When Wearable Technology Meets Computing in Future Networks: A Road Ahead

Invited Paper

Aleksandr Ometov[*]
aleksandr.ometov@tuni.fi
Tampere University
Tampere, Finland

Olga Chukhno
olga.chukhno@unirc.it
Mediterranea University of Reggio Calabria
Reggio Calabria, Italy
Tampere University
Tampere, Finland

Nadezhda Chukhno
nadezda.chukhno@unirc.it
Mediterranea University of Reggio Calabria
Reggio Calabria, Italy
Universitat Jaume I
Castellon, Spain

Jari Nurmi
Elena Simona Lohan
jari.nurmi@tuni.fi
elena-simona.lohan@tuni.fi
Tampere University
Tampere, Finland

ABSTRACT

Rapid technology advancement, economic growth, and industrialization have paved the way for developing a new niche of small body-worn personal devices, gathered together under a wearable-technology title. The triggers stimulated by end-users interest have introduced the first generation of mass-consumer wearables in just the past decade. Evidently, the trailblazing ones were not designed with strict energy-consumption restrictions in mind. Thus, wearable-computing-related research remained fragmented. Advanced and sophisticated batteries and communication technologies could be already procurable on devices. Additional solutions for efficient utilization of processing power are still a white spot on the wearable technology roadmap. A-WEAR EU project aims to enhance the understanding of how the superimposition of those technologies would improve wearable devices' energy efficiency, with the research area being far from saturation. We foresee enormous room for research as the Edge computing paradigm is emerging towards hand-held devices.

CCS CONCEPTS

• **General and reference** → **Cross-computing tools and techniques**; • **Hardware** → **Networking hardware**; **Wireless devices**; *Emerging architectures*; • **Computer systems organization** → *Distributed architectures*; • **Networks** → *Network topology types*; **Wireless access networks**.

[*]Corresponding author: A. Ometov, email: aleksandr.ometov@tuni.fi

CF '21, May 11–13, 2021, Virtual Conference, Italy

ACM ISBN 978-1-4503-8404-9/21/05.
https://doi.org/10.1145/3457388.3458614

KEYWORDS

Wearables, Wireless Networks, Computing, Challenges, EU projects

ACM Reference Format:
Aleksandr Ometov, Olga Chukhno, Nadezhda Chukhno, Jari Nurmi, and Elena Simona Lohan. 2021. When Wearable Technology Meets Computing in Future Networks: A Road Ahead: Invited Paper. In *Computing Frontiers Conference (CF '21), May 11–13, 2021, Virtual Conference, Italy*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3457388.3458614

1 PROJECT INFORMATION IN BRIEF

The rapidly developing market of wearable devices is expected to grow exponentially in the forthcoming years. It is forecast to expand at more than a 20% growth rate annually and reach over 40 billion EUR per year in the next five years with more than 150 billion EUR by 2028 [10]. The proliferation of wearables is thus expected to increase steadily over the following decades, with a predominant transition from bracelets and sports trackers to more intelligent and more feature-rich wearables.

Wearable technology has a tremendous impact on a variety of industry verticals, and, very shortly, smart wearables are expected to disrupt most business sectors, such as industrial, health, and sport domains, and are going to reshape the industrial landscape as smart interconnected spaces. Our firm belief is that the industry, in its broadest sense, will benefit from this research, and a new cohort of researchers/innovators will be trained in a multi-disciplinary fashion to address the open challenges in the field.

As a response to the wearable technology development, the H2020 MSCA EJD/ITN A-WEAR project is aiming at both societal and research goals[1]: to educate 15 Early Stage Researchers (ESRs) and to bring new benefits to the general well-being among the end-users. The project's main target groups in wearables applications are: social applications, such as eHealth and social networking, and industrial applications, such as automation halls, industrial robotics, and the automotive industry. These applications are chosen because

[1]See more about A-WEAR at http://a-wear.eu

they have different requirements in terms of computational costs, communications latency, precision, security, and privacy of both communication and localization and related trade-offs.

All of the A-WEAR ESRs have already passed the first-year mark of their three-year research career and formalized their first research results in the field of wearable technology[2].

In a compact form, the A-WEAR project's main Research Objectives are as follows.

- **RO1**: To create novel multi-layer knowledge for dynamic wearable networks in terms of localization, connectivity, privacy, and security;
- **RO2**: To identify vulnerabilities and offer innovative solutions in crowdsourced-, cloud-, edge-, and fog-based wearable architectures;
- **RO3**: To design and develop privacy-enhanced and location-aware wearable technologies;
- **RO4**: To devise new Medium Access Control (MAC) low-latency algorithms and protocols for wearable communications, especially in the frequency bands of the future, such as mmWave spectrum;
- **RO5**: To develop new open-source software platforms for wearables in social/eHealth/industrial applications.

