



UNIVERSITY OF LEEDS

This is a repository copy of *Impact of Distributed Processing on Power Consumption for IoT Based Surveillance Applications*.

White Rose Research Online URL for this paper:
<http://eprints.whiterose.ac.uk/149141/>

Version: Published Version

Proceedings Paper:

Yosuf, BA, Musa, M, Elgorashi, T et al. (1 more author) (2019) Impact of Distributed Processing on Power Consumption for IoT Based Surveillance Applications. In: Proceedings of the 21st International Conference on Transparent Optical Networks (ICTON 2019). ICTON 2019: 21st International Conference on Transparent Optical Networks, 09-13 Jul 2019, Angers, France. IEEE . ISBN 978-1-7281-2779-8

<https://doi.org/10.1109/ICTON.2019.8840023>

© 2019 IEEE. This is an author produced version of a paper accepted for publication in 2019 21st International Conference on Transparent Optical Networks (ICTON). Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. Uploaded in accordance with the publisher's self-archiving policy.

Reuse

Items deposited in White Rose Research Online are protected by copyright, with all rights reserved unless indicated otherwise. They may be downloaded and/or printed for private study, or other acts as permitted by national copyright laws. The publisher or other rights holders may allow further reproduction and re-use of the full text version. This is indicated by the licence information on the White Rose Research Online record for the item.

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.



eprints@whiterose.ac.uk
<https://eprints.whiterose.ac.uk/>

Impact of Distributed Processing on Power Consumption for IoT Based Surveillance Applications

Barzan A. Yosuf, Mohamed. Musa, Taisir Elgorashi, and J. M. H. Elmirghani

School of Electronic and Electrical Engineering, University of Leeds, Leeds, LS2 9JT, United Kingdom

E-mail: {elbay@leeds.ac.uk, M.Musa@leeds.ac.uk, T.E.H.Elgorashi@leeds.ac.uk, J.M.H.Elmirghani@leeds.ac.uk}

ABSTRACT

With the rapid proliferation of connected devices in the Internet of Things (IoT), the centralized cloud solution faces several challenges, out of which, power consumption is one of the top priorities among the research community. In this paper, we evaluate the impact of demand splitting over heterogeneous processing resources in an IoT platform, supported by Fog and Cloud infrastructure. We develop a Mixed Integer Linear Programming (MILP) model to study the gains of splitting resource intensive demands among IoT nodes, Fog devices and Cloud servers. A surveillance application is considered, which consists of multiple smart cameras capable of capturing and analyzing real-time video streams. The PON access network aggregates IoT layer demands for processing in the Fog or the Cloud, which is accessed through the IP/WDM network. For typical video analysis workloads, the results show that, splitting medium demand sizes among IoT and Fog resources yields a total power consumption saving of up to 32%, even if these layers can host only 10% of the total workload and this can reach up to 93% for lower number of demands, compared to the centralized cloud solution. However, the gains in power savings from splitting decreases as the number of splits increases.

Keywords: IoT surveillance, PON, energy efficiency, fog, distributed processing.

1. INTRODUCTION

The Internet of Things (IoT) paves the way for a plethora of applications that contribute significantly to enhancing our daily lives, in domains such as security, agriculture and health care, to name a few. It is estimated that, by the end of 2020, the IoT will host between 50 billion and 200 billion devices [1]. One of the classes of IoT devices are IP-enabled smart cameras that are expected to be deployed in future smart cities for real-time surveillance and video analysis purposes [2], [3]. In a news article published in 2013 by The Telegraph, it is reported that there is one surveillance camera for every 11 people in the UK [4]. These devices will generate massive amounts of data and will demand further processing in order to extract knowledge and make informed decisions. In conventional cloud computing, all of the demands must be aggregated and transported over the network to distant data centers housing enormous numbers of servers [5]. This approach can be problematic because it introduces a great pressure on the already over-stressed network, specifically in terms of bandwidth, energy and other resources[1]. There is a growing consensus among academic researchers on the importance of prioritizing energy conservation among other challenges due to its adverse impact on the environment [6]. To address the aforementioned challenges, Fog computing was introduced to extend the cloud functionalities as close as to where the data is being generated, e.g. at the “edge” of the network [7]. The fog computing paradigm proposes for the utilization of idle computational resources available at the “edge” of the network, allowing for the creation of a shared and highly virtualized micro-data center. Having said that, Fog computing is not proposed to replace the Cloud, rather, the goal is to harness the benefits of both paradigms. Here, service requests that are resource intensive, and which may not be able to be entirely run on the constrained Fog devices, is run using the extensive computational power of the cloud data centers. Likewise, those services that can be hosted within the “edge” nodes can avoid the costly overhead of the network and cloud data centers [8]. As depicted in

