Distributed Uplink Offloading for IoT in 5G Heterogeneous Networks under Private Information Constraints

Endre H. Hjort Kure, Member, IEEE, Paal Engelstad, Senior Member, IEEE, Sabita Maharjan, Member, IEEE,
Stein Gjessing, Member, IEEE, and Yan Zhang Senior Member, IEEE.

Abstract—The expected influx of Internet of Things (IoT) in 5G will provide new opportunities for uplink traffic offloading. In general, base stations with proximity require lower transmission power of the IoT device (IoTD), thus saving energy consumption as spectral efficiency (SE) of the transmissions increase. By letting IoTDs send to base stations with better link conditions the IoTDs’ battery lifetime is prolonged. In this work we present a many-to-many offloading scheme for uplink traffic. The scheme works when link conditions are private information and gives incentives to all involved players to participate. We believe this approach is better suited for the expected complex ecosystem of 5G base station cells. The sensitivity analyses show that there is a limited gain by requiring that the link conditions are public knowledge. Further, the suggested market optimizes the SE for all involved players. Numerical results show that the IoTDs can on average increase their SE with 25% and their spectral energy efficiency with 40%. The networks which are offloaded to and from can both expect an increase in the SE of 1%-6%. Sensitivity analyses show that the market equilibrium’s benefits are robust as they stay positive for a range of different network configurations. Also, the work proves that market equilibrium is stable and unique. To derive the equilibrium, two approaches are presented, a closed form solution and a distributed algorithm, that both are solvable in polynomial time.

I. INTRODUCTION

I

T is expected that 5G will be more adapted to Internet of Things (IoT) than previous mobile broadband technologies, as one of the targets for 5G is IoT [1]. Already, LTE is becoming more IoT focused with extension protocols such as Narrow Band IoT (NB-IoT) [2]. It is expected that single cells will support thousands of devices [3], separating 5G from previous technologies and shifting the throughput focus from throughput per unit to number of units with throughput.

5G operators are also expected to cooperate in a greater extent, through infrastructure sharing [4] due to the entailing cost of a full roll-out. Hence, one operator might carry traffic for another due to operational requirements, either for the base station or the users. This is referred to as offloading and can be done in both uplink and downlink.

5G will not be a homogenous network due to an increase in number of base station cells (cell densification) and the use of offloading [3]. The setup of 5G dictates that numerous cells of the same or different radio access technologies (RATs) will overlap. This creates a mesh of different paths that traffic can travel to a device. Further, 5G will be designed to deliver on opposing parameters such as latency, throughput and energy efficiency (EE) [3]. These features together with the overlapping base station cell structure, will create an ecosystem of cell types.

Heterogeneous networks (and the cell ecosystem) restrict coordinating mechanisms in two ways that are often neglected in models. First, the scheme must be distributed in a many-to-many fashion. A centralized scheme requires a market maker or an unification of utility functions, both being highly unlikely as base stations and associated users are naturally distributed within different local environments. Second, the network state is mostly private. Assuming that all network states are public information is the same as requiring that all involved entities have an updated representation of the network. As internet and associated protocols are best effort, this cannot be guaranteed within time limits. This aspect is especially important for radio access networks (RANs) where both traffic and spectral efficiency (SE) are stochastic parameters. Network states might be forecasted, but current state is needed for accuracy, reducing its applicability for third parties. Also, a related issue is the length of the prediction period. Longer time periods dictate increased accuracy on forecast of averages, but at the same time the variability will also increase. Hence, third parties could predict average network states on longer time periods (e.g. days) but it would not be applicable in a 5G dynamic network setting.

In IoT, uplink offloading is an upcoming area as it can increase an IoT device’s (IoTD) battery lifetime. IoTDs are cost efficient and battery based [5], rendering them with low computational power and limited power reserves. There is a surjective relationship between SE and EE [6], such that EE increases in SE up to a threshold value. Since protocols are standardized and IoTDs have limited transmission power control, this relationship is positive. Increasing SEs of transmissions will therefore increase EE, reducing the energy...
consumption. In general, a base station with proximity to an IoTD will provide better SE due to less noise and shorter travelling distance to the receiver. Thus, optimizing SE will be one way to increase battery lifetime of the IoTDs.

In this paper we investigate the implications of having a distrusted market mechanism where link conditions are private information. We present a new resource efficient market scheme that incentivise coexisting 5G base stations to participate in uplink offloading of IoTDs’ traffic. Most offloading schemes do not respect both of these requirements (i.e. distributed and private information). The presented work is to the authors’ knowledge the first of its kind. The main contributions are:

1) A new type of traffic offloading mechanism for IoT uplink traffic in 5G is presented. The scheme is subject to a stochastic environment, making the link conditions private information.

2) We prove that the mechanism provides a market equilibrium that is unique and stable. Further, we show that the equilibrium optimize the trading such that all involved base stations have incentives to provide resource efficient offloading.

3) As the market equilibrium is unique, we provide a closed form solution to the offloading problem. Further, we show that under special conditions a distributed algorithm that can be used to achieve the market equilibrium. Both approaches find the equilibrium in polynomial time.

4) Extensive numerical simulations are provided. They display how the market equilibrium behaves with regard to site specific parameters.

The remainder of this paper is structured as follows: Section II reviews related work and Section III presents the general system model along with the evaluation criteria used. Then, Section IV describes the problem and mathematical properties of the equilibrium. Section V contains the closed form solution of the problem, while Section VI presents the distributed algorithm. Section VII displays the numerical results and includes an associated discussion. The conclusion is presented in Section VIII.

II. RELATED WORK

As our scheme is the first to our knowledge to focus on many-to-many offloading in uplink IoT, the comparable literature is limited. Related areas such as other collaboration schemes in uplink traffic and offloading schemes for downlink traffic are reviewed in this section.

Uplink traffic schemes have mainly focused on power adaption of the user equipment to reduce the interference or bandwidth assignment, either through collaboration [7, 8] or as a centralized optimization problem in the base station [9]. As IoTDs have limited ability to calculate and adjust these parameters both approaches are less applicable. This shifts the focus towards schemes that shortens the distance between the IoTDs and the receiving antenna, which have been investigated thoroughly for downlink conditions. An overview over downlink offloading technologies of mobile data is provided in [10]. The work discusses offloading from LTE to WiFi, which is further discussed in [11], where they distinguish between non-delayed and delayed offloading. The former optimizes offloading on current network status, while the latter optimizes offloading based on the spatial distribution of antennas and users’ mobility patterns. We limit the discussion to non-delay offloading, as neither uplink traffic composition nor the IoTDs’ spatial movements are known.

With overlapping RANs, the non-delay offloading can be categorized into centralized schemes (e.g. constrained optimization problems) and distributed schemes. Only the latter is applicable for our scenario and have mainly been investigated with game theory. Wang et al. [12] and Gao et al. [13] both developed a multiple seller and multiple buyer framework for downlink traffic, based on a Stackelberg game. Shah-Mansouri et al. [14] focused on pricing power and presented a setup where a mobile base station could offload its traffic to two WiFi RANs with different pricing power. The pricing power was further investigated by Li et al. [15], showing that with overlapping coverage, the equilibrium will not be stable due to price competition. A general underlying assumption in the research described above is that all information is public knowledge.

As mention earlier, having some information as private knowledge is a natural consequence of a complex 5G network. If some information is private, auctions have been used to coordinate the players’ incentives, but at the cost of having a centralized coordinating unit. Paris et al. [16] suggested a framework where a single base station operator could lease capacity from several WiFi access points through the use of combinatorial auctions. The operator might have a budget for offloading expenses and several different operators might be in the same area, causing increased complexity not accounted for. Auctions done in parallel add combinatorial problems as the outcome of one auction affects the results of the others. Iosifidis et al. [17] suggested the use of an iterative double auction to circumvent the problem. However, if the link conditions are unstable, the suggested iterative approach might not clear the market. Hossain et al. [18] suggested an approach that avoided using iterations, at the cost of not guaranteeing an optimal solution.

