Fluid Composition of Intermittent IoT Energy Services

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Abstract—We propose a novel fluid composition approach of wireless energy services in a crowdsourced IoT environment. The proposed approach selects an optimal set of dynamic energy services according to the consumer’s requirements. We leverage the mobility patterns of the crowd in confined areas to capture the intermittent behavior of IoT energy services. We model the IoT energy services based on their mobility patterns to propose a knapsack-based heuristic for the fluid composition. Experimental results demonstrate the efficiency of the proposed approach.

Keywords—Crowdsourcing; Wireless Energy; IoT environment; Fluid composition; Intermittent services;

I. INTRODUCTION

The concept of the Internet of Things (IoT) has emerged as a result of the pervasive presence of wireless sensors and embedded systems [1]. Physical things are being connected to the Internet and augmented with sensors, computing resources, and network connectivity. These capabilities may be abstracted as IoT services with functional and non-functional properties (i.e., Quality of Service (QoS)) [2]. For example, sensing health-related information by a smartwatch is an IoT service where the functionality is sensing bio-signals from the body. The accuracy of signals and their freshness represent QoS attributes [1].

Crowdsourcing leverages IoT services to create a self-sustained ecosystem. Crowdsourcing IoT services refers to sharing services among nearby IoT devices [3]. Examples of crowdsourced IoT services include computing offloading [4], environment monitoring [5], and wireless energy sharing [6]. A smartphone with low battery power may for instance elect to receive energy from nearby wearables using Wifi. The focus in this paper is on wireless energy sharing.

The concept of wireless energy sharing (i.e., crowd charging) has been introduced recently to provide IoT users with ubiquitous power access through crowdsourcing [7] [6]. Energy sharing provides a green and convenient alternative to charge IoT devices. For example, a smartwatch can be recharged using the harvested energy of nearby smart shoes. The IoT devices can harvest energy from different sources, i.e., the kinetic movement of IoT users or their body heat [8]. Several wireless energy transfer technologies allow the delivery up to 3 Watts power within 5-meter distances to multiple receivers e.g., Energous® [1] and Wi-Charge® [2].

Crowdsourcing energy as a service is the process of delivering wireless energy from IoT service providers to IoT users (i.e., consumers). Energy providers participate in the crowdsourced energy ecosystem for the following reasons. They might share energy altruistically to contribute to a green IoT environment. They can also be egotistic since energy is a vital resource for IoT devices. Therefore, providers would not be interested in sharing their energy unless they receive a satisfying incentive to compensate for their resource consumption. There is a body of research that considers incentives for crowdsourced IoT services [5] [9]. In this paper, we focus on composing crowdsourced energy services. We assume that the providers are already incentivized by existing incentive models [9].

The composition of IoT energy services is expected to play an important role in the crowdsourced IoT environment [10]. A single energy service may not satisfy the consumer’s requirement. The preferred solution is to select an optimal set of services according to the requirement of the consumer [11]. Service composition has been extensively researched [12]. IoT services exhibit flexible and dynamic features. Conventional composition techniques may not be a good fit for energy services for the following distinct characteristics:

• Flexibility. Energy service consumers do not have any lock-in contracts like traditional services. Assuming crowdsourced energy services are represented by time intervals, consumers may invoke services for the full-time interval or only partially according to their preferences.

• Intermittent behavior. Energy providers may exhibit an intermittent behavior in a confined area at their advertised time. The energy providers do not necessarily commit to their initial advertisement. Energy services do not have any Service Level Agreement (SLA) [11]. They may move freely inside the confined area. For example, an IoT user in a coffee shop may go to the counter to place an order and comeback [13].

• Best-effort composition. There is no failure if the composed services do not fulfill the exact requested energy amount. Any obtained amount is usable by the consumer. Unlike the binary traditional service composition [14] [12].

1https://www.energous.com/  
2https://wi-charge.com/
the best-effort composition provides the best possible combination of services in terms of QoS properties and the consumer constraints.

