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# The Role of Big Data Analytics in Industrial Internet of Things

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## Abstract

Big data production in industrial Internet of Things (IIoT) is evident due to the massive deployment of sensors and Internet of Things (IoT) devices. However, big data processing is challenging due to limited computational, networking and storage resources at IoT device-end. Big data analytics (BDA) is expected to provide operational- and customer-level intelligence in IIoT systems. Although numerous studies on IIoT and BDA exist, only a few studies have explored the convergence of the two paradigms. In this study, we investigate the recent BDA technologies, algorithms and techniques that can lead to the development of intelligent IIoT systems. We devise a taxonomy by classifying and categorising the literature on the basis of important parameters (e.g. data sources, analytics tools, analytics techniques, requirements, industrial analytics applications and analytics types). We present the frameworks and case studies of the various enterprises that have benefited from BDA. We also enumerate the considerable opportunities introduced by BDA in IIoT. We identify and discuss the indispensable challenges that remain to be addressed as future research directions as well.

*Keywords:* Internet of Things, cyber-physical systems, cloud computing, analytics, big data.

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## 1. Introduction

Industrial Internet of Things (IIoT) (also known as Industry 4.0), which was initially conceived as a vision by the German government, is currently attributed as the fourth industrial revolution. The technology ecosystem underpinning IIoT is mainly the integration of cyberphysical systems (CPS) [1], Internet of Things (IoT), cloud computing [2–4], automation (e.g. intelligent

6 robots in product assembly lines) [5], Internet of services [6], wireless technologies, augmented  
7 reality [7] and concentric computing [8], amongst others. Advances in such related areas as IoT,  
8 big data analytics (BDA), cloud computing and CPS have fuelled the formation of IIoT activities  
9 to deliver unprecedented flexibility, precision and efficiency to manufacturing processes [9, 10].  
10 Given this cross-platform integration, IIoT systems need to ensure interoperability, virtualisa-  
11 tion, decentralisation, real-time capability, service orientation, modularity and security across all  
12 verticals [11]. However, these systems are perceived to have qualities, such as self-awareness,  
13 self-prediction, self-comparison, self-configuration, self-maintenance and self-organisation [12].

14 BDA is a related area that enables IIoT systems to deliver value for data captured from cross-  
15 platform integration. BDA refers to the process of collecting, managing, processing, analysing  
16 and visualising continuously evolving data in terms of volume, velocity, value, variety and ve-  
17 racity [13]. Big data in IIoT systems arise due to unbounded internal and external activities  
18 relevant to customers, business operations, production and machines [14]. BDA processes in  
19 IIoT systems manage the collected data using multiple transient and persistent storage systems  
20 that provide on-board, in-memory, in-network and large-scale distributed storage facilities across  
21 IIoT systems [15, 16]. The granularity of data processing facilities for BDA processes in IIoT  
22 systems vary from resource-constrained IoT devices to resourceful large-scale distributed cloud  
23 computing systems [17]. Similarly, analytic operations differ in terms of descriptive, prescrip-  
24 tive, predictive and preventive procedures [14]. In addition, BDA processes must ensure real-time  
25 knowledge visualisation across multiple IIoT systems. A proper integration of BDA processes  
26 into IIoT systems is perceived to maximise value creation to evolve business models for profit  
27 maximisation [14, 18].

### 28 *1.1. Motivation*

29 Although IIoT [19–24] and BDA [13, 25–31] have been widely studied separately, only a  
30 few studies including [32] have explored the convergence of the two domains.

31 Big data production in IIoT is evident due to large-scale deployment of sensing devices and  
32 systems in pervasive and ubiquitous industrial networks. Given that the concept of IIoT systems  
33 is still evolving, complete integration and implementation of BDA processes in IIoT systems are  
34 unavailable yet [32, 33]. Existing surveys on IIoT systems focus on concepts related to adoption  
35 of IIoTs [34, 35], the integration of IIoTs and edge cloud computing systems [36], industrial

36 marketplaces for IIoTs [4], big data and virtualisation technologies for IIoT systems [37], tech-  
37 nological advancements relevant to CPS in IIoT systems [38], smart manufacturing [39] and big  
38 data applications for business operations [40–42]. We introduced the concept of the concentric  
39 computing model (CCM) for BDA in IIoT in our previous work [32] whereby we outlined the  
40 discussion on different layers of CCM and discussed the relevant research challenges that must  
41 be addressed to fully enable CCM for BDA in IIoT. However, to the best of our knowledge, a  
42 detailed review on BDA implementation for IIoTs is still lacking in the existing literature. Thus,  
43 the current study presents the key operations of BDA for value creation in IIoT systems. On the  
44 basis of BDA concepts, this study surveys earlier contributions relevant to data analysis in IIoT  
45 systems.

## 46 1.2. Contributions

47 The main contributions of this study are listed as follows.

- 48 • We build a case of BDA for IIoT systems whereby the role and entire process of BDA  
49 are discussed. The study sets a theoretical ground to understand modern automated data  
50 pipelines for enriching intelligence in IIoT systems.
- 51 • We investigate existing state-of-the-art research studies on IIoT in terms of BDA. In this  
52 context, we categorise and classify the literature by devising a taxonomy.
- 53 • We present frameworks and case studies whereby BDA processes are adopted to improve  
54 the overall performance of IIoT systems.
- 55 • We present several research opportunities, challenges and future technologies to minimise  
56 the research gaps between state of the art (i.e. proposed in the literature) and state of the  
57 practice (i.e. adopted by industries in practice).

58 The rest of the paper is organised as follows. Section 2 discusses the key concepts relevant  
59 to BDA in IIoT systems, followed by a detailed survey of existing technologies and algorithms  
60 in Section 3. Section 4 presents the taxonomy, and Section 5 highlights a few frameworks and  
61 relevant case studies. Section 6 presents the opportunities, open challenges and future directions.  
62 Section 7 provides the concluding remarks.

## 63 2. BDA in IIoT Systems

64 This section presents a detailed discussion on different aspects of big data adoption in IIoT  
65 systems. To this end, several design principles, which should be considered prior to configuring  
66 and deploying IIoT systems, are highlighted. The role of BDA and its life cycle is discussed in  
67 detail to deliver end-to-end intelligence in IIoT systems.

