# Maximizing Consumer Satisfaction of IoT Energy Services

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Abstract. We propose a novel Quality of Experience (QoE)-aware framework to crowdsource IoT energy services efficiently. The proposed framework leverages the provisioning of energy services as an auxiliary to increase consumers' satisfaction. A novel QoE model is developed as a metric to assess the consumers' satisfaction with the provisioning of energy services. Two novel composition algorithms, namely, Partial-Based (PB) and Demand-Based (DB) approaches, are proposed to ensure the highest QoE for consumers. Both approaches leverage the providers' flexibility and shareable nature of energy services to efficiently allocate services and optimize the QoE. A set of extensive experiments is conducted to evaluate the proposed approaches' efficiency and effectiveness.

**Keywords:** Quality of Experience IoT Services Energy Services Energy Sharing; Crowdsourcing Incentive IoT

## 1 Introduction

Internet of Things (IoT) is a paradigm that enables everyday objects (i.e., things) to connect to the internet and exchange data. IoT devices, such as smartphones and wearables, usually have augmented capabilities including sensing, networking, and processing [1]. Abstracting the capabilities of these IoT devices using the service paradigm may yield to multitude of novel IoT services [2]. These IoT services may be exchanged between IoT devices as crowdsourced IoT services. For example, an IoT device may offer WiFi hotspots or wireless energy services to charge other IoT devices [2]. These crowdsourced IoT services present a convenient and cost-effective solutions [2]. Our focus is on wireless energy sharing services among IoT devices.

Energy-as-a-Service (EaaS) is the abstraction of the wireless delivery of energy among nearby IoT devices [3][2]. EaaS is an IoT service where energy is delivered from an energy provider (e.g., a smart shoe or smartphone) to an energy consumer (e.g., a smartphone) through wireless means. EaaS may be deployed through the newly developed "Over-the-Air" wireless charging technologies [4][5]. Several companies, including Xiaomi<sup>1</sup>, Energous<sup>2</sup>, and ossia<sup>3</sup>, are currently developing wireless charging technologies for IoT devices over a distance. For example, Energous developed a device that can charge up to 3 Watts power within a 5-meter distance.

<sup>&</sup>lt;sup>1</sup> mi.com

 $<sup>^2</sup>$  energous.com

 $<sup>^{3}</sup>$  ossia.com

The crowdsourced EaaS ecosystem is a dynamic environment that consists of providers and consumers congregating in microcells. A microcell is any confined area where people may gather (e.g., coffee shops). In this ecosystem, IoT devices may share energy with nearby IoT devices. A key aspect to unlocking the full potential of the EaaS ecosystem is to design an end-to-end Service Oriented Architecture (SOA) to share crowdsourced energy. We identify three key components of the SOA: energy service provider, energy service consumer, and super-provider. In this architecture, providers advertise services, consumers submit requests, and super-provider (i.e., microcell's owner) manage the exchange of energy services between providers and consumers. This paper focuses on managing energy sharing from the super-provider perspective.

Super-provider typically focus on ensuring that customers keep coming back to their businesses. Their revenue is usually directly related to *foot traffic* [6]. Customer *satisfaction* is therefore paramount as a strategy to either maintain or increase the business target revenue [7]. A key objective is to ensure that customers have the *best experience*. We propose to use energy sharing as a key ingredient to provide customers with the best quality of experience when visiting the business. For example, a case study showed that "Sacred", a cafe in London, had a noticeable increase in foot traffic after installing wireless charging points<sup>4</sup>.

We define a Quality of Experience (QoE) metric to represent the level of satisfaction across energy consumers over a period of time in a specific microcell. Note that QoE is different from Quality of Service (QoS). QoE uses QoS as a base to express satisfaction of a service over a period of time. QoE has traditionally been used in domains that assess how users perceive a service [8][9][10]. Our proposed environment requires the use of a different type of QoE. In particular, we identify the following three aspects that shape the new QoE definition: (1) crowdsourced environment resources are usually limited and cannot fulfill all consumers' requirements. Hence, assessing consumers' satisfaction should consider the limited available resources. Energy services may be provided partially due to the limited resources and the shareable nature of energy services, e.g., a single service may be split into smaller services and provided among multiple consumers. In a limited resource environment, consumers' experience with partial services differs from complete services. (3) Consumers' satisfaction with energy services will indirectly impact their experience with the super-provider's microcell. Therefore, our research focuses on the super-provider's perspective of QoE.

Assessing the QoE from a super-provider's perspective usually entails measuring the aggregated satisfaction of consumers over time. Consumer's satisfaction is defined as meeting or exceeding a set of expected service goals [11]. In this context, we define consumer satisfaction as receiving the requested energy or part of it. We focus on optimizing the QoE by efficiently provisioning and fulfilling the consumers' energy requirements.