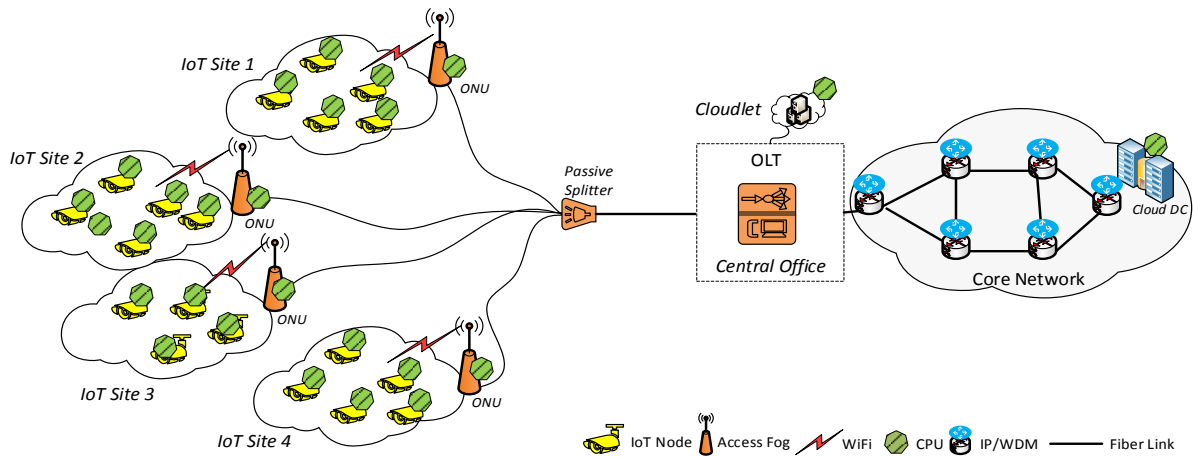


Figure 1, Fog nodes act as intermediary processing servers between the Cloud-DC and the IoT devices. Fog nodes can be deployed anywhere as long as they can have access to connectivity to the internet. Fog nodes can provide storage to cache sensed data, and processing to extract intelligence from it. Devices connected to Fog nodes can be, but not limited to: switches, routers, embedded devices, surveillance cameras, etc [9]. Optical-based networks have been hailed to offer high bandwidths, reduced latency and improved energy efficiency for bit-rate hungry applications, compared to the other technologies such as copper based communication systems or LTE [10]. Our previous work presented energy efficient solutions in cloud and core networks using MILP techniques considering a variety of scenarios including renewable energy, network coding, and virtualization [23] – [37]. The remainder of this paper is organized as follows: In Section 2, the model architecture is described. Section 3 includes performance evaluation and results followed by Section 4 in which we provide our conclusions.

