Big data analytics in the context of internet of things and the emergence of real-time systems: a systematic literature review

Article *in* International Journal of High Performance Systems Architecture · January 2018

DOI: 10.1504/IJHPSA.2018.10015191

1 author:

Tahereh Sonia Saheb
Tarbiat Modares University

Big data analytics in the context of internet of things and the emergence of real-time systems: a systematic literature review

Tahereh Saheb

Management Studies Centre,
Tarbiat Modares University,
Jalal Highway, Tehran, Iran
Email: t.saheb@modares.ac.ir

Abstract: This paper is a systematic review of the papers on the field of IoT big data analytics (IoT BDA) with a concentration on real-time feature of the IoT systems. This paper shows that IoT BDA have challenged the relational databases in various forms, such as in terms of their flexibility, anomaly detection, real-time response, next-generation of hardware-software installment, and interoperability of multitude systems. This paper also explores the new feature of IoT BDA, challenges of security, privacy and interoperability within an IoT BDA systems, IoT BDA platforms, new and advanced analytical methods, and new system architectures and frameworks that are designed and developed by the papers. This paper also explores two main application of a mobile sensor and app in an IoT BDA system. This paper triggers broader discussion regarding future research agenda in the field of real time analysis of IoT big data both in practice and in theory.

Keywords: big data analytics; BDA; internet of things; real-time analysis; streaming analysis.

Reference to this paper should be made as follows: Saheb, T. (2018) 'Big data analytics in the context of internet of things and the emergence of real-time systems: a systematic literature review', *Int. J. High Performance Systems Architecture*, Vol. 8, Nos. 1/2, pp.34–50.

Biographical notes: Tahereh Saheb received her PhD in Science Technology Studies from the RPI, NY. Her research interest is on the role of third platform technologies of IoT, big data, cloud and mobile on enterprise and organisational transformation in developing countries.

1 Introduction

Data analytics is not a new phenomenon. What has made big data analytics (BDA) more appealing is its ability to analyse unstructured data that is generated by the internet of things or IoT. The machine research reports that the total number of IoT connections will grow to 27 billion in 2025, a CAGR of 16 per cent (Buckland et al., 2016). This report explains that by 2025, over 2 zettabytes of data will be produced by the IoT devices. In regard to revenues driven by the IoT, the machine research reports that

> "The total IoT revenue opportunity will be USD3 trillion in 2025 (up from USD750 billion in 2015). Of this figure, USD1.3 trillion will be accounted for by revenue directly derived from end users in the form of devices, connectivity and application revenue. The remainder comes from upstream and downstream IoT-related sources such as application development, systems integration, and hosting and data monetization" (Scales, 2016).

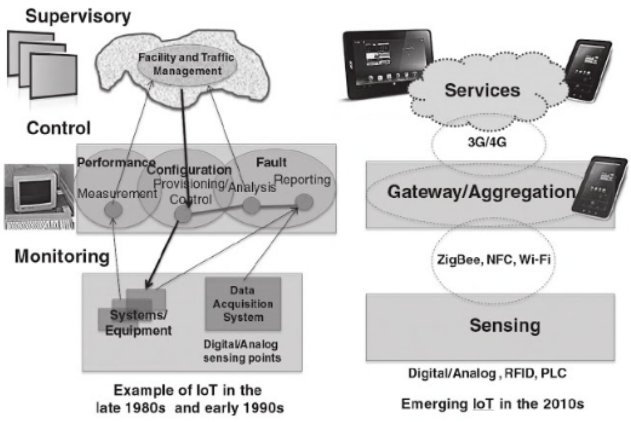
Some call IoT as a prominent driver of the 4th industrial revolution with disruptive impacts on enterprises and also everyday lives (Geng, 2017). What are these devices? We can name sensors, networks, standards, augmented intelligence, and augmented behaviour (Holdowsky et al., 2015).

The utilisation of IoT devices is important as it provides enterprises with disruptive benefits resulted from new generation of predictive and forecasting analytics, such as real-time analysis of workflows, stream processing of events, business intelligence that is acquired from GPS data, mobile sensors, and GIS based visual analytics (e.g., Behmann and Wu, 2015). The major outcome of next-generation formats of analytics is an agile environment with speedy and improved judgment of the events and behaviours and taking insightful decisions.

All of the advanced analytics derived of IoT devices are generated by two kinds of data: big stream and big data [Buyya and Dastjerdi, (2016), p.61]. Big stream or little data are 'transient data that is captured constantly from IoT smart devices' and big data are 'persistent data and knowledge that is stored and archived in centralised cloud storage' (ibid).

Early adoption of IoT was different than today's IoT. Figure 1 explains some of these differences. These differences were mainly due to the expensive cost of computer networks and their limited performance, memory, and storage. Today's IoT devices are less expensive and have higher capacity memory, and storage capacity. As a result of these advancements, not only enterprises can deliver macro values, but also can share and sell their IoT data at larger scale. As a result, we have entered into a new era, and the emergence of service market, such as big data as a service, insight s as a service, etc.

Figure 1 Contrast between early and current IoT functional model



Source: Behmann and Wu (2015)

An IoT environment has three major characteristics: it is collaborative, it is event driven and reactive and it is dynamic and adaptive (Grabis and Kirikova, 2011). It is collaborative as some loosely connected components that work simultaneously run on distributed devices and collaborate in order to generate a desired functionality. It also continuously reacts to a large number of events from physical environments. Devices and collaborations are also dynamically established in order to provide information to support actionable insights.

The research question that has driven this study focuses on how BDA differs from traditional analytics in the context of IoT environments? This paper aims to provide a taxonomy of BDA and IoT environments to understand disruptions and transformations erupted across industries and businesses by the use of IoT objects and BDA.

More specifically, the aims of this paper are:

- To identify applications of IoT BDA.
- To explore the new features of IoT BDA with a concentration on real-time analysis of event and stream data.
- To investigate major security, privacy, and interoperability challenges of IoT BDA.
- To explain proposed architectures, solutions and frameworks.
- To identify the role of assistive technologies of mobile and cloud in IoT BDA projects.
- To explore types of business insights, and data mining techniques.

This paper provides a thorough representation of BDA generated by IoT devices with a concentration on the real-time feature of these systems. This paper has five major parts: it starts with the research methodology and the results of the systematic review. The next part of the paper is descriptive analysis of the papers. The central theme of this paper is real-time identity of data, analysis, response and actions enabled by analysis of IoT big data. With having this central theme, the paper addresses challenges of relational database systems in order to continue the paper with the emergence of real-time, stream, and event analysis of IoT BDA systems. The paper continues its discussion of real-time analysis with big data mining techniques and methods. This part ends with actionable insight gained from IoT BDA.

After reviewing the analytical aspects, the paper addresses the challenges of security, privacy and interoperability in IoT BDA systems. The paper then addresses how the challenge related to IoT BDA has led to the development of the various architectures, frameworks and solutions.

The next part of the paper is addressing the role of assistive technologies of mobile and cloud with a focus on how these technologies have advanced real-time IoT BDA. The paper ends with discussion and conclusion and recommendation for future studies.

2 Research method

This research is grounded in literature review in order to identify and investigate the existing knowledge on applications of IoT, major challenges of traditional analytics systems, the proposed solutions and architectures, impacts of complementary technologies of mobile and cloud on IoT BDA, and type of business insights and data mining algorithms. This research attempts to put forward a comprehensive picture of BDA whose data is generated by IoT devices. This study adopts a systematic literature review and follows a scientific and transparent process throughout the study to make the review process less biased and more comprehensive and precise. The review process is driven by the following research questions: what are the major applications, challenges, proposed architectures, and types of business insights and data mining algorithms in an IoT environment? And what complementary technologies have assisted IoT BDA? After identifying the major questions, the study process was continued by identifying the subject areas, relevant studies, and the exclusion/inclusion criteria. Studies that were not related to an analytics solution were excluded as only those research that were related to BDA use case whose data was generated by an IoT device were included. So those research that have investigated infrastructure, and technical aspects of an IoT/big data project were excluded. The paper included only studies that have investigated an application of an IoT device and have studied an IoT BDA issue. During the process, we did not exclude any discipline and we included all disciplines who met the criteria of inclusion. Since IoT and BDA are emerging research topics, the study reviews papers published after January 2015 until May 2017. The relevant publications were identified by forming research strings that combined the key words of 'IoT BDA' with a different range of terms and phrases. The initial focus of the research is on IoT devices whose data are used for an analytic purpose. The study identified around 25 research strings and submitted them to a panel of experts (n = 12) from different disciplines in order to validate the review protocol. Through using wildcard symbols, the study reduced the number of research strings to 25, as for instance, 'IoT' returned studies that were not related to a BDA study. We searched the database research engines combining the key words of 'IoT', 'big data', 'analytics', and 'BDA'.

The study was started on March 12, 2017 and ended on June 6, 2017. The most time-consuming part of the study was validation of the research strings by the experts. The study reviewed scholarly peer reviewed journals, periodicals, and proceedings of conferences by exploring the following databases: Scopus (Elsevier), IEEE Explorer, InderScience, and Google Scholar. The study also reviewed publications of specialised sources and journals, such as *Journal of Medical Internet Research*, *Sensors Journal*, and Multidisciplinary Digital Publishing Institute (MDPI).

We limited the search to the abstract, title, and keywords. A total of 222 papers were downloaded and reviewed. We conducted a quality appraisal to determine the clarity of the papers' contribution to the research questions. At this stage, 42 papers were identified. A further four more papers were also considered relevant. Cross-referencing yielded five more papers for inclusion. The final list became 51 papers. All of these papers had explicit indication of BDA in an IoT environment.

