Challenges and Recommended Technologies for the Industrial Internet of Things: A Comprehensive Review

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4 authors, including:

Mina Younan
Minia University

Essam H Houssein
Minia University Faculty of Computers and Information

Mohamed Elhoseny
Mansoura University

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Challenges and recommended technologies for the industrial internet of things: A comprehensive review

Mina Younan [a], Essam H. Houssein [a], Mohamed Elhoseny [b,c], Abdelmgeid A. Ali [a]

[a] Faculty of Computers and Information, Minia University, Egypt
[b] Faculty of Computers and Information, Mansoura University, Egypt
[c] Scientific Group for Research and Technology (SGRT), Egypt

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ABSTRACT

Physical world integration with cyber world opens the opportunity of creating smart environments; this new paradigm is called the Internet of Things (IoT). Communication between humans and objects has been extended into those between objects and objects. Industrial IoT (IIoT) takes benefits of IoT communications in business applications focusing in interoperability between machines (i.e., IIoT is a subset from the IoT). Number of daily life things and objects connected to the Internet has been in increasing fashion, which makes the IoT be the dynamic network of networks. Challenges such as heterogeneity, dynamicity, velocity, and volume of data, make IoT services produce inconsistent, inaccurate, incomplete, and incorrect results, which are critical for many applications especially in IIoT (e.g., health-care, smart transportation, wearable, finance, industry, etc.). Discovering, searching, and sharing data and resources reveal 40% of IoT benefits to cover almost industrial applications. Enabling real-time data analysis, knowledge extraction, and search techniques based on Information Communication Technologies (ICT), such as data fusion, machine learning, big data, cloud computing, blockchain, etc., can reduce and control IoT and leverage its value. This research presents a comprehensive review to study state-of-the-art challenges and recommended technologies for enabling data analysis and search in the future IoT presenting a framework for ICT integration in IoT layers. This paper surveys current IoT search engines (IoTSEs) and presents two case studies to reflect promising enhancements on intelligence and smartness of IoT applications due to ICT integration.

1. Introduction

Components of the Wireless Sensor Networks (WSNs) integrated in daily life objects (e.g., lamb, car, persons, etc.) in order to give piece of information about their states on the Internet. This integration produces a new paradigm called the Internet of Things (IoT), which was originated for the first time by Kevin Ashton in 1999 [1]. Now the IoT becomes a technology of connecting everyday things and objects to the Internet for monitoring, controlling, and understanding their surrounding environment [2,3]. Heterogeneous networking architectures (WSNs, Vehicular Networks, Mobile Communication Networks, etc.) produce extra paradigms such as Body Sensor Network (BSN) and Web of Things (WoT), etc. The WoT relays on RESTful web services and web tools for enabling its users to get benefits of the IoT in a visual form [4,5]. WoT is called the future IoT. In brief, WSNs evolved into the IoT, which then evolved into the WoT [6]. Heterogeneous IoT (HetIoT) [2] is a new paradigm for expressing that IoT is being employed in numerous application areas, such as (environmental monitoring, smart home, smart city, intelligent transportation, advanced manufacturing, etc.) [7–10].

Industry 4.0 or Industrial IoT (IIoT) expresses the industrial use cases applications of the IoT (e.g., tracking sales and goods for predicting future business issues), which means that IIoT is a subset of the IoT [11]. The term industry 4.0 is used to reflect economic impact, while IIoT is used to reflect technological improve in industry. IIoT applications basis on how to utilize capabilities and facilities of sensors communications to improve production processes in the industry, while IoT applications concentrate on enabling its user to be in more comfortable environments (e.g., smart home) [11]. Industry automation already includes devices communications, but IIoT takes benefits of IoT global connections in industrial applications. Sisinni et al. [11] summarize relation between IoT,

E-mail addresses: mina.younan@mu.edu.eg (M. Younan), essam.halim@mu.edu.eg (E.H. Houssein), mohamed_elhoseny@mans.edu.eg (M. Elhoseny), dr_abdelmgeid@mu.edu.eg (A.A. Ali)

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IIoT, Industry 4.0, and Cyber Physical Systems (CPS) such as follows:

- Industry 4.0 ⊂ IIoT ⊂ IoT. - Industry 4.0 = IIoT ∩ CPS.

IIoT focuses mainly on interoperability between manufacturing systems to trigger automation and synchronization for closed ecosystems more rapidly. According to McKinsey [12,13], interoperability affects 40% from the IoT benefits. Machine learning, big data, fog computing, cloud computing, and blockchain technologies enable IoT to build secure digital transformation blocks (i.e. transformational IoT). In this review, this composition of technologies (data science and information communication technologies) is referred as (ICT). These technologies work together to fulfill potential of IoT for creating billions or trillions of dollars in business (i.e., IIoT). The core of ICT integration in the IIoT is to allow gaining incredible insights and decisions for enhancing manufacturing and production processes. IIoT is sustained by machine learning and big data, because it mainly depends on machine-to-machine communications. Thus technologies that enable automated decision support and services like discovery, searching, and information exchange are recommended especially for the IIoT and generally for the IoT. Major challenge faces the IIoT is number of Smart Things (SThs), which are in increasing fashion (exponential growth) [3,14] and expected to reach the order of billions in the next years.

There will be nearly 50 billion devices connected to the Internet [15,16], with a $14.4 trillion business opportunities in the industry (according to Cisco Systems). Regardless of this increasing number of daily life heterogeneous objects, extra sensors and devices also join the IoT in order to increase accuracy of sensed data, which results in big data streams. Answering real-time queries becomes challenging task; where IoT search engines (IoTSEs) fight against keeping indices as up-to-date as possible [3,17]. IoTSEs are essential for the IIoT and IoT in order to reveal their potential in the consumer and industrial applications. IoTSE is studied in more details in this review. Because IIoT is a subset from the IoT, main architecture and challenges are clarified in general on the IoT. But regarding the IIoT, case studies are discussed in the field of health-care and smart transportation.

Therefore, the contribution of this paper is to present an exhaustive overview for the future IoT and related challenges shading the light on the required data science and information communication technologies (ICT) such as artificial intelligence, cloud computing, etc. Industrial IoT (IIoT) takes benefits of IoT in business applications. Because IoT is inclusive than IIoT, almost work in this review on the architecture, challenges, and required services are common for the IoT and IIoT. For revealing most of their benefits, ICT are required to be integrated in a form that enhance search and discovery services: This review presents general IoT architecture and main challenges on each layer discussing their root causes, surveys current research work on ICT in the IoT. This paper surveys current IoT search engines (IoTSEs) and opportunities to integrate ICT to enhance SThs search and discovery. Also it studies how IIoT applications (e.g., smart transportation and health-care) get benefits form ICT implementations. New research trends are discussed at the end of this review.

The remainder of this article is ordered such as shown in Fig. 1. Section 2 presents a literature review about scalability of the future IoT and resulting big data followed by ICT implementations in the IoT. Section 3 discusses the IoT architecture and highlights challenges on each layer, while Section 4 reviews most relevant ICT focusing on how they can be integrated to enhance the IoT. Section 5 studies thoroughly IoT search engines problems, current related work, and suggested ICT enhancement to present search service for human and machine. Section 6 shows the impact of using ICT in the IoT on two case studies. Finally, future research directions are discussed in Section 7 followed by conclusion in Section 8.

2. Literature review

The IIoT has become one of the key development technologies that adds smartness to our business life. Major IIoT characteristics, but not limited, include large scale networks and applications, devices and networks heterogeneity, huge number of connected devices, dynamic devices' states and measurements, and resulting massive data produced. Because heterogeneity and scalability are two faces for one coin, and the same for huge data and dynamicity (i.e., real-time data streams), this section is organized into four subsections. First subsection discusses current studies on heterogeneity of resources and scalability for enabling scalable IoT. Second subsection presents current research work on IoT data streams followed by discovery and search in the IoT. Fourth subsection surveys current ICT implementations in the IoT.

2.1. Heterogeneity and scalability

Scalability in IoT, for integrating everything into the Internet, requires standardized communication protocols and new distributed and dynamic network models and topologies. Kyu Lee et al. [14] present a review on the future IoT architecture for connected exponential number of daily life objects to the IoT. They highlight technical details of the IoT infrastructure (i.e., focusing

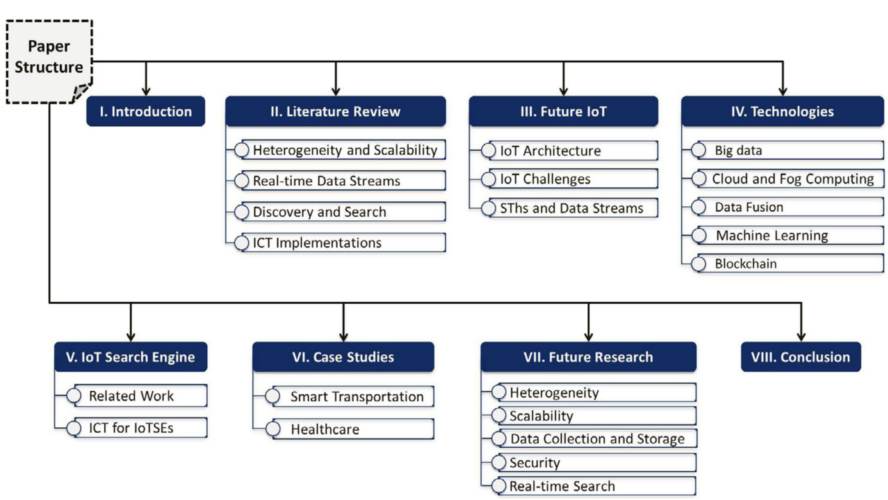

Fig. 1. Paper structure.