### 68 2.1. Design Principles for IIoT Systems

69 The designs of IIoT systems involve seven principles [11], as depicted in Fig. 1. Firstly,  
70 interoperability must be ensured amongst different technologies, such as CPS, IoT devices and  
71 concentric computing systems. Wireless data communication technologies play an unparalleled  
72 role to realise an interoperable system. Secondly, virtualisation technologies at all levels must  
73 be considered for efficient service provisioning and delivery across IIoT systems. Virtualisation  
74 varies in terms of platforms, networks, data, operating systems and applications. Thirdly, decen-  
75 tralisation must be conducted to ensure highly distributed IIoT systems. Decentralisation varies  
76 in terms of system-wide data processing and data storage. Fourthly, IIoT systems must provide  
77 real-time feedback to all stakeholders. Fifthly, service-orientation must be guaranteed whereby  
78 all system functions are implemented in the form of service-oriented architecture (SOA). Sixthly,  
79 modular approach must be adopted for system implementation. Lastly, system-wide security  
80 must be considered as core principle. The BDA process for IIoT systems must be designed in  
81 consideration of the above-mentioned principles.

### 82 2.2. Rise of Big Data in IIoT Systems

83 Big data in IIoT systems emerge from a plethora of technologies. CPS refers to the integration  
84 of physical machine components with on-board computations and networking facilities [38, 43].  
85 CPS and IoT devices act as the backbone of IIoT systems and thus generate massive amount of  
86 raw data streams, which result in big data [44]. Therefore, real-time analysis of these data can  
87 improve machine health and lead to defect-free product manufacturing [1, 34, 45].

88 IoT devices in IIoT systems refer to devices that can remotely sense and actuate in industrial  
89 environments [46]. IoT devices either work as stand-alone devices that roam around industrial  
90 environments or are attached with existing CPS to perform certain predefined actions [47]. The  
91 on-board sensing facilities in IoT devices lead the generation of big data, which may become

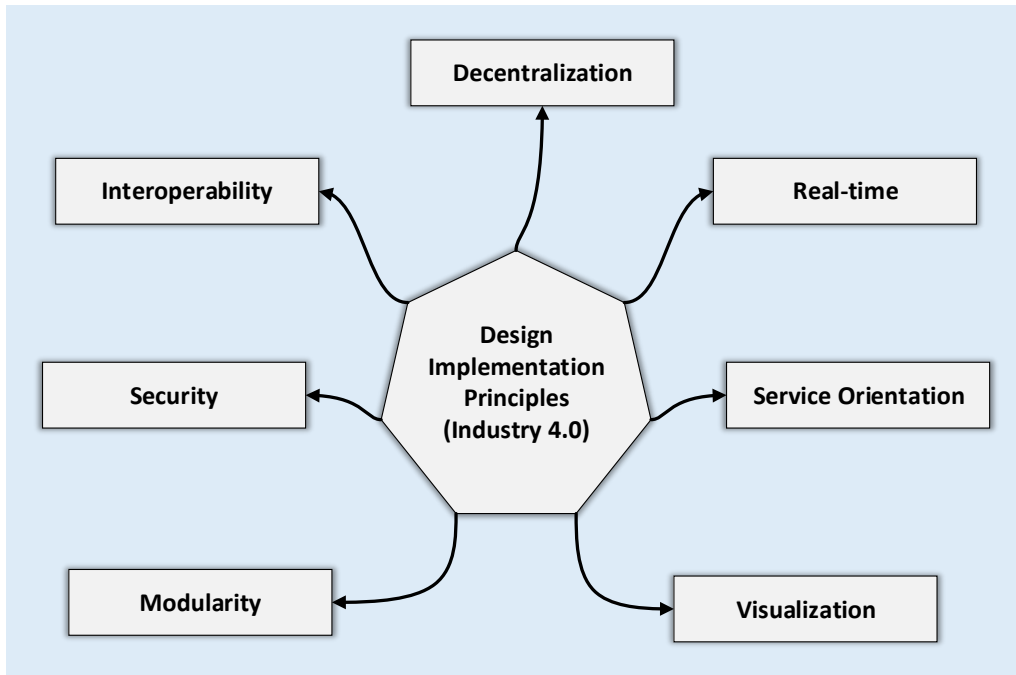


Figure 1: Seven design implementation principles for Industry 4.0 systems.

92 useful for value creation in enterprises. The integration of CPS and IoT devices results in massive  
 93 back-end cloud service utilisation for the execution of BDA processes [48]. To achieve massively  
 94 customised production, the number of cloud services can be grown immensely. Thus, BDA can  
 95 facilitate in-service selection, service orchestration and real-time service provisioning [49].

### 96 2.3. Concentric Computing Model for BDA in IIoT

97 Recent evolution in sensing and computing technologies has opened new avenues for big  
 98 data processing. Concentric computing refers to the large-scale highly distributed comput-  
 99 ing systems based on a wide range of devices and computing facilities in different form fac-  
 100 tors [8]. Concentric computing offers big data processing at sensors levels, endpoints in IIoT  
 101 systems, edge servers, and centralised and decentralised cloud computing systems, as illustrated  
 102 in Fig. 2 [14, 36, 50]. Despite their small size and limited computational power, sensors and  
 103 IoT devices have the ability to filter and reduce raw data streams by using on-board smart data  
 104 reduction strategies [51]. However, edge servers at gateways and centralised computing clusters  
 105 have the ability to distribute the computing load for BDA applications [52, 53]. Multistage exe-

106 cution, automating, and management of BDA processes (i.e., data engineering, data preparation  
107 and data analytics) are necessary in concentric computing environments (such as sensors and  
108 wearable devices as endpoints, IoT devices, edge servers, and cloud computing servers) [54].

#### 109 2.4. Big Data Analytics for Delivering Intelligence in IIoT Systems

110 BDA processes are executed as a result of multistage highly interdependent application com-  
111 ponents (Fig. 3). These components are categorised as follows.

##### 112 2.4.1. Data Engineering

113 Data engineers build computing and storage infrastructure to ingest [55], clean [56], con-  
114 form [57], shape [58] and transform [59] data. IIoT systems produce and ingest big data from  
115 inbound enterprise operations and outbound customer activities. The raw data at the earliest  
116 stage need further processing to improve the quality and establish the relevance with IIoT ap-  
117 plications. Therefore, data wrangling and cleaning methodologies help select relevant datasets  
118 in case of historical data or data streams in case of streaming data. Data conformity procedures  
119 are applied to ensure relevant, correctly collected big data. Data shaping and transformation

