

Maximizing the Wearable Network Lifetime through Virtualized Application Function Chaining

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Abstract—The smart devices usage is growing rapidly driven by innovative new smart wearables and service offerings. This has led to applications that utilize multiple devices around the body to provide immersive environments such as mixed reality that rely on a number of different types of functions and require considerable resources. Thus one of the major challenges in supporting these applications is dependent on the battery lifetime of devices that provide the necessary functionality. The focus of this paper is to improve the battery efficiency through intelligent resources utilization. We show that, when the same resource is available on multiple devices that form part of the wearable system, it is possible to consider them as a resource pool and further utilize them intelligently to improve the system lifetime via function virtualization. We formulate the intelligent function allocation algorithm as a Mixed Integer Linear Programming (MILP) optimization problem and propose an efficient heuristic solution. Next, we demonstrate the orchestration of the virtualized functions in order to achieve specific functionalities. The experimental data driven simulation results show that approximately 40-50% system battery life improvement can be achieved with proper function allocation and orchestration.

Index Terms—smart wearable devices; wearable computing; energy utilization

I. INTRODUCTION

Interest and popularity of mobile and wearable devices is persistent and is increasing due to the variety of attractive applications and services provided on top of them. Among them, Mixed Reality is expected to drive the future demand as they utilize advanced capabilities of the smart wearables and hand-held devices that allows users to interact with immersive virtual environments with real objects [6]. On the other hand, many novel services including mixed reality are extremely resource hungry as much as revolutionary.

These applications continuously use three types of functions, namely sensing, processing and communication (short-range and long-range) that we refer as ‘application functions’. These application functions require a considerable amount of system resources such as energy, computation, and memory. Among these, energy has been identified as the most challenging, as the battery technology is not keeping pace with growth in demand. As a result, current resource heavy wearable applications that rely on wearable devices cannot be used for long periods of time [28], [25].

According to Cisco, average devices and connections per capita in North America will rise to 12.9 by 2021 [5]. These devices can be classified as either a Tier 1 or a Tier 2 device depending on their functional capabilities that also reflects the

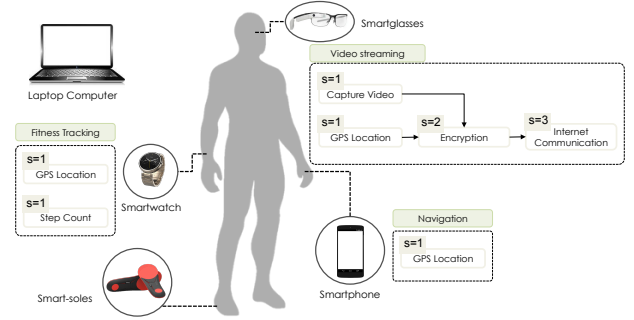


Fig. 1. An overview of a personal area network.

resources they possess [17]. Tier 1 devices, *e.g.* smartphone, smartwatch and smartglasses, are more resourceful than the Tier 2 devices and have the capability of performing all three types of the functions described earlier that many applications require. On the other hand, Tier 2 devices, *e.g.* heart-rate sensor, smart-sole, etc. basically perform sensing functionality and has short-range communication. They are generally paired with a Tier 1 device. These devices are already interconnected and form a personal area network (PAN). There is a significant overlap in functionalities provided by the PAN devices, especially among the Tier 1 devices [15]. In the example PAN in Fig.1, all three Tier 1 devices can perform GPS sensing, step counting and provide Internet access. However, each device is likely to have specific use cases (*i.e.* fitness tracking, navigation and video streaming), which combine and use these primary functions in different orders. Therefore, as the devices in a PAN are interconnected, it is possible to consider them as providing a pool of functional capabilities that are distributed and often replicated in multiple of the devices.

This opens up the possibility of utilizing capabilities across devices on a PAN. However, the current system implementations limit the accessibility of resources on the other devices and wearables are considered simple peripheral sensors, although they already have and will increasingly have even more capabilities to perform more advanced functions [17], [11]. Methods of overcoming these limitations and allowing seamless access to the resources on a PAN and in close proximity has been proposed [17], [27], [21]. These approaches allow the functions to be implemented and the applications to access them without considering the exact location of the function. To achieve the correct *Functionality* while fully leveraging the distributed resources, the sequences of functions (function chains) execution needs to be guaranteed. Therefore,

the challenge is to determine the criteria for the selection of the path of the function chain, and how does this dynamic function chaining can be implemented where the functions are virtualized to enable seamless accessibility similar to network function orchestration in software defined networks [1], [3]. This requires the design of an optimal application function orchestration algorithms. This paper shows that optimal application function orchestration is NP-hard, but that it possible to achieve near optimal function orchestration using a heuristic algorithm that finds the best function allocation by considering the function chaining in order to maximize the system lifetime, and make the following contributions.

- Define design goals for the wearable system energy resource management considering the current trends in wearable devices as well as surveying diverse set of users to understand user expectations.
- Formulate the function allocation problem in wearable systems as a Mixed Integer Linear Programming (MILP) optimization to maximize the wearable system lifetime whilst satisfying all functional requirements.
- Derive the linear programming approximation factor and show the requirement of efficient heuristic algorithm under practical constraints, which is followed by an efficient heuristic algorithm incorporating function orchestration.
- Demonstrate the feasibility of implementing the proposed heuristic algorithm on real devices by comparing the computational time on a smartphone and a smartwatch.
- Evaluate the proposed heuristic solution accuracy, efficiency, and robustness, against the currently used function allocation methods and methods proposed in the literature by conducting experimental data driven simulations. The results show that dynamic function allocation increases the system lifetime by $\sim 50\%$ compared to the existing common non-collaborative function allocation methods and $\sim 40\%$ compared to the collaborative function allocation methods proposed in the literature.

The rest of this paper is organized as follows. We first overview the related work and complementary systems. Next, we present the function allocation problem formulation followed by efficient algorithms for function allocation including function orchestration. Then, we evaluate the proposed algorithms and also the feasibility of increasing wearable system lifetime with experimental driven simulations. Finally, we provide the conclusions.

II. RELATED WORK

The concept of application function virtualization (AFV) is an extension and generalization of the concept of network function virtualization (NFV). As in the case with NFV, one of the challenges is the chaining of the functions (service function chaining - SFC) to achieve the dual objectives of providing the required services, and maximizing the service lifetime.