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Table 1
A brief summary for most relevant research works.

Category	Ref.	Year	Method
Scalability & Heterogeneity	[2]	2018	Survey future IoT architecture, research trends, and proposed solutions.
	[14]	2017	Survey IoT architecture focusing on number of SThs in the network layer.
	[20]	2017	Proposes a semantic interoperability model based on RDF and SPARQL.
	[22]	2017	Use BLE profile based on DDS with common data format.
	[23]	2016	
	[24]	2012	
	[25]	2009	Services oriented middleware.
	[26]	2007	
	[21]	2016	Extract common attributes from datasets (e.g., unique id, creation date, etc.).
Big data	[27]	2018	Propose a generic framework consisting of three phases for processing and analyzing real-time big data in smart transportation systems.
	[28]	2017	Survey: advances in big data and IoT and requirements.
Heterogeneity & Big data	[29]	2017	Use the idea of plug-in (Similar to [30]) for integrating new rules for extracting common attributes from datasets for receiving, storing and accessing SThs' data.
	[31]	2017	Propose a framework (CSF) based Semantic Fusion.
	[32]	2014	A retrieval system (Acrost) based on semantic awareness.
	[33]	2013	
	[34]	2009	
	[35]	2009	Semantic middleware.
	[36]	2008	

on the network layer), clarify difficulty of using client-server model in the future IoT, and discuss current research projects in Europe, Asia, and the United States.

For enlarging applications scale in the IoT, authors in [18] study challenges and opportunities to integrate data fusion in ubiquitous environments, while authors in [19] survey cloud and IoT integration (i.e., CloudIoT) discussing main facing challenges such as heterogeneity and security, they also recommend future search on some features such as efficiency of power consumption, storage, handling large volume of data, etc.

Jabbar et al. [20] propose a semantic interoperability model (IoT-SIM) for integrating heterogeneous IoT devices in healthcare domain. Heterogeneity in the IoT means implementing different communication protocols, data formats, and technologies. In their proposed framework, data analytics were applied on collected datasets and transformed into Resource Description Framework (RDF) to add semantics, where SPARQL was used as a query language. Montori et al. [21] propose an architecture for fusing heterogeneous data from multiple sources by generalizing common metadata in datasets, such as (stream id, stream name, geolocalization, description, etc.) in JSON format from different data sources (ThingSpeak and SparkFun). For the technical part, Park et al. [22] use Bluetooth Low Energy (BLE) profile adaptor for solving communication interoperability among SThs based on distributed data services middleware.

Qiu et al. [2] describe future IoT with heterogeneity (HetIoT); they discussed future IoT layers, related challenges and current solutions. For enabling integration of heterogeneous computing and services, Razzaque et al. [23] review existing middleware solutions called orchestrator and extract set of requirements, related to middleware services and infrastructure. Functional requirements for middleware services are: discovering and managing data, resources, events, and codes, while nonfunctional requirements are: security, ease-of development, integrity, availability, etc. The architectural requirements are: service-oriented, distributed, context-aware, lightweight, and autonomous. A brief summary for some selected research works that address heterogeneity in the IoT is shown in Table 1.

2.2. Real-time data streams

IoT applications continuously enhance the connectivity of objects which resulting in huge data streams. Tonjes et al. [37] proposed a framework for addressing real-time data stream analysis gap using semantics. Wu et al. [29] proposed a framework called *HSFRH-IoT* for data retrieval from hybrid IoT storage based in plug-in idea of integrating new formats definitions and rules for extracting common attributes, while, Guo et al. [31] proposed a framework called Crowdsourcing Semantic Fusion (CSF), which implements semantic fusion on two levels (document level and object level) for improving IoT media big data retrieval. Discussed challenges were: (1) data providers (resources) heterogeneity, (2) storage heterogeneity (i.e., data formats), (3) multi-expression (e.g., amounts of noise), and (4) dissemination socialization.

Ahmed et al. [28] discussed big data requirements (connectivity, storage, QoS, real-time analytics, and benchmark) and concluded that IoT data become useless without analytics. Big data techniques are concentrated on data storage and processing services, while data analytics enable business decisions to be taken in different IoT applications such as smart transportation and smart home. They recommended implementing semantics and applying seamless integration and interoperability for solving protocols' heterogeneity. Babar and Arif [27] propose an architecture framework for smart transportation, which consists of three phases for real-time big data processing, first phase for filtering, reduction, and data transformation, second phase for processing and analyzing data. The third phase is for making decisions and managing events. Summary of research works that address real-time big data in the IoT is shown in Table 1.

2.3. Discovery and search

As mentioned above, communication between humans-machines in the IoT has been extended into those between machines-machines [10]. Number of human users of the IoT will be less than number of SThs [17]. The IoT uses web tools (i.e., WoT) to provide its users with abstract and summarized data about SThs and Entities of Interests (EoIs) in visual forms in the real-time (i.e., using dynamic pages like AJAX pages) [38]. On the other hand, in the future IoT, machines will not wait to get instructions and information from its users, but it will take almost of their decisions in the real-time depending on decisions taken by other machines. This recommends the future IoT to provide services for preparing and summarizing such huge and highly frequently data in a convenient form for heterogeneous SThs and EoIs. So doing

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search and performing analytics on IoT data streams in the real-time becomes significant and challenging tasks [17,39].

Recently, some solutions were proposed for enhancing discovery and search services in the IoT. Surveys [3,4,38,39] study current motivation scenarios, challenges, and presented solutions for searching and discovery problem in the IoT and the WoT. Research works interested in presenting solutions in this area could be categorized based on their goals into two main classes: (a) research works propose new architectures for IoT and WoT search engines (IoTSEs and WoTSEs), and (b) research works present some solutions for enhancing IoTSEs and WoTSEs performance [3]. Dyser [40], Shodan [41,42], SenseWeb [43], Thingful [44], IoT-SVKSearch [45], Thingseek [46], WoTSF [17] are some examples of research works on IoTSE and WoTSEs architectures. Datta and Bonnet [47] propose a framework presents simple RESTful services for discovering and accessing indexed resources' URIs. Research work [48–50] tackle problem of indexing large volume of data in the IoT. Truong et al. [51] propose a new method for searching for similar sensors based on their context. DiscoWoT [30] is a service for discovering SThs written in multiple formats. For the same purpose, other solutions like [52], which aggregates GPS data for estimating traffic state, could be integrated as well.

2.4. ICT implementations

In accordance with our knowledge, there is no research paper is consecrated to survey the impact of integrating ICT in the IoT for addressing challenges of the future IoT and enabling search and discovery services for SThs and resources. There are few research papers that present partial topics from ICT in the IoT (e.g., machine learning implementation, utilization of big data tools in the IoT, etc.). Research work [53] presents a comprehensive survey on the required technologies for sensing and networking layers (communications, networking, etc.), and recommends services such as searching and discovery services for enabling and realizing scalable IoT in the future (discussed in more details in [54]). But they didn't mention the ICT and their impact on the future IoT. They shaded the light on two main challenging issues: IoT network size and networks coexistence (i.e., network heterogeneity) and recommended using standardized approaches for enabling global identity and discovery for things and services in secure manners.

Automatic discovery and search for IoT data and resources in the real-time are key services that future IoT should provide [17,54,55]. Most of industrial applications in IIoT usually require automated decision support. Thus ICT [56] based computational intelligence such as data fusion [15,57], machine learning [58], data mining [59], cloud computing [60], context aware computing [16], etc. would have a major impact on the future IoT. These technologies enable dealing with the massively produced and frequently changed data, in order to achieve the open IoT ecosystem of heterogeneous systems and platforms (i.e., a fully integrated system of systems that capable of making real-time decisions).

Because ICT enable interoperability at device and application levels [6,56], ICT could be organized into two levels: (a) infrastructure level, for enabling devices communication and information exchange, and (b) data level, for understanding and extracting knowledge data in the real-time for making decisions and controls.

