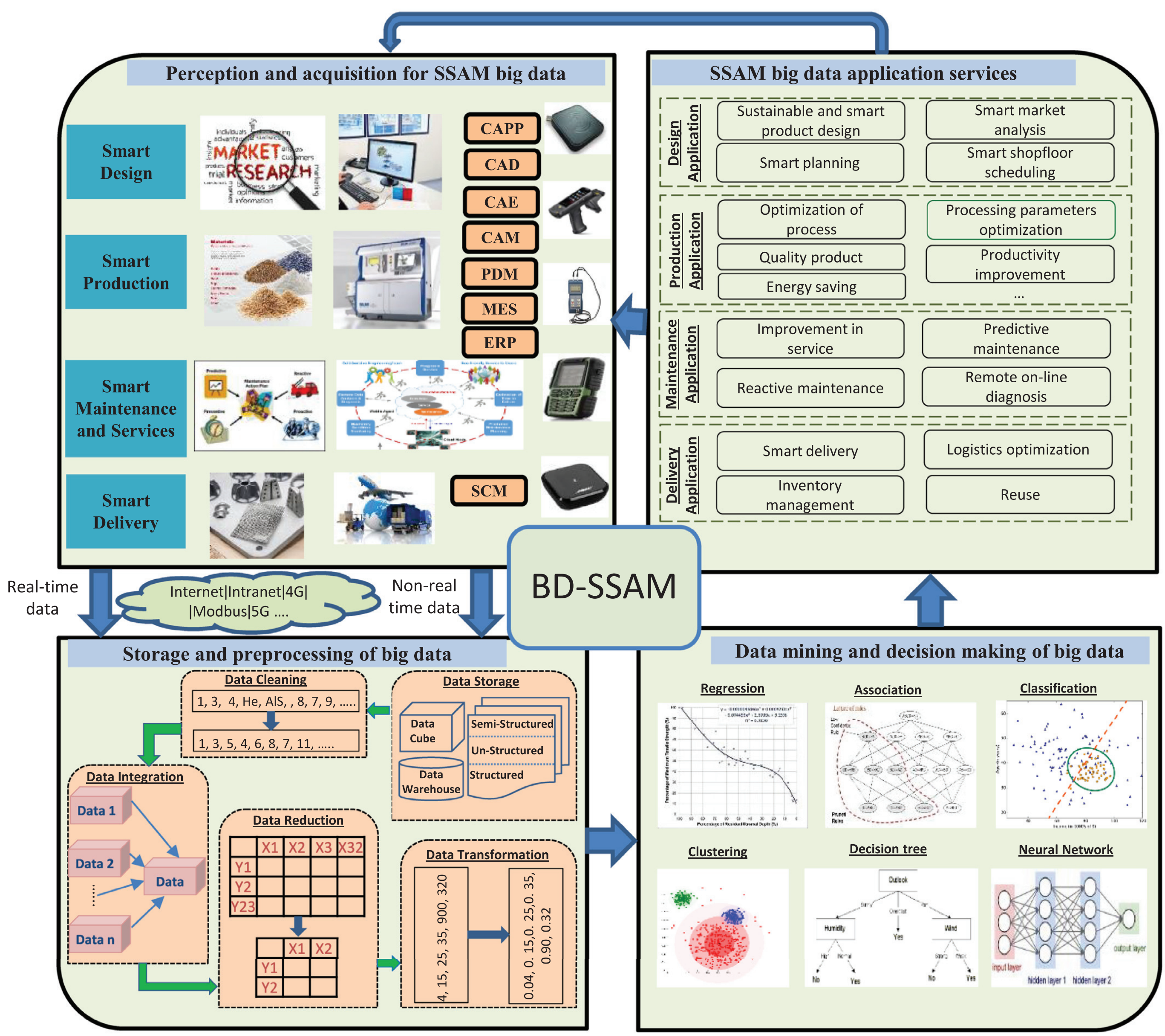


Fig. 4. A BDA framework for SSAM.

working layer of the framework.

3.2. Storage, preprocessing, integration and management of SSAM big data

The real-time and non-real-time data of the entire product manufacturing cycle of AM enterprises is collected, which composes of a great amount of unstructured, structured and semi-structured data [67]. The conventional data storage and management tools and technologies are not enough to further process and handle the too huge, complex and complicated data effectively. Consequently, this layer is supportive for the further proceeding of the storage disordered and huge datasets or data cubes by using Extensible Markup Language (XML), Not only Structured Query Language (NoSQL) and Distributed Database system (DDBS)[68]. For the non-real-time product manufacturing cycle data processing, the Hadoop computing framework is applied [68]. The real-time computing framework Storm is applied for heavy real-time processing of AM product manufacturing cycle data [69], [70]. In this layer, the flow of data for preprocessing and management is followed by the sequence mentioned below and also shown in Fig. 4 (bottom left):

I Data storage method
II Data Cleaning method
III Data integration method
IV Data reduction method
V Data transformation method

Initially, AM product manufacturing cycle data are chosen to form a data cube, and to construct a manufacturing cycle data warehouse so that the SSAM big data could be integrated by pre-defined logics [71]. The established data warehouses are used to store and manage the manufacturing cycle data cubes, and to describe the complex logic relationship among massive manufacturing cycle data cubes. Next, the generated manufacturing cycle data cubes have a great number of redundancies, which is reduced by data cleansing operation. The general models which are applied for data cleaning are information structure model [72] and RFID-Cuboid model [73]. During cleaning operation, set of manufacturing cycle data cube from manufacturing cycle data warehouse is the input which gives the output in an organized set of manufacturing cycle data cube that transmits significant information about manufacturing cycle status.

Moreover, meta-models are developed to integrate the huge data which consists of design, market, production, maintenance, dimensional quality, product delivery, logistics, etc. [74]. The integrated data sets are obviously still massive, which may be infeasible for data analyses. Consequently, a data reduction process is made to acquire a reduced illustration of the data set that is much smaller in volume, but it must hold the veracity of the original data. Furthermore, the concise manufacturing cycle data is transformed so that the subsequent data mining method may be more effective, and the patterns found may be easier to recognize [74]. Finally, the preprocessed SSAM big data are stored in various above-mentioned data management systems such as DDBS for further utilization in decision making.

3.3. Data mining and decision-making of SSAM big data

Throughout the entire product manufacturing cycle of AM enterprises, a huge amount of data is generated in the form of 4Vs

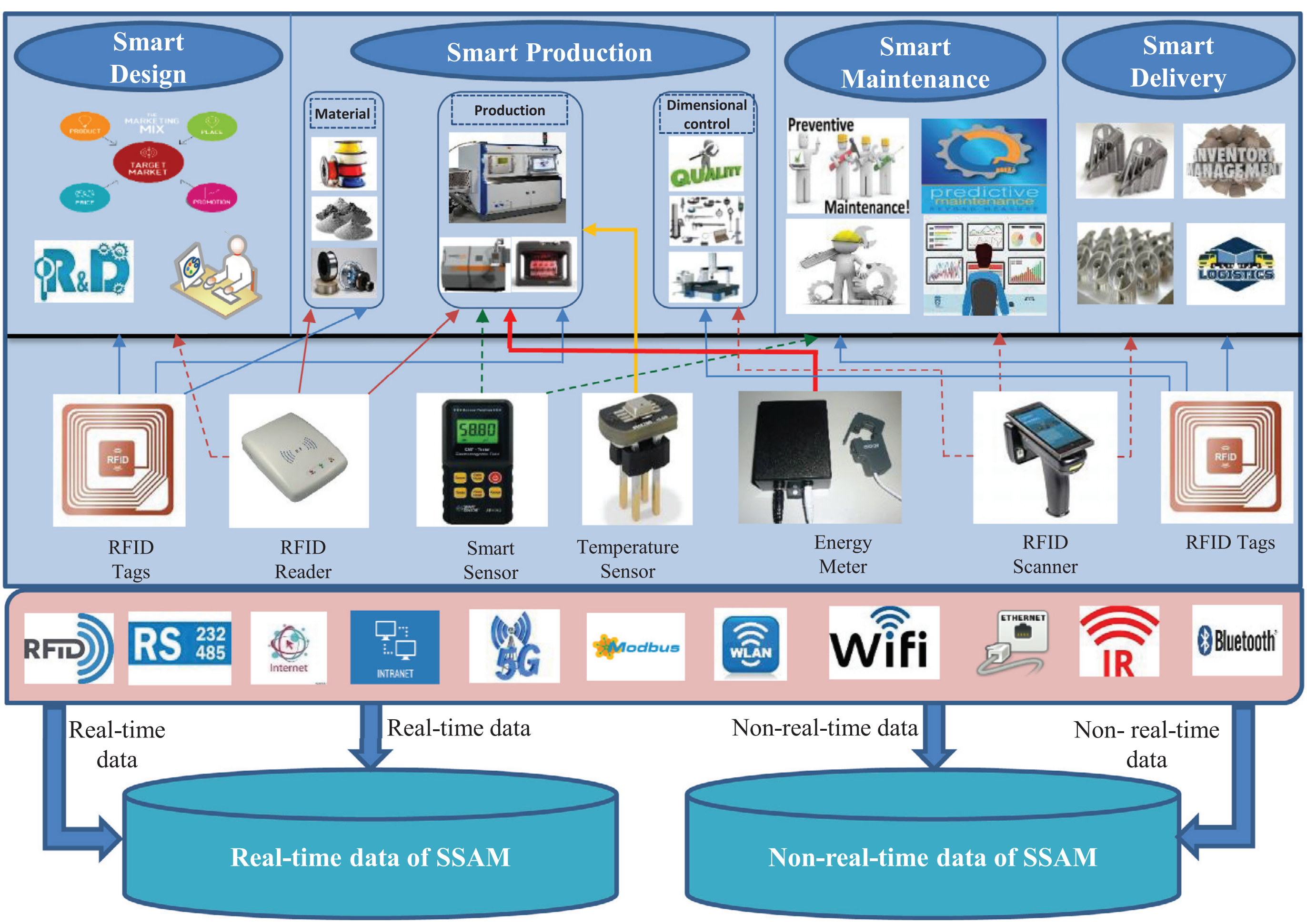


Fig. 5. Big data perception and acquisition framework of product manufacturing cycle for SSAM.