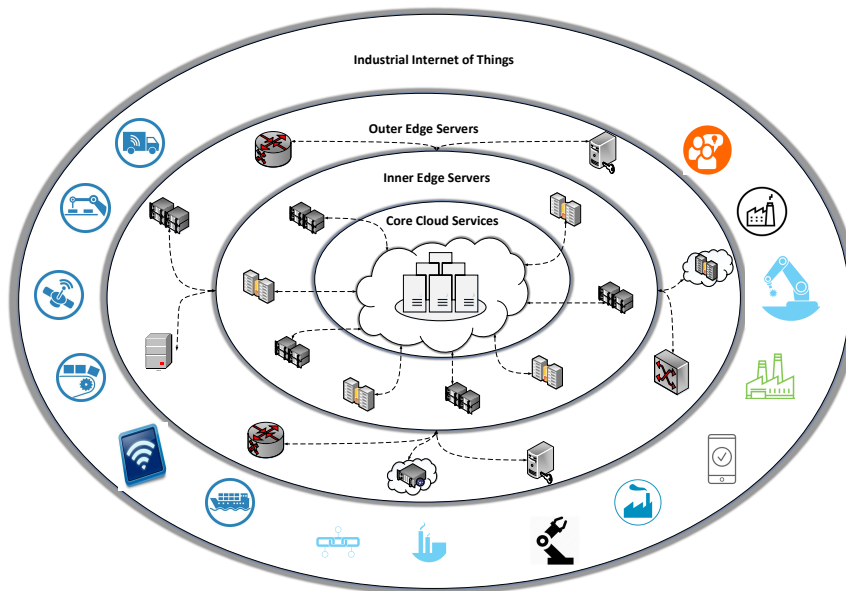


Figure 2: Industrial IoTs and Multilayer Computing Resources

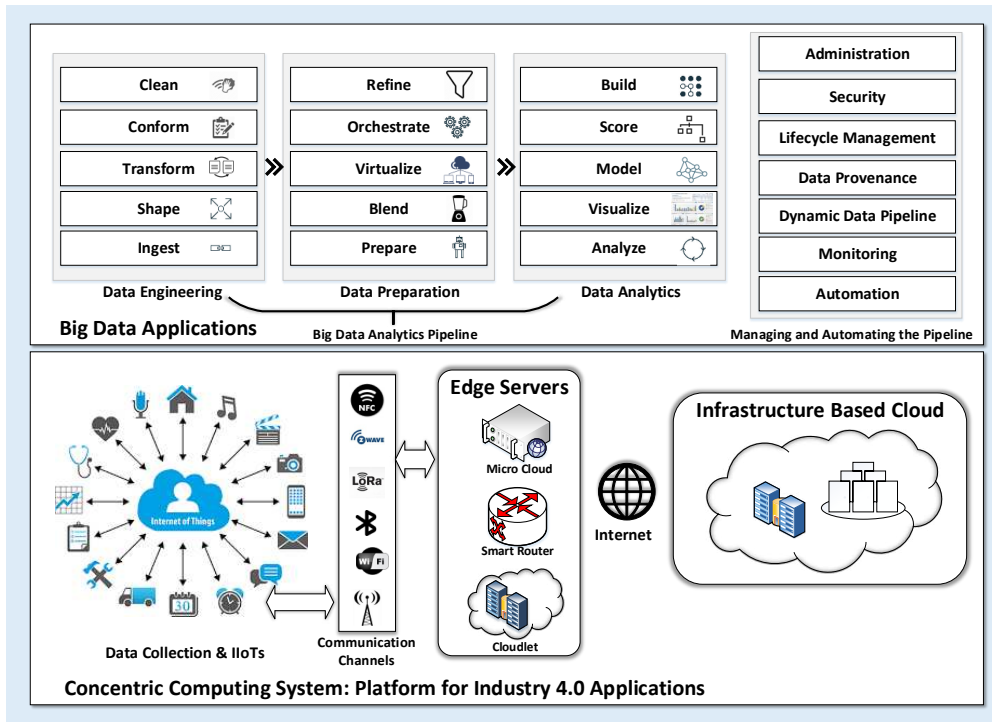


Figure 3: Multistage execution, automating, and management of BDA processes (i.e., data engineering, data preparation and data analytics) in concentric computing environments (such as sensors and wearable devices as endpoints, IoT devices, edge servers, and cloud computing servers) [32].

120 methodologies help improve data quality by reducing the number of attributes and converting  
 121 data formats for uniform data processing.

#### 122 2.4.2. Data Preparation

123 Big data emerge in raw form with large volume and enormous speed, and data scientists spend  
 124 70% – 80% of their time in data preparation activities [60]. Big data are refined using statistical  
 125 methods to handle unstructured, unbalanced and nonstandardised data points efficiently [61]. In  
 126 addition, data refinement helps summarise voluminous data to reduce overall complexity. As a  
 127 result, the spatiotemporal attributes of big data in IIoT systems vary. Ultimately, data locality is  
 128 necessary to reduce in-network traffic and latency in big-data applications [61]. Location-aware  
 129 highly virtualised data infrastructure can address these issues. However, data blending, which is  
 130 the process of combining data from multiple sources, becomes complex. Accordingly, further



131 involvement by data scientists [62] is required to perform data cleaning and noise removal [63].  
132 Detection methods for outliers and anomalies are also needed to prepare big data for further  
133 analysis [64, 65].

#### 134 *2.4.3. Data Analytics*

135 The analytic processes in IIoT systems are executed in multiple phases [66]. Data scientists  
136 generate learning models from high-quality well-prepared data. After the model is developed,  
137 model scoring operations are performed by giving sample datasets and finding and ranking the  
138 attributes in datasets/data streams. The correctly tuned models are deployed in production envi-  
139 ronments to find the knowledge patterns from future data.

#### 140 *2.4.4. Managing and Automating the Data Pipeline*

141 Although existing literature still lacks the concept of automated data pipelines in IIoT sys-  
142 tems, BDA processes are executed as a sequence of operations during data engineering, prepara-  
143 tion and analytics. Therefore, a holistic approach is needed to execute and administer BDA  
144 processes across all layers of concentric computing systems. Life cycle management is needed  
145 for full process execution from raw data acquisition to knowledge visualisation and actuation.  
146 Data provenance, that is, designating ownership of data to different stack holders, also needs  
147 serious attention to ensure system-wide control on data [67]. The continuous evolution in data  
148 streams results in knowledge shift that enforces data pipelines to adaptively reconfigure analytic  
149 processes. The data pipelines need to be continuously monitored for change detection, and the  
150 entire BDA process needs to be re-executed to produce high-quality results [68]. In security  
151 perspective, the cross-platform execution of BDA processes demands secure operations at IoT  
152 device, CPS and big data levels [69].

### 153 **3. Technologies and Algorithms for BDA in IIoT systems**

154 A common example of IIoT systems is the concept of a smart factory system (SFS) [36]. The  
155 key attributes of SFS and its subsystems are self-awareness, self-organisation, self-maintenance,  
156 self-prediction, self-configuration and self-comparison [12]. This section presents the review of  
157 early studies that presented BDA in the context of SFS and IIoT systems [12] in consideration of  
158 the aforementioned autonomy related attributes (Table 1).