We introduce the concept of fluid composition considering the above characteristics of the crowdsourced IoT environment. The novelty of our proposed solution is that intermittent energy services are composed without any lock-in contracts or SLA. The fluid composition permits the partial consumption and re-invocation of intermittent services to collect the maximum amount of energy with the best QoS properties. If one of the component services disconnects temporarily and comeback (i.e., intermittent behavior), the composition framework must decide between waiting for the intermittent service or switching to another service.

To the best of our knowledge, existing energy service composition approaches do not consider the mobility and the intermittent behavior of the crowdsourced energy service providers [10]. In this paper, we propose a novel model for mobile and intermittent crowdsourced energy services which is a major extension of the deterministic energy service model in [10]. The indoor mobility patterns are predictable when people regularly visit confined areas such as restaurants and coffee shops [13][15]. We leverage these mobility patterns to propose a fluid composition approach. The proposed approach finds an optimal selection of services ahead of time after estimating the mobility patterns and the cost of all disconnections and switches between available services. The main contributions are:

- A novel service model to represent the intermittent behavior of crowdsourced IoT energy services.
- A heuristic-based fluid composition algorithm to select an optimal set of intermittent IoT energy services.

II. MOTIVATING SCENARIO

We describe a scenario where a number of people gather in different places, i.e., confined areas (e.g., coffee shops, restaurants, movie theatres) within the downtown of any major city (see Figure 1). We assume that city dwellers will use their wearables to harvest energy [16]. Note that existing wearable technology allows for the harvesting of several microwatts to a few watts [8][16]. Users wearing a harvester on each leg can generate enough power to charge up to four smartphones by walking for one hour at a comfortable pace e.g., PowerWalk3. This provides an opportunity for IoT devices to share spare energy wirelessly with nearby devices. The distance between IoT devices exchanging energy may reach five meters to ensure a successful wireless transmission [6]. The IoT devices and wearables are assumed to be equipped with wireless energy transmitters and receivers using products such as Energous and Wi-Charge.

We will use the following scenario: An IoT user in a food court needs to recharge their smartphone to be able to run some important applications, e.g., make a call or use email. The IoT user launches the following request: User $x$ requires an amount of energy $E$ in the location $L$ during the period $[s, t]$. All energy requests are processed by a centralized edge-based IoT coordinator, i.e., a router in a confined area (see Fig. 1). Multiple IoT energy service providers are advertising their energy services in the food court at the same time. The advertisement presents information about the provided service, e.g., the service location, start time and end time, the provided energy amount. Note that, the wireless energy transfer can be performed only in a predefined range between the providing and the consuming IoT devices [6]. A neighboring energy service may drop out temporarily at any moment due to the mobility of device owners, e.g., an IoT user may go out to have a phone call and come back (see Figure 2(a)). Therefore, the intermittent mobility of IoT devices affects the validity of any composition of available IoT energy services as the delivery of the expected amount of energy may not be guaranteed. The component services may not provide the exact advertised energy amount because of their disconnections.

Typically, people develop certain routines in confined areas [13]. They tend to define a set of preferences inside a specific confined place. For example, a user may select a preferred seat in the food court. They would sit and chat for a while. The user then would go to order food, they would wait in the line, order, and come back to their seat. The user goes back to receive the order. Finally, they leave the food court after finishing the food. The place

3https://www.bionic-power.com/
preferences and habits build a mobility pattern for IoT users in confined areas. Capturing the mobility of energy providers permits us to estimate the real availability of crowdsourced energy services. Several prediction models are proposed to capture the indoor mobility patterns of the crowds. Estimating the availability of intermittent services within the range of the consumer allows the selection of a high-accurate composition of crowdsourced energy services in a dynamic environment. The effective availability of intermittent services is affected by the frequency and the length of the temporary disconnections (see Figure 2 (b). The reactive composition which considers all the disconnections and switches at every disconnected service to a new one provides a high-accurate solution. However, the reactive composition lacks runtime efficiency in the highly dynamic crowdsourced environment. The reactive composition is also costly in terms of time and energy for every new connection establishment. An edge-based IoT coordinator requires a lightweight composition framework to deal with dynamic IoT energy services. We formulate our composition problem as “finding the optimal composition that solves the trade-off between effectiveness and runtime efficiency.”

