Searching for Internet of Things Resources: Requirements and Outlook

Chapter · March 2019

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Contents

Chapter 1

On Searching for the IoT Resources: Requirements and Outlook

Abstract

With the prevalence of networked sensor technologies, collecting data from the physical environment and (automated) interactions with devices ranging from actuator and sensor nodes is a growing trend. The volumes of dynamic data that are collected from the physical world are increasing exponentially and extracting meaningful information from them has become a challenging task. The Internet of Things (IoT) is an umbrella term that refers to integrating the physical (smart) objects into the digital world (i.e. Internet). IoT leverages the exploitation of the 5G network capabilities to enable more devices and objects to connect to the network and communicate with each other with low latency and high response time. Moreover, the scale, distribution, dynamicity and heterogeneity nature of IoT resources raise a set of challenges in data processing and analytics. The current information retrieval and access methods for the Web are not applicable for dealing with the data deluge to provide efficient and scalable practical IoT dynamic applications and solutions. This chapter discusses the requirements and challenges of designing and developing effective IoT solutions.

1.1 Introduction

The Internet of Things (IoT) has emerged as a paradigm that bridges the gap between physical and digital worlds by providing connections and communication between physical objects (Things) in the real world to the digital world (Internet). Leveraging Web standards and communication technologies that allows IoT resources, collecting and exchanging their data with other resources on the Web is often described under the umbrella term of Web of Things (WoT). The core concept of IoT/WoT is an evolution of using various networking and communication technologies and data analytics. For example, Radio Frequency IDentification (RFID) is utilised to capture object context (e.g. location), and sensor motes are attached to vehicles and trains to monitor and analyse transportation systems. Machine learning methods are applied to IoT data and resources to make predictions and provide recommendations and prescriptive actions and analytics.

The availability of IoT data opens up new business opportunities across multiple verticals such as environment (e.g. smart metering and agriculture), industry (e.g. supply chain and intelligent transport systems) and healthcare (e.g. activity tracking and healthcare monitoring). It is expected that 50-100 billion Internet-enabled devices will be connected to the Internet by 2020 [26]. As a result, myriad of streaming, high-scale, heterogeneous and spatiotemporal data will be collected and published by billions of heterogeneous sensors and resources in a real-time manner. The dynamicity and ad-hoc nature of underlying IoT resources make accessing and processing their data and services a challenging task [12]. Moreover, the high latency (i.e. the time the data takes to reach a destination and come back to its source) in the cellular networks limit the effectiveness of IoT solutions and applications. To unleash the potential of IoT, there is a need for fast, reliable, efficient and high-capacity networks.

The current cellular networks capabilities limit the effectiveness of IoT solutions and applications in terms of capacity, latency, mobility, reliability and speed [2]. The 5G networks are expected to revolutionise and lead to significant growth in the IoT across multiple verticals. IoT leverages the exploitation of the 5G network capabilities by allowing more devices and objects to connect to the network and communicate with each other with low latency and high response time. The network is expected to meet different performance requirements for various IoT applications ranging from low latency and mobility on demand of tracking vehicles in traffic control applications to reliable, secure and delay-sensitive applications (e.g. healthcare monitoring) [8]. This enables developing smart and powerful IoT ecosystems.

The architecture of 5G networks has to address the limitations associated with the current cellular networks on the communication level; however, the deluge of data produced by a large number of resources make access and analysis this data a challenging task. The current information access and retrieval solutions on the Web are far from ideal. Most of the existing solutions rely on pre-defined links between resources and are mainly tailored to process text-based data [11]. To this end, indexing, search, and discovery methods to address the inherent features and characteristics of IoT data in dynamic and ad-hoc networks have a potential impact on efficient access and use of available IoT data and resources [14].

The rest of the chapter is organised as follows: Section 1.2 states the special characteristics of IoT data. Section 1.3 discusses the key components and requirements for developing effective IoT applications. Searching for IoT resources and data and its key challenges are discussed in Section 1.4. Section 1.5 concludes and discusses the areas for further research.

1.2 Special characteristics of IoT data

IoT resources are continuously generated data as data streams. The massive amounts of data streams have particular characteristics that are different from conventional data streams [5]. The data is collected from heterogeneous resources with a different format and various quality and granularities. The data is not only large in volume, but it is also continuous, dynamic with spatial and temporal dependency (i.e. spatiotemporal) [4, 14]. IoT data streams are often collected and published with meta-data, and consequently, the streams have a wide variety of representations.