159 *3.1. Mass Product Customization towards IIoT Lean Manufacturing*

160 Although the main objective of IIoT systems is to maximise production considering massive  
161 customisation in accordance with customer requirements, the existing literature still lacks an  
162 end-to-end predictive analytics framework. Computational intelligence-based methods, such as  
163 self-organising map (SOM) algorithms, are used to optimise big data for feeding in the produc-  
164 tion systems and enable massively customised product manufacturing [70]. The neural network-  
165 based SOM algorithm effectively enables smart production cycle in SFS. The cycle is based on  
166 a close loop within a sequence of operations, including smart design, manufacturing, produc-  
167 tion and services whereby feedback is collected after each cycle and subsequent operations at  
168 each stage are improved. Clustering-based big data optimisation is another approach whereby k-  
169 means clustering algorithms are used to cluster the attributes from customer data. The produced  
170 clusters are used to intelligently improve the design process in the product life cycle [71]. An-  
171 other alternate for massive product customisation is the adoption of cloud-based manufacturing  
172 systems whereby big data integration is performed in cloud computing systems [72]. However,  
173 the resultant big data are integrated from multiple sources, such as social media data streams  
174 relevant to customer behaviour and IIoT data streams from manufacturing systems. This type  
175 of cloud-based manufacturing benefits from open innovation and cross-continent physically iso-  
176 lated product manufacturing.

177 *3.2. Industrial Time Series Modeling*

178 The achievement of zero-defect in SFS is a major challenge. In SFS, all manufacturing  
179 components are perceived to be highly connected to ensure high-quality production. The term  
180 zero-defect refers to ensuring high-quality production during the execution of a complete manu-  
181 facturing process [45]. To this end, industrial time series modelling ensures the proper monitor-  
182 ing of all manufacturing components during operations. However, data collection from multiple  
183 components results in high-dimensional data streams. The neo-fuzzy neuron (NFN) time series  
184 modelling method is adopted by IIoT systems. NFN can collaboratively connect the input data  
185 streams with the final outputs. NFN benefits from the convergence of input data, which results  
186 in decreased data streams and thus less iteration for learning model generation [73].

### 187 *3.3. Intelligent Shop Floor Monitoring*

188 The term physical Internet (PI) refers to the integration of cloud manufacturing with wireless  
189 and networking technologies. PI in IIoT systems provides the backbone to IIoTs and smart  
190 manufacturing object tracking systems based on radio-frequency identification. These smart  
191 manufacturing objects represent different forms of products during manufacturing after each  
192 process [47]. However, IIoT systems need to track these smart objects during production to  
193 ensure that analytic processes provide intelligent shop monitoring. Researchers have proposed  
194 a BDA-based approach for the trajectory clustering of moving objects in shop floors. Although  
195 initial findings have been previously presented, a component-based BDA architecture is still  
196 necessary to develop highly optimised and intelligent smart object tracking systems for shop  
197 floor monitoring [47]. Performance analysis and exception diagnosis model have been proposed  
198 and tested using Petri nets and decision tree algorithms [47]. The model shows feasibility, and  
199 its real implementation in IIoT systems may help correctly quantify the results.

### 200 *3.4. Industrial Microgrids*

201 Massive data production in IIoT systems is evident due to feature-rich sensory and large-scale  
202 deployment of IIoTs in SFS [74]. Therefore, manufacturing and environmental data, along with  
203 energy consumption data, can lead towards optimised energy utilisation in SFS. The application  
204 of BDA processes on these data silos can help improve planning, managing and utilising energy.  
205 Researchers have proposed BDA analytics methods for industrial-level microgrid planning in  
206 SFS. However, quantifiable studies that can lead towards efficient microgrid planning in IIoT  
207 systems are still required [74].

### 208 *3.5. Monitoring Machine Health*

209 Prognostic health monitoring (PHM) helps find the machine behaviour for value creation  
210 during mechanical operations and facilitate machine data collection and management for the  
211 early diagnoses and prediction of machine faults. Several studies have performed analysis of  
212 PHM data [75–77]. In accordance with multiple International Standards Organisation and In-  
213 ternational Electrotechnical Commission and Society of Automotive Engineering standards, the  
214 authors of [76] analysed ontological models developed from PHM data. These ontological mod-  
215 els represent the hierarchical and semantic relationships amongst different machine components.  
216 The remaining useful life of machine components, faults, errors and failures during machine

217 operations has also been explored. Studies have also presented dependency and failure mode  
218 analyses of different machine components. The analysis of PHM data helps plan and schedule  
219 machinery maintenance activities, thereby supporting in finding maintainable machine compo-  
220 nents before total failure. However, finding the relationship amongst different attributes and the  
221 failure impact of understudied machine components on other components in large-scale manu-  
222 facturing environments is a challenging task [77].

### 223 3.6. *Intelligent Predictive and Preventive Maintenance*

224 Predictive and preventive maintenance are the key requirements of large-scale IIoT sys-  
225 tems [11]. The BDA process can help in off-line prediction (*i.e.*, performing prediction on the  
226 basis of historical data) and online maintenance (*i.e.*, maintaining machines without shutting  
227 down the manufacturing units). Researchers have integrated Hadoop and Storm technologies for  
228 big data processing and used neural network-based methods for prediction [78]. The concept of  
229 adopting BDA for intelligent predictive maintenance is novel. However, new avenues need to be  
230 explored to fully realise a real-time prediction system.

## 231 4. Taxonomy

232 Figure 4 presents the taxonomy that is devised on the basis of data sources, analytics tools,  
233 analytics techniques, requirements, industrial analytics applications and analytics types.

### 234 4.1. *Data Sources*

235 In an industrial environment, numerous sources of data production, such as sensors, enter-  
236 prise resource planning (ERP) systems, manufacturing execution systems (MES), supervisory  
237 control and data acquisition (SCADA) systems, customer relationship management (CRM) sys-  
238 tems and machine/IoT devices. ERP systems enable organisations to employ a system that is  
239 composed of multiple integrated applications for managing business needs and automating many  
240 back-office functions related to technology, services and human resources. MES helps keep  
241 the track record of all manufacturing information in real time and receive up-to-date data from  
242 robots, machine and IoT devices [79]. SCADA systems are used to monitor and control a plant  
243 or equipment in industries (*e.g.* telecommunications, water and waste control, energy, oil and gas  
244 refining and transportation). CRM systems are commonly used to manage a businesscustomer

245 relationship. Machines and IoT devices are also deployed in industries to perform specific tasks,  
 246 which generate an enormous amount of data on a daily basis. Applying analytics solutions to the  
 247 collected data through all the above-mentioned systems, machines and IoT devices can extract  
 248 valuable information that can help in decision-making purposes.

249 **4.2. Analytics Tools**

250 Several analytics tools are required to gain insights into a large amount of industrial data.  
 251 These tools include analytics software, algorithm repository, visualisation tools, modelling tools  
 252 and online analytics packages. Analytics software helps make predictions about unknown events.  
 253 An algorithm repository is a crowd-sourced repository of algorithms that is designed by analysts  
 254 using a common set of languages and a common interface. Visualisation tools help present data  
 255 in advanced formats (e.g. infographics, dials and gauges, geographic maps, sparklines, heat  
 256 maps and detailed bar, pie and fever charts). Modelling tools are used to define and analyse data  
 257 requirements for supporting business processes within the scope of corresponding information  
 258 systems in industries. Online analytics packages help keep track of and analyse data about web  
 259 traffic.