- *Infrastructure Level.* Authors in [6], discuss IoT layers and required technologies for devices identification and communication (i.e., on the hardware level). Also, they recommended factors such as energy, latency, topology, scalability, security, and throughput to be considered in the future IoT architecture. For the IoT architecture (i.e., Hardware technologies for sensing and networking layers), there are two types of technologies [61]: (a) data acquisition technologies (e.g., barcode, radio-frequency identification (RFID), etc.) and (b) networking technologies (e.g., Wi-Fi, ZigBee, etc.).
  Lin et al. [62] survey IoT architecture and study the impact of fog computing on the IoT for decreasing response time required for accessing data from central cloud servers. They also presented an overview for security and privacy issues in the IoT. For the same purpose, Information Flow of Things (IFoT) framework was proposed in [63] for processing real-time IoT streams depending on distributed components instead of the cloud. Main challenges for real-time processing are timeliness and huge data (i.e., require intelligent system for understanding contents). The research work [10] presents an overview for the IoT discussing required hardware technologies for leveraging the IoT connections from machine-to-human to machine-to-machine; where intelligent decisions control these connections.
- *Data Level.* Most of surveys on the IoT concern with WSNs, IoT architecture, applications, and security and privacy issues, while few papers are on heterogeneity, data fusion, and context awareness. Authors in [2] spot the light on data fusion, decision making, energy consumption, and security issues as future research trends for the future IoT. Integrating data fusion technology in the IoT can reduce networking traffic, energy consumption, and enhance the accuracy of the results [15], and results in optimizing the IoT performance [64]. Alam et al. [15] surveyed data fusion in the IoT, they discussed mathematical methods, IoT environments, opportunities, challenges, and applications' areas that could benefit from the data fusion. Pires et al. [65] implemented data fusion techniques for identifying mobile activities, they classified techniques into four types and concluded that choice of best technique rely on types of sensors, data representation, and constraints of sensors and algorithms.
  Bagley et al. [66] present a prototype for live video transmission via distributed data service (DSS) middleware highlighting importance of existence of such services in the future IoT, especially for smart transportation applications. DSS provides a solid bridge for heterogeneous platforms and applications. Medjahed et al. [67] propose a tele-monitoring system called *EMUTEM* for elderly people, which implements multi-modal fusion based on fuzzy logic in order to increase system accuracy and robustness. They use fuzzy logic, because (1) it deals with imprecision and uncertainty, (2) has a wide range of operators, and (3) works on numeric and symbolic computations. Khaleghi et al. [68] propose an IoT system in the field of fish farming industry, which optimizes data fusion values by using maximum likelihood estimation. Authors in [51] propose a framework using fuzzy logic for searching for similar sensors that produce similar readings. Authors in [59] present a survey for discussing data mining technologies in the IoT (clustering, classification, and pattern mining). They also conclude that integration of cloud computing, big data, and smart grid with the IoT increase life smartness and partially solve problem of increasing number of devices connected and their data produced. Data fusion, filtering, abstraction, compression, summarization, prediction are hot research issues, also technologies of incremental learning and data securing have a critical impact on the future IoT. Authors in [33] recommended using middleware solutions for managing context in the IoT.

To sum up, all research works discussed in this section reflect the importance of ICT integration in the IoT to build a new vision for the future IoT concentrating on how the IoT architecture should be to enhance services it presents in order to face incremental challenges on SThs and data levels. Standardization in the future IoT

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should be enhanced [53], because it eases extensibility and interoperability between SThs. Also sharing context information taking benefits of the cloud computing and edge computing eases mobility and transition between SThs and can aide in reducing additional costs and efforts for deploying and managing extra SThs. Enabling extensible context awareness makes the IoT loosely coupled. Summary of research works that implement or recommend some of ICT for the future IoT is shown in Table 1. On the light of this study, this review puts an initial vision for ICT integration to serve IoTSEs to crawl, index and search IoT data in the real-time (details in Section 5).

3. The future IoT

The IoT has many definitions, in general, The IoT could be defined as a dynamic network of networks, where sensors and actuators allow states of things (e.g. persons, objects, etc.) they attached to be monitored and controlled through the Internet [38]. In brief, the attached sensors and actuators add smartness to ordinary things and their environments to be SThs and intelligent spaces [59]. Functionalities of SThs could be abstracted as services. As IoT in more inclusive than IIoT, this section discusses main layers of IoT architecture and related challenges followed by main causes of these challenges.

3.1. The architecture of the future IoT

IoT architecture could be organized into different number of layers according to business requirements [6], for example, the architecture of telecommunications systems consists of sensing, accessing, networking, middleware, and application layers. Wan et al. [69] discussed IIoT architecture on three main layers: physical layer, control layer, and application layer. Authors in [2,6,14] organized the architecture of the IoT into main four layers (see Fig. 2) such as follows:

- *Sensing layer (perception layer [62])*, where smart devices (e.g., RFID, GPS) are deployed in the infrastructure layer. IIoT supports communication between SThs and the cloud [69]. Main characteristics of this layer are heterogeneity and big number of SThs used to build IoT applications. Most of these devices have limited resources and different capabilities. The infrastructure layer implements different technologies such as Wi-Fi, WSN, etc., where SThs provide different connectivity (i.e., heterogeneity based network level). Power consumption is a critical challenge that could be solved by using alternative power resources (e.g., natural resources) and implementing wireless recharging technologies for difficult and critical events and places. Implementing some technologies for filtering and fusing sensed data and reduces power consumption for sending data to fog and cloud servers [15].Cloud capabilities enable data providers in the IoT to store massive information and perform analysis, and decisions making tasks. Fog layer decreases distance between SThs and the cloud. AI is required for the IIoT, which mainly basis on interoperability between SThs for enabling automated decisions support.
- *Networking layer*, where some protocols, such as IPv6 over Low power Wireless Personal Area Networks (6LowPAN), Z-wave, etc. are used for securing communications in the IoT [61,62]. Network topologies or models (e.g., star, scale-free, etc.) are implemented to transmit data to the third layer (cloud layer) through sink nodes. This layer should provide best topologies for covering different areas. Power consumption also relays on the implemented topology. Transmission bandwidth should be balanced with network performance, resources consumption, and reality of sensed data for recording data on the cloud. Such challenges require implementing machine learning and big data technologies for classifying sensed data and determining the main critical events that need to be scheduled with high priority for the periodical check, which also depends on extracting prediction patterns from historical learned data.
- *Cloud layer (services layer [6])*, Because SThs have limited resources and capabilities, the cloud layer receives and process data from other layers. Heavy resources consumption algorithms for data mining and retrieval for making smarter decisions are implemented on the cloud.
- *Application layer (interface layer [6])*, Most of daily life applications in the IoT are of type WSN applications, which require friendly interfaces for normal users (i.e., graphical user interfaces (GUI)) and machine (i.e., RESTful APIs) to ease information exchange and utilization. Searching and getting real-time information reveal potential benefit of the IoT. Machine learning and data retrieval technologies could enhance such services. This layer should enhance API services for allowing automatic machine services calling. In general, critical feature of the future IoT that highlight its potential benefits is to enable human users and machines to discover and search for things and services and allow data sharing between different networks.

3.2. Challenges of the future IoT

General IoT design considerations: scalability, energy consumption, devices throughput, latency, network topology, security and safety are discussed in [70] and referred by Da Xu et al. in [6]. In order to deal with heterogeneous devices, features such as scalability, interoperability, etc. are recommended for the future IoT

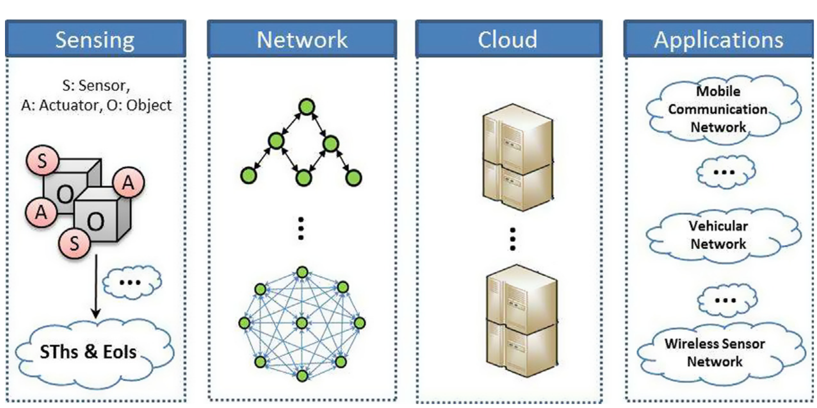

Fig. 2. Future IoT Architecture.

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architecture [6]. Lin et al. [62] shade the light on two main features that should be addressed in the future IoT: interoperability between various networks (i.e., applications) and heterogeneity of things (i.e., SThs). Authors in [23] discuss and organize IoT characteristic into two levels; IoT infrastructure characteristic and IoT applications' characteristics. Main IoT characteristics that concerns to our review are: heterogeneity, scalability, dynamicity, mobility, availability, resource constraints, and huge real-time data (historical and real-time data streams) written in different types and formats [3,17,48].

Fig. 3(a) shows Scopus [71] analysis report on the topic "IoT challenges" from 2010 to 2019; this figure indicates research progress on *IoT challenges*. Fig. 3(b) shows citation reports from Web of Science [72] core collection between 2010 and 2018 on the topic of *IoT challenges* almost of research paper concentrates on the fields of computer science, engineering, and telecommunications.