IoT data is a type of big data. There are five intrinsic characteristics of big data (5 V's) [10]; Volume, Variety, Velocity, Veracity and Value. The variety is increasing while technology is advancing and the amount of data is growing while network-enabled devices are connecting to the Internet. IoT data does not only have big data characteristics, but IoT

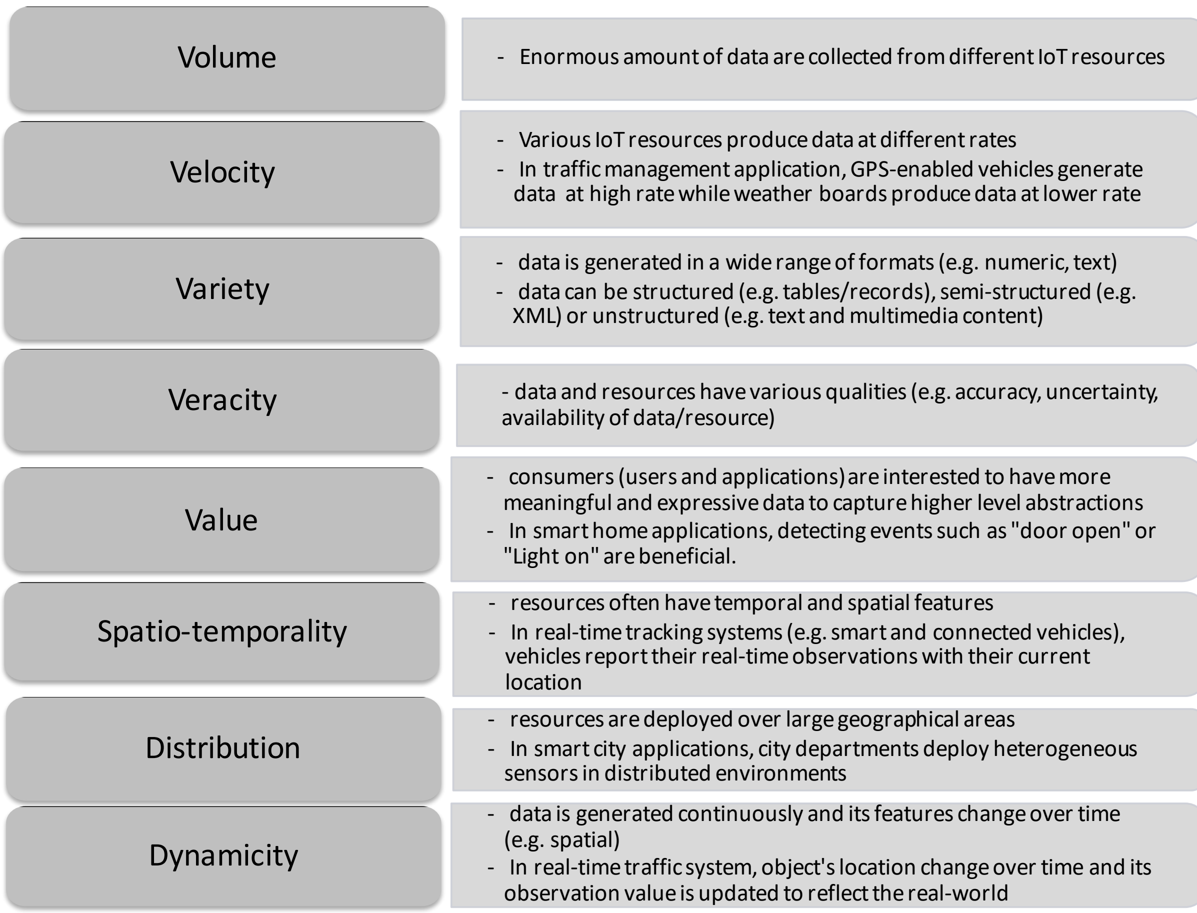

Figure 1.1: Characteristics of IoT data

data has also dynamicity, distribution and spatio-temporality characteristics [14]. Different IoT applications have different requirements and collect various types of data. For example, different services communicate directly with mobile devices to track their locations in smart connected vehicles and traffic monitoring applications [6]. In real-time railway application, GPS unit is associated with each train to enable users finding departures and arrivals in a real-time. The characteristics of IoT data is summarised in Figure 1.1.