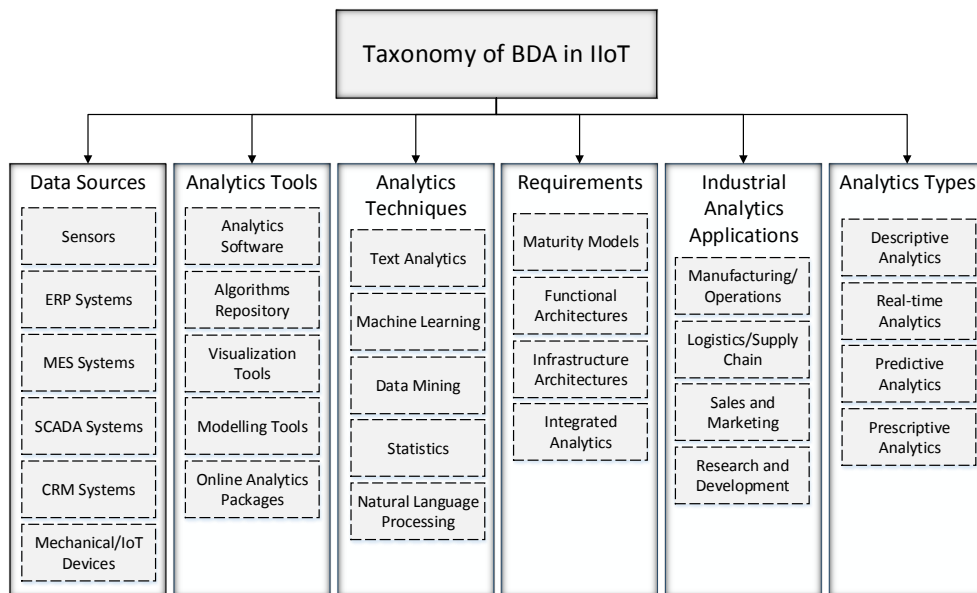


Figure 4: Taxonomy of BDA in IIoT

Table 1: BDA Implementations in IIoT Systems

Ref.	Problem(s)	Objective(s)	Analytic Component(s)	Mode	Strengths	Limitations	Potential Solutions
[71]	Finding accurate customers' attributes for mass customization.	Self-prediction	Genetic Algorithm k-means clustering	Historical data	Smart product development Rapid response to customer needs	Needs to be implemented for real-time, Lacks large-scale validation in BDA environments	Deep Learning for BDA
[70]	Finding accurate customers' attributes for mass customization.	Self-prediction	Self-organizing map	Historical data	Smart product development Rapid response to customer needs	Needs to be implemented for real-time, Lacks large-scale validation in BDA	Re-enforcement learning algorithms
[72]	Enabling product customization and personalisation	Self-configuration Self-organization	Highlighted, but no real implementation discussed	Streaming data	An end-to-end model for massive production and personalisation	No real implementation	Use-case implementation
[73]	Achieving zero-defect problem	Self-configuration	Neo-Fuzzy Neuron	Batch data	Performs industrial process monitoring and modelling	Accuracy needs to be improved	Using alternate ML algorithms
[47]	implementing Physical Internet concept in manufacturing shop floors	Self-prediction	Decision trees	Batch data	The implementation results in better prediction rate	Performance values for different workers needs to be well-defined to control the rate of overestimation	Using alternate ML algorithms
[74]	Developing a proactive and sustainable micro-grid	Self-prediction	A generic framework for knowledge discovery	Batch Data	An end-to-end approach for microgrid data analysis	Efforts are needed to explore analytics for full value chain level knowledge discovery in industrial microgrids	BDA Platform for full value chain Analytics
[78]	Active preventive maintenance	Self-maintenance	Neural Networks	Batch data	Real-time active maintenance	Need to be investigated with real-time streaming data	Real-time BDA platform

### 260 4.3. Analytics Techniques

261 Various analytics techniques that can help obtain value from big industrial data are available,  
262 thereby leading to making fast and better decisions. These analytics techniques include text  
263 analytics, machine learning, data mining and statistical and natural language processing (NLP)  
264 techniques. Text analytics helps derive high-quality information by unveiling patterns and trends  
265 using statistical pattern learning. Machine learning techniques enable industrial devices and  
266 machines to enter into a self-learning mode without being explicitly programmed. Data mining  
267 solutions enable enterprises to transform raw data into knowledge. Statistical tools help collect,  
268 summarise, analyse and interpret large amounts of industrial data, which lead to knowledge  
269 discovery. In an industrial environment, NLP tools are used to extract and analyse unstructured  
270 data.

### 271 4.4. Requirements

272 Certain requirements should be incorporated whilst developing new analytics systems for  
273 IIoT. These requirements include maturity models, functional architecture, infrastructure archi-  
274 tecture and integrated analysis. Maturity models help measure and monitor the capabilities of  
275 analytics systems. They also help measure the effort required to complete a specific development  
276 stage. In summary, these models help monitor the health of an organisations big data programs.  
277 Functional architecture is an architectural model that helps identify the functions of analytics  
278 systems and their interactions. In addition, it defines how system functions work together to  
279 perform a specified system mission. In an industrial environment, analytics systems must be  
280 developed such that they can handle an enormous amount of data in real time. In this context,  
281 big data infrastructure requires experienced scientists to design the infrastructure from existing  
282 equipment in an industrial paradigm. One of the key requirements for analytics systems is that  
283 they should support the integrated analysis of multiple types of industrial IoT data.

### 284 4.5. Industrial Analytics Applications

285 Typical industrial analytics applications across the industrial value chain are as follows: man-  
286 ufacturing/operations, logistics/supply chain, marketing/sales and research and development.  
287 The use of predictive analytics in manufacturing can lead to rescheduling a maintenance plan  
288 prior to machine failure by considering past machine performance history. Moreover, it can help  
289 develop decision support systems for industrial processes. The appropriate use of analytics can

290 play an important role in the logistics/supply chain (*e.g.* condition monitoring, supply chain op-  
291 timisation, fleet management and strategic supplier management). Analytics can help identify  
292 failing parts during product usage through sensor readings and gradually improve product char-  
293 acteristics (research and development). In the marketing field, analytics tools enable enterprises  
294 to predict and enhance future sales (*e.g.* help in determining seasonal trends that can lead to  
295 developing an adaptive marketing strategy).