NFV enables the functions that are provided by proprietary hardware to being able to run on open hardware, thus reducing the capital and operational expenditure. However, to provide

specific network service in an NFV enabled network, it requires the traffic to traverse multiple of the virtualized function instances in a defined order. Unlike in the hardware implementation of the network functions, the virtualization of the functions makes this too complex and inefficient [18]. More specifically, the virtualized functions are topology dependent and difficulties occurs during the configuration [22]. Therefore, much attention has been paid to developing mechanisms for chaining virtualized functions or orchestration by both the research community and standardization authorities [12], [1].

In order to perform function chaining, it is required to have knowledge about the available services via the virtualized function instances and their reachability. There are several approaches available for SFC that extends the currently available methods [13], [26]. The architectural designs proposed by the standardizing authorities [12] build on top of the basic NFV architectures proposed by [8]. Similarly, in our design, we build our function chaining architecture on top of the proposed application function virtualization (AFV) architecture in [17] and extend it to incorporate function chaining. These architectural designs for function chaining have the following approaches; 1) having a separate management system to orchestrate the function chaining [8], [19], which allows the control plane to have the overview of the availability of function instances and how they can be accessed, and 2) allowing the data packets to carry the controlling signals within its header [12], [23].

Our design combines both the approaches but generalizes it to be used with AFV requirements, which leads to different objectives such as energy minimization [14], best outcome [24], minimum latency [2], minimum monetary cost [4], etc. None of these proposed schemes consider application function virtualization and attempts to combine the different objectives to maximize the system lifetime. Also, we identified that as these existing approaches are mostly deployed in fixed networks, they do not consider the energy constraints, whereas dynamic changes of device capabilities, e.g. remaining battery power, are a primary concern for wearable networks. For example, exchanging control signal packets between nodes is not considered as a significant overhead in NFV, but in our problem, every packet consumes significant amount of energy and the remaining battery power is constantly changing in all devices.

III. PROBLEM FORMULATION

Multiple of the PAN devices replicate the same function. Therefore, our hypothesis is that *if the devices on the same PAN collaborate with each other to harness the power of common functions, it is possible to provide better utility to the user.*

A. Virtualized Application Function Chaining

AFV architecture proposed in [16] enables the seamless accessibility to all of the functions available in the PAN. However, it does not discuss the function chaining in any details. In this paper, we consider AFV as the baseline for application function chaining and present an architecture (*cf.*

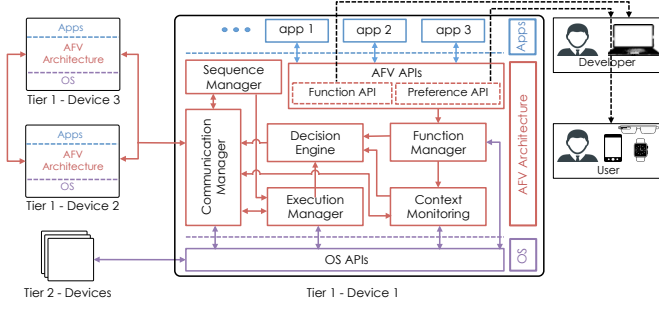


Fig. 2. Architectural design for function chaining.

Fig. 2) that extend/modify the AFV architecture to incorporate function chaining and provides better utility to the user.

The function requests from applications are received via the *AFV APIs*, and the *Context Monitoring* module periodically monitors device, application and user context as detailed in [16]. The function requests are managed by the modified *Function Manager* module. In addition to aggregating requests where possible [16], this module is responsible for preparing the function requests for the sequencing by adding a sequence number. The *Decision Engine* determines the optimal mapping of application functions depending on the optimization objective as detailed in Section IV. The *Communication Manager* maintains efficient Inter-device and Intra-device communication with the assistance of the *Sequence Manager* in order to maintain the proper sequence of functionalities. Also, *Sequence Manager* triggers the *Function Execution* module that performs function invocation on devices.

B. User Study: Wearable System Lifetime

Wearable system lifetime can be defined in multiple ways as per individual user requirements. Therefore, we first conducted a user study to understand user requirements in terms of lifetime of devices on a PAN. We collected responses from 70 users who uses more than one wearable or a hand-held device. These users belong to different age groups (20-60 years) and come from different backgrounds (e.g. Healthcare, Education, Technology, Student, Sales/Service, etc.). Our analyses showed that it is more about their preferred functionality, instead of their preferred device. However, the availability of the user preferred functionalities are replicated in today's Tier 1 devices, and even some applications are designed to incorporate the functionalities of other devices as well (e.g. mixed reality applications). In light of these user responses, we define the wearable system lifetime as *the time until all of the Tier 1 devices on the PAN have their battery energy*. This is followed by our problem statement *how to maximise the battery life of Tier 1 devices whilst satisfying all functional requirements*.

C. Function Allocation Problem

Thus the objective is to allocate each function request $r_f^i \in R_i$ from each device $i \in D$ to function implementations $v_f \in V_i$ in different devices in the correct order whilst maximizing the system lifetime. In other words, for each instance, it is required to maximize the lifetime of the Tier 1 device on the PAN with the lowest battery life. We define

TABLE I
DEFINITIONS OF NOTATIONS

Symbol	Definition
D	- Set of devices in PAN
V_i	- Set of functions in device $i \in D$
R_i	- Set of requests made from device $i \in D$
T	- Interval in between two executions of the algorithm
$f_{v_f}^i$	- Implementation energy of a function $v_f \in V_i$ per T time units
c_{j,r_f}^i	- Energy of per T time units communication for the request for the function v_f from device i ($r_f^i \in R_i$) that is made to device j (receiving energy excluding the idle cost). $c_{j,r_f}^i = 0$ if $j = i$
c_{j,v_f}^i	- Energy of per T time units communication for the request made from device j to the virtual function $v_f \in V_i$ (transmission energy excluding the idle cost). $c_{j,v_f}^i = 0$ if $j = i$
H_i	- Idle energy for device $i \in D$
T_i	- lifetime of $i \in D$ in T time units
T_i^*	- Expected minimum lifetime of $i \in D$ in T time units
E_i	- Remaining energy of $i \in D$
U_i	- Energy usage of $i \in D$ with in T time units
C_i	- Current energy usage of $i \in D$ with in T time units
A_i	- Assigning energy usage of $i \in D$ with in T time units

the lifetime of a device as the ratio of $(E_i / (C_i + A_i))$. We then formulate the function allocation problem as a *Mixed Integer Linear Programming (MILP)* problem in (1). Table I summarises the definitions for all the used symbols.