The rest of the paper is organized as follows. Section 2 describes the technological synergy that may be achieved by coupling communication and computing paradigms with wearables. Next, Section 3 outlines the main challenges related to the integration and future operation of those technologies. The last section provides a summary of the analyzed literature.

2 WEARABLES AND COMPUTING IN FUTURE NETWORKS

Historically, the advent of small, inexpensive, battery-powered computing devices has opened new frontiers for developing a wide variety of small form factor devices being interconnected in a Peer-to-Peer (P2P) manner or through the world wide web. That first step in miniaturization allowed the Internet of Things (IoT) paradigm to emerge and, later on, for the Internet of Wearable Things (IoWT) to become a separate personal cloud-oriented niche [9, 61].

Broadly speaking, the IoWT is formed by a mixture of various smart wearable devices, ranging from smart shoes to sophisticated head-mounted displays. Commonly, modern wearable devices are not anymore dedicated to serving one function but are already equipped with various sensors, communication, and computing modules allowing for continuous data extraction, processing, and transmission [42].

Unprecedentedly, many new challenges and open questions for scientific, research, and industrial communities have been raised to realize that wearables became a standalone segment separated from smartphones. It fostered an expansion in the number of already versatile applications resulting in increasing demand for wearable devices' performance.

As of today, this segment still faces numerous constraints, such as communication-related constraints, computational power, security/privacy limitations, lack of standardization, among others [23, 32]. However, one of the primary and still-insurmountable obstacles for wearables is the limited battery life [52]. To this end, developing energy-efficient wearable solutions is paramount to extend devices' battery life while meeting application performance requirements.

To start with, the current 5G systems and the upcoming generation of cellular/wireless systems (differently notes as 5G+/6G/B5G) aim to ensure maximum flexibility and operational efficiency from current and future infrastructures. Unlike the previous mobile deployments, presently integrated 5G also offers a solution to reduce energy consumption within a network and on the user-device side. The technological advances (key technologies) of 5G include, among others, mmWave communications, Software-Defined Networking (SDN), Network Functions Virtualization (NFV), and Multi-Access Edge Computing (MEC) (formerly Mobile Edge Computing) [6, 38].

In its turn, beyond 5G systems are expected to migrate more towards higher frequencies, e.g., THz communications, and ensure radio frequency convergence between sensing, communications, and positioning tasks [8]. Consequently, networks are evolving to utilize SDN, NFV primarily, and cloud-native architectures to enable dis-aggregation and primary functions' virtualization [16]. This aspect leads to the separation of the control plane and user plane and introduces network slicing and MEC capabilities, thus, opening the highway for novel applications with higher flexibility and adaptability demands.

Apart from utilizing more advanced airspace interface technologies, beyond 5G networks would comprehensively engage the virtualization technology and practice more programmable approaches to software networking in the field of worldwide telecommunications infrastructure [18].

Notably, the oncoming communication era is designed to support various bandwidth and computational-hungry applications, e.g., extended reality (XR) broadcasting (including augmented, virtual, and mixed reality (AR/VR/MR)) [1], ultra-high definition (UHD) video streaming [43], and proximate gaming [34], which is especially essential for wearable applications. The benefits of coupling beyond 5G communication technology on higher frequencies are huge bandwidths, high data rates, and, simultaneously, a decrease in the antenna size enabled by very short wavelengths. Overall, the evolution of networks towards beyond 5G ensures lower power expenses from the overhead transmission perspectives.

When it comes to energy-efficiency improvement, the opportunity to develop wearable-targeted remote in-network computational offloading solutions becomes possible [33]. Generally, the distinct main computing paradigms, such as Cloud where the execution is made entirely in a remote way, Fog with the computation on neighboring network nodes, and Edge with the delegation of the computations to the closest power-independent device in the network, commonly act in a similar manner but behave differently in the case of systems with strict and critical reliability or latency requirements [27]. It is especially present for operation cases in dynamic, unreliable or uncertain conditions coming into action due to high mobility, low coverage, or heavy load. Today, the broadly adopted solution for many vendors, including Apple and Google, is computational offloading from wearables to smartphones, being the most energy-hungry hand-held devices with growing power consumption constraints.

[2]See A-WEAR Zenodo repository for Open Access publications: https://zenodo.org/communities/a_wear/

Giving a sharper focus on wearable-targeted computing, we can already distinguish several potential candidate paradigms, see Fig. 1, compared to broadly utilized smartphone gateway (1) or Cloud (5). These include, essentially, an unfamiliar device offloading via Device-to-Device (D2D) links (2), MEC (4), Mist Computing (4)-(6), Mobile Cloud Computing (MCC) (2)-(5), Mobile ad-hoc Cloud Computing (3), and many others [59]. The paradigms vary tremendously, requiring heavy research from communications, hardware design, security, and privacy perspectives. Moreover, due to various applications, the developed computational offloading systems should also adapt and learn based on multiple factors and their dynamics, bringing even more complexity.