We also adopted a thematic analysis of the literature review and seven initial codes and categories were generated to guide the review. The categories are as follows: Applications of IoT, major challenges, the proposed solutions and architectures, inclusion of complementary technologies of mobile and cloud, data mining algorithm, and type of business insights. The coders also identified additional aspects that were absent in the literature. At this stage, we estimated Krippendorff's alpha or Kalpha It is a reliability measure irrespective of the number of observers, sample size, and absence of missing data (Krippendorff, 2007). In order to estimate the Kalpha, two judges coded each of our subsample of 52 articles. The judges used a nominal scale ranging from 1 to 6: 1 = applications of IoT, 2 = major challenges, 3 = the proposed solutions and architectures, 4 = impacts of complementary technologies of mobile and cloud, and 5 = data mining algorithm, and 6 = type of business insights. Then we uploaded the coded data into IBM SPSS Statistics (version 24) in order to judge the inter-rater reliability of the coded variables. The Kalpha value was 0.82 that is an evidence of reliability in content analysis.

3 Descriptive analysis

Table 1 illustrates the overall distribution of the IoT BDA literature that covers six major application of BDA in an IoT environment. As the table shows, Smart City (27%) and industrial/manufacturing IoT (23%) are the major application of IoT that the papers have reviewed. Transportation and Health are respectively the other popular applications of IoT being reviewed by the papers. Of the total 52 articles, 34.6% of the papers have addressed the issue of integration of devices within an IoT environment. The majority of papers, 71% have proposed a solution, architecture and framework for better analysis of IoT data. In regard to the inclusion of emerging technologies of mobile and cloud, 21% of papers have directly and explicitly have mentioned mobile technologies; and 17% have addressed the inclusion of cloud systems in their IoT BDA projects. In regard to the kind of business analysis, we classified into two categories of predictive analysis and real-time analysis. I should mention that one paper could be included in both categories as it could be both predictive and real-time. In regard to real-time analysis, we included papers that have explicitly mentioned 'real-time analysis' or 'real-time processing' in their papers. In regard to papers on the predictive analysis category, we also included papers whose kind of analysis was not directly mentioned 'predictive analysis' but based on their definitions of analysis type, it was implied prediction. Of the paper, 29% have explicitly mentioned real-time analysis and processing in their papers. Of the 52 papers, 20 papers have explicitly allocated to a special kind of predictive analysis and a case study.

4 IoT BDA and challenges of relational database management systems (RDBMS)

Data analytics is not a new phenomenon. However, fast-paced generation of vast amount of data by IoT devices has generated many challenges for traditional systems of acquiring, storing, managing and analysing data called RDBMS. These systems do not have adequate capacities for unstructured and event data specially produced by IoT devices in smart environments. This challenge is observable at many industries and sectors. Howell et al. (2017) argue that the convergence of building information modelling with the smart water field will 'transcend existing operational barriers'. Shapsough et al. (2016) argue that despite the common belief that equals smart education with 'conventional e-learning systems like MOOCs', IoT offers 'far beyond the capabilities of current system'. Tan et al. (2016) discuss that traditional data management techniques and analytical methodologies are not 'sustainable' anymore as organisations face challenges to 'right size the work force, increase labour productivity, increase customer satisfaction and at the same time improving product quality and reliability'.

IoT and BDA can disrupt the RDBMS in various forms, such as in terms of their flexibility, anomaly detection, real-time response, next-generation of hardware-software instalment, and interoperability of multitude systems. As the literature shows, IoT BDA requires the following improvement in traditional systems:

4.1 Flexible data platforms

Non-flexible data platforms are the major challenges of IoT BDA use cases (Cheng et al., 2015). These legacy platforms do not deliver 'context-awareness and intelligence into all kinds of applications and services' (ibid). Flexibility is critical for IoT BDA. Given the growth of various data sources, it is necessary that next-generation analytics platforms sustain performance, address future requirements, and support or integrate with other tools of discovery, capture, preservation or management of big data. Big data platforms such as Ayasdi, Datameer, Informatica are answers to the need for flexible IoT BDA platform.

4.2 Next generation software-hardware solutions

In a smart city environment in which various sensors are applied to monitor and control the parking system, an 'ancient parking system' (Hans et al., 2015) is not responsive for an optimised parking space usage, improved efficiency of parking operations or a smooth traffic flow. Next generation of smart systems require various perquisites, such as a number of software solutions (i.e., Python, PHP web gateway with MySQL database, cloud based storage and mobile applications) (Hans et al., 2015) or a 'real-time operating system (RTOS)' (Venkataraman and Chitra, 2015).

4.3 Interoperability of the multitude systems

The core of an IoT environment is connectivity among individuals, processes and objects; therefore, interoperability between all of these connections is very important. It is necessary that fragmentation among horizontal platforms be reduced; and disparate, disconnected and overlapping solutions could easily connect to each other. Several solutions are offered in the literature in order to increase interoperability of analytic systems, such as improving software flexibility and hardware-based security (Talluri, 2017). The growth of open platforms has also required new protocols. Increasing openness and interoperability cannot be tackled by 'current simple standard protocols' (Ahlgren et al., 2016). Ahlgren et al. (2016) study the GreenIoT platform in Sweden to show the idea of open data and interoperability for smart cities.

Semantic web technologies are one of the technologies that are being associated with IoT to facilitate the communication of heterogamous objects in IoT applications (Hwang and Chen, 2017) as they can 'bring together large data models with dynamic data streams' (ibid). Semantic web technologies are considered as one of the implementation methods for dynamically accessing streaming data in the cloud (Vermesan and Friess, 2013) as well.

4.4 Real-time response systems (RTRS)

One of the major shortcomings of the RDBMS, as it was implied earlier, is their inefficacy in real-time response to emergencies and anomalies. Through technologies, such as complex event processing or CEP, next generation of emergency systems can monitor event sources and generate alerts (Sheriff et al., 2015). IoT has played a major role in the growth of RTRS in emergencies. The main vision of IoT is creating smart environments, in which basic information from any of networked and autonomous agents are shared efficiently in real-time. In emergencies, RFID sensor networks and other technologies such as GPS or infrared sensor detection can spontaneously update the status, requirements and other information of an emergency situation and enable real-time response. In the case of smart cities, Rizwan et al. (2016) stresses the need for a real-time system in order to update traffic details in real-time. To them, this real-time system is low cost and can replace the current traffic management and alert system since these legacy systems are not sufficient for the needs of smart traffic management system or STMS.

4.5 Real-time anomaly detection systems

One of the other shortcomings of RDBMS is their inefficiency in real-time detection of abnormal data and events (Dani et al., 2015). Consequently, the extension of 'legacy detection capabilities' is a major goal in improving RDBMS. The goal of new systems is to identify in real-time anomalies that are buried in IoT big data and then to alert users of them in real-time. Through real-time anomaly detection, industries can identify patterns in data that do not conform to an expected and normal behaviour. Through real-time big data anomaly detection engines, organisations will learn normal behaviours in complex and sensor-rich environments, and detect abnormal behaviours in real-time.