$$\text{Minimize} \left\{ \text{Max of} \left\{ \left\lceil \frac{(C_i + A_i)}{E_i} \right\rceil \forall i \in D \right\} \right\} \quad \text{where}$$

$$A_i = \sum_{v_f^i \in V_i} f_{v_f^i} \cdot w_{v_f^i} + \sum_{j \in D} \sum_{r_f^i \in R_i} c_{j,r_f^i} \cdot x_{j,r_f^i} + \sum_{j \in D} \sum_{v_f^i \in V_i} c_{j,v_f^i} \cdot y_{j,v_f^i} + H_i \cdot z_i \quad (1)$$

Such that:

1. $w_{v_f^i}, x_{j,r_f^i}, y_{j,v_f^i}, z_i \in \{0, 1\};$
 $\forall (r_f^i \in R_i), \forall (v_f^i \in V_i), \forall (i, j \in D)$
2. $c_{j,r_f^i}, c_{j,v_f^i} = 0$; if $j = i$
3. $x_{j,r_f^i} = \begin{cases} 1; & \text{if } v_f^j \in V_j; \forall (r_f^i \in R_i), \forall (i \in D) \\ 0; & \text{else} \end{cases}$
4. $\sum_{j \in D} x_{j,r_f^i} = 1; \forall (r_f^i \in R_i), \forall (i \in D)$
5. $x_{j,r_f^i} = y_{i,v_f^j}$
6. $w_{v_f^i} = \begin{cases} 1; & \text{if } \sum_{j \in D} y_{j,v_f^i} \geq 1; \forall (v_f^i \in V_i), \forall (i \in D) \\ 0; & \text{else} \end{cases}$
7. $z_i = \begin{cases} 1; & \text{if } \sum_{j \in D} \sum_{r_f^i \in R_i} x_{j,r_f^i} \geq 1 \text{ or } \sum_{j \in D} \sum_{v_f^i \in V_i} y_{j,v_f^i} \geq 1 \\ 0; & \text{else} \end{cases}$
8. $\left[\frac{C_i}{E_i} + \frac{1}{E_i} * \left[\sum_{v_f^i \in V_i} f_{v_f^i} \cdot w_{v_f^i} + \sum_{j \in D} \sum_{r_f^i \in R_i} c_{j,r_f^i} \cdot x_{j,r_f^i} + \sum_{j \in D} \sum_{v_f^i \in V_i} c_{j,v_f^i} \cdot y_{j,v_f^i} \right] \right]$

$$\sum_{j \in D} \sum_{v_f^i \in V_i} c_{j,v_f^i} \cdot y_{j,v_f^i} + H_i \cdot z_i \leq \frac{1}{T_i^*}; \forall (i \in D)$$

A_i depends on the energy consumption of each function, *Function Cost* and the energy consumption for the data transfer in between two devices (*Communication Cost*), if the function is allocated to another device. Therefore, the additional overhead of data transmission among wearables is considered within the *Communication Cost* in the problem formulation. *Communication Cost* consists of two parts, i.e. *data transferring cost*, and *idle cost*. The data transferring cost can be either due to data transmission from/to a function invocation in device j to the request r_f^i in $i \in D$ (c_{j,r_f^i}), or the data transmission from/to the function v_f in device i to the $j \in D$ (c_{j,v_f^i}). The *idle cost* in device i (H_i) is due to the waiting time before closing the connection.

The first constraint shows that the execution of a function or an assignment of a function request can only be 'yes' or 'no' [0/1]. Specifically, $w_{v_f^i} = 1$ if the function v_f is executing in device i , $x_{j,r_f^i} = 1$ if the request for the function v_f from device i ($r_f^i \in R_i$) is assigned to device j , $y_{j,v_f^i} = 1$ if the request for the virtual function v_f from device j is assigned to device i , and $z_i = 1$ if the idle communication energy is considered. Secondly, the communication costs are zero if the function invocation device and the requesting device are the same. Third constraint expresses that the request r_f is mapped to device j only if the function v_f is available in the device j . The forth constraint expresses that each of the requests is assigned exactly to one of the devices that has the function. Next constraint shows that if the communication cost is considered for a particular communication in between device i and j , both the devices need to consider the costs. The constraint 6 shows that a function will invoke only if any of the requests are assigned to the function in the device. Next, if any communication is happening, the idle communication is to be considered. Finally, if there are any requirements for any of the devices to be alive for a certain time, that requirement is to be satisfied.

In this problem formulation, the objective function and the constraints always have a linear relationship with each of its variables. However, some variables in this problem formulation has to have binary values. As an example, the assignment of a function to a request is either *true*(1) or *false*(0). Therefore, this problem formulation is equivalent to *Mixed Integer Liner Programming (MILP)* problem.

IV. FUNCTION ALLOCATION ALGORITHM

Solutions to MILP problems are known to be *NP-hard* [9] and the potential approaches can be broadly categorised into: i) *Exact Algorithms* that guarantee to find an optimal solution, but may take an exponential number of iterations; ii) *Approximation Algorithms* that provide sub optimal solutions in polynomial time, and provides a bound on the degree of sub optimality; and iii) *Heuristic Algorithms* that provide sub

optimal solutions, but do not guarantee the quality of the solutions, and do not guarantee the polynomial time solutions.

A. Exact Algorithms

Even though the exact methods assure the optimal solutions, the complexity grows exponentially. However, the methods such as *brute force search* and *branch and bound* [7] can be used where the number of devices and the functions are very low in the case of AFV chaining.

B. Linear Programming (LP) Approximations

However, when the number of devices and available functions increase, the use of exact methods become impractical due to the increase in computational complexity. Therefore, the general practice is to use approximation methods. Most of these methods are based on linear programming. In these methods, the integer constraints in the original MILP problem are replaced with the linear constraints to solve the LP problem. With these methods, optimal solutions can be obtained in polynomial time and lead to the *lower bound* of the original MILP problem solutions. If any variable that is to be an integer variable in the original problem is a non-integer in the LP relaxation solutions, these values are rounded to the nearest integer. The rounding in these *integral solutions* lead to sub-optimal solutions. A greedy method is required to find the *integral solutions* without significantly increasing the cost. The *approximation factor* is defined as the ratio in between *integral solution* and the *lower bound*.

