Distributed Energy Bank Optimization Towards Outage Aware Sustainable Cellular Networks

Ashutosh Balakrishnan, Swades De, and Li-Chun Wang

Abstract—Grid connected and solar powered base stations (BSs) acting as distributed energy sources are increasingly becoming a popular solution to mobile operators. These networks experience double stochasticity due to the space-time variations in energy harvest and BS traffic. Hence, accurate and efficient green energy outage estimation in such networks is a challenging task. In this work, we propose a complutationally efficient cooperative energy transfer based distributed energy bank strategy to alleviate green energy outage and design energy sustainable networks. We first develop low-complexity Markovian frameworks to estimate green energy outage in a standalone BS without energy cooperation (WEC) and a multi-BS energy-cooperative (EC) setting, respectively. For the WEC system, we present a computationally efficient three-state discrete time Markovian statistical model, while the multi-BS EC framework is characterized by a two-state Markov model. The energy outage is studied as a function of capital expenditure (CAPEX), manifesting engineering insights from a service provider's perspective. Subsequently for the EC framework, we formulate a CAPEX optimization problem by jointly optimizing the BS cluster size and solar provisioning on individual BSs. Our results demonstrate that the proposed EC framework alleviates the green energy outage significantly, providing computational efficiency gains and CAPEX savings over the state-of-art approaches.

Index Terms—Cooperative energy transfer, computation efficiency, energy sustainability, solar powered base station, traffic-energy imbalance

1 Introduction

The advent of Internet of Things (IoT), powered by the rise of 5G and beyond communications (B5G) [1], is expected to significantly increase the number of base stations (BS) in the communication network to cater to the increased user service demands [2]. Since BS is the most energy intensive system in a communication network [3], B5G communications are expected to contribute significantly to an increased network energy consumption and hence carbon footprint [4].

Solar powered and grid connected BSs are becoming attractive to mobile network operators as a cost effective and energy efficient solution [5], [6]. However, the intermittent nature green energy harvest in these networks result in occurrence of random energy outages. Due to the inherent double stochasticity in cellular traffic and energy harvest, this outage analysis is nontrivial [7]–[10]. Hence, accurate and computationally efficient estimation of green energy outage is of great interest.

1.1 Related work and motivation

Traditionally, BS clustering is performed depending on the frequency reuse factor [11]. Modern B5G communication systems generally use unity frequency reuse factor, i.e., full-frequency reuse [12], thus removing the need for frequency allocation based BS clustering.

The existing works pertaining to estimation of energy outage have relied on computationally intensive Markovian frameworks [7], [8]. For instance, the framework in [7], which considers a purely solar provisioned standalone BS, modeled the traffic arrival as well as energy harvest as separate discrete time Markov chains (DTMC) comprising of a large number of states. The framework in [9] proposes a Markov chain based solar energy harvest model, decomposing the energy harvest into numerous states for a residential framework. The authors in [10] propose a markov chain based strategy to dimension the energy harvesting system in a cellular framework. Additionally, the frameworks in [7], [8] also decompose the battery level into a large number of states, thereby further increasing the system computational complexity. The authors in [13] have proposed a Markovian framework to design a green residential framework.

It is notable that, in a grid connected solar powered system green energy outage needs to be estimated at every time index (depending on the time granularity, it is usually at every hour) [14]. Thus, a Markovian framework comprising of a large number of states, as in [7], is computationally too intensive. Furthermore, since this computation is typically performed in the cloud data-center, it eventually leads to a higher energy consumption [15], [16]. The authors in [17] proposed a framework to optimally dimension an energy