IoT challenges have different meaning in each layer. For example, heterogeneity in IoT data differs from those in IoT devices and Networks [14,23]. Heterogeneity appears in IoT data when they are written in different formats like RDF, microdata, and microformats, and in IoT devices when non-standardized naming for SThs properties are used, while in IoT networks when different technologies and protocols are implemented [2,14].Thus challenges related to the first three layers (sensor, network, and cloud) are classified into three categories (see Fig. 4): (1) data challenges, (2) SThs challenges, and (3) Network challenges; where corresponding challenges in these classes have the same back color, i.e., dependences between challenges, for example, yellow diamonds represent scalability factors and results in each challenge class. Recommendations of the application layer are discussed at the end of this sub-section.

- *Devices challenges:* In the same network SThs may speak different protocols with different capabilities, thus converting things to SThs, by attaching sensors and devices to them in order to express things states, should take into consideration commensurability of devices communication capabilities. Each STh produces some information about itself and may share this information with other SThs to calculate state of certain EoI (e.g., room state) [38]. None standardized naming is one of the main challenges, where manufactures with no standardized naming, which also deployed in IoT with different naming. Truong et al. [51] proposed a framework for searching for similar sensors which are of the same type and read similar readings. This framework could be used for solving none-standardized naming challenge by importing description of similar sensors. Ontologies are used for this purpose as well. In addition to the GPS attribute, SThs need to handle their logical path for enabling human users know their absolute locations, but in some cases such as in vehicle system, SThs are movable devices, thus it is a critical challenge specially for tracking systems. Summary of challenges are shown in Fig. 4(a).
- *Network challenges:* Research in the IoT scalability (i.e., Network challenges) concentrates on how to leverage the infrastructure layer of the IoT to connect almost objects and things to the Internet to give information about themselves achieving scalability of the future IoT [38,73]. The IoT partially solves this issue (i.e., scalability) by using standard IP and 6LoWPAN protocols [14]. Thus, the IoT is considered as the global system of very thing support IP connection to the Internet. The integration of cloud computing with the IoT enlarges the scale of applications in different fields. Fog Computing comes with the need for requirements of interoperability, low latency and mobility of objects [53,74]; Where it provides a great performance for calling and responding services in the IoT [62]. In order to convert spaces to smart spaces, SThs localization and distribution in WSN and the IoT need to be studied and optimized. Sharing data between IoT applications will reduce number of connected devices, required storage spaces, and the required efforts for managing them as well. Adapting topology structure to be large or wide enough for integrating daily life objects is critical feature for the future IoT, specially for smart transportation systems, which partially aide for large-scale in the future IoT. Future IoT is expected to connect everything on the earth to the Internet and convert many "impossible" to possible [59], Summary of challenges are shown in Fig. 4(b).
- *IoT data challenges:* Data in the IoT could be categorized into: (1) *data bout things* (e.g., ID, type, logical address, etc.) and (2) *data generated by things* (e.g., sensed values like temperature, humidity, occupancy, power consumption, etc.) [59]. SThs in IoT applications generate massive and huge data (i.e., it is called huge scale [29]), which results in big data. To partially solve big data problem, sensors are recommended to filter and clean data in order to keep only interested data [59] and share it with their base stations (i.e., gateways) once a critical change occurs [38]. IoT data may be written in different formats [38], and change frequently. This massive data are collected from multiple sources (i.e., heterogeneous) and measure different attributes, thus it is called multisource and multidimensional scalar [29]. Thus data retrieval in the IoT faces big challenge due to wide scale of IoT applications in different fields and constraints of user involvement. Heterogeneous IoT data may suffer from inconsistence, inaccuracy, quality, and time sensitivity. Accessing real-time information in IoT applications requires implementation of big data techniques [28] for enabling data collecting, storing, retrieving, mining, and sharing. Big data characteristics are discussed next. Summary of challenges are shown in Fig. 4(c).

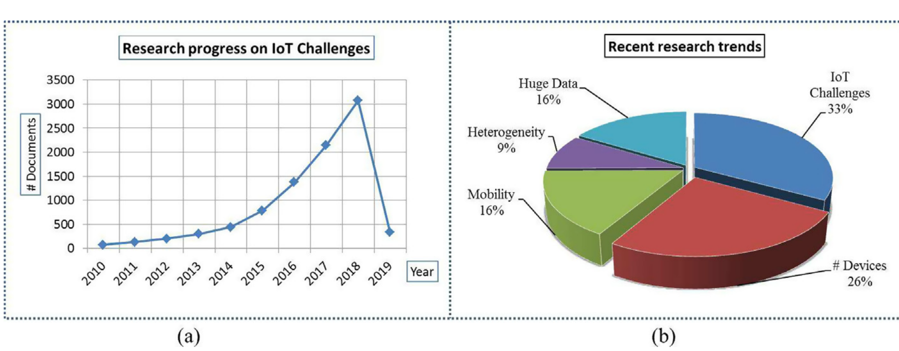

Fig. 3. Scopus analysis for: (a) research progress on IoT challenges, (b) progress level on main IoT challenges.

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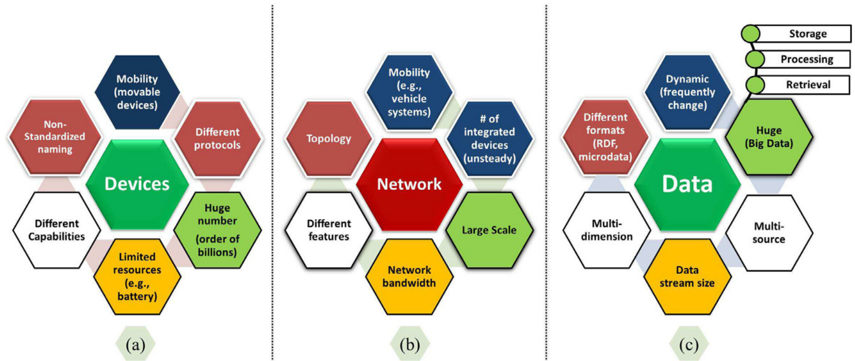

Fig. 4. IoT Challenges: (a) device level, (b) network level, (c) data level.

- *The fourth layer* requires some recommendations but not limited for enabling IoT services for its users (human and machines), they are:
  - –Integration between legacy web pages and IoT (i.e., WoT).
  - Searching for real-time information.
  - –Enabling historical analysis and future prediction for events and SThs states.
  - –Sharing information between different IoT applications.
  - –Allowing automatic analysis on selected IoT devices and networks.
  - –Knowledge extraction.
  - –Enabling information browsing in a visual form.
  - –Enabling automatic services discovery and execution through RESTful APIs.
  - –Integrating extra devices and services (i.e., dynamic applications for dynamic networks)
  - –Leveraging IoT services to be on the cloud Taking benefits of the edge-cloud and middleware

To sum up, main challenges based on SThs and data could be summarized into three terms for each; (1) huge number of SThs, which produce big data, (2), heterogeneity of SThs, which produce heterogeneous data (i.e., multi-sources and multi-dimensions), and (3) mobility of SThs and frequent change of data (i.e., dynamicity).

3.3. SThs and data streams

Proliferation of SThs is the main source of big data in the IoT, for example, heterogeneous devices in smart transportation systems produce big data to cover multiple features, conditions, and situations. Main causes of the highly increased number of SThs and EoIs could be summarized into: (1) Rapid advances and enhancement in hardware development and manufacturing give the chance for more devices to be connected to the Internet with extra capabilities, (2) because sensor nodes still have restricted resources like batteries, memories, etc. the need for enhancing faulty tolerance in sensor networks, requires to deploy extra number of sensors nodes, (3) certain phenomenon may need extra nodes for sensing complementary part, and (4) making accurate decisions in the IoT depends on accuracy of sensed data, which could be done by deploying a lot of sensor nodes in the monitored environment. This results in increasing number of sensors or SThs to be exponential. Thus, in the next few years, number of SThs will be much more than number of normal users [17].

The question here is *how the human users follow and deal with such huge sensed data in the real-time*. In the future IoT, most of real-time decisions depend on machine-to-machine communication. No doubt, data mining techniques will be one of the main ICT for solving problems of large volume data in the IoT [59].

4. Technologies for the future IoT

The future IoT, cloud computing, and big data become the main research goals in the Europe's Horizon 2020 [14]. Artificial intelligence (AI) and data mining are best solutions for managing huge data flows and storage. AI methods include fuzzy logic (relay on "if-else" rules), and neural networks (relay on existence of a transformation function). Data mining steps are data preparation, filtration, aggregation, selection, transformation, mining and pattern evaluation. This section discusses big data, sensor fusion, cloud and fog computing, and blockchain technologies in order to clarify their relations and impact on IoT applications. Fig. 5(a) presents number of queries on ICT and IoT using Google search engine, this chart indicates that big data, machine learning and blockchain technologies are highly required over the last five years (i.e., recent research papers focus on data level). Fig. 5(b) shows citation analysis report created using web science knowledge tools on ICT integration in the IoT from 2010 to 2018.