(volume, velocity, variety, and value), which is challenging to investigate it by using the traditional methods of analysis. In this framework, an impressive technology that has potential to determine hidden knowledge from the large AM product data sets is applied, which is data mining models (e.g. clustering, classification, association, neural network, prediction, etc.) [66]. By combining the AM product processing analysis approaches and methods of big data mining [66], valued information and knowledge can be revealed from these AM product manufacturing cycle data sets. From these mined results, smart and sustainable AM product decision makings for application services will be provided to AM enterprise managers [66].

3.4. SSAM big data application services

This application services layer can be seen from the top right of Fig. 4; big data application services are applied to deliver significant real-time and non-real-time applications based on mined information and knowledge for end-users [66], [74]. For the various manufacturing cycle phases, numerous forms of application services are planned in this layer of the framework. Specifically, sustainable and smart product design, smart shop floor scheduling, optimization of AM process, AM processing parameters optimization, reduction in energy consumption, logistics optimization, sustainable and smart maintenance, predictive maintenance, smart delivery, etc. are designed for SSAM, which is favorable for promoting CP strategy in the sustainable and smart AM environment. By the implementation of smart decision making and real-time feedback, the services mentioned above are applied in the AM enterprises for efficient and sustainable smart production.

4. Key technologies for big data analytics sustainable and smart AM

Big data of SSAM plays a vital role in the whole product life cycle of AM enterprises. In the BOL, it is an important asset for innovative products, and it can also reduce waste and emissions with the EOL decision making which means that the product can be remanufactured and reused. Though it is problematic to capture overall and real-time data of product life cycle, particularly products' data after being distributed to customers [75].

4.1. Big data perception and acquisition for SSAM

An overall framework model for heterogeneous and real-time product manufacturing cycle, big data perception, and acquisition of SSAM are developed which is shown in Fig. 5 [75]. The configurations of several IoT and smart devices are the fundamentals for gathering heterogeneous, real-time and multisource data of fabricated products and things of SSAM environment (Table 1). During the entire product manufacturing cycle of SSAM process, IoT and smart devices are positioned at the manufacturing resources and main areas of the products in the machine, workshop, and factory level (see in Fig. 5) [66].

Primarily, the RFID tags are configured adequately on the technical documents and reports of quality, design, production of products and maintenance of machines which play significant roles throughout the product manufacturing cycle. Moreover, the RFID tags are configured on the parts design and models for accurate tracking. RFID tags are also deployed to different types of AM materials like powder, wire, and liquid which are used at different AM systems. RFID readers are installed at different locations of the entrance of factory, CAD rooms, material handling, warehouse, tool stores, laboratories, etc. The AM machines are also properly tagged.

The energy consumption data capturing is also vital for the SSAM and CP strategy. The energy consumption can be measured from the power consumption of the AM systems which is equivalent to the product of real time electrical current and voltage. Different smart sensors and smart meters (i.e. temperature sensors, pressure sensors,

Table 1
Information of configuration of IoT devices for the data acquisition of additive manufacturing environment.

IoT devices	Type of IoT device	Monitoring Resources/Location	Purpose/ Objective
RFID Tags	Ultra-high frequency (UHF)	Drawings/ Models/Material	To trace and monitor real-time data information of drawings and material.
RFID Tags	UHF	Product/ tools/AM machines/ pallet/ operators/ AGV/ QC document/etc.	To trace and track the real-time data of product, manufacturing process, usage, etc.
RFID Reader/ Scanner	UHF	Material /Product/ maintenance/ etc.	To identify and track the critical components of the overall product manufacturing cycle.
Smart Sensor	Temperature sensor	AM machine/ workshop	Monitoring temperature data of machine, processing bed of product, and also the workshop work.
Smart sensor	Pressure sensors	Machines/ Compressors	To monitor the pressure data of machines, product manufacturing, air supply, etc.
Smart sensors	Voltage and current sensors	AM machines/ workshop	To monitor the electrical energy consumption information of AM machines, compressors, pumps, etc.

current sensors, voltage sensors, vibration sensors, etc.) are applied to monitor and collect big data of temperature, pressure, energy consumption, etc., during the whole production process. The log of the data is maintained in the AM systems for the each second during the AM processing for building of a product and it is also displayed on the control panel on machine. By the IoT devices and sensors, the temperature, gas, pressure, etc., data is continuously monitored and collected.

Furthermore, the maintenance data of AM machines during the product manufacturing process is also recorded by suitable smart sensors and tags (see Fig. 4). Due to the implementation of the SSAM environment, some maintenance and malfunctioning issues of AM systems are solved by the online internet or other sources like cloud computing. The RFID tags and readers are also configured on the product inventory, delivery and logistics sections for making the smart delivery. Moreover, through the standard communication protocols [66], such as RFID, RS-232/485, Internet, Intranet, WLAN, Modbus, 5G, etc. technologies, the collected multi-source, non-real-time, and real-time data is transferred to enterprises databases.

4.2. Big data mining and knowledge sharing for SSAM

Fig. 6 is the closed-loop big data mining and knowledge sharing structure of SSAM, which comprises of the data and knowledge layer, model layer, and objective layer.

4.2.1. Data and knowledge layer

Data and knowledge layer contain heterogeneous, multi-source, real-time, non-real-time, and knowledge data of product manufacturing cycle of SSAM which has four dimensions which are as follows:

- The dimension of data type contains the data of whole product manufacturing cycle for the SSAM, such as AM design data, material data, AM process data, market analysis data, customers' demand data, maintenance data, quality data, inventory data, delivery data, energy data, etc.

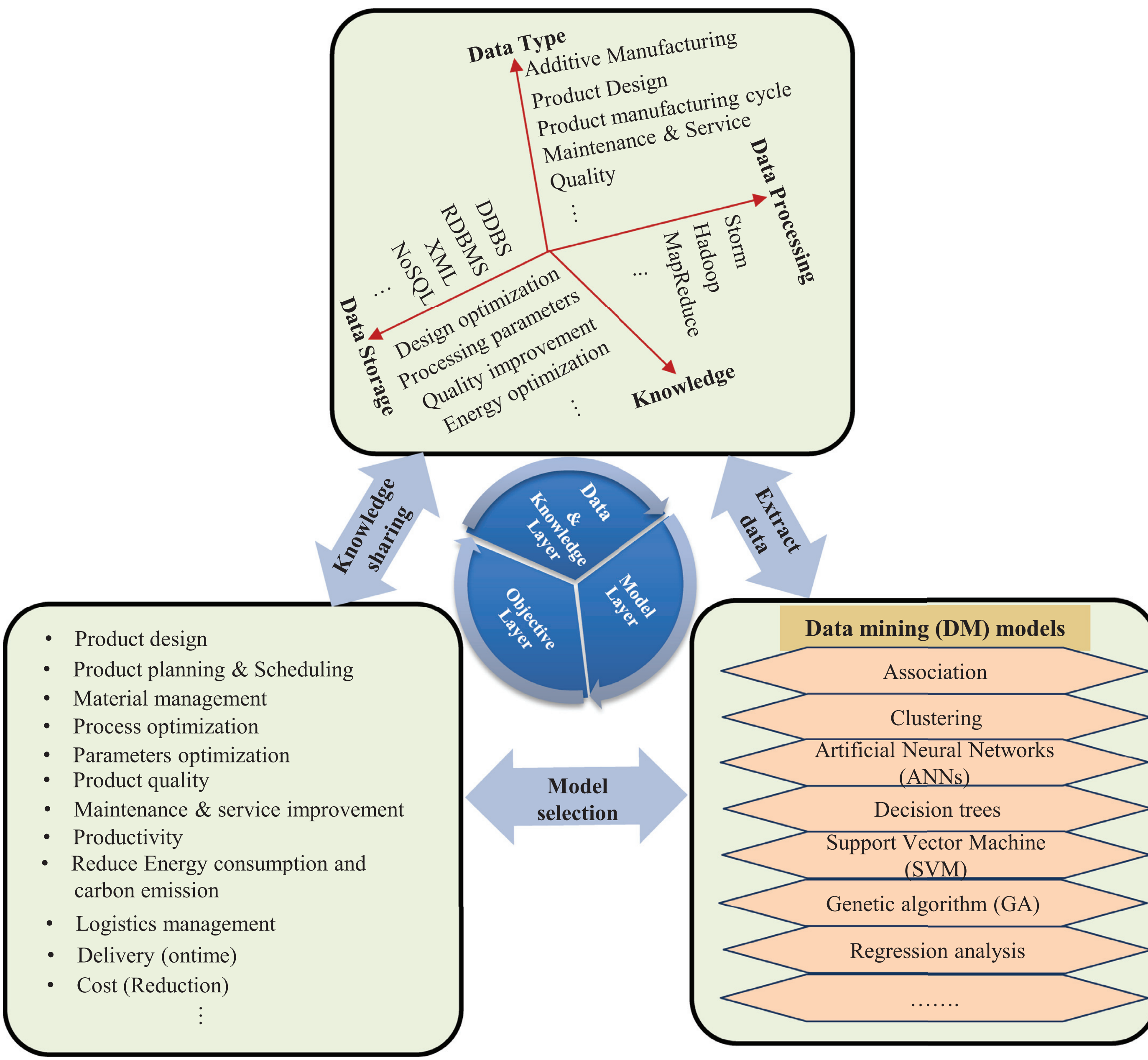


Fig. 6. Big data mining and knowledge sharing structure for SSAM.