2. IOT-BASED SURVAILLANCE MODEL

The architecture shown in

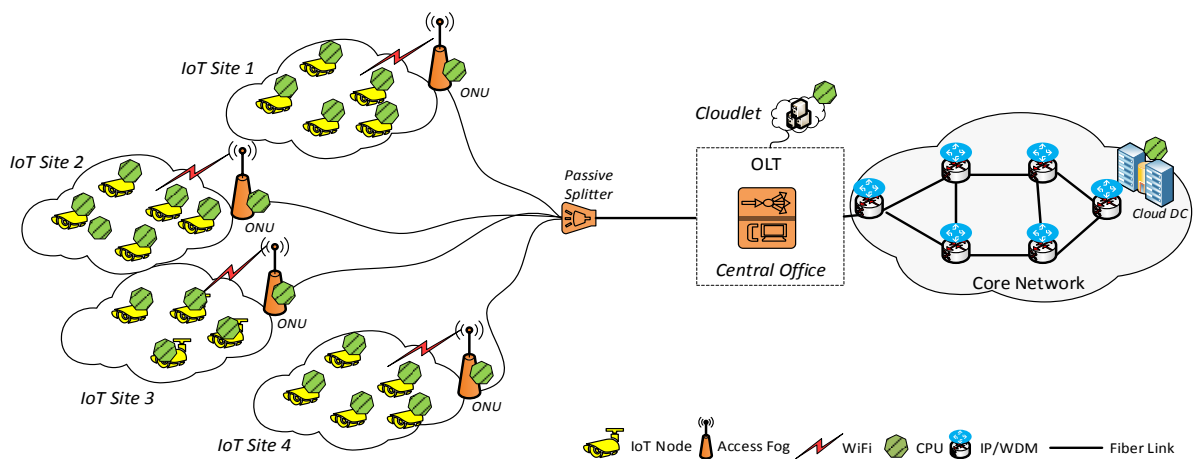


Figure 1 consists of four main layers: 1) IoT, 2) Access Fog, 3) Edge Fog and 4) Cloud-DC. The first layer consists of multiple IoT devices that are deployed into different sites, connected to each other and the Cloud through the PON access network. The second and the third layers are part of the PON access network. The ONU devices aggregate the service demands from the IoTs and they are capable of either relaying the aggregated demands onto the next layer or hosting them locally for processing. Likewise, the OLT node acts as the metro node, gateway to the core network as well as being a micro-DC. The fourth layer is the core network linking up multiple core nodes through IP/WDM technologies and providing access to the distant Cloud-DCs. We consider IoT devices such as surveillance cameras that generate requests for processing video streams. These requests are assumed to have the flexibility of being distributed among as many processing nodes as possible. In order for any node to take part in processing a request (partially or fully), the source node must transport the same data to the processing node(s) in question, hence, the bandwidth requirement is part of the request unless the request is

hosted locally. In this work, we develop a model using Mixed Integer Linear Programming (MILP). We report the results obtained using the MILP and focus on the impact of distributed processing on the total power consumption. There are two main parts to the total power consumption, which are a) the power consumed due to the network and 2) power consumed due to processing. The sum of these two parts is minimized subject to the flow conservation constraint and the capacity conservation constraints.

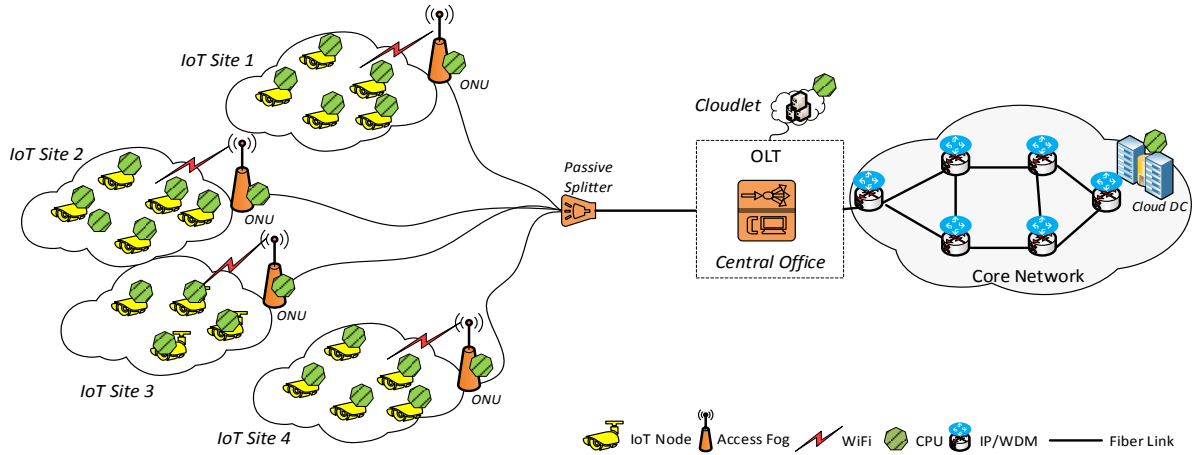


Figure 1: A surveillance application utilizing IoT-based PON networks.