III. INTERMITTENT ENERGY SERVICE MODEL

The intermittent crowdsourced energy services are provided by peoples’ wearables. The mobility pattern of IoT users in a smart city allows the estimation of energy services’ availability. However, the available services may deliver energy intermittently due to their movement within the confined area (i.e., micro-mobility). The micro-mobility of IoT energy providers may cause disconnections of the wireless energy delivery. Each individual may concur a unique experience in a particular place. This experience may create an attachment of people to that particular place reflected in a set of habits. These habits may define the mobility pattern of individuals in confined areas. We leverage mobility patterns to define the intermittent energy service model.

Definition 1. An intermittent crowdsourced IoT energy service CES is represented as a tuple < Eid, Eownerid, F, Q, A, In > where Eid is a unique service ID, Eownerid is a unique ID for the owner of the IoT device, F is the set of CES functionalities offered by an IoT device, Q is a tuple of < q1, q2, ..., qn >, A and In are the spatio-temporal patterns which capture the mobility of energy services. Each qi denotes a QoS property of CES. A is a temporal function for the estimation of the availability of CES inside the confined area at the advertised time. In is time series to represent the intermittent behavior of CES.

Definition 2. Crowdsourced Energy Service Consumer request. An energy service request is defined as a tuple Q = < t, l, RE, C1, du >, where t refers to the timestamp when the request is launched. l refers to the location of the consumer. We assume that the consumer is stationary at their location l after launching their energy request. RE represents the required amount of energy. C1 is the maximum intensity of the wireless current that a consuming IoT device can receive. du refers to the charging period.

Definition 3. Crowdsourced Energy Service Quality Attributes. Quality parameters i.e., QoS allow users to distinguish among crowdsourced IoT energy services. QoS parameters are defined as a tuple < l, r, st, et, DEC, I, Tsr, Reli >: l is the location of the consumer. r is the range between the providing and consuming IoT devices which allows a successful wireless energy delivery. st and et represent the start time and end time of a crowdsourced energy service respectively. DEC is the deliverable energy capacity. I is the intensity of the wirelessly transferred current. Tsr represents the transmission success rate. Reli is the reliability QoS.

The spatio-temporal features of the IoT energy services (i.e., l, st and et) are defined based on the pattern of time spent in regularly visited places e.g., coffee shops or food courts using their daily activity model. DEC and Reli are estimated by the energy usage model of the IoT device. I and Tsr are defined based on the specifications of the IoT devices providing services. The intermittent mobility patterns of IoT energy services are defined as:

- **Availability**: The availability of an intermittent service is the probability distribution of service provider’s location inside the confined area C during the advertised time interval. We denote the availability A of a service i within a confined area C as a tuple Ai(C, ti, loci, θi). Here, ti = {ti0, ti1, ti2, ..., tin} is the set of timestamps between the start sti and the end time eti of service i, loci = {loci0, loci1, loci2, ..., locin} is the set of locations of the service i within the confined area C. Each θik ∈ θi is the probability that the service i is in the location loci at the timestamp tik, θi(ti = loci) = f(Hi, C). The probability distribution function f can be obtained by statistical methods applied on the historical records Hi of service i in the confined area C.