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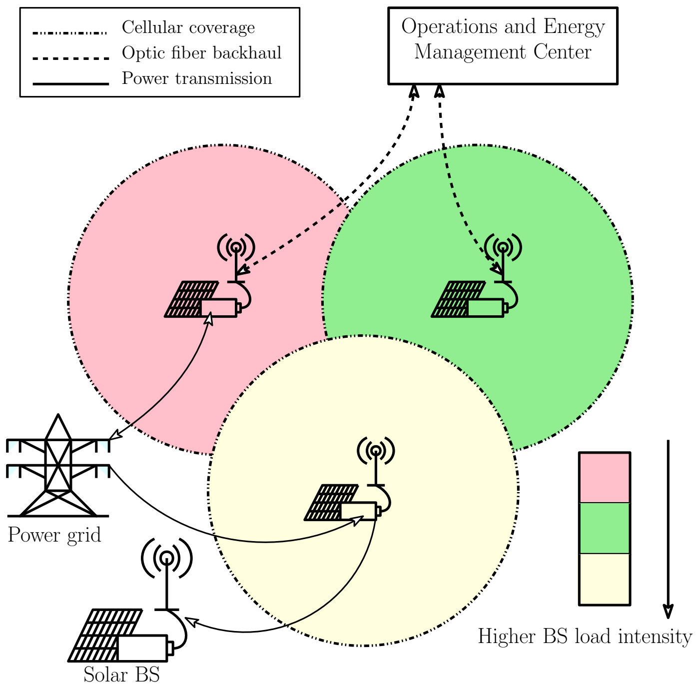
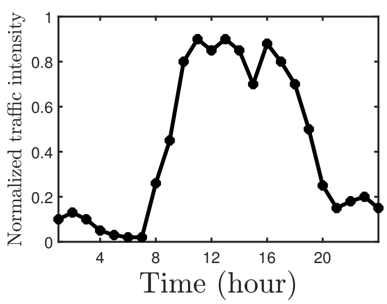


(a)



(b)

Figure 1: Illustration of (a) traffic-energy imbalance prone grid connected and solar powered multi BS network and (b) the average traffic profile.

efficient standalone solar powered BS.

In contrast to the prior art [11], [12], we consider BS clustering from energy sharing perspective. Grid connected and solar powered networks experience randomness in energy harvest as well as BS load, resulting in spatio-temporal traffic-energy imbalances [18], [19]. These imbalances are generally inhomogeneous, depending on the skewness of user traffic and energy harvest of a BS relative to other BSs in the network. By modeling the traffic skewness which can be experienced at a BS, we explore cooperative green energy transfer amongst the networked solar powered BSs using the smart grid infrastructure. The cooperative energy transfer based distributed energy bank strategy among the BSs aims to take advantage of the space-time varying traffic-energy imbalances, thus improving the temporal green energy utilization, alleviating green energy outages, and eventually attaining energy sustainability without drawing energy from the power grid. *To the best of our knowledge, this is the first work to study BS clustering depending on the degree of traffic-energy imbalance, from an energy sustainability viewpoint.*

Unlike the approaches in [7], [8], as an advance, we propose a three-state Markov model characterizing the battery level of a standalone solar powered BS. We argue that since the battery level is a function of energy harvest and cellular traffic, it is redundant to decompose them into separate Markovian states. In contrast to the current state of the art frameworks that rely on data-driven models, our proposed model does not rely on the assumption that the accurate future cellular traffic and energy harvest information is known beforehand. Instead, we consider a general scenario where the cellular traffic and energy harvest are randomly distributed, and further statistically characterize the green energy storage of a BS. In a multi-BS distributed energy bank setting, we argue that modeling the system of BSs using a combined Markovian framework is expected to provide significantly higher computational resource saving, compared to modeling the individual BSs separately.

1.2 Contributions

The key contributions in this work are as follows:

1) We present a stochastic analysis of green energy storage in a grid connected and solar powered cellular network with traffic-energy imbalance at the BSs, and derive the probability density function (PDF) of battery level.
2) For a standalone grid connected solar powered BS, i.e., without energy cooperation (WEC), we model the BS battery energy storage level using a three state DTMC and show its reduced computational overhead with respect to the existing competitive approaches. This Markov model is used to compute the optimal solar provisioning (capital expenditure or CAPEX) required to achieve a sustainable WEC system.
3) Considering multi-BS scenario, we propose a computationally efficient distributed energy bank based energy cooperation (EC) strategy, and the system of BSs net energy state is modeled using a two-state DTMC. Optimal CAPEX is computed for the system of BSs, and the cooperating BS cluster size and solar provisioning required at each BS is jointly optimized to achieve grid energy independence.
4) The probability of consecutive hour energy outage is derived and its general expression for k consecutive hours is presented for WEC as well as EC system.
5) The energy outage performance of the EC system is compared with the WEC system and the existing competitive frameworks under varied traffic skewness. Our results demonstrate that the EC model significantly improves energy outage in addition to reduced computational overhead as well as CAPEX.

1.3 Organization

Section 2 outlines the system model along with the traffic and energy profiles. Section 3 presents the analysis of WEC framework for a standalone grid connected and solar powered BS. The analysis of multi-BS distributed energy bank based EC model is presented in Section 4. The system simulation based performance results are presented in Section 5. Section 6 concludes the paper.