Table 1 Descriptive analysis of the papers addressed in this study

Big data analytics in an IoT environment		*References*	*Number*	*%*
Application of IoT	Health IoT	Khasaei et al. (2015), Keshan et al. (2015), Kan et al. (2015), Sheriff et al. (2015), Gachet et al. (2016), Sundhara and Bairavi (2016), Vuppalapati et al. (2016) and Almotiri et al. (2016)	8	15
	Smart City	Hans et al. (2015), Cheng et al. (2015), Strohbach et al. (2015), Nadargi and Thirugnanam (2016), Guo et al. (2016), Howell et al. (2017), Mazhar et al. (2016), Psomakelis et al. (2016), Vijayalajshmi and Muruganand (2016), Reddy et al. (2016), Ahlgreen et al. (2016), Jin et al. (2016), Usurelu and Pop (2017) and Bashir and Gill (2016)	14	27
	Industrial/ manufacturing IoT	Wang et al. (2015), Bodin et al. (2015), Dani et al. (2015), Cao and Truong (2016), Kapil (2016), Baudoin et al. (2016), Jesse (2016), Lee et al. (2015), Isaka et al. (2016), Chen et al. (2016), Zhong et al. (2017) and March and Scudder (2017)	12	23
	Transportation	Venkatarama and Chitra (2015), Bruwer and Booysen (2015)Author: Please confirm if the pronoun used is correct., Kannimuthu et al. (2016), Parkinson and Bamford (2016), Li et al. (2016), Lee and Tso (2016), Rizwan et al. (2016), Schatzinger and Lim (2017), and Junior et al. (2017)	9	17
	Supply chain	Xhafa et al. (2015), Fukui (2016) and Tan et al. (2016)	3	8
	Others	Vemula and Gangdharan (2016) (financial service), Li (2015) (natural disasters), Kim and Park (2015) (sport), Paul et al. (2016) (social IoT) and Shapsough et al. (2016) (education)	5	10
Major challenges reviewed in the literature	Security/privacy	Bodin et al. (2015), Nadargi and Thirugnanam (2016), Kannimuthu et al. (2016), and Almotiri et al. (2016)	4	9
	Interoperability	Bodin et al. (2015), Cheng et al. (2015), Khazaei et al. (2015), Strohbach et al. (2015), Wang et al. (2015), Vemula and Gangadharan (2016), Jesse (2016), Li et al. (2016), Lee et al. (2015), Guo et al. (2016), Isaka et al. (2016), Howell et al. (2017), Reddy et al. (2016), Ahlgren et al. (2016), Fukui (2016), Schatzinger and Lim (2017), March and Scudder (2017) and Jin et al. (2016).	18	34.6
Proposing solutions/architecture/framework/systems/ methods		Hans et al. (2015), Cheng et al. (2015), Dani et al. (2015), Khazaei et al. (2015), Strohbach et al. (2015), Venkataraman and Chitra (2015), Xhafa et al. (2015), Wang et al. (2015), Cao and Truong (2016), Nadargi and Thirugnanam (2016), Baudoin et al. (2016), Vemula and Gangadharan (2016), Gachet et al. (2016), Jesse (2016), Li (2015), Lee et al. (2015), Kim and Park (2015), Kannimuthu et al. (2016), Guo et al. (2016), Parkinson and Bamford (2016), Isaka et al. (2016), Sundhara and Bairavi (2016), Li et al. (2016), Howell et al. (2017), Rathore et al. (2016), Psomakelis et al. (2016), Reddy et al. (2016), Vuppalapati et al. (2016), Chen et al. (2016), Ahlgren et al. (2016), Fukui (2016), Zhong et al. (2017), Lee and Tso (2016), Rizwan et al. (2016), Jin et al. (2016), Usurelu and Pop (2017) and Bashir and Gill (2016).	37	71
Inclusion of complementary technologies of mobile and cloud	Mobile technologies	Hans et al. (2015), Kan et al. (2015), Venkataraman and Chitra (2015), Vemula and Gangadharan (2016), Li (2015), Kannimuthu et al. (2016), Li et al. (2016), Vuppalapati et al. (2016), Fukui (2016), Shapsough et al. (2016) and Rizwan et al. (2016)	11	21
	Cloud technologies	Hans, et al. (2015), Khazaei et al. (2015), Sheriff et al. (2015), Cao and Truong. (2016), Gachet et al. (2016), Jesse (2016), Li (2015), Isaka et al. (2016) and Ahlgren et al. (2016)	9	17
Kind of business insight	Predictive analysis	Dani et al. (2015) (maintenance analytics/anomaly detection)	20	38
		Keshan et al. (2015) (physiological sensor analysis)		
		Strohbach et al. (2015((smart grid analysis)		
		Kan et al. (2015) (disease pattern recognition)		
		Sheriff et al. (2015) (predictive-prescriptive, pre-emptive analysis)		
		Xhafa et al. (2015) (big data stream analytics)		
		Bakshi (2016) (network core/edge analytics)		
		Bruwer and Booysen (2015) (smartphone based driver behaviour analysis)		

Table 1 Descriptive analysis of the papers addressed in this study (continued)

Big data analytics in an IoT environment		*References*	*Number*	*%*
Kind of business insight	Predictive analysis	Gachet et al. (2016) (sensor's information analytics/predictive modelling with R)	20	38
		Kim and Park (2015) (risk analysis)		
		Guo et al. (2016) (principal component analysis)		
		Parkinson and Bamford (2016) (accident prediction)		
		Isaka et al. (2016) (image analysis)		
		Zhong et al. (2017) [big data analytics for radio-frequency identification (RFID) logistics data]		
		Lee and Tso (2016) (predictive maintenance)		
		Shapsough et al. (2016) (mobile based educational assessment)		
		Rizwan et al. (2016) (traffic predictive analysis)		
		March and Scudder (2017) (predictive maintenance)		
		Jin et al. (2016) (personal data analytics)		
		Tan et al. (2016) (quality analytics)		
	Real-time analysis	Cheng et al. (2015), Khazaei et al. (2015), Strohbach et al. (2015), Venkataraman and Cjitra (2015), Xhafa et al. (2015), Bakshi (2016), Jesse (2016), Li (2015), Mazhar et al. (2016), Psomakelis et al. (2016), Chen et al. (2016), Lee and Tso (2016), Shapsough et al. (2016), Rizwan et al. (2016) and March and Scudder (2017)	15	29

5 IoT BDA and the emergence of real-time, stream and event analysis

One of the major characteristics of IoT BDA is its real-time analysis of events and data streams. And as result, we observe the emergence of new processing engine, called event stream processing (ESP) that I will explain later in the paper. One major innovative type of analysis in an IoT BDA is event processing. Dineshreddy and Gangadharan (2016) divide their proposed IoT based framework for financial service sector into five layers of event processing and analytics, and four other layers of application, integration, communication and physical device management. But what does an IoT event or stream analysis mean?

5.1 Definitions of event and stream analysis

SAS (2015, p.14) defines an IoT event as an "occurrence happening at a determinable time and place, with or without the participation of human agents, that can be recorded as a collection of fields containing DATA" for making intelligent decisions (Cheng et al., 2015), accurate 'forecast' (Cheng et al., 2015; Khazaei et al., 2015; Strohbach et al., 2015; Parkinson and Bamford, 2016; Isaka et al., 2016; Fukui, 2016), predictive analysis (Khazaei et al., 2015), and capturing new patterns and behaviours (Kan et al., 2015).

As I mentioned earlier, one of the emerging feature of IoT BDA is ESP and it is a subcategory of CEP. It focuses on working with events in motion or event streams. Sheriff et al. (2015, p.1) define CEP as "continuous and timely processing of events as they occur using appropriate encompasses methods, techniques, and tools." They believe that CEP either can be used alone or in combination with BDA and IoT in healthcare industry.

One of the major differences that IoT has erupted in the world of BDA is its ability in conducting real-time and stream analytics. This kind of analytics is empowered through the emergence of unstructured data produced by various sources, such as IoT devices and sensors. Various definitions of stream or real-time analysis is offered in the literature. Some scholars (Xhafa et al., 2015) consider big data stream processing as one of the 'most important computing trends nowadays', and explore application of big data stream processing in sectors, such as supply chain monitoring system (Xhafa et al., 2015).

Jerry Baulier, Senior director of SAD R&D, ESP (2015, p.4) discusses that "streaming analytics typically means making analytically informed decisions in milliseconds, while examining many thousands of events per second, generated from many millions of devices which can also be enriched by many other disparate sources of data."

The above mentioned definition clarifies three major aspect of IoT BDA:

1 'milliseconds' decision making (through real-time systems)
2 data of 'millions of devices' (and consequently the challenge of integration)
3 inclusion of non-real-time systems (batch processing or near-real-time analysis) as a component of stream analytics.

Therefore, streaming analytics is not restrained to real-time systems and analytics.

5.2 *Real world applications of real-time analysis of event and stream data*

Some scholars believe that IoT is a general term and specific IoT objects should be clarified. Therefore, some scholars classify some IoT objects as industrial IoT (Wang et al., 2015; Lee et al., 2015; Boudoin, 2016, Jesse, 2016), internet of heart (Kan et al., 2015), internet of everything (IoE) (Nadargi and Thirugnanam, 2016, Jesse, 2016), social IoT (Paul et al., 2016), and health IoT (Kumar and Bairavi, 2016; Almotiri et al., 2016), IoTH or the IoT and humans (O'Reilly, 2014).

Various studies have addressed the production, analysis and management of IoT real-time data in various sectors and industries. One of the major sectors is health in which the 'internet of hearts' play a major role (Kan et al., 2015) as it enables 'real-time management of multi-sensor signals'. Internet of hearts is introduced as a new cardiac mHealth system enabling BDA in large-scale IoT environments.

One of the other applications of real-time systems is in regard to smart transportation, such as fleet management systems (Venkataraman and Chitra, 2015) or real-time STMSs (Rizwan et al., 2016). While the former system develops real-time tracking of vehicles that uses smart phone applications (Venkataraman and Chitra, 2015), the latter acquires real-time streaming data for BDA (Rizwan et al., 2016).

The other sector in which real-time analysis plays a major role is in disaster and emergency management (Li et al., 2016). However, Li (2015) believe that due to the lack of computational power of IoT devices and the vertical isolation of IoT devices, some challenges hinder real-time responses (ibid). In order to solve challenges regarding to IoT BDA, some solutions, such as the connected open platform for smart objects (COAST) (ibid) is introduced. As Li (2015) describes, platforms like COAST enables smart objects, such as robots, drones and smartphones to negotiate autonomously and to deploy additional resources on itself, on other objects or in the cloud (ibid).

Studying human behaviour is one of the other real-world areas in which real-time response can play a major role (Paul et al., 2016). The new concept of IoTH or the IoT and Humans, as O'Reilly (2014) calls it, has opened new ways for discovering how cooperation among humans and things differently in smart situations. In this domain, Paul et al. (2016) introduces the new concept of SmartBuddy, in which through analysing data generated by various devices, such as smartphones, social networks and smart cities, intelligent spaces can be developed to sense human activities or actions and also the evolution of the ecosystems.

The other area in which IoT can play a major role is in the smart management of smart buildings. One of the challenges in regard to real-time analysis in smart buildings is storing and analysing large amount of high-speed real-time smart building data (Bashir and Gill, 2016). To solve this real-time associated challenge, Bashir and Gill (2016) introduces an integrated IoT BDA (IBDA) framework.

One of the other real-time solutions is related to smart city data and dashboards. City agencies can make their city operations more efficient and quicker though insights gained from data collected from IoT sensors available through city dashboards. Usurelu and Pop (2017) review various smart city dashboards around the world. Their study shows that the data of the following smart city dashboards are real-time data: Amsterdam City Dashboard, Dubai Personal Dashboard, Bandung Smart City Dashboard, CityEye and search – the-city dashboard.

Real-time data is important as Munish Khetrapal, managing director of solutions for smart and connected communities of Cisco says: "a two minutes' faster response to an emergency can save thousands of dollars" (Hamblen, 2016).