Our work therefore stands out from others as we focus on an uplink scenario applicable for IoT that is distributed and subject to private information constraints.

III. SYSTEM MODEL

The system model is an abstraction of 5G and IoT. The main features of our model is given as follows:

1) The offloading is system initiated as the IoTDs have computational power constraints, rendering link optimization to the operators.

2) As the IoTDs are power constrained, only the 5G receiving base station will have the ability to broadcast state information of a transmission.

3) The link conditions (allocated SEs) are private information for two reasons. First, the links depend on the allocated uplink bandwidth and the IoT’s mobility,
both being hard to predict for third parties. The allocation of uplink bandwidth in LTE is a NP-hard problem [19]. The location of an IoTD is public knowledge only if broadcasted. Second, broadcasting is unlikely from a commercial viewpoint as disclosing the information could reduce the base station’s bargaining power.

4) We put less focus on the consequence of prediction errors of link conditions as they can be predicted with reasonable high accuracy [20, 21] given that the current state is known.

5) We use state predictions for medium long time intervals (e.g. 100 milliseconds - 1 second) [20].

With these abstractions the model can be described as a system of several 5G base stations covering the same geographical region. The \( I := \{1,2,...,I\} \) large cell 5G base stations (LCBSs) are commercially owned and serve a set of IoTDs. The LCBSs have larger coverages than the \( N := \{1,2,...,N\} \) smaller privately owned small cell 5G base stations (SCBSs) that are distributed in the same geographical area. The SCBSs have non-overlapping coverage between each other. Each base station will have a subset of other base stations it interacts with. Hence, \( N_i \) is the subset of SCBSs that LCBS i has IoTDs stationed in the vicinity of. \( I_n \) is the subset of LCBSs with IoTDs in the vicinity of SCBS n. \( N \) and \( I \) are the sizes of the given subsets. The SCBSs could be part of a community network such as the telecom operator Guifi.net\(^1\), securing overall network management, where each base station has the autonomy to decide on market participation. All the base stations operate selfishly. As a convention we use \(-i\) or \(-n\) to denote all base stations except i or n. The associated variable will then be scripted in bold as it represents multiple variables.

It is in both the IoTDs’ and the SCBSs' interest to incentivise the SCBSs to participate in an offloading scheme. Therefore, the LCBSs broadcast their average link conditions to the IoTDs in each SCBS’s coverage area, as well as their budgets for offloading. The budget size is an indirect estimate of unwillingness of the commercial operator to install an additional base station. If the budget is low (zero) the LCBS operator would prefer to pay for an additional base station to alleviate the current traffic demand instead of using offloading. Similar assumptions regarding budgets are often used in downlink traffic offloading settings [12, 13, 16, 17].

It is a prerequisite for the SCBSs to know their pricing power for a functional market to exist. The SCBSs in unattractive areas where the LCBSs have good link conditions will have a relative low pricing power. If the pricing power is unknown or not existing (as in perfect competition), classical economical theory dictates that marginal pricing should be used. This removes the possibility of profits for the SCBSs along with incentives to participate. The average link conditions dictate the SCBSs’ relative pricing power and must therefore be shared.

For a given time period, each SCBS broadcasts a price \( y_n \) for carrying uplink traffic from IoTDs within its coverage area. Once an LCBS receives a price, it decides the amount

\(^1\)https://guifi.net/en/what_is_guifinet, visited 02.05.18

\( y_n \) for carrying uplink traffic from IoTDs within its coverage area. Once an LCBS receives a price, it decides the amount

of uplink traffic that should be delivered over that SCBS’s interface, thereby saving its own radio resources. Each LCBS optimizes its decision based on all the IoTDs it is serving, both inside and outside the coverage areas of the SCBSs. The physical layout along with the communication structure is shown in Fig. 1. The LCBS instructs the IoTDs whether or not to offload, making the offloading decision independent of the initial IoTD association rules used.

Traffic is modelled per IoTD group (i.e. area) instead of per IoTD. An IoTD group is the IoTDs in the vicinity of an SCBS belonging to an LCBS. Similar abstractions are done in the case of downlink traffic [12, 13], and can be justified on the basis that there could be hundreds of IoTDs within the coverage of a single base station. Thus, several IoTD groups may exist within the coverage of an SCBS or an LCBS, each IoTD group with its own set of parameters. Each operator is free to choose data aggregation schemes for its IoTDs’ data streams [22, 23]. The data aggregation schemes will be reflected in the traffic demand of the given area (i.e. IoTD group). The uplink traffic can come from both stationary and mobile IoTDs. Due to the short time validity of link estimates, an IoTD will stay covered by the SCBS for the entire time validity of the link condition’s estimate. Each IoTD group has a single but separate link to their associated SCBS and LCBS. A link between a base station and an IoTD group is stochastic to capture varying conditions (e.g. non-connectivity).

Using these traffic abstractions, we focus on the average performance of the IoTDs and abstract away idiosyncratic information such as the IoTD’s battery, antenna complexity, detailed location and mobility pattern. This renders that interference is not focused upon since it will be IoTD location dependent.

As seen in Fig. 1 the traffic offloaded is governed by the price. This creates a hierarchical decision structure, where the SCBSs first decide on their price and then the LCBSs
In the remaining of this section we will discuss the link conditions and the evaluation criteria. Although, we use traffic offloading from 5G to 5G as an example, the model is also applicable to other RAT technologies such as 5G to WiFi or 5G to LTE as an example, the model is also applicable to other RAT technologies such as 5G to WiFi. The suggested Stackelberg game is solved using backward induction. Therefore, the utility functions of the LCBSs are an indicator of how efficient the network is at transporting traffic, while the latter being the efficiency related to the energy usage.

**Definition 1.** SEE is defined as $\frac{\text{bits}}{\text{radio resource used}}$. The assigned SE value for a time period between an LCBS and an IoTD group in the area of an SCBS is given by $\phi$ while the SE for the same IoTD group to the SCBS is given by $\theta$. $\phi$ and $\theta$ are only known by the associated base station before traffic offloading occurs. They are stochastic parameters and follow discrete distributions unique for each base station. The term “link condition” refers to the assigned SE.

The definition of SE follows that of [26]. It follows that average SE for the SCBS RAN is the traffic weighted average of $\phi$, and average SE for the LCBS RAN is the traffic weighted average of the $\phi$. Given Definition 1, an increase in average SE, for both SCBSs and LCBSs, is only possible if offloaded traffic is relieved from the links with the lowest SE and to the links with the highest SE.

User equipment in LTE [27] and 5G base station [28] power usage consist of two parts, a fixed $e_{in}^{\text{fixed}}$ and a load dependent $e_{in}^{\text{load}}$ energy cost. As IoTDS will exist in a 5G environment we adapted the models as shown in (1) to describe an IoTD group’s total energy usage. An IoT group’s traffic demand for a time period is denoted as $d_{in}$.

$$e(d_{in},x_{in})_{in} = e_{in}^{\text{fixed}} + e_{in}^{load} \left( \frac{d_{in} - x_{in}}{\phi_{in}} \right) + \frac{x_{in}}{\theta_{in}}$$

The aggregated energy per IoTD group is affected by the offloading decision as it determines the amount of load dependent energy that is used on uplink traffic. The load dependent energy usage is a function of the offloaded traffic to the SCBS $x_{in}$, the traffic to the LCBS ($d_{in} - x_{in}$), the IoT group’s traffic demand $d_{in}$ and the SE ($\phi$ and $\theta$) of the associated links.

**Definition 2.** SEE is defined as $\frac{\text{bits}}{\text{radio resource used}{\div}joule} = \frac{SE}{e(d_{in},x_{in})_{in}}$.