- **Intermittent provision**: The intermittent provision In of an IoT energy service i to an energy request Q is modeled as a tuple Ini(Q, Ai, Pr) where Ai is the availability distribution for all timestamps ti = {t0, t1, t2, ..., tn} between the start sti and the end time eti of service i. Pr is the corresponding energy provision distribution for all timestamps based on the location of the service. The provision distribution Pr presents the wireless energy provision status at each timestamp tik ∈ ti = {t0, t1, t2, ..., tn} as follows:

\[ Pr_{ik} = 1 \text{ if } D_h(Q, l, i) \leq r_i; \quad 0 \text{ otherwise} \]
Definition 4. Fluid composition. Given a set of intermittent crowdsourced IoT energy services; \( S_{CES} = \{CES_1, CES_2, \ldots, CES_n\} \) and a request \( Q = < t_1, l_i, r_i > \) in a confined area \( C \), the fluid composition framework relies only on the advertisement and the estimation of the mobility patterns to select and compose IoT energy services ahead of time. The optimal composition can transfer the required amount of energy \( RE \) considering the intermittent behavior of nearby services.

We transform the fluid composition problem into a temporal knapsack problem [20] as follows:

Maximize \( Composite.DEC = \sum CES_i.DEC \)

Where \( Composite \) is the composition of intermittent \( CES_i \), \( CES_i \) are the component services of \( Composite \).

We consider the following assumptions:

- The providers may move freely inside the confined area \( C \). This movement leads to the intermittent wireless IoT energy delivery.
- Energy can be provided wirelessly if and only if the distance between the providing and consuming devices is equal or less than a predefined range \( r \).
- Two or more energy services can be composed simultaneously if and only if the sum of their current transfer intensity \( I_i \) is lower or equal the intensity of the request. \( \sum I_i \leq CI \) [17].
- We assume that it is possible to invoke services partially.

The temporal knapsack algorithm composes crowdsourced IoT energy services based on their advertisement. However, Energy services typically exhibit an intermittent behavior. We leverage the spatio-temporal patterns captured by the proposed service model to present a novel framework for composing intermittent energy services (see figure 3).

The framework consists of three phases: (i) It starts by selecting the composable IoT energy services based on the request duration and the advertisement of energy providers. (ii) The framework then evaluates the intermittent behavior of candidate energy services based on their mobility patterns. (iii) The proposed heuristic composes an optimal set of candidate energy services ahead of time as follows: Tolerating the stable but slightly intermittent candidate services. Substituting the disconnected services by the most stable available services.

A. Spatio-temporal selection of IoT energy services

Initially, we select and compose the IoT energy services according to their spatio-temporal features and the request duration [10][11]. The spatio-temporal selection algorithm consists of three steps:

1) We select the composable services based on their advertisement. All available services within the request duration are considered temporally composable services. Selected services must be within the range of the energy consumer to be spatially composable and allow the wireless energy transfer [11].

2) We chunk the request duration into smaller temporal chunks based on the advertisement of composable service. We assume that energy services can be decomposed and consumed partially. The energy consumer may switch to other energy services within the request duration. We define all the possible timestamps where the consumer may switch to another service. Each timestamp is either the start or the end time of available services [10].

3) We apply the 0/1 knapsack algorithm at each chunk by considering the wireless intensity compatibility between the consuming and providing IoT devices. We maximize the acquired energy at each chunk by combining the partial services with respect to their wireless current intensity, i.e., the aggregated intensity of composed partial services at a chunk must be lower or equal the compatibility intensity \( CI \) of the consumer [11].

B. Evaluation of intermittent IoT energy services

The service model utilizes the mobility pattern \( A_i(C, t_i, loc_i, \theta_i) \) to capture the disconnections whenever the energy service \( i \) moves inside the confined area \( C \). The intermittent provision pattern \( Ir_i(Q, A_i, Pr_i) \) defines the disconnections between the service \( i \) and the request \( Q \). The frequency of disconnections reflects the stability of the wireless energy provision. Energy services are more stable when the disconnections are less frequent. We define a stability score \( STB_i(Q) \) for a service \( i \) toward an energy request \( Q \) by the frequency of disconnections as follows:

\[
STB_i(Q) = 1 - \frac{1}{|et_i - st_i| - \sum_{k \in t_i} Pr_{ik}}, k \in t_i
\]

Where, \( st_i \) and \( et_i \) represent the start and end time of service \( i \). \( Pr_{ik} \) is the provision status of service \( i \) to the energy request \( Q \) at timestamp \( k \in t_i \). \( t_i \) represents all the time points for the time interval of service \( i \).