#### 296 4.6. Analytics Types

297 Analytics has four types: descriptive, real-time, predictive and prescriptive analytics. De-  
298 scriptive analytics helps gain insights into historical data (*e.g.* number of defective items in the  
299 past and the reason for the defects). Meanwhile, real-time analytics enables enterprises to be-  
300 come aware of current situations (*e.g.*, current status and location of a product and detection  
301 of a faulty machine). By contrast, predictive analytics helps identify potential issues that can  
302 occur in advance by using statistical and machine learning techniques (*e.g.* expected inventory  
303 levels, anticipated demand levels, and prediction of equipment failure). Lastly, prescriptive ana-  
304 lytics provides advice or suggestion on the best possible action that an end user should take (*e.g.*  
305 whether a machine is receiving the right raw materials in the correct amount).

### 306 5. Frameworks and Case Studies

307 Value creation is a major sustainability factor in modern enterprises whereby BDA processes  
308 are becoming the primary driver in creating values for customers and enterprises [80]. IIoT  
309 systems are no exception. BDA processes can facilitate the amalgamation of customer and enter-  
310 prise data to ensure massively customised production with zero defects. IIoT systems essentially  
311 integrate historical and real-time stored and streaming data at various levels. This multisource  
312 data integration leads to highly effective designs for new business models. Enterprises focus  
313 on different aspects of industry-wide value creation mechanisms, such as defining value propo-  
314 sitions, value capturing mechanisms, value networks and value communication strategies for  
315 internal and external stakeholders [18]. Ideally, BDA processes can facilitate enterprise-level  
316 value creation whereby inbound intelligence is obtained by creating value for internal enterprise  
317 operations. Alternatively, outbound intelligence leads towards value creation for customers. De-  
318 spite these opportunities, unlocking the perceived value from BDA technologies is challenging.  
319 The existing literature presents only a few such frameworks and use cases as follows.



### 320 5.1. *SnappyData*

321 SnappyData is an open-source BDA framework that integrates Apaches Spark and GemFire  
322 technologies [81]. Apaches Spark is adopted for big data processing, whereas GemFire facil-  
323 itates highly scalable in-memory transactional data storage. The strength of SnappyData is its  
324 unified BDA engine that facilitates the performance of different types of analytical operation,  
325 such as online transaction processing, online analytical processing and streaming the data an-  
326 alytics of operational data. Despite its high performance, SnappyData still underperforms in  
327 cases with highly streaming data, which causes a bottleneck in real-time interactive visualisation  
328 performance.

### 329 5.2. *Ipanera*

330 Soilless food production systems, such as Ipanera, are being aligned with IIoT systems [82].  
331 Ipanera continuously monitors water level and fertilizer quality in a field and generates insights  
332 for self-configuration. Although researchers have presented the concept, the Ipanera architecture  
333 involves multiple layers of physical devices and systems. It includes sensor nodes at the end  
334 points that actively collect data streams and transfer them to nearby IIoT clusters. These clusters  
335 are responsible for end point management, communication and configuration in a field. In addi-  
336 tion, IIoT clusters provide feedback to end points to reconfigure their data collection behaviour.  
337 IIoT clusters transfer data streams to distributed analytics servers that run Apaches Hadoop [83],  
338 MapReduce [84] and Spark [85] technologies for data processing and BDA. Ipanera provides  
339 support for streaming analytics that is used to trigger alerts for end points in case a new event is  
340 detected. Persistent storage and on-the-air configurations are two innovative features of the Ipan-  
341 era architecture. This architecture is currently under development; hence, the complete design of  
342 the proposed architecture is still unavailable.

### 343 5.3. *Fault Detection Classification*

344 Large-scale distributed cyber manufacturing systems are based on multiple interconnected  
345 but geographically dispersed manufacturing units [86]. The fault detection and classification  
346 (FDC) framework finds manufacturing faults in products. The core of the FDC architecture  
347 is the integration of IoT devices into CPS and cloud computing technologies. IoT devices in  
348 production facilities continuously collect and analyse data streams to detect various signals that  
349 are transferred to back-end cloud servers. These cloud servers execute BDA processes to detect

350 and classify faulty products using deep belief networks based on deep learning methods [87, 88].  
351 FDC was analysed by deploying it in a car headlight manufacturing unit that produced reliable  
352 results.

#### 353 *5.4. BDA Architecture for Cleaner Production*

354 The term cleaner production refers to ensuring reduced environmental impacts during the  
355 execution of the entire product life cycle. It is based on three phases [89]. The first phase is  
356 about product design and manufacturing. The second phase involves product use, service pro-  
357 visioning and maintenance. The third phase is concerned with product remanufacturing, reuse  
358 and recycling. Considering the importance of such clean technologies, researchers have pro-  
359 posed a four-stage BDA architecture. In the first stage, the architecture considers value creation  
360 objectives during a products life cycle, such as improving product designs and ensuring energy  
361 efficiency, proactive maintenance and environmental efficiency. In the second stage, big data  
362 acquisition and integration are performed using IoT devices. In the third stage, big data are pro-  
363 cessed using Apaches Hadoop and Storm technologies. Finally, BDA processes are executed  
364 in the fourth stage whereby the architecture provides clustering, classification, association rule  
365 mining and prediction-related algorithms. The proposed architecture was evaluated and tested  
366 on an axial compressor manufacturing unit. The annual reports of the production unit show that  
367 the proposed architecture realises all the value creation objectives for cleaner production.

#### 368 *5.5. Smart Maintenance Initiative: Railway Case Study*

369 Apart from SFS, Japan is attempting to upgrade its railway system to a new level by adopting  
370 IIoT systems for the smart maintenance of railway tracks [90]. To achieve its smart maintenance  
371 vision, Japans railway is adopting IIoT, BDA and automation technologies. The smart mainte-  
372 nance vision will provide a solution to four challenges: 1) ensuring condition-based maintenance,  
373 2) providing work support through artificial intelligence (AI), 3) managing railway assets and 4)  
374 performing database integration. The progress details of Japans railway towards this vision are  
375 available in this report [90] for interested readers.

## 376 **6. Opportunities, Research Challenges, and Future Technologies**

377 Considering the vision of IIoT systems, BDA will evidently help enterprises in the value  
378 creation process. BDA processes will maximise operational efficiency, reduce product develop-

379 ment cost, ensure massively customised production and streamline the supply chain management.  
380 However, this review shows that the existing literature is considerably lagging behind this vision.  
381 Table 2 presents the summary of research challenges and their perceived solutions to fully adopt  
382 IIoT systems in BDA.

### 383 *6.1. Opportunities*

384 The adoption of BDA processes in IIoT systems results in multidimensional research oppor-  
385 tunities.

#### 386 *6.1.1. Automation and AI*

387 The enrichment of intelligent features can lead towards highly optimised and automated in-  
388 dustrial processes [91, 92]. Therefore, AI will be the core component of big data optimisation  
389 and analytics, which will result in highly efficient industrial processes [93]. Future IIoT systems  
390 will integrate and ingest big data from various online and off-line and inbound and outbound op-  
391 erations. The integration of customer and enterprise data will result in high-dimensional, multi-  
392 million variable datasets. AI methods will help optimise and analyse such big datasets [94, 95].