For the LP representation, the constraints of the function allocation problem defined in (1) should be changed as follows.

1. $\sum_{j \in D} x_{j,r_f^i} \geq 1; \quad \forall (r_f^i \in R_i), \forall (i \in D)$
2. $w_{v_f^i} \geq x_{i,r_f^i}; \quad \forall (v_f^i \in V_i), \forall (i \in D)$
3. $w_{v_f^i} \geq y_{j,v_f^i}; \quad \forall (v_f^i \in V_i), \forall (j \in D), i \neq j$
4. $y_{i,v_f^j} \geq x_{j,r_f^i}$
5. $z_i \geq x_{j,r_f^i}; \quad \forall (v_f^i \in V_i), \forall (i \in D), j \neq i$
6. $z_i \geq y_{j,v_f^i}; \quad \forall (v_f \in V_i), \forall (i \in D), j \neq i$
7. $\left[\frac{C_i}{E_i} + \frac{1}{E_i} * \left[\sum_{v_f^i \in V_i} f_{v_f^i} \cdot w_{v_f^i} + \sum_{j \in D} \sum_{r_f^i \in R_i} c_{j,r_f^i} \cdot x_{j,r_f^i} + \sum_{j \in D} \sum_{v_f^i \in V_i} c_{j,v_f^i} \cdot y_{j,v_f^i} + H_i \cdot z_i \right] \right] \leq \frac{1}{T_i^*}; \quad \forall (i \in D)$

Lower Bound: From the solutions to the LP approximation, we get a solution for the system lifetime, i.e. the lifetime of the device d that is the minimum among the other devices. The optimal solutions for LP approximation ($OPT(LP)$) is called the lower bound of the solutions to *MILP* problem. The lower bound calculation is shown in (2). However, the optimal solution to the LP approximation does not guarantee a integral solution. Therefore, we need to obtain the integral solution from the $OPT(LP)$ solution.

$$OPT(LP) = \frac{C_d}{E_d} + \frac{1}{E_d} * \left[\sum_{v_f^d \in V_d} f_{v_f^d} \cdot w_{v_f^d} + \sum_{j \in D} \sum_{r_f^d \in R_d} c_{j,r_f^d} \cdot x_{j,r_f^d} + \sum_{j \in D} \sum_{v_f^d \in V_d} c_{j,v_f^d} \cdot y_{j,v_f^d} + H_d \cdot z_d \right] \quad (2)$$

Integral Solution: Greedy methods or certain rules sets leads to the integral solution. The below mentioned are the rules that we define in order to find the integral solution.

- If any request from d is not 100% assigned to any one of the other devices in the $OPT(LP)$ solutions, it should be assigned to d itself.

$$\text{If } x_{d,r_f^d} > 0; x_{d,r_f^d} = 1 \ \& \ f_{v_f^d} = 1 \ \& \ x_{j,r_f^d} = 0; \forall j \neq d$$

- If any percentage of any of the requests from other devices is assigned to d , that means the requests can not be fulfilled by any of the other devices. Because, if it is possible, these will not be added to the device d that increases the cost.

$$\text{If } y_{j,r_f^d} > 0 \ \& \ \forall j \neq d; y_{j,r_f^d} = 1 \ \& \ f_{v_f^d} = 1$$

In the worst case, all the requests from the device d is to be fulfilled by the device d itself. In addition, all the requests from other devices that has the [*self-functioning cost* > *communication cost*] is to be run in the device d . Hence, the cost for the worst case integer solution (INT_{sol}^W) is calculated as in (3).

$$INT_{sol}^W = \frac{C_d}{E_d} + \frac{1}{E_d} * \left[\sum_{v_f^d \in V_d} f_{v_f^d} + \sum_{j \in D} \sum_{v_f^d \in V_d} c_{j,v_f^d} + H_d \right] \quad (3)$$

In the best case for the optimal solution (INT_{sol}^B) for $OPT(LP)$, all the requests from device d would be fully allocated in a way that ensures the minimum cost to d . Then, none of the requests from any of the other devices are allocated to d .

$$INT_{sol}^B = \frac{C_d}{E_d} + \frac{1}{E_d} * \left[\sum_{v_f^d \in V_d} f_{v_f^d} \cdot w_{v_f^d} + \sum_{j \in D} \sum_{r_f^d \in R_d} c_{j,r_f^d} \cdot x_{j,r_f^d} + H_d \cdot z_d \right] \quad (4)$$

Approximation Factor: The approximation factor (AF) for a minimization problem is defined as the ratio of the cost of integral solution to the cost of LP optimal solution [10]. We considered the worst case integral solution for the AF calculation. The AF is calculated as in (5).

The AF for a minimization problem is always greater than 1. However, this method of AF calculation depends on the variable values and sometimes it would give a huge value. Therefore, LP approximation method is unsuccessful of dealing with hard capacities as in this problem. Also, the linear programming representation of this specific problem suffers

TABLE II
ENERGY USAGE FOR T TIME UNITS. (*energy usage in d_i , . . . , energy usage in d_n*)

$v_{i,x}$	f	$r_{1,1}$	$r_{n,x}$
$v_{1,1}$	$f_{1,[1,1]}, \dots, f_{n,[1,1]}$	$c_{1,[r_{1,1}], [v_{1,1}]}, \dots, c_{n,[r_{1,1}], [v_{1,1}]}$	$\dots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$v_{n,x}$	$f_{1,[n,x]}, \dots, f_{n,[n,x]}$	$c_{1,[r_{1,1}], [v_{n,x}]}, \dots, c_{n,[r_{1,1}], [v_{n,x}]}$	$\dots$

from another aspect that is the increment of the number of variables as the number of function types and devices are increased.

$$AF = \left[C_d + \sum_{v_f^d \in V_d} f_{v_f^d} + \sum_{j \in D} \sum_{v_f^d \in V_d} c_{j,v_f^d} + H_d \right] / \left[C_d + \sum_{v_f^d \in V_d} f_{v_f^d} \cdot w_{v_f^d} + \sum_{j \in D} \sum_{r_f^d \in R_d} c_{j,r_f^d} \cdot x_{j,r_f^d} + \sum_{j \in D} \sum_{v_f^d \in V_d} c_{j,v_f^d} \cdot y_{j,v_f^d} + H_d \cdot z_d \right] \quad (5)$$

C. Heuristic Algorithms

As explained earlier, heuristic methods neither guarantee the solutions with polynomial time complexities, nor the optimality of the solution. Therefore, the design of the heuristic methods have to be crafted to give a nearly optimal solution without increasing the computational complexity significantly.