The limited availability of energy is a key challenge that may hinder the super-provider from optimizing the consumers' QoE [2]. For instance, an energy consumer might not find their requested energy at a certain time in the microcell, resulting in an unsatisfying experience. In this context, using traditional resource allocation algorithms may incur uneven energy sharing for some con-

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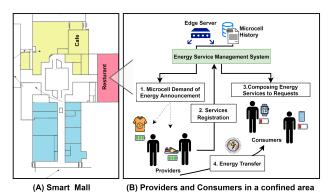


Fig. 1: IoT energy services environment

sumers. Therefore, we propose a QoE-driven service provisioning framework to satisfy energy consumers in a crowdsourced IoT environment. The framework requires prior knowledge of providers' temporal preferences and the microcell energy demands. The proposed framework leverages the *shareable* nature of energy services to split the energy between consumers if the required energy is more than the available energy[3]. Intuitively, the super-provider may prefer to offer part of the required services to all consumers than offering it to some of them. Hence, we propose a heuristic Partial-Based (PB) approach which splits services among consumers in the case of low energy availability. Another possible solution is to leverage *flexible* providers that offer services on *multiple* time slots by allocating their services to the most demanding slots. Intuitively, this may ensure a better distribution of the available services. Therefore, we additionally propose a heuristic Demand-Based (DB) approach. The DB approach extends the PB approach by prioritizing the allocation of services based on the highest demanding time slots. The main contributions of this paper are:

- -A novel Quality of Experience (QoE) model for crowdsourced energy services.
- -A framework for QoE-driven composition of IoT energy services.
- -An experimental analysis with two implementations of the proposed QoE-driven energy composition framework.

# 1.1 Motivating Scenario

We describe a scenario in a confined place (i.e., microcell) where people congregate, e.g., cafes,and restaurants (see Fig.1 (A)). Each microcell may have several IoT devices acting as energy providers or consumers (see Fig.1 (B)). The superprovider aims to leverage the crowdsourced energy services as a tool to enhance the consumers' experience. We assume all local energy services and requests are submitted and managed at the edge, e.g., a router in the microcell (see Fig.1(B)). We assume that the super-provider offers incentives to encourage energy sharing in the form of credits. These would be used to receive more energy when the providers act as consumers in the future [2] We assume the super-provider has a prior knowledge of the Microcell Energy Demand ( $\mathcal{MED}$ ) in the microcell over a period of time (T) (see Fig.2 (A)). The  $\mathcal{MED}$  may be estimated based on previous history [12]. The  $\mathcal{MED}$  is represented in terms of the requested energy in each time slot, e.g., 700 mAh at time slot  $t_1$ . The granularity of the time slots can also be estimated based on the previous history of the microcell [2].

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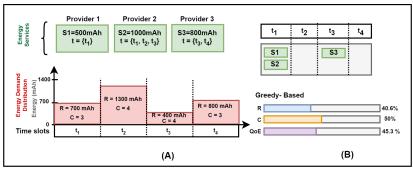


Fig. 2: (A) Microcell energy demand and providers services (B) Greedy energy provisioning approach

We also assume that the super-provider has prior knowledge of the providers preferences in terms of time and energy service attributes. An incentive model is employed to predict the amount of energy that would be available for consumption [13]. For instance, provider 1 in Fig.2 (A) wants to offer the energy service S1 with 500 mAh at time  $t_1$ . Another example, provider 2 wants to offer S2 at time slots  $t_1$ ,  $t_2$ , or  $t_3$ . We assume the provider would stay for the full-time slot. We also assume that the provider's service amount is fixed and can be split among multiple time slots. For instance, provider 2 may share part of their service S2 on  $t_1$ , e.g., 300 mAh, and the other part at  $t_2$  or  $t_3$ . We also assume a single energy provider may share their spare energy with multiple energy consumers, within a specific time interval. The super-provider uses rewards to encourage providers to share energy. Rewards may come in the form of stored credits to providers. A provider receives a reward based on an incentive model [13].

The super-provider will allocate services to time slots to serve as many consumers as possible to maximize their quality of experience in the microcell. However, it is challenging to fulfill multiple energy requirements with limited energy services [2]. For example, in Fig.2 (A), the total energy demand  $(\sum R)$  is 3200 mAh, and the total available energy services  $(\sum S)$  is 2300 mAh. The available services may fulfill 71.9% of the energy requests which cannot be fully provisioned with the temporal constrains of services and requests. Therefore, satisfying all consumers with their under-provisioned requests is more challenging.