Table 1: Parameter notations used in the paper

Notation	Parameter
$\mathcal{B}$	Number of networked BSs
L	BS load $\sim \mathcal{N}(\mu_L(t), \sigma_L^2)$
H	BS energy harvest $\sim \mathcal{N}(\mu_H(t), \sigma_H^2)$
γ_b	Skewed traffic fraction subjected on BS b
ζ	Traffic skewness parameter
P	Power consumption of a BS
N_{trx}	Number of transceivers in a BS
P_{max}	BS maximum downlink transmit power level
$P_\circ$	BS static power consumption
$B(t)$	Hourly battery level indicator
B_{max}	Battery upper storage capacity
B_{cr}	Battery critical threshold
N_B	Number of batteries equipped with a BS
δ	Battery depth of discharge
$\mathbb{P}_{ij}$	Transition probability from state $i \to j$
$\underline{\mathrm{T}}_{WEC}$	Transition matrix for the WEC framework
$\underline{\pi}_{WEC}$	Steady state matrix for WEC framework
P_k	Probability of k consecutive hour energy outage
H_a	Average energy harvest
E_a	Average BS load
η	PV panel efficiency
R_{PV}	PV panel rating
$C(k)$	CAPEX as a function of k hour energy outage
E^S	Amount of transferable green energy
D	Amount of deficit energy
T	Length of time horizon
S	Number of states in the Markovian framework
$G(b,t)$	Amount of grid energy purchased by a BS b at t
C_{PV}	Cost of unit PV panel
C_B	Cost of unit storage battery
L_{PV}	Lifetime of unit PV panel
L_B	Lifetime of unit battery

2 System Model

We consider a smart-grid connected and solar powered cellular communication network, having $\mathcal{B}$ BSs, as illustrated in Fig. 1(a). The BSs are individually solar provisioned, i.e., equipped with photo voltaic (PV) panels and storage batteries, as well as connected to the power grid for energy sharing when needed. The BSs are connected to the core network using optic fibre wired links. The BSs send regular data like traffic/ energy harvest to the Operations and Energy Management Center (OEMC) implemented at the core network using these backhaul links. In the upcoming subsections, we delineate the probabilistic traffic, energy harvest, BS power consumption, and green energy storage profiles. The parameters used in this paper and their notations are provided in Table 1.

2.1 Traffic and energy harvest profile

The traffic arrivals at the grid connected solar powered BS are considered to be distributed as a truncated Gaussian, with hourly varying mean $\mu_L(t)$ and variance σ_L^2. Mathematically, the hourly BS load $L(t) \sim \mathcal{N}(\mu_L(t), \sigma_L^2)$. The mean of the hourly varying traffic is shown in Fig. 1(b) [20]. It is assumed that the users can displace within the network but no new user can enter the network. The hourly energy harvest at the BS is modeled as a truncated Gaussian distribution with hourly varying mean $\mu_H(t)$ and variance σ_H^2. Mathematically, $H(t) \sim \mathcal{N}(\mu_H(t), \sigma_H^2)$. The hourly energy harvest $H(t)$ and hourly BS load $L(t)$ are assumed to be uncorrelated and independent to each other.

The solar powered cellular network is prone to traffic-energy imbalances due to the space-time variation of energy harvest and BS load. For a multi-BS network, the BSs are considered subjected to skewed traffic load $L_b(t)$ resulting in traffic-energy imbalance in some of the BSs [6], such that at any time, a random BS is significantly heavily loaded as compared to other BSs in the network. We model the skewed traffic framework [21] as shown below for analysis.

$$\gamma_b(t) = \frac{e^{\zeta \times b}}{\sum_{b=1}^{\mathcal{B}} e^{\zeta \times b}} \tag{1}$$

$$s.t. \sum_{b=1}^{\mathcal{B}} \gamma_b(t) = 1 \text{ and } L_b(t) = \gamma_b(t) \times L(t). \tag{2}$$

Here, $\gamma_b(t)$ represents the skewed traffic fraction subjected on to BS b and $\zeta \in [0, \infty)$ refers to traffic skewness parameter capturing the degree of traffic imbalance among the networked BSs. It may be noted that $\zeta = 0$ corresponds to a homogeneous load scenario, whereas $\zeta > 0$ corresponds to higher traffic inhomogeneity.

