Towards the Distributed Edge – An IoT Review

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***Abstract*— The internet of Things (IoT) architecture was originally envisaged as a two-layer technical platform, with sensors collecting data at the edge with minimal compute requirements, solely to prepare and transporting the data to a centralized or cloud based infrastructure for processing. This model is suitable in some scenarios, for example where data is being stored for historical, regulatory or trending usage however in other use cases such as health monitoring for acute illness or autonomous vehicle computer vision the latency in transporting this data to a remote location for processing may cause latencies that would seriously affect performance of the application. There are many different and sometimes overlapping definitions of IoT topologies being discussed within industry. This paper reviews this original topology of an IoT solution, and different techniques and layers available to alleviate the issues inherent of the original paradigm, and how a new method of defining at these topologies is gaining speed.**

Keywords*— *Internet of Things, Topologies, Fog, Edge, Core, MEC

I. Introduction

The Internet of things is a simple concept – using sensors to collect data in the physical world then transporting this data to web based compute and storage platforms (Want, et al., 2015) to be analysed using big data, machine learning and artificial intelligence techniques (Chin, et al., 2017). The goals are to provide better understanding of the physical world, leading to more accurate decision making such as automation of physical tasks based on historical information and knowledge, or improved outcomes for a wide range of vertical marketplaces, such as agriculture through manufacturing, smart buildings, healthcare and energy management industries.

II. The Capabilities of "Things"

The 'Things' in an internet of things solution (Chui, et al., 2010)' must present three separate abilities to enable processing:

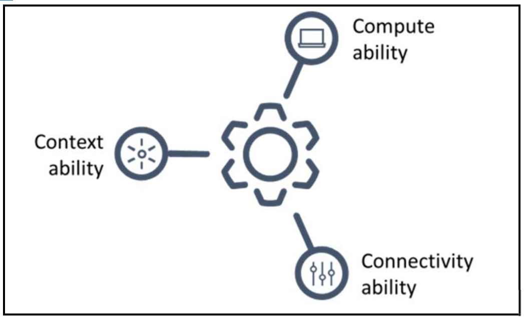

Figure II.1 "Thing" Abilities

Table 1 "Thing Abilities" Defined

Context Ability.	Devices should be able to sense physical data, be that temperature, vibration, pressure, video signals, blood pressure etc.
Compute ability.	The device needs to be able to make sense of this data, and understand what to do with the values it is sensing
Connectivity ability.	The device then needs to communicate this information to the wider platform for further use.

Due to rapid deployment and scalability (Brenner, et al., 2014) capabilities the IoT backbone has been very much led by cloud based platforms (Aazam, 2015) that provide storage and compute platforms, using a Platform as a Service (PaaS) model, such as Microsoft Azure, Amazon EC2 and Google App Engines. These platforms provide tools for manipulating, analysis and reporting on this data – tools such as Microsoft Power BI, Pivotal Cloud Foundry and PTC ThingWorx either as part of a Software as a Service (SaaS) or allows the user to run their own software on the data, in public (Or in some cases on-premise) cloud environments.

It is estimated that the number of sensors globally will grow to over 26 billion by 2050 (Gartner, 2017) These sensors will collect datasets of extremely different data types. Key differentiating features of these datasets are:

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Magnitude of scale:	The number of sensors in the solution creating data to provide the 'picture' of the physical environment. E.g. A water heating boiler in a hole may only have 2-3 sensors, whereas a cooling system in a hotel may have many thousand sensors creating data.
Data Size	The actual storage (in bytes) required to store the sensor dataset. A Sensor can create widely different data sizes, from a few bytes such as a temperature monitor, through to many gigabytes of data in a CT Scan.
Longevity	Focuses on data retention – how long does the data need to be kept for? There are many different requirements for data retention – some data is transient, and only used to make a decision at the time of collection, other data may need to be kept for months, or perhaps forever, for reasons such as providing rich data sets for machine learning algorithms (Chin, et al., 2017) or regulatory (Stuurman & Kamara, 2016) compliance.
Urgency	Each sensor dataset may have different criticality dependent upon the business requirements. For example in an Assisted Living (Tong, 2014) environment there may be data gathered on the usage of the appliances on the home, to ensure the patient is eating, drinking, or has adequate environmental conditions, , but also monitoring critical data points as well, such as blood sugar (Sheta, et al., 2015) or a fall monitor.
Latency	Solutions that are used to closecouple different physical systems together with strict latency requirements between the sensor collecting the data (Oh & Chae, 2007), being processed and action taken by the control device in the system in a matter of milliseconds (Weiner, et al., 2014) examples of such being power generation & smart grid management, and in autonomous transport, vehicle to vehicle communications.