The other domain of IoT for real-time response is within industries. Here, we face the concept of IIoT or industrial IoT. One of the functions of industrial IoT is real-time and predictive control and maintenance (March and Scudder, 2017; Chen et al., 2016) in instances, such as leakage of toxic gases in large-scale petrochemical plants (Chen et al., 2016): "The real-time algorithms on data processing, data analysis and decision making are necessary for an intelligence framework to improve the timeliness of dynamic processes in industrial production/service" (ibid). March and Scudder (2017) believe that implementation of predictive maintenance will lead enterprises to adopt service-oriented business models instead of product-oriented models.

6 Real-time big data mining in the context of IoT BDA

IoT means everyday objects connect to each other to the internet (Fortino and Trunifo, 2016). As Jesse (2016, p.276) defines, IoT is a 'sensor-enhanced internet' with seven major dimensions: sensitivity, linearity, measurement range, response time, accuracy, repeatability, and resolution (ibid). BDA, on the other hand, deals with the analysis of data generated by various sources, such as IoT devices and objects. Table 2 shows the various sources of IoT data that are processed and analysed in the literature.

Big data mining algorithms are useful tools in extracting hidden patterns and information from IoT big data. Novel algorithms have enabled real-time and unsupervised detection of anomalies (Dani et al., 2015), in systems and markets and forecasting of patterns and behaviours.

Streaming analytics of IoT big data requires novel algorithms. In this context, real-time anomaly detection has significant practical application for various industries. Use cases, such as predictive maintenance analytics (Dani et al., 2015; March and Scudder, 2017), personalised individual stress analytics (Keshan et al., 2015), grid monitoring (Strohbach e al., 2015), quality analytics (Strohbach et al., 2015; Tan et al., 2016), recognition of disease patterns (Kan et al., 2015), driver behaviour monitoring (Bruwer and Booysen, 2015), railway accidents detection (Parkinson and Bamford, 2016), and real-time traffic density analytics

(Rizwan et al., 2016) have given actionable insights to various industries in real-time.

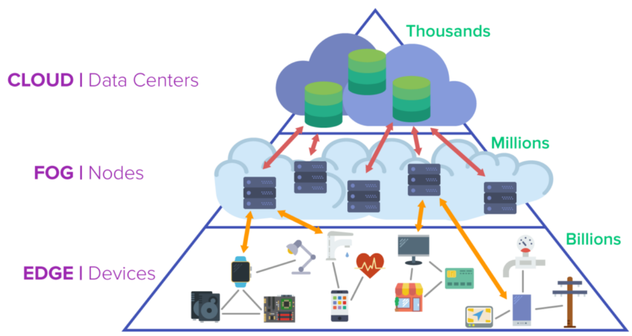
Table 2 Data sources of IoT BDA

Sources of IoT BDA	*References*
Parking sensors	Hans et al. (2015)
Smartwatch	Bodin et al. (2015)
Smart city data	Cheng et al. (2015), Paul et al. (2016), Mazhar et al. (2016), Psomakelis et al. (2016) and Usurelu and Pop (2017)
Physiological data	Keshan et al. (2015), Kan et al. (2015), Gachet et al. (2016), Sundhara and Bairavi (2016)
Sensors in grain warehouse	Cao and Truong (2016)
Smart home data	Nadargi and Thirugnanam (2016), Jin et al. (2016) and Bashir and Gill (2016)
Financial data of customers	Vemula and Gangadh (2016)
Vehicle tracking data	Kannimuthu et al. (2016)
Smart utility data	Guo et al. (2016), Howell et al. (2017) and Reddy et al. (2016)
accidents data	Parkinson and Bamford (2016)
Sensors on smartphones /mobile applications	Hans et al. (2015), Paul et al. (2016), Vuppalapati et al. (2016), Shapsough et al. (2016) and Junior et al. (2017)
Camera data	Isaka, et al. (2016)
Fire monitoring sensors	Vijayalakshmi and Muruganand (2016)
Spatio-temporal data	Chen et al. (2016)
Inventory data	Fukui (2016)
Shop floor sensors	Zhong et al. (2017)
Transportation sensors	Lee and Tso (2016), Rizwan et al. (2016) and Schatzinger and Lim (2017)
Manufacturing data	March and Scudder (2017)
Infusion pumps data that are attached to NICU beds	Khazaei et al. (2015)

Novel data mining algorithms have enabled real-time forecasting (Cheng et al., 2015; Dani et al., 2015; Strohbach et al., 2015; Parkison et al., 2016; Isaka et al., 2016; Fukui, 2016) has been significantly applied in industries such as energy (Strohbach et al., 2015) and sales (Fukui, 2016). In the literature, we observe the use of the following machine learning algorithms: the classification (Keshan et al., 2015; Bruwer and Booysen, 2015), SVM classifier (Sundhara and Bairavi, 2016; Júnior et al., 2017), fast recursive algorithm (Guo et al., 2016), and other algorithms like, artificial neural network, random forest, Bayesian networks (Júnior et al., 2017) in their processing of IoT BDA.

Traditionally, organisations analyse data that is at the core of their network but with the advent of IoT objects, sensor data should be analysed closer to its source and be aggregated for core analysis. Therefore, the main goal of edge computing is locating computing power closer to the source of the data. Edge computing (Sathi, 2016; Bakshi, 2016) is one of the major solutions in IoT BDA in order to optimise cloud computing system to process data that is at the edge of the network and close to the source of the data. Wikipedia defines edge computing as "pushing the frontier of computing applications, data, and services away from centralised nodes to the logical extremes of a network. It enables analytics and data gathering to occur at the source of the data. This approach requires leveraging resources that may not be continuously connected to a network such as laptops, smartphones, tablets and sensors". On the other hand, fog computing, which was coined by Cisco, means extending cloud computing anywhere at the system, from cloud to the edge (Graph 2.0).

Figure 2 Edge and fog computing (see online version for colours)



Source: PubNub.com

As it mentioned by the GE digital, the edge computing consortium identifies the following business consequences of edge computing:

- predictive maintenance
  - a reducing costs
  - b security assurance
  - c product-to-service extension (new revenue streams)
- energy efficiency management
  - a lower energy consumption
  - b lower maintenance costs
  - c higher reliability
- smart manufacturing
  - a increased customer demands mean product service life is dramatically reduced
    - 1 customisation of production modes
    - 2 small-quantity and multi-batch modes are beginning to replace high-volume manufacturing
- flexible device replacement
  - flexible adjustments to production plan
  - rapid deployment of new processes and models.

7 Actionable insights gained from Iot BDA

The ultimate goal of conducting BDA is acquiring actionable insights regarding future for purposes such as implementing faster strategic actions, reducing data acquisition time and cost, increasing competitive power in market, etc. As Table 4 shows, various analysis types are conducted by the scholars and researchers in order to gain actionable insight from the analysis. The main advantage of real-time analysis, as the studies show, is that they are accessible as they enter a system. As IBM explains, functions of real-time analysis or RTA are:

1 system availability monitoring (SAM)

2 RTA resource monitoring.

These functions are available through real-time data or RTD, which are data that is delivered immediately, and with no delay, after they are collected from various sources. Most of these analysis are in the form of real-time analysis (Cheng et al., 2015; Khazaei et al., 2015; Strohbach et al., 2015; Venkataraman and Cjitra, 2015; Xhafa et al., 2015; Bakshi, 2016; Jesse, 2016; Li et al., 2016; Mazhar et al., 2016; Psomakelis et al., 2016; Chen et al., 2016; Lee and Tso, 2016; Shapsough et al., 2016; Rizwan et al., 2016; March and Scudder, 2017).

Predictive analysis uses various statistical techniques in order to analyse current data in order to make predictions about future. A large number of studies have also conducted predictive analysis of the IoT data:

- Dani et al. (2015): maintenance analytics/anomaly detection
- Keshan et al. (2015): physiological sensor analysis
- Strohbach et al. (2015): smart grid analysis
- Kan et al. (2015): disease pattern recognition
- Xhafa et al. (2015): big data stream analytics
- Bruwer and Booysen (2015): smartphone based driver behaviour analysis
- Gachet Páez et al. (2016): sensor’s information analytics
- Kim and Park (2015): risk analysis
- Guo et al. (2016): principal component analysis
- Parkinson and Bamford (2016): accident prediction
- Isaka et al. (2016): image analysis
- Zhong et al. (2017): BDA for radio-frequency identification (RFID) logistics data
- Lee and Tso (2016): predictive maintenance
- Shapsough et al. (2016): mobile based educational assessment
- Rizwan et al. (2016): traffic predictive analysis
- March and Scudder (2017): predictive maintenance
- Jin et al. (2016): personal data analytics
- Tan et al. (2016): quality analytics.

8 Security, privacy and interoperability challenges of IoT BDA

IoT devices have provided innovative sources of data (that can be very sensitive data) in order to enable individuals and processes to interact with the world around them. Ironically, it has also provided new tools for hackers to interrupt internet, mobile, IoT and cloud systems as well. The root challenge is that in many instances, the interconnection of thousands of smart objects happens over the current internet infrastructures that are not protective enough against hackers. Almotiri et al. (2016) mention that in IoT based m-health systems, security is one of the major challenges. And this challenge spins over across industries. For instance, because of the lack of infrastructure in an IoT based vehicle tracking system, security and privacy is low (Kannimuthu et al., 2016). Privacy-and security-aware management of personal data and devices that are located and embedded in the midst of personal lives of people and organisations is an issue that has also been addressed in the literature.