- The dimension of data storage consists of various database enterprises which are used for storage of the heterogeneous data, structured data, semi-structured data, and unstructured data, such as DDBS, RDBMS, XML, NoSQL, etc.
- The third dimension of this layer is data processing. Different data processing computing software is applied for the cleaning, reduction, integration, and transformation of real-time and non-real-time captured data [66]. The mainly applied computing systems are Hadoop, Storm, MapReduce, etc.
- The final dimension of this layer is the knowledge data, which is very helpful for deciding on the available data from the previous knowledge sharing. This dimension contains data of design optimization, optimized processing parameters, quality improvement data, energy optimization (reduction in energy consumption and carbon emission), maintenance data, data relevant to the processing of different materials in the AM, and other various types of data.

4.2.2. Model layer

The model layer is also identified as a method layer which principally discusses the data mining models. Data mining models can generally be characterized as descriptive and predictive [53]. Descriptive data mining models include summarization, clustering, and association general model. Summarization models used correlation analysis and scatter plots for determining the relationship between the input and output variables [53]. Association general model can be used to assess the AM product design scheme, and to investigate the quality factor of AM product, etc. Predictive DM modeling can be characterized as statistical-based (S-based) methods, DT-based algorithms, ANN-based algorithms, classification methods, etc. [53] The prediction general model can be used to estimate the maintenance cycle in AM systems.

Furthermore, the other DM models include genetic algorithms (GA), Bayesian estimation, Apriori algorithms, support vector machine (SVM), regression analysis, etc. Then an appropriate model of data mining will be nominated to extract data from the data layer and discovering knowledge from them.

4.2.3. Objective layer

The objective layer is also known as an application or demand layer. On the basis of review of sustainable smart manufacturing [1] and additive manufacturing [10], in present investigation, the manufacturing application of the objective layer principally comprises of improving product design, optimization of processing parameters, improving productivity, product quality improvement, optimizing AM process, reducing energy consumption, and improvement in material management. This layer also includes improving delivery and shop-floor logistics, providing predictive maintenance service, reduction in carbon emissions, reducing environment effects, etc.

Conferring to diverse demands of the objective layer, appropriate data mining model, and real-time data of the product manufacturing cycle are carefully chosen to carry out the knowledge discovery [66]. For example, the processing parameters can be optimized and predicted by determining the mining algorithm like a regression, genetic algorithm or artificial neural network.

The big data mining and knowledge sharing analysis of the SSAM environment illustrate that closed-loop structure begins from application and knowledge sharing objectives, and in conclusion, meets application objectives [66]. Initially, application objectives are predicted in the data and knowledge layer. Then, by different goals or demands, the adaptive data mining models are designated and developed. The data mining models have been selected on the main rule which means the data mining models have abilities of store-memory, evolution, and self-learning. Moreover, appropriate real-time data is extracted to implement data mining. Lastly, information and knowledge are attained to meet the application objectives of AM enterprises [28], [66].

5. Benefits of SSAM

The leading-edge technologies applications are growing continuously in the current AM environment to make it SSAM, which may be produced a massive amount of data during AM product designing, AM fabrication processes, and maintenance of the product, etc., and it can be composed during the whole product manufacturing cycle. The following benefits can be extracted by the customers and manufacturers

5.1. Market demands perception and prediction

With the revolution in manufacturing style from mass to customized production, determining customer demands and preferences have grown gradually significant for the manufacturers [1]. Mourtzis [76] focused on the aspects that affect manufacturing network performance for mass customization and also presented the work relevant to the design, planning, and control of manufacturing networks in the field of mass customization and personalization.

AM products demand increased due to its ability to build unique and complex structure parts. Precise perception and prediction of customers' demands and preferences are productive resources for producers to make their products better fit the requirements of customers, and to make sophisticated faithfulness and revenue. The huge capacities of data associated with customer demands (e.g., customer behaviors and evaluations, user feedback, online reviews, and sentiments, etc.) can be gathered and integrated from numerous sources for mining actionable visions by the use of big data analytics. These visions can be applied to forecast market demands appropriately, and the probable market magnitude, margin, the number of competitors and the level of distinction among AM products can also be predicted [1].

5.2. Improvement in product design

In the SSAM framework, the remote product manufacturing cycle data that affect product design can be combined and investigated to create imperative intuitions about enhancements and revolutions in the AM product [1]. Topology optimized products have also been designed with minimum material consumption and higher strength. Producers have recognized that BDA is an effective tool for categorizing the hidden requirements and cultivating the efficiency of selection about several design substitutes [1]. So, smart products are redesigned according to the feedback of the customer.

5.3. AM product quality improvement

The real-time data of AM resources (e.g., materials, operators, WIP, etc.) can be monitored by the configuration of smart devices. There are lots of quality control points organized along the manufacturing line, and a huge amount of data are generated during the raw materials (i.e., powder, wire, etc.) provision to production workshop to the packing of AM products for final delivery [1]. BDA is applied by AM manufacturers to discover supplementary methods to lessen faults of process and to rising production, which can be obtained by applying several data analysis algorithms and models to the manufacturing processes. Moreover, BDA can be utilized to connect the process and equipment level data to metrology data to make more precise predictions about production failures [1].

5.4. Energy consumption control and reduction

In the current manufacturing scenarios, management of energy and lessening of emissions are two essential responsibilities for any manufacturing enterprise (i.e., subtractive or additive manufacturing). With the continuous implication of smart devices, meters, and sensors throughout the entire manufacturing cycle of product and process, huge size of real-time energy consumption data from manufacturing and operation process can be gathered [28], [66]. The energy consumption data offer a huge potential to reduce energy consumption and to enhance the decisions of energy proficiency management. Big data inputs can also help managers to recognize and calculate the wastage points and to lessen or disregard them in real-time [1].

5.5. Intelligent predictive maintenance and services

Through IIoT, real-time data of the product manufacturing cycle can be collected and evaluated, which would help to improve maintenance and service decisions [1]. The AM product operation status data is collected and communicated to the producer who is a vital asset for maintenance decisions, and AM producers can investigate data to estimate indicators to control whether system performance is declining. These investigations can support producers to precisely forecast when the products may fail [1]. This may lead to intelligent predictive maintenance and services.

6. Case study scenario

For the implementation of the proposed framework of BDA for SSAM, a case study of the AM industry is demonstrated for proof of concept. The principal objective of the case study was to show how the proposed framework benefited the AM enterprises and how sustainable and smart AM was done by applying advanced information and manufacturing systems. The performance of the AM processes can be enhanced by the execution of proposed BD-SSAM framework, such as design innovation, reduction in energy consumption, reduction in processing time with enhancement in productivity, improvement in product quality with optimizing processing parameters, etc. A full explanation of application study is stated in the forthcoming sections.

6.1. Case description

The framework is implemented in a company, which is specialized in the arena of AM technology and working on the different AM techniques. The case company is Xi'an Ruite 3D Technology Co. Ltd. (http://www.xaruite.com/), which has a wide range of AM systems for manufacturing of products of metals, polymers, ceramics, etc. The company is providing facilities of AM to their respected customers from various industrial fields like automobiles, aerostructures, biomedicals, electronics, customer goods, etc.

The objective of the case study is to demonstrate an association between the implementation of SSAM big data analytic practices and economic benefits for the AM company. So, we have considered the BOL stage (product manufacturing cycle). The company has different AM systems like SLM systems, SLS systems, FDM systems, etc. The present case study was performed on the SLM 280HL systems, which is