Table II shows the energy usage for T time units for all the possible requests to functionality mappings. The first column shows the available functionalities $[v_{i,x}]$ (*i.e.* the function x in device i). The second column shows the functionality cost of the function $v_{i,x}$. The cell entries of this column is a series of cost values, where each value in this series is the cost for each device in the network. However, only the device i will have the cost in a particular series and the cost for all the other devices are zero.

The columns from column 3 show the communication cost for the functionality assignment for the requests $r_{i,x}$, where the request is coming from the device i for the function x . Similar to other columns, the cell entries in each column is a series of cost values, where each value in this series is the cost of communication for each device in the network. If the requesting device and the functioning device are different, both devices have the communication cost. On the other hand, if the request is assigned to the same device, the communication cost is zero. If the devices that is neither the requesting nor the functioning device, the communication cost is again zero. The values for C_i , E_i , H_i and T_i^* for each device are fed to the algorithm. The values for E_i and T_i^* do not change over the iterations for one solution search. However, C_i and H_i would change their values depending on the selection of functions and the requests during each iteration.

The algorithm runs for each type of function separately as a particular function request can only be satisfied with the

invocation of the same type of function. The algorithm works as follows for a particular function type x , and described in Algorithm 1. The system lifetime is calculated as in (6). Let's assume that T^{**} is the initial system lifetime that is calculated without assigning the requests. First, we select a function v ($v_{i,x}$) and a set of requests R_v that minimizes the system lifetime reduction from the earlier system lifetime. And once the function and the set of requests are selected, the set of requests are assigned to the function and remove from further considerations. However, the function is still considered with the functioning cost of zero, as it is already executing for the assigned requests. Then the current energy usage C_i for the devices are reassigned with the cost ($C_i + A_i$). Then, the H_i is replaced by the value ($H_i - H_i \cdot h_i$), where h_i indicates whether the device i is involved in communication with any of the other devices. This is continued until all the request for function type x is assigned to one of the devices where the function x is available. Then the same procedure is conducted for all the function types. In order to achieve the best results, we start with the function types that have the highest *Function Cost* and/or *Communication Cost*. Then we perform for the functions in the descending order of these cost values.

Algorithm 1: Function Allocation Algorithm

Input: (R_v, D_v, m, f, c, T)

Output: assignment $\sigma : R_v \mapsto D_v$
 $T^* = T^{**};$
repeat

 Select $v \in D_v$ and $R \subseteq R_v$ s.t. $\forall r \in R$: that minimize $\frac{T^* - T}{|R|}$
 $R_v \leftarrow R_v - R; f_v = 0$
 $C_i \leftarrow C_i + A_i$
 $T = T^*$
 $h_i = \begin{cases} 1; & \text{if } \sum_{r \in R} c_{i,r,v} > 0; \\ 0; & \text{else} \end{cases}$
 $H_i \leftarrow H_i - H_i \cdot h_i$
 $(R_v \mapsto D_v) \leftarrow (R_v \mapsto D_v) + (R \mapsto v)$
until $R_v \neq \emptyset$;

$$T = \text{Min} \left\{ \left[\frac{C_i}{E_i} + \frac{1}{E_i} * \left[\sum_{v_f^i \in V_i} f_{v_f^i} \cdot w_{v_f^i} + \sum_{j \in D} \sum_{r_f^i \in R_i} c_{j,r_f^i} \cdot x_{j,r_f^i} \right. \right. \right. \\ \left. \left. \left. + \sum_{j \in D} \sum_{v_f^i \in V_i} c_{j,v_f^i} \cdot y_{j,v_f^i} + H_i \cdot z_i \right] \right]^{-1} (\forall i \in D) \right\} \quad (6)$$

D. Virtualized Function Chaining in FAA

In the previous section, we show how the proposed heuristic method of FAA runs for each type of functions separately and assigns these functions optimally. In this section, we show the incorporation of function chaining in FAA in order to find the optimal path of the function chain.

Each of the real world application has its own sequence of functions (cf. Fig. 1). In this figure, the sequence number 's' is labeled for each of the function in each application. One device may have multiple of the applications running at

a particular time. Therefore, a particular sequence of functions $S = [s_1, s_2, \dots, s_n]$ is defined for each application 'a' in device 'd'. Therefore, each request has its unique *Request ID* ($< d, a, s >$).

At first, all the types of function requests that has the sequence number $s = 1$ are considered. Next, the FAA is performed for each of the function type and finds the best allocation for each type. Then it considers the functions in the ascending order of the sequence number. In order to maintain function chaining, a log is maintained as the FAA is performed. This log contains $< \text{chain identification } (d, a), \text{ sequence number } (s), \text{ function type } (f_i), \text{ function requesting device } (d_r), \text{ function performing device } (d_f) >$. After performing FAA for all function types for a particular s value, the FAA then starts allocating functions to the requests that are next in the sequence ($s + 1$). At this point, the FAA does not consider that these requests are coming from the original requesting devices, but they are considered as coming from the devices where the previous request in the chain is allocated to.

V. EVALUATION

We first present the performance analysis of FAA in terms of accuracy, efficiency, and robustness. Next, we evaluate the wearable system lifetime improvement using virtualized function chaining with an use case scenario that is emulated with an experimentally measured energy consumption values.

A. Performance Analysis of FAA

1) *Simulation Setup:* For this analysis, we consider a wearable system with three devices, where each device is installed with the proposed virtualized function chaining modules. Each function chain is simulated to have the same number of functions that is gradually increased up to ten functions per device. Therefore, having 10 functions to be allocated in each device means that there are 30 different functions to be executed in the wearable network, which is a reasonably large wearable network load. We consider every function is of different type and the energy consumption of each function (*Function Cost*) is normally distributed with average μ of 200mJ per minute, and the standard deviation of (σ) such that $\sigma = 0.1 * \mu$. We consider that each function uses 13.5KB of data per minute (i.e. a typical amount of data generated from a sensing function per minute [17]) that needs to be transferred to the next function in the chain once in every minute. We consider that the three devices have 400mAh, 450mAh, and 500mAh battery capacities (i.e. the normal battery capacity of the available smart wearable devices)¹, and each of the experiment starts with 100% of battery charge in all the devices.