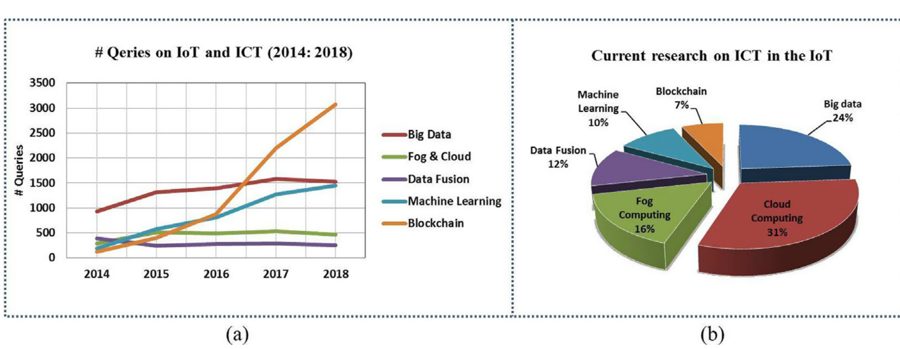

Fig. 5. (a) Google analysis: number of queries on ICT and IoT (b) ICT implementations in IoT.

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4.1. Big data

Structured and unstructured datasets with large volumes refers to big data, which are convenient for processing large datasets in the IoT [75]. Traditional data processing techniques couldn't be used with the high increased data volumes in the IoT [16]. Due to massive connected number of STHs and EoIs to the Internet, the IoT concentrates on big data and AI to make inferences and decisions from sensory datasets. IoT big data has different characteristics when compared to common big data problems [76]. Main attributes are:

- *Volume (due to IoT scalability):* large volume data may produce conflict meanings (vagueness); as a result it requires to be checked for assessing quality and value. Deploying multiple similar sensors allows increasing data accuracy but results in producing extra noise data.
- *Velocity (due to high sensitivity for changes):* frequent change of data recommends the IoT to check accuracy and consistency of its data (veracity).
- *Heterogeneity (due to IoT dynamicity):* this property may be demonstrated in writing IoT in different formats to assess different attributes.
- *Time and location correlation:* most of sensed data in IoT applications record time and sensing location.

4.2. Cloud and fog computing

Because IoT connects everything to the Internet, then gaining real-time access for controlling and monitoring objects that change their locations and data frequently becomes more challenging and tedious task. Edge computing technologies is essentially for allowing interoperability between STHs [74] and for enabling IoT objects to gain cloud computing facilities [3] (i.e., bring the cloud closer to STHs), where these technologies target to make IoT closer to computation stations. Edge computing [77] implementations are: fog computing, mobile-edge, and cloudlet, these concepts are closer to each other, they have a common purpose, which is to build middle layer between STHs and the cloud). Gateway, base-station server and data center are examples for fog computing, mobile-edge, and cloudlet, respectively. This means that each concept has a specific role in the middle layer, more details about these concepts are in [78]. Here, fog computing is referred as a general concept for the edge computing.

Fog/Edge computing enables IoT gateways for performing lower level of computations for reducing response time (i.e., local computations) and network traffic [77]. Fog layer works as a middle layer of middle services; where it presents facilities for storage (cloud) and response time (STHs) [79]. Services such as fault tolerance and security could be performed by edge computing gateways in enhanced manner. Fig. 6 summarizes the relation between IoT objects (STHs and EoIs), Cloud computing, and Edge computing (gateways).

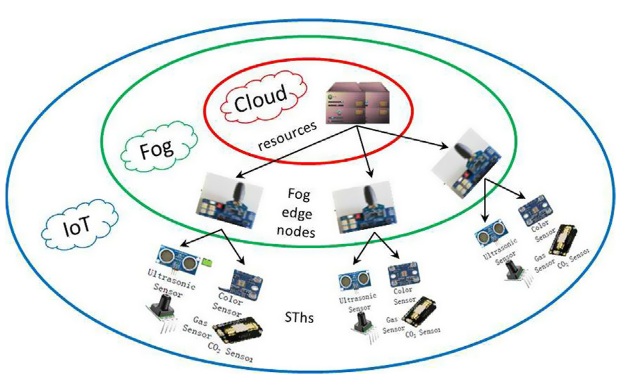

Fig. 6. Relation between IoT devices (STHs), Fog nodes, and Cloud.

4.3. Data fusion

Analysis technologies should be integrated into the IoT to solve resulting challenges by enabling smart decisions making; one of the most valuable technologies is sensor fusion or data fusion [15]. Sensor fusion has many definitions, but it could be defined in general as the process of comparing, filtering, and combining row data or derived data from multiple sources to extract new information that is better than those individual row data [80,81]. Data fusion has many useful applications, it is used as fault diagnosis tool for damage detection problems of mechanical systems [82]. In this review it is used as a purging strategy for sensory data in order to reduce redundancy indexing. Elmenreich [83] presents an introduction to sensor fusion and describe its methods (e.g., inference methods), algorithms (e.g., the Kalman Filter [84]) and applications (e.g., robots). Data Fusion features in brief [15]: (a) merging data in optimal manner, (b) extracting intelligence from raw data, (c) substitute for low accuracy data generated by low-power resources, (d) hiding critical information, and (e) providing abstract knowledge about fused results.

Sensor fusion techniques could be categorized based on multiple criteria. Castanedo [80] presents different criteria for classifying data fusion techniques and clarifies characteristics based on: (1) input and output relation, (2) data types for input and output parameters, (3) abstraction level, (4) data fusion type, and (5) data fusion architecture. Authors in [15] perform data fusion on four levels (pixel, signal, feature, and decision). Also it could be categorized based on type of sensors configurations [80] as follows:

- *Complementary (integral configuration):* this type of data fusion could be done for sensors that have indirect independence, where their data are combined together to draw a complete picture concerning certain environmental phenomenon or condition. For example, deploying different sensors such as (temperature sensors, humidity sensor, etc.) for assessing the weather forecast, existence of almost sensors gives complete information about the weather forecast.
- *Competitive (redundant configuration):* this type of data fusion targets ensuring existence or not of certain phenomena by doing a vote of confidence between sensors, where they are independent and measure the same phenomena. For example, when some temperature sensors (of the same type) are deployed in different locations in a certain region, their measurements are compared to make a final decision about the temperature in that region
- *Cooperative (distinct configuration):* when independent sensors are deployed to give a piece of information that are combined to present a final decision about certain EoI. For example, when some types of sensors. For example, a room is considered as an EoI in smart home, where it hosts three types of sensors, (a) light sensor, (b) motion detection sensors, and (c) sound sensor, room state is assessed if it is calm room or not by combining the three measurements of those sensors.

4.4. Machine learning

AI, specially machine learning (ML) plays a critical role in predicting future events, making decisions, controlling systems based on historical data [76]. AI acts as a brain for the body IoT. Performing analytics on big heterogeneous data streams in the real-time raises the integration of Complex Event Processing (CEP) in various types

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of the IoT application areas [85]. IoT data analytics based on historical and real-time data becomes complex task, where it could be used for predicting future SThs states. Akbar et al. [85] use ML coupled with CEP for that purpose. They highlight that combination between ML and CEP enhances IoT performance in health-care and manufacturing sectors. Authors in [17,40] build their prototypes for implementing search services in the IoT and WoT based on prediction models generated from the historical data and indexed in their databases. As mentioned previously, fuzzy logic is used and implemented in different applications such as sensor search in [53]. Deep learning will has high impact on the future IoT, Authors in [76] presents a survey on deep learning in the IoT for handling big data streams at different levels. IoT data could be found at three levels; (a) SThs, (b) Edge devices, and (c) IoT cloud. Deep learning technique could be implemented on the first two levels for performing fast analytics, while on level (c) for big data analytics.

4.5. Blockchain

Recently blockchain has been integrated in a wide span of application areas: finance, government, health-care, etc. [86], which leads the authors of [87] to study its impact on the IoT. Blockchain is a type of data structure that implement distributed leger with Bitcoin that use public key cryptography for enabling secure transactions in peer-to-peer networks [87–89], where each element in the chain references to the hash of the previous one [87]. Powerful benefits of the blockchain enhance IoT security [90] and allow IoT data to be accessed in decentralized manner (e.g., IBM Watson IoT Platform), immutability also increase its power for detecting malicious actions. Smart contracts (self-executed scripts) solve costly management for the exponential increased number of SThs.

The nature of the blockchain technology solves cloud server downtime in the IoT [88,91]. Sagirlar et al. [91] suggested a hybrid architecture for the integrating blockchain in the IoT Called Hybrid-IoT. Blockchain and IoT technologies add new business opportunities in almost of application areas, especially in the industry, government, and health-care sectors [87,92,93], where IoT devices provide real-time data about products using automatic services (RESTful), also IoT technology is used for tracking objects in the network, and on the other side, the blockchain provide shared leger for manage information in the business transactions [89] in order to achieve efficiency, reduce costs, and remove single point failure, i.e., blockchain serves as proof of transactions completeness [92] and enables building decentralized IoT using private ledgers to secure transactions between devices.

Supply chain solutions in commerce take benefits [87,88] like (a) saving time consumed for ensuring the shipment process (no need for third party authentications), (b) pertinent shipment, (c) sharing services (services marketplace), (d) accurate prediction for manufacturing materials, (e) better alignments for stocks and inventories, and (f) tracking sales provided by IoT services. Autonomous vehicle application in blockchain (self-driving cars) records and shares participants information (owners, manufacturers, financing firms, etc.) for enabling services such as self-deriving, self-detection for recharging or refueling, etc. [88,89].