2.2 BS power and battery profile

The hourly power consumption of a BS is computed as [3]

$$P(t) = N_{trx}P_\circ + N_{trx}P_{max}\Delta L(t) = \Theta_1 + \Theta_2 L(t) \tag{3}$$

where $\Theta_1 = N_{trx}P_0$ and $\Theta_2 = N_{trx}P_{max}\Delta$ are constants. N_{trx} is the number of transceiver antennas per BS, $P_\circ$ is the static power consumption, Δ is the power amplifier efficiency, and P_{max} is the maximum BS downlink power as mandated by Federal Communications Commission (FCC).

Lemma 1. *The BS power consumption $P(t)$, is Gaussian distributed as $P(t) \sim \mathcal{N}(\Theta_1 + \Theta_2\mu_L(t), \Theta_2^2\sigma_L^2)$.*

Proof. Since $L(t) \sim \mathcal{N}(\mu_L(t), \sigma_L^2)$, $\mathbb{E}[L^2(t)] = \sigma_L^2 + \mu_L^2(t)$ [22]. Further,

$$\begin{aligned} &\mathbb{E}[P(t)] = \mathbb{E}[\Theta_1 + \Theta_2 L(t)] = \Theta_1 + \Theta_2\mu_L(t). \\ &\text{Also, } \mathbb{E}[P^2(t)] = \Theta_1^2 + \Theta_2^2\sigma_L^2 + \Theta_2^2\mu_L^2 + 2\Theta_1\Theta_2\mu_L(t). \\ &\text{Hence, } var[P(t)] = \mathbb{E}[P^2(t)] - \mathbb{E}[P(t)]^2 = \Theta_2^2\sigma_L^2. \end{aligned} \tag{4}$$

□

Depending on the hourly energy harvest $H(t)$ and BS power consumption $P(t)$, the hourly battery level is computed as follows:

$$B'(t) = B(t-1) + \underbrace{H(t) - P(t)}_{Z(t)} \tag{5}$$

$$\text{where, } Z(t) \sim \mathcal{N}(\underbrace{\mu_H(t) - \Theta_1 - \Theta_2\mu_L(t)}_{\mu_Z(t)}, \underbrace{\sigma_H^2 + \Theta_2^2\sigma_L^2}_{\sigma_Z^2}). \tag{6}$$

Thus, the hourly battery level can be considered as the difference of two random variables $(H(t) - L(t))$, with $B(t-1)$ being a constant scalar at hour t. The battery level, $B'(t)$, is distributed as

$$B'(t) \sim \mathcal{N}(B(t-1) + \mu_Z(t), \sigma_Z^2). \tag{7}$$

The battery level is constrained between the upper storage capacity denoted as $B_{max} = N_B \times B_{cap}$ and the lower critical threshold denoted as $B_{cr} = \delta \times N_B \times B_{cap}$. Here, N_B is the number of batteries equipped with a BS, B_{cap} is the capacity of individual battery, and δ is the depth of

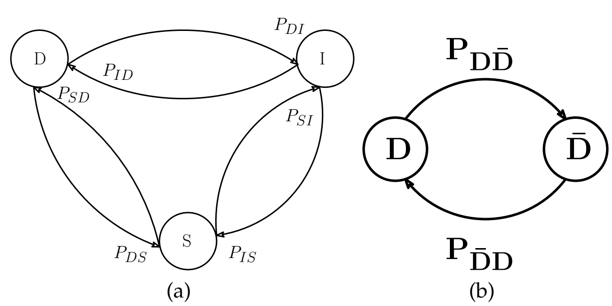


Figure 2: Markovian model of green energy storage in the grid connected solar powered (a) WEC framework (b) EC framework.

discharge. The battery level constrained between B_{cr} and B_{max} is given as

$$B(t) = \min\{\max\{B'(t), B_{cr}\}, B_{max}\}. \tag{8}$$

In the upcoming sections, we consider two distinct network operation strategies, namely, the WEC based standalone BS systems and the EC framework in a multi-BS cluster setting.

3 Standalone Solar Powered WEC Framework

In WEC mode of operation the BSs trade energy with the power grid without having the flexibility to share energy amongst the BSs. First we discuss the Markovian state modeling, followed by a probabilistic analysis of the framework.