The energy consumption for the data transfer in between two devices (*Communication Cost*) consists of two parts, i.e. *data transferring cost*, and *idle cost* that is caused due to the waiting time before closing the connection. In general, the *idle cost* is almost 80% from the *Communication Cost*

¹<https://www.gsmarena.com>

during Bluetooth transmission of $\sim 10KB$ of data. The *Communication Cost* for a function is as same as the average *Function Cost* (200mJ per minute). However, we consider that all the communication in between devices (10KB of data for each function) is performed once per minute, and all at once. Therefore, the *idle cost* is shared among the number of functions in the chain. Hence, as the number of functions in the function chain is increased, the *Communication Cost* per function is decreased.

We then compare the system lifetime increment of (FAA) against the following;

- **OPTIMAL** - The optimal solution for every FAA instance obtained from the brute force method.
- **MANUAL** - A random selection of one device in the wearable system to execute each function request. This method is analogous to asking the user to select function allocation.
- **EACH** - Every device in the wearable system perform all functions independently which is the usual practice with current cross device wearable applications.
- **FAA_{AFV}** - The most related function allocation algorithm proposed in the literature [17]. However, this work does not consider function chaining. Therefore, we modified **FAA_{AFV}** to incorporate function chaining as described in Section IV-D.

2) *Accuracy, Efficiency and Robustness of FAA*: We measure the percentage increment of the system lifetime when using FAA (Algorithm 1) compared to the four existing approaches. Fig. 3(a) shows the percentage system lifetime increment by using FAA when the number of functions in the function chain is increased. As being a heuristic solution method, FAA provides a suboptimal solution. However, the error of this heuristic solution to the OPTIMAL solution is minimal where it has less than 5% average error even when the number of functions in the chain is 10. On the other hand, the system uptime increment becomes much significant compared to MANUAL, EACH, and **FAA_{AFV}**, as the length of the function chain is increased. This is due to that the FAA optimizes the allocation of more functions when the length of the chain is increased. This behavior is even applicable when the number of function chains are increased, where more function requests are optimized by FAA. In particular, FAA improves system lifetime approximately 50% compared to non-collaborative function allocation such as MANUAL and EACH methods and improves by 40% compared to collaborative function allocation such as **FAA_{AFV}**. Moreover, we can observe that the confidence interval (CI) is much larger in the solutions compared to the MANUAL approach as this approach allocates functions randomly.

As mentioned in Section IV-C, the heuristic methods of solutions for the *MILP* problems does not guarantee the efficient solution methods. Therefore, we measure the computation time for the FAA algorithm as a measure for the efficiency of the algorithm, and the results are shown in Fig. 3(b). Also, we compared the computation time with

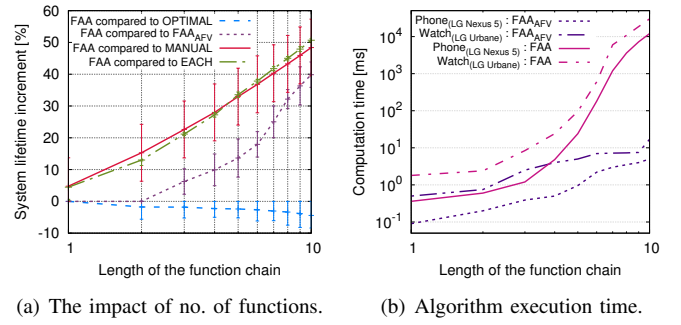


Fig. 3. Accuracy, Efficiency and Robustness of FAA Algorithm

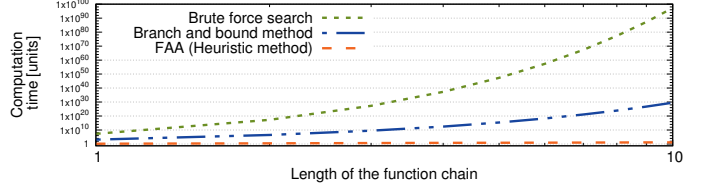


Fig. 4. Time complexities.

the **FAA_{AFV}**. Both of these algorithms were developed in Android as wearable/mobile applications and measured the time usage of calculations. We use Nexus5 as the smartphone example and LG Watch Urbane as smartwatch example. As per the results, even when the number of functions per device is 10, FAA provides near optimal solutions within 1 second (note the log axes), where the exact method (brute force search) takes few hours to calculate the optimal solution. Moreover, the FAA algorithm execution time is comparable with the algorithm execution time of **FAA_{AFV}**, but provides higher quality solutions than **FAA_{AFV}**.

As shown in Fig. 3(a), a PAN consists of 3 devices and when the number of functions per device is changed from 1 to 10, a minimal error with the optimal solution is maintained by the FAA algorithm. Also, these sub optimal results are provided within 1 second for all the values of the number of functions (cf. Fig. 3(b)). These results express the robustness of the proposed FAA algorithm for realistic use case scenarios.

3) *Computational Complexity of FAA*: Let's assume that the number of function types is x , number of devices that are capable of executing each function is n , and number of requests for a particular function type is r . The calculated computational complexity of FAA is $O(nx2^r)$. The complexity of FAA is linear for the number of function types x (i.e. length of the function chain). We compared the computational complexity of FAA with the computational complexities of exact solution algorithms (*brute force search* - $O(n^rx)$, and *branch and bound* - $O(n^x)$). Fig. 4 shows the comparison of the computational time in FAA and *exact methods*. As in Section V-A2, we considered three devices and all three devices are requesting for a function ($n, r = 3$). These results show that the FAA provides results with only $\sim 5\%$ error within up to $\sim 10^{100}$ times reduced computational complexity to the *exact solutions*.