The definition SEE follows that of [29]. SEE is calculated per IoT group. The bits referred to in Definition 1 and Definition 2 refer to the aggregated traffic per IoTD group.

**IV. THE MARKET MODEL**

The suggested Stackelberg game is solved using backward induction. Therefore, the utility functions of the LCBSs are presented first along with the decisions taken (step 2 in Fig. 1 and Fig. 2). Then, the SCBSs’ utility functions are presented, and it is shown how their decisions (step 1 in Fig. 1 and Fig. 2) follow the structure of a non-cooperative game.

The role of private information is only important for the SCBSs’ utility and is therefore first discussed in Section IV-B.
For the LCBSs their decisions only depend on the prices and their own link conditions both being known when their offloading decisions are made. Mathematical properties of the market equilibrium are presented at the end of the section.

A. The LCBS’s utility and optimal offloading

As shown in Fig. 1 each LCBS serves a set of IoTDs, making its utility function an aggregate of IoTDs’ utility functions. As each LCBS’s spectrum will have parts with different reach, the traffic in each SCBS’s location will be transmitted with different parts of the spectrum. It is beneficial for each LCBS to offload such that most resource blocks over the entire spectrum are freed. The freed resources resulting from offloading, may provide better sending rates for IoTDs inside and outside the area of the SCBSs. With modelling operator initiated offloading, the LCBS utility function is a function of all its serving IoTD groups’ utility. Each IoTD group’s utility function is increasing and concave in available data rate. The choice of utility function is motivated by the law of diminishing marginal return, and this function appropriately captures the relative preference ordering of the LCBS’s offloading for the IoTD groups. Furthermore, a logarithmic function has been widely used for describing utility for user equipment [12, 30, 31] and for wireless sensor network [32, 33, 34]. As the logarithm is not defined for 0, the utility function is shifted with the positive parameter \( r_i \) to account for the situations where it is optimal not to offload traffic.

\[
U^{LCBS}_i = \sum_{n \in N_i} \ln(r_i + \frac{x_{in}}{\phi_{in}})
\]

(2)

The offloaded traffic \( x_{in} \) is mainly offloaded from areas with poor link conditions as it releases the most resource blocks. The freed resource blocks are given by \( \frac{x_{in}}{\phi_{in}} \), with the link condition \( \phi_{in} \) being private information of the LCBS.

Definition 3. The reach factor, \( r_i \), denotes an LCBS’s spectrum’s ability to reach all locations in its coverage area.

The reach factor determines how an LCBS values spreading offloading across multiple links to free the maximum number for resource blocks. With higher values of \( r_i \), the LCBSs will prioritize to release a larger amount of resource blocks rather than having them equally distributed over the entire spectrum. Each LCBS aims at maximizing the utility for its users as given by (3) and constrained (3a)-(3c).

\[
\max_{x_{in}} U^{LCBS}_i
\]

s.t. \( x_{in} \geq 0 \ \forall n \in N \)  
(3a)

\( x_{in} \leq z_{in} \ \forall n \in N \)  
(3b)

\( \sum_{n \in N_i} y_n x_{in} \leq B_i \)  
(3c)

An LCBS can only offload non-negative traffic volumes as given by (3a). Likewise, (3b) shows that the traffic is bounded by \( z_{in} \geq 0 \), where \( z_{in} = \min(l_{in}, d_{in}) \) with \( l_{in} \) being the access limit set by the receiving SCBS and \( d_{in} \) being the traffic demand of the IoTDs. The \( l_{in} \) has been introduced to handle two cases as it limits the traffic an IoTD group might offload. First, scheduling restrictions resulting from the SCBS’s choice of uplink scheduler [35]. Second, special agreements the SCBS may have with some of the LCBSs, either through strategic partnership or side payments.

The LCBS’s leasing budget \( B_i \) sets the limit of the total cost of offloading traffic \( \sum_{n \in N_i} y_n x_{in} \), as shown by (3c). The budget is a function of the alternative cost of installing and operating an additional base station. Determining and allocating these costs precisely is a research topic that has received limited attention [36, 37]. The leasing budget will also depend on commercial and financial features of the LCBS operator, as investing in an additional base station requires both time and capital reserves from the operator.

The problem is a convex optimization problem and is solved with Lagrange optimization. The associated Lagrange function is given in (4), where \( \alpha_i, \beta_i \) and \( \gamma_i \) are the associated Karush-Kuhn-Tucker (KKT) multipliers.

\[
\mathcal{L}^{LCBS}_i = \sum_{n \in N_i} \ln(r_i + \frac{x_{in}}{\phi_{in}}) - \gamma_i(\sum_{n \in N_i} y_n x_{in} - B_i) + \alpha_i x_{in} - \beta_i (x_{in} - z_{in})
\]

(4)

The complimentary constraints are given by (4a)-(4d).

\[
\gamma_i(\sum_{n \in N_i} y_n x_{in} - B_i) = 0 \quad (4a)
\]

\[
\alpha_i x_{in} = 0 \quad (4b)
\]

\[
\beta_i (x_{in} - z_{in}) = 0 \quad (4c)
\]

\[
\gamma_i \geq 0 \quad (4d)
\]

The necessary first order conditions, derived by \( \frac{\partial \mathcal{L}^{LCBS}_i}{\partial x_{in}} = 0 \), produce the optimal offload traffic given by (5).

\[
x_{in} = \frac{1}{\gamma_i \phi_{in} + \beta_i} - r_i \phi_{in}
\]

(5)

Depending on the values of \( \alpha_i, \beta_i \) and \( \gamma_i \), different conditions for the optimal \( x_{in} \) arise. We start by investigate the case \( 0 < x_{in} < z_{in} \), that is when \( \alpha_i = 0 \) and \( \beta_i = 0 \). Eq. (6) is derived from (5) and (4a). The budget will always be fully expended giving the optimal offloading strategy resulting in \( \gamma_i > 0 \), except when \( \sum_{n \in N_i} z_{in} y_n \leq B_i \).

\[
\gamma_i = \frac{N_i}{B_i + \sum_{n \in N_i} y_n r_i \phi_{in}}
\]

(6)

Eq. (7) gives the optimal value of \( x_{in} \) and is derived from (6) and (5).

\[
x_{in} = \frac{B_i + \sum_{m \in N_i} y_m r_i \phi_{in}}{N_i y_n} - r_i \phi_{in}
\]

(7)

Eq. (7) implies the existence of a price range \( [y_{in}^{min}, y_{in}^{max}] \) for where each LCBS is price sensitive. If the price is equal or less then \( y_{in}^{min} \), \( x_{in} = z_{in} \), while if the price is equal or larger then \( y_{in}^{max} \), \( x_{in} = 0 \). The range is given by (8) and (9).
The corresponding Hessian matrix $H_L$ is given by (11) as always negative while all other elements are given by (12) as zero.

$$\frac{\partial^2 U_{\text{LCBS}}}{\partial x_i^2} = -\frac{1}{(r_i \phi_{in} + x_i)^2} \quad \forall \; n \in \mathcal{N}_L$$

$$\frac{\partial^2 U_{\text{LCBS}}}{\partial x_i \partial x_m} = 0 \quad \forall \; m, n \in \mathcal{N}_L \mid m \neq n$$

In the general case, the solution is constrained by the budget $B_i$ with the optimal $x_{in} \leq z_{in}$, making (7) suited for describing the optimal offloading strategy of the LCBSs. In this work we focus on the general case. If the optimal $x_{in}$ is larger than $z_{in}$ then the scenario is limited either by the LCBS's IoTDS's traffic demand, $d_{in}$ or the SCBSs access limits $l_{in}$, which both are deemed as special cases of the general case.

As given by Definition 3, the reach factor describes the LCBS's spectrum's ability to reach all locations in the covered area.

**Lemma 2.** There exists an $r_i$ such that all offloaded traffic derives only from the links with the relative worst link conditions.