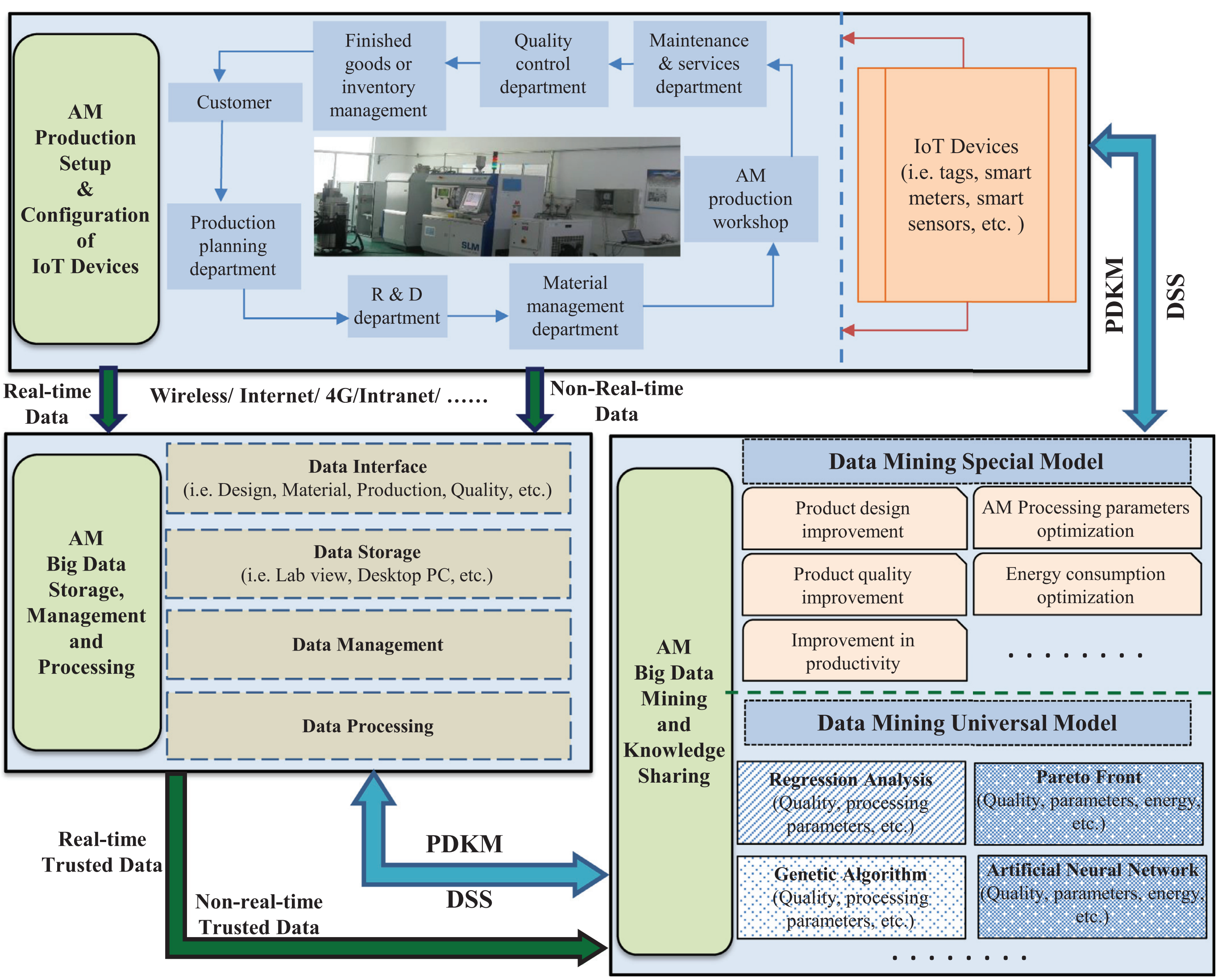


Fig. 7. The overall framework of BD-SSAM for the application scenario.

a product of SLM solutions, Germany.

The company has many new tasks to accomplished on time to meet customer requirements. Previously, the company has produced products of titanium alloys, nickel alloys, steel alloys, etc. The company has new tasks of fabricating parts of the pump from AlSi10Mg alloy. So, it was also a pleasant task for us to implement our BD-SSAM framework for manufacturing of AlSi10Mg alloy products in the company which would be beneficial for it. Previously, the company provides different products to their customers in a traditional business model like other Chinese manufacturing companies. So, the company decided to transform its conventional business model into a sustainable smart manufacturing model, which would be a system integration and service-driven [1], [77].

6.2. BDA framework of SSAM for the application scenario

Firstly, the framework of BD-SSAM for the product manufacturing cycle (BOL stage) is developed which is shown in Fig. 7.

6.2.1. Case study experimental methodology

Before going to the framework discussion, it is better to discuss the experimental methodology of the case study. An SLM 280 HL system is used for the manufacturing of products, which is shown in Fig. 8, and also an energy monitoring system is shown on the right side of Fig. 8. The SLM system is equipped with 02 fiber laser beams of 0.40 kW laser power. The powder material is AlSi10Mg, which is broadly used in automobiles and other industries. The powder morphology of AlSi10Mg alloy is shown in Fig. 9, and its chemical composition is mentioned in Table 2.

There are numerous types of processing parameters used in SLM, but the most suitable and relevant parameters are laser power, scan speed, hatch distance, and layer thickness. The combined effect of these four processing parameters is called the Energy density, which is denoted as E_D and described in Eq. (1).

$$E_D = \frac{P_L}{(V_s \times h_d \times t_l)} \tag{1}$$

where P_L is laser power, V_s is scanning speed, h_d is hatch distance, and t_l is layer thickness.

The suitable combination of these processing parameters is very significant for fully dense and good quality products with better strength. For this case study, we were started from a single-track, then a single layer, and finally fabricated bulk samples for parameter optimization. Additionally, the thin-walled specimens were produced for further testing, and finally, the final product is manufactured. As above-mentioned, initially the parameters and their levels were defined by the preliminary experimentation on the single track, single layer and then the multi-layer fabrication from the SLM process. Then, the full experimental study flowchart is shown in Fig. 10. The processing conditions and parameter details are presented in Table 3.

6.2.2. Acquisition and sensing of AM big data

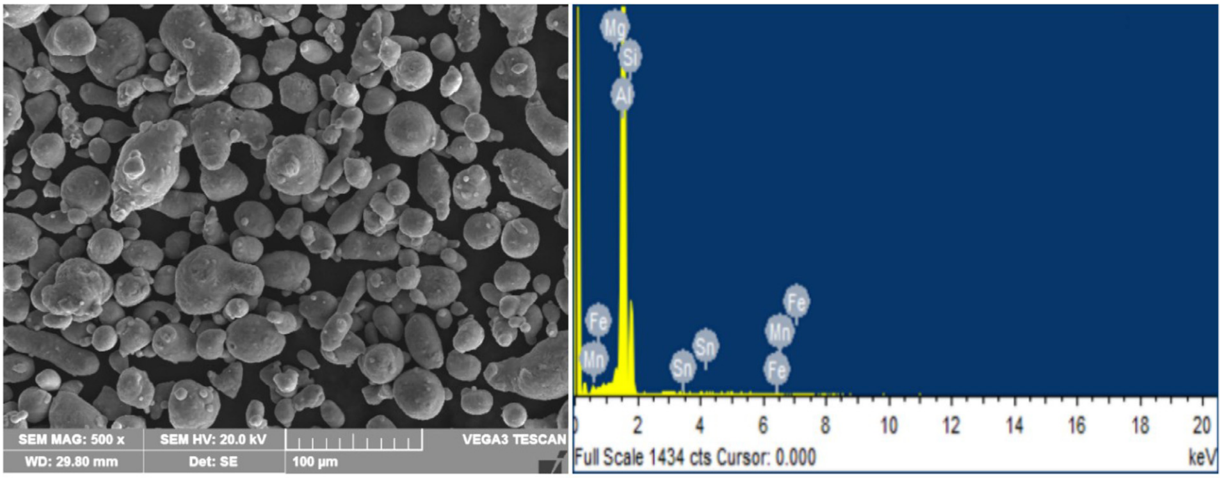
The AM production setup of the company is shown at the top of Fig. 7. It can be observed that manufacturing is done in a closed-loop structure, and all departments of the company are interconnected with each other. All departments' data is continuously monitored and controlled by the execution of different IoT devices at different locations and positions according to their requirements (already discussed in Section 4.1), and data is also gathered from other sources, which are mentioned in Table 4. The closed-loop starts with the customers' demands. Then, the demands come to the production planning and control (PPC) department. The PPC department sees the requirement of the customer if the product already manufactured from previous experience and knowledge available, then the demand is forward to R & D department for drafting and issue of proper drawings and model, otherwise the R & D of the new product required. Then, the models and drawings are issued to production department for adequate manufacturing of the product.

During the production, the maintenance and services department is interconnected with the production and other departments for proper tackling of any malfunctioning of AM systems or any other related equipment like pumps, compressors, electric supply, etc. After the fabrication of SLM products, it is appropriately cut off from the substrate by applying the wire EDM. Then, the different other processes were performed on the product as per requirement such as sand-blasting, stress-relieving, heat treatment, machining, shot peening, etc.

Furthermore, the surface and dimensional quality, strength, etc. of the product is measured. Then, the qualified product goes to the finished goods area and finally it would be delivered to the customers. Then, the customer's feedback is taken for further improvement of the product or service of the company. For the all above discussion, a considerable amount of multi-source, real-time, and non-real-time data is collected, such as design, drawings, production, various processes, quality, maintenance, energy consumption, etc.

For the collection of the big data of the whole product manufacturing cycle, various types of IoT devices like UHF RFID tags, RFID reader, smart meters, smart sensors, the voltage sensor, the current sensor, etc. are configured at various locations (Table 4). A massive amount of data is also gathered from different external types of equipment such as surface roughness meter, digital vernier caliper,

Fig. 8. Experimental system for fabrication of product and data acquisition.



(a) (b)

Fig. 9. AlSi10Mg powder; (a) morphology, (b) EDS analysis.

Table 2
Chemical Composition of AlSi10Mg alloy powder (EDS analysis).

%Al	%Si	%Mg	%Fe	%Sn	%Mn
Bal	11.28	0.49	0.11	0.32	0.12

hardness testing machine, tensile testing, SEM, OM, etc. which are applied for the qualification of the SLM product (presented in Table 4). Using the devices mentioned above, processing parameters and SLM products' real-time data can be sensed and collected.

During the SLM process, the data from different IoT devices and sensors is monitored on the control panel, and stored in the SLM machine database system. The data is gathered for every second of SLM processing and continuously monitored on the control panel screen. The sampling rate of data display on the control panel screen is 5 s. Any malfunctioning or variations in the sensor data is observed continuously, and tackled efficiently. The processing time, and energy consumption data were also taken and monitored by the smart devices, which are shown in Fig. 8.