1.3 Key design requirements for IoT applications

The large-scale of the network-enabled devices imposes challenges in collecting, aggregating, and processing their data and services on the network. The process chain from collecting real-world observation data up to making the data accessible on the Web is discussed in [4]. However, indexing and ranking processes are not considered within the process. On the other hand, the IoT life cycle from data production to data querying and analysis is presented in [1]. The indexing and ranking processes are not included in the cycle.

Similar to [14], the process chain from sensing and collecting IoT measurement and observation data up to making them discoverable for end-users is shown in Figure 1.2. IoT heterogeneous devices have to connect and communicate autonomously with each other and with the Internet. Data can be aggregated and summarised from different data sources with various data types. Meaningful abstractions from raw sensor data allow inferring a higher-level description of the data and enable representing the data in machine-readable/ human understandable.

Data can be published with or without abstraction and aggregation. For example, different sources of data are aggregated in traffic monitoring applications (e.g. vehicle traffic flow, pedestrian activity). The data can then be abstracted to inform users about traffic status updates(e.g. low/high traffic, recommended routes). Getting the temperature of a particular room requires raw sensory temperature readings without aggregation or abstraction. Different IoT applications require different representation of data to users (human and applications). IoT data can be archived (i.e. historical data) and stored in information repositories for building predictive models to monitor/detect phenomenon/events.

Publishing sensor data with semantic annotation and meta-data enrich data representation and make data more interpretable and interoperable [4]. Indexing and ranking mechanisms of IoT resources are required to provide faster and efficient real-time data retrieval to answer given user queries. The following lists the key design considerations for IoT applications.

Figure 1.2: The process chain for collecting data up to make them discoverable and searchable

1.3.1 Collection and communication

Sensory devices are key enablers to collect observation and measurement data about the real-world environment. The data collected by devices should be integrated with other resources on the Web; however, resources interact and communicate via different interfaces and protocols. Resources do not only have a different interface, but they also provide different types of data (e.g. numeric, text, media). Sensor Web Enablement (SWE) [1] standard has been proposed to access and exchange data between heterogeneous resources in a standard way through Web service interface.

IoT devices have limited power, memory and processing capabilities. Dealing with data deluge generated by IoT resources at the source level is not a practical approach. The basic approach is to collect observation and measurement data from sensory devices at a base station to perform some processing on the data; however, continuous transmission of measurement and observation data incurs high communication costs for sensory devices. Some mechanisms and strategies have been proposed to reduce the communication between sensor nodes and a base station by predicting the recent sensor readings at both sensor and base station and sensory devices required to transmit their data if they deviate significantly from the predicted values such as [25, 13]. Such approaches can effectively reduce the energy consumption for each sensory devices and consequently, prolong network lifetime, especially for battery-powered nodes.

The key requirements for sensing and communication include having a unified identifier for each resource and providing a way of interaction and communication between different IoT resources and how the IoT resources should be discovered and accessed. Sensor devices can be detected automatically (i.e. active resource discovery), or devices should be registered manually by the device owner (i.e. passive resource discovery) [16, 14].

1.3.2 Aggregation and abstraction

IoT resources are distributed and provide data with a different structure, qualities and various granularities. The key challenge in data aggregation is that the data from multiple resources

[1] http://www.opengeospatial.org/projects/groups/sensorwebdwg

has different data models and formats. There are different approaches to aggregate data from various resources. For example, temperature measurements from multiple sensors in a monitored area are aggregated together by averaging measurement values. The aggregation can also be from different types of resources such as traffic monitoring application where data from various resources are aggregated to identify the traffic update status. There are also other in-network aggregation techniques where an aggregated node collects observations and measurements from different sensors are aggregated them into one data packet.

Abstractions are less granular data; it creates a high-level description data from sensory raw data [15]. Abstractions could have two levels. Low-level abstraction is about inferring abstracted information from a single source of data. High-level abstraction includes deriving abstracted information from multiple sources. Meaningful abstraction allows deriving information from data such as events and patterns. We refer the interested reader to the detailed discussion in [14] on different aggregation and abstraction approaches.