**Proof.** Let $\phi_{\text{min}}$ be the worst link condition, with associated $x_{min}$ and price $y_{min}$. With complete offloading to an SCBS, $x_{min} = \frac{B_i}{y_{min}}$ and (7), the following can be derived:

$$y_{\min} = \frac{B_i + \sum_{m \in \mathcal{N}_L \mid m \neq n} y_m r_i \phi_{im}}{(N_i - 1) r_i \phi_{in}}$$

The optimal $x_{in}$ was derived given the condition that $0 < x_{in} < z_{in}$. Let the set $\mathcal{N}_i^+ := \{ n \in \mathcal{N}_L \mid y_n \geq y_{\min} \}$ be the SCBSs that the LCBS does not offload to, and $\mathcal{N}_i^- := \{ n \in \mathcal{N}_L \mid y_n \leq y_{\min} \}$ the set of SCBSs that the LCBS offloads as much traffic as possible to. The set of SCBSs where $x_{in}$ is price sensitive is given by $\mathcal{M}_i = \mathcal{N}_i \setminus (\mathcal{N}_i^+ \cup \mathcal{N}_i^-)$. By following the same logic as used to derive (7) the optimal decision is given by Eq. (10).

$$x_{in} = \begin{cases} 0 & \text{if } y_n \geq y_{\text{max}} \\ z_{in} & \text{if } y_n \leq y_{\text{min}} \\ \frac{B_i + \sum_{m \in \mathcal{M}_i} y_m r_i \phi_{im} - \sum_{n \in \mathcal{N}_i^+} y_n z_{in}}{|\mathcal{M}_i|} & \text{else} \end{cases}$$

With $r_i \geq r_{\text{min}}$, the LCBS will only offload to the SCBSs with the relative worst link conditions. □

**B. The SCBS's utility and optimal pricing**

As shown in Fig. 1 and Fig. 2, each SCBS sets a price which the LCBSs respond to. Before the SCBS sets a price, it creates an estimate for the link condition of the period, given by $\theta_{nw}$, having a finite set of possible states $\mathcal{W} := \{1, 2, \ldots, W\}$. Hence, each SCBS will create a set of price points $y_{nw}$ that will be optimal given its current prediction of the link condition. Since the link conditions are private information, the played price $y_n \in \{y_{nw} \forall n \in \mathcal{N}, w \in \mathcal{W}\}$ will be observed by the other players with $E(y_n) = \sum_{w \in \mathcal{W}} \mathbb{P}(\theta_{nw}) y_{nw}$, where $\mathbb{P}(\theta_{nw})$ is the probability of $\theta_{nw}$. Each SCBS has an energy cost of $c_n$ per resource block it receives for processing, and it receives $\frac{2d_{in}}{y_{nw}}$ resource blocks of traffic from the offloading IoTDSs. Likewise, the link condition between an LCBS and an IoTG group is private to the LCBS such that $\phi_{inv}$ can take $\mathcal{V} := \{1, 2, \ldots, V\}$ states. The associated conditional probability is given by $\mathbb{P}(\phi_{inv}|\theta_{nw})$, and the utility function for each SCBS given $\theta_{nw}$ is presented by (14):

$$U_{\text{SCBS}} = (y_{nw} - \frac{c_n}{\theta_{nw}}) \sum_{v \in \mathcal{V}} \mathbb{P}(\phi_{inv}|\theta_{nw}) (x_{in}|\phi_{inv})$$

The utility function is dependent on $x_{in}$ which is a function of the current SCBS strategy $y_n$ and the other SCBS's strategies $y_{-n}$ as given by (7). For each $\theta_{nw}$, the SCBS aims at maximizing its expected utility. It is restricted to only sell its current capacity $P_n \theta_{nw}$. Each SCBS has a dedicated share of the uplink traffic which is traded on, making $P_n$ the number of resource blocks allocated for uplink trading over the time period. The constraints are enforced through access management. For LTE the structure is the same as for 5G. For WiFi (802.11a) $P_n \in [0, 1]$, denoting the share of bandwidth allocated for uplink, as WiFi has downlink and uplink traffic sharing of the channel.

The presented model is focused on the amount of resource blocks $P_n$ ($\geq 100$) and not the scheduling of individual resource blocks. The uplink scheduling is a well studied problem, and the associated optimization problem is often solved with heuristics due to its computational complexity [19, 35, 38]. Schedulers might impose restrictions on the amount of traffic handled from a specific source (e.g. round-robin scheduler [24]). This is addressed by incorporating the exogenous parameter $l_{in}$, limiting the traffic an IoTG group might offload.

For other commodities such as power and gas, the price has an upper limit representing a bound either set by the regulating forces or the government. We adopt a similar notion, setting $C_{\text{max}}$ as the maximum valid price an operator can charge for the service. The problem is given by (15) with constrains (15a) - (15c).
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\[ \max_{y_{nw}} \mathcal{L}_{SCBS}^{nw} \]

s.t. \( \sum_{i \in I_n} \mathcal{L}_{\phi_{inv}}^n(x_{inv}|\phi_{inv}) \leq P_n \theta_{nw} \)

\[ y_{nw} - \frac{c_n}{\theta_{nw}} \geq 0 \]

\[ y_{nw} \leq C_{max} \]

Following the logic used to derive (7), (16) denotes the Lagrange function where \( \lambda_{nw} \), \( \mu_{nw} \) and \( \nu_{nw} \) are the associated KKT multipliers.

\[ \mathcal{L}_{SCBS}^{nw} = (y_{nw} - \frac{c_n}{\theta_{nw}}) \sum_{i \in I_n} \mathcal{L}_{\phi_{inv}}^n(x_{inv}|\phi_{inv}) - \lambda_{nw} \sum_{i \in I_n} \mathcal{L}_{\phi_{inv}}^n(x_{inv}|\phi_{inv}) - P_n \theta_{nw} \]

\[ - \mu_{nw}(y_{nw} - \frac{c_n}{\theta_{nw}}) - \nu_{nw}(y_{nw} - C_{max}) \]

The associated complimentary constraints are given by (16a)-(16d).

\[ \lambda_{nw}(\sum_{i \in I_n} \mathcal{L}_{\phi_{inv}}^n(x_{inv}|\phi_{inv}) - P_n \theta_{nw}) = 0 \]

\[ \mu_{nw}(y_{nw} - \frac{c_n}{\theta_{nw}}) = 0 \]

\[ \nu_{nw}(y_{nw} - C_{max}) = 0 \]

\[ y_{nw}, \lambda_{nw}, \mu_{nw}, \nu_{nw} \geq 0 \]

Until now, the equations have been treated as if the link conditions are public knowledge. To derive the optimal \( y_{nw} \), we combine the optimal reaction function of LCBSs (7) and Lagrange function of the SCBS given by (16). As (7) contains information that is not available prior to the price setting decision (\( y_{nw} \) and \( \phi_{inv} \)), these values remain unknown and expected values are used instead. The expected values depend on the probability distributions and values of \( \theta \) and \( \phi \). As the price \( y_{nw} \) of SCBS depends on its \( \theta_{nw} \), the expected value of each SCBS price will be \( \mathbb{E}(y_{nw}) = \sum_{w \in \mathcal{W}} \mathcal{P}(\theta_{nw})y_{nw} \). The expected values of \( \phi \) is \( \mathbb{E}(\phi_{inv}) = \sum_{w \in \mathcal{W}} \mathcal{P}(\phi_{inv})\phi_{inv} \) for a given \( \theta \). In the initial stages of the game, \( \mathbb{E}(y_{nw}) \) will change as it depends on actions taken by the SCBS. \( \mathbb{E}(y_{nw}) \) is independent of action taken and will not change unless the distribution changes. Further, the expression is simplified by introducing \( \mathcal{B} = \sum_{i \in I_n} \frac{B_i}{N_i} \), \( \mathcal{R}_{nw} = \sum_{i \in I_n} \frac{N_i}{N_i} \mathcal{P}(\phi_{inv})y_{nw} \) and \( \Omega_{nw} = B + \sum_{i \in I_n} \frac{\mathcal{P}(\theta_{mu}|\theta_{nw})\mathcal{P}(\phi_{inv}|\theta_{mu})y_{nw}}{\theta_{nw}} \) giving (17).