Also, any malfunctioning in the SLM system parts, e.g. problem in powder recoater which not properly placed powder during printing is monitored and solved online by smart cloud computing network. It means smart maintenance is performed during processing of SLM process within a very short time.

After the accomplishment of the SLM process, the heat treatment processes have been performed on the fabricated product according to the final requirement and usage. Then, the dimensional and surface quality of the SLM manufactured product has performed by applying various dimensional measurement equipment. All the data of the processes and devices as mentioned earlier have been gathered and sensed.

6.2.3. AM big data storage, management, and processing

A considerable amount of multi-source, real-time, and non-real-time data of different data interfaces of design, material, SLM production, quality, maintenance, etc. is communicated and transmitted through the various data transmitted technologies like Intranet, Wireless, Internet, etc. Distributed methods are applied for storage and management of the whole AM process data, but here the data was stored in the SLM system and company PCs for the handling of unstructured, semi-structured, and structured data.

For the present study, the company PCs have stored and managed his previous data to manufactured products for their customers. For this new task of AlSi10Mg products, the company needs R&D, which is thoroughly described in the flowchart of Fig. 10. All the real-time and non-time data is collected during all samples and products' manufacturing. During manufacturing, all malfunctioning data of the SLM system is also gathered. There were also performed different heat treatment cycles like stress relieving, solution heat treatment, artificial aging on the test specimens and the final product [78]. All data of the heat treatments is also stored for future processing. The qualification data of the test specimens is also stored.

It would be observed that key additive manufacturing responses such as the densification, porosity, surface roughness, dimensional quality, tensile strength, processing time, energy consumption, etc. are influenced by processing parameters of laser power, scanning speed, hatch distance and layer thickness. The overall big data is collected for the a/m responses and processing parameters, which is further integrated and analyzed for sustainable and smart manufacturing.

6.2.4. AM big data mining and knowledge sharing

By using the BDA theories, the data mining models are developed, which are applied for attaining hidden knowledge from the enormous real-time and overall manufacturing phase big data. The optimization of manufacturing phase of different responses and parameters are also achieved. By uniting the knowledge with product data & knowledge management (PDKM) or decision support system (DSS), the objectives of the SSAM enterprise can be accomplished, and it can also be applied to select more environmentally beneficial raw material and cleaner energy [75].

It can be observed from the bottom right of Fig. 7 that the data mining universal and specific models are developed according to several requirements of AM enterprises. There are four kinds of general models formed in this framework, which are GA, artificial neural network (ANN), Pareto front, regression analysis. The GA model can be applied to optimize the processing parameters and also investigate the improvement in the AM product quality. The ANN general model can be applied to predict the optimized energy consumption conditions and even for the reduction or prediction of maintenance cycle.

Furthermore, different forms of particular data mining models are also developed, like product design improvement, AM processing parameters optimization, product quality improvement, energy consumption optimization, prediction of maintenance, improvement in productivity, etc. These data mining models have been constructed for achieving specifically targeted objectives so that the associations among BOL of AM big data, the unique models, and the data mining results are 'one-to-one' [74]. For example, if the customer projects the improvement of product quality, then the unique model of product quality improvement is selected. For achieving this objective, the control processing parameters of the model are optimized, which have been

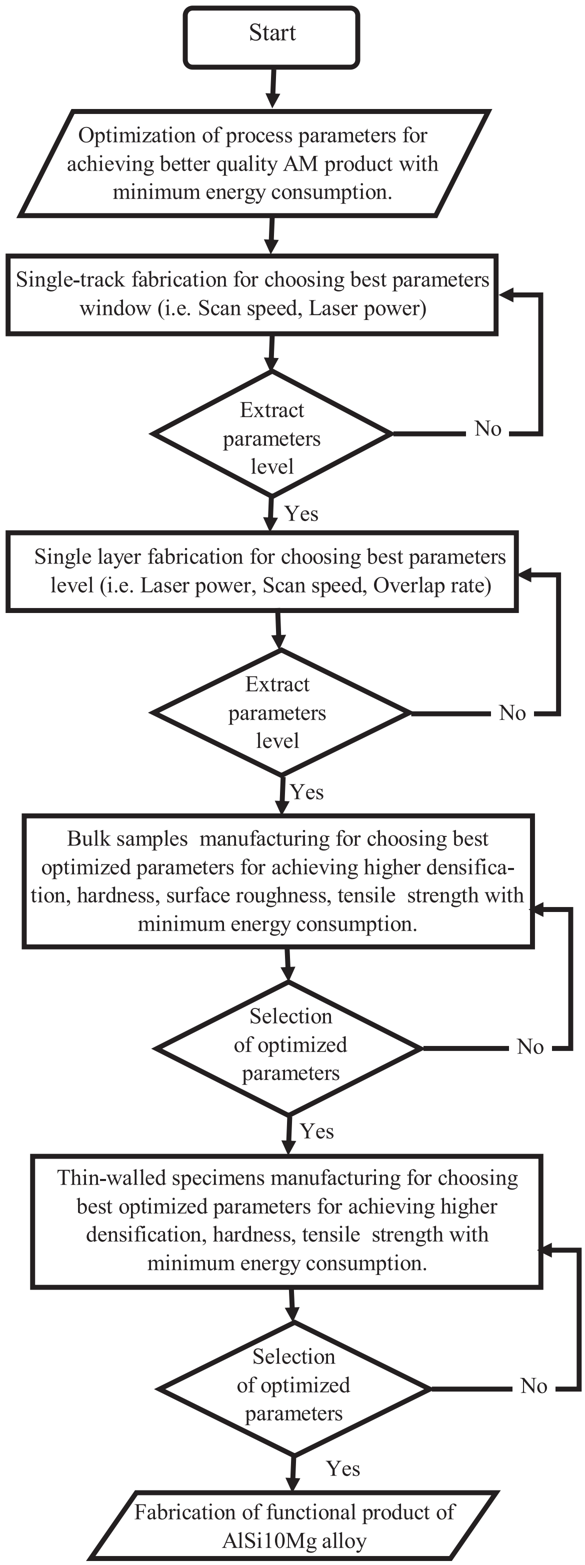


Fig. 10. Overall flowchart for the experimental methodology.

given the results of excellent product quality; the obtained results are stored in PDKM, whose knowledge is further applied in the future. The other unique models also have similar establishing principles.

7. Results and discussions

In this section, the experimental results will be discussed step by step by following the flowchart of Fig. 10. It starts from a single layer and have been completed to the final product of the customer.

Table 3
Control processing parameters with technical description of SLM system.

Experimental conditions	Processing parameters/ Conditions	Description / Values
General parameters (used in all testing)	AM System	SLM 280 HL (SLM Solutions, Germany)
	Powder Material	AlSi10Mg
	Atmosphere	Argon inert gas
	Oxygen content (%)	< 0.1%
	Beam focus diameter (mm)	0.08
	Building direction	Vertical
	Scanning strategy	67 °Checkboard
	Layer Thickness (mm)	0.03
Single track printing (1st Exp)	Laser Power (kW)	0.06 - 0.36 (6 levels)
	Scan Speed (m/s)	0.10 - 1.10 (6 levels)
Single track printing (2nd Exp)	Laser Power (kW)	0.30 - 0.40 (6 levels)
	Scan Speed (m/s)	0.30 - 1.05 (6 levels)
Single layer samples	Laser Power (kW)	0.32 - 0.40 (3 levels)
	Scan Speed (m/s)	0.60 - 0.90 (3 levels)
	Overlap rate (%)	0.20 - 0.35 (4 levels)
Multiple layers samples (Bulk and tensile samples)	Laser Power (kW)	0.32 - 0.40 (3 levels)
	Scan Speed (m/s)	0.60 - 0.90 (3 levels)
	Overlap rate (%)	0.25 - 0.35 (3 levels)
	Hatch distance (mm)	0.071 - 0.116
Thin-walled samples (Wall thickness study)	Laser Power (kW)	0.32
	Scan Speed (m/s)	0.90
	Hatch distance (mm)	0.080
	Wall Thickness (mm)	0.50 - 5.0 (12 levels)
Thin-walled samples (parameters optimization)	Laser Power (kW)	0.32 – 0.38 (3 levels)
	Scan Speed (m/s)	0.73 – 1.07 (3 levels)
	Hatch distance (mm)	0.08 - 0.13 (3 levels)
	Wall Thickness (mm)	1.0 – 3.0 (3 levels)

7.1. Results of the single-track scanning

SSAM framework work starts with defining the initial processing parameters, which are best suited to AlSi10Mg material parts. From the previous knowledge and literature survey, the two processing parameters are prime important for SLM process which are laser power and scanning speed. We have initially defined the laser power from 0.06 kW to 0.36 kW and scanning speed from 0.10 m/s to 1.10 m/s for printing of single-track samples.

The results of the surface were observed on the optical microscope (OM), which is shown in Fig. 11. In the SLM process, a moving heat source is applied for the melting of material, which causes the flow of material in the assigned path of the laser beam. Consequently, single tracks during SLM solidify with a distinctive chevron pattern, which can be seen on top of each track (see Fig. 11) [79]. The distinctive chevron pattern represents the direction of motion of the heat source (in SLM is laser beam), which is shown in optical micrographs of Fig. 11.