Fig.2 (B) presents the outcome of a greedy FCFS, i.e., first come first served, allocation strategy for the available energy [14]. In greedy, the time slots and services will be scheduled based on their start time. For instance, in Fig.2 (A) even though S2 can be offered in  $t_1$ ,  $t_2$  and  $t_3$ , S1 will be allocated to  $t_1$  because it comes first in terms of time. The greedy strategy does not leverage the shareable nature of energy services or the providers' flexibility which may affect the energy allocation efficiency and impact the consumers' experience. Therefore, the greedy strategy may not be a good fit in this context. For example, in Fig.2 (B), the greedy-based approach could only fulfill 1300 mAh from the total demand which is equivalent to 40.6%. Moreover, the total number of consumers ( $\sum C$ ) in Fig.2(A) is 14 and the greedy approach could offer energy to 7 consumers which is equivalent to 50%. In this context, we consider the size of fulfilled requests and the number of fulfilled consumers in assessing the quality of experience. In this example, using the greedy approach resulted in 45.3% of consumers' QoE.

Allocating the limited available energy with the time constraints of both services and requests represents critical challenges for efficient and QoE-aware provisioning of IoT energy services. We propose a framework that will compose the energy services to maximize the consumers' experience. Our framework leverages leverage the providers' *flexibility* and *shareable* nature of energy services to efficiently allocate services and optimize the QoE.

## 2 Preliminaries

We consider the scenario of energy sharing in a microcell M during a time interval T. T is divided into a set of  $\{t_1, ..., t_n\}$  where  $t_i$  is a predefined time period, e.g., one hour. We use the below definitions to formalize the problem.

**Definition 1: Energy-as-a-Service (EaaS).** We adopt the definition of EaaS in [3]. An energy service (EaaS) is a tuple of  $\langle E_{id}, E_{pid}, F, Q \rangle$ , where  $E_{id}$  is an energy service ID,  $E_{pid}$  is a provider ID, F is the function of sharing wireless energy, Q is a set of non-functional (QoS) attributes, including:

- $-p_{ae}$  is the amount of energy shared by the provider.
- $-p_{loc}$  is the location of the energy provider  $\langle x, y \rangle$ .
- $-p_t$  is the set of time intervals  $\langle t_s, t_e \rangle$  a provider may offer their energy.

**Definition 2: Energy Service Request (ER).** We adopt the definition of ER in [13]. An ER is a tuple of  $\langle E_{id}, E_{cid}, F, QR \rangle$ , where  $ER_id$  is an energy request ID,  $E_{cid}$  is a consumer ID, F is the function of receiving energy wirelessly by an IoT device, QR is a set of non-functional attributes, including:

- $-c_{re}$  is the amount of requested energy.
- $-c_{loc}$  is the location of the energy consumer  $\langle x, y \rangle$ .
- $-c_t$  is the time interval  $\langle t_s, t_e \rangle$  of requiring energy.

**Definition 3: Microcell Energy Demand**  $\mathcal{MED}$ .  $\mathcal{MED}$  is the total amount of requested energy during a time interval T (See Fig.2). T is divided into time slots. We define  $\mathcal{MED}$  by aggregating the amount of required energy per time slot. Therefore, the definition of  $\mathcal{MED} = \{t_1, t_2, ..., t_n\}$  where t is a tuple of < d, rwd, re, nc, ER >. Here d is a predefined time in the time interval of the microcell T, e.g., [9:00 AM -10:00 AM]. rwd is the reward of providing the required energy re. We compute rwd using the incentive model proposed by [13]. We assume that the super-provider will use the microcell history to compute the energy demand in advance. nc is the number of consumers in the microcell at time slot t. ER is the set of available requests in the microcell at time slot t.

**Definition 4: Quality of Experience (QoE).** QoE is defined as an objective function to measure consumers' satisfaction with energy provisioning in a microcell M within a predefined time interval T. The function definition is:

$$QoE(M) = F(T, \mathcal{ES}, \mathcal{MED}) \tag{1}$$

where  $\mathcal{ES}$  is the set of energy services and  $\mathcal{MED}$  is the microcell energy demand.

## 2.1 Problem Definition

Given a set of n energy services  $\mathcal{ES} = \{EaaS_1, EaaS_2, ..., EaaS_n\}$  and a set of m energy requests  $\mathcal{ER} = \{ER_1, ER_2, ..., ER_m\}$  in a microcell M. The superprovider advertise the microcell energy demand  $\mathcal{MED}$ . Energy providers register their services in terms of: (1) the amount of energy  $p_{ae}$  (2) the time slots  $t_i$  to offer their services. The super-provider uses the providers preferences to allocate their

services to time slots. The allocation approach aims at fulfilling the maximum number of requests and thereby maximize the QoE. We formulate the service composition problem to a time-constrained optimization problem as follows:

- Maximize  $QoE(M) = F(T, \mathcal{ES}, \mathcal{MED}),$ Subject to:
- $-t_i.re > 0$  for each  $t_i \in T$ ,
- $EaaS_i.P_t \subset t_i.d$  for each  $EaaS_i \in \mathcal{ES}$ .