The key requirements for data aggregation include aggregating and combining data from multiple resources (e.g. sensors, Web) where each resource might have different data models and structures and various qualities.

1.3.3 Representation and publication

IoT data is collected from heterogeneous resources with different granularity, and various quality and data providers have different ways of published their data. The collected data is stored in a central repository or a distributed cloud [17]. The data can have different data attributes (e.g. numeric, categorical) and stored in various formats (e.g. CSV, XML, JSON). The data can be enriched by meta-data to enable interoperability with other data resources [4]. The data is often accessed through Web service/API. The data should also be represented and interpretable in a machine-understandable and human-readable format.

Several standards have been developed by different organisations such as the Internet Engineering Task Force (IETF), The Internet Protocol for Smart Objects (IPSO) Alliance and other. The standards are to offer connectivity for IoT resources. Different organisations and standardisation are discussed in [14]. On the other hand, the best practice of publishing and accessing spatial data on the Web is discussed in [28]. The way the data is published and represented has a direct impact on the crawling, discovery and access of the data. The key challenge in representing and publication is that we do not have a unified framework or standardisation for publishing and representing the collected data.

1.3.4 Indexing and discovery

In Web search engines, Web pages are indexed to allow fast search and data retrieval. Similarly, IoT data and resources are indexed for efficient access and discovery. In IoT, we can construct indexing based on the type of applications. Indexing can be built for IoT data or resources [14]. Data can be indexing based on the spatial and contextual features (e.g. location). For instance, the spatial property of the data can be presented in Longitude, Latitude and Altitude coordinates. One way to index the data based on spatial feature is space-filling curves (e.g. Z-order) where the coordinates are mapped into one dimension (i.e. a key) such as [5, 34, 12]. Such approaches allow discovering the data based on a constructed key.

Indexing could be based on thematic data (e.g. specific term, field). For instance, In [19], indexes are built on a selected set of XML fields of the meta-data of the connected resources to the network. Tree-based indexes have been proposed in literature; however, most of the existing approaches do not allow updates or updating the constructed tree is computationally expensive [14]. Moreover, indexing can be constructed on resources such that the discovery is based on finding a resource that can answer a user query. For instance, a distributed in-network indexing approach has been proposed in [11]. The indexes are based at a gateway after clustering the resources based on their spatial properties. A tree structure is built based on the type of services the resources provide. However, the tree based on a pre-defined type of services. Other approaches such as [7, 30] are based on semantic indexing of the description of IoT resources.

Indexing IoT data and resources has a direct link with data discovery. While indexing organises IoT resources and data to allow efficient access and discover, discovery utilises the constructed indexes to respond to user queries. The dynamic nature of IoT data and resources requires having an adaptive and efficient indexing approaches. The approaches should be updated efficiently taking into account that a new resource or data might be added to the constructed indexes.

1.3.5 Query and ranking

Users expect to find meaningful information from raw sensory data. Therefore, the main objective of real-time processing and discovery the IoT data is to convert the contextual information of raw measurement and observation sensor data into useful and actionable knowledge to design and develop smart applications that can respond to end-user queries. However, accessing a specific part of data to provide a real-time analysis with minimal network communications to adhere the communication, sensing, and power constraints of some sensory devices is a challenging task. Data query can be described by three parts; accessing the right location to get the right data at the right time. The accessing process is based on the user's queries (search). A query could be composed of type, location, and time attributes. In this case, it is called "Exact query". For instance, get the temperature value (type) in London (location) now (time). Other possible types of queries exist such as proximate, range, and composite queries [5]. Data discovery could be limited by the interval time (time between two consecutive data streams) in the processing of data for disaster monitoring.

Ranking is about prioritisation the resources given a set of criteria such as data quality, resource availability and others. Different ranking mechanisms have been proposed based on multiple criteria such as Quality of Information (QoI), Quality of Service (QoS) and user feedback. In [18], data quality model is developed. The model is based on a set of data quality attributes of the sensors such as accuracy, completeness and accuracy while responding to queries. However, the model is based on the sensors' precision provided by their manufacturer. In such a case, a sensor provides a valid data even if it has failures.