Each IoT deployment has to look at each of these constraints, and identify a solution that will deliver an optimum solution to meet the business requirements of the end user. The early definitions of the internet of things, or internet for things (Ashton, 2011) describes a two layer technical platform where data is collected by sensors at the edge and then transported to a cloud platform for processing. Due to the constraints mentioned above, other topologies are emerging into IoT environments to enable successful solutions. A number of variations on the traditional cloud based platforms are becoming predomiant. We shall look at each of these, and compare their scope, capabilities and optimum use cases.

The original definitions of IoT discuss two distinct zones in solutions – the edge, and the cloud, . These definitions could also be defined as outside and inside of data center, see Figure 1 Initial IoT Topology below. There is evidence that this initial model is changing, with more data being processed outside of these traditional data centers. (van der Mullen, 2017) comments that "Currently, around 10% of enterprise-generated data is created and processed outside of a traditional data center or cloud. By 2022, Gartner predicts this figure will reach 50%"

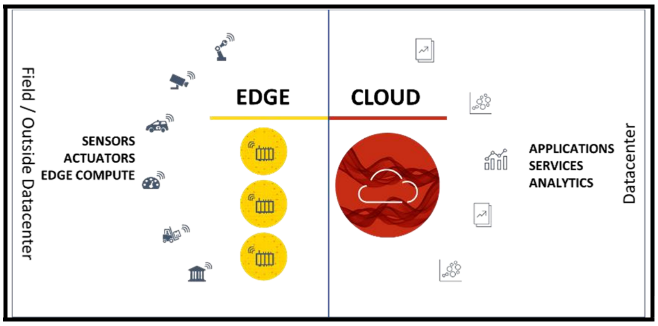

Figure II.2 Initial IoT Topology

As these datasets grow exponentially, and due to the constraints mentioned previously, more compute capabilities will have to move from the datacentres, and into the field, closer to where the data is created. This follows the historical IT swings from centralized to distributed compute platforms:

Table 2 Distributed & Centralized processing

Centralised	Distributed
Mainframe	
	Client/Server
Mini Computer	
	Internet
Cloud Computing	
	Internet of Things

III. EMERGING TOPOLOGIES

A number of different additions to this original topology are emerging, mainly segregating the edge ie. In the field, but also straddling into the datacenter environment. There are a number of prevalent topologies currently available which provide different capabilities in the IoT solution, these are shown in the figure below.

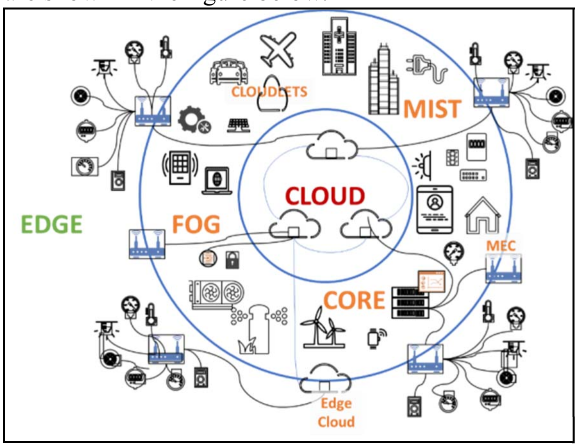

Figure 3 Extensions to IoT topology

A. Edge Computing

In the original IoT topology, smart sensors would collect data, and send them back to the cloud for processing. As one of the key enablers of the IoT is the proliferation of sensors and actuators, mainly driven by reducing price of sensors (Gubbi, et al., 2013), adding compute and connectivity capabilities through either through wired (RS232/422/485 etc.), wireless (Wi-Fi, SigFOX, LARA, BLE, ZigBee etc.) or Radio (3&4G/LTE etc.) technologies will considerably increase costs of the devices, and more importantly management of the devices- especially in large sensor arrays.

In manufacturing environments, programmable logic circuits (PLCs) already undertake the context and compute capabilities, however frequently do not have connectivity capabilities or if they do, they are proprietary in nature (Xu, et al., 2016). Conversely one of the main reasons the Internet of Things is becoming more prevalent is due to the reduced price of commodity sensors and actuators (Gubbi, et al., 2013) – adding connectivity and compute capabilities would provide pricing and implications for large sensor arrays.