#### 393 *6.1.2. Human Machine Interaction*

394 Wearable computing and augmented reality technologies are leading towards new human-  
395 machine interaction models and interfaces [96, 97]. The enrichment of such interaction models  
396 with real-time knowledge patterns from big data systems will result in highly productive and rich  
397 user interfaces. In addition, robotics technologies (for physical and virtual robots) will be widely  
398 adopted by future IIoT systems. Therefore, BDA processes will enrich intelligence to produce  
399 highly autonomous and self-sustaining non-obtrusive systems.

#### 400 *6.1.3. Cybersecurity, Privacy, and Ethics*

401 Cybersecurity will become an essential requirement due to connected intelligence in IIoT  
402 systems. BDA processes will help provide real-time cyber threat intelligence by analysing se-  
403 curity attacks, privacy leaks, unauthorised data access and unethical data collection [98]. In  
404 addition, BDA processes will help analyse network and information security-related enterprise  
405 data to find anomalies, outliers, threats, attacks and vulnerabilities across IIoT systems [99].

#### 406 *6.1.4. Universal Standards*

407 The adoption of BDA processes is still in its initial stage; thus, existing systems may not  
408 be compliant with universal standards across all or multiple industries [2, 100]. New universal  
409 standards are required to define the type of big data that the industries can collect from customers,  
410 determine how data should be secured, preserved and shared and identify the stakeholders who  
411 will benefit from the data. In addition, standards must also ensure the perceived benefits to  
412 customers in exchange for their personal data. These universal standards will help address ethical  
413 issues in big data systems and create value for customers by providing personalised products and  
414 services.

#### 415 *6.1.5. Protocols for Interoperability*

416 Practically, multiple industries are involved in the entire process from customer data acqui-  
417 sition to finished product/service and supply chain management [2]. Interoperability is a major  
418 consideration among different industries; however, new protocols are required to realise fully  
419 interoperable IIoT systems. These protocols can lead towards value creation for enterprises, al-  
420 though a few questions must be addressed, such as what are the interoperability parameters, how  
421 will BDA processes be executed in cross-industry systems and how will heterogeneity in data,  
422 computing technologies and industrial production systems be handled. A well-defined interop-  
423 erability protocol can help answer these questions.

#### 424 *6.1.6. End-to-end Industrial Analytics*

425 Big data in IIoT systems evolves from multiple inbound and outbound data sources, such as  
426 customer data and operational data from finance, marketing, human resources, IoT devices, CPS  
427 and manufacturing systems [101]. Nevertheless, existing systems manage all these data sources  
428 separately to execute BDA processes. An opportunity exists to develop an end-to-end industrial  
429 analytics pipeline that can handle big data from various data sources in parallel and find highly  
430 correlated knowledge patterns that emerge across entire IIoT systems [102].

#### 431 *6.1.7. Precision Manufacturing*

432 BDA processes can help enrich precision manufacturing systems [103]. The classification  
433 and categorisation of customers needs and behaviour-related data can lead towards innovative  
434 product designs. Enterprises will be able to offer the right products and services to the right cus-

435 tomers. Precision manufacturing will considerably help in equal value creation for customers and  
436 enterprises. Early examples of precision manufacturing systems are available in the healthcare  
437 industry [104]. However, these systems should be integrated into IIoT systems [103].

## 438 *6.2. Research Challenges and Future Technologies*

439 Considering the opportunities, research efforts are required to improve the entire technology  
440 ecosystem for IIoT systems.

### 441 *6.2.1. Big Data Process Integration into IIoT Systems*

442 Ideally, IIoT systems should execute real-time highly interactive big data applications. In  
443 practice, however, considerable effort is required for planning, creating, deploying, maintaining  
444 and continuously improving domain-specific big data processes for each industry. Future BDA  
445 processes should be able to provide real-time knowledge patterns and industry-wide intelligence  
446 through single dashboard applications. In this regard, all legacy and state-of-the art data sources  
447 should be vertically aligned such that enterprises can easily analyse and correlate different indus-  
448 trial processes and operations.

### 449 *6.2.2. Orchestrating BDA Applications Using Concentric Computing*

450 Concentric computing systems provide computational and storage support through different  
451 devices and systems [8]. Thus, massive heterogeneity should be addressed in terms of processing  
452 capabilities, in-memory and disk-based storage systems, battery-powered and fully powered de-  
453 vices and systems and multiple communication channels with varying bandwidth capacities [17].  
454 Big data applications on top of concentric computing systems should be designed by considering  
455 efficiency objectives in terms of storage, in-network data movement, energy consumption, pri-  
456 vacy, security and real-time knowledge availability [105, 106]. In this regard, priority should be  
457 given to devices and systems near data sources. This approach can help maximise value creation  
458 for enterprises in terms of operating cost for big data systems. Given that maximum data collec-  
459 tion, filtration and processing are performed before data arrive in cloud computing systems, the  
460 operational costs for data storage and cloud service utilisation will therefore be minimised [80].  
461 Another benefit of concentric computing systems is their ability to ensure real-time or near real-  
462 time intelligence near end points, IoT devices and other data sources in IIoT systems [36].

463 *6.2.3. Emerging and Complimentary Technologies for IIoT Systems*

464 On the one hand, BDA adoption is increasing in IIoT systems. On the other hand, IIoT sys-  
465 tems should address massive heterogeneity without compromising overall operational efficiency  
466 due to emerging, complementary technologies, such as IoT. Considering this condition, a few  
467 technologies will become integral parts of future IIoT systems.

468 Virtualisation is the essence of distributed systems, such as cloud computing systems and  
469 concentric computing systems. Virtualisation is traditionally performed at multiple levels, such  
470 as operating systems, networks, storage, applications and hardware. Operating system-level vir-  
471 tualisation is the most common whereby operating system kernels and functions are virtualised  
472 as virtual machines (VMs). However, the mobility of IoT devices requires continuous VM mi-  
473 gration among different computer servers [2, 107]. Containerisation is the emerging technology  
474 that is gradually replacing VMs by sharing a single kernel among different applications on the  
475 same type of operating systems. Containerisation technologies offers more secure and faster pro-  
476 cessing; hence, they have become highly beneficial for addressing timeliness and latency issues  
477 when BDA processes are executed using VMs [108].