Physical security vulnerability of IoT devices, accessible IoT software over network, weak Wi-Fi security are several challenges that have made IoT objects vulnerable to hacking. One of the major questions regarding security of IoT is “how can pervasive sensing and analytics systems preserve and protect user security?” (Bodin et al., 2015). The other issue in this domain is in regard to the privacy of information of users, such as their location or their identity (Nadargi and Thirugnanam, 2016). To solve this issue, Nadargi and Thirugnanam (2016) have recommended a framework to create user privacy aware through detection of work sensitive content of smart home environment data while preserving privacy of identify and location privacy of IoT devices.

An IoT environment is composed of thousands of objects, individuals and processes whose integration and communication is a major challenge, especially to get real-time data, such as city data, and processing these data (Rathore et al., 2016). One of the “biggest challenge presented to an organization is understanding how to integrate these devices with the back-end systems, building the data correlation and analytics while ensuring the security of the overall systems” (Bodin et al., 2015). One of the other challenges is how to integrate data streams and events that are mainly produced by IoT objects with the existing data (ibid); or how to integrate various disjointed analytics and data sources techniques in hybrid model of network core and edge analytics (Bakshi, 2016).

One of the other concepts that scholars have addressed is the IoE (Nadargi and Thirugnanam, 2016). This concept was coined by CISCO and defines it as "the networked connection of people, data, process and things. The IoE is made up of many technology transitions, including the internet of things" (CISCO, 2017).

Table 3 Proposed solutions, architectures, and applications of IoT BDA

Author	*Proposed solution and application domain*	*Description*
Cheng et al. (2015)	A live city data and analytics platform	A system architecture for smart city platform designers: a live city data and analytics platform, called CiDAP, which was employed for a 'large scale running smart city test bed, SmartSantander'.
Khazaei et al. (2015)	An analytical model for health analytics systems	An analytical model to predict the amount of storage, memory and computation power required for a new cloud-based health analytics system.
Sheriff et al. (2015)	A reference framework for healthcare informatics	This study proposes a reference framework for a holistic healthcare informatics and analytics solution to integrate and leverage the advantages of BDA, CEP and IoT.
Xhafa et al. (2015)	A software chain architecture	A software chain architecture that utilised five components of sensor, extractor, parser, formatter and outputter.
Wang et al. (2015)	A framework for offshore support vessels	A new framework integrating BDA and industrial IoT technologies for offshore support vessels in order to help maritime companies increase their output and productivity.
Nadargi and Thirugnanam (2016)	A framework for smart homes	A framework to create user privacy aware within smart home environments IoT application.
Bakshi (2016)	A general hybrid model	A hybrid model of big data analytics with network core and edge analytics in order discuss the analytic capabilities of this hybrid model
Boudoin (2016)	A roadmap for industrial IoT	A roadmap for industrial internet application in oil and gas industry.
Vemula and Gangadharan (2016)	An architecture based on IoT for banking and finance sector	An architecture based on IoT for banking and finance sector by studying different banking applicants flow with IoT-intelligence and analysing user's data.
Gachet et al. (2016)	A general approach for sensors' information processing and analytics	A general approach for sensors' information processing and analytics based on big data concepts.
Lee et al. (2015)	An IoT based cyber physical system for industrial informatics analytics	An IoT based cyber physical system for industrial informatics analytics with the integration of various proprietary data analytics systems. They design a context awareness based service platform for industrial informatics analytics with 5 layers of IoT, infrastructure, data, analytical and presentation
Kannimuthu et al. (2016)	A mythology for assessing the quality of IoT based VTS	A 'novel methodology' for assessing the quality of IoT based vehicle tracking system (VTS). Their research shows that (quality of experience) QoE can improve the performance of surveillance systems in vehicle tracking system.
Guo et al. (2016)	A platform for big data management	A 'novel platform' for big data management, processing and analysis of modern power systems which includes of four subsystems: big data acquisition, big data analysis, decision making assistance and information integration.
Kumar and Bairavi (2016)	An automatic monitoring framework	Through analysing data from sensors on the patients' brain, care takers receive constant notification.
Psomakelis et al. (2016)	A service oriented architecture-based platform	A service oriented architecture –based platform, called RADICAL for the retrieval and analysis of big datasets that are stemmed from social networking sites and IoT devices.
Vuppalapati et al. (2016)	A framework for integration	A framework to integrate mobile and health sensors with the electronic health records.
Chen et al. (2016)	A collaborative sensing intelligence framework	A collaborative sensing intelligence framework to facilitate the cooperatively of analytics with integrating massive spatial-temporal data from different sources and time points.
Fukui (2016)	A system approach for the dynamic integration of analytics processing	A system approach for the dynamic integration of analytics processing by using digital technology into the existing supply chain business processes.
Zhong et al. (2017)	A big data analytics for RFID logistics data	A big data analytics for radio-frequency identification (RFID) logistics data by defining different behaviours of smart manufacturing objects (SMOs). This study extends the physical internet concept into manufacturing shop floors.

Table 3 Proposed solutions, architectures, and applications of IoT BDA (continued)

Author	*Proposed solution and application domain*	*Description*
Jin et al. (2016)	A human-centric safe and secure framework of ubiquitous living environments	A human-centric safe and secure framework of ubiquitous living environments (Ubi-Liven) for the elderly people towards seamless integration of the cyber-enabled ubiquitous holistic living support system with a physical living environment.
Usurelu and Pop (2017)	A solution, named My City Dashboard, for real-time data processing	A solution, named my city dashboard, for real-time data processing, with a special focus on scalability and modularity, in smart cities mainly an analytic processing pipeline and a dashboard prototype for their solution.

In order to solve the following challenges, several solutions are offered in the literature. To tackle technical risks raised by the 'convergence of the internet and physical objects' (Jesse, 2016), IoT requires new standards and protocols (Kannimuthu et al., 2016; Jesse, 2016) to deal with new complexities of data analytics, to handle the growth of data, to guarantee interoperability, and to extract sense from data (ibid).

Some of the other challenges of IoT especially IoT based tracking systems such as a vehicle tracking system are scalability, technology integration, performance, reliability, quality of service, and security (Kannimuthu et al., 2016).

One of the solutions is connecting the objects to a cloud system (Reddy et al., 2016). For instance, in India, as Reddy et al. (2016) argue, none of the solar power plants are connected so they cannot perform analytical analysis of the produced solar energy. They argue that connection of these objects to a cloud system will make the analysis easier. Connection of the aforementioned IoT objects in a solar power plant will make the analysis of the performance, productivity and efficiency of these systems easy.

Within health industry, integrating health data from body sensors and mobile sensors used by patients with the electronic health records not only provides a more comprehensive picture of patients but also will facilitate connection with doctors (Vuppalapati et al., 2016).

9 Proposed architectures, frameworks and solutions

A majority of work in the literature is devoted to proposing architectures, frameworks, and solutions. Nowadays, data is one of the most valuable currencies for a data driven economy. This type of economy needs to continuously implement improvement in order to better serve in the market. Therefore, some of the scholars have proposed new solutions, architectures and platforms for better acquiring, storing, processing and analysing of IoT big data. Table 3 is a summary of these studies and their proposed solutions.

As Table 3 shows, a large number of solutions and applications are offered within the domain of IoT BDA literature. I have classified the solutions into the following categories:

- Development of IoT BDA platforms: one solution is the development of a system architecture for a live city data and analytics platform (Cheng et al., 2015); a platform for smart home environments (Nadargi and Thirugnanam, 2016); a hybrid model of BDA with network core and edge analytics (Bakshi, 2016); a 'novel' platform for big data management modern power systems which includes of four subsystems: big data acquisition, big data analysis, decision making assistance and information integration (Guo et al., 2016); a service oriented architecture – based platform, called RADICAL for the retrieval and analysis of big datasets that are stemmed from social networking sites and IoT devices (Psomakelis et al., 2016); a solution, named My City Dashboard, for real-time data processing (Usurelu and Pop, 2017).
- Development of new and advanced analytical methods: proposed solutions are: development of an analytical model (Khazaei et al., 2015); a reference framework to leverage advantages of BDA, CEP and IoT (Sheriff et al., 2015); a framework to integrate BDA and iIoT technologies (Wang et al., 2015); a general approach for sensors' information processing and analytics based on big data concepts (Gachet Páez et al., 2016); an IoT based cyber physical system for industrial informatics analytics (Lee et al., 2015); a mythology for assessing the quality of IoT based VTS (Kannimuthu et al., 2016); a BDA for RFID logistics data by defining different behaviours of smart manufacturing objects (SMOs) (Zhong et al., 2017); a human-centric safe and secure framework of ubiquitous living environments (Jin et al., 2016).
- Development of new systems architectures and frameworks: a software chain architecture (Xhafa et al., 2015); an architecture based on IoT for banking and finance sector (Dineshreddy and Gangadharan, 2016); an automatic monitoring framework for sensor's health data (Kumar and Bairavi, 2016); a framework to integrate mobile and health sensors with the electronic health records (Psomakelis et al., 2016); a collaborative sensing intelligence framework (Chen et al., 2016); a system approach for the dynamic integration of analytics processing (Fukui, 2016).