Research works [40,87] present comprehensive survey on blockchain challenges and opportunities, and discuss deployment considerations. According to the best of our knowledge, blockchain faces the following challenges to be integrated in the IoT:

- The main obstacle for the blockchain technology is the scalability, which will be increased due to exponential number of SThs in the IoT, consequently, transactions conflicts may increase.
- Blockchain security check in each transaction requires agreements from all sharing node in the network to be accomplished, as a result number of transactions will be increased (security check and updating information after transactions), which causes higher latencies compared with centralized database systems. Moreover, maintaining encryption keys and hash codes is tedious task.
- Enforcement rules of smart contracts are limited.
- Sharing large information between nodes face limited resources of SThs.
- Blockchain requires SThs in the IoT to be live almost of the time, which consumes more energy.

To sum up, Table 2 presents a list of recent ICT implementations in the IIoT to clarify integration of these technologies in IIoT applications (e.g., smart home, health-care, and smart traveling) and services (e.g., improving wireless communication and networking, security, real-time monitoring, and data analytics).

This research proposes simple architecture for integrating ICT in the IIoT for enabling SThs discovery and search(see Fig. 7). Data fusion could increase robustness of sensed data, which are then reduced once final conclusions are calculated (i.e., complex events are extracted). Dyser search engine [40] reduces sensed data by indexing prediction models that summarize how data changed over time unit. The research work [106] could enhance fog edge nodes to make local decisions using data summarization techniques to reduce data volume that need to be stored on the cloud (i.e., store data on a local server for fast response). Above this layer some optimization algorithms could be implemented in order to store meaningful information in fewer volumes. Machine learning technologies (e.g., fuzzy logic [107]) enable decision making and automatic control (discussed above). Machine learning algorithms presents promising solutions for resources discovery and search in the IoT by extracting main features that represent EoIs states to be indexed in higher indices like indices' structure of the WoTSF

Table 2
Examples for ICT Implementations in IoT.

ICT	Ref.	Year	Description
Machine Learning	[94–97]	2019, 2019, 2017, 2016	Wireless communication, security, and data analytics. Networking: making automatic decisions for balancing network traffic, online clustering, and anomalies detection and prediction.
Machine Learning and Blockchain	[98]	2018	Security: this research compare between security degree that these technologies provide, and how convenient they are with tiny constrained IoT devices.
Machine Learning and Bigdata	[99]	2018	Real-time monitoring for large scale systems (e.g., manufacturing systems) Implementing hybrid prediction model on special platforms like Kafka for detecting faults during manufacturing.
Cloud Computing and Machine Learning	[100]	2018	Summarize ML algorithms implementations in different IoT applications such as smart home, health-care, etc. Survey current implementation on the cloud and fog computing.
Data Fusion	[101,57]	2019, 2018	Used as a data preparation technique for implementing incremental learning on IoT data streams; where its output is a set of features depending on aggregation functions such as maximum, average, ...etc. Data analytics: weather forecasting, traffic monitoring.
Cloud Computing, Bigdata, Data Fusion, and Blockchain	[102–105]	2018, 2018, 2017, 2017	Smart Traveling. Health-care Services. Security services and applications.

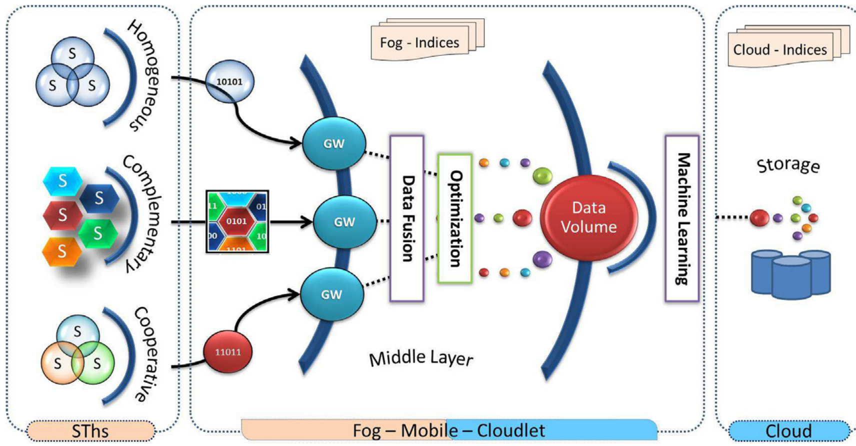

Fig. 7. The proposed architecture for integrating ICT in the future IoT.

framework [5]. In addition, prediction models are used to index large volume of data increasing its prediction sense to retrieve semi-real information about SThs in their applications [17,40]. Also this architecture proposes to big data algorithms implementation for efficient storage and retrieval.

5. IoT search engine (IoTSE)

The future IoT should presents a lot of critical services that leverage applications benefits to its users; this review discusses the main common services for most of IoT applications. Recently, researchers spot the light on real-time services like searching and discovery for IoT resources, such as shown in Fig. 8. Articles [2,14,39,60,73,75] highlight needs for existing such services in the future IoT.

General web search engines go beyond keyword search in the web, while in IoTSEs, SThs and their dynamic states and measurements should be taken into account. In addition to related work discussed above in sub-section (*Discovery and Search*). Based on most recent and relevant research papers, this section discusses challenges, solutions and recommended services for building smart IoTSEs.

5.1. Related work

Pattar et al. [3] concluded their comprehensive research with future work directions targeting generating special search engine that addresses IoT challenges. One of these directions is a need for an efficient indexing mechanism that sort and rank IoT data. Authors recommended that Geohash encoding is one of the key technologies that should be used for addressing the problem of indexing spatiotemporal data. Also they concluded that current crawlers or spiders have no ability to reach every STh in IoT applications, which are distributed with exponential number in very smart environment as mentioned previously. Further, due to frequent change of SThs states (i.e., their locations and reads or measurements), the crawling process becomes a hot research point in the future IoT. As a result deep learning and regression techniques are recommended to predict and search in real-time data streams.

Tran et al. [39] discussed open issues for crawling, which are: (a) detecting data sources, (b) extracting resource automatically in XML or JSON format, and (c) automatic integration of different resources by using aggregation methods. They also discussed open issues for indexing, which are: (a) live outdating of sensors indices, which recommended to index prediction models instead, (b) needs for new distribution and deployment strategies for keeping indices as small as possible. Also, they suggest implementing user subscription in search engine; where this idea could be useful in enhancing crawling schedule. Dyser [40], a search engine proposed by Ostermaier et al. for the IoT, takes benefit of traditional search engines like Google to get static information about EoIs performing keyword search, then it looks up for the resulting list of EoIs in its indices to get relevant prediction patterns expanding them to predict EoIs states. Limitations of Dyser are: (1) index size was built on SThs level, and (2) crawling processes need to be optimized to consume less time.

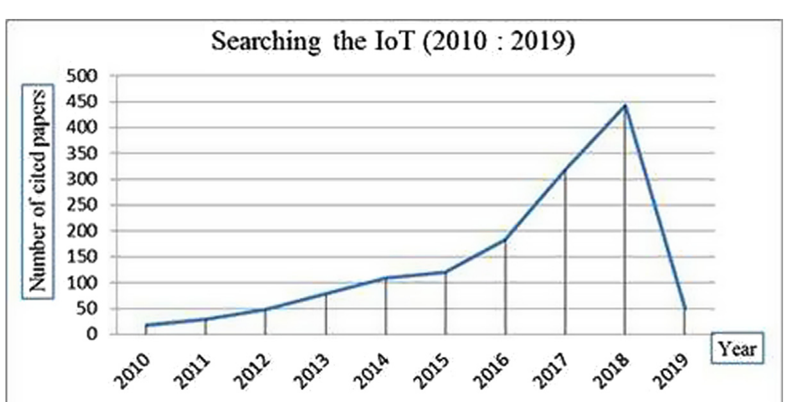

Fig. 8. Scopus analysis for research trends on IoTSE.

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The WoTSF framework was proposed by Younan et al. [17] for searching in the WoT, which reduces dyser index by building two types of indices, where indices in the higher layer are built on EoIs states using aggregation methods. Each IoT network handles its own index. WoTSF speed crawling process by using the idea of putting the server root file (Google optimization). WoTSF limitations crawling process need to be optimized on the level of the scalable IoT resources. It works on the application layer of the IoT (i.e., WoT). Yaqoob et al. [73] discuss requirements for scalable IoT architecture in the future, one of the selected requirements is information retrieval based quality of services from scalable IoT resources (i.e., searching). Data fusion and similarity search will be integrated in the future IoT. Zhao et al. [32] propose a retrieval system for the IoT based on semantic awareness and topic discovery.