3. PERFORMANCE EVALUATION AND RESULTS

Our evaluation scenario considers a typical IoT setting as depicted in

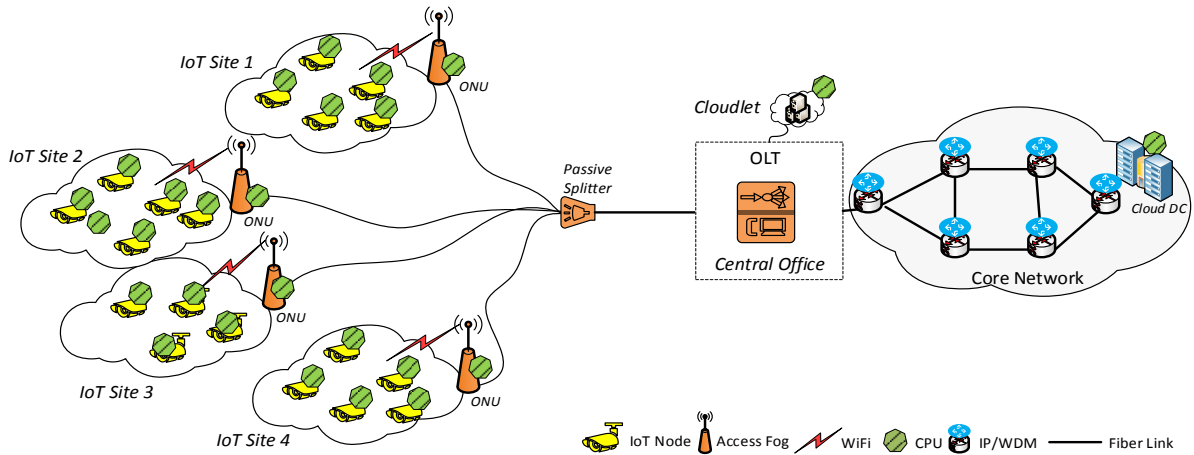


Figure 1, where the network consists of 20 IoT devices that are distributed among 4 sites, with each site being connected to a single ONU. A group of the IoT sites is connected to a single OLT device which is located at the network operator's central office (CO) and acts as a metro node [11]. The IoT devices are the sources of the demands and we make the assumption that these demands are flexible in that they can be split among K processing nodes. This assumption is an extension to our previous work in [12]. A service request consists of demands for processing (in MIPS) and bandwidth to transmit data (in Mbps). We assume that all service requests are homogenous among the IoT devices and that the same amount of traffic is transported to all the nodes that process a portion or all of the requested demand. It is assumed IoT devices are smart in nature and thus can process demands locally using their onboard CPUs. In addition, we assume all IoT devices communicate through the WiFi (IEEE 802.11g) protocol with a supported bit rate of 54Mbps. It is important to note that we only consider uplink traffic, as this is reported to carry a much larger proportion of the data generated by IoT networks [13]. Furthermore, we assume the number of CPU instructions required to process one bit of data remains constant throughout our evaluations.

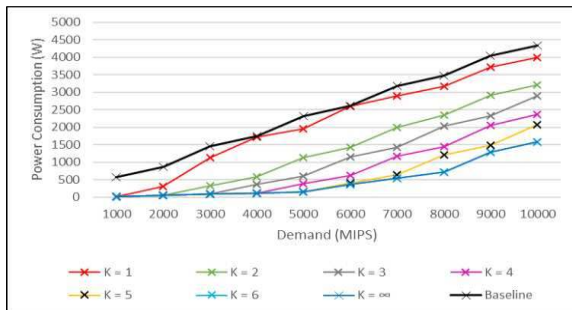
We estimate the CPU intensity (e.g. instructions/bit) per IoT request using data extracted from studies in the literature. In [14], it is reported that 870 instructions/bit are required for object recognition using the traditional Compress-Then-Analyze (CTA) paradigm. Thus, we take a conservative approach and for all of our

evaluations we assume 1000 instructions/bit are required to process the video files captured by the IoT devices. As for the bandwidth requirement, we use an online tool to estimate the required data rates for different resolutions and this was estimated to be between 1 Mbps and 10 Mbps, which covers video resolutions between 640×360 to 1280×720 at 10 frames per second [15]. The CPU workload intensity is then calculated by multiplying the instructions/bit by the maximum traffic requirement. Henceforth, this makes the CPU demand proportional to the size of the traffic due to the assumption that, the higher the traffic, the more features a video file will hold, thus more CPU instructions are required to process that file.