\[ \mathcal{L}_{SCBS}^{nw} = (y_{nw} - \frac{c_n}{\theta_{nw}})(\frac{\Omega_{nw}}{y_{nw}} - R_{nw}) - \lambda_{nw}(\Omega_{nw} - R_{nw} - P_n \theta_{nw}) \]

\[ + \mu_{nw}(y_{nw} - \frac{c_n}{\theta_{nw}}) - \nu_{nw}(y_{nw} - C_{max}) \]

In Eq. (17), \( \Omega_{nw} \) depends on the other SCBSs prices, making the price setting a non-cooperative game as shown in Fig. 2. The first order optimum condition is achieved when \( \frac{\partial \mathcal{L}_{SCBS}^{nw}}{\partial y_{nw}} = 0 \), giving (18) and (19).

\[ R_{nw} = (\frac{c_n}{\theta_{nw}} + \lambda_{nw})\frac{\Omega_{nw}}{y_{nw}} + (\mu_{nw} - \nu_{nw}) \]

\[ y_{nw}^2 = (\frac{c_n}{\theta_{nw}} + \lambda_{nw})\frac{\Omega_{nw}}{R_{nw} - (\mu_{nw} - \nu_{nw})} \]

Eq. (18), (7) and (16a) give the value of the KKT multiplier \( \lambda_{nw} \) as shown in (20).

\[ \lambda_{nw} = y_{nw} - \frac{c_n}{\theta_{nw}} - \frac{\mathbb{E}(\theta_{mu}|\theta_{nw})\mathbb{E}(\phi_{inv}|\theta_{mu})y_{nw}}{\mathbb{E}(\theta_{mu}|\theta_{nw})\mathbb{E}(\phi_{inv}|\theta_{mu})} \]

Eq. (21) denotes the optimal value of \( y_{nw} \) and is derived from (20) and (19).

\[ y_{nw} = \frac{\Omega_{nw}}{R_{nw} + P_n \theta_{nw}} \]

Eq. (21) is the SCBS’s best response function to the other SCBS’s prices. If \( y_{nw} > C_{max} \), then \( y_{nw} = C_{max} \) is played, but that dictates a very regulated market that is not of particular interest to a generic situation. Therefore, the case of \( y_{nw} < C_{max} \) is focused on. An SCBS will only participate in a game where it has positive utility, and will expect to price itself out of participating in a game if Eq. (22) holds true.

\[ \mathbb{E}(\theta_{mu}|\theta_{nw})\mathbb{E}(\phi_{inv}|\theta_{mu}) > K_{nw} \]

where:

\[ \mathbb{E}(\phi_{inv}|\theta_{mu}) = \frac{\mathbb{E}(\phi_{inv} | \theta_{mu})}{\mathbb{E}(\theta_{mu} | \theta_{nw})} \]

Lemma 3. \( \mathcal{U}_{SCBS}^{nw} \) is strictly concave in its own strategy.

Proof. Lemma 1 gives that each LCBS has a unique response to the observed price \( y_{nw} \in \{y_{nw} \forall \eta \in \mathcal{N}_w \in \mathcal{W} \} \). The response function of the LCBSs (7) and the SCBS’s utility (14) give the SCBS’s utility expressed in prices as seen in (23). Eq. (24) shows that the second order partial derivative is always negative, making an SCBS strictly concave in its own strategy, \( y_{nw} \).

\[ \mathcal{U}_{SCBS}^{nw} = (y_{nw} - \frac{c_n}{\theta_{nw}}(\frac{\Omega_{nw}}{y_{nw}} - R_{nw})) \]

\[ \frac{\partial^2 \mathcal{U}_{SCBS}^{nw}}{\partial y_{nw}^2} = -2 \frac{c_n \mathbb{E}(\theta_{mu}|\theta_{nw})\mathbb{E}(\phi_{inv}|\theta_{mu})y_{nw}}{\mathbb{E}(\theta_{mu}|\theta_{nw})\mathbb{E}(\phi_{inv}|\theta_{mu})} \]

Lemma 4. The non-cooperative price setting game between SCBSs has a unique Stackelberg equilibrium.

Proof. It follows from Rosen [39] that there exists at least one NE as each SCBS is strictly concave in its own strategy (given by Lemma 3) and the strategy set is closed and bounded (\( y_{nw} \in [0, C_{max}] \)). Let matrix \( H = [G + G^T] \) where \( G \) has...
a matrix element \( G_{ij} = \frac{\partial^2 Q_{SCBS}}{\partial y_{nw}} \), giving \( H \) the structure described by (25) and (26),

\[
H_{ij} = \begin{cases} 
\frac{\partial^2 Q_{SCBS}}{\partial y_{nw} \partial y_{mu}} & \text{if } n = m \cup w = u \\
\frac{\partial^2 Q_{SCBS}}{\partial y_{nw} \partial y_{mu}} + \frac{\partial^2 Q_{SCBS}}{\partial y_{nw} \partial y_{mu}} & \text{else}
\end{cases}
\] (25)

\[
\forall i = (n-1)W + w, j = (m-1)W + u,
\]

\[
n, m \in \mathcal{N}, w, u \in \mathcal{W}
\]

\[
\frac{\partial^2 Q_{SCBS}}{\partial y_{nw} \partial y_{mu}} = \begin{cases} 
\text{Eq. (24)} & \text{if } n = m \cup w = u \\
0 & \text{if } n = m \cup w \neq u
\end{cases}
\] (26)

where:

\[
A_{mnw} = \mathbb{P}(\theta_{mu}|\theta_{nw}) \sum_{i \in \mathcal{I}_w, v \in \mathcal{V}_n} (\phi_{imv} \theta_{ma})_{\frac{\theta_{imv}}{N_i} y_{nw} y_{mu}}
\]

\[
\forall n, m \in \mathcal{N}, w, u \in \mathcal{W}
\]

It is a sufficient condition for matrix \( H < 0 \) to guarantee that the NE is unique [39]. Matrix \( H < 0 \) if \( \gamma H \gamma^{T} < 0 \) where \( \gamma = [y_{nw} \forall n \in \mathcal{N}, w \in \mathcal{W}] \), and this will be proven in the remaining part of this section.

\[
\gamma H \gamma^{T} = \sum_{n \in \mathcal{N}, w \in \mathcal{W}} 2y_{nw}^{2} \frac{\partial^2 Q_{SCBS}}{\partial y_{nw}^{2}}
\]

\[
+ \sum_{n, m \in \mathcal{N}, w, u \in \mathcal{W}} \sum_{|n \neq m \cup w \neq u|} c_{nm} \Omega_{nw} \theta_{nw} y_{nw}
\]

The first part of (27) can be simplified to:

\[
\sum_{n \in \mathcal{N}, w \in \mathcal{W}} 2y_{nw}^{2} \frac{\partial^2 Q_{SCBS}}{\partial y_{nw}^{2}} = -4 \sum_{n \in \mathcal{N}, w \in \mathcal{W}} c_{nm} \Omega_{nw} \theta_{nw} y_{nw}
\] (28)

The second part of (27) can be simplified to:

\[
\sum_{n, m \in \mathcal{N}, w, u \in \mathcal{W}} \sum_{|n \neq m \cup w \neq u|} c_{nm} \Omega_{nw} \theta_{nw} y_{nw}
\]

\[
= \sum_{n \in \mathcal{N}, w \in \mathcal{W}} c_{nm} \Omega_{nw} \theta_{nw} y_{nw} + \sum_{m \in \mathcal{N}, u \in \mathcal{W}} c_{nm} \Omega_{nw} \theta_{nw} y_{nw}
\] (29)

Eq. (30) is a combination of (27)-(29) showing that \( \gamma H \gamma^{T} < 0 \). Thus, the NE is unique. The expression \( \sum_{w \in \mathcal{W}} c_{n}(\Omega_{nw} + B) \) is always positive. As the followers (LCBSs) have a unique response to the price vector \( \gamma \), and the leaders have a unique NE determining the \( \gamma \), the corresponding Stackelberg equilibrium is also unique.

\[
\gamma H \gamma^{T} = -2 \sum_{n \in \mathcal{N}, w \in \mathcal{W}} c_{n}(\Omega_{nw} + B) \theta_{nw} y_{nw}
\] (30)

Constraint (15a) ensures that the expected traffic is less than capacity, thus there might be situations where more traffic than capacity is sold. If a guarantee is to be given, each SCBS must convey a limit \( l_{in} \) per link. This will create the possibility of unused capacity, since the LCBSs’ offloading is dictated by the values of \( \phi \). In the following analyses we assume that market condition given by (15a) is accepted by the LCBSs.