478 Large enterprises traditionally adopt highly coupled SOAs, which are difficult to test and re-  
479 sult in high maintenance cost. Microservices are emerging alternatives to SOAs whereby highly  
480 scalable and loosely coupled cloud services are orchestrated [109]. The microservice architec-  
481 ture can be adopted best for BDA processes because these processes should be executed across  
482 multiple platforms and devices in IIoT systems [110]. The details of microservice architectures  
483 implementation are available in [111] for interested readers.

484 The multipoint, multisite and high-dimensional data production in IIoT systems results in  
485 complex big datasets. Graph and network theories can help reduce this massive complexity [112].  
486 Graph data structures and big graph analytics methods can be adopted to separate, map and  
487 analyse big data in different graph formats. The adoption of big graph analytics can lead towards  
488 efficient and highly optimised execution of BDA processes across IIoT systems.

Table 2: Summary of Research Challenges and their Perceived Solutions

Type	Issues	Causes	Solutions
Cybersecurity	<ul style="list-style-type: none"> <li>- Internal Attacks</li> <li>- External Attacks</li> </ul>	<ul style="list-style-type: none"> <li>- Security Vulnerabilities</li> <li>- Openness of Systems</li> </ul>	<ul style="list-style-type: none"> <li>- Intelligent Monitoring Tools Needed</li> <li>- Deployment of End-to-End Security Models is Essential</li> <li>- System-wide Forensic Analysis should be performed periodically</li> </ul>
Privacy	<ul style="list-style-type: none"> <li>- Identity Breaches</li> <li>- Personal Data Theft</li> <li>- Business Data Leakage</li> </ul>	<ul style="list-style-type: none"> <li>- Bad Security Models</li> <li>- Absence of Standard Operating Procedures</li> <li>- Weak Data and Information Sharing Policies</li> </ul>	<ul style="list-style-type: none"> <li>- Using Data Anonymisation Protocols</li> <li>- Privacy preserving interaction models for users, devices, and systems</li> </ul>
Big Data Processing	<ul style="list-style-type: none"> <li>- Bad Data Integration</li> <li>- Missing Data Streams</li> <li>- High Latency</li> </ul>	<ul style="list-style-type: none"> <li>Heterogeneous Data Sources</li> <li>- Mobility and Connectivity Issues</li> <li>- Data overloading and Bandwidth Limitations</li> </ul>	<ul style="list-style-type: none"> <li>- Intelligent Real time Data Fusion</li> <li>- Device-centric big data processing architectures</li> <li>- Concentric Computing Models</li> </ul>
Standardization	<ul style="list-style-type: none"> <li>- Difficulty in Interoperability and and System Integration</li> </ul>	<ul style="list-style-type: none"> <li>- Absence of Global Standardization Body</li> </ul>	<ul style="list-style-type: none"> <li>- Developing Local, Regional, Industry-specific, and Global Standards</li> </ul>
Connectivity and Communication	<ul style="list-style-type: none"> <li>- Bad and Inaccurate Data Transfer</li> <li>- Data Loss</li> <li>- High Latency</li> </ul>	<ul style="list-style-type: none"> <li>- High Mobility</li> <li>- Large Data Streams</li> <li>- Congestion</li> </ul>	<ul style="list-style-type: none"> <li>- Need to create always-on, ultra-high available and reliable communication protocols</li> </ul>
Scalability	<ul style="list-style-type: none"> <li>- Resource Discovery</li> <li>- Data offloading</li> <li>- Data Management</li> </ul>	<ul style="list-style-type: none"> <li>- Low Processing Power at device-end</li> <li>- Massive Data Production</li> <li>- Realtime Actuation</li> </ul>	<ul style="list-style-type: none"> <li>- Near-device data processing, In-memory Data Processing, Edge Computing</li> </ul>
System management	<ul style="list-style-type: none"> <li>- Difficult to deploy, configure, monitor, and control large scale IIoT networks</li> </ul>	<ul style="list-style-type: none"> <li>- Cloud-centric</li> </ul>	<ul style="list-style-type: none"> <li>- Device-centric</li> </ul>
Efficiency	<ul style="list-style-type: none"> <li>- High Energy Utilization</li> <li>- Resources-constraints</li> <li>- Device-overloading</li> </ul>	<ul style="list-style-type: none"> <li>- Always-on IIoT Devices and Systems</li> <li>- Massive and Continuous Data Generation and Device Operations</li> <li>- On-device Data Management and Analytics</li> </ul>	<ul style="list-style-type: none"> <li>- Enabling Energy, memory, and computation-efficient algorithms and processes for big data processing, management and analytics in IIoTs</li> </ul>

489 Emerging technologies, such as fog computing and blockchain, can play a pivotal role in  
490 BDA for IIoT [113]. Fog computing has been widely used in IoT devices [114], particularly  
491 those for IIoT and smart manufacturing, for localised and timely data processing and storage,  
492 and primarily to offset long delays that can be incurred in a cloud environment [115]. Blockchain  
493 is the underlying technology for bitcoins; however, it has been foreseen as a distributed ledger  
494 that can provide decentralised storage for data generated by IoT devices. Data are stored in a  
495 blockchain ledger with high integrity, authenticity, resiliency and trust [116]. All transactions  
496 are cryptographically signed by IIoT devices and validated in a decentralised manner without  
497 an intermediary. The data origin is validated before being recorded on the ledger. Moreover,  
498 blockchain smart contracts can be used to provide decentralised authentication, management and  
499 control access to data generated by IIoT devices. Smart contracts are basically codes that are  
500 executed by all blockchain miners, and the execution outcome is verified and agreed upon by  
501 all mining nodes. Furthermore, given the limited computing, networking and storage capacities  
502 of IIoT devices, fog nodes are envisioned to be equipped with cloud and blockchain interfaces  
503 in the future to communicate and interface with the cloud environment and the blockchain net-  
504 work [116].

## 505 **7. Conclusions**

506 The vision of Industry 4.0 to connect manufacturing systems with distributors and consumers  
507 can only be achieved by adopting IIoT and BDA processes as core components for value creation.  
508 This paper discusses the rise of big data in IIoT systems and presents a detailed survey of related  
509 technologies, algorithms, frameworks and case studies. A detailed taxonomy is provided to  
510 classify the key concepts in this important research area. Several indispensable frameworks  
511 and case studies are outlined and discussed. Furthermore, we present a detailed discussion of  
512 future opportunities, technologies and research challenges. We conclude that the adoption of  
513 BDA in IIoT systems is still in its early stage. Research on complementary components of IIoT  
514 systems, such as IoT devices, augmented reality and CPS, is also in its infancy. Current BDA  
515 systems provide generic frameworks for data engineering, preparation and analysis. However,  
516 considerable effort is required to alter existing BDA processes to meet the demands of IIoT  
517 systems. Future research should be conducted to devise new standards for interoperability among  
518 cross-Industry 4.0 BDA platforms and to provide capability for end-to-end reliable application



519 processing by considering the anatomy of concentric computing systems.

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