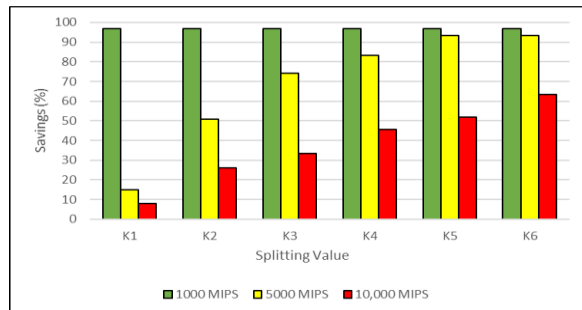
We also estimate the processing capacities (in MIPS) of all of the devices, using the data extracted from the technical report in [16]. It is reported that high-end Intel CPUs execute 4 instructions per clock cycle (Hz). We believe it is reasonable to assume that IoT type CPUs execute a single instruction per Hz hence, the number of instructions executed per Hz is multiplied by the device’s clock frequency (GHz), in order to estimate the total capacity in MIPS. It is expected that the higher in the network hierarchy of fog-based framework a node is, the larger its computational power due to the assumption that it should provide resources for a larger set of connected devices in the lower layers of the hierarchy [6]. Thus, we assume the Access Fog nodes’ processing capacity is more than double that of the IoT’s, hence each Access Fog is assumed to execute 2 instructions per Hz. We use the data of the Raspberry Pi Zero W and 2 as representative examples of IoT and Access Fog devices, respectively. Networking devices that are highly shared (such as OLTs/metro nodes, core nodes) [10], are assumed to adopt a fully proportional power profile in which idle power consumption is not considered. This is a reasonable assumption because these devices are already activated by other services such as residential broadband users. However, the rest of devices of interest (networking and processing) that are dedicated to the IoT are assumed to consume idle power. The network within the core layer consists of two layers, the IP layer and the optical layer. In the IP layer, an IP router is deployed at each node to aggregate access network traffic. The optical layer is used to interconnect the IP routers through optical switches and IP/WDM technologies [17]. We assume the power consumption of all of the core network components is fully load proportional and we use the energy per bit approach as described thoroughly in [17]. We also take PUE into account for all of the devices in the network, except those in the IoT and Access Fog layers because these devices do not have any cooling requirements [18]. The results were obtained using AMPL/CPLEX software running on a High performance computer with 16 cores processor and 256 GB of RAM. All of the parameters used in the MILP model, both networking and processing, are summarized in Table 1.

DEVICE TYPE	POWER CONSUMPTIONS (WATTS)				CAPACITY		EFFICIENCIES		PUE	
	Network		CPU		Gbps	MIPS	Watts/ Gbps	Watts/ MIPS	Network	CPU
	Max	Idle	Max	Idle						
IoT (Rpi Zero W)	0.56[19]	0.34	3.6 [20]	0.33 [20]	0.054[21]	1000	4.1	0.33	1	1
Access Fog (Rpi 2)	15[22]	9	12.5 [20]	2[20]	0.3[22]	2400	20	0.44	1	1
Edge Fog / Cloudlet	48[7]	-	363[23]	112[23]	2.4[7]	10800	20	0.023	1.5[10]	2.5[17]
IP/WDM node	1182[17]	-	-	-	40[17]	-	29.6	-	1.5[10]	-
Metro	Switch	1766[7]	-	-	256[7]	-	6.9	-	1.5[10]	-
	Router	4550[7]	-	-	560[7]	-	8.1	-	1.5[10]	-
Cloud DC	LAN Switch	1766[7]	-	363[23]	112[23]	256[7]	6.9	0.023	1.5 [10]	2.5[17]
	LAN Router	4550[7]	-							

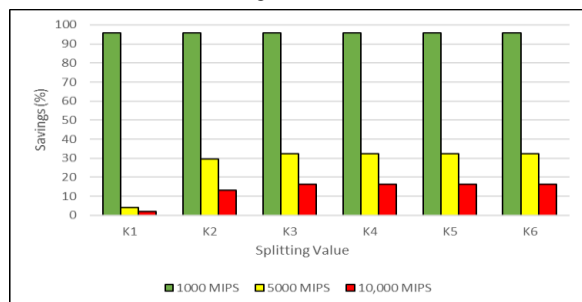
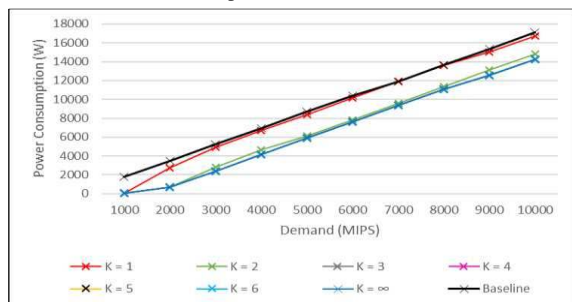
Table 1: Networking and processing parameters used in the MILP model.