The length of a disconnection also affects the energy provision. An energy consumer sets their request for a period
Algorithm 1 Heuristic-based fluid composition

Input: $Q.l$, $Q.t$, $Q.du$, $Q.CI$, NearbyS
Output: Composite component energy services during $Q.du$

// Defining substitute services
1: for $S_i \in $ NearbyS do
2: if $STB_i(Q) \leq \mu$ then
3: if $Ads_i(Q) > D$ then
4: $NearbyS.remove(i)$
5: else
6: // look for substitute services
7: $Subs_i = \emptyset$
8: for All $dis \in i$ and $[dis.st - dis.et] \geq G$ do
9: $Subs_i = Subs_i \cup$ Find services($dis.st, dis.et$)
10: // merge substitutes with initial service $i$
11: $i = i \cup Subs_i$
12: // Chunking the query based on the advertisement of NearbyS services
13: $Chunk_k.st \leftarrow Q.l$
14: for int $t = Q.l$ to $Q.t + Q.du$ do
15: if $(\forall CES \in$ NearbyS and $t = st_{CES}$ or $t = et_{CES}$) then
16: $Chunk_k.et \leftarrow t$
17: // create new chunk
18: if $t \neq Q.t + Q.du$ then
19: $Chunk_{k+1}.st \leftarrow t$
20: $t \leftarrow t + 1$
21: // apply 0/1 knapsack optimization at each chunk
22: for $C \in Chunk_k$ do
23: // miniComposite is the local composition in a chunk
24: // miniCES is the set of partial service within a chunk
25: miniComposite $\leftarrow \emptyset$
26: While(miniCES $\neq \emptyset$)
27: $S_{max} \leftarrow$ Max(miniCES)
28: miniCES $\leftarrow$ miniCES $\setminus \{S_{max}\}$
29: if (Composite(miniComposite, $max$)) then
30: miniComposite $\leftarrow$ miniComposite $\cup \{max\}$
31: End While
32: Composite $\leftarrow$ Composite $\cup \{miniComposite\}$
33: return Composite

of time $Q.du$. Long service disconnections cause considerable loss according to the consumer temporal preferences. We also evaluate services based on their disconnection time. $ADis_i$ is the disconnection time ratio. It represents the accumulated disconnection time relatively to the initial service availability time.

$$ADis_i(Q) = \sum_i^m \frac{dis_i}{et_i - st_i}$$

where $DIS_i = \{dis_1, dis_2, ..., dis_n\}$ are the disconnections of service $i$ from the energy request $Q$. Any time interval $[m, m + dis] \in [st_i, et_i]$ is considered as a disconnection if and only if: $\tau \in DIS_i \iff Pr_i.m = 0 \land Pr_i(k + dis) \land \forall j \in \tau, Pr_i.j = 0$

We utilize these two metrics to select the best candidate energy services in the fluid environment to provide the optimal spatio-temporal composition.

C. Fluid composition of crowdsourced IoT energy services

The fluid composition composes the intermittent energy services based on their stability and disconnection metrics. We propose the following modifications of the spatio-temporal composition algorithm to incorporate intermittent energy services:

1) Brute-force spatio-temporal fluid composition: The disconnected services may be considered as a set of independent services. The temporal knapsack composition [10,19] can be utilized on this new set of disconnected services. However, this composition technique is inefficient and very costly in a dynamic environment. A considerable amount of energy is lost because of the increasing number of switches between partial services. Every switching triggers a new connection establishment between the consuming and a providing device which requires energy [17][11]. The computing time increases significantly by applying the 0/1 knapsack algorithm at every new chunk.