TABLE III
ENERGY COST ASSOCIATED TO EACH CONSIDERED FUNCTION

Function	Energy cost		
	Phone	Watch	Glasses
Connectivity (Data Transferring [mW] - Idle [mJ])			
Bluetooth	520 - 605	180 - 190.3	164 - 191.85
WiFi	790 - 66	480 - 50	460 - 52
Processing [mW]			
Encoding	1400	860	900
Sensing [mW]			
Video Capturing [20]	-	-	2963
GPS Location	166	148	155
Step Count	-	5	-

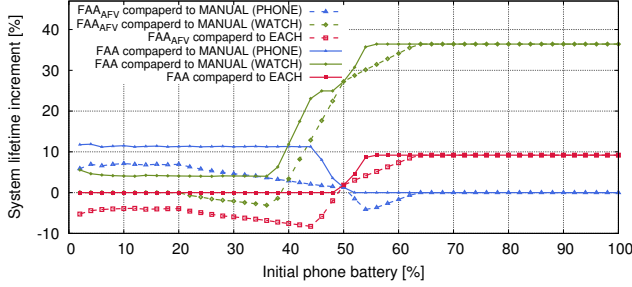


Fig. 5. Use case scenario.

4) *Emulating Multiple Use Case Scenarios*: Next, a use case scenario with real energy cost values is emulated and present the accuracy and robustness of FAA. For the emulation, we experimentally measured energy consumption values for the functions with real devices, and used the corresponding values to model each scenario that involves multiple functions, e.g. we added up the (sensing + Bluetooth transmission) energy to emulate a device that sense and transmit data. We consider a PAN that consists of two devices (smartphone and smartwatch), and applications installed in each of the device request accelerometer data in FASTEST speed for the indoor navigation. The application updates in every 30 seconds, and therefore, the data is processed by the applications in every 30 seconds. We modelled this scenario as two requests for the function of ‘*accelerator data in FASTEST speed*’ are made by two devices in the PAN that required to receive data in every 30 seconds. The power requirement specified in Table III are used for the calculations and the smartphone and smartwatch have 2300mAh and 410mAh battery capacities respectively.

We implemented FAA and also the algorithm proposed in [17]. Fig. 5 shows the system lifetime increment of using each FAA algorithm, compared to different methods of existing function allocation, i.e. EACH and MANUAL (smartphone/smartwatch). The initial battery percentage of the smartphone is changed along with the experiment, providing multiple use case scenarios. As per the results, FAA algorithm always selects the optimal function allocation at all the values of initial phone battery percentages. However, FAA_{AFV} is not always being the optimal, as the objective of FAA_{AFV} is minimising the total energy of the system rather than increasing the system lifetime. Therefore, the system up time increment is not always

effective for FAA_{AFV} as the selection of FAA_{AFV} decreases the system lifetime compared to some of the common function allocation method (EACH, MANUAL) for certain initial phone battery conditions. The results show that the FAA provides accurate results at different levels of initial battery status.

B. Evaluation with Real World Scenarios

We consider a real world scenario that consists of five devices as shown in Fig. 1 and they are already inter connected. It has three Tier 1 devices (smartphone, smartwatch, smartglasses), one Tier 2 device (smart-sole) that has the GPS sensing capability, and also a (laptop computer) that has the highest computational capabilities. However, the laptop computer is not always attached with the user, and therefore, we refer to it as an extended PAN device. Resource hungry gaming application in the smartglasses involves in video streaming. It captures the video of the surrounding, adds the GPS location data, encrypts data and streams to another external party. The smartwatch is running a fitness tracking application that requires GPS location and step count at the same time. Also, a navigation application is running in the smartphone that requires GPS location. Here, the user/developer has specified preferences to run the ‘*Capture Video*’ function in the smartglasses, and the ‘*Step Count*’ function in the smartwatch. Therefore, these two functions are assigned accordingly at the beginning of the FAA. The remaining function requests are allocated as per the FAA. The specified energy values in Table III is used to emulate the real world scenarios. The smartphone, smartwatch and smartglasses has 2300mAh, 410mAh and 570mAh battery capacities respectively. In order to calculate the default energy usage, we consider the smartphone can retain for 2 days with the default energy drainage, smartwatch and smartglasses retain one day. These were obtained from the specifications for real devices.

Fig. 6 shows the percentage of system lifetime increment compared to the current default method of function allocation (i.e. the device itself is performing all the functions), against the availability of the Tier 2 device (smart-soles) and the extended PAN device (laptop computer). When the tier 2 device and the extended PAN device are available for a longer time period, the system uptime increment inclines. However, after a certain time, the system lifetime can not be further increased, and that is where each graph is plateaued. This is because that, even all the processing and sensing are fully allocated to the laptop computer and the smart-sole, while allocating the minimum possible amount of workload to the Tier 1 devices, the Tier 1 devices will get their batteries drained out and limit the further increment of the system lifetime.

Moreover, same as in Section V-A2, it can be observed that the percentage system lifetime increment is much more significant compared to the default function allocation when the length of the function chain is increased. Also, the FAA algorithm proposed in this paper outperforms the FAA_{AFV} at each scenario of availability of the devices.

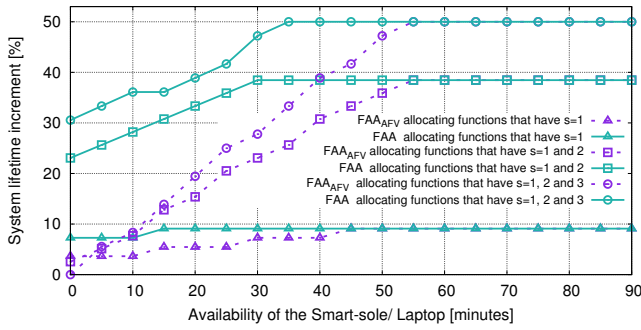


Fig. 6. Function Chaining.

VI. CONCLUSION

One of the major constraints of wearables is the battery capacity, and as a result, this leads to poor user experience as the application lifetimes become limited. Moreover, the current non-efficient resources utilization exacerbates this problem. It is clear that one of the most practical solutions to the problem is to leverage the resources of multiple devices on the personal area network. However, this requires efficient coordination of the pool of resources that are available and the orchestration of their use.

To the best of our knowledge, this paper presented the first proposal for application function orchestration, and showed that it is possible to maximize the overall wearable system lifetime using a heuristic algorithm of function allocation. The percentage system lifetime increases with the length and the number of function chains as it increases the number of optimized function allocations. For a particular use case of 3 devices and 10 function types, the proposed heuristic method of function allocation increases the system lifetime by $\sim 50\%$ compared to the existing common non-collaborative function allocation methods, *i.e.* manual allocation and allocation to all devices, and by $\sim 40\%$ compared to the most related collaborative function allocation method proposed in the literature. However, the heuristic solution methods used in the proposed algorithm maintains a minimal error with the optimal solutions while providing a significant improvements in the time complexity and efficiency. We also demonstrated the practical feasibility of executing the proposed algorithm on real devices in near real time by implementing it on a smartphone and a smartwatch.