5.2. ICT for IoTSEs

Fig. 9 summarizes current features of IoT applications and data and indicates resulting challenges that face IoTSEs. On the light of related work discussed in this section, this survey proposes some recommendations, organized into three levels: SThs, network, and data; for overcoming search challenges shown in Fig. 9. This architectural analysis could enhance IoTSE performance by preparing data (e.g., filtering, reduction, summarization, etc.), and selecting most effective titles (i.e., most live and expressing data) for building multi-level indices for IoT applications. This architecture also enables IoTSE to build crawl scheduling for keeping indices as up-to-date as possible. These recommendations could partially overcome almost IoTSE challenges. For more flexibility, IoTSEs are recommended to support query format that human and machines can understand (i.e., implement semantic meaning and provide RESTful services). Once users write their queries, IoTSE semantically analyze queries and serve them using parallel computing to retrieve and rank results after assembling.

A summary of recommended ICT based a set of criteria that IoTSE could provide, is indicated in Table 3. Data fusion technologies have to be integrated for increasing data accuracy and consistency, while machine learning is for extracting and assessing data titles to be indexed. In this layer, SThs put their signature every time they sense critical or abnormal readings for enhancing learning algorithms that could be used for initiating crawling schedule. Securing data could be achieved using blockchain, where SThs put their communication logs in IoT ledger [115]. Technologies like fog computing in the second layer should decrease response time and enable IoTSE to get high level indices like WoTSF [17]. Sensor search [51], Dyser [40], and WoTSF [17] implement/depend on machine learning and fuzzy logic for building their indices. ThingSeek framework [46] is a search engine based cloud computing. Search engines like Shodan [41], which crawl SThs to index their banners recommend blockchain technology to be implemented in a manner that secure crawling process for SThs.

In addition to fog computing, blockchain and semantic middleware are recommended to for securing transactions and enabling

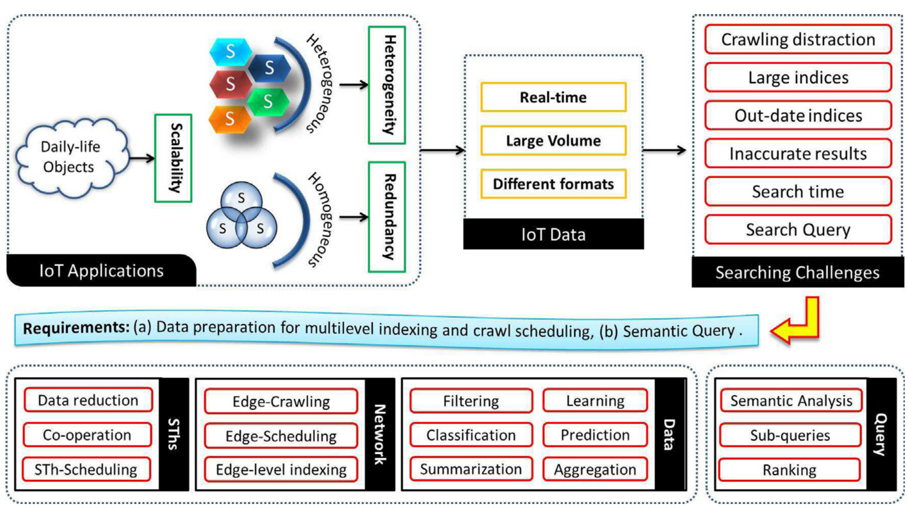

Fig. 9. IoTSE recommended services on the light of IoT challenges.

Table 3
Recommended ICT in IoT layers for enabling real-time IoTSE based on set of related works.

Criteria (Features)	IoT layer	Challenges	ICT	Ref.	IoTSE Service
Real-time monitoring, searching, knowledge abstraction, summarization, visualization	Apps	Human and machine queries, data sharing	RESTful APIs, Blockchain, AI, Semantic	[17] [51] [92] [93]	Query analysis
Accurate, consistent, real-time, easy to store and retrieve, readable (human and machine)	Data	Large volume, different format, different meanings, analysis, storage, retrieval	Big data, Cloud, Machine learning, Data structure, AI, Ontologies	[16] [27] [48] [49] [60] [76]	Search, Index, Rank
Low latency, high management, scalable, secure (availability)	Network	Scalability, protocols, security, latency, devices discovery	Fog computing, Blockchain, Big data, Machine learning, 6LowPAN, topologies, semantic middleware	[23] [28] [31] [50] [89] [108]	Crawling
Fault tolerance, ideal consumption (resource), live response, secure (integrity)	Device	Limited resources, heterogeneity, dynamic states, dynamic sensing	Data fusion, Clustering, Machine learning, Blockchain	[107] [109] [110] [111] [112] [113] [114]	Crawling, Sensing

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interoperability between applications [74]. Because low-level indices are built in the second layer, then big data and machine learning have to be integrated as well. Third layer, where all sensed data are stored, cloud computing enhances IoTSE to run heavy algorithms to extract abstracted knowledge from a huge data. The application layer, where queries are received, semantic technologies should be implemented to enable normal users to retrieve their intended information. Because machines are considered as users in the IoT, then REDTful APIs have to be the core of IoT implementations.

Special search engines in the IoT targets searching by meaning and real-time queries. To accomplish such types of queries, IoTSEs have to build indices in a way that ease updating and data retrieval processes. Distributing indices to be available on the fog edge networks presents promising solutions [48–50] (e.g., Geo-hash [3]). Create a hybrid method taking benefits from the related work, such as in [17,40,48,50] for creating indices that allow specific and general search queries. Search engines' developers should take of their account deep learning, prediction models and regression techniques for data analysis and correlation [3]. This native solution could balance between index update and data freshness [39].

Data fusion saves consumed power for sending more frequently changed measurements by sending abstract and accurate measurements. Scheduling critical events enable base-stations and gateways to pull and ask critical SThs about their measurements in the right time as possible [17]. Such services will enable search engines spiders to crawl IoT networks following a set of priorities that is identified by networks themselves. Blockchain could be integrated in most of IoT layers; for example, in perception layer (on things level) digital signature mechanism of the blockchain ensures data integrity by allowing only authorized things to modify their data [90].

6. IoT case studies

By IoT definition in [116], the IoT enables its users and components (people, objects, things, etc.) to communicate anywhere at any time, which makes the IoT has a lot of applications [117] in different fields such as industry, agriculture, security, smart home, health-care, transportation, etc. [2]. Extra applications are discussed in [6,118–120]. Most of the IoT applications could be categorized as sub-components in the smart city application like smart health-care and smart transportation, etc. [118]. This section discusses two high risky applications to reflect ICT impacts on the IIoT: (a) smart transportation and (b) health-care.

6.1. Smart transportation

Smart transportation is a central measurement for the perfection of life in modern cities. It increases the quality of services (QoS) presented to its citizens [27]. The future IoT enhances transportation systems by providing rich information in the real-time so that users, administrators, and machines in such systems can make a decision about certain actions in the right time [52].

Problems but not limited in the transportation systems are traffic congestion, risky road conditions, safety, and pollution [8]. The IoT should provide security issues for (1) drivers by warning them with alerts in smart cars [121], (2) passengers by informing near ambulances with current accidents and critical issues occurred on the way, (3) administrators by studying crowd seasons and providing some developments for transportation, and (4) machines by preventing them from going on critical actions [2].

Main services in the smart transportation system are monitoring vehicles and objects, sensing devices' ranges and risky road conditions, and sharing sensitive data between system parts in the real-time to make accurate decisions. Qinglu Ma et al. [52] proposed an approach for estimating real traffic speed based on GPS data aggregation, and they concluded that calculating mean speed is closer to real measurements. Smart cities implement roadside infrastructures by deploying multiple sensors, cameras, actuators, etc. to sense and collect data about environmental conditions on the road (e.g., such as road conditions, vehicle conditions, and traffic conditions). This system collects data from multi-sensory environments, thus data fusion and fuzzy logic play an important role in this application area [8].

To sum up, future IoT should improve intelligent transportation systems, by improving the safety and traffic control, and develop algorithms for selecting best interfaces for alarm, detecting fast moving objects, and making more accurate decision automatically. Big data analytics can extract valuable information form raw sensed and captured data form sensors and cameras [27].

6.2. Health-care

IoT presents more enhancements generally in normal life and especially in the health-care sector by observing patients and helping them in their life using wearable devices. The impact of the IoT on the health-care is to present health-care services with high quality and with little costs [122]. Examples of IoT applications in the field of health-care: (a) wearable devices that are used for diagnosis Alzheimer disease [123], (b) monitoring heart rate, blood pressure, and extra vital measurements, and (c) tracking and guiding aging individuals [122]. The recommended and expected features concerns the IoT in the near future are: easy install and management for SThs, providing simple connectivity, enhancing information analytics, solving problems of interoperability, heterogeneity, and security and privacy issues [20,124].

ICT enable the IoT to plan, analysis, monitor, and control quality of services in the field of diagnosis and treatment. Data integrity is critical in this field, which recommended almost of IIoT applications in the health-care field to handle fault tolerance by integrating multiple shipments or inventing new algorithms for handing this issue [125]. Blockchain is a promising solution for handling security issues in this field such availability, data integrity, etc.