Fig. 11 shows the processing maps of a single-track for the SLM processed AlSi10Mg powder. The laser power and scan speed have a significant influence on the surface stability of the single track. The analysis of single track could provide a solid basis for determining the process window. Four types of zones existing in the single track were identified as partial making, good consolidation, excessive balling, and over-burning which are also shown in Fig. 11. The partial making and excessive balling are presented by discontinuous tracks and the drops formation, and the good consolidation is characterized by the continuous tracks [80].

The sets of processing parameters for the working powder express geometrical characteristics and continuity of SLM tracks. The molten

Table 4
Information of configuration of IoT and other devices for the data acquisition.

IoT/ other devices	Sensor/ UHF type	Monitoring resources/Location	Purpose/ Objective
Tags	-	Drawings/ Models/Material/Product/ tools/AM machines/operators/ QC document/etc.	To trace and monitor real-time data information of drawings, material, product, SLM process, usage, etc.
Smart sensor	Temperature sensor	AM machine/ workshop	Monitoring and controlling temperature data of the SLM system, processing bed of product, and workshop.
Smart sensor	Pressure sensors	Machines/ Compressors/etc.	To monitor the pressure data of the SLM machine, Sandblasting machine, compressor, air supply, etc.
Smart sensors	Voltage and current sensors	AM machines/ workshop	To monitor the electrical energy consumption information of AM machines, compressors, pumps, etc.
Vernier calliper	-	SLM products	Measuring the dimensional quality of built product
Surface roughness tester	-	SLM products	Measuring the surface quality of the built product
Scanning electron microscope (SEM)	-	SLM powder and products	To measure the morphology of powder and products, EDS analysis, Microscopic analysis, fracture surfaces analysis.
LECO hardness tester	-	SLM components	To measure the hardness of the built components
Tensile testing machine	-	SLM built tensile specimens	To measure the mechanical properties of SLM products such as UTS, yield strength, breakage elongations, stress-strain curves, etc.

material builds a cylinder-like track due to surface tension. For continuous tracks formation, penetration into the substrate or the previously sintered layer has the additional stabilizing effect [81]. But deep penetration causes keyhole, which is unacceptable in SLM because it can stimulate porosities in the final SLM product due to the collapse of molten pool and gas bubbles locked in the material. Balling is dependent on scan speed and is built due to instability promoted by higher scanning speeds and surface tension of material when using large layer thickness powder. Surface tension plays an important role in the crystal growth and porosity formation of metal during solidification [82]. The mechanism of discontinuity, irregularities, distortion, and balling-effect may be connected with granulomorphometric characteristics of the powder and inhomogeneity in powder layer thickness, thermo-physical properties of materials, energy input parameters including laser power, scan speed, and spot size; melt hydrodynamics, etc. [79].

It can be observed from Fig. 11 that the single tracks are non-continuous at the laser power of 0.06 kW and 0.12 kW, which would be caused due to low laser energy which could not melt the powder properly. Specifically, it can be seen at # 6 single tracks at a laser power of 0.06 kW and a scan speed of 1.10 m/s (see Fig. 11). Stable zones of single tracks are formed at a scan speed from 0.30 to 0.90 m/s and at the laser power of 0.18 kW, 0.24 kW, 0.30 kW, and 0.36 kW (see Fig. 11). At higher scan speed (1.10 m/s), the laser energy cannot melt the particles completely and initiate balling effect, which leads to unstable and irregular tracks. At low scan speed (0.10 m/s), over burning of the tracks occurs due to excessive energy exposed on the powder (see Fig. 11). Consequently, stability of the single tracks is achieved by optimizing the laser power and scanning speed, and proper layer thickness deposition.

A single track is built not only from powder positioned directly under the laser spot during the SLM process. The adjacent powder particles are also involved in this process due to conduction through the substrate and neighboring particles, scattering of radiation, capillary phenomena, etc. [79]. The denudation zone, i.e., area without powder after scanning of laser can be twice as large as the width of the track [83], which describes the geometrical features of the tracks and finally the morphology of layers. For stable single tracks, the widths of the single line were measured, as shown in Fig. 12. It was found that width of the single track varied from 37 to 288 μm. The track width decreased with the reduction of laser power and the increase of scanning speed. From the above analysis, it was found that the single tracks manufactured with laser power of 0.18–0.36 kW and scan speed of 0.30–0.90 m/s are stable. But, more stable results of single tracks were achieved between 0.30–0.40 kW of laser power.

In the 2nd experimental design of the single-track, the laser power was taken from 0.30 kW to 0.40 kW with an interval of 0.02 kW, and scanning speed was chosen from 0.30 m/s to 1.05 m/s with an interval of 0.15 m/s. The experimental design is based on full factorial DoE design with six levels and two factors. By applying 6^2 full factorial design, total single tracks with 36 combinations of laser power and scan speed were printed on a substrate. Then, the fabricated single tracks were observed with the OM of Olympus GX51, and the processing parameters were more refined for further processing of making single and multi-layer.

From the analysis of optical microscopic (OM) images, the width of a single track is measured, which is from 95.42 to 210.56 μm, and the results are presented in Fig. 13. From OM investigations, it was observed that the smooth, stable, and continuous single tracks and their width within good range are for the laser power from 0.32 kW to 0.40 kW and scan speed of 0.60 m/s to 0.90 m/s. For 0.30 kW laser power, at some points the single tracks are not stable or not continuous, and the same behavior is observed for low scan speed below 0.60 m/s and high scan speed of 1.05 m/s (see Fig. 13). It can also be observed in Fig. 13 that higher width of track is detected for 0.38 kW and 0.30 m/s.

Furthermore, on the basis of initial measurements, the process

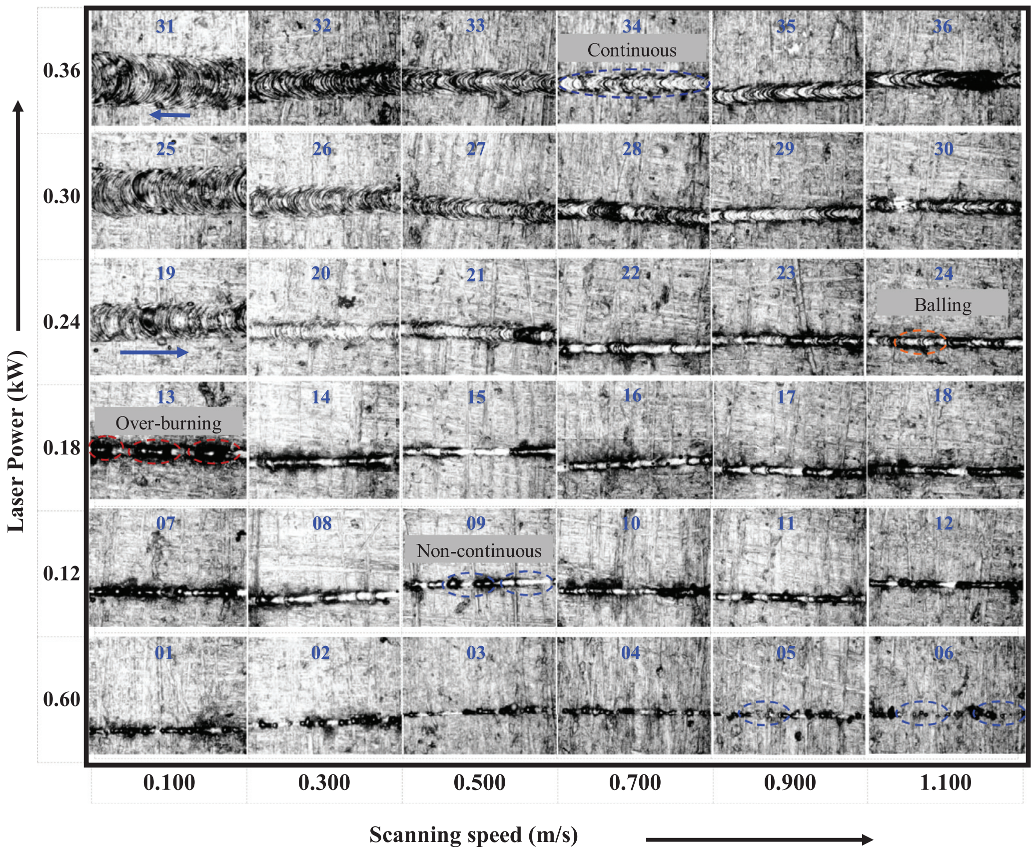


Fig. 11. Optical images of the surface morphologies of SLM-processed AlSi10Mg single tracks at laser power from 0.06 kW to 0.36 kW (interval of 0.06 kW) and scanning speed from 0.10 m/s to 1.10 m/s (interval of 0.20 m/s).

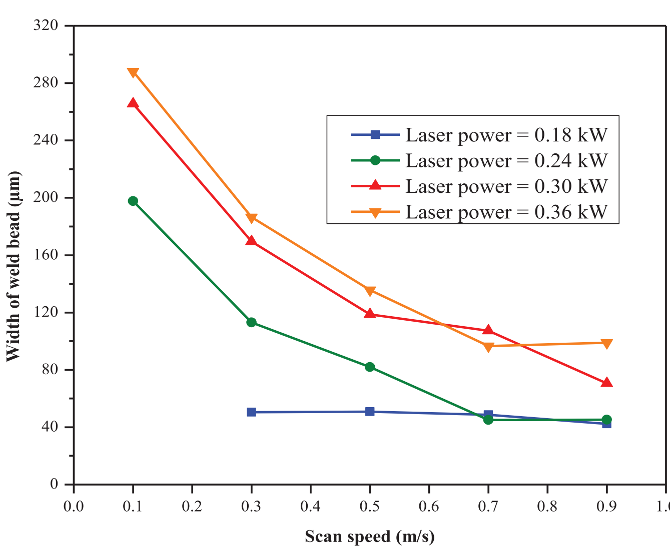


Fig. 12. Width of the weld bead of single tracks versus scanning speed at different power of the laser beam. The thickness of the deposited powder layer is 0.03 mm. Scanning speed = 0.10 m/s-0.9 m/s for laser power = 0.18 kW, 0.24 kW, 0.30 kW and 0.36 kW.