2) Heuristic-based fluid composition: We propose a heuristic-based composition algorithm using the temporal knapsack algorithm. The objective of the heuristic is to find the optimal composition of intermittent energy services solving the trade-off between composition accuracy and runtime efficiency. Algorithm 1 presents the pseudocode of the heuristic-based fluid composition. Given a set of composable services based on their advertisement NearbyS, the heuristic verifies the mobility patterns (i.e., availability A and provision intermittence I in section [11]) for all composables services. The heuristic does not consider short disconnections (see short disconnections in figure 4). If the aforementioned stability metric $STB$ is higher than a predefined stability threshold $\mu$ the candidate service will be discarded. However, if the candidate service has a stable mobility pattern with few long disconnections according to the accumulated disconnection score $ADis$, the heuristic then finds one or more substitutes for each long disconnection (Lines 1-8) (see long disconnections in figure 3). The heuristic algorithm establishes a connection with the intermittent service and its substitute services proactively. This composition strategy avoids the addition of more chunks by considering the service and its substitutes as a single service (Line 9). The heuristic chunks the request duration based on the advertised time intervals of available services (Lines 10-16). The initial services and their substitutes are temporally composed using the initial chunks and the 0/1 knapsack algorithm (Lines 17-25). Relying on the initial chunking and toleration of short disconnections makes the heuristic-
based composition runtime efficient compared to the brute-force which defines fine grained chunking considering all disconnections (see section V-C). The substitute services provide a patch to recover all the disconnections of the initial advertised service. This lightweight process to reconstruct the initial advertised service is the main reason of increasing the accuracy of the heuristic based composition.

V. Experiments

We evaluate the effectiveness of the proposed fluid composition approach by assessing the composition performance in a failure-prone crowdsourced mobile IoT environment. We also evaluate the scalability of the fluid composition algorithm by measuring the computation time while varying the requests number. We compare the proposed approach with two state of the art composition algorithms, (i.e., static spatio-temporal composition [11] and a lossy Web service composition [14]) and with the brute-force approach.

A. Datasets and experiment environment

To the best of our knowledge, it is challenging to find dataset about the energy wireless transfer among human-centric IoT devices. We create a crowdsourced IoT environment scenario close to reality. We mimic the energy harvesting and sharing behavior of the crowd by utilizing QLD smartgrid[4] an energy sharing smart-grid of 25 houses in Queensland Australia equipped with solar panels. These houses harvest energy from the solar panels, consume energy and share their spare energy by pushing it back to the smartgrid (i.e., energy providers) to cater for other houses if their produced energy is not sufficient for their requirements. Similarly, the energy requirements of a request $Q.RE$ are also generated from the daily energy consumption of the houses. QLD smartgrid contains the daily energy data of the 25 houses in Queensland for two years [April 2012 to March 2014]. Energy consumption and production is recorded every 30 minutes. Each house has 730 records. Each record has 48x2 fields for the produced and the consumed energy at every 30 minutes. In our experiment, we define the energy service QoS parameters, the deliverable energy capacity $DEC$ and the intensity of the transferred current $I$ from

\[ \text{Table I}\]

| Parameters of the experiments setting |
|--------------------------------------|
| **QoS** | **Dataset** | **value** | **Query parameters** | **Dataset** | **value** |
| **Start time** | Yelp | Check-in | **Start time** | Yelp | Check-in |
| **End time** | Uniform distribution | Uniform distribution | **End time** | Uniform distribution | Uniform distribution |
| **Energy capacity** | Renewable energy sharing | Provided energy | **Energy capacity** | Renewable energy sharing | Consumed energy |

Figure 5. The effectiveness of fluid composition for short services (a) Successfully served queries Vs stability of intermittent services (b) Successfully served queries Vs length of intermittent disconnections (c) CPU time for short services