Table 4 Analytics types of IoT BDA

Analysis type	*Description*	*Author*
Maintenance analytics and anomaly detection	Detecting abnormal data in cases such as an aircraft condition monitoring systems and the driven insight is used for the anticipation of aircraft maintenance operations.	Dani et al. (2015)
Physiological sensor analysis	Can be used for personalised individual stress analysis of automobile drivers. The goal is to analyse the health of vehicles' drivers; therefore, reducing road accidents.	Keshan et al. (2015)
Disease pattern recognition and network analytics	Real-time management and compact representation of multi-sensor signals generated by internet of hearts.	Kan et al. (2015)
Complex event analysis	Healthcare analysis	Sheriff et al. (2015)
Behaviour analysis	Smartphone based driver behaviour analysis	Bruwer and Booysen (2015)
Sensor analysis	Sensor's information analytics/predictive modelling with R	Gachet et al. (2016)
Sport analysis	Sport analytics and risk monitoring	Kim and Park (2015)
Principal component analysis	Analysis of modern power systems	Guo et al. (2016)
Accident prediction analysis	Predicting safety risks by analysing rail accidents	Parkinson and Bamford (2016)
Image analysis	Integrating image analysis techniques and integration and production results data to achieve quality and productivity improvements in the short term, and to generate improvement suggestions and perform optimisation throughout the supply chain	Isaka et al. (2016)
Big data analytics for radio-frequency identification (RFID) logistics data	Data analytics for RFID logistics data by defining different behaviours of smart manufacturing objects	Zhong et al. (2017)
Personal data analytics	To provide holistic support for the elderly's activities of daily living and healthcare.	Jin et al. (2016)
Quality analytics	Quality analytics in a big data supply chain and commodity data analytics for quality engineering	Tan et al. (2016)
Real-time analysis	Smart city management	Cheng et al. (2015)
	To use real-time data and predictive analytics algorithms to dynamically manage preventive maintenance policies.	March and Scudder (2017)
	Health informatics for neonatal intensive care units	Khazaei et al. (2015)
	Grid analysis to deliver analytical services to citizens and urban decision makers through the use of an integrated big data analytical framework.	Strohbach et al. (2015)
	Real-time implementation of RTOS based vehicle tracking system	Venkataraman and Cjitra (2015)
	Analysing big data stream from flight radar24 global flight monitoring system	Xhafa et al. (2015)
	Network core/edge analytics	Bakshi (2016)
	The disruption of the value chain and the rise of new software ecosystems	Jesse (2016)
	Dangerous driving behaviour detection using smartphone sensors	Li et al. (2016)
	Smart city	Mazhar et al. (2016)
	Analysis of big datasets stemming from social networking (SN) sites and internet of things (IoT) devices, collected by smart city applications and socially-aware data aggregation services	Psomakelis et al. (2016)
	To develop a collaborative sensing intelligence (CSI) framework, combining collaborative intelligence and industrial sensing intelligence.	Chen et al. (2016)
	Predictive maintenance to improve train reliability, customer service, system maintenance and even in asset management	Lee and Tso (2016)
	Mobile based educational assessment to provide almost real-time assessment services to various types of educational stakeholders including teachers, principals, parents and educational planners.	Shapsough et al. (2016)
	Traffic predictive analysis to provide a real-time smart traffic management system for smart cities	Rizwan et al. (2016)

10 Assistive technologies and the advancement of real-time IoT BDA

10.1 Mobile technology

In order to provide a holistic and comprehensive picture of the real world, technologies such as mobile and cloud are integrated into IoT solutions. While the contribution of cloud systems is mainly to hosting analytics solutions and integrating all data sources in a cloud space, mobile technologies including sensors and applications that are generators of big data. Kan et al. (2015) explains that "pervasive sensing and mobile technology deployed in large-scale IoT systems lead to the accumulation of big data". Some studies define smart objects, such as smartphones as "autonomous agents in negotiation and deploying additional resources" (Li et al., 2016). Rathore et al. (2016) define mobile technologies as valuable sources to meet the needs of urban public and the smart development of cities. Two major application of smartphone apps and sensors are utilised in

1 ECG monitoring and personalised medicine (Kan et al., 2015; Vuppalapati et al., 2016)

2 in smart transportation systems (Venkataraman and Chitra, 2015; Dineshreddy and Gangadharan, 2016; Bruwer and Booysen, 2015; Li et al., 2016; Júnior et al., 2017; Rizwan et al., 2016).

10.1.1 Real-time ECG monitoring and personalised medicine

One of the major application of mobile technologies in an IoTBDA projects is in health care in which mobile-based ECG sensing devices (Kan et al., 2015) play a major role. We can mention two technologies of mobile and e-network smart health (ibid). Four components of e-network smart health as Kan et al. (2015) describe are:

1 mobile-based ECG sensing device

2 space-time representation of cardiac electrical activity

3 optimal model-based representation of ECG signals

4 dynamic network embedding for disease pattern recognition (ibid).

Mobile sensors, such as accelerometers, location detection, wireless connectivity and cameras have also played a huge impact on personalised medicine (Vuppalapati et al., 2016). Patients do not require to carry bulky instruments for continuous monitoring of their health status. 24/7 ECG monitoring through mobile sensors or sensor-based patches is becoming important both in homecare and clinical settings. In their proposed IoT based architecture, Dineshreddy and Gangadharan (2016) mention mobile as one of the major component of a physical device management layer.

10.1.2 Real-time tracking of things and dangerous behaviours

The other domain in which smartphones have played a role is for real-time tracking of things, people, pets and vehicles (Venkataraman and Chitra, 2015). In this case technologies, such as global positioning system and the general packet radio service are used to receive data of the position of the vehicles, objects, people and even pets; and then updated information is sent to applications such as a fleet management mobile application (ibid).

In addition to real-time monitoring of things, smartphones can also be used for dangerous behaviours, such as driving behaviour (Li et al., 2016) in systems such as driver risk behaviour monitoring system, vehicle safe driving system or usage based insurance (UBI). Smartphone sensors are also used for classification of driving data of drivers with higher performance in order to better characterise the driver aggressiveness profile (Júnior et al., 2017). The other usage of smartphones in a smart transportation system is exploration of the density of traffic at various places through a mobile application (Rizwan et al., 2016).

MEMS are also considered as one of the key technologies for the mobile and connected environments. Bruwer and Booysen (2015) compare GPS and MEMS (micros electro-mechanical systems) sensors and conclude that "the MEMS inertial sensors outperform GPS platform in terms of sampling rate, battery life and the accuracy with which acceleration, braking, swerving and cornering can be detected". MEMS are mainly used in airbag systems, driver information systems, engine management, transmission control, vehicle dynamics and active suspension systems.

10.2 Cloud systems

Not only mobile technologies have played an important role in real-time IoT BDA, cloud systems have also played a significant role. As 'ubiquitous assistive technologies' (Jin et al., 2016), cloud systems have significantly facilitate real-time analysis and processing of big data generated by IoT. For instance, fog and edge computing that we mentioned earlier in this paper is enabled by cloud systems. Also, IoT application enablement platforms (AEP) have been very practical in transferring of sensor data to cloud systems (Jesse, 2016). IoT AEP as a form of Platform as a Service enables developers to rapidly deploy IoT applications. In these platforms, deployment is easy and flexible; user interfaces are developer-friendly, system architectures are cogent and on top of that they are scalable (ibid).

Cloud systems have been extensively utilised across many industries. For instance in healthcare, health locations, such as ICU has 'great potential' (Khazaei et al., 2015) for creating cloud-based health analytics solutions. Artemis cloud project was developed, for instance, to prevent diseases or to detect earlier condition onset detection (ibid). Bioinformatics cloud are also believed to be 'ideal for integrating both data and software tool' [Sheriff et al., (2015), p.2].

One of the biggest application of IoT and cloud systems are in industrial sector; for instance for monitoring important information in food production (Cao and Truong, 2016), or in production management systems (Isaka et al., 2016). One example is the works of Hitachi in developing the next generation production management system that uses IoT technology and cloud services. The goal of this project is to utilise "image analysis techniques and integration with production results data to achieve quality and productivity improvements in the short term, and to generate improvement suggestions and perform optimization throughout the supply chain by combining these techniques and results data with big data analytics over the long term" (Isaka et al., 2016).

In sum, cloud systems can increase the performance, productivity and efficiency of disparate systems, such as solar energy systems by connecting these systems to a cloud space (Reddy et al., 2016).

11 Discussion and agenda of future studies

While many studies have confirmed the value that IoT BDA can add to enterprises, many current systems are unable to deliver capabilities of IoT systems, such as real-time analysis of unstructured data. As a result, many scholarly studies have focused on the limitations of the legacy systems in order to propose solutions to better unleash the potentials of data gathered from IoT objects. We discussed that most solutions are either the introduction of new platforms or new analytical methods or new architectures and frameworks.

One of the major strength of the literature is that it provides real world empirical evidences to offer new models, architectures and solutions. And various industries are studied, which has resulted into specific categorisation of IoT, such as health IoT, industrial IoT, etc.

IoT big data have enabled enterprises to conduct new forms of analytics that were not possible by former systems, such as BI or OLAP systems. As Table 3 Shows the direction of analysis in an IoT context is mainly focused on predictive and real-time analysis of events and data streams that are generated by IoT objects. CEP and ESP are the major characteristics of IoT BDA in applications such as smart homes, smart transportation, smart traffic management, etc.

The literature has also addressed some challenges in the world of IoT BDA. One of the major challenges in an IoT BDA context is the integration of data that is produced by disparate small objects. Integration of data that are produced in various systems is a critical perquisite for any accurate predictive or real-time analysis. As a result, new concepts such as Social IoT are introduced in order to increase communication of devices in a social network.

The main question that this paper raises is that what aspects of IoT BDA should the future studies address?

One major shortcoming of the paper is that IoT BDA servitisation is not highlighted in the literature. The papers have mainly explored specific use-cases addressing a specific type of analysis. The growth of servitisation offered by IoT is undeniable. Therefore, it is necessary that the future studies addresses challenges and solutions regarding servitisation, such as IoT insight as a service, IoT analytics as a service.