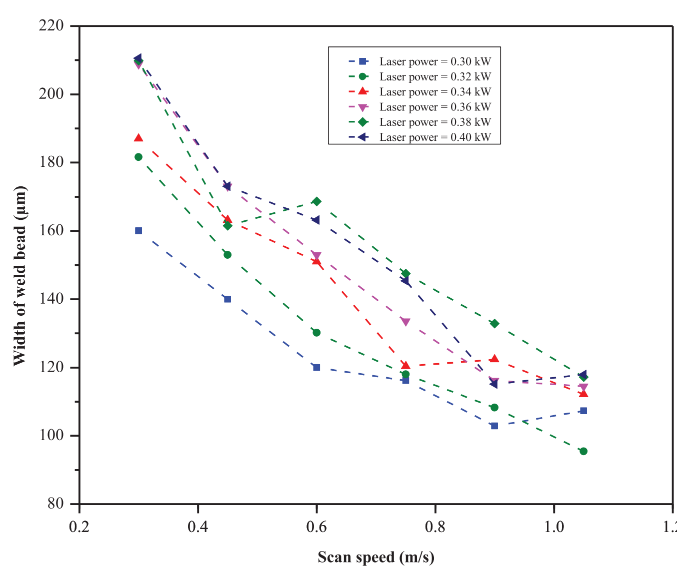


Fig. 13. Width of the single tracks versus scanning speed at different power of the laser beam at layer thickness of 0.03 mm. Scanning speed = 0.30 m/s −1.05 m/s and laser power = 0.30 kW – 0.40 kW.

window is selected for parameters, which are mentioned in Table 3. So, we have taken more measurements for single tracks widths for the 09 parameter combinations (mentioned in Table 5), and their average value is taken for further processing.

7.2. Results of the single-layer printing

The single-layer samples were built on the processing parameters of laser power from 0.32 kW to 0.40 kW (interval of 0.04 kW), scanning speed of 0.60 to 0.90 m/s (interval of 0.15 m/s) and overlap rate from 20 to 35% (with an interval of 5%). A total of 36 Nos samples were built by applying full factorial design (6^k).

Table 5
Optimized and stable width of single tracks for different combinations of laser powers and scan speed.

Levels	1	2	3	4	5	6	7	8	9
Laser Power [kW]	0.32	0.32	0.32	0.36	0.36	0.36	0.40	0.40	0.40
Scan speed [m/s]	0.60	0.75	0.90	0.60	0.75	0.90	0.60	0.75	0.90
Width of single track [μm]	136.5	124.1	109.0	148.0	130.6	118.6	155.2	139.5	125.4

Single-tracks geometric characteristics knowledge is helpful in the determination of hatch distance of laser beam scanning, which, together with selected scanning strategy, governs the quality of a single SLM layer [79]. Analysis of the morphology of a single layer, in turn, is critical and important in the selection of the optimal strategy for the fabrication of fully-dense and porosity free products. If the hatch distance is more than width of single-track, powder is melted in order of different tracks. Non-optimal hatch distance can affect the information of gaps between tracks in a single layer, which origins chains of pores in the ultimate SLM product [79].

The hatch distance is calculated for each test trails based on single-track width and the changing overlap rate [by using Eq. (2)]. Previously discussed that hatch distance is very important for stable tracks. The single-layer area of 8 mm × 8 mm is printed with 0.03 mm layer thickness. 36 groups single layer samples were printed by following processing parameters shown in Table 3 and Table 5.

$$h_d = W(1 - O_R) \tag{2}$$

where h_d is the hatch distance [μm], W is the width of the single track [μm], O_R is the overlap rate. The single layers were examined for surface morphology with the Olympus GX51 optical microscope. The measurements were repeated three times for each processing condition.

It was observed that morphology of single layer was stable for the overlap rate of 25%, 30%, and 35% because of the low hatch distance, which is better for continuity of tracks and pore-free structure. The results of the surface morphology on the OM was revealed that the processing parameters and their levels were suitable for further manufacturing of bulk samples. But, for further processing, the three levels of overlap rate were used as 25%, 30%, and 35%.

7.3. Results of the bulk samples fabrication

The bulk samples were made by using processing parameters of laser power, scanning speed, overlap rate and layer thickness as mentioned in Table 3 [78]. There is a total of 81 Nos (03 sets) bulk samples (see Fig. 14(a)) were fabricated to study the effect of processing parameters on the density, porosity, hardness and surface quality [78], [84]. A total of 27 Nos cuboid samples were produced to make tensile specimens and study tensile behavior. The energy consumption during the whole SLM process was also measured for each sample with different combinations of processing parameters.

The heat treatment processes of solution heat treatment (SHT) at 530 °C and 540 °C for 02 h was performed on 02 sets of bulk samples, and one set with SHT at 530 °C was further processed for artificial aging (AA) for 12 h [78]. The surface quality, densification, strength, and microstructural behavior were studied in the heat treatment conditions and compared with samples of as-built (AB) condition specimens [78], [84]. It concluded that the densification was enhanced to 99.94% by applying SHT at 530 °C and 99.87% in AA in comparison to as-built 98.17%. The porosities were also decreased by the heat treatments due to fine grain structure and strong bonding among the powder particles. Heat treatment has an excellent effect on the reduction of porosities of the AB samples. It was also confirmed from OM and SEM images that highly dense parts had lower porosity [78].

For the sustainable and smart additive manufacturing, the sustainability factor of energy consumption has been considered for parameters optimization regarding meeting quality requirements. The results of densification, porosity, tensile strength, hardness and surface quality have been investigated and analyzed on different combinations of processing parameters. We have defined a criterion for parts qualification such as densification ≥ 98%, porosity ≤ 2%, tensile strength ≥ 350 MPa, hardness ≥ 110 HV and surface roughness ≤ 5 μm. We have optimized process parameters which meeting above-mentioned quality criteria by applying pareto front and statistical regression analysis.

The best-optimized parameters obtained are the laser power of 0.32 kW, scanning speed of 0.90 m/s, overlap rate of 25%, and hatch distance of 0.08 mm which have consumed low specific energy

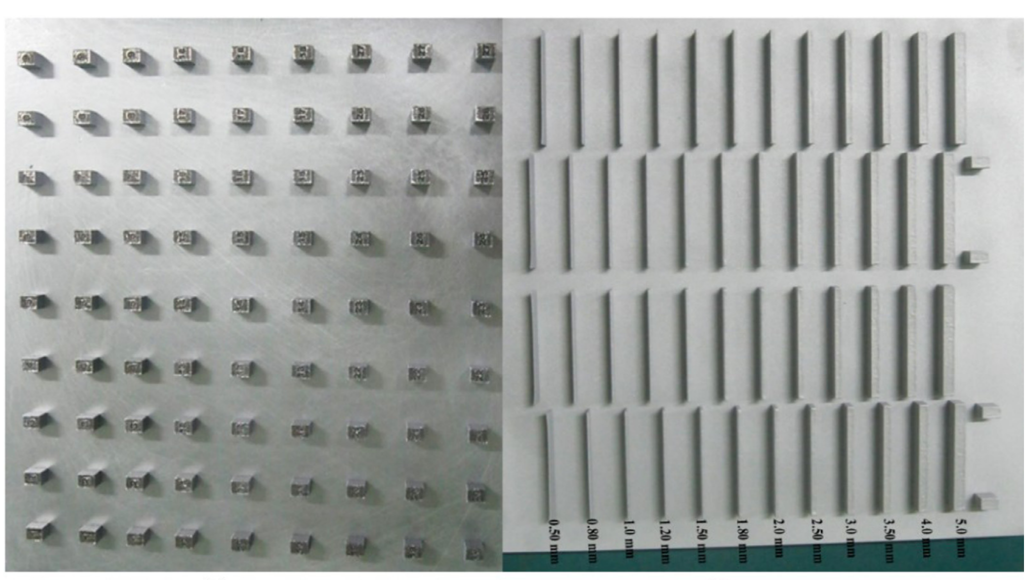


Fig. 14. Fabricated SLM specimens for the case study: (a) Bulk samples; (b)Thin-walled specimens.

consumption (SEC) of 369.54 MJ/kg. In comparison to other processing parameters combination, these optimized parameters have consumed 27.80% less SEC, which is very beneficial for sustainability and cleaner production.

7.4. Results of the thin-walled specimens

By the implementation of our SSAM framework in the company, we have initially achieved the best processing parameters from the manufacturing of thin-walled specimens, which will be further utilized in the production of functional products of the aerospace and automotive industry.

7.4.1. Study the influence of wall thickness

In this study, the thin-walled specimens of various wall thickness (i.e. from 0.5 mm to 5.0 mm, as mentioned in Table 3) were fabricated for investigation of densification, porosity, mechanical properties, hardness, surface and dimensional quality, and microstructural characteristics in the AB, SHT, and AA conditions (see Fig. 14(b)) [85–88].