Where  $P_t$  is the time interval  $\langle t_s, t_e \rangle$  a provider of  $EaaS_j$  may offer their energy,  $t_i.d$  is the duration of a time slot i in the time interval of the microcell T, and  $t_i.re$  is the required energy re at time slot i.

The goal of the composition is to efficiently allocate the available energy services to time slots. The objective function attempts to optimally assign energy services according to their spatio-temporal features, providers' preferences and required energy in time slots. The spatial aspect in energy service focuses on a geographical cell. The temporal aspect focuses on the times of energy service provisioning. We use the following assumptions to formulate the problem.

- -Providers energy size is fixed during composition.
- -Providers are available in all their selected time slots.
- -Providers may offer partial services to multiple consumers at the same time.
- -Consumers' time windows do not overlap with time slots.
- -Providers and consumers have fixed location during energy sharing.
- -The microcell has *multiple* providers and *multiple* consumers.
- -There is no energy loss in sharing. As the technology matures, we anticipate that the devices will be able to share more energy, and the energy loss of sharing will become minimal [2].
- -The exact amount of required energy for a microcell is given [15].
- -A reward system is used to incentivize providers to offer their service [13].
- -A trust framework is used to preserve the privacy of the IoT devices [16].

## 3 Quality of Experience Model

The Quality of Experience (QoE) in a microcell is measured based on the *number of satisfied consumers* and the *amount of fulfilled requests*. Recall, the time interval of the microcell is divided into time slots. Therefore, QoE for each time slot  $t_i$  will be computed using the following attributes:

-Satisfaction Ratio: We define the Satisfaction Ratio (SR) as the number of consumers who received their requested energy or part of it. We compute SR per time slot t as follows:

$$SR = \frac{|\{ER \in \mathcal{ER} \mid ER \text{ is completed \& } c_t \in d\}|}{|\mathcal{ER}|}$$
(2)

Where  $\mathcal{ER}$  is the set of all requests in time slot t, |.| is the cardinality of the set,  $c_t$  is the request time, and d is the time duration of t.

**-Fulfillment Ratio:** The satisfaction ratio is not enough to measure QoE. For example, if we have a set of energy requests in mAh  $\mathcal{ER} = \{10, 20, 20, 70\}$ , serving the first 3 consumers is not equal to serving the last 3 due to the different amount of requested energy. Therefore, We define the Fulfillment Ratio  $(\mathcal{FR})$  based on the percentage of fulfillment for each request. We compute FR

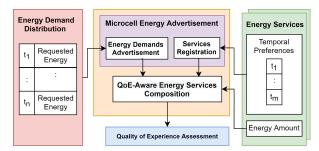


Fig. 3: Quality of experience driven service composition framework

per time slot t as follows:

$$\mathcal{FR} = \sum_{i=1}^{n} \left( w_i \times \frac{Received\_Energy_i}{Requested\_Energy_i} \right)$$
 (3)

where n is the number of all energy requests in t, and  $w_i$  is the weight of the request over the total amount of requested energy in t.

Quality of Experience: As previously stated, We define the QoE in a microcell based on the satisfaction ratio  $\mathcal{SR}$  and fulfillment ratio  $\mathcal{FR}$  of each time slot t. Therefore, we compute the QoE(M) as the following:

$$QoE(M) = \alpha \times \left(\sum_{i=1}^{m} SR_i \times \beta_i\right) + (1 - \alpha) \times \left(\sum_{i=1}^{m} FR_i \times \gamma_i\right)$$
(4)

where m is the number of time slots in the microcell's time interval T.  $SR_i$  is the satisfaction ratio of a time slot computed by Eq.2.  $\beta_i$  is the weight of a time slot  $t_i$  which is its number of consumers over the total number of consumers in T.  $FR_i$  is the ratio of fulfillment of the time slot computed by Eq.3.  $\gamma_i$  is the weight of a time slot  $t_i$  which is its total required energy over the total amount of required energy in T.  $\alpha$  is a user-defined weight between zero and one to define the weight of  $SR_i$  and  $FR_i$  in QoE.

## 4 Quality of Experience Framework

We introduce a quality of experience composition framework for managing energy services to enhance consumers' QoE (See Fig.3). The framework is divided into three phases: (1) Microcell energy advertisement, (2) Composing energy services, and (3) Quality of experience assessment. In the first phase, the superprovider will advertise the energy demand of the microcell and receives providers' preferences. In the second phase, the super-provider will compose energy services to maximize the QoE. In the last phase, the super-provider will assess the QoE for the resulted composition.