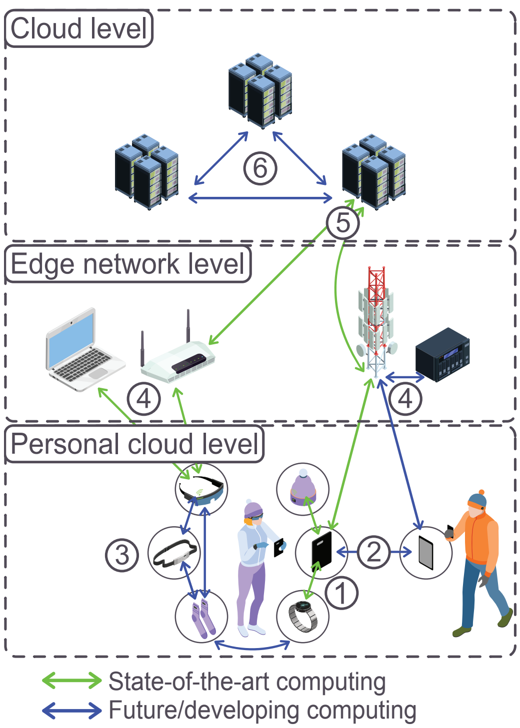

Figure 1: Opportunities for computational offloading in wearable-focused infrastructures.

3 RELATED CHALLENGES

As we move towards a more interconnected ecosystem, the volume of data generation will continue to grow, primarily pushed by the 5G technologies and beyond, which provide continuous connectivity, faster download speeds, greater network capacity, ultra-low latency, increased reliability, and availability, and improved quality experience. However, not only technologies are developing, but also the problems that surround them.

Although the centralized cloud has traditionally been utilized to manage, process, and store data, it poses two major problems: (i) processing latency should be as short as milliseconds, but it can be critical; (ii) all of this data creates a significant bandwidth load. In contrast, Edge computing offers a solution to the latency problem by moving critical processing to the Edge network [21, 26]. Edge devices can collect and process data in real-time, allowing them to respond faster and more efficiently. However, there are challenges related to the devices' capabilities, including software and hardware development, to handle the offloaded computing load.

Various computing paradigms demonstrate excellent capabilities and introduce new methods to improve system performance. In practice, those are sometimes viewed as mutually exclusive approaches to network infrastructure while they may function in different ways, using one does not preclude the use of others. In this context, some approaches have been proposed to address this problem (e.g., IoT cognitive gateways [20], a platform that automatically determines the best environment for executing a task [19], and a framework for scheduling applications in hybrid public-private cloud [7]). However, automatic switching between computing paradigms is, in any case, a problem for future research.

Another problem related to data transmission is the migration of services or Digital Twins of wearable devices, for instance, from one Edge server to another [3]. When a user moves across different geographical locations [12], e.g., from home to the workplace, the service/Digital Twin may need to be migrated to follow the user's device and maintain Edge computing advantages. However, the determination of an optimal migration decision is challenging because of the trade-off between the migration and data transmission costs [51]. On the one side, migrating a service/Digital Twin may incur network overhead or even interrupt the connection. On the other side, not relocating may increase the data transmission delay between the user and the Edge server. In the literature, there are several approaches to reduce the transmission delay in traditional wireless communication networks concerning the migration procedure [47, 49, 50, 60]. However, ensuring seamless migration among Edge servers is still an issue that needs to be investigated.

Simultaneously, compressive sensing is becoming increasingly popular from a lower layer perspective, especially for IoWT applications that use sparse data signals. It is a signal acquisition and recovery technique that allows receivers to recover the actual signal using significantly fewer samples than the Nyquist criteria require. Compression has been proven to provide several benefits such as efficient bandwidth and power consumption, which are the two most crucial network resources in [13, 35]. However, not all wearable applications use sparse signals. Therefore, some studies suggest using an adaptive compression definition to dynamically adjust the sampling rate for applications involving random and variable signals. For example, various activity recognition applications can use very dynamic data cues from inactivity to intense action [56].

Likewise, processing and transferring large amounts of generated data is another challenge for wearable devices with limited computing and communication capabilities. The generated datasets usually contain a lot of correlated or redundant data. Thus, reducing the generated dataset by using efficient data compression techniques can significantly improve the performance and efficiency of the device [40].

Moreover, the lack of network resources and computing capabilities is still a challenge in wearable systems. D2D communications are applied to increase the system capacity thanks to data offloading and reuse gain [15]. In MCC, users can accelerate computing with the help of D2D technology [48]. Joint utilization of D2D communications and MEC technologies is expected to improve the cellular networks' computation capacity with the tasks offloading to nearby D2D and an Edge devices [17]. Besides, group communication is applied in scenarios where the same data must be sent to multiple devices [5]. For example, D2D clusters can be used for the multicast service quality improvement [29].