The best relative density was attained for 0.50-mm-wall thickness specimens in the AB, SHT and AA conditions with a maximum relative density of 99.92% in the AA condition, and the minimum relative density of 93.42% was achieved for 1.50-mm-wall-thickness specimen in SHT condition. The AA is beneficial for the low-wall-thickness specimens for improving their densification. The AA heat treatment has a comparable effect on the porosity of lower-wall-thickness specimens (i.e., from 0.50 to 2.0 mm) which means that the porosities of thin-walled specimens have been reduced by applying AA in comparison with AB condition. The minimum porosity of 0.08% is observed in the 0.50-mm-wallthickness specimen. It is also observed from OM and SEM images that the porosities were increased in sizes and quantity till 1.50 mm wall thickness (except 0.50-mm-wall-thickness specimens). Moreover, the porosities were reduced gradually with an increase in wall thickness to 5.0 mm for the AB, SHT and AA conditions [86].

In the as-built (AB) condition, the average minimum hardness of 102.4 HV was achieved for a 1.0 mm wall thickness specimen, and the average maximum hardness of 137.3 HV was attained for 5.0 mm wall thickness specimen. It is also observed that the hardness was reduced from 0.50 mm to 1.0 mm wall thickness and then improved till 5.0 mm wall thickness specimens [85].

The SLM processed thin-walled specimens had a tensile strength of 188.4–364.0 MPa, 154.2–215.1 MPa and 197.9–274.2 MPa in the AB, SHT and AA conditions respectively. The breakage elongation of 3.76–12.04%, 10.82–20.66% and 5.13–11.22% was examined in the AB, SHT and AA conditions respectively. It has observed that the mechanical properties of AlSi10Mg thin-walled specimens are comparable to the casted AlSi10Mg material A360.0 [89]. The strength and ductility were higher because the thin-walled specimens were fabricated under the optimal process parameters, and the relative density is greater than 93% and nearly equal to 100% for some specimens.

The purpose of above-mentioned studies was to investigate the effect of wall thickness on the densification, porosity and mechanical characteristics of the thin-walled specimens. The heat treatment was also applied on the thin-walled specimens to study its influence on the quality characteristics of AlSi10Mg alloy by SLM process. The heat treatment has positively influence on the enhancement of densification and mechanical properties, and reduction in the porosities of the thin-walled specimens.

It is concluded from this study that the densification and mechanical characteristics were varied with varying the wall thickness. Moreover, the study is further extended to study the different process parameters influence on various wall thicknesses for manufacturing of quality product with minimum energy consumption for the SSAM. So, we have finalized the three wall thicknesses for our further study which are 1 mm., 2 mm and 3 mm. These wall thicknesses are our optimal wall thickness which have done significant influence on the densification and mechanical characteristics.

7.4.2. Study the influence of processing parameters

The thin-walled samples were manufactured by using processing parameters of wall thickness, laser power, scanning speed, and hatch distance as mentioned in Table 3. The specimens were fabricated to study the effect of processing parameters on the density, porosity, hardness and tensile behavior. The energy consumption during the whole SLM process is also measured.

For the sustainable and smart additive manufacturing, the sustainability factor of energy consumption has been considered for parameters optimization regarding meeting quality requirements. The results of densification, tensile strength, and hardness have been investigated and analyzed on different combinations of processing parameters. We have defined a criterion for parts qualification such as densification ≥ 98%, porosity ≤ 2%, tensile strength ≥ 320 MPa, hardness ≥ 100 HV and breakage elongation ≥ 10%. We have optimized process parameters which meeting above-mentioned quality criteria by applying pareto front and statistical regression analysis.

The best-optimized parameters obtained are the laser power of 0.35 kW, scanning speed of 1.07 m/s, and hatch distance of 0.13 mm which have consumed low specific energy consumption (SEC) of 205.4 MJ/kg. On the above -mentioned optimized parameters, the responses have achieved values of 98.95% relative density, 1.05% porosity, 334.1 MPa tensile strength, 101.7 HV hardness and breakage elongation of 10.01%. In comparison to other processing parameters combination, these optimized parameters have consumed 57.3% less SEC, which is very beneficial for sustainability, carbon emission and cleaner production.

We have also optimized processing parameters with better quality characteristics and minimum energy consumption. These optimized parameters are 0.35 kW of laser power, 1.07 m/s of scanning speed, and 0.105 mm of hatch distance and have achieved densification of 98.75%, porosity of 1.25%, tensile strength of 358.1 MPa, breakage elongation of 14.67% and hardness of 106.2 HV with SEC of 249.2 MJ/Kg. When comparing to other processing parameters combination, these optimized parameters have consumed 48.3% less SEC which is very beneficial for SSAM.

By the efficient implementation of SSAM framework, the above-mentioned parameter collection and their results will be used by the manufacturers and designers according to the demands of our valued customers. Actually, in practical applications, there are different kinds of needs according to the qualification of a product, and the customer has a different demand for a product. So, our optimized parameters will be used for the manufacturing of efficient and effective products according to the requirements of the customer.

7.5. Results of the impeller pump manufacturing

The above-mentioned optimized parameters have been utilized by the company for manufacturing of pump components and other components of AlSi10Mg alloy (see Fig. 15). For the SSAM, the sustainability perspective of AM is also considered that the product quality meeting customer's requirement, use less energy which beneficial to environment, and product cost and productivity is also better. By considering these SAM perspectives, we have used the optimized parameters which gives better product quality with minimum energy consumption, and also good productivity with minimum processing time and cost. Finally, it can be extracted from our case study that our SSAM framework will be effectively implemented by the company by manufacturing different components of AlSi10Mg.

8. Managerial implications

Managerial significances could be generated from key findings and concealed knowledge of BDA, which are beneficial when several

Fig. 15. The impeller of pump fabricated by AlSi10Mg alloy by SLM.

departments' managers are making sustainable and smart additive manufacturing decisions subsequently [28]. Targeting at the product manufacturing cycle of additive manufacturing products, four managerial implications of the developed framework are included, particularly for the marketing department, R&D department, production department, and service department [75].

- The marketing department is responsible for classifying the unspoken needs of the forecast customers' and promising customers. When a more accurate aiming is established and forwarded, then it is worthwhile to match several products with numerous customers, respectively. BDA makes it conceivable to pick the most appropriate customers from the excessive number of customers' data.
- The R & D department inputs for AM will be increased in the future, which may be due to the development and usage of innovative technologies for the manufacturing of cleaner production. There is a massive amount of data generated for the making of suitable solutions in the conceptual design stage, for making decisions in the detailed design stage, and realization of AM product innovative design. The BDA is applied to categorize the most correlative examples as detailed as possible to give direction for the innovative product development [75].
- In the production department, BDA and SSAM framework should be applied to manage the production of AM systems, improve the energy efficiency of AM systems, and monitor the quality of AM product. With the provision of IoT devices and smart meters, an enormous amount of real-time, heterogeneous, and multi-source data of production is collected. Moreover, with the assistance of BDA, the optimization of processing parameters relevant to product quality, energy consumption, workshop scheduling decisions, etc. could be comparatively easy to attain. The energy proficiency of AM systems could also be enhanced.
- In the services department, the customers' satisfaction is increased by the state-of-the-art service strategies, such as, real-time monitoring service of product quality and predictive maintenance service which should be attained by continuous monitoring of product's status. BDA would be applied to analyze the huge gathered data.

9. Conclusions

In the present paper, BDA, AM, and SSM have been studied together, which were investigated in academia and industry separately. These are the advanced manufacturing technologies and lies in the Industry 4.0. AM is an emerging technology that is widely applied in manufacturing enterprises for the production of unique and complex shapes products. The authors of this paper made the following important contributions:

- Firstly, by combining the key technologies of sustainable manufacturing, smart manufacturing, and additive manufacturing, the term SSAM was created, which applied throughout the article. The concept of SSAM did not exist in a precise form before, but it is critical to advance knowledge in this field.
- Secondly, a conceptual framework of BDA in SSAM (BD-SSAM) was proposed for the product manufacturing cycle of AM products. The proposed framework can be utilized as a guideline to select the related product manufacturing cycle stages that influence on the sustainable production of a specified AM enterprise.
- Thirdly, the big data acquisition and integration procedures established, which were applied for gathering real-time, multisource and heterogeneous data for AM and then further processing for useful output.
- Fourthly, the data mining approaches could be applied to expose the association between sustainable production performance and AM processing parameters. Furthermore, the processing parameters have been optimized to production performance by improving product quality, productivity, and reducing energy consumption and emission which is beneficial for smart manufacturing and CP.

The proposed BD-SSAM framework has been evidenced in an application scenario in a company. The new emerging company has the task of manufacturing of components of pumps of AlSi10Mg alloy by using the SLM system. A flowchart and framework were developed for the company. The real-time data can be attained and communicated to the AM enterprise database. With the help of BDA and by the use of algorithms, the process parameters of SLM have been optimized for improving product quality, reduction in energy consumption, and improve productivity.

The limitation of the present study is that the proposed BD-SSAM framework is applied only on the BOL stage of product life cycle due to the available resources and configuration of IoT devices in the company. The proposed framework is only applied to 1 AM system (i.e. SLM system), and the algorithm for data analysis, such as association, classification, and clustering are not studied in this paper.

Future research works will be carried out on the application of this framework on the whole lifecycle stages, and development of the algorithms to optimize and prediction of the processing parameters of the AM for various AM techniques and multiple materials.

Declaration of Competing Interest

None.

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Supplementary materials

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