Compare to the interoperability challenge, security and privacy challenges have received less attention in the literature. It is been reported that between June and November of 2016, around one billion malware-based incidences occurred (O'Brien, 2017), and it is difficult for traditional analytic tools and infrastructures to tackle against complex and high volume malware attacks. It is necessary that the literature devotes more effort to different aspects of security and privacy related to IoT BDA; such as security of infrastructures and networks, data privacy, security issues related to data management and integrity and reactive security. The attention of the literature has been mainly on the privacy and security issues of user's data.

The literature has also marginalised the prescriptive or autonomous analytics. The process of decision making changes by the advent of prescriptive analysis as analytics become the most powerful advisor of CEOs and decision makers. Most of the analytics that have been addressed in the literature are on prediction by real-time data generated by the small objects.

In connection to this gap, the other issue that is marginalised in the literature is the lack of addressing algorithmic decision making. The ability to offer the best what-if scenarios is depended on the development of algorithms as they are the key enabler to reach to the automation of decision making processing. Instead of a passive following of programmed instructions, machine learning algorithms learn from experiences and make them as a vital element of an IoT big data platform. One other research topic marginalised in the literature, in this regard, is discovering anomalies or patterns outside of a normal flow pattern.

12 Conclusions

IoT BDA plays a major role in the empowerment of modern businesses offering real-time management of events and processes. There is no doubt that IoT BDA adds enormous values to enterprises; however, it is still at its beginning stages. To increase its potentials, new architectures, platforms and solutions are offered in order to better extract, integrate, store, and process IoT big data in real-time. Through systematic review of IoT BDA, this study presents a useful starting point for the application of IoT BDA, mainly real-time analysis, across various industries and sectors. This study argues that with identifying the major applications, challenges, solutions and architectures of IoT BDA, enterprises can maximise value creation.

References

Ahlgren, B., Hidell, M. and Ngai, E.C-H. (2016) 'Internet of things for smart cities: interoperability and open data', *IEEE Internet Computing*, Vol. 20, No. 6, pp.52–56.

Almotiri, S.H., Khan, M.A. and Alghamdi, M.A. (2016) 'Mobile health (m-health) system in the context of IoT', in *IEEE International Conference on Future Internet of Things and Cloud Workshops (FiCloudW)*, pp.39–42 IEEE [online] http://ieeexplore.ieee.org/abstract/document/7592698/.

Bakshi, K. (2016) 'Big data analytics approach for network core and edge applications', in *Aerospace Conference, 2016 IEEE*, pp.1–10 IEEE [online] http://ieeexplore.ieee.org/abstract/document/7500560/.

Bashir, M.R. and Gill, A.Q. (2016) 'Towards an IoT big data analytics framework: smart buildings systems', in *High Performance Computing and Communications; IEEE 14th International Conference on Smart City; IEEE 2nd International Conference on Data Science and Systems (HPCC/SmartCity/DSS), 2016 IEEE 18th International Conference on*, pp.1325–1332, IEEE, [online] http://ieeexplore.ieee.org/abstract/document/7828529/.

Baudoin, C.R. et al. (2016) 'Deploying the industrial internet in oil and gas: challenges and opportunities', in *SPE Intelligent Energy International Conference and Exhibition, Society of Petroleum Engineers* [online] https://www.onepetro.org/conference-paper/SPE-181107-MS.

Behmann, F. and Wu, K. (2015) *Collaborative Internet of Things*, 1st ed., Chichester, West Sussex, Wiley, UK.

Bodin, W.K., Jaramillo, D., Marimekala, S.K. and Ganis, M. (2015) 'Security challenges and data implications by using smartwatch devices in the enterprise', in *2015 12th International Conference and Expo on Emerging Technologies for a Smarter World (CEWIT)*, pp.1–5, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7338164/.

Bruwer, F.J. and Booysen, M.J. (2015) 'Comparison of GPS and MEMS support for smartphone-based driver behavior monitoring', in *2015 IEEE Symposium Series on Computational Intelligence*, pp.434–441, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7376644/.

Buckland, E., Ranken, M., Arnott, M. and Owen, P. (2016) *IoT Global Forecast and Analysis 2015-25* [online] https://machinaresearch.com/report/iot-global-forecast-analysis-2015-25/ (accessed 20 July 2017).

Buyya, R. and Dastjerdi, A.V. (2016) *Internet of things: Principles ad Paradigms*, MK Morgan Kaufmann.

Cao, T-D. and Truong, H-L. (2016) 'Analyzing and conceptualizing monitoring and analytics as a service for grain warehouses', in *Recent Developments in Intelligent Information and Database Systems*, pp.161–171, Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-31277-4_14.

Chen, Y., Lee, G.M., Shu, L. and Crespi, N. (2016) 'Industrial internet of things-based collaborative sensing intelligence: framework and research challenges', *Sensors*, Basel, Switzerland, Vol. 16, No. 2, https://doi.org/10.3390/s16020215.

Cheng, B., Longo, S., Cirillo, F., Bauer, M. and Kovacs, E. (2015) 'Building a big data platform for smart cities: experience and lessons from santander', in *2015 IEEE International Congress on Big Data (BigData Congress)*, pp.592–599, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7207275/.

CISCO (2017) *Internet of Everything: Glossary* [online] http://ioeassessment.cisco.com/ (accessed 20 July 2017).

Dani, M.C., Freixo, C., Jollois, F-X. and Nadif, M. (2015) 'Unsupervised anomaly detection for aircraft condition monitoring system', in *Aerospace Conference, 2015* IEEE, pp.1–7, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7119138/.

Dineshreddy, V. and Gangadharan, G.R. (2016) 'Towards an 'internet of things' framework for financial services sector', in *2016 3rd International Conference on Recent Advances in Information Technology (RAIT)*, pp.177–181, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7507897/.

Fortino, G. and Trunfio, P. (Eds.) (2016) *Internet of Things Based on Smart Objects: Technology, Middleware and Applications* (Softcover reprint of the original 1st ed. 2014 edition) Springer.

Fukui, T. (2016) 'A systems approach to big data technology applied to supply chain', in *2016 IEEE International Conference on Big Data (Big Data)*, pp.3732–3736, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7841041/.

Gachet Páez, D., Morales Botello, M.L., Puertas, E. and De Buenaga, M. (2016) 'Health sensors information processing and analytics using big data approaches', in *Internet of Things. IoT Infrastructures: Second International Summit, IoT 360° 2015*, Rome, Italy, 27–29 October 2015, Revised Selected Papers, Part I, pp.481–486, Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-47063-4_52.

Geng, H. (Ed.) (2017) *Internet of Things and Data Analytics Handbook*, 1st ed., Wiley, Hoboken, New Jersey.

Grabis, J. and Kirikova, M. (2011) 'Perspectives in business informatics research', *10th International Conference, BIR 2011*, Riga, Latvia, 6–8 October 2011, Proceedings, Springer Science and Business Media.

Guo, Y., Feng, S., Li, K., Mo, W., Liu, Y. and Wang, Y. (2016) 'Big data processing and analysis platform for condition monitoring of electric power system', in *Control (CONTROL), 2016 UKACC 11th International Conference on*, pp.1–6, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7737581/.

Hamblen, M. (2016) *Cisco Names 10 Cities Using Its Cloud-Based Smart Service*, 14 November 2016 [online] http://www.computerworld.com/article/3141452/internet-of-things/cisco-names-10-cities-using-its-cloud-based-smart-service.html (accessed 10 July 2017).

Hans, V., Sethi, P.S. and Kinra, J. (2015) 'An approach to IoT based car parking and reservation system on Cloud', in *2015 International Conference on Green Computing and Internet of Things (ICGCIoT)*, pp.352–354, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7380487/.

Holdowsky, J., Matho, M., Raynor, M. and Cotteleer, M. (2015) *Inside the Internet of Things (IoT) A Primer on the Technologies Building the IoT* [online] https://dupress.deloitte.com/dup-us-en/focus/internet-of-things/iot-primer-iot-technologies-applications.html.

Howell, S., Rezgui, Y. and Beach, T. (2017) 'Integrating building and urban semantics to empower smart water solutions', *Automation in Construction* [online] http://www.sciencedirect.com/science/article/pii/S0926580517301759 (accessed 15 August 2017).

Hwang, K. and Chen, M. (2017) *Big-Data Analytics for Cloud, IoT and Cognitive Computing*, 1st ed., Wiley, Chichester, UK, Hoboken, NJ.

Isaka, H., Nagayoshi, H., Yoshikawa, H., Yamada, T. and Kakeno, N. (2016) 'Next generation of global production management using sensing and analysis technology', *Hitachi Review*, Vol. 65, No. 5, pp.47–52.

Jesse, N. (2016) 'Internet of things and big data – the disruption of the value chain and the rise of new software ecosystems', *IFAC-PapersOnLine*, Vol. 49, No. 29, pp.275–282.

Jin, Q., Wu, B., Nishimura, S. and Ogihara, A. (2016) 'Ubi-Liven: a human-centric safe and secure framework of ubiquitous living environments for the elderly', in *2016 International Conference on Advanced Cloud and Big Data (CBD)*, pp.304–309.

Júnior, J.F., Carvalho, E., Ferreira, B.V., De Souza, C., Suhara, Y., Pentland, A. and Pessin, G. (2017) 'Driver behavior profiling: An investigation with different smartphone sensors and machine learning', *PLoS One*, Vol. 12, No. 4, p.e0174959.