(a) Power consumption vs. demand size in scenario 1.



(b) Total savings achieved in scenario 1.



(e) Power consumption vs. demand size in scenario 2.

(c) Total savings achieved in scenario 2.

Figure 2: Total power consumptions and power savings under different demand and splitting scenarios.

Figure 2a and Figure 2b show the total power consumptions and savings in scenario 1 for different workload sizes per IoT device, respectively. In this scenario it is assumed 5 IoT devices are generating demands for services. In Figure 2a, it is shown that, with every increase in the number of splits per IoT demand, savings in total power consumption can reach up to 93%, compared to always processing in the Cloud-DC (baseline). Interestingly, in Figure 2b, it can be observed that for medium sized demands (5000 MIPS) splitting into 2 (K2) achieves a total saving of 35% compared to not splitting (K1). Whereas splitting the demands into 3 (K3) drops the savings down to 24% and at K4 down to 9%. Also at K5 and K6 savings are comparable due to the demands inability to split among the local and Fog layers due to computation capacity constraints.

In the second scenario, it is assumed that all of the IoT devices (20 IoTs) are simultaneously generating requests for computational resources. Likewise, Figure 2c and Figure 2d show the total power consumptions and savings for different workload sizes per IoT device, respectively. It is shown in Figure 2d that splitting medium demand sizes among IoT and Fog resources can still yield a total saving of up to 32%, even if the aforementioned layers can host only 10% of the total workload. It is worthy of mention that in both scenarios, single node placement (K1) achieves negligible savings relative to the savings achieved by splitting onto multiple processing nodes. For instance, in Figure 2d, for high demand sizes (10,000 MIPS), the saving can be as low as 8% and 15% in the first scenario. This is due to the fact that, the lower layers (IoT and Access Fog) cannot accommodate such high demand sizes, thus, the workload must be accommodated by the Edge Fog (Cloudlet) and the Cloud-DC. The networking and processing overheads at these two layers are responsible for the dip in the savings. Also Figure 2d shows that for medium demands, savings are comparable beyond K1 due to the lack of computational resources. However, for higher demands computational resources are exhausted after K2, hence splitting does not achieve any savings.

4. CONCLUSIONS

In this paper, we introduced the results obtained using a MILP model which evaluates the impact of distributed processing on the total power consumption, in an IoT over Fog and Cloud framework. The total power consumption is minimized by splitting the IoT demands optimally among the available processing nodes. Our results showed that maximum splitting (K6) yields significant savings (up to 93%) in power consumption when the number of IoT requests are low (5 IoT requests) and demands are of medium size. On the other hand, when the number of IoT device requests increase to 20, savings of up to 32% can still be achieved, even if 10% of the total workload could be allocated to the IoT and Fog layers. For less intensive tasks, regardless of splitting, savings of 95% in the total power consumption was achieved due to the fact that demands could be hosted locally on the IoT device(s).

ACKNOWLEDGEMENTS

The authors would like to acknowledge funding from the Engineering and Physical Sciences Research Council (EPSRC), INTERNET (EP/H040536/1), STAR (EP/K016873/1) and TOWS (EP/S016570/1) projects. The first author would like to acknowledge his PhD funding from the Engineering and Physical Sciences Research Council (EPSRC). All data are provided in full in the results section of this paper.