Figure 6. The effectiveness of fluid composition for long services (a) Successfully served queries Vs stability of intermittent services (b) Successfully served queries Vs length of intermittent disconnections (c) CPU time for long services

\[ \text{https://data.gov.au/dataset} \]
We use the Yelp\(^5\) dataset to simulate the spatio-temporal features of crowdsourced energy services and requests. This dataset contains several information about the crowd’s behavior in different venues in multiple metropolitan cities e.g., coffee shops, restaurants, libraries, etc. People may check-in, rate and recommend these venues. In our experiment, we only focus on people’s check-ins information into confined areas e.g., coffee shops. We consider the Yelp_checkin table. For each venue (business_id), we extract the crowd size (Checkins) at each hour (hour) of the day (weekday). We assume these people as IoT users. They may offer energy services from their wearables while staying in a confined area. We define spatio-temporal features of energy services by generating the check-in and check-out timestamps of customers to confined areas using the previously extracted data from Yelp_checkin table. For example, the start time \(st\) of an energy service from an IoT user is the time of their check-ins into a coffee shop. Energy request time \(Q.t\) and duration \(Q.du\) are also generated from check-in and check-out times of customers.

We match the two datasets Yelp and QLD smartgrid by randomly mapping each energy service \(S_i\) starting at \(st_i\) and ending at \(et_i\) with the produced energy during the same period from one of the 25×730 records. Similarly, the required energy \(Q.RE\) is also randomly selected from one of the 25×730 records according to the request duration \(Q.du\). We normalize all the energy measurement values for all records from Watt hour to miliampere hour (mAh) to mimic the energy provided and consumed by IoT devices e.g., smartphone and wearables. Table I recapitulates the experiments parameters. To mimic the intermittent behavior of wireless energy delivery in confined areas, we augment our dataset by generating random disconnections for all the services. We implement a parameterized randomizer for all the energy services. The disconnections are monitored using two parameters, their frequencies and their lengths.

B. Effectiveness

We investigate the effectiveness of the fluid composition by comparing the number of successfully served requests by each algorithm. We use two features of intermittent services to evaluate the performance. The stability of an intermittent service which reflects the number of disconnections. The accumulated disconnection ratio which represents the intermittence and the lost energy. We compare the heuristic-based fluid composition with the static composition [11] (see Figure 7). The goal of this initial comparison is to highlight the non usability of static spatio-temporal composition algorithms in a highly dynamic crowdsourced IoT environment.

We run the static and fluid composition algorithms on energy services and requests with different duration length, provided, and requested energy. We increase the dynamicity by varying the number of services’ disconnections gradually. It is obvious that the static composition performs poorly with intermittent services. This behavior is expected because the algorithm has been designed for static energy services. All intermittent services are not selected which is reflected on the poor performance of the static composition even when the dynamicity of the crowdsourced IoT environment is low.

Second, we run the brute force, the heuristic-based, and the traditional composition algorithm [14] on short and long services to understand the performance behavior in more details. In short services, the more stable services, the better performance of all algorithms (see Figure 5 (a)). The brute force composition has the best performance because it considers all the possible chunks. The traditional (i.e., lossy) composition has the least performance regardless the stability of the service due to filtering out the highly intermittent services from the beginning. The heuristic performance is comparable with the brute force because it does not filter out highly intermittent services and attempts to find substitutes at each disconnection. Figure 5 (b) also presents the performance behavior of the composition algorithms against the accumulated disconnection time of intermittent services. The brute force and the heuristic perform well, and they fulfill the requirements of a large number of requests unlike the lossy composition. A considerable accumulated disconnection time means the creation of several sub services which can be discovered by the brute force and the heuristic.