## 4.1 Microcell Energy Demand Advertisement

In this phase, the super-provider computes the reward for each time slot based on the amount of required energy using the incentive model in [13]. Then, the system will announce the required energy and rewards for the whole microcell using Definition 3. Energy providers will register based on their preferences in terms of their energy amount and the time slots they will be available (See Fig.2).

## Algorithm 1 Partial-Based Composition of Services

```
Input: \mathcal{MED}, \mathcal{ES}, threshold
Output: energy_comp
 1: for t_i in \mathcal{MED} do
 2:
      selectedES = \{\}
      demand = t_i.re
 3:
      for es_i in t_i.\mathcal{ES} do
 4:
 5:
         if demand > 0 then
            demand = demand - es_j.p_{ae}
 6:
 7:
            energy\_comp.add(t_i, es_i)
 8:
            selectedES.add(es_i)
            if demand < 0 then
 9:
10:
              es_i.p_{ae} = demand * -1
              demand = 0
11:
12:
            else
              Remove_Service(es_i, \mathcal{MED})
13:
       if demand = 0 then
14:
15:
         Assign\_Energy(t_i.\mathcal{ER}, selectedES)
16:
      else
17:
         Assign\_Partial\_Energy(t_i.\mathcal{ER}, selectedES, nc, threshold)
18: return energy_comp
```

## 4.2 Energy Services Composition

This phase aims to compose energy services to maximize the QoE. We propose two heuristic approaches to compose energy services: *Partial-Based* (PB) and *Demand-Based* (DB). The PB composition is inspired by the FCFS resource allocation algorithm [14]. The PB approach, splits services among consumers if the required energy is more than the available energy. Intuitively, offering part of the services will satisfy more consumers than offering it to some of them. The DB composition is inspired by the priority allocation algorithm [14]. The DB approach extends the PB approach by prioritizing slots with the highest demanding to ensure services availability. We discuss each approach below.

Partial-Based Energy Services Composition The Partial-Based (PB) composition aims at maximizing the QoE by composing services for each time slot based on the first come first served approach. For example, if a provider offers their services on two-time slots, the algorithm will assign the service for the earlier time slot. If the time slot did not need the service, the service will be assigned to the next time slot. Moreover, PB chunks services between energy consumers if the available energy services are not enough to fulfill the total required energy in the time slot. Intuitively, offering part of the required services to all consumers is more satisfying than offering it only to some of them.

Algorithm 1 presents the PB service composition. For every time slot  $t_i$ , the algorithm retrieves the total required amount of energy (Line 3). Then, for each registered service es in t, the algorithm keeps adding services to the set of selected services until the required energy is fulfilled or all the available services have been selected (Lines 4 - 13). Note that if a service was partially needed, then the service available amount will be updated to be used by other registered time

## Algorithm 2 Demand-Based Composition of Services

```
Input: \mathcal{MED}, \mathcal{ES}, threshold
Output: energy_comp
 1: SMED = \mathbf{sort}(MED, nc: descending, re: descending)
 2: for t_i in \mathcal{SMED} do
      selectedES = \{\}
 3:
 4:
      demand = t_i.re;
 5:
      sortedES = \mathbf{sort}(t_i.\mathcal{ES}, nt: ascending)
      for es_i in sortedES do
 6:
 7:
         if demand > 0 then
           demand = demand - es_j.p_{ae}
 8:
9:
           energy\_comp.add(t_i, es_j)
           selectedES.add(es_i)
10:
11:
           if demand < 0 then
12:
              es_i.p_{ae} = demand * -1
              demand = 0
13:
14:
            else
              Remove_Service(es_j, SMED)
15:
16:
      if demand = 0 then
17:
         Assign_Energy(t_i.\mathcal{ER}, selectedES)
18:
      else
19:
         Assign\_Partial\_Energy(t_i.\mathcal{ER}, selectedES, nc, threshold)
20: return energy_comp
```

slots (Lines 9 - 11). Moreover, if a service was fully used by a time slot, then it will be removed from other registered time slots (Lines 12 - 13). After processing all services, if the energy demand of the slot is zero, the algorithm assigns the selected services to requests (Lines 14 - 15). If the energy demand is not fulfilled, the algorithm distributes the available services among available requests (Line 17). If the service chunks are smaller than the threshold, consumers will be removed and the service will be shared among the rest. The threshold prevents dividing services into small neglectable chunks. The composition of the selected services will be returned in Line 18.