Edge devices provide capabilities, correlating data from multiple input protocols and mediums, undertaking local processing, such as data compression, or decision making using Artificial Intelligence algorithms (Vermesan, et al., 2017), providing connectivity to TCP/IP via IP Networks, WiFi or radio access networks(RAN), interfacing to proprietary networking and industrial connectivity protocols and providing security and encryption of data (Doukas, Maglogiannis, Koufi, Malamateniou, & Vassilacopoulos, 2012).

Another key role of edge compute devices, or gateways, is to provide continuous operation, running rulesets locally (Gremban, et al., 2018) even during outages or latency issues on the WAN connectivity back to the Cloud infrastructure.

B. Mobile Edge Compute (MEC)

Mobile edge computing is a recent technology stack, which Is becoming an ESTI standard to provide standard for a virtualised compute platform in conjunction with Network Function Virtualisation (NFV). This allows sharing of network and compute capabilities virtually anywhere, and will enable reduced. deployment time and centralised management of remote compute capabilities (Hu, et al., 2015). Ideally located on new mobile base stations to offer localised storage, compute and connectivity for cellular/mobile users providing them low latency, high bandwidth. By opening this MEC environment up to more than just cellular users, ETSI speculates that "The characteristics and capabilities offered by a MEC platform can be leveraged in a way that will allow proximity, context, agility and speed to be used for wider innovation that can be translated into unique value and revenue generation" (Hu, et al., 2015). (Tran, et al., 2017) discusses the use of MEC and the use of commodity server platforms to provide MEC capabilities, and identified 5 key areas for MEC architectures to become successful:

Table 3 Key areas for MEC Architectures

Deployment Scenarios & Resource Management	How to identify where the best locations to physically install the MEC platforms, and how to manage them remotely

Computational Caching and offload	The combination of compute and storage locally can provide increase in compute capability and speed to the user, whilst reducing traffic to the cloud connections. There are challenges here around deciding what to cache, as each user's compute requirements may have unique data requirements, unlike content caching and so traditional popularity algorithms may not be suitable for computational caching purposes
IoT Applications and Big Data Analytics	MEC can help reduce and refine datasets before sending back to big data platforms for analysis / deep learning and
Mobility Management	Ensuring continuous connectivity for mobile users is a key consideration for MEC, with trajectory predictions (of the user) enabling the caching of data amongst MEC network nodes
Security and Privacy	As there are multiple compute points, at remote locations the attack surface is increased exponentially over a traditional cloud platform. Privacy of the user's compute requirements is also a key concern for MEC systems.

C. Fog Computing

(Chiang & Zhang, 2016) describes "Fog is an emergent architecture for computing, storage, control and networking that distributes these services closer to end users along the Cloud-to-Things continuum.". Fog computing was first introduced as a concept by Cisco in 2012 (Bonomi, et al., 2012) and is described therein as "the cloud close to the ground". The goals of Fog computing is to place local compute capabilities close to mobile users, who can utilise high speed connectivity (such as WiFi) to connect with high bandwidth and low latency, in comparison to 3G/4G/LTE connectivity directly to a cloud infrastructure. One of the key capabilities Fog Computing offers over traditional cloud computing is that of locational awareness – the compute capabilities can tailor responses to users dependant on their physical location.

This definition has expanded to a wider subset of users than just mobile/cellular users and contemplates how moving compute, storage and connectivity to virtualised environments closer to the edge will provide change in practice for IT, to enable development, provisioning, network management etc. to deliver these distributed In compute environments. (Vaquero & Rodero-Merino, 2014).

D. Core Computing

The principle of core computing is to provide localised data center capabilities within geographical proximity of the edge devices (Guo, et al., 2017) on low latency networks. This data center data capability allows for large scale compute and storage (Stimpson & Cummings, 2014) enabling localised machine learning and training, where prediction accuracy is driven by size of datasets (Jin, et al., 2010), which in turn and supports AI capabilities pushing rulesets back to edge devices (Clayton, et al., 2016) for actuator control, or training the algorithms on what data needs to be pushed back to the core for further analysis, or be processed at the edge only. A good example of the Edge – Core – Cloud continuum would be that of a Wind farm (Fulton III, 2017) . At the edge in each windmill, IoT edge gateways (Lee & Nair, 2016) collect sensor data from multiple sensors, and provide monitoring and management of the windmill, RPM speed, energy output, speed overload parameters, and feeds this data to a Core data center, onsite. Here information from each of the windmills, alongside external data for example wind predictions, can be analysed to overview the entire farm capabilities, but also provide data back down to each windmill, to improve efficiency and management – for example to shut down the entire farm during very high wind events. Overall production data can then be provided to a cloud platform, either publicly or privately hosted (Bowen, 2013). The grid management can also provide the signals for synchronisation of power onto the distribution grid, back to each of the generating farms, and they in turn can regulate the waveform to integrate into the grid. (Blaabjerg, et al., 2006)