V. THE CLOSED FORM SOLUTION

Lemma 4 ensures a unique solution, and since the SCBSs’ best response functions (21) are linearly dependent on each other, they can be solved simultaneously as a linear system given by (31) where \( \tilde{\gamma} = [y_{nw} \forall n \in \mathcal{N}, w \in \mathcal{W}] \).

\[
A \tilde{\gamma} = \tilde{B}
\] (31)

The matrix \( A \in \mathbb{R}^{\mathcal{N} \times \mathcal{W}} \) has a form defined by (32).

\[
A := \begin{bmatrix} D_{1} & -E_{1}^{2} & \ldots & -E_{1}^{N} \\
-2 & E_{2}^{2} & \ldots & -E_{2}^{N} \\
\vdots & \vdots & \ddots & \vdots \\
-E_{N}^{1} & -E_{N}^{2} & \ldots & D_{N} \end{bmatrix}
\] (32)

\[
D_{n} \in \mathbb{R}^{\mathcal{W} \times \mathcal{R}}
\]

is a submatrix with only values of zero except at the diagonal elements, where, \( f(\theta_{nw}) = R_{nw} + P_{n} \theta_{nw} \). The submatrix \( E_{n} \in \mathbb{R}^{\mathcal{W} \times \mathcal{W}} \) has only non-zero elements with \( g(\theta_{nw}, \theta_{nw}) = \mathbb{P}(\theta_{nw} \mid \theta_{nw}) \sum_{\phi_{imv} \in \mathcal{V}_n} \phi_{imv} \Omega_{nw} \theta_{nw} \). \( \tilde{B} \) is a column vector of size \( \mathbb{R}^{\mathcal{N} \times \mathcal{W}} \) with all elements being \( B \).

Lemma 5. The system has a closed form solution if \( R_{nw} + P_{n} \theta_{nw} > 0 \forall n \in \mathcal{N}, w \in \mathcal{W} \).

Proof. Lemma 4 guarantees the existence of a unique NE, but it does not guarantee matrix \( A \) being invertible. If either of the sub-matrices \( D \) contain a zero value on the diagonal, the determinant will be zero, making \( A \) singular. The diagonal has at least one zero value if \( R_{nw} + P_{n} \theta_{nw} = 0 \forall n \in \mathcal{N}, w \in \mathcal{W} \), making the rows linear dependent. This situation occurs only for LCBSs that cannot receive traffic from an area, and the corresponding SCBS allocates all its resource blocks to its owner.

With conditions set by Lemma 5 fulfilled, the system can be solved with Eq. (35).

\[
\tilde{\gamma} = A^{-1} \tilde{B}
\] (35)
The specific values of the \( y_{nw} \) are given by Cramer's rule (36) [40], where \( |A| \) is the determinant of \( A \) and \( |A_j| \) is the determinant where the \( j \)th column is replaced with \( \bar{B} \).

\[
y_{nw} = \frac{|A_j|}{|A|} \quad \forall j = W(n-1) + w, n \in \mathcal{N}, w \in \mathcal{W} \tag{36}
\]

\( y_{nw} \) is the optimal price played for every corresponding \( \theta_{nw} \) estimates of the SCBS.

VI. DISTRIBUTED MARKET
AND SHARING OF INFORMATION

If the links' probability distributions are uncorrelated, then Algorithm 1 can be used to acquire the optimal price strategy for each SCBS in a decentralized fashion. All the players (SCBSs and LCBSs) know their own distribution of \( \theta \) and \( \phi \). In order for each SCBS to know its own expected best response, it has to keep track of the latest price played per \( \theta \). The vector \( \bar{p} \) is used to track the played price, such that \( \bar{m}[\theta] = y_{nw} \) and \( \bar{w}[\theta] \) is the associated probability of \( \theta \). \( \bar{b} \) is a boolean vector used to keep track of \( \theta \). \( \alpha \) is used as threshold for changes in the expected price. The algorithm depends on that SCBSs report (broadcast) an expected value of the played price \( \bar{y}_m = \mathbb{E}(y_m) \) and the LCBSs report the expected link conditions \( \bar{r}_{im} = \bar{r}(\phi_{im}) \).

Each LCBS has its own updating frequency that depends on the distributions of \( \phi \). An LCBS knows its values of \( \phi \) when determining the amount of traffic to offload. The expected values of \( \phi \) are independent of the actions taken by the LCBSs, and they are solely a function of the distribution. Thus, the expected values need only to be broadcast if the distributions change. Changes in the expected values will change the pricing power, and thus potentially the market equilibrium.

The distributed algorithm can be adapted to handle correlated link conditions, by making all players broadcast historic values of the link conditions (\( \theta \) and \( \phi \)) with timestamps in bulks, called “bulk messages”. The correlation could be calculated by each base station from its own observations and bulk message data. Such an approach would require minimal additional signalling, as bulk messages would replace the sending of the expected values. The updating frequency and the size of bulk messages would be a trade-off between historical values already available and new information contained within the bulk messages.

**Lemma 6.** Algorithm 1 will converge regardless of the probability distribution of \( \theta \) and \( \phi \).

**Proof.** The calculations only depend on the expected values reported by the LCBSs and the SCBSs. Therefore, by definition, the underlying distributions are abstracted away.

A. Motivation for information sharing

An offloading market holds benefits for both SCBSs and LCBSs, motivating for information sharing.

The possibility of an extra income of offloading provides an additional incentive for private owners to invest in an SCBS. An SCBS is incentivised if it retains a profit from participating in the market scheme. The best strategy for an SCBS that does not know its pricing power is to price it as if in a perfect competitive market. If there are no pricing power, the best strategy is to price according to marginal cost (\( c_r \)). In this setting, no profit would be obtained and there would be no incentives to participate, as the primary reason for having a private 5G base station is not offloading. It is therefore a prerequisite that the relative pricing power of the SCBSs are conveyed.

Also, the offloaded traffic will free capacity such that the LCBSs can serve IoTDS inside and outside the offloading area of the SCBSs with additional resources. It is therefore in each LCBS’s interest that the average values of \( \phi \) are shared along with its own budget.

There is a difference between having a market and being truthful in reporting the average values, as expected by Algorithm 1. Both the SCBSs and the LCBSs can deceive by wrongly report \( \bar{y}_m \) and \( \bar{r}_{im} \) to increase their own gain. However, the gain is limited as the deception will be discovered as the players build history.

**Lemma 7.** The reported expected values of \( \bar{y}_m \) and \( \bar{r}_{im} \) in Algorithm 1 can be checked with historic price values \( y_m^t \) and offloaded traffic rates \( x_m^t \).