Fog computing, cloud computing, and big data technologies enhance IoT health-care applications [126,127], E.g., big data classification for Electrocardiographic (ECG) signals [128]. Authors in [58] proposed a framework for cancer diagnosis based machine learning and big data. Data analysis, fusion, filtering, and compression are main local data processing of smart gateways (UT-GATE) in the fog edge layer of the IoT architecture discussed in [129], where gateways act as a middle layer between SThs and the cloud. Authors in [130] propose a health-care IoT architecture consisting of three phases for data collecting, transferring, and big data storing. This architecture has two main parts: (a) Meta Fog-Redirection (MF-R) part for collecting and storing sensed data by implementing big data technologies, and (b) Grouping and Choosing (GC) part for securing patients' information between the cloud and fog edge layers.

7. Future research directions

Up on our best of knowledge based on most earlier surveys on the IoT such as [2–4], the future IoT have to efficiently handle and secure data and SThs. Main future research issues concentrate on the following points and summarized in Table 4.

7.1. Heterogeneity

Service oriented architecture (SOA) plays a key role in systems or devices heterogeneity in the IoT [6]. It is recommended to implement different data transfer between heterogeneous

Table 4
A Summary for future research recommendations.

Category	Ref.	Year	Future Recommendations
Scalability & Heterogeneity			– Large-scale and self-organization for IoT.
	[2]	2018	– Rational and heterogeneous topologies.
	[79]	2018	– Fog layer.
	[14]	2017	– Big data (collecting, processing, etc.).
			– Network to network data sharing.
	[20]	2017	– Syntactic interoperability and security issues.
	[22]	2017	– Combining the BLE profile adaptor with Beacon.
	[73]	2017	– Distributed index for scalable the IoT.
	[21]	2016	– Natural language processing (NLP) techniques.
	[23]	2016	– Functional requirements (e.g., resources discovery and management).
	[24]	2012	– Non-functional requirements (e.g., availability, integrity, etc.).
	[25]	2009	– IoT infrastructure (e.g., interoperability).
	[26]	2007	– Networking
Big data	[27]	2018	– Increase system efficiency for huge datasets.
	[6]	2014	– Implement ICT in the IoT.
			– handling and processing data at device level or gateway level.
	[79]	2018	– implementing semantics and using rule engines for annotated data.
	[28]	2017	– solving problem of heterogeneous protocols (fog layer).
			– in brief (Data provenance, governance, regulation, management, and security).
Heterogeneity & Big data	[74]	2018	– Fog layer.
	[79]	2018	– Mining and analysis techniques on the massive heterogeneous IoT data.
			– Improve quality of information extraction using different workflows.
	[31]	2017	– Implement different fusion approaches on object level.
			– Incorporate CSF in real world.
	[32]	2014	– Scalable and context aware middleware.
	[33]	2013	– Implementing dynamic and automatic algorithms for knowledge extraction.
	[34]	2009	– Enhance search performance.
Security	[131]	2018	– Enhance hardware components for enabling parts replacement.
			– Developing lightweight algorithms, protocols, and anti-malware solutions.
	[132]	2017	– Lightweight attribute-based encryption (ABE).
			– Policy-hidden ABE for data confidentiality.
Real-time Search	[27]	2018	– Data Preparation.
	[17]	2016	– Crawling.
	[73]	2017	– Indexing.
	[32]	2015	– Query.

resources [2], and to use distributed middle layers between heterogeneous platforms [23]. Cloud computing allows for implementing data unification algorithms. Heterogeneity in IoT devices may lead for using different protocols, which requires the future IoT manage connections between them. Ahmed et al. [28] recommend to solve problems of heterogeneous protocols (e.g., CoAP, MQTT, XMPP, HTTP, etc.) by applying seamless integration and interoperability. Fog layer is a promising solution on the hardware level [74] by enabling heterogeneous protocols and on the data level [79] by implementing internal semantics and computations. Grouping devices on two levels (physical and logical) is a promised solution in this case [14]. Data fusion techniques are recommended for handling data at device level or gateway level. Also Implementing semantics and using rule engines for annotated data [28] is a research trend for solving data heterogeneity in the IoT.

7.2. Scalability

Research trends that aim to reduce development costs, enhance marketing speed, and improve quality of services, result in enlarging the IoT scale. One of the main impacts on the IoT scalability is standardization of the communication protocols (IP), which ease the connection for almost devices [38]. The Chinese project *Internet Plus* aims to make cooperation between the IoT supports and the manufacturers to establish the standardization strategy [14]. Using RESTful APIs, STHs can communicate and interact to exchange their data [14,38]. As mentioned in [14] client-server model is not applicable for the future IoT. The API CoAP (based on TinyOS) enables integration of client and server to IoT. Fog layer is an essential solution for enabling interoperability that affects the IoT scale [74].

7.3. Data collection and storage

Collecting data from smart spaces should cover their required features, thus optimization on sensors or STHs localizations is recommended. Cloud computing technology gives the IoT the ability for handling large scale data and implementing big data technologies. As mentioned previously, IoT components are restricted with some features like battery, memory, and wireless communications, so big data techniques is a hot research area to be applicable with these constraints. Fog computing enhances IoT performance to call and respond services. Authors in [2] recommend scheduling emergency events, self-organization, big data transfer and integration, and building large-scale network model ensuring network coverage and connectivity for the future IoT, i.e., by implementing best topologies for managing nodes and saving resources (e.g., battery). The research work [7] recommended the following: (a) integration between IoT systems to share data, which reduce number of required nodes (STHs) that need to be installed to cover the same features that other IoT system may provide. Thus heterogeneity and standardization become critical features, (b) developing unification algorithms for collecting data, and (c) implementing robustness algorithms for analyzing and comparing large scale data.

7.4. Security

Threads issues concerning security and privacy in the IoT may cause harmful and highly cost damages in most of IoT applications especially health-care and smart home applications. Yang et al. [133] present a comprehensive survey on IoT security classifying threads following the IoT architecture. The authors in the research

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work [132] study network architecture such as resources constraints and self-organization, list security and privacy requirements such as location and identity privacies, and take in their account how to secure data aggregation on the cloud based IoT.

Security threats in the IoT could be categorized mainly into three levels, as mentioned in [131,133], following the main architecture of the IoT: (a) perception level (devices), where some components are replaced for gaining access or stealing encryption keys, (b) transition level (network), where middleware layers affected by *DoS*, and (c) application level (data), where services and data become unavailable.

Limited resources restrict implementations of some security and encryption algorithms and also enforced the IoT to use the cloud as a computational and storage resource, which raises new challenges in IoT security and privacy [132], thus lightweight attribute-based encryption (ABE) is recommended to be used as a solution for fine-grained cipher-text access control, and policy-hidden ABE is recommended for data confidentiality. Authors in [131] recommended trust management and security in the future IoT. They recommend future research on the following points for securing devices and data in the IoT: (a) Hardware manufacturer should enhance components for enabling parts replacement in the internal components (i.e., on the device level), (b) developing lightweight algorithms for encrypting messages balancing between security level and consumed time and resources and enhancing privacy protection issues, and (c) developing secure and lightweight routing protocols and anti-malware solutions.

7.5. Real-time search

As mentioned above in sections *Literature Review and IoT Search Engine (IoTSE)*, existence of such service could leverage benefits of the IIoT. From the study of most recent research papers (e.g., [3,4,11,33,40]) in this area, this paper proposes an architecture for integrating ICT in the IIoT (Fig. 7) for fulfilling recommended services in IoTSEs (Fig. 9) such as: (a) data preparation (i.e., filtering, reduction, clustering, etc.) [17,27,37,40,111], (b) crawl scheduling (based on frequent changes in states and readings) [17,46], (c) multi-level indexing (implementing fog-technology for decreasing response delay) [17,73] (see Fig. 7), (d) human and machine query (implement semantic meaning and provide RESTful services to be accessed by machines) [32,38,40].

8. Conclusion

Internet of Things (IoT) has been integrated in almost of daily life objects and applications in different fields. Industrial IoT (IIoT) concerns with the business and financial applications which focuses on interoperability among machines. Increasing number of SThs in these new technologies results in many challenges such as heterogeneity, real-time streaming, big data, privacy and security, etc. IIoT requires automated decision support for connections in the sensing layer between machines (SThs). Information Communication Technologies (ICT) present promising solutions that address and handle most of these challenges. Proceeding from this point, this review was organized to present a comprehensive review about: current research work on heterogeneity and scalability, real-time big data, and ICT implementations, and discovery and search for SThs. Searching for resources, data, and SThs is a common service that enables IoT users (human and machine) to get benefit and share information between applications. Sharing and extracting information in the IoT and IIoT reveal more than 40% from their potentials. This review discusses main data science and ICT: big data, cloud and fog computing, data fusion, machine learning, and blockchain to clarify their impact on the future IoT. Impacts of ICT are clarified on smart transportations and healthcare use cases.

IoT search engines (IoTSEs) could enhance their performance by integrating such technologies, Dyser and WoTSF have to implement machine learning to extract repetition patterns in SThs measurements. IoT crawlers enhance their performance by analyzing extracted patterns to schedule SThs URIs. Blockchain enable IoT devices to secure themselves from fake crawling. To guide researchers for the recent trends in the IoT, this review ended by the future research directions (challenges and promising work on each challenge): heterogeneity, scalability, task scheduling, data storage (on the cloud), security, and real-time search that enable IoTSEs to present services in a global and secure manners.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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