E. Edge Cloud

(Jang, et al., 2017) describe Edge-Cloud as "…a collection of smart objects such as IoT devices dynamically form an edge cloud allowing acquiring, storing, communicating, and processing of information done at the edge of the network." An example of an edge cloud would be a home, where multiple devices peer to peer (p2p) devices communicate with each other, then a centralised system would provide a node to a distributed cloud architecture. (Lopez, et al., 2015)

F. MIST

MIST computing acknowledges the fact that in low powered environments, communications can take up to five times as much power as sensing, and so a devices should only deliver the information that has been requested, when it is requested, through a subscriber provider model, over an adaptive and dynamic network infrastructure. MIST solutions require that the model provide contextually aware information, rather than raw data, to the user (Yogi, et al., 2017). Mist implementations, such as Thinnect focus on the 'last 100M' of the IoT continuum, with small dataset stack size (100KB) it is suited to very low energy usage models, such as energy harvesting sensors, and allows the sensors and actuators undertake tasks which are simple, or have lower computational requirements locally. Where more complex precessing is required, the information provided from the sensors is passed back to gateways in the fog environment for further computation, thus reducing latency and bandwidth utilisation (Preden, 2017)

G. Cloudlet

Cloudlets are defined as being (Uehara, 2017; Panda, et al., 2013) a middle tier between mobile devices, and the cloud, and their goal is to provide reductions in latency by handling localised queries closer to the mobile user – a good example would be in autonomous vehicles (Klas, 2015), where traffic signals will provide data locally to a car for processing, rather than via a remote cloud solution.

IV. The Distributed Edge

All of the topologies above discuss different technical solutions for IT systems to interface with the real world, collect data, transport and process this data into meaningful solutions. overcome problems of acquiring, transporting and processing data across different technologies. (Davis, Shih, & Marcham, 2018) proposes that the original EdgeCloud topology can be refined to acknowledge the movement of compute away from the cloud encompass the principles that:

- The edge is a location, not a thing;
- There are lots of edges, but the edge we care about today is the edge of the last mile network;
- This edge has two sides: an infrastructure edge and a device edge;
- Compute will exist on both sides, working in coordination with the centralized cloud. There is within this schema, definitions and distinctions made between the Infrastructure Edge where compute is extended from the cloud to close to the physical item data is being collected from (Vogler, Schleicher, Inzinger, & Dustdar, 2015) and the Device Edge, where the sensors, actuators and other interfaces connect with the physical world.

V. Conclusions

All of the topologies discussed focus on one major area, that being the decentralization of compute and data, through different mechanisms. The goal of each topology it to provide better user experience, through localisation (Ramnath, et al., 2017) (McAllister, et al., 2017), reduced latency (Kotamsetty, 2016) and improved security (Lincke, et al., 2015) (King & Awad, 2016). Due to the wide variations of IoT requirements, a number of overlapping topologies exist, from the sensor or actuator though local environments, to decentralised or core cloud capabilities, and reaching out to public, private or hybrid clouds (Li, et al., 2014). Some of these topologies provide a full stack for connectivity and compute (Cirani, et al., 2015), others purely the transport – for each IoT deployment understanding of the data type, its sensitivity to latency (Williams & Dejanovic, 2002) and whether it needs to be processed by itself, or in conjunction with other datasets such as historical information are some of the factors that will dictate which topologies are best suited to the individual solution.

As these different topologies such as the distributed core emerge, schemas for holistic data management, and end to end security of IoT environments will be critical to successful deployments, this is an area that further research should be undertaken, to identify and provide end to end capabilities for this exponentially growing marketplace.

Acknowledgment

This research was made possible by the contributions of Science Foundation Ireland, SFI and through Confirm the Irish Centre for Smart manufacturing.

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