**Proof.** The average played prices per SCBS will per definition converge to the expected price as seen in (37), where \( y_m^t \) is the historic prices played by an SCBS at time \( t \). In the long run, an SCBS can only affect its average price by playing suboptimal prices.

\[
\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} y_m^t = \bar{y}_m \tag{37}
\]

The values of \( \bar{r}_{im} \) should match the average offloaded traffic \( x_m^t \) as given by (38). Likewise, \( x_m^t \) is the traffic offloaded for time \( t \).

\[
\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \left( y_m^t - \frac{B_i + \sum_{m \in \mathcal{N}} y_m^t x_m^t}{N_i \bar{y}_m} + \bar{r}_{im}\right) = 0 \tag{38}
\]

**Lemma 7** shows that the average value of \( y_m \) and \( x_m \) should converge to a set of values given by \( \bar{y}_m \) and \( \bar{r}_{im} \). The players
that are found to be untruthful are excluded from the game by the other players, rendering their utility to zero. The threat of exclusion makes it rational for the players to be truthful initially before historic data exist.

B. Time Complexity

With lemma 4, the solution space must be concave. Algorithm 1 performs iterative steps along the solution’s surface of the problem. The iteration uses a constant time in calculating the price. The algorithm is performed for all the players for each iteration, hence $O(N)$. When there are multiple values of $\theta$, all the $\theta$ values of each player has to be played at least once for the algorithm to stop. With any given probability distribution the average time for each $\theta$ to appear is $\frac{1}{p(\theta)}$. On average it will take $\arg \max_{w \in W} \frac{1}{p(\theta(w))}$ for each player to play all its $\theta$, and it is given by the discrete probability distribution of $W$. The overall complexity is therefore $O(\arg \max_{w \in W} \frac{N}{p(\theta(w))})$. As the complexity is linear in the problem size, it can be solved in polynomial time. The algorithm converges due to the concave surface of the solution space. The convergence is shown empirically in the next section.

VII. Numerical Results

In this section, we first describe the parametrization of the model and then the properties of the suggested market scheme.

A. Model parametrization

In the base case $I = 7$ and $N = 15$, with the $B_i = 10$ for all LCBSs and $c_r = 0.01$ for all the SCBSs. The cardinality of each subset is such that $N_i = N \forall i \in I$ and $I_n = I \forall n \in N$. Each SCBS operates with a 10 MHz bandwidth giving 48 resource blocks in parallel [41], where only 10% of them are allocated for offloading such that $P_n = 4.8$. Each IoTD will need a few Kbps of uplink traffic, but with numbers of several hundred IoTDs in an area, the aggregated need is in Mbps. Thus, $d_{in} = 2$ Mbps for each area. The numerical results provide a lower bound for the scheme’s effectiveness for the LCBSs as $r_1 = 1$. With the given reach factor, the LCBSs deem it preferable to spread the resource blocks at the account of maximizing number of freed blocks.

The link condition states can be derived in two ways, either through a lookup table for a give SNR as done in [19], or base them on the possible channel quality indicator rates of LTE [25] and symbol encoding. As neither the cell noise nor the transmission power of IoTDs are known, we chose the latter with six symbol encoding, setting $W = 4$ with $\bar{v} = [0.35, 0.48, 0.65, 0.8]$ and $V = 3$ with $\bar{v} = [0.17, 0.28, 0.39]$. Both the vectors’ values are denoted in Mbps per resource block sent continuously for one second. The suggested ranges of $W$ and $V$ are such that they overlap, with the SCBSs having a better average link conditions than the LCBSs.

Without measurements from 5G and IoTDs it is hard to derive a representative distribution for the link conditions. Lemma 6 decouples the distributed algorithm from the underlying link distributions, enabling high-level approximation. This is done by viewing the noise and attenuation sources as independent sources with “on”/“off” states. When all the sources are “on”, the link conditions will be in the worst state. Each source has equal probability of being in either state, abstracting the link distributions to binomial distributions.

B. The equilibrium and associated sensitivity analysis

As a baseline for comparing schemes, the status quo of not having any market mechanism in place was used, making the relative difference in SE ($\Delta SE$) and SEE ($\Delta SEE$) the gain of the proposed market. For comparable averages, the traffic weighted averages of SE and SEE were used when available, else the average of the associated $\phi$ and $\theta$ were used. Two types of signals are used in the presented scheme; negotiate the market equilibrium and the offloading decisions. The former is only sent between the base stations. They are given in bytes per second, which is insignificant when compared to the base stations’ transport network’s capacity which may be in hundreds of Mbps. The latter is sent in downlink from the LCBS to its IoTDs and can be added on existing signalling between the two. As offloading is a binary decision of each IoTD, only set inclusion signals are needed. Using Bloom filters [42], the set information can be compress into a few bytes even for large groups of IoTDs. The signalling costs are therefore considered insignificant and not included in the evaluation of the market schemes.

The market equilibrium is efficient as it increases the evaluation criteria, raising the SE and the SEE of the involved players. The equilibrium’s SE increasing properties are stable as the number of SCBSs increase. Fig. 3 shows that the average SE increase for the SCBSs, the LCBSs and the IoTDs. The equilibrium’s effect on SE is highest for the IoTDs as the SCBSs provide better overall link conditions than the LCBSs. Both the SCBSs and the LCBSs experience a positive increase in SE. This is due to the traffic being offloaded from the links with the worst links in LCBS network to best ones in the SCBS network. The increase in SE for the IoTDs is mirrored in the increase of SEE as shown in Fig. 4. Further, the figure shows that the equilibrium’s effect depends on the IoTD group’s parameters of $e_{in}^{fixed}$ and $e_{in}^{load}$. The effect on SEE decreases in relative size of $\frac{e_{in}^{fixed}}{e_{in}^{load}}$. Depending on the parameters, the IoTDs can achieve $\Delta SEE$ increase on average with more than 40%.

The equilibrium is sensitive to the network configurations as presented in Fig. 5, where the sensitivity to the reach factor, the traffic demand and the number of base stations are shown. An increase in the reach factor makes the LCBSs less price sensitive and more sensitive to values of $\phi$. This causes higher utility for each of the LCBSs as the parameters increase, while the SCBSs’ utilities are unaffected. Further, the traffic demand reaches a point where it is no longer a constraint, and the average utility function of the LCBSs and the SCBSs flattens out. For the base case, the limit is around 400 Kbps per SCBS area. A general observation is that the utility decreases in the network’s relative size. That is, the LCBSs’ average utility decreases, while the SCBSs’ average utility increases as the
The number of LCBS increases. The opposite effect is observed when the number of SCBS increases.

The presented market scheme is robust as the SE is optimized for the different configurations of the network as seen in Fig. 6. With a reach factor increase, the LCBSs prioritize

Fig. 3. The plot gives an overview of the average relative increase in SE (ΔSE) for the SCBSs, the LCBSs and the IoTDs as the number of SCBSs increase. The relative increase is calculated against the baseline of not having any market mechanism in place. Thus, the gain of the proposed solution is shown. The average increase of SE is 1% for the LCBSs, 6% for the SCBS and 25% for the IoTDs. Each value is the average of 1000 simulations with equilibrium prices.

Fig. 4. The plot shows the average relative increase in SEE (ΔSEE) for the LCBSs with different parameter values of $e_{\text{fixed}}^\phi$ and $e_{\text{load}}^\phi$. The relative increase is calculated against the baseline of not having any market mechanism in place. The gain is in the range of 30%-42% depending on the values of $e_{\text{fixed}}^\phi$ and $e_{\text{load}}^\phi$ along with the number of SCBSs. Each value is the average of 1000 simulations with equilibrium prices.

Fig. 5. The plot shows the average utility of the LCBSs and the SCBSs with respect to the reach factor, the traffic demand, the number of LCBSs and the number of SCBSs. Each value is the average of 1000 simulations with equilibrium prices.

Fig. 6. The plot shows the average relative increase in SE (ΔSE) for the LCBSs and the SCBSs as a function of the reach factor, the traffic demand and the number of LCBSs. The relative increase is calculated against the baseline of not having any market mechanism in place. Each value is the average of 1000 simulations with equilibrium prices.