Overall in the IoT applications, it is essential to allow users to query (search) on a particular term and near (real-time) analysis respond while other data are arriving and devices are connecting. Query results should be based on some ranking criteria. It could be based on user requirements (e.g. fast response) or resource requirements (e.g. quality of services, resource availability). Most of the existing IoT systems and frameworks are complex or centralised which make them a hindrance to scalability for large-scale and uncoordinated networks of devices and resources [21, 9, 16, 20]. Figure 1.3 shows how users can interact with IoT applications. The diversity of how users can interact with IoT applications suffices for designing and developing a wide range of IoT applications and allow stakeholders to recognise the full potential of the IoT.

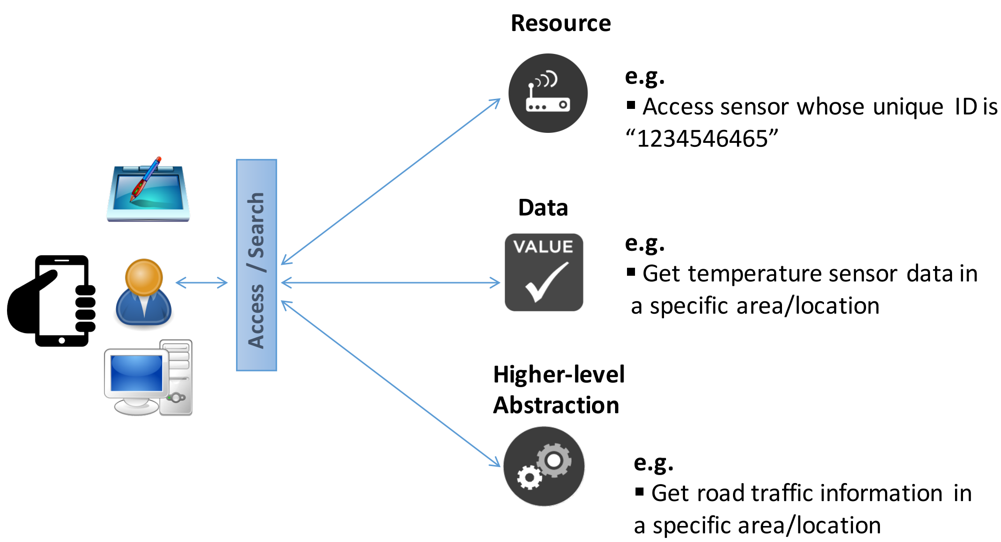

Figure 1.3: How users can interact with IoT applications [14]

1.4 Searching for the Internet of Things

IoT data is often generated in ad-hoc and dynamic environments. Various aspects have an impact when designing IoT discovery and search solutions. Reliability, uncertainty and quality among others are key concerns in designing IoT solutions [3]. Users should be able to specify different requirements of requested data concerning the accuracy, reliability, energy, and availability [23].

Providing data discovery in a real-time manner and gain valuable insights, and actionable knowledge is a challenging task. Ranking search and query results based on given requirements (such as resource quality or precision) [14]. Queries can be answered based on a similarity search in IoT resources [27]. A similarity search could be beneficial to provide a measurement of neighbourhood node if data from a specific sensor unexpectedly is not available. IoT solutions should have a balance between the expressiveness of data description and complexity of data model [4]. The application should also automatically abstract, aggregate, and integrate data from newly connected IoT devices and services into the network while continuously analysing data and responding to user queries in a real-time manner. The solutions should also have highly optimised processing and discovery mechanisms that are tailored to eliminate response time and provide immediate results for user queries.

The scalability of data processing and search is another important issue. Software-defined solutions have been proposed to address this issue [32]. The solutions enable distributing a processing task among multiple available resources. The spontaneous interaction between resources is another key issue [33]. IoT devices are often deployed in an ad-hoc and dynamic environment. The devices have limited process and computation capabilities. To this end, devices might spontaneously interact with each other. IoT solutions and networks should handle such interactions efficiently. On the other hand, mobile sensors produce different sensor readings over time due to varying its location. Conventional Web search engines are limited to address the dynamicity nature of IoT. They assume that Web page content is updated slowly, and consequently, Web indexes are updated and refreshed every couple of days [33]. IoT indexes should be adaptive and updated frequently. The update rate depends on how often the underlying data changes [14]. In addition, there is no standardised way of crawling IoT resources. Crawling is about how resources can be discovered and connected to the network, and their features can be integrated into indexes. Overall, IoT requires (auto) discovery and (near) real-time searching and processing mechanisms.