In our future work, we intend to extend our implementation to develop a cross-device function allocation framework that can be utilized by application developers to take advantage of the power of common functionalities available on the PAN.

REFERENCES

- [1] M. F. Bari, S. R. Chowdhury, R. Ahmed, and R. Boutaba, "On orchestrating virtual network functions," in *Proc. of the IEEE CNSM '15*, 2015, pp. 50–56.
- [2] D. Bhamare, M. Krishnamoorthy, and A. Gumaste, "Models and algorithms for centralized control planes to optimize control traffic overhead," *Computer Communications*, vol. 70, no. C, pp. 68 – 78, 2015.
- [3] J. Blendin, J. Rckert, N. Leymann, G. Schyguda, and D. Hausheer, "Position paper: Software-defined network service chaining," in *EWSDN*, 2014, pp. 109–114.
- [4] M. Bouet, J. Leguay, and V. Conan, "Cost-based placement of vdpf functions in nfv infrastructures," in *Proc. of the NetSoft*, 2015, pp. 1–9.
- [5] Cisco, "The Zettabyte Era: Trends and Analysis," 2017. [Online]. Available: <https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni-hyperconnectivity-wp.html>
- [6] E. Costanza, A. Kunz, and M. Fjeld, "Human machine interaction," D. Lalanne and J. Kohlas, Eds. Springer-Verlag, 2009, ch. Mixed Reality: A Survey, pp. 47–68.
- [7] L. Dupont, "Branch and bound algorithm for a facility location problem with concave site dependent costs," *International Journal of Production Economics*, vol. 112, no. 1, pp. 245–254, 2008.
- [8] ETSI, "Network Functions Virtualisation (NFV); Architectural Framework," *ETSI GS NFV 002 v1.2.1*, vol. 1, pp. 1–21, 2014.
- [9] M. Grötschel, "Primal heuristics for mixed integer programs," Ph.D. dissertation, Technical University of Berlin, 2006.
- [10] L. Guo and H. Shen, "Efficient approximation algorithms for the bounded flexible scheduling problem in clouds," *IEEE TPDS*, vol. 28, no. 12, pp. 3511–3520, 2017.
- [11] H. Kolamunna, J. Chauhan, Y. Hu, K. Thilakarathna, D. Perino, D. Makaroff, and A. Seneviratne, "Are wearables ready for secure and direct internet communication?" *GetMobile: Mobile Comp. and Comm.*, vol. 21, no. 3, pp. 5–10, Nov. 2017.
- [12] J. Halpern and C. Pignataro, "Service function chaining (sfc) architecture," *IETF RFC, 7665*, 2015.
- [13] W. John, K. Pentikousis, G. Agapiou, E. Jacob, M. Kind, A. Manzanini, F. Risso, D. Staessens, R. Steinert, and C. Meirosu, "Research directions in network service chaining," in *IEEE SDN4NFS*, 2013, pp. 1–7.
- [14] H. Kim and N. Feamster, "Improving network management with software defined networking," *IEEE Communications Magazine*, vol. 51, no. 2, pp. 114–119, 2013.
- [15] H. Kolamunna, J. Chauhan, Y. Hu, K. Thilakarathna, D. Perino, D. Makaroff, and A. Seneviratne, "Are wearables ready for https? on the potential of direct secure communication on wearables," in *2017 IEEE LCN*, 2017, pp. 321–329.
- [16] H. D. Kolamunna, K. Thilakarathna, D. Perino, D. Makaroff, and A. Seneviratne, "Seamless resources sharing in wearable networks by application function virtualization," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2018.
- [17] H. Kolamunna, Y. Hu, D. Perino, K. Thilakarathna, D. Makaroff, and A. Seneviratne, "AFV : Enabling Application Function Virtualization and Scheduling in Wearable Networks," in *Proc. of the UbiComp '16*, 2016, pp. 981–991.
- [18] T. W. Kuo, B. H. Liou, K. C. J. Lin, and M. J. Tsai, "Deploying chains of virtual network functions: On the relation between link and server usage," in *IEEE INFOCOM 2016*, 2016, pp. 1–9.
- [19] Y. Li and M. Chen, "Software-defined network function virtualization: A survey," *IEEE Access*, vol. 3, pp. 2542–2553, 2015.
- [20] R. LiKamWa, Z. Wang, A. Carroll, F. X. Lin, and L. Zhong, "Draining our Glass: An Energy and Heat Characterization of Google Glass," 2014.
- [21] S. Oh, H. Yoo, D. R. Jeong, D. H. Bui, and I. Shin, "Mobile plus: Multi-device mobile platform for cross-device functionality sharing," in *MobiSys '17*, 2017, pp. 332–344.
- [22] P. Quinn and T. Nadeau, "Problem statement for service function chaining," *IETF RFC, 7498*, 2015.
- [23] P. Quinn, U. Elzur, and C. Pignataro, "Network Service Header (NSH)," IETF, Internet-Draft draft-ietf-sfc-nsh-28, Nov. 2017, work in Progress.
- [24] S. Sahhaf, W. Tavernier, M. Rost, S. Schmid, D. Colle, M. Pickavet, and P. Demeester, "Network service chaining with optimized network function embedding supporting service decompositions," *Computer Networks*, vol. 93, no. Part 3, pp. 492 – 505, 2015.
- [25] S. Seneviratne, Y. Hu, T. Nguyen, G. Lan, S. Khalifa, K. Thilakarathna, M. Hassan, and A. Seneviratne, "A survey of wearable devices and challenges," *IEEE Communications Surveys Tutorials*, vol. 19, no. 99, pp. 2573–2620, 2017.
- [26] L. Sun, H. Dong, and J. Ashraf, "Survey of service description languages and their issues in cloud computing," in *SKG2012*, 2012, pp. 128–135.
- [27] N. Vallina-Rodriguez and J. Crowcroft, "ErdOS: Achieving Energy Savings in Mobile OS," in *Workshop on MobiArch*, 2011, pp. 37–42.
- [28] J. Williamson, Q. Liu, F. Lu, W. Mohrman, K. Li, R. Dick, and L. Shang, "Data sensing and analysis: Challenges for wearables," in *Proc. of the ASP-DAC*, 2015, pp. 136–141.