CASE: A Joint Traffic and Energy Optimization Framework Toward Grid Connected Green Future Networks

Ashutosh Balakrishnan, Swades De, and Li-Chun Wang

Abstract—**Renewable power provisioning of the base stations (BS) in addition to the traditional power grid connectivity presents an interesting prospect towards realizing green future network services. Designing such dual-powered systems is challenging due to the presence of space-time varying stochasticity in traffic and green energy harvest at each BS. These traffic and green energy imbalances result in non-optimal network green energy utilization and thus resulting in a higher grid energy purchase to the mobile operator. In this paper, we present a novel coverage adjustment and sharing of energy (CASE) framework that exploits the user traffic load and green energy availability imbalances across the networked BSs towards maximizing the operator profit and designing energy sustainable system. The profit maximization problem is formulated considering the networked BSs to have the flexibility of load aware coverage adjustment and green energy sharing capability among themselves, in addition to trading energy with the grid. The proposed CASE framework first leverages the spatio-temporal traffic and energy inhomogeneities and performs load management for maximizing user quality of service (QoS). The CASE strategy then distributes the residual energy imbalance across the BSs and maximizes the utilization of temporal green energy harvest across the BSs. The proposed strategy is compared with only coverage adjustment, only sharing of energy, and a benchmark without CASE based framework. Our simulation results indicate significant improvement in user QoS and operator profit, up to 18% and 39% respectively at high skewness scenario, in addition to fully utilizing the green energy potential in the network.**

Index Terms—**Dual powered cellular network, green communication network services, coverage adjustment, energy sharing, operator profit, energy sustainability**

I. Introduction

Achieving greenness through network energy savings is one of the key objectives in 6G communication network services [1]. The Information and Communication Technology (ICT) sector currently consumes around 10% of global electricity [2]. The rapid evolution of the Internet of Things (IoT) alongside the advent of 6G based future networks is estimated to significantly increase the number of mobile subscribers by around 13% in the upcoming years [3], [4]. Significant research has been conducted on the user-end service quality and energy efficiency [5].

A wireless communication service system consists of network devices, base station (BS), and the core network. The BS, which is a transceiver system responsible for communicating with the devices, is the most energy intensive entity in a communication system, taking up to 58% of the energy consumed by a communication system [6]. Further, recent studies have shown that a standalone diesel powered BS is estimated to consume about 1500 liters of diesel per month, generating around 4000 Kg of CO_2. With continually increasing user quality of service (QoS) demands, the number of BSs in the network is expected to grow, resulting in an estimated increase in network energy consumption by 170% in the coming years [7]. Hence, it is important to address the energy efficiency from network services perspective, besides from the users perspective.

Apart from energy efficiency, cost expenditure incurred to the mobile network services operator has emerged as a crucial parameter for system capacity planning [8]. Various costs borne by the mobile service provider include initial network deployment costs (termed as capital expenditure, CAPEX) and operational costs required to manage daily network operations (termed as operational expenditure, OPEX). There is an urgent need to realize operator cost aware system solutions taking the operator cost also into account in addition to the energy considerations, so that the solutions can be readily accepted and deployed by the industry [2]. Hence, scalability of the system solution has become equally pertinent as energy efficiency.

A. Motivation

Provisioning the BSs with renewable energy sources (e.g., solar, wind, etc.) in addition to the traditional power grid connectivity presents a potential solution to achieve greenness as well as cost profitability to the operator [9]. Grid connected and renewable energy powered communication networks are becoming increasingly attractive, as it enables to enhance energy and cost profitability. The spatially distributed BSs can be networked by leveraging the smart grid infrastructure, and the BSs can be intelligently controlled to transfer (sell or procure) green energy among themselves or trade energy with the smart grid. A major challenge in grid connected and solar powered network is the dynamic space-time varying nature of

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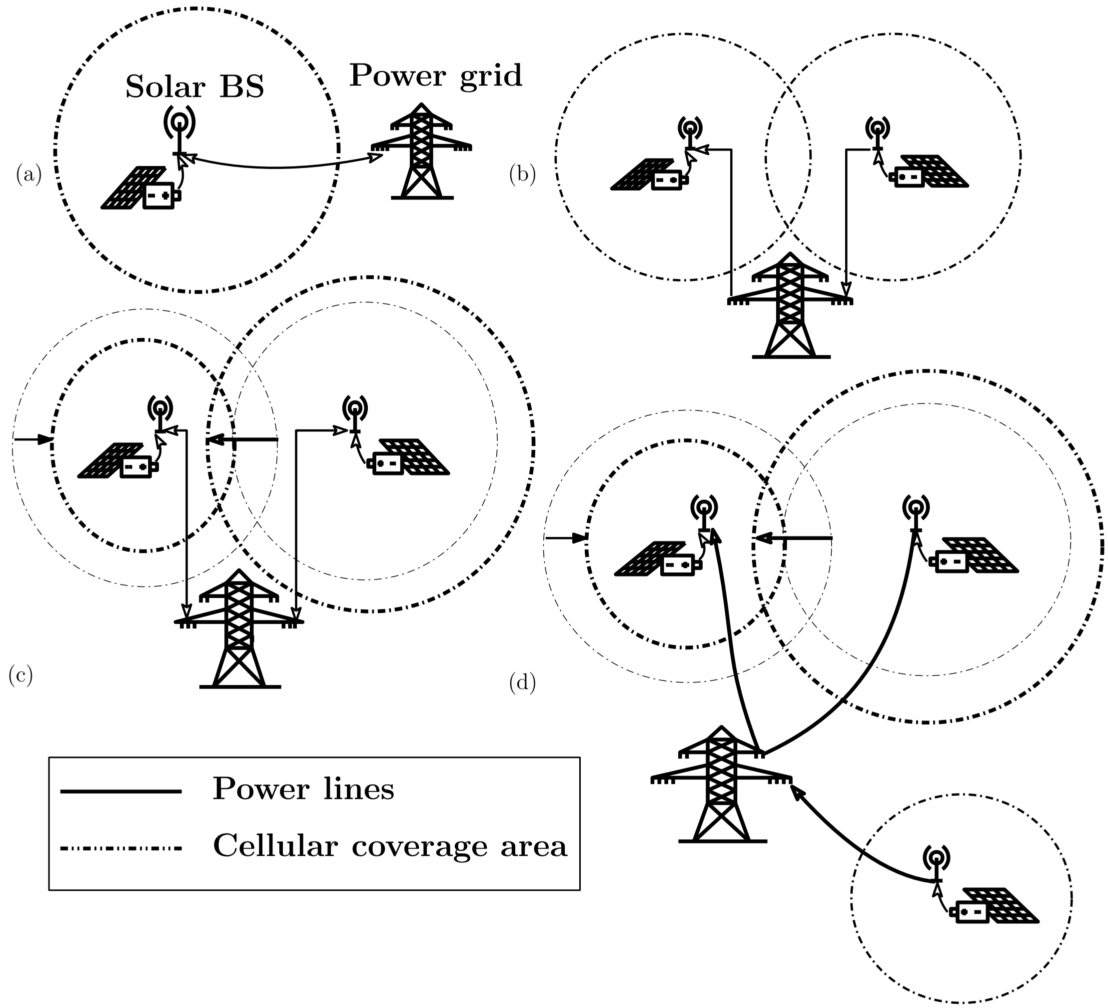

Figure 1: Illustration of (a) isolated grid-connected and renewable energy powered BS (as an example, we use solar power), (b) BS load aware energy sharing, (c) BS green energy aware coverage adjustment based load management, (d) proposed CASE framework for green cellular network services.

BS traffic and green energy harvest at each BS. The presence of this dual stochasticity results in skewed non-homogeneous traffic and green energy imbalances across the network.

Most of the works in the literature have optimized system design either with respect to traffic [8] or green energy [10]. We argue that pure traffic aware or green energy aware optimization frameworks will not be able to fully utilize the green energy potential in the network. Due to the inherent space-time varying stochasticity in BS traffic and green energy harvest, in a multi-BS scenario, only load management or only energy management strategies perform sub-optimally in terms of operator revenue and user QoS. The system performance is significantly impacted especially at higher traffic load and energy skewness levels across the BSs.

Hence, as an advance, in this paper we propose a joint traffic and green energy optimization based cooperative coverage adjustment and sharing of energy (CASE) framework. The framework exploits spatio-temporal traffic and energy inhomogeneities across the networked BSs by leveraging the grid connectivity to aid better QoS, higher profit on network services, as well as green energy sustainability. To this end, the proposed framework also estimates the optimal CAPEX which should be provisioned with each BSs towards achieving greenness, i.e., energy sustainability. We will discuss the paper positioning with respect to the literature in greater detail in Section II. Next we discuss the key contributions in this paper.

B. Contributions

The key contributions are as follows.

1) In the proposed joint traffic and green energy optimization based CASE framework, the traffic load and green energy inhomogeneities across the networked and grid-connected BSs are utilized for provisioning better QoS while enhancing in network service profit. An analytical framework is developed to realize cost profitable green future network services by jointly optimizing the BS traffic and green energy harvest in the network, wherein the BSs flexibly perform load aware coverage adjustment and energy sharing.
2) The mobile service operator profit maximization problem is formulated by analytically modeling the space-time varying traffic-energy imbalances in addition to accounting for the physical constraints. The operator profit is observed to depend on the number of users served, the amount of energy shared among the BSs, and the solar provisioning at each BS, i.e., CAPEX.

Table I: Comparison of state-of-the-art with current work

	Purely renewable energy harvesting without grid connectivity	Grid connected and renewable energy harvesting	Load management	Energy management
[11]		✓		
[12], [13], [14], [15]	✓		✓	
[16], [17]			✓	
[18], [19], [8]		✓	✓	
[10], [20]–[22]		✓		✓
This work, CASE		✓	✓	✓

3) For a given CAPEX, the profit maximization problem is decomposed into two independent sub-problems, QoS maximization and green energy utilization maximization, respectively. The sub-problems are independently solved and the optimal performance expressions are derived. Further, optimum CAPEX to achieve an energy sustainable system is computed.
4) The proposed CASE framework is compared with the state-of-the-art strategies namely only coverage adjustment (only CA) [8], only sharing of energy (only SE) [10], and the benchmark without CASE (w/o CASE) framework [23]. Besides achieving energy sustainability, significant gains in user QoS and service operator profit, up to 18.38% and 39.38% respectively, are observed at high skewness scenario.

C. Organization

The paper layout is as follows. Section II outlines the state-of-the-art and motivates the framework exploiting traffic and energy imbalances. Section III presents the system model. Section IV presents network service operator profit maximization formulation through the proposed CASE framework. Section V presents the key results, observations, and inferences, followed by the conclusion in Section VI.

II. Related Works

In this section we discuss the state-of-art techniques towards green communication networks. The existing techniques can be broadly classified into two categories depending on the BS power source and the network operation strategy. We will discuss the state-of-art pertaining to both these classes.

A. On the basis of BS power source

Traditionally the BSs have been powered through the on-grid supply [16], [17], generating carbon footprint. Recently there has been an interest towards exploring renewable power supplies to the BS and reduce the on-grid energy purchase.

Achieving carbon neutrality using renewable energy supplies like solar or wind energy to power the BSs has been a popular strategy [11], [24], [25]. In such frameworks, the BSs rely on green energy harvest to meet the load demands rather than procuring energy from the power grid. While renewable energy powered frameworks are highly energy efficient, they are prone to climatic influence which increases the randomness of green energy harvest. These networks require to be over-provisioned with renewable energy supplies to avoid random energy outages, thereby incurring significant CAPEX to the mobile network service operator.

To overcome the shortcomings of purely renewable energy powered communication systems, dual-powered, i.e., networks wherein the BS is powered with renewable energy source in addition to power grid connectivity are emerging as an attractive option as shown in Fig. 1(a). In this paper, as a use case, we consider solar energy as the renewable energy source to the BSs. Next we discuss related works wherein the system design is performed based on the network operation strategy.

B. On the basis of network operation strategy

State-of-art achieving energy-efficient communication networks on the basis of network operation strategy involved can be further classified as load or traffic management and energy management frameworks. We discuss both these distinct sub-categories in detail below.

1) Load management frameworks

Load management strategies to reduce network energy consumption includes intelligent BS sleeping [12], cell breathing frameworks [13], [26], and intelligent user offloading/association strategies [8], [18], [19], [27]–[33]. The motivation behind such analysis is to reduce/offload the energy starved BS by transferring load to other BSs/network access points as shown in Fig. 1(c). Recent frameworks proposed in [12], [13] have considered intelligent BS sleeping strategies to reduce network energy consumption. The authors in [27], [19], [31] studied optimum resource allocation in cellular networks to achieve optimal BS energy consumption. The authors in [32] proposed cell activation framework to balance energy consumption and QoS satisfaction in wireless networks.

The framework in [8] presents a coverage adjustment (only CA) based strategy to design energy efficient networks. While such frameworks are very effective, there are possibilities that due to distributed nature of the BSs, the temporal green energy available in the network might not be fully utilized. Intuitively, frequently altering BS antenna power level in cell-breathing frameworks is not very convenient to the operator. Moreover, such frameworks are constrained by a finite power radiating budget, thereby limiting the user QoS [34].

Recent frameworks have also analyzed the possibility of reducing the number of BSs in the network through network coding [16], [17] to achieve energy efficient networks. While this strategy may be useful in homogeneous load scenarios, the cellular networks are generally subjected to space-time varying inhomogeneous loads. In such inhomogeneous traffic scenario, having a limited number of BSs in the network may limit the network performance, thereby reducing the user QoS.

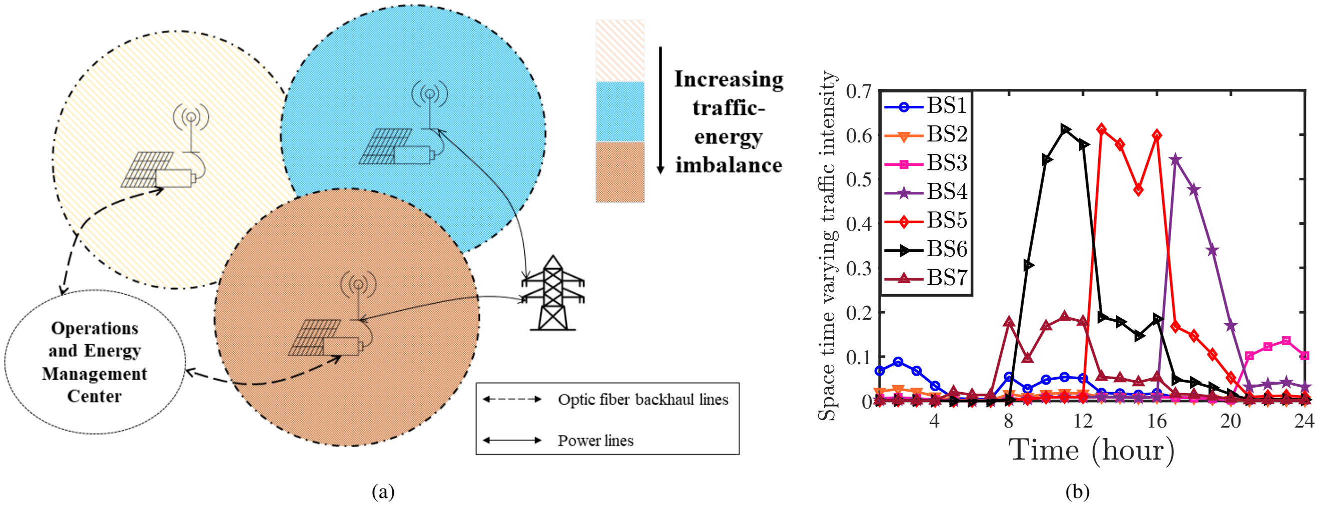

Figure 2: Illustrating (a) space varying traffic-energy imbalances, (b) space-time varying traffic-energy imbalances in grid connected and renewable energy powered cellular network at $\zeta = 1.2$ for a network of seven BSs.

2) *Energy management frameworks*

Energy management strategies proposed in [10], [20]–[22], [35] aim to reduce the network energy consumption by intelligently exploiting the space-time inhomogeneites in BS load and energy harvest, thereby improving temporal green energy utilization as shown in Fig. 1(b). While such sharing of energy (only SE) based frameworks as in [10] are extremely effective in reducing the grid energy procurement and minimizing the carbon footprint, they are limited by finite green energy storage capacity and finite antenna power radiation limit [34] due to which a BS cannot serve a large number of users associated with it. Hence, at skewed traffic inhomogeneities, the performance of such energy management strategy degrades, resulting in reduction of user QoS.

Beyond the current literature, to fully leverage the effects of space-time varying traffic-energy imbalances, we consider a joint traffic and energy management involving networked cellular coverage adjustment and energy sharing across the cells, as well as energy trading with the grid, as depicted in Fig. 1(d). The proposed joint traffic-energy management framework is aimed to benefit in terms of better user QoS, higher service revenue to the operator, as well as green energy sustainability. The lacuna in the literature is summarized and our proposed CASE strategy is positioned in Table I.

III. System Model

We consider the downlink of a grid connected and solar powered wireless communication network. A closed area A having U users is considered which is covered by a set of B BSs. The user distribution is modeled as a homogeneous binomial point process of density λ. At the design and deployment stage, K-Means clustering algorithm is used to compute the optimal BS locations. It is assumed that each BS is individually solar provisioned with N_{PV} photovoltaic (PV) panels and N_B storage batteries, in addition to power grid connectivity as show in in Fig. 2(a). Each BS is connected with the operations and energy management center (OEMC), which is implemented at the core network and communicates with the BSs through optical fiber based backhaul connection. The BSs also have the flexibility to transfer energy among each other through the existing grid infrastructure. Let the BSs and users associated with the BSs be represented as $\mathcal{B} = \{1, 2, \ldots, B\}$ and $\mathcal{U} = \{U_1, U_2, \ldots, U_b\}$ $\forall$ $b \in \mathcal{B}$, respectively, with the total network users being $U = \sum_b U_b$. Each BS b is assumed to have a coverage area of radius R_b and a downlink transmit power level P_b with $0 \le P_b \le P_m$. The BSs have the flexibility to modify their coverage areas, share energy among each other, or trade energy with the grid as shown in Fig. 1(d). In the upcoming subsections we model the BS load intensity and energy harvest characteristics.

A. *BS load intensity profile*

The hourly net traffic intensity in area A is denoted as $\rho(t)$ [36]. The hourly varying load intensity at a BS b is represented as $\rho_b(t)$, such that $\sum_{b=1}^{B} \rho_b(t) = \rho(t)$. Additionally, due to dynamic user displacement in the network, the BSs may experience skewed space-time varying traffic which is modeled through a skewness intensity factor ζ. Mathematically $\rho_b(t) = \Gamma_b(t) \times \rho(t)$, where $\Gamma_b(t)$ represents the skewness of load intensity subjected on a BS and is given as,

$$\Gamma_b(t) = \frac{e^{\zeta \times b}}{\sum_{b=1}^{B} e^{\zeta \times b}}, s.t., \sum_{b=1}^{B} \Gamma_b(t) = 1. \tag{1}$$

Thus, $\rho_b(t) = (\Gamma_b(t) \times \rho(t)) = U_b(t)/U$. Note that, $\zeta \ge 0$, with $\zeta = 0$ denoting the homogeneous load scenario, whereas $\zeta > 0$ represents increasing load inhomogeneity. The space time variation of user traffic is illustrated in Fig. 2(b).

B. *Resource allocation and BS power profile*

In this subsection we discuss resource allocation in the network and compute the power profile of a BS. It is assumed that the BSs are dynamically allocated the frequency spectrum depending on the fraction of users associated with them. Hence, BS b is allocated a bandwidth $BW_b = BW \times \rho_b(t)$, with BW denoting the total bandwidth availability. Further, each user associated with BS b is allocated equal bandwidth

Table II: Parameter notations used in the paper

Notation	Parameter
A	Closed area under observation
B	Number of BSs
P_m	Maximum downlink transmit power level
$\rho_b(t)$	Traffic intensity at BS b at time t
ζ	Skewness intensity factor
BW_{ub}	Frequency resource allocated to user u by BS b
r_{ub}	Rate achieved at user u by BS b
P_{ub}	Power allocated to user u by BS b
g_{ub}	Channel gain at user u when associated with BS b
σ^2	Power spectral density of AWGN
d_{ub}	Distance of u from BS b
n	Path loss exponent
N_{tr}	Number of transceivers at BS
P_s	Static power consumption by a BS
E_b	Energy consumption by BS b
θ	Constant denoting slope of dynamic power consumption
N_{PV}	Number of PV panels
N_B	Number of storage batteries
B_m	Maximum energy storage capacity at a BS
B_{cap}	Unit battery capacity
B_c	Critical threshold level of battery storage
δ	Depth of discharge
$L_b(t)$	Battery level of BS b at time t
$ED(t)$	Number of energy-deficient BSs at t
ES	Number of energy-sufficient BSs at t
$D_b(t)$	Deficit energy at BS b at time t
SH_b	Sharable green energy with BS b
R_{serve}	Revenue earned by serving users
R_{sell}	Revenue earned by selling energy back to grid
C_{share}	Cost incurred in sharing energy among the BSs
C_{buy}	Cost incurred in procuring energy from grid
$CAPEX$	Capital expenditure incurred
C^b	Price of buying unit energy from power grid
G_b	Grid energy procured from power grid
C_{sh}	Price of unit energy sharing using grid infrastructure
E_b^{sh}	Amount of energy shared to an energy-deficit BS
C_{sell}	Price of selling unit energy back to grid
E_b^{sell}	Amount of energy sold to grid by BS b
θ_{th}	QoS rate guarantee
π_{ub}	User-BS association indicator variable

resource $BW_{ub} = BW_b/U_b$. The rate achievable by a user u when associated with BS b is given as,

$$r_{ub}(t) = BW_{ub}\log_2(1 + SNR_{ub}(t)),$$
$$\text{with, } SNR_{ub}(t) = \frac{P_{ub}(t)g_{ub}(t)}{(BW_{ub}\sigma^2)d_{ub}^n} \geq \theta_{th}. \tag{2}$$

Here, P_{ub} denotes the downlink power transmitted by BS b to user u, g_{ub} denotes the channel gain between user u and BS b, σ^2 denotes the power spectral density (PSD) of additive white Gaussian noise, d_{ub} denotes the physical distance between the user and BS, n denotes the path loss exponent, and θ_{th} signifying the QoS requirement per user.

The user QoS is defined as the minimum rate guarantee in terms of the minimum required signal to noise ratio (SNR) θ_{th}. Hence, a user is considered to be served by the network, only if the user has an SNR higher than θ_{th} when associated with a BS. The BS energy consumption consists of the static energy P_s required to power the BS hardware and the dynamic energy consumption ($P_b = \sum_u P_{ub} = \rho_b \times P_m$) which varies with the BS load. The hourly BS energy consumption is

$$E_b(t) = N_{tr} \times (P_s + \theta P_b(t)), \tag{3}$$

with N_{tr} denotes the number of transceiver antennas on the BS and θ being a constant.

C. Energy harvest profile

Each BS b is assumed to be provisioned with N_{PV} PV panels through which the BS harvests $H_b(t)$ green energy, stored in N_B storage batteries. The BS has a finite green energy storage capacity, $B_m = N_B \times B_{cap}$ with B_{cap} denoting the individual battery capacity. The BS storage is also assumed to have a critical threshold below which the batteries wont discharge, denoted as $B_c = \delta \times N_B \times B_{cap}$. Here δ denotes the depth of discharge decided by mobile service operator. The temporal evolution of BS green energy storage level is,

$$\begin{aligned} L'_b(t) &= L_b(t-1) + H_b(t) - E_b(t), \\ L_b(t) &= \min\{\max\{L'_b(t), B_c\}, B_m\}. \end{aligned} \tag{4}$$

Depending on the residual green energy level, a BS is classified as energy-deficient if $L'_b(t) < B_c$, or energy-sufficient if $L'_b(t) \geq B_c$. Thus, the BSs are grouped temporally into two disjoint sets. Let the number of energy-deficient and energy-sufficient BSs at time t be ED and ES, such that $ED + ES = B$. The net deficit energy at the energy-deficient BSs in the network is computed as, $D(t) = \sum_{b=1}^{ED} D_b(t) = \sum_{b=1}^{ED}(B_c - L'_b)$. Similarly, the net sharable energy available with the energy-sufficient BSs (indexed by b') in the network is: $SH(t) = \sum_{b'=1}^{ES} SH_{b'}(t) = \sum_{b'=1}^{ES}(L'_{b'} - B_c)$.

It may be noted that the main component of BS energy consumption is in its signal transmission to the downlink users [34]. Traffic reception (which is due to uplink communication) is relatively a much less energy intensive activity [37]. Since the core objective in this paper is studying the green energy-traffic imbalance at the BSs and exploiting it via joint coverage adjustment and sharing of energy, downlink communication of the BSs sufficiently captures that motive. Therefore, for analytical simplicity and clarity of conveying the main claim, we have focused on the downlink traffic only. Based on the reasoning above, we further emphasize that the main claims in this paper are expected to remain valid even with the additional consideration of uplink traffic communication [37]. In Section IV, mathematical formulation of the various aspects on mobile operator profit maximization are presented.

IV. Operator Profit Maximization Formulation

The net profit/loss to a mobile service operator depends on five cost parameters: revenue earned by serving users (R_{serve}), revenue earned by selling energy back to the power grid (R_{sell}), cost incurred to service operator in energy sharing (C_{share}), cost incurred to service operator in purchasing energy from the grid (C_{buy}), and CAPEX incurred by the service operator in solar provisioning the BSs ($CAPEX$). It may be noted that C_{buy} is included for a general analytical framework, though in a networked and grid-connected BS with green energy aware CAPEX the BSs will not procure energy from the grid. Also, the energy sharing cost through the power grid connectivity is borne by the mobile service operator towards power grid infrastructure maintenance. The sustainable grid energy procurement independent design is discussed in greater detail in Sections IV-B and IV-C.

The unconstrained operator profit maximization problem is,

$$\max P = R_{serve} + R_{sell} - C_{share} - C_{buy} - CAPEX. \tag{5}$$

The cost parameters are mathematically defined below.

The CAPEX is a function of number of BSs, number of PV panels and storage batteries provisioned with a BS, and their corresponding lifetimes L_{PV}, L_B and unit costs C_{PV}, C_B. It is computed as,

$$CAPEX = B \times \left(\frac{N_{PV} C_{PV}}{L_{PV}} + \frac{N_B C_B}{L_B} \right). \tag{6}$$

C_{buy} refers to the operational cost incurred to the operator in procuring energy from the grid, if the BSs become energy-deficient. With G_b denoting the total energy procured (in units) by an energy deficient BS b from the grid, mathematically,

$$C_{buy} = \sum_{t=1}^{T} C^b \times \sum_{b=1}^{ED} G_b(t). \tag{7}$$

C_{share} refers to the cost incurred to the operator in performing energy transfer from the energy-sufficient BSs to the energy-deficient BSs. With E_b^{sh} denoting the total green energy transferred (in units) to a energy-deficient BS from energy-sufficient BSs, mathematically,

$$C_{share} = \sum_{t=1}^{T} C_{sh} \times \sum_{b=1}^{ED} E_b^{sh}(t). \tag{8}$$

R_{sell} refers to the revenue earned by the operator in selling excess sharable energy present with the energy-sufficient BSs to the power grid. With E_b^{sell} denoting the total energy sold (in units) back to the power grid, mathematically,

$$R_{sell} = \sum_{t=1}^{T} \sum_{b=1}^{B} C_{sell} E_b^{sell}(t). \tag{9}$$

Finally, $R_{serv} = \sum_{t=1}^{T} \sum_{b=1}^{B} C_{Serv} U_b(t)$ represents the revenue earned by an operator by serving users in the network. For a given CAPEX, the net profit can be expressed as

$$\begin{aligned} P' = \sum_{t=1}^{T} \sum_{b=1}^{B} C_{Serv} U_b(t) + \sum_{t=1}^{T} \sum_{b=1}^{B} C_{sell} E_b^{sell}(t) - \\ \sum_{t=1}^{T} \sum_{b=1}^{B} C_{sh} E_b^{sh}(t) - \sum_{t=1}^{T} \sum_{b=1}^{B} C^b G_b(t). \end{aligned} \tag{10}$$

It is notable that P' is not a function of time; rather it is a function of CAPEX provisioning. It is discussed in detail in Section IV-C. $C_{sell}, C_{sh},$ and C^b, respectively denote the price of selling, sharing, or purchasing unit energy to (through or from) the grid. C_{serv} denotes the daily revenue earned by serving the users. From (10), we observe that $C_{buy}, C_{share},$ and R_{sell} depend on the CAPEX provisioning on a BS. These three parameters are influenced by changing CAPEX and depend on the quantum of energy harvest. On the contrary, C_{serv} is represents the user QoS satisfaction, which is not governed the CAPEX provisioning. Hence, we break the service operator profit maximization in two parts; we first solve for user QoS maximization and then solve the problem containing cost parameters which are influenced by CAPEX.

A. User service maximization problem

The user service maximization problem is given as,

$$\begin{aligned} P_1 : \max_{U_b} \sum_{t=1}^{T} \sum_{b=1}^{B} C_{Serv} U_b(t) \\ s.t.,\ U_b : SNR_{ub} \geq \theta_{th}, u \in \{U_b\} \forall b \in B. \end{aligned} \tag{11}$$

The problem P_1 is equivalent to maximizing the instantaneous sum rate of the network given as,

$$\begin{aligned} & P_2 : \max_{\pi_{ub}, P_{ub}} \sum_{b=1}^{B} \sum_{u=1}^{U} \pi_{ub} BW_{ub} \log_2 \left(1 + \frac{P_{ub} g_{ub}}{(BW_{ub} \sigma^2 d_{ub}^n)} \right) \\ & s.t.,\ C1.\ \pi_{ub} \in \{0,1\} \xrightarrow{\text{relaxed as}} \pi_{ub} \in [0,1] \\ & C2.\ \sum_{b=1}^{B} \pi_{ub} = 1, \\ & C3.\ \pi_{ub} \geq 0, \\ & C4.\ P_b = \sum_u P_{ub} \leq P_m \\ & C5.\ P_{ub} \geq \theta_{th} BW_{ub} \sigma^2 d_{ub}^n / g_{ub}. \end{aligned} \tag{12}$$

Constraint $C1$ indicates that a user can either be associated with a BS or be out of service. $C2$ indicates that at a time a user can be associated with only one BS. $C4$ constraints the power allocation by a BS to a upper limit P_m as per the Federal communications commission (FCC) limits. $C5$ constraints the network to meet the user QoS. Due to constraint $C1$, this problem is a 0-1 knapsack combinatorial optimization problem, and is NP hard in nature. To solve the problem, we relax C1 such that, $\pi_{ub} \in \{0,1\} \longrightarrow \pi_{ub} \in [0,1]$, i.e., we change the space of the optimization variable $\pi_{ub} \in \mathbb{Z}^+ \longrightarrow \mathbb{R}^+$. After performing this relaxation, the objective function of problem P_2 is now a convex problem with affine constraints. It may be noted that $C5$ denotes the user QoS constraint given in (2). The Lagrangian to P_2 is,

$$\begin{aligned} & \mathbb{L}(\underline{\pi}, \underline{P}, \underline{\alpha}, \underline{\beta}, \underline{\gamma}, \underline{\delta}) = \sum_{b=1}^{B} \sum_{u=1}^{U} \pi_{ub} BW_{ub} \log_2 \left(1 + \frac{P_{ub} g_{ub}}{(BW_{ub} \sigma^2 d^n ub)} \right) \\ & + \sum_u \alpha_u \left(\sum_b \pi_{ub} - 1 \right) + \sum_b \gamma_{ub} \left(\sum_u P_{ub} - P_m \right) \\ & - \sum_b \sum_u \beta_{ub} \pi_{ub} - \sum_u \delta_u (P_{ub} - \theta_{th} BW_{ub} \sigma^2 d_{ub}^n / g_{ub}). \end{aligned} \tag{13}$$

Solving the Lagrangian we get,

$$\sum_u P_{ub} = P_b = \frac{\exp \sum_u \left(\frac{(\beta_{ub} - \alpha_u) \ln 2}{BW_{ub}} \right) - U_b}{\sum_u g_{ub} / (BW_{ub} \sigma^2 d^n ub)}$$

$$\text{or,}\ P_b^* = \min \left\{ \frac{\exp \sum_u \left(\frac{(\beta_{ub} - \alpha_u) \ln 2}{BW_{ub}} \right) - U_b}{\sum_u g_{ub} / (BW_{ub} \sigma^2 d^n ub)}, P_m \right\}, \tag{14}$$

$$\text{and,}\ \left(\sum_u \pi_{ub} \right)^* = U_b^* = \sum_u \left(\frac{(\delta_u - \gamma_{ub}) \ln 2 g_{ub}}{BW_{ub}^2 \sigma^2 d_{ub}^n} \right). \tag{15}$$

It can be observed that the optimal values of the objective variables are a function of the Lagrange-dual multipliers. In order to compute these dual variables, we use sub-gradient based search [38] to compute and update the variables, as

$$\alpha_u(i+1) = \alpha_u(t) - S_1[\sum_b \pi_{ub} - 1] \tag{16}$$

$$\beta_{ub}(i+1) = \beta_{ub}(t) - S_2[\pi_{ub}] \tag{17}$$

$$\gamma_b(i+1) = \gamma_b(t) - S_3[P_b - P_m] \tag{18}$$

$$\delta_u(i+1) = \delta_u(t) - S_4[BW_{ub}\log_2(1+P_b\theta_1(u)) - r_0]. \tag{19}$$

Here, S_j represents the step size used to update the dual variables, and i is the number of iterations. Problem P_2 was based on instantaneous sum rate maximization. To study the effects of averaging the stochastic fading channel, we formulate an expected rate maximization problem. From (2), the only parameter introducing randomness is the channel gain g_{ub}. The channel between the user u and the BS b is assumed Rayleigh fading, resulting in the power gain to be exponentially distributed. Let $P_{ub}/(BW_{ub}\sigma^2 d_{ub}^2) = K$.

Lemma 1. *Probability density function (PDF) of rate achievable by a user over a Rayleigh fading channel is*

$$\begin{aligned} f_R(r) = \exp\left\{1 - \exp\left(\frac{r\ln 2/BW_{ub})}{K}\right)\right\} \times \\ \left(\frac{\ln 2 e^{r\ln 2/BW_{ub}}}{BW_{ub} \times K}\right). \end{aligned} \tag{20}$$

Proof.

$$\begin{aligned} F_R(r) &= \mathbb{P}[R \le r] = \mathbb{P}\left(r_{ub} \le r\right) \\ &= \mathbb{P}\left(g_{ub} \le \frac{e^{r\ln 2/BW_{ub}} - 1}{K}\right) \end{aligned} \tag{21}$$

Using transformation of random variables, we get the PDF of rate achievable as shown in (20). □

Using the derived PDF, the expected rate comes to be

$$\mathbb{E}_R(r) = \frac{BW_{ub}}{\ln 2} e^{1/K} E_i(1/K) \tag{22}$$

Here, $E_i(.)$ represents the euler integral. This expression can be approximated [39] as

$$\mathbb{E}_R(r) = \frac{BW_{ub}e^{-1/K}}{\ln 2}\left(-E + \ln\left(1/K\right) + 1/K\right), \tag{23}$$

with E being Euler's constant (E = 0.5772157). The modified expected rate maximization formulation is shown below.

$$\begin{aligned} P_3: \max_{\pi_{ub}, P_{ub}} & \sum_{b=1}^{B}\sum_{u=1}^{U} \pi_{ub}\frac{BW_{ub}e^{-1/K}}{\ln 2}\left(-E + \ln\left(1/K\right) + 1/K\right) \\ s.t., & \; C1 - C4, \\ & C5.\; P_{ub} \ge \theta_{th} BW_{ub}\sigma^2 d_{ub}^2. \end{aligned} \tag{24}$$

It may be noted that $C5$ now denotes the expected SNR constraint. We use the sub-gradient based search discussed before to solve P_3. The green energy maximization problem is discussed in the next subsection.

B. Green energy utilization maximization problem

In the previous subsection, we computed the optimal load at each BS. After fixing the demand at each BS, in this subsection, we intelligently decide the amount of green energy to be shared, sold, or purchased from the power grid.

As discussed in Section III-C, depending on the BS green energy storage status, at any point in time a BS can be either energy-deficient or energy-sufficient. We propose that an energy-deficit BS can meet the deficit energy by two ways: either the BS can utilize the sharable green energy in the network through cooperative energy transfer by the energy-sufficient BSs or procure the deficit energy directly from the power grid. Thus, from a network perspective, $D(t) = E^{sh}(t) + G(t)$, where $G(t)$ denotes the energy to be procured by energy-deficient BSs from the power grid.

An energy-deficit BS is aided to meet its existing deficit from energy-sufficient BSs and only then procure from the power grid, if needed further. Similarly, the energy-sufficient BSs after meeting the requirements of the deficient-BSs can sell the surplus sharable green energy back to the power grid. These steps are also aligned with the objective of maximizing the opportunity of green energy usage for communication. To achieve this, the price to be paid for unit energy transfer from the networked BSs needs to be higher than price associated with selling unit energy to the grid, but lower than the price associated with purchasing unit energy from the grid, i.e., $C_{sell} < C_{sh} < C^b$. In this scenario, the energy-deficient BSs have a cheaper alternative of meeting the deficit energy through energy transfer by the networked energy-sufficient BSs, rather than directly purchasing energy from the grid. Similarly, the energy sufficient BSs also have an incentive to earn a higher price for their sharable green energy rather than selling it to the grid at a lower price.

Two specific scenarios may happen at a time instant t depending on the amounts of net deficit or sharable energy, i.e., $D(t)$ or $SH(t)$. These two scenarios are detailed below.

$$\text{If } SH(t) \ge D(t): \begin{cases} G(t) = 0 \\ E^{sell}(t) = SH(t) - D(t) \\ E^{sh}(t) = D(t). \end{cases} \tag{25}$$

$$\text{If } SH(t) < D(t): \begin{cases} G(t) = D(t) - SH(t) \\ E^{sell}(t) = 0 \\ E^{sh}(t) = SH(t). \end{cases} \tag{26}$$

In the above equations, $E^{sell}(t)$ represents the temporal energy which can be sold by energy-sufficient BSs to the power grid and $E^{sh}(t)$ represents the amount the temporal green energy which is shared among the networked BSs. From (25) and (26), we infer that,

$$\begin{aligned} E^{sh}(t) &= \min\{D(t), SH(t)\}, \\ \text{and } E^{sell}(t) &= \min\{SH(t) - D(t), 0\}. \end{aligned} \tag{27}$$

For a given CAPEX, the Green energy utilization maximization problem from (10) is,

$$\max \sum_{t=1}^{T}\sum_{b=1}^{B} C_{sell}E_b^{sell}(t) - \sum_{t=1}^{T}\sum_{b=1}^{B} C_{sh}E_b^{sh}(t) - \sum_{t=1}^{T}\sum_{b=1}^{B} C^b G_b(t). \tag{28}$$

Using equations (25), (26), and (27) we simplify (10) as,

$$= \sum_{t=1}^{T}\left(\sum_{b=1}^{B} C_{Serv}U_b(t) + (C^b - C_{sell} - C_{sh})\sum_{b=1}^{ED} E_b^{sh}(t) + \underbrace{C_{sell}\sum_{b'=1}^{ES} SH_{b'}(t) - C_{buy}\sum_{b=1}^{ED} D_b(t)}_{=(C_{sell}SH(t)-C_{buy}D(t)),\ \text{constant at } t}\right). \tag{29}$$

Thus, the above problem has a single decision variable E_b^{sh} representing the amount of green energy transferred to a energy-deficient BS from the energy-sufficient BSs. The problem can be simplified as,

$$P_4 : \max_{E_b^{sh}} \ (C^b - C_{sell} - C_{sh})\sum_{b=1}^{ED} E_b^{sh}(t) + constant(t) \tag{30}$$

The optimal solution to this problem (Appendix-B, [10]) is

$$E_b^{sh}(t) = \begin{cases} D_b(t), & \text{if } D(t) \leq SH(t) \\ \left(D_b(t)\sum_{b'=1}^{ES} SH_{b'}(t)\right) / \sum_{b=1}^{ED} D_b(t), & \\ & \text{if } SH(t) < D(t). \end{cases} \tag{31}$$

From (10) and (30), we infer that the profit maximization problem contains two decision variables, U_b i.e., users being served in the network and E_b^{sh}, representing the amount of energy shared to a deficit BS in the network. Hence, maximizing user service and green energy utilization in the network leads to increasing the service operator profit. Both the decision variables are independent to each other. Hence, maximizing both these variables individually will be equivalent to maximizing them together. It may be noted that the current framework does not impose any penalty on the operator for not meeting user QoS requirements of all active users in the network. If the operator does not meet user QoS, operator earns less service revenue. Hence, to maximize profit, the operator strives to meet the QoS requirements of the temporally active network users.

The working steps of the proposed CASE framework is illustrated through Fig. 3. The framework involves the BSs first sending the energy harvest data and load data to the OEMC through fiber-optic backhaul lines, which is used to compute the battery level of each BS. The OEMC then classifies each BS as energy-deficient (if the battery level is below an operator defined threshold) or energy-sufficient (if the battery level of the BS is above that threshold). Depending on the BS class, the deficit energy required per energy-deficient BS or excess sharable energy with each energy-sufficient BS after serving its current load is computed. The

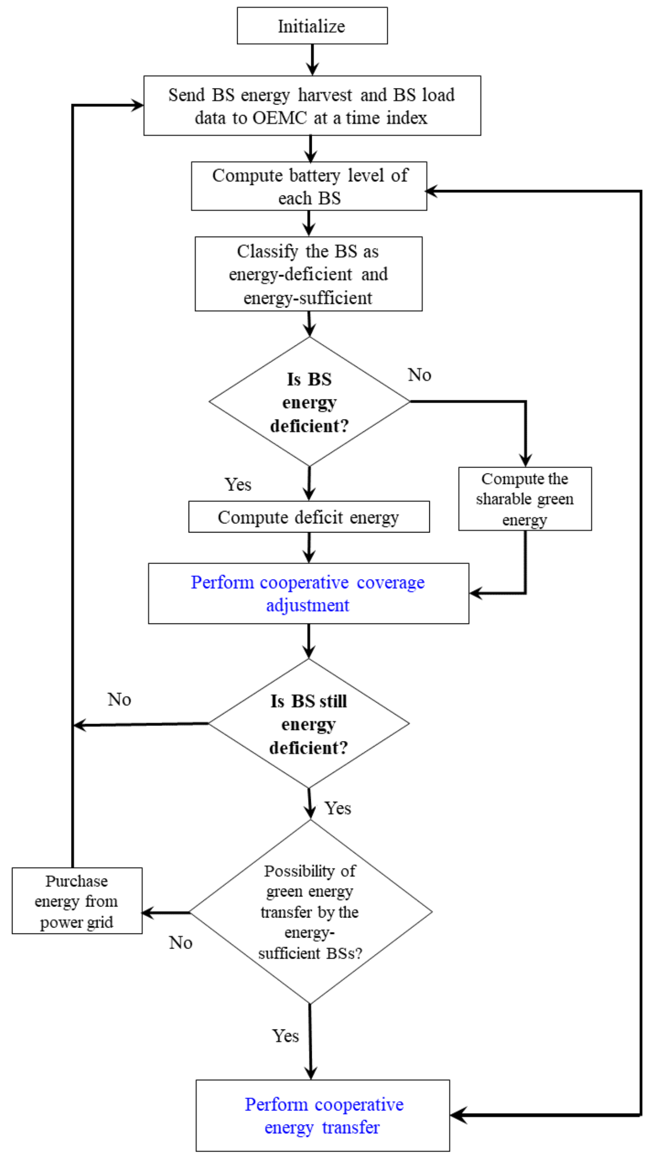

Figure 3: Illustration of the proposed CASE framework.

CASE strategy first performs cooperative coverage adjustment among the networked BSs to alleviate the load of energy-deficient BSs. In the cooperative coverage adjustment process, the OEMC checks if the neighboring BSs of the energy-deficient BS have capacity to offload some users. If the neighboring BSs can offload and cater to some users of the energy-deficient BS, then the user association is changed and cellular coverage areas are modified accordingly.

After performing cooperative coverage adjustment, there might still be a possibility that due to the reconfigured BS loads, some BSs might have some additional green energy in there respective energy storage. Hence cooperative energy sharing is performed by the OEMC to ensure complete utilization of green energy at that time instant. If no BS requires aid from the energy-sufficient BSs then the remaining sharable energy is sold to the power grid. In the event where there is no sharable energy remaining with any energy-sufficient BS, but the energy-deficient BSs still require energy to meet user QoS, then energy is procured from the power grid. This cycle is repeated at each time instant, so as to minimize the grid energy procurement and guarantee user QoS to the full extent. The complexity of the proposed CASE framework is $\mathbb{O}(T \times B^2)$, i.e., the complexity is linear with time, but increases quadratically with the number of BSs.

It may be noted that the number of users being served by a BS is limited by the FCC regulation on antenna power radiation. Similarly, the amount of green energy transferred in the network is limited by the storage battery capacity with each BS. Thus, the operator profit for a given CAPEX provisioning cannot be indefinitely high; instead it is limited by these two practical physical limitations.

In the upcoming subsection, we will discuss energy-sustainable CAPEX design for the proposed framework.

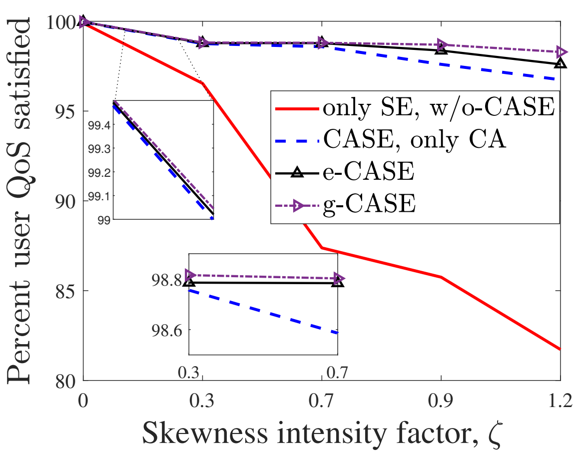

Figure 4: Illustrating variation of user QoS satisfaction with skewness intensity factor in the proposed CASE, expected-CASE (e-CASE), global-CASE (g-CASE), and other competitive state of art frameworks.

C. Sustainable system formulation

In this subsection, we aim to design self-sustainable BS clusters, i.e., the BSs are independent of grid energy procurement and hence carbon free. The service operator profit maximization P' formulated in (10) was for a given CAPEX, i.e., P' is a function of CAPEX provisioning (number of PV panels and storage batteries per BS). To compute the optimum solar provisioning at each BS such that the BS cluster becomes sustainable, we solve P_5 formulated below.

$$\begin{aligned} P_5 : \min_{B,N_{PV},N_B} \; & P'(N_{PV}, N_B) + CAPEX(N_{PV}, N_B) \\ s.t., \; & C6.\ B \geq 2 \in \mathbb{Z}^+ \\ & C7.\ 0 \leq N_{PV} \leq N_{PV}^M \\ & C8.\ 0 \leq N_B \leq N_B^M \\ & C9.\ D(t) = 0. \end{aligned} \tag{32}$$

P_5 is an integer programming problem as B, N_{PV} and $N_B \in \mathbb{Z}^+$. We solve P_5 using exhaustive search technique. Constraint $C6$ denotes that at least two BSs are required for traffic and energy cooperation. $C7$ and $C8$ constraint the number of PV panels and storage batteries to be positive integers. N_{PV}^M and N_B^M denote the upper limit of solar CAPEX provisioning derived in [10]. These bounds are useful in reducing the complexity of the exhaustive search, which is given as $\mathbb{O}(N_{PV}^M \times N_B^M)$. Constraint $C9$ denotes that the temporal deficit energy is zero, implying that the system has achieved independence from grid energy procurement. In the upcoming section, we discuss the key results and observations.

V. Results and Discussion

In this section we discuss the key results and observations. As state-of-art, we compare the performance of the proposed CASE framework with the baseline without CASE (w/o CASE), only coverage adjustment (only CA) and, only energy sharing (only SE) based frameworks. The frameworks are compared on the basis of user QoS satisfaction (Fig. 4), sharable green energy (Fig. 5(a)), CAPEX provisioning to achieve sustainability (Fig. 5(b)), and net service operator profit (Fig. 6).

The parameter values used in simulations are $A = 1$ km^2, $B = 7$, $BW = 20$ MHz, $T = 8760$, $\lambda = 3000$, $P_m = 40$ W [34], $n = 2$ [40], $\sigma^2 = -150$ dBm/Hz [41], $P_s = 118.7$ W [42], $\theta = 4.7$ [34], $\delta = 0.3$ [42], $\theta_{th} = 15$ dB [41], $B_{cap} = 2460$ Wh [42], $C^b = 0.079$ USD [43], $C_{sh} = 0.015$ USD, $C_{sell} = 0.057$ USD [44], $C_{serv} = 1.31$ USD [45], $C_{PV} = 1300$ USD [46], $C_B = 216$ USD [47]. The simulations have been performed in MATLAB R-2022b.

The simulations have been performed using annual solar harvest data of New Delhi city, obtained from National Renewable Energy Laboratory [48]. The cooperating BSs are assumed to be in the same locality. Hence, for the numerical simulations the energy harvest at each BS has been assumed to be equal. The network dynamics arise due to BS load variations, which result in variation of BS power consumption and BS green energy storage levels. The skewness intensity factor introduced in Section III-A captures the extent of network traffic dynamics.

The skewness intensity factor ζ modeled through (1) represents the fraction of higher traffic a BS experiences as compared to the balanced load scenario (when $\zeta = 0$). As ζ increases, any random BS in the network experiences a higher skewed fraction of traffic. We have simulated the system up to $\zeta = 1.2$, which corresponds to around 80% higher traffic than the balanced scenario. While ζ can take more higher values, we restricted our studies with up to 80% traffic imbalance. This is because, skewness levels higher than $\zeta = 1.2$ are not practical and have a low probability of occurrence in reality.

A. User QoS performance

The user QoS performance is measured in terms of the number users whose QoS is being guaranteed (cf. Section IV-A), which is shown in Fig. 4. The problems formulated in P_2 (CASE) and P_3 (expected CASE or e-CASE) were relaxed to make the problems tractable. Global optimum user QoS performance (g-CASE) is computed by exhaustive search method. Qualitatively the nature of the plots in Fig. 4 for the CASE, e-CASE, and g-CASE are similar to each other. Quantitatively, it is observed that the expected sum rate maximization results in a marginally better performance than the instantaneous sum rate solution especially at higher skewness conditions. This behaviour may be attributed to

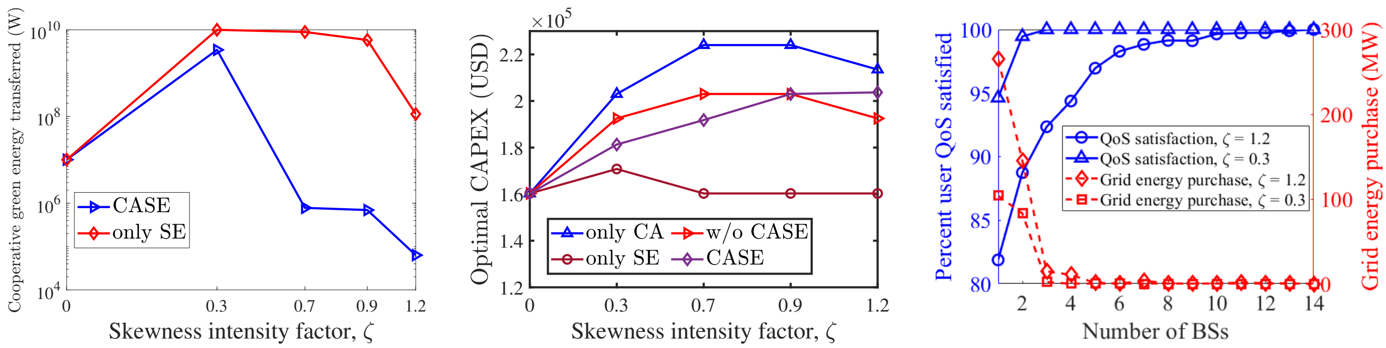

Figure 5: (a) Green energy utilization as a function of traffic-energy skewness; (b) optimal CAPEX for energy sustainability versus traffic-energy skewness; (c) user satisfaction and grid energy requirement as a function of networked BS cluster size.

the fact that since we are analyzing from a BS perspective, expected sum rate maximization results in averaging out the stochastic channel behaviour, resulting in marginally higher performance especially at higher skewness. Both the instantaneous and expected rate solutions perform marginally poor than the g-CASE, which is essentially due to the constraint $C1$ relaxation. It is also inferred from Fig. 4 that coverage adjustment based methods perform significantly better than non-coverage adjustment frameworks (only SE, w/o CASE), and the performance is more profound with increasing skewness factor (up to 18.38% gain at extreme skewness, $\zeta = 1.2$).

Thus, it is inferred that the proposed coverage adjustment based framework provides significant improvement in user QoS performance over the other competitive approaches.

B. Sustainable design

Through Fig. 5(a) we illustrate the cooperative green energy shared in the network among the BSs, thereby improving the temporal green energy utilization through the proposed CASE framework. It is inferred that amount of green energy shared in the proposed CASE framework decreases with increasing relative skewness of the BS loads. it is also inferred that the proposed framework performs poorly as compared to the 'only SE' framework. In this regard, it may be noted that Fig. 5(a) should be analyzed together with Fig. 4, wherein it is observed that the user QoS performance of the proposed CASE framework is much better than the 'only SE' framework. Thus, signifying that the loss in green energy shared is actually being used up in improving the user QoS.

Fig. 5(b) shows the variation of optimal solar CAPEX required to be provisioned to achieve energy sustainability with increasing relative skewness of load inhomogeneity. It is observed that the 'only SE' framework attains sustainability with the least CAPEX. This is because the 'only SE' involves a significant amount of green energy sharing (as depicted in Fig. 5(a)), which results in reducing the CAPEX required to achieve sustainability. It may be noted that while the only SE framework incurs least CAPEX, the user QoS is severely affected with increasing traffic inhomogeneity (Fig. 4).

It is observed that at lower skewness the proposed CASE framework incurs much lesser CAPEX to achieve energy sustainable network over 'without CASE' framework, while as the relative skewness increases the optimal CAPEX required for the proposed CASE is marginally higher than the 'without CASE' strategy. This behaviour in the nature of optimal CAPEX plot is explained as follows. At lower skewness, the CASE incurs lesser CAPEX than the baseline, i.e., 'without CASE' because cooperative energy sharing results in improving the green energy utilization within the network, thus reducing the CAPEX. As the relative skewness increases, it is observed from Fig. 4 that the CASE strategy results in serving a higher number of users in the network, thus improving the user QoS satisfaction. Due to catering to higher users in the network, the CASE framework experiences lesser green energy cooperative sharing (as illustrated through Fig. 5(a)). On the contrary, the 'without CASE' framework is observed to result in much lesser user QoS guarantee in the network, resulting in lower CAPEX as compared to CASE at higher relative skewness levels to attain energy-sustainability.

In Fig. 5(c), we illustrate the variation of user satisfaction and grid energy procurement with number of BSs at skewness levels, $\zeta = 0.3, 1.2$. While the user QoS satisfaction curves have an increasing nature, the grid energy procurement curve is observed to follow a decreasing nature, with increasing number of BSs in the network. The proposed cooperative framework results in formation of self sustainable BS clusters. From Fig. 5(c) it is inferred that at higher skewness level, more BSs are required to cooperate with each other in terms of network services like load and energy management. For instance, when the network is subjected to a higher load inhomogeneity of $\zeta = 1.2$, around 13 BSs are required to meet 100% network user QoS alongside achieving net zero grid energy procurement. On the contrary, at $\zeta = 0.3,$, around 8 BSs are sufficient to meet the user QoS in addition to forming a sustainable BS cluster.

The above observations demonstrate that, besides improved QoS, the CASE framework offers appreciable CAPEX reduction in achieving a green energy sustainable system.

C. Operator profitability

Finally, through Fig. 6 we illustrate the variation of operator net profit with increasing traffic inhomogeneity. It is inferred that the proposed CASE framework significantly outperforms the baseline w/o CASE framework, with higher gains at in-

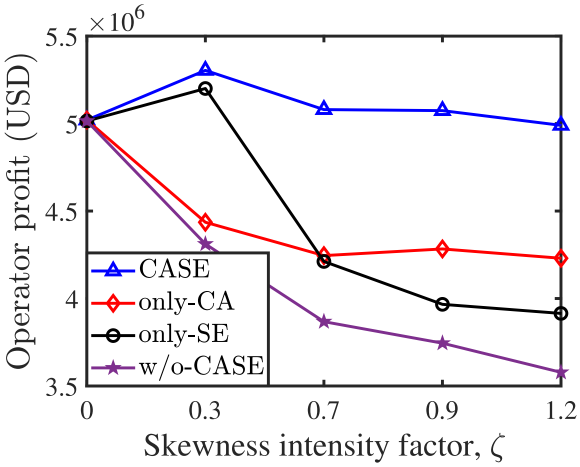

Figure 6: Variation of operator profit in the proposed CASE framework and other competitive state of art, with a cluster of seven BSs.

creased skewness levels. It is observed that the CASE initially competes with the only SE framework at lower skewness levels, but at higher skewness levels CASE competes with the only CA framework. One reason may be attributed to the fact that at lower skewness levels, in the CASE and only SE frameworks, there is much greater green energy transferred in the network (Fig. 5(a)), which assists in cutting down the grid energy procurement thereby reducing the OPEX as well as CAPEX (Fig. 5(b)). As the skewness levels increase, the only SE framework (in the absence of load management) loses out on user service revenue (Fig. 4). At higher skewness levels, the only CA framework loses out to the proposed CASE framework due to higher grid purchase in the absence of energy transfer. Quantitatively, the proposed CASE framework is observed to offer gains up to 13.49%, 24.21%, and 39.38% respectively, over the only CA, only SE, and w/o CASE frameworks at extreme skewness levels.

These results indicate that, the proposed CASE framework exploits higher traffic and energy skewness levels better, to achieve higher profits to the network services operator. This is in contrast with the other state-of-art frameworks, where the operator profit reduces significantly at higher skewness levels.

VI. Conclusion

This paper has presented a novel joint traffic and green energy optimization (CASE) framework in a grid connected and solar powered cellular framework. The proposed framework has been designed to exploit the traffic and energy imbalances across the networked BSs to fully utilize the green energy potential in the network towards realizing cost profitable green future networks. The CASE framework has been observed to improve the user QoS significantly, in addition to improving the mobile services operator's profit. With respect to the state-of-art strategies in the literature, the proposed framework has been noted to extract more prominent performance advantages in higher traffic-energy imbalance scenarios. The proposed framework is expected to pave the way towards green future communication networks.

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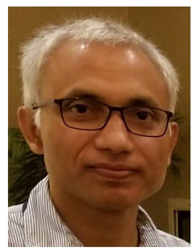

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