REFERENCES

- [1] F. Liang et al., "A Survey on the Edge Computing for the Internet of Things," *IEEE Access*, vol. 6, pp. 6900–6919, 2017.
- [2] B. Cheng, G. Solmaz, F. Cirillo, E. Kovacs, K. Terasawa, and A. Kitazawa, "FogFlow: Easy Programming of IoT Services Over Cloud and Edges for Smart Cities," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 696–707, 2018.
- [3] S. Y. Jang, Y. Lee, B. Shin, and D. Lee, "Application-aware IoT camera virtualization for video analytics edge computing," *Proc. - 2018 3rd ACM/IEEE Symp. Edge Comput. SEC 2018*, pp. 132–144, 2018.
- [4] D. Barrett, "One surveillance camera for every 11 people in Britain, says CCTV survey," 2013. [Online]. Available: <https://www.telegraph.co.uk/technology/10172298/One-surveillance-camera-for-every-11-people-in-Britain-says-CCTV-survey.html>. [Accessed: 19-Mar-2019].
- [5] L. Tian, H. Wang, Y. Zhou, and C. Peng, "Video big data in smart city: Background construction and optimization for surveillance video processing," *Futur. Gener. Comput. Syst.*, vol. 86, pp. 1371–1382, 2018.
- [6] L. F. Bittencourt et al., "The Internet of Things, Fog and Cloud Continuum: Integration and Challenges," *Internet of Things*, vol. 3–4, pp. 134–155, 2018.