Demand-Based Energy Services Composition The Demand-Based (DB) composition goal is to maximize QoE by giving priority to time slots with higher energy demand. The intuitive idea of the DB approach is that high-demanding time slots will require more services. Thus, services should be assigned to them prior to less demanding time slots which may ensure a better distribution of the available services. For instance, if a provider offers their service on two-time slots, the algorithm will assign the service to the more demanding time slot. If that time slot does not need the service, the service will be assigned to the next time slot. This indicates that the order of time slots in composing services matters because if a service is used in a time slot, it will be removed from others. Removing a service from a time slot may affect the amount of available energy and thus the number of served and satisfied consumers. Moreover, DB approach maximizes the QoE by chunking services between energy consumers if the available services are not enough.

Algorithm 2 presents the DB service composition. The algorithm starts by sorting the time slots in a descending order based on the number of consumers nc, then the amount of requested energy re (Line 1). The goal of sorting is to start composing services for the most demanding time slots. As some services may be registered in multiple services, using these services for the most demanding time slots may offer a better experience. Line 4 retrieves the total required amount of energy for each time slot  $t_i$ . Then, for every time slot, the registered services will be sorted in ascending order based on the number of time slots a service was registered in. This sort will allow us to start with the least connected services. In other words, using such services may impact less number of time slots than using services that are registered in many time slots. Then, for each registered service es in t, the algorithm keeps adding services to the set of selected services until the required energy is fulfilled or all the available services have been selected (Lines 6 - 15). Similar to the PB approach, if a service was partially needed, then the service available amount will be updated to be used by other registered time slots (Lines 11 - 13). Moreover, if a service was fully used by a time slot, then it will be removed from other registered time slots (Lines 14 - 15). After processing all services, if the energy demand of the slot is zero, the algorithm assigns the selected services to requests (Lines 16 - 17). If the energy demand is not fulfilled, the algorithm distributes the available services among available requests (Line 19). If the service chunks are smaller than the threshold, consumers will be removed and the service will be shared among the rest. The threshold prevents dividing services into small neglectable chunks. Line 20 returns the composition of the selected services.

## 4.3 Assessing Quality of Experience

The super-provider assesses the QoE of each proposed composition in this phase. The QoE is computed using the model discussed in Section 3. The assessment of QoE gives an indicator of consumers' satisfaction in the microcell.

#### 5 Evaluation

We compare the proposed composition approaches, Partial-Based composition (PB), and Demand-Based Composition (DB), with the resource allocation algorithms, namely, first come first served allocation (Greedy), and Max-Min Fair allocation (Max-Min) [14][2]. The Greedy approach is a modified FCFS algorithm where the time slots and services will be scheduled based on their start time. The Max-Min is a modified Max-Min Fair allocation where services that can be offered in multiple time slots will be split among these time slots using the a Max-Min technique. We evaluate the effectiveness and the efficiency of each approach.

#### 5.1 Dataset Description

We used a real dataset generated from the developed app in [17]. The dataset consists of energy transfer records between a provider (smartphone) and a consumer (smartphone). The records attributes are the provider ID, consumer ID, transaction date, time, energy services' and requests' amount, and transfer duration. We use the energy dataset to generate the QoS parameters for the energy services and requests. For instance, the amount of a wireless charging transfer in mAh is used to define the amount of requested/provided energy. In addition, the energy dataset records of a wireless charging transfer duration are used to define the end time of each request/service.

Table 1: Experiments Variables

Variables	Value
Energy dataset for coffee shop 8 in April	16830
Number of services & requests	[300-2000]/run
Number of time slots	6
	5 - 100%
Requested energy	5 - 100%
Time interval	6 hours
Service registration	[1-3] time slots / service

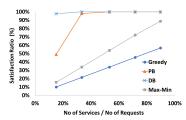


Fig. 4: The average of satisfaction ratio

We augmented the dataset of the energy sharing to mimic the behavior of the crowd within microcells by utilizing a dataset published by IBM for a coffee shop chain with three branches in New York city<sup>5</sup>. The dataset consists of transaction records of customers purchases in each coffee shop for one month. Each coffee shop consists of, on average, 560 transnational records per day and 16,500 transaction record in total. We use the IBM dataset to simulate the spatio-temporal features of energy services and requests. Our experiment uses the consumer ID, transaction date, time, location, and coffee shop ID from each record in the dataset to define the spatio-temporal features of energy services and requests, e.g., start and location of energy service or a request. We ran a total of 7000 experiments with 6-time slots each time slot was an hour long. In each run, the providers' temporal provision preferences were registered randomly to [1-3] time slots. In addition, the number of services and requests varied between 300 to 2000 per run depending on the experiments' setting. For each run, we used the proposed approaches to compose energy services. We then measured the QoE for each composition. Table 1 presents the experiments parameters.