Approximate computing is another promising technique that allows to trade precision in exchange for increased energy or performance [45]. Many wearable applications may not require very accurate results, instead, results that are "good enough" can serve the purpose [53]. Thus, approximation has become an effective method for improving the performance and energy efficiency of devices with limited resources [57]. However, it comes with many problems, such as determining the minimum required precision, identifying approximate problems, and monitoring the results of the application [31]. Therefore, efficiently implemented approximation techniques can achieve optimal performance gains in latency, speed/execution time, and battery consumption [2, 14].

Finally, yet importantly, going beyond 5G networks, Machine Learning (ML) and Artificial Intelligence (AI) at the network Edge become essential for future applications, including but not limited to personal smart device experiences, smart city operation, and computing, robotics, and autonomous traffic settings [36, 46]. The reason is the rise in wearable devices whose functionalities are steadily substituting smartphones' ones [41]. AI and learning on Edge devices will improve computation quality and design new opportunities for services and applications. However, learning requires massive computation capability to ensure intricate training and work with inference methodologies and large datasets.

Nonetheless, innovative ML algorithms for low latency and power-hungry data processing are among the fastest-growing areas. It affects almost all industry sectors due to its promise of performance in unstructured data analysis, such as image processing and time series analysis. Learning from more complex data to perform complex tasks is significantly influenced by the development of new equipment, methodologies, and other techniques borrowed from the machine learning field [28]. However, the challenge remains to achieve low latency and low processing power with such algorithms. One of the potential promising approaches is to analyze and manipulate various sources of valuable data using artificial intelligence tools and thus open up new possibilities for significantly increasing the variety of applications for wearable devices [24, 39, 58].

From the AI on Edge perspectives, the computational requirements are as follows: (i) the algorithm's throughput should be consistently stable to meet real-time constraints without losses; (ii) the processing latency should be comparatively low. There is still a need for advances approaches to the AI processor architecture. Moreover, Edge devices should offer enough computational capacity despite their limitations, e.g., thermal or form factor size. Furthermore, high privacy protection should be ensured in case the Edge node has no reliable Internet connection. However, smart wearable devices, which support on-line applications alongside the Edge AI, have to protect their private information [37]. Therefore, enabling dedicated security is paramount of importance in future wearable systems [4, 25]. While the problems of security and privacy [11, 55], power and computational efficiency [22, 30, 44] in Edge AI have already been of interest in recent studies, research in this area is ongoing.

To summarize, the main issues in current and future wearable devices with regard to computing and wireless technologies are presented in Table 1.

4 SUMMARY

Delegating wearable computing tasks is already being enabled by a series of existing communications and computing technologies, including Edge/Fog and Cloud computing, forthcoming 5G+/6G networks, and standardized security solutions. However, almost nothing has been devoted to addressing the combination of the technologies mentioned above, focusing on wearable devices with their stringent requirements compared to, e.g., smartphones.

A-WEAR project aims to bridge this critical gap by exploring the following fundamental principles:

- The separation of network nodes into elements that ensure the operation of the "user plane" and "control plane" protocols, which significantly increases the flexibility in terms of scaling and deployment placement of individual components of network nodes;
- The implementation of network elements in the form of virtual network functions;
- The support for simultaneous access to centralized and local services, which allows implementing the concept of Edge computing;
- The definition of a converged architecture that combines various types of access networks;
- The support for uniform algorithms and authentication procedures;
- The support for stateless network functions, where the compute resource is separate from the storage resource;
- The roaming support with traffic routing both through the home routed and with a local breakout in the guest network;
- The exploration of the optimal displacement of network functions and network elements of the future infrastructure and remote computing.

ACKNOWLEDGMENTS

This work was supported by the funding from European Union's Horizon 2020 Research and Innovation programme under the Marie Skłodowska Curie grant agreement No. 813278 (A-WEAR: A network for dynamic wearable applications with privacy constraints).

REFERENCES

[1] Asad Ali, Olga Galinina, and Sergey Andreev. 2020. Modeling System-Level Dynamics of Direct XR Sessions over mmWave Links. In *Proc. of IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*. IEEE, 1–7.

[2] Massimo Alioto. 2017. Energy-Quality Scalable Adaptive VLSI Circuits and Systems beyond Approximate Computing. In *Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017*. IEEE, 127–132.

[3] Claudia Campolo, Antonio Iera, Antonella Molinaro, and Giuseppe Ruggeri. 2019. MEC Support for 5G-V2X Use Cases through Docker Containers. In *2019 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 1–6.

[4] Tung-Chien Chen, Wei-Ting Wang, Kloze Kao, Chia-Lin Yu, Code Lin, Shu-Hsin Chang, and Pei-Kuei Tsung. 2019. NeuroPilot: A Cross-Platform Framework for Edge-AI. In *2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)*. IEEE, 167–170.

Table 1: Summary of the main challenges related to wearable computing in future networks.