Surprisingly, the brute force has a poor performance against long intermittent services (see Figure 6 (a) and (b)). Unlike short services, disconnected long services have the same wireless current intensity. If two long services are not composable, their sub services also cannot be composable. Thus, even the exhaustive chunking, 0/1 knapsack cannot find composable services at these chunks. The heuristic and the lossy algorithm consider longer chunks because their chunking method relies only on the initial advertisement of services. They also assess intermittent services to select only long stable services to find stable substitutes.

C. Scalability

We evaluate the scalability of the fluid composition to ensure an efficient deployment of the proposed framework.

\(^5\)https://www.yelp.com/dataset
on an edge-based IoT architecture. The edge-based IoT coordinator composes intermittent energy services in a dynamic crowdsourced IoT environment. We compare the average execution time of three different composition techniques. We run each algorithm on 480000 crowdsourced energy services. We vary the number of available services for each request from 1 to 9. figures [5] (c) and [6] (c) represent the behavior of the three different algorithms for short and long services. The results show that the execution time increases as the \((\text{number of services/number of queries})\) increases. This performance behavior is expected from all the composition techniques because of the increase in the number of services from IoT users.

The brute force composition takes longer execution time for short and long services. The lossy composition does not require a long execution time because it filters out highly intermittent services before starting the composition. However, the brute force considers every disconnection and defines new sub-services which generate multiple chunks. In addition to the time required by the 0/1 knapsack algorithm at each chunk. The heuristic-based composition takes longer execution time than the lossy composition because it does not filter out the intermittent services. The heuristic algorithm attempts to patch the disconnections of intermittent services by exploring the nearby available services which take considerable time before the composition. However, the heuristic-based composition relies on the initial chunking based on the advertisement of available services. Applying the 0/1 knapsack algorithm on the initial chunks takes less time than applying the algorithm on all the new chunks generated from all disconnections.

VI. RELATED WORK

Energy consists of a significant challenge in many wireless application domains, including IoT and wireless sensor networks. Self-harvesting energy from natural sources using wearables such as body movement and heat provides a significant source of energy [21]. A new emerging body of research attempts to integrate harvesting energy into designing IoT objects [8][16]. **Energous Wattup** provides a prototype for wireless charging by eliminating direction requirement which creates an opportunity of sharing energy between IoT devices. Service computing is a key enabler for wireless energy sharing. Several service composition techniques have been proposed in pervasive and ubiquitous computing recently. such as cloud computing, sensor-cloud services [22] and social networks [2]. In sensor-cloud, services are composed according to their spatio-temporal features. They also must fulfill consumer preferences (QoS). Neiat et al. [22] design and implement a spatio-temporal service composition framework. The spatio-temporal service composition framework has been extended to describe and compose region services like WiFi hotspots. Their goal is to provide the most convenient trip plan from point A to point B with the best crowdsourced WiFi coverage. User preferences are used to define the spatial and temporal composability models of segment services [11]. Existing composition techniques are not applicable for intermittent crowdsourced energy services due to the unique features of energy services, unique requirement for energy composability and the intermittent behavior. The proposed approach adds a new contribution to the existing related studies [10][11]. The proposed service model captures functional and QoS requirements of energy services. The proposed spatio-temporal composition framework considers the intermittent behavior of crowdsourced energy services in a dynamic IoT environment. The proposed heuristic algorithm estimates the impact of services’ intermittence to select the optimal composition which delivers the required energy within the shortest disconnection time between the consuming device and the providers. This work is one of the earliest contributions to compose mobile crowdsourced energy services in a dynamic IoT environment.

VII. CONCLUSION

We propose a novel fluid spatio-temporal composition framework to crowdsource energy services from IoT devices. We develop a composition approach which estimates the stability of spatio-temporal composition plans and provides the optimal composition in the predefined time interval and location. We conduct a set of experiments to investigate the scalability and the effectiveness of the proposed composition technique. Results show that the proposed approach is able to provide the most stable composition with the minimal disconnection time. In future work, we will develop a semi reactive composition of mobile energy services.

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