3.1 Markov modeling and probabilistic analysis

The green energy storage battery level is characterized by a Markov model with three-states, namely, deficit (D), intermediate (I), and surplus (S), as shown in Fig. 2(a). A BS is termed to be in deficit, intermediate, or surplus state if, $B'(t) < B_{cr}$, $B_{cr} \leq B'(t) \leq B_{max}$, or $B'(t) > B_{max}$, respectively. The state transition matrix corresponding to the three states is represented below as

$$\underline{\mathrm{T}}_{WEC} = \begin{pmatrix} \mathbb{P}_{DD} & \mathbb{P}_{DI} & \mathbb{P}_{DS} \\ \mathbb{P}_{ID} & \mathbb{P}_{II} & \mathbb{P}_{IS} \\ \mathbb{P}_{SD} & \mathbb{P}_{SI} & \mathbb{P}_{SS} \end{pmatrix} \tag{9}$$

where $\mathbb{P}_{ij}$ is the probability of transition from state $i \rightarrow j \ \forall \ i, j \in \{D, I, S\}$. Below we derive closed form expressions for each of the transition probability element in the matrix, $\underline{\mathrm{T}}_{WEC}$.

1) *Transition from deficit state to deficit state:*

$$\begin{aligned}
\mathbb{P}_{DD} &= \mathbb{P}(B'(t) \leq B_{cr} \mid B(t-1) \leq B_{cr}) \\
&= \mathbb{P}(B(t-1) + H(t) - L(t) \leq B_{cr} \mid B(t-1) \leq B_{cr}) \\
&= \mathbb{P}(H(t) - L(t) \leq B_{cr} - B(t-1)) \times \\
&\qquad \mathbb{P}(B(t-1) \leq B_{cr}) \\
&= \mathbb{P}(Z(t) \leq B_{cr} - B(t-1)) \times \\
&\qquad \mathbb{P}(Z(t-1) \leq B_{cr} - B(t-2)) \\
&= \mathbb{P}\left(\frac{Z(t) - \mu_Z(t)}{\sigma_Z} \leq \frac{B_{cr} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \times \\
&\quad \mathbb{P}\left(\frac{Z(t-1) - \mu_Z(t-1)}{\sigma_Z} \leq \frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) \\
&= \mathbb{Q}\left(\frac{-B_{cr} + B(t-1) + \mu_Z(t)}{\sigma_Z}\right) \\
&\qquad \times \mathbb{Q}\left(\frac{-B_{cr} + B(t-2) + \mu_Z(t-1)}{\sigma_Z}\right).
\end{aligned} \tag{10}$$

2) *Transition from deficit state to surplus state:*

$$\begin{aligned}
\mathbb{P}_{DS} &= \mathbb{P}(B'(t) \geq B_{max} \mid B'(t-1) \leq B_{cr}) \\
&= \mathbb{P}(Z(t) \geq B_{max} - B(t-1)) \times \\
&\qquad \mathbb{P}(Z(t-1) \leq B_{cr} - B(t-2)) \\
&= \mathbb{P}\left(\frac{Z(t) - \mu_Z(t)}{\sigma_Z} \geq \frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \times \\
&\quad \mathbb{P}\left(\frac{Z(t-1) - \mu_Z(t-1)}{\sigma_Z} \leq \frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) \\
&= \mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \times \\
&\qquad \mathbb{Q}\left(\frac{-B_{cr} + B(t-2) + \mu_Z(t-1)}{\sigma_Z}\right).
\end{aligned} \tag{11}$$

3) *Transition from deficit state to intermediate state:*

$$\begin{aligned}
\mathbb{P}_{DI} &= \mathbb{P}(B_{cr} \leq B'(t) \leq B_{max} \mid B'(t-1) \leq B_{cr}) \\
&= \mathbb{P}(B_{cr} - B(t-1) \leq Z(t) \leq B_{max} - B(t-1)) \times \\
&\qquad \mathbb{P}(Z(t-1) \leq B_{cr} - B(t-2)) \\
&= \mathbb{P}\left(\frac{B_{cr} - B(t-1) - \mu_Z(t)}{\sigma_Z} \leq \frac{Z(t) - \mu_Z(t)}{\sigma_Z} \leq \frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \\
&\quad \times \mathbb{P}\left(\frac{Z(t-1) - \mu_Z(t-1)}{\sigma_Z} \leq \frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) \\
&= \left(\mathbb{Q}\left(\frac{B_{cr} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) - \mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right)\right) \times \\
&\qquad \mathbb{Q}\left(\frac{-B_{cr} + B(t-2) + \mu_Z(t-1)}{\sigma_Z}\right).
\end{aligned} \tag{12}$$