Challenge	Groups	Refs.	Observed existing approach
Seamless switching between computing paradigms	A, N, HW	[20]	Cognitive IoT gateway equipped with skills of intelligent distribution between the Edge and cloud using machine learning
		[19]	Platform for seamless software mobility among the nodes of an Edge-cloud environment
		[7]	Framework for scheduling applications over hybrid / heterogeneous networks
Migration of services / Digital Twins	A, DP, N	[47]	Algorithm for latency aware replica placement
		[60]	Algorithm for optimal service migration strategy based on dynamic programming
		[49]	Algorithm for users' workload distribution in response to movement around the MEC network based on the regularization technique
		[50]	Real-time service migration solution based on Markov Decision Process
Energy-efficient data gathering network	A, N, SW	[13]	Adaptive compressive sensing scheme that offers simultaneous compression and encryption in a lightweight fashion
		[56]	Data-driven compressive sensing framework for the energy-efficient wearable sensing
		[54]	Adaptive compressed classification architecture for activity recognition
Lack of network resources	A, N, DP	[15]	D2D technology as a solution to increase system throughput by offloading data and reusing benefits
		[17]	D2D communications and MEC system symbiosis to increase the processing power of the entire system
Low quality-of-service indicator	A, N	[29]	Cluster-based multicast methods for D2D communications
Insufficient computing capabilities	A, N, HW	[48]	Computation offloading scheme, which leverages computing resources through D2D links to improve MCC performance
Discovery of inefficient computing resources	A, N	[48]	Carefully designed access restrictions to allow users to maximize the computing resources of nearby mobile devices without spending much power on discovering other devices
	N, DP	[2, 14]	Approximate and beyond approximate computing techniques
Classification problems, anomaly detection, forecasting problems	DP, SW	[24, 39, 58]	Applying machine learning approaches to decrease the impact on the overall execution
Aspects of AI/ML on Edge	A, N	[4]	Cross-platform framework that ensures the superior Edge AI ability
	N	[55]	ML-based authentication in IoT systems
		[11]	Framework based on the convergence of Blockchain and AI
Lack of power and computational efficiency for ML/AI eneblers	SW, HW	[30]	Ultra-low-power on-chip training and inference commands
		[44]	In-memory architectures based on the compute models
		[22]	Static random-access memory-based compute-in-memory architecture for multi-bit precision deep neural networks training

A – Architecture N – Networking DP – Data Processing
HW – Hardware specific SW – Software specific

[5] Nadezhda Chukhno, Olga Chukhno, Giuseppe Araniti, Antonio Iera, Antonella Molinaro, and Sara Pizzi. 2020. Challenges and Performance Evaluation of Multicast Transmission in 60 GHz mmWave. In *Proc. of International Conference on Distributed Computer and Communication Networks*. Springer, 3–17.

[6] Olga Chukhno, Nadezhda Chukhno, Giuseppe Araniti, Claudia Campolo, Antonio Iera, and Antonella Molinaro. 2020. Optimal Placement of Social Digital Twins in Edge IoT Networks. *Sensors* 20, 21 (2020), 6181.

[7] Anirban Das, Andrew Leaf, Carlos A Varela, and Stacy Patterson. 2020. Skedulix: Hybrid Cloud Scheduling for Cost-Efficient Execution of Serverless Applications. *arXiv preprint arXiv:2006.03720* (2020).

[8] C. De Lima, D. Belot, R. Berkvens, A. Bourdoux, D. Dardari, M. Guillaud, M. Isomursu, E. S. Lohan, Y. Miao, A. N. Barreto, M. R. K. Aziz, J. Saloranta, T. Sanguanpuak, H. Sarieddeen, G. Seco-Granados, J. Suutala, T. Svensson, M. Valkama, B. Van Liempd, and H. Wymeersch. 2021. Convergent Communication, Sensing and Localization in6G Systems: An Overview of Technologies, Opportunities and Challenges. *IEEE Access* (2021), 1–1. https://doi.org/10.1109/ACCESS.2021.3053486

[9] F. John Dian, Reza Vahidnia, and Alireza Rahmati. 2020. Wearables and the Internet of Things (IoT), Applications, Opportunities, and Challenges: A Survey. *IEEE Access* 8 (2020), 69200–69211.

[10] Digital business and transformation hub: i-SCOOP. 2020. Wearables Market Outlook 2020: Drivers and New Markets. https://www.i-scoop.eu/wearables-market-outlook-2020-drivers-new-markets/.

[11] Abir El Azzaoui, Sushil Kumar Singh, Yi Pan, and Jong Hyuk Park. 2020. Block5gintell: Blockchain for AI-enabled 5G Networks. *IEEE Access* 8 (2020), 145918–145935.

[12] Qiang Fan and Nirwan Ansari. 2019. On Cost Aware Cloudlet Placement for Mobile Edge Computing. *IEEE/CAA Journal of Automatica Sinica* 6, 4 (2019), 926–937.