Kan, C., Chen, Y., Leonelli, F. and Yang, H. (2015) 'Mobile sensing and network analytics for realizing smart automated systems towards health internet of things', in *2015 IEEE International Conference on Automation Science and Engineering (CASE)*, pp.1072–1077, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7294241/.

Kannimuthu, S., Somesh, C.K., Mahendhiran, P.D., Bhanu, D. and Bhuvaneshwari, K.S. (2016) 'Certain investigation on significance of internet of things (IoT) and big data in vehicle tracking system', *Indian Journal of Science and Technology*, Vol. 9, No. 39 [online] http://52.172.159.94/index.php/indjst/article/view/87427.

Keshan, N., Parimi, P.V. and Bichindaritz, I. (2015) 'Machine learning for stress detection from ECG signals in automobile drivers', in *2015 IEEE International Conference on Big Data (Big Data)*, pp.2661–2669) IEEE [online] http://ieeexplore.ieee.org/abstract/document/7364066/.

Khazaei, H., Mench-Bressan, N., McGregor, C. and Pugh, J.E. (2015) 'Health informatics for neonatal intensive care units: an analytical modeling perspective', *IEEE Journal of Translational Engineering in Health and Medicine*, Vol. 3, pp.1–9.

Kim, N.J. and Park, J.K. (2015) 'Sports analytics and risk monitoring based on hana platform: sports related big data and IoT trends by using HANA in-memory platform', in *2015 International SoC Design Conference (ISOCC)*, pp.221–222, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7401795/.

Kumar, K.S. and Bairavi, K. (2016) 'IoT based health monitoring system for autistic patients', in *Proceedings of the 3rd International Symposium on Big Data and Cloud Computing Challenges (ISBCC–16')*, pp.371–376) Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-30348-2_32.

Lee, C.K.M., Yeung, C.L. and Cheng, M.N. (2015) 'Research on iot based cyber physical system for industrial big data analytics', in *2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pp.1855–1859, IEEE.

Lee, T. and Tso, M. (2016) 'A universal sensor data platform modelled for realtime asset condition surveillance and big data analytics for railway systems: developing a 'smart railway' mastermind for the betterment of reliability, availability, maintainbility and safety of railway systems and passenger service', in *SENSORS, 2016* IEEE, pp.1–3, IEEE.

Li, F., Zhang, H., Che, H. and Qiu, X. (2016) Dangerous driving behavior detection using smartphone sensors', in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp.1902–1907, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7795864/.

Li, Z. (2015) COAST: a connected open platform for smart objects', in *2015 2nd International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*, pp.166–172, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7402060/.

March, S.T. and Scudder, G.D. (2017) 'Predictive maintenance: strategic use of IT in manufacturing organizations', *Information Systems Frontiers*, pp.1–15.

Mirse, H.P. Fim, C. and Bamford, F.G. (2016) *The Potential for Using Big Data Analytics to Predict Safety Risks by Analysing Rail Accidents* [online] https://pdfs.semanticscholar.org/b7a6/0acb8c401fdc1b3c2a0fdd43f9f714b95ad1.pdf.

Nadargi, A. and Thirugnanam, M. (2016) 'Addressing identity and location privacy of things for indoor – case study on internet of everything's (IoE)', in *Proceedings of the 3rd International Symposium on Big Data and Cloud Computing Challenges (ISBCC–16')*, pp.377–386, Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-30348-2_33.

O'Brien, S. (2017) *Challenges to Cyber Security and How Big Data Analytics Can Help*, 4 May 2017 [online] https://www.datameer.com/company/datameer-blog/challenges-to-cyber-security-and-how-big-data-analytics-can-help/ (accessed 10 July 2017).

O'Reilly, T. (2014) *#IoTH: The Internet of Things and Humans*, 16 August 2014 [online] https://www.oreilly.com/ideas/ioth-the-internet-of-things-and-humans (accessed 10 July 2017).

Parkinson, H.J. and Bamford, G.J. (2016) 'Big data and the virtuous circle of railway digitization', *INNS Conference on Big Data*, October, pp.314–322, Springer, Cham.

Paul, A., Ahmad, A., Rathore, M.M. and Jabbar, S. (2016) 'Smartbuddy: defining human behaviors using big data analytics in social internet of things', *IEEE Wireless Communications*, Vol. 23, No. 5, pp.68–74.

Psomakelis, E., Aisopos, F., Litke, A., Tserpes, K., Kardara, M. and Campo, P.M. (2016) 'Big IoT and social networking data for smart cities: algorithmic improvements on big data analysis in the context of RADICAL city applications', *ArXiv Preprint ArXiv:1607.00509* [online] https://arxiv.org/abs/1607.00509 (accessed 10 July 2010).

Pugh-Jones, P. (2015) 'Streaming analytics and IoT', Presented at the *SAS Forum*, United Kingdom [online] https://www.sas.com/content/dam/SAS/en_gb/doc/other1/events/sasforum/slides/day2/pjone-internet-things.pdf (accessed 10 July 2010).

Rathore, M.M., Ahmad, A. and Paul, A. (2016) 'IoT-based smart city development using big data analytical approach', in *IEEE International Conference on Automatica (ICA-ACCA)*, pp.1–8, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7778510/.

Reddy, B.V., Sata, S.P., Reddy, S.K. and Babu, B.J. (2016) 'Solar energy analytics using internet of things', *International Journal of Applied Engineering Research*, Vol. 11, No. 7, pp.4803–4806.

Rizwan, P., Suresh, K. and Babu, M.R. (2016) 'Real-time smart traffic management system for smart cities by using Internet of things and big data', in *International Conference on Emerging Technological Trends (ICETT)*, pp.1–7, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7873660/.

Scales, I. (2016) *IoT 2025: 27 billion devices spewing 2 zettabytes of data and generating $3 trillion|TelecomTV* [online] http://www.telecomtv.com/articles/iot/iot-2025-27-billion-devices-spewing-2-zettabytes-of-data-and-generating-3-trillion-13872/ (accessed 20 July 2017).

Schatzinger, S. and Lim, C.Y.R. (2017) 'Taxi of the future: big data analysis as a framework for future urban fleets in smart cities', in *Smart and Sustainable Planning for Cities and Regions*, pp.83–98, Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-44899-2_6.

Shapsough, S., Hassan, M., Shapsough, S.E. and Zualkernan, I.A. (2016) 'IoT technologies to enhance precision and response time of mobile-based educational assessments', in *2016 International Conference on Computational Science and Computational Intelligence (CSCI)*, pp.202–205, I EEE [online] http://ieeexplore.ieee.org/abstract/document/7881338/.

Sheriff, C. I., Naqishbandi, T. and Geetha, A. (2015) 'Healthcare informatics and analytics framework', in *2015 International Conference on Computer Communication and Informatics (ICCCI)*, pp.1–6, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7218108/.

Strohbach, M., Ziekow, H., Gazis, V. and Akiva, N. (2015) 'Towards a big data analytics framework for IoT and smart city applications', in *Modeling and Processing for next-Generation Big-Data Technologies*, pp.257–282 Springer [online] http://link.springer.com/chapter/10.1007/978-3-319-09177-8_11.

Talluri, R. (2017) *How to Bring True Interoperability to the Internet of Things | Network World* [online] http://www.networkworld.com/article/3183538/internet-of-things/how-to-bring-true-interoperability-to-the-internet-of-things.html (accessed 22 July 2017).

Tan, J.S., Ang, A.K., Lu, L., Gan, S.W. and Corral, M.G. (2016) 'Quality analytics in a big data supply chain: commodity data analytics for quality engineering', in *Region 10 Conference (TENCON), 2016 IEEE*, pp.3455–3463 IEEE [online] http://ieeexplore.ieee.org/abstract/document/7848697/.

Usurelu, C-C. and Pop, F. (2017) 'My city dashboard: real-time data processing platform for smart cities', *Journal of Telecommunications and Information Technology*, No. 1, p.89.

Venkataraman, A. and Chitra, P. (2015) 'Real time implementation of RTOS based vehicle tracking system', *Biosciences Biotechnology Research Asia*, Vol. 12, No. 1, pp.237–241.

Vermesan, O. and Friess, P. (Eds.) (2013) *Internet of Things: Converging Technologies for Smart Environments and Integrated Ecosystems*, River Publishers.

Vijayalakshmi, S.R. and Murugananda, S. (2016) 'Study and analysis of internet of things for monitoring fire', *International Journal of Control Theory and Applications*, Vol. 9, No. 13, pp.6261–6265.

Vuppalapati, C., Ilapakurti, A. and Kedari, S. (2016) 'The role of big data in creating sense EHR, an integrated approach to create next generation mobile Sensor and wearable data driven electronic health record (EHR)', in, *2016 IEEE Second International Conference on Big Data Computing Service and Applications (BigDataService)*, pp.293–296, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7474387/.

Wang, H., Osen, O. L., Li, G., Li, W., Dai, H-N. and Zeng, W. (2015) 'Big data and industrial internet of things for the maritime industry in northwestern Norway', in *TENCON 2015-2015 IEEE Region 10 Conference*, pp.1–5, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7372918/.

Xhafa, F., Naranjo, V., Caballé, S. and Barolli, L. (2015) 'A software chain approach to big data stream processing and analytics', in *2015 Ninth International Conference on Complex, Intelligent and Software Intensive Systems (CISIS)*, pp.179–186, IEEE [online] http://ieeexplore.ieee.org/abstract/document/7185183/ (accessed 10 October 2017).

Zhong, R.Y., Xu, C., Chen, C. and Huang, G.Q. (2017) 'Big data analytics for physical internet-based intelligent manufacturing shop floors', *International Journal of Production Research*, Vol. 55, No. 9, pp.2610–2621.