4) *Transition from intermediate state to deficit state:*

$$\begin{aligned}
\mathbb{P}_{ID} &= \mathbb{P}(B'(t) \leq B_{cr} \mid B_{cr} \leq B'(t-1) \leq B_{max}) \\
&= \mathbb{Q}\left(\frac{-B_{cr} + B(t-1) + \mu_Z(t)}{\sigma_Z}\right) \times \\
&\quad \left(\mathbb{Q}\left(\frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) - \mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right)\right).
\end{aligned} \tag{13}$$

5) *Transition from intermediate state to intermediate state:*

$$\begin{aligned}\mathbb{P}_{II} &= \mathbb{P}\left(B_{cr} \leq B'(t) \leq B_{max} \mid \right.\\ &\qquad \left. B_{cr} \leq B'(t-1) \leq B_{max}\right)\\ &= \left(\mathbb{Q}\left(\frac{B_{cr} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) - \right.\\ &\qquad \left.\mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right)\right) \times\\ &\left(\mathbb{Q}\left(\frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) - \right.\\ &\qquad \left.\mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right)\right).\end{aligned} \tag{14}$$

6) *Transition from intermediate state to surplus state:*

$$\begin{aligned}\mathbb{P}_{IS} &= \mathbb{P}(B'(t) \geq B_{max} \mid B_{cr} \leq B'(t-1) \leq B_{max})\\ &= \mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \times\\ &\left(\mathbb{Q}\left(\frac{B_{cr} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right) - \right.\\ &\qquad \left.\mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right)\right).\end{aligned} \tag{15}$$

7) *Transition from surplus state to deficit state:*

$$\begin{aligned}\mathbb{P}_{SD} &= \mathbb{P}(B'(t) \leq B_{cr} \mid B'(t-1) \geq B_{max})\\ &= \mathbb{Q}\left(\frac{-B_{cr} + B(t-1) + \mu_Z(t)}{\sigma_Z}\right) \times\\ &\qquad \mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right).\end{aligned} \tag{16}$$

8) *Transition from surplus state to intermediate state:*

$$\begin{aligned}\mathbb{P}_{SI} &= \mathbb{P}(B_{cr} \leq B'(t) \leq B_{max} \mid B'(t-1) \geq B_{max})\\ &= \left(\mathbb{Q}\left(\frac{B_{cr} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) - \right.\\ &\qquad \left.\mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right)\right)\\ &\qquad \times \mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right).\end{aligned} \tag{17}$$

9) *Transition from surplus state to surplus state:*

$$\begin{aligned}\mathbb{P}_{SS} &= \mathbb{P}(B'(t) \geq B_{max} \mid B'(t-1) \geq B_{max})\\ &= \mathbb{Q}\left(\frac{B_{max} - B(t-1) - \mu_Z(t)}{\sigma_Z}\right) \times\\ &\qquad \mathbb{Q}\left(\frac{B_{max} - B(t-2) - \mu_Z(t-1)}{\sigma_Z}\right).\end{aligned} \tag{18}$$

Using these transition probabilities, the steady state long-term averaged probabilities are computed from the system of equations given below.

$$\underline{\pi}_{WEC} = \underline{\pi}_{WEC}\underline{\mathrm{T}}_{WEC}, \text{ and } \sum_i \pi_i = 1 \tag{19}$$

where $\underline{\pi}_{WEC} = \{\pi_D, \pi_I, \pi_S\}$ and $i \in \{D, I, S\}$.

3.2 Probability of consecutive hour energy outage

In this subsection we will derive the closed form probabilistic expression for consecutive k hour green energy outage in a WEC framework.

Theorem 1. *The probability of k consecutive hour green energy outage or blackout for the WEC model is given as*

$$P_k = \mathbb{P}_{DD}^{k-1}(\mathbb{P}_{DI} + \mathbb{P}_{DS}) \times (\pi_S\mathbb{P}_{SD} + \pi_I\mathbb{P}_{ID}). \tag{20}$$