[13] Alexandros Fragkiadakis, Pavlos Charalampidis, and Elias Tragos. 2014. Adaptive Compressive Sensing for Energy Efficient Smart Objects in IoT Applications. In *Proc. of 4th International Conference on Wireless Communications, Vehicular Technology, Information Theory and Aerospace & Electronic Systems (VITAE)*. IEEE, 1–5.

[14] Avrajit Ghosh, Arnab Raha, and Amitava Mukherjee. 2020. Energy-Efficient IoT-Health Monitoring System using Approximate Computing. *Internet of Things* 9 (2020), 100166.

[15] Akhil Gupta and Rakesh Kumar Jha. 2015. A Survey of 5G Network: Architecture and Emerging Technologies. *IEEE Access* 3 (2015), 1206–1232.

[16] Yixue Hao, Daxin Tian, Giancarlo Fortino, Jing Zhang, and Iztok Humar. 2018. Network Slicing Technology in a 5G Wearable Network. *IEEE Communications Standards Magazine* 2, 1 (2018), 66–71.

[17] Yinghui He, Jinke Ren, Guanding Yu, and Yunlong Cai. 2019. D2D Communications Meet Mobile Edge Computing for Enhanced Computation Capacity in Cellular Networks. *IEEE Transactions on Wireless Communications* 18, 3 (2019), 1750–1763.

[18] Yun Chao Hu, Milan Patel, Dario Sabella, Nurit Sprecher, and Valerie Young. 2015. Mobile Edge Computing—A Key Technology Towards 5G. *ETSI white paper* 11, 11 (2015), 1–16.

[19] Fatemeh Jalali, Timothy Lynar, Olivia J Smith, Ramachandra Rao Kolluri, Claire V Hardgrove, Nick Waywood, and Frank Suits. 2019. Dynamic Edge Fabric Environment: Seamless and Automatic Switching among Resources at the Edge of IoT Network and Cloud. In *Proc. of IEEE International Conference on Edge Computing (EDGE)*. IEEE, 77–86.

[20] Fatemeh Jalali, Olivia J Smith, Timothy Lynar, and Frank Suits. 2017. Cognitive IoT Gateways: Automatic Task Sharing and Switching Between Cloud and Edge/Fog Computing. In *Proc. of the SIGCOMM Posters and Demos*. 121–123.

[21] Congfeng Jiang, Xiaolan Cheng, Honghao Gao, Xin Zhou, and Jian Wan. 2019. Toward Computation Offloading in Edge Computing: A Survey. *IEEE Access* 7 (2019), 131543–131558.

[22] Hongwu Jiang, Xiaochen Peng, Shanshi Huang, and Shimeng Yu. 2020. CIMAT: A Compute-In-Memory Architecture for On-chip Training Based on Transpose SRAM Arrays. *IEEE Trans. Comput.* 69, 7 (2020), 944–954.

[23] Lucie Klus, Elena Simona Lohan, Carlos Granell, and Jari Nurmi. 2019. Crowdsourcing Solutions for Data Gathering from Wearables. In *Proc. of XXXV Finnish URSI Convention on Radio Science*.

[24] Lampros C Kourtis, Oliver B Regele, Justin M Wright, and Graham B Jones. 2019. Digital biomarkers for Alzheimer's Disease: The Mobile/Wearable Devices Opportunity. *NPJ digital medicine* 2, 1 (2019), 1–9.

[25] Yen-Lin Lee, Pei-Kuei Tsung, and Max Wu. 2018. Techology Trend of Edge AI. In *Proc. of International Symposium on VLSI Design, Automation and Test (VLSI-DAT)*. IEEE, 1–2.

[26] Niko Mäkitalo, Timo Aaltonen, Mikko Raatikainen, Aleksandr Ometov, Sergey Andreev, Yevgeni Koucheryavy, and Tommi Mikkonen. 2019. Action-Oriented Programming Model: Collective Executions and Interactions in the Fog. *Journal of Systems and Software* 157 (2019), 110391.

[27] Niko Mäkitalo, Aleksandr Ometov, Joona Kannisto, Sergey Andreev, Yevgeni Koucheryavy, and Tommi Mikkonen. 2017. Safe, Secure Executions at the Network Edge: Coordinating Cloud, Edge, and Fog Computing. *IEEE Software* 35, 1 (2017), 30–37.

[28] Jan Masek, Radim Burget, Lukas Povoda, and Malay Kishore Dutta. 2016. Multi–GPU Implementation of Machine Learning Algorithm Using CUDA and OpenCL. *International Journal of Advances in Telecommunications, Electrotechnics, Signals and Systems* 5, 2 (2016), 101–107.

[29] Leonardo Militano, Massimo Condoluci, Giuseppe Araniti, Antonella Molinaro, Antonio Iera, and Gabriel-Miro Muntean. 2015. Single Frequency-based Device-to-Device-enhanced Video Delivery for Evolved Multimedia Broadcast and Multicast Services. *IEEE Transactions on Broadcasting* 61, 2 (2015), 263–278.