- [7] F. Jalali, K. Hinton, R. Ayre, T. Alpcan, and R. S. Tucker, "Fog computing may help to save energy in cloud computing," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1728–1739, 2016.
- [8] V. B. Souza, X. Masip-Bruin, E. Marin-Tordera, W. Ramirez, and S. Sanchez, "Towards distributed service allocation in Fog-to-Cloud (F2C) scenarios," 2016 IEEE Glob. Commun. Conf. GLOBECOM 2016 - Proc., pp. 0–5, 2016.
- [9] H. Atlam, R. Walters, and G. Wills, "Fog Computing and the Internet of Things: A Review," *Big Data Cogn. Comput.*, vol. 2, no. 2, p. 10, 2018.
- [10] C. Gray, R. Ayre, K. Hinton, and R. S. Tucker, "Power consumption of IoT access network technologies," 2015 IEEE Int. Conf. Commun. Work., pp. 2818–2823, 2015.
- [11] Y. Zhang, P. Chowdhury, M. Tornatore, and B. Mukherjee, "Energy efficiency in telecom optical networks," *IEEE Commun. Surv. Tutorials*, vol. 12, no. 4, pp. 441–458, 2010.
- [12] B. Yosuf, M. Musa, T. Elgorashi, A. Q. Lawey, and J. M. H. Elmirghani, "Energy Efficient Service Distribution in Internet of Things," *Int. Conf. Transparent Opt. Networks*, vol. 2018–July, pp. 1–4, 2018.
- [13] Z. T. Al-Azez, A. Q. Lawey, T. E. H. El-Gorashi, and J. M. H. Elmirghani, "Energy efficient IoT virtualization framework with passive optical access networks," *Int. Conf. Transparent Opt. Networks*, vol. 2016–August, pp. 1–4, 2016.
- [14] C. Delgado, J. R. Gállego, M. Canales, J. Ortín, S. Bousnina, and M. Cesana, "On optimal resource allocation in virtual sensor networks," *Ad Hoc Networks*, vol. 50, pp. 23–40, 2016.
- [15] M. Kašpar, "BANDWIDTH CALCULATOR." [Online]. Available: <https://www.cctvcalculator.net/en/calculations/bandwidth-calculator/>. [Accessed: 20-Mar-2019].
- [16] "Cisco Industrial Benchmark," 2016. [Online]. Available: https://www.cisco.com/c/dam/global/da_dk/assets/docs/presentations/vBootcamp_Performance_Benchmark.pdf. [Accessed: 16-Mar-2018].
- [17] A. Q. Lawey, T. E. H. El-Gorashi, and J. M. H. Elmirghani, "Distributed energy efficient clouds over core networks," *J. Light. Technol.*, vol. 32, no. 7, pp. 1261–1281, 2014.
- [18] M. Y. Arslan, I. Singh, S. Singh, H. V. Madhyastha, K. Sundaresan, and S. V. Krishnamurthy, "Computing while charging: Building a Distributed Computing Infrastructure Using Smartphones," 8th Int. Conf. Emerg. Netw. Exp. Technol., pp. 193–204, 2012.
- [19] RasPi.TV, "How much power does Pi Zero W use?" [Online]. Available: <http://raspi.tv/2017/how-much-power-does-pi-zero-w-use>. [Accessed: 21-Mar-2019].
- [20] "Raspberry Pi FAQs." [Online]. Available: <https://www.raspberrypi.org/help/faqs/>. [Accessed: 16-Mar-2018].
- [21] Thepihut, "USB Wifi Adapter for the Raspberry Pi." [Online]. Available: <https://thepihut.com/products/raspberrypi-zero-w>. [Accessed: 21-Mar-2019].
- [22] "Cisco ME 4600 Series Optical Network Terminal Data Sheet - Cisco." [Online]. Available: <https://www.cisco.com/c/en/us/products/collateral/switches/me-4600-series-multiservice-optical-access-platform/datasheet-c78-730446.html>. [Accessed: 16-Mar-2018].
- [23] L. Nonde, T. E. H. El-gorashi, and J. M. H. Elmirghani, "Energy Efficient Virtual Network Embedding for Cloud Networks," *Energy Effic. Virtual Netw. Embed. Cloud Networks*, vol. 33, no. 9, pp. 1828–1849, 2015.
- [24] J. M. H. Elmirghani, T. Klein, K. Hinton, L. Nonde, A. Q. Lawey, T. E. H. El-Gorashi, M. O. I. Musa, and X. Dong, "GreenTouch GreenMeter core network energy-efficiency improvement measures and optimization," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 10, no. 2, pp. A250-A269, Feb 2018.
- [25] M. Musa, T.E.H. El-Gorashi and J.M.H. Elmirghani, "Bounds on GreenTouch GreenMeter Network Energy Efficiency," *IEEE/OSA Journal of Lightwave Technology*, vol. 36, No. 23, pp. 5395-5405, 2018.
- [26] H.M.M., Ali, A.Q. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, "Future Energy Efficient Data Centers With Disaggregated Servers," *IEEE/OSA Journal of Lightwave Technology*, vol. 35, No. 24, pp. 5361 – 5380, 2017.
- [27] X. Dong, T.E.H. El-Gorashi and J.M.H. Elmirghani, "On the Energy Efficiency of Physical Topology Design for IP over WDM Networks," *IEEE/OSA Journal of Lightwave Technology*, vol. 30, pp.1931-1942, 2012.
- [28] M. Musa, T.E.H. El-Gorashi and J.M.H. Elmirghani, "Bounds for Energy-Efficient Survivable IP Over WDM Networks with Network Coding," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 10, no. 5, pp. 471-481, 2018.
- [29] M. Musa, T.E.H. El-Gorashi and J.M.H. Elmirghani, "Energy Efficient Survivable IP-Over-WDM Networks With Network Coding," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 9, No. 3, pp. 207-217, 2017.
- [30] A. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, "BitTorrent Content Distribution in Optical Networks," *IEEE/OSA Journal of Lightwave Technology*, vol. 32, No. 21, pp. 3607 – 3623, 2014.
- [31] A.M. Al-Salim, A. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, "Energy Efficient Big Data Networks: Impact of Volume and Variety," *IEEE Transactions on Network and Service Management*, vol. 15, No. 1, pp. 458 - 474, 2018.
- [32] X. Dong, T. El-Gorashi, and J. Elmirghani, "Green IP Over WDM Networks With Data Centers," *Lightwave Technology, Journal of*, vol. 29, no. 12, pp. 1861-1880, June 2011.
- [33] N. I. Osman, T. El-Gorashi, L. Krug, and J. M. H. Elmirghani, "Energy Efficient Future High-Definition TV," *Journal of Lightwave Technology*, vol. 32, no. 13, pp. 2364-2381, July 2014.
- [34] X. Dong, T. El-Gorashi, and J. Elmirghani, "IP Over WDM Networks Employing Renewable Energy Sources," *Lightwave Technology, Journal of*, vol. 29, no. 1, pp. 3-14, Jan 2011.
- [35] A.N. Al-Quzweeni, A. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, "Optimized Energy Aware 5G Network Function Virtualization," *IEEE Access*, vol. 7, 2019.
- [36] M.S. Hadi, A. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, "Patient-Centric Cellular Networks Optimization

- using Big Data Analytics,” IEEE Access, vol. 7, 2019.
- [37] M.S. Hadi, A. Lawey, T.E.H. El-Gorashi, and J.M.H. Elmirghani, “Big Data Analytics for Wireless and Wired Network Design: A Survey, Elsevier Computer Networks, vol. 132, No. 2, pp. 180-199, 2018.