Fig. 7. The plot shows the best played price $y_{\text{play}}$ for the different possible $\theta$ of SCBSs in shades of green along with the expected price given in orange. The plot converge fully at the 320th iteration.

The distributed algorithm converges fast as the game progresses, reaching an equilibrium where no player can expected a higher gain by deviating. Fig. 7 shows that the expected price converges as the optimal price played per $\theta$ stabilizes. Since the game is stochastic with changing values of $\theta$ and $\phi$, the equilibrium varies with each predicted value of the link conditions. The strategies of the SCBSs and the LCBSs are bounded as shown in Fig. 8.

No player can deceive the others without being discovered as the history builds. As stated in Lemma 7, the average of the historic values converges to the expected values as shown in Fig. 9. The transparency makes it rational to be truthful

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when reporting the average values, as deceiving players are excluded from the market.

The value of having public information is limited as seen in Fig. 10. The figure shows the four possible information sharing scenarios from all information being private to all being public knowledge. The respective values are given as percentile difference from the base case (bc). Two observations can be derived from the presented figure. The first observation is that the difference in the average utility is less than ±0.1% for both the LCBSs and the SCBSs. This implies that there is little incentive for the players to derive the true link conditions. This lack of difference derives from the scheme being based on average values. Even though the SCBSs fail at pricing their service correctly, the errors are both positive and negative. The over- and underpricing of their services counter effect each other, making the expected averages equal. However, the pricing errors have an effect on the standard deviation, which is the second observation. The standard deviation of the utility increases for LCBSs while decreases for the SCBSs as information becomes public knowledge. The near 100% decrease in the standard deviation with no increase in the average utility suggests that the SCBSs with public information make better pricing decisions. The correct pricing effect is also observed in the small decrease in average utility for the LCBSs as the SCBSs’ links conditions are public information. The LCBSs experience the opposite effect as the information becomes public, increasing the the standard deviation in the average utility.

The accuracy of the base stations’ link predictions is a trade-off that is expressed in the model in two ways, either the updating frequency increases or safety margins offsetting the link predictions are added to account for the uncertainty. Both ways will only affect the values of input parameters, while the presented model will still be valid and applicable.

### VIII. Conclusion

This work presents a novel scheme for a many-to-many offloading market for uplink traffic where the link conditions are private information. The market incentivises all involve base stations to optimize resource use such that the spectral efficiency (SE) increases. More over, the work has three key features deriving from the suggested scheme.

First, the presented scheme optimizes both the SE and the spectral energy efficiency (SEE) of all the involved players. The base stations experience an increase in average SE in the range of 1-6%, while the Internet of Things devices (IoTDs) experience an increase of 25%. Thus, the scheme performs optimization across the radio access networks (RANs), leveraging on the difference in SE of the links and decreasing the overall resource usage. Further, the IoTDs’ increase in SE is also reflected in the SEE, which is increasing with approximately 40%. It implies that the scheme provides less resource usage for the IoTDs in their uplink traffic, which infer an increased battery lifetime of the IoTDs. In addition, sensitivity analyses show that the market equilibrium’s gain stays positive for various network configurations, making it
robust. The robustness of the SE optimizing properties makes the suggested scheme applicable for a wide range of scenarios.

Second, we prove both stability and uniqueness of the equilibrium, and provide two approaches to derive the equilibrium. The first one being a closed form solution applicable to most market scenarios, while the other one being a distributed algorithm that requires certain market conditions. The distributed algorithm requires that the link conditions of each player are uncorrelated, which we believe is a good abstraction for most uplink scenarios. Thus, our work presents two approaches for other researchers to derive a market price structure that leads to SE optimization.

Third, the value of public information is limited, with less than ±0.1% in the expected average utility of both the small cell 5G base stations (SCBSs) and the large cell 5G base station (LCBSs). This discovery has a large impact on protocol design and signalling, since it implies that the value of distributing state updates is limited. Simplified protocols will therefore provide the same benefits as more complex ones, but with the added benefit of being easier to implement and govern. Our scheme also show an asynchronous change in standard deviation in the average utility as information becomes public. If either of the LCBSs or SCBSs are risk adverse (reduced preference for variation), the two player groups will have opposing preference of information sharing, which could affect the market.

The distribution of the link conditions ($\theta$ and $\phi$ values) give the system’s flexibility and with that the benefits of our suggested scheme. An increased distribution spread will also increase the benefits of the scheme. However, measurement studies of IoTTDs in 5G environments are needed to understand the spread and the full potential of uplink offloading markets.

Our research can be extended to address the limitation imposed by using renewable energy or latency constraints in the IoT devices. The presented scheme needs only small modifications to apply to uplink LTE and WiFi, thus making it suitable for all major radio access technologies.

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Endre Hegland Hjort Kure received his MSc in Industrial Economics and Technology Management from Norwegian University of Science and Technology, Norway, in 2013. He is currently pursuing a PhD degree in networks and distributed systems at Simula Research Laboratory, and at University of Oslo, Norway. His current research interests include wireless networks, modelling uncertainty in systems and flexibility optimization.

Paal Engelstad received his Ph.D. degree in networks and distributed systems from the University of Oslo, Norway, in 2005. He currently holds a full Professor position at the Institute of Technology Systems at the University of Oslo and an Adjunct Professor position at Oslo Metropolitan University. His current research interests include wireless networks, network security, Internet of Things and machine learning.

Sahita Maharjan (M’09) received the Ph.D. degree in networks and distributed systems from the Simula Research Laboratory, and University of Oslo, Norway, in 2013. She is currently a Senior Research Scientist at the Simula Metropolitan Center for Digital Engineering, Norway, and an Associate Professor at the University of Oslo. Her current research interests include wireless networks, network security and resilience, smart grid communications, Internet of Things, machine-to-machine communication, software-defined wireless networking, and the Internet of Vehicles.

Stein Gjessing is a professor of Computer Science in Department of Informatics, University of Oslo. He received his the Cand. Real. degree from the University of Oslo, and the Dr. Philos. degree from the University of Oslo. He acted as Head of the Department of Informatics for 4 years from 1987. Gjessing’s original work was in the field of programming languages and programming language semantics, in particular related to object oriented concurrent programming. He has worked with computer interconnects and computer architecture for cache coherent shared memory, with DRAM organization, with ring based LANs and with IP fast reroute. His current research interests are Routing and Resilience in IP networks, IoT and Smart Grid Communications.

Yan Zhang is a Full Professor at the Department of Informatics, University of Oslo, Norway. He received a PhD degree in School of Electrical & Electronics Engineering, Nanyang Technological University, Singapore. He is an Associate Technical Editor of IEEE Communications Magazine, an Editor of IEEE Transactions on Green Communications and Networking, an Editor of IEEE Communications Surveys & Tutorials, an Editor of IEEE Internet of Things Journal, and an Associate Editor of IEEE Access. He serves as chair positions in a number of conferences, including IEEE GLOBECOM 2017, IEEE VTC-Spring 2017, IEEE PIMRC 2016, IEEE CloudCom 2016, IEEE ICC 2016, IEEE CCNC 2016, IEEE SmartGridComm 2015, and IEEE CloudCom 2015. He serves as TPC member for numerous international conference including IEEE INFOCOM, IEEE ICC, IEEE GLOBECOM, and IEEE WCNC. His current research interests include: next-generation wireless networks leading to 5G, green and secure cyber-physical systems (e.g., smart grid, healthcare, and transport). He is IEEE VTS (Vehicular Technology Society) Distinguished Lecturer. He is also a senior member of IEEE, IEEE ComSoc, IEEE CS, IEEE PES, and IEEE VT society. He is a Fellow of IET. He received the award “Highly Cited Researcher” (top 1% by citations) according to Clarivate Analytics.