[30] Venkata Pavan Kumar Miriyala and Masatoshi Ishii. 2020. Ultra-Low Power On-chip Learning of Speech Commands with Phase-change Memories. *arXiv preprint arXiv:2010.11741* (2020).

[31] Sparsh Mittal. 2016. A Survey of Techniques for Approximate Computing. *ACM Computing Surveys (CSUR)* 48, 4 (2016), 1–33.

[32] Aleksandr Ometov, Yulia Bardinova, Alexandra Afanasyeva, Pavel Masek, Konstantin Zhidanov, Sergey Vanurin, Mikhail Sayfullin, Viktoriia Shubina, Mikhail Komarov, and Sergey Bezzateev. 2020. An Overview on Blockchain for Smartphones: State-of-the-Art, Consensus, Implementation, Challenges and Future Trends. *IEEE Access* 8 (2020), 103994–104015.

[33] Aleksandr Ometov, Dmitry Kozyrev, Vladimir Rykov, Sergey Andreev, Yuliya Gaidamaka, and Yevgeni Koucheryavy. 2017. Reliability-Centric Analysis of Offloaded Computation in Cooperative Wearable Applications. *Wireless Communications and Mobile Computing* 2017 (2017).

[34] Susanna Paasovaara and Thomas Olsson. 2016. Proximity-Based Automatic Exchange of Data in Mobile Gaming: Studying the Experiences of StreetPass Users. In *Proceedings of the 9th Nordic Conference on Human-Computer Interaction*. 1–10.

[35] Sonali Padalkar, Aditya Korlekar, and Utkarsha Pacharaney. 2016. Data Gathering in Wireless Sensor Network for Energy Efficiency with and without Compressive Sensing at Sensor Node. In *Proc. of International Conference on Communication and Signal Processing (ICCSP)*. IEEE, 1356–1359.

[36] Ella Peltonen, Mehdi Bennis, Michele Capobianco, Merouane Debbah, Aaron Ding, Felipe Gil-Castiñeira, Marko Jurmu, Teemu Karvonen, Markus Kelanti, Adrian Kliks, et al. 2020. 6G White Paper on Edge Intelligence. *arXiv preprint arXiv:2004.14850* (2020).

[37] Pawani Porambage, Tanesh Kumar, Madhusanka Liyanage, Juha Partala, Lauri Lovén, Mika Ylianttila, and Tapio Seppänen. 2019. Sec-EdgeAI: AI for Edge Security Vs Security for Edge AI. *The 1st 6G Wireless Summit,(Levi, Finland)* (2019).

[38] Waleed Bin Qaim, Aleksandr Ometov, Antonella Molinaro, Ilaria Lener, Claudia Campolo, Elena Simona Lohan, and Jari Nurmi. 2020. Towards Energy Efficiency in the Internet of Wearable Things: A Systematic Review. *IEEE Access* (2020).

[39] Zhen Qin, Yibo Zhang, Shuyu Meng, Zhiguang Qin, and Kim-Kwang Raymond Choo. 2020. Imaging and Fusing Time Series for Wearable Sensor-based Human Activity Recognition. *Information Fusion* 53 (2020), 80–87.

[40] Mohammad Abdur Razzaque, Chris Bleakley, and Simon Dobson. 2013. Compression in Wireless Sensor Networks: A Survey and Comparative Evaluation. *ACM Transactions on Sensor Networks (TOSN)* 10, 1 (2013), 1–44.

[41] Walid Saad, Mehdi Bennis, and Mingzhe Chen. 2019. A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems. *IEEE network* 34, 3 (2019), 134–142.

[42] Salwa Saafi, Jiri Hosek, and Aneta Kolackova. 2020. Cellular-enabled Wearables in Public Safety Networks: State of the Art and Performance Evaluation. In *Proc. of 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE, 201–207.

[43] Kei Sakaguchi, Thomas Haustein, Sergio Barbarossa, Emilio Calvanese Strinati, Antonio Clemente, Giuseppe Destino, Aarno Pärssinen, Ilgyu Kim, Heesang Chung, Junhyeong Kim, et al. 2017. Where, When, and How mmWave is Used in 5G and Beyond. *IEICE Transactions on Electronics* 100, 10 (2017), 790–808.

[44] Xin Si, Yung-Ning Tu, Wei-Hsing Huanq, Jian-Wei Su, Pei-Jung Lu, Jing-Hong Wang, Ta-Wei Liu, Ssu-Yen Wu, Ruhui Liu, Yen-Chi Chou, et al. 2020. 15.5 A 28nm 64Kb 6T SRAM Computing-in-Memory Macro with 8b MAC Operation for AI Edge Chips. In *Proc. of IEEE International Solid-State Circuits Conference-(ISSCC)*. IEEE, 246–248.