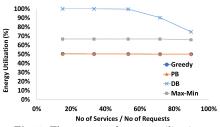
# 5.2 Evaluation of the Composition Framework

We ran six experiments to determine the effectiveness and efficiency of the proposed approaches. The experiments evaluated the approaches in terms of their satisfaction rate, fulfillment rate, quality of experience, impact of thresholds and computation cost. We run the approaches in different settings by changing the ratio of services to requests in the time interval T. We gradually increased the ratio from 15% to 90%. We repeated the experiment 1000 times at each point and considered the average value for each approach.

Quality of Experience Evaluation As previously stated, we compute the QoE based on SR and FR (See Sec.3). In this subsection, we study the impact of each ratio, then we evaluate the QoE.

The first experiment compares the  $\mathcal{SR}$  of the proposed approaches PB and DB, against Greedy and Max-Min. As previously stated,  $\mathcal{SR}$  represents the number of consumers who received energy fully or partially. Therefore, a high  $\mathcal{SR}$  of a composition ensures a higher number of satisfied consumers and thereby a better QoE. The  $\mathcal{SR}$  of a time slot is computed using Eq.2 and then averaged for the microcell similar to the first part of Eq.4. Fig.4 presents the average  $\mathcal{SR}$  in the microcell for each approach. The x-axis in Fig.[4-7] represents the ratio of the number of energy services to requests. In Fig.4, the  $\mathcal{SR}$  increases when the number of available services increases for all the composition approaches. For instance, when the ratio of services to requests is 80%, all approaches provide a higher  $\mathcal{SR}$  compared to the ratio is 20%. This observation can be explained by

<sup>&</sup>lt;sup>5</sup> https://ibm.co/2O7IvxJ



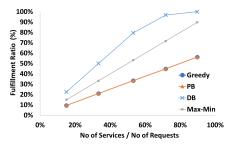


Fig. 5: The average of energy utilization

Fig. 6: The average of fulfillment ratio

the availability of services to offer energy. The more services available, the more requests can be fulfilled. The proposed approach PB performs better than Greedy as it splits the available energy between the consumers as partial services, unlike the Greedy approach which fulfills a request fully before serving the next request. For the same reason PB also performs better than Max-Min. Even though, Max-Min has a better energy utilization by splitting energy services fairly between time slots (See Fig.5), a fair distribution of energy does not necessarily result in equally satisfied consumers as in the time slots. This is due to the different energy requirements of consumers. In addition, the proposed approach DB gives the best results as it prioritizes the time slots that have the highest demand in terms of the number of consumers and amount of required energy. Recall the order of time slots in composing services is crucial because if a service is used in a time slot, it will be removed from others. Removing a service from a time slot may affect the amount of available energy and thus the number of served consumers. Prioritizing the most demanding time slots allows DB to have more services to use, and therefore increases  $\mathcal{SR}$  by increasing the number of fulfilled consumers.

The second experiment compares the  $\mathcal{FR}$  of each approach. As previously stated,  $\mathcal{FR}$  presents the rate of fulfillment for each request. Therefore, a high  $\mathcal{FR}$  of a composition ensures a higher level of satisfaction for consumers and thereby a better QoE. The  $\mathcal{FR}$  of a time slot is computed using Eq.3 and then averaged for the microcell similar to the second part of Eq.4. Fig.6 represents the average  $\mathcal{FR}$  in the microcell for each approach. In Fig.6, the  $\mathcal{FR}$  increases when the number of available services increases for all the approaches. This observation can be explained by the availability of services to offer energy. PB performs similar to Greedy in terms of  $\mathcal{FR}$ . This is an expected behaviour since both approaches start with the same time slots and, therefore, have the same set of available services. The difference between both approaches is in the way they share energy among consumers, i.e., complete services in Greedy and partial services in PB. Moreover, Max-Min has a better  $\mathcal{FR}$  because it has better energy utilization (see Fig.5). A higher energy utilization is achieved by splitting energy services fairly between time slots. DB gives the best results as it prioritizes the time slots that have the highest demand as discussed in the previous experiment.

The third experiment compares the QoE using all approaches. As previously stated, the QoE presents the overall satisfaction of consumers across time. Therefore, a high QoE of a composition indicates a higher level of satisfaction for consumers. The QoE is computed using Eq.4. Note that we used  $\alpha = 0.5$  to give equal weight for both  $\mathcal{SR}$  and  $\mathcal{FR}$ . Fig.7 presents the average QoE using each approach. In Fig.7, similar to the previous experiments, the QoE increases when

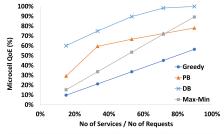
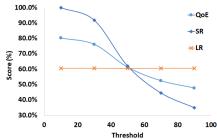


Fig. 7: The average of quality of experience



**Fig. 8:** The average of  $\{QoE, SR, FR\}$  using PB composition

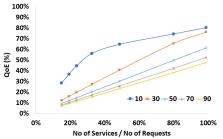


Fig. 9: The average of QoE using PB composition with various thresholds in a microcell