There are some initial works on developing IoT/WoT search engines. Dyser has been proposed [22]. Dyser assumes that each sensor has a meta-data description in the HTML page that can be crawled. Dyser employs a probabilistic model to predict the sensor that might be communicated with while answering a user query. The main shortcoming for the engine is that users must be aware of the state names for all objects to query them. Snoogle is another search engine for indexing and ranking entities [29]. Indexing entities are based on using IPs. Moreover, indexing relies on building inverted indexes for all connected entities and the IPs are managed at a Key Index Point (KeyIP). However, building indexes based on IPs that might change is not an efficient way. MAX is another human-centric search [31]. MAX assumes that each device has RFID tags and once a query is received, it then broadcasts to all physical devices to find a response from one of them which is computationally expensive. Moreover, the search engine does not support indexing or tanking mechanisms.

Wolfram-Alpha [2] and Thingful [3] are another examples of discovery knowledge and services engines. Thingful is considered a search engine for public IoT services. It allows users to search for a service that is provided by connected IoT devices of different categories such as environment (e.g. temperature, humidity, and pressure), energy (e.g. light, battery), and health (e.g. smart weight to report user's fitness) in different locations. Users can register and share observation and measurement data of their objects and devices. The major drawback of Thingful is the unavailability of real-time data. Search results include all data sources. However, these sources might not be available at search time. This does not guarantee real-time measurements, especially environmental observations such as temperature and humidity that are usually changing over time. Other deficiencies are trust, security, and quality. Many resources provide the same type of measurement in the same location, but there is no guarantee to what extent these resources are trustworthy and with good quality and precision.

Wolfram-Alpha is a computational knowledge discovery engine. It is based on Mathematica that is often known as Wolfram Language (`http://www.wolfram.com/mathematica/`). The engine allows a user to register their own Internet-connected things such as Twitter, email, Raspberry Pi [4] and others. Each registered device/service has a unique "databin" and data is updated from each databin every 30 seconds [5]. The main shortcoming is that users can search and query resources if they know their databins. Moreover, Wolfram-Alpha has Wolfram Data Framework (WDF) that summarises and integrates data into a meaningful and expressive form [6].However, there is no available information about its architecture and technical details. We refer the interested readers to a discussion on other IoT engines in [24, 14].

Overall, the main problem in the current IoT/WoT search engines is that they do not provide efficient search and discovery for IoT data and resources. They allow querying data

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[2] http://www.wolframalpha.com/
[3] http://thingful.net/
[4] http://www.raspberrypi.org/
[5] http://blog.wolfram.com/2015/03/04/the-wolfram-data-drop-is-live/
[6] http://www.wolfram.com/data-framework/

from resources; however, there is no deep analysis and mining of collected data to enable answer complex user queries. Scalability and/or distributed processing and analysis are still key issues [14].

1.5 Conclusion and outlook

In ubiquitous computing, smart sensors are used to report, monitor, and track physical environment. IoT incorporates the concept from ubiquitous computing. However, there is still fuzziness on defining the real capabilities of IoT given the current status of real-time big data analytics researches. Advances in big data analysis techniques is a key-enabler for providing IoT environments and applications with (near) real-time analysis. On the other hand, the emergence of 5G technologies will also unleash the potential of IoT applications by providing a new spectrum of effective communication models and usage and allowing more devices and sensors to connect to the network. It is therefore foreseeable that IoT will have high potential and ecological impact on citizens in the physical environments with the advancement of 5G technologies and big data analytics in the near future.

Building IoT/WoT search engines is on-going research. In this chapter, we underline challenging in discovery and processing mechanisms. The future research directions of IoT will also depend on creating large-scale ecosystems of IoT systems that can work and collaborate with each other to share and exchange data and services. While scalability, (near) real-time analysis linked to quality and granularity of the data and access policies are critical components of designing future IoT systems, security, provisioning, reliability, and trust will also be crucial components of any design in future IoT data/service access and discovery systems. There has been recent work on adopting block-chain technologies into IoT. For accountability and audit-ability, data permissions based on smart contracts using block-chain can be achieved such that there is no need of central trusted authorities or intermediaries for providing reliable data integrity between device owners and data consumers and consequently reducing the cost of deployment. In critical infrastructure, block-chain solutions can provide a history of connected IoT resources for troubleshooting purposes.

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