[45] Phillip Stanley-Marbell, Armin Alaghi, Michael Carbin, Eva Darulova, Lara Dolecek, Andreas Gerstlauer, Ghayoor Gillani, Djordje Jevdjic, Thierry Moreau, Alexandros Daglis, et al. May, 2020. Exploiting Errors for Efficiency: A Survey from Circuits to Algorithms. *ACM Computing Surveys (CSUR)* 53, 3:51 (May, 2020).

[46] Nikolai Stepanov, Daria Alekseeva, Aleksandr Ometov, and Elena Simona Lohan. 2020. Applying Machine Learning to LTE Traffic Prediction: Comparison of Bagging, Random Forest, and SVM. In *Proc. of 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE, 119–123.

[47] Xiang Sun and Nirwan Ansari. 2017. Avaptive Avatar Handoff in the Cloudlet Network. *IEEE Transactions on Cloud Computing* (2017).

[48] Nguyen Ti Ti and Long Bao Le. 2017. Computation Offloading Leveraging Computing Resources from Edge Cloud and Mobile Peers. In *Proc. of IEEE International Conference on Communications (ICC)*. IEEE, 1–6.

[49] Lin Wang, Lei Jiao, Jun Li, Julien Gedeon, and Max Mühlhäuser. 2018. MOERA: Mobility-agnostic Online Resource Allocation for Edge Computing. *IEEE Transactions on Mobile Computing* 18, 8 (2018), 1843–1856.

[50] Shiqiang Wang, Rahul Urgaonkar, Murtaza Zafer, Ting He, Kevin Chan, and Kin K Leung. 2019. Dynamic Service Migration in Mobile Edge Computing Based on Markov Secision Process. *IEEE/ACM Transactions on Networking* 27, 3 (2019), 1272–1288.

[51] Shangguang Wang, Jinliang Xu, Ning Zhang, and Yujiong Liu. 2018. A Survey on Service Migration in Mobile Edge Computing. *IEEE Access* 6 (2018), 23511–23528.

[52] James Williamson, Qi Liu, Fenglong Lu, Wyatt Mohrman, Kun Li, Robert Dick, and Li Shang. 2015. Data Sensing and Analysis: Challenges for Wearables. In *Proc. of 20th Asia and South Pacific Design Automation Conference*. IEEE, 136–141.

[53] Greg Wilson, Jennifer Bryan, Karen Cranston, Justin Kitzes, Lex Nederbragt, and Tracy K Teal. 2017. Good Enough Practices in Scientific Computing. *PLoS computational biology* 13, 6 (2017), e1005510.

[54] Ling Xiao, Yu Meng, and Kai Wu. 2018. Adaptive Compressed Classification for Energy Efficient Activity Recognition in Wireless Body Sensor Networks. In *Proc. of 4th International Conference on Big Data Computing and Communications (BIGCOM)*. IEEE, 41–45.

[55] Liang Xiao, Xiaoyue Wan, Xiaozhen Lu, Yanyong Zhang, and Di Wu. 2018. IoT Security Techniques Based on Machine Learning: How do IoT devices use AI to enhance security? *IEEE Signal Processing Magazine* 35, 5 (2018), 41–49.

[56] Kai Xu, Yixing Li, and Fengbo Ren. 2017. A Data-driven Compressive Sensing Framework Tailored for Energy-Efficient Wearable Sensing. In *Proc. of International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 861–865.

[57] Qiang Xu, Todd Mytkowicz, and Nam Sung Kim. 2015. Approximate Computing: A Survey. *IEEE Design & Test* 33, 1 (2015), 8–22.

[58] Hongxu Yin and Niraj K Jha. 2017. A Health Decision Support System for Disease Diagnosis Based on Wearable Medical Sensors and Machine Learning Ensembles. *IEEE Transactions on Multi-Scale Computing Systems* 3, 4 (2017), 228–241.

[59] Ashkan Yousefpour, Caleb Fung, Tam Nguyen, Krishna Kadiyala, Fatemeh Jalali, Amirreza Niakanlahiji, Jian Kong, and Jason P Jue. 2019. All One Needs to Know about Fog Computing and Related Edge Computing Paradigms: A Complete Survey. *Journal of Systems Architecture* 98 (2019), 289–330.

[60] Xiang Yu, Maolin Guan, Mingxia Liao, and Xia Fan. 2018. Pre-Migration of Vehicle to Network Services Based on Priority in Mobile Edge Computing. *IEEE Access* 7 (2018), 3722–3730.

[61] Konstantin Zhidanov, Sergey Bezzateev, Alexandra Afanasyeva, Mikhail Sayfullin, Sergey Vanurin, Yulia Bardinova, and Aleksandr Ometov. 2019. Blockchain Technology for Smartphones and Constrained IoT Devices: A Future Perspective and Implementation. In *Proc. of IEEE 21st Conference on Business Informatics (CBI)*, Vol. 2. IEEE, 20–27.