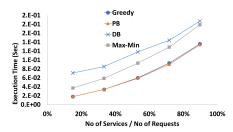


Fig. 10: The average execution time of all composition

the availability of services increase. PB approach performs better than Greedy in terms of QoE due to its higher  $\mathcal{SR}$  as discussed in the first experiment. Additionally, PB preforms better than Max-Min when the number of energy services is less than the request. This is because in a limited resources environment PB will satisfy more consumers (higher  $\mathcal{SR}$ ) by partially fulfilling their requests. However, when there is enough services, Max-Min will better utilize the energy to completely fulfill requests (higher  $\mathcal{FR}$ ). Moreover, the DB approach gives the best results due to its higher  $\mathcal{SR}$  and  $\mathcal{FR}$ .

Threshold Impact Evaluation The following two experiments study the impact of thresholds on the PB approach. Recall that PB and DB approaches split energy between consumers based on a defined threshold. The threshold prevents dividing services into small neglectable chunks. The experiments of both PB and DB gave the same behavior. Thus, we are only presenting the results of PB.

Fig.8 represents the impact of the threshold on the three previously tested attributes: SR, FR, and QoE. We tested the PB approach with a 99% ratio of services to requests. The x-axis in Fig.8 represents the threshold of partial services. FR does not change as the threshold increases, because it relies on the order of time slots and not the size of distribution (threshold) as discussed in the previous experiment. Also, both SR and QoE decrease as the threshold increases due to the thresholds' size. When the threshold's size increases, fewer consumers will be served. A lower number of fulfilled consumers results in low SR and thereby a low QoE.

The fifth experiment compares the impact of the threshold on the QoE with different ratios of services to requests. We tested the PB approach with thresholds of {10, 30, 50, 70, 90}. In Fig.9, the QoE increases when the number of available services increases for all threshold values. Additionally, the QoE for threshold 10 is the highest among all due to the threshold's size. When the size

of the threshold is small, more consumers will be served. A higher number of fulfilled consumers results in high SR and thereby a high QoE.

Computation Efficiency Evaluation The execution time for all approaches increases with the increase in services' availability (See Fig.10). This is due to the increase in processing time to assign these services.

## 6 Related Work

Energy sharing services have been introduced as an alternative ubiquitous solution to charge IoT devices [18]. Several studies have addressed challenges related to fulfilling the requirements of energy consumers [3][16][19]. A temporal composition algorithm was proposed to compose energy services to fulfill a consumer's energy requirement [3]. The algorithm proposed the use of fractional knapsack to maximize the provided energy. An elastic composition was proposed to address the reliability of highly fluctuating energy providers [16]. The composition uses the concepts of soft and hard deadlines to extend the stay of a consumer and select more reliable services. The intermittent behavior of energy services was addressed by a fluid approach [19]. The approach uses the mobility patterns of the crowd to predict the intermittent disconnections in energy services then replace or tolerate theses disconnections. Other studies tackled challenges from a provider's perspective [13][20]. An context-aware incentive model was proposed to address the resistance in providing energy services [13]. Another article addresses the commitment of energy consumers to receive their initiated requests [20]. Existing literature in energy services addresses issues from a consumer or a provider perspective [18]. To the best of our knowledge, challenges related to the microcell perspective such as the QoE are yet to be addressed.

Quality of experience (QoE) has several definitions in the literature based on the field of research [8][21][22]. However, all existing definitions focus on assessing the quality of an application or a service based on the perception of the end-users. In addition, most of the literature focuses on assessing the QoE for multimedia applications. For instance, A method was proposed to gauge gaming QoE under system influencing factors such as delay, packet loss, and frame rates [23]. Another study proposed "Kaleidoscope" as an automated solution to evaluate Web features [10]. As previously stated, the existing research focuses on assessing the QoE of a service based on the perception of the end-users. To the best of our knowledge, assessing the QoE in energy services is not explored yet. In addition, using energy services as a tool to enhance QoE in other microcell-based services is yet to be addressed.

#### 7 Conclusion

We proposed an energy service composition framework that evaluates QoE in a microcell. A new QoE based-assessment was proposed to capture the overall satisfaction across consumers over a period of time. A two QoE-driven composition of energy service were proposed. The Partial-Based (PB) approach uses partial services to maximize the number of satisfied consumers and thereby increase the QoE. The Demand-Based (DB) approach uses partial services and prioritizes the most demanding time slots to maximize the number of satisfied consumers and their level of fulfillment and thereby increase the QoE. Experimental results show that DB outperforms all the evaluated approaches. The efficiency of the

proposed approaches was investigated against a Greedy approach. Future direction is to consider the probability of change in the microcell energy demand.

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