Proof. The probability that the WEC model will transit to a deficit state D in the next $k = 1$ consecutive time slots, irrespective of the current state is given by

$$\begin{aligned}P_1 &= \pi_S\mathbb{P}_{SD}\mathbb{P}_{DS} + \pi_S\mathbb{P}_{SD}\mathbb{P}_{DI} + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DI} + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DS}\\ &= \pi_S\mathbb{P}_{SD}(\mathbb{P}_{DS} + \mathbb{P}_{DI}) + \pi_I\mathbb{P}_{ID}(\mathbb{P}_{DI} + \mathbb{P}_{DS})\\ &= (\mathbb{P}_{DI} + \mathbb{P}_{DS}) \times (\pi_S\mathbb{P}_{SD} + \pi_I\mathbb{P}_{ID}).\end{aligned} \tag{21}$$

Similarly, the probability that the WEC model will transit to state D in the next two time slots, irrespective of the current state is given by

$$\begin{aligned}P_2 &= \pi_S\mathbb{P}_{SD}\mathbb{P}_{DD}\mathbb{P}_{DS} + \pi_S\mathbb{P}_{SD}\mathbb{P}_{DD}\mathbb{P}_{DI}\\ &\qquad + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DD}\mathbb{P}_{DI} + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DD}\mathbb{P}_{DS}\\ &= \mathbb{P}_{DD}(\mathbb{P}_{DI} + \mathbb{P}_{DS}) \times (\pi_S\mathbb{P}_{SD} + \pi_I\mathbb{P}_{ID}).\end{aligned} \tag{22}$$

By mathematical induction, the probability that the state will remain in deficit state D for k consecutive time slots (hours) is derived as

$$\begin{aligned}P_k &= \pi_S\mathbb{P}_{SD}\mathbb{P}_{DD}^{k-1}\mathbb{P}_{DS} + \pi_S\mathbb{P}_{SD}\mathbb{P}_{DD}^{k-1}\mathbb{P}_{DI}\\ &\qquad + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DD}^{k-1}\mathbb{P}_{DI} + \pi_I\mathbb{P}_{ID}\mathbb{P}_{DD}^{k-1}\mathbb{P}_{DS}\\ &= \mathbb{P}_{DD}^{k-1}(\mathbb{P}_{DI} + \mathbb{P}_{DS}) \times (\pi_S\mathbb{P}_{SD} + \pi_I\mathbb{P}_{ID}).\end{aligned} \tag{23}$$

□

Next, we compute the CAPEX in the WEC framework as a function of consecutive hour energy outage probability.

3.3 Outage aware CAPEX planning in WEC Model

In this section we aim to compute the optimal CAPEX in the WEC framework as a function of the consecutive hour energy outage. CAPEX is defined as the capital expenditure incurred to the mobile operator in solar provisioning the networked BSs. Considering the unit cost of N_{PV} PV panels C_{PV} [23] having a life expectancy L_{PV} and unit cost of N_B storage batteries C_B [24] having a life expectancy L_B, CAPEX is computed as

$$C = C_{PV}N_{PV}/L_{PV} + C_BN_B/L_B. \tag{24}$$

The life expectancy of a PV panel ($L_{PV} = 25$ years [25]) is generally much larger than that of a storage battery. The lifetime of storage battery L_B is a function of the number of charging-discharging cycles it operates, in addition to the operating temperature and depth of discharge δ [17].

Let the average energy harvest in a day over an annual time frame be denoted as H_a and the average daily load subjected on a grid connected solar BS be given as E_a. Let us assume, in general $E_a \geq H_a$. Therefore, the mean storage capacity needed per day is $(E_a - H_a)$. Further, on an average, the minimum number of storage batteries with individual capacity B_{cap} needed per day is,

$$N_B = \lceil (E_a - H_a)/B_{cap} \rceil. \tag{25}$$

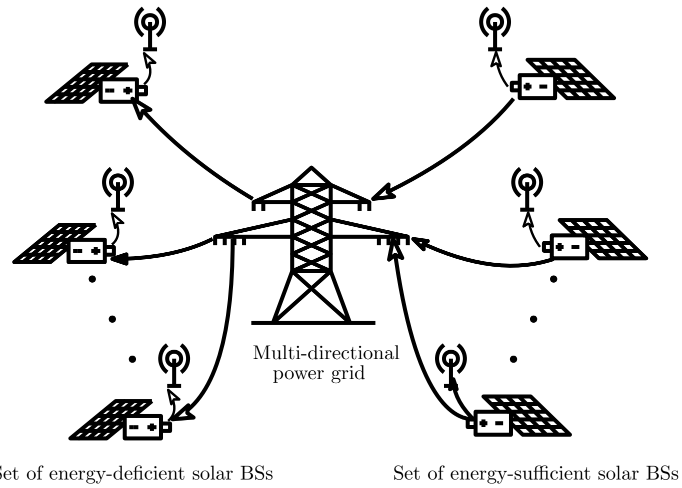


Figure 3: Proposed energy cooperation based communication network.

Considering the battery depth of discharge δ, the minimum number of batteries needed per day is

$$N_B = \lceil ((E_a - H_a)(1+\delta)) / B_{cap} \rceil . \quad (26)$$

We obtained the probability of outage in terms of consecutive number of hours (k) as P_k in (20). Therefore, on an average, the number of days in a year, that the BS will experience green energy outage is computed as $D_o(k) = (365 \times 24 \times P_k)$. Hence, on an average, the minimum batteries needed to serve the outage days is,

$$N_B(k) = \left\lceil \frac{(E_a - H_a)(1+\delta)}{B_{cap}} \right\rceil D_o(k) \quad (27)$$

with L_B representing the battery lifetime (in days). Thus, the optimum average number of storage batteries required annually in a WEC framework will be computed as $N_B^O = \sum_k P_k \times N_B(k)$. Similarly, the optimal average number of PV panels required to be provisioned with a standalone WEC BS for an annual time frame is

$$N_{PV}^O = (H_a \times 365)/(\eta \times R_{PV}). \quad (28)$$

Here, $(H_a \times 365)$ denotes the average annual energy harvested by a R_{PV} rated PV panel, with an efficiency η. Hence, the net optimal CAPEX incurred as a function of the consecutive hour green energy outage probability (i.e., $f(P_k)$) is given as

$$C^O = C_B N_B^O / L_B + C_{PV} N_{PV}^O / L_{PV} = f(P_k). \quad (29)$$

In the upcoming section, we extend the analysis to a multi-BS model and invoke the flexibility of energy cooperation among the BSs.

4 Distributed Energy Bank Based EC Framework

This section presents a computationally efficient multi-BS EC framework, wherein the networked solar BSs have the additional flexibility to transfer the green energy stored in individual batteries among each other using the existing power grid infrastructure as in Fig. 3. In the upcoming sections we first present the Markovian EC framework followed by CAPEX planning and operator revenue analysis.

4.1 Markov modeling

For a set of $\mathcal{B}$ BSs, each BS in the EC framework is hourly classified as energy-sufficient if $B'(t) \geq B_{cr}$, or energy-deficient if $B'(t) < B_{cr}$. The energy-sufficient BSs are proposed to have *transferable green energy* of quanta $E^S(t) = B'(t) - B_{cr}$ and the energy-deficient BSs require to be supplied *deficit energy* of quanta $D(t) = B_{cr} - B'(t)$.

Let the energy-sufficient BSs at each hour be indexed by $b', s.t., \ 1 \leq b' \leq J$. Similarly let the energy-deficient BSs be hourly indexed by $b, s.t., \ 1 \leq b \leq I$. It is notable that a BS can be either energy sufficient or energy deficient, hence the sets of BSs are disjoint to each other, with $I + J = \mathcal{B}$.

The system of BSs operating in the proposed EC framework is modeled as a DTMC such that at a given hour, the set of $\mathcal{B}$ BSs are in either of the two distinct states, namely, energy deficit (D) and non-deficit ($\overline{D}$) state, as shown in Fig. 2(b). The multi-BS EC system is said to be in state D if the net surplus green energy with the energy-sufficient BSs is less than the net energy deficit required by the energy-deficient BSs. Mathematically, $\sum_{b'}^{J} E^S(b',t) < \sum_{b}^{I} D(b,t)$.

The EC system is in state $\overline{D}$ if the net surplus green energy with the networked BSs is greater than the energy deficit experienced by energy-deficient BSs. Mathematically, $\sum_{b'}^{J} E^S(b',t) \geq \sum_{b}^{I} D(b,t)$.

Therefore, instead of modeling each BS as a three state DTMC, we consider the entire set of BSs as a two state Markov process, thus considerably decreasing the computational space. The corresponding transition matrix for the EC framework is given as

$$\underline{\mathrm{T}}_{EC} = \begin{pmatrix} \mathbb{P}_{DD} & \mathbb{P}_{D\overline{D}} \\ \mathbb{P}_{\overline{D}D} & \mathbb{P}_{\overline{D}\overline{D}} \end{pmatrix}. \quad (30)$$

Here, $\mathbb{P}_{ij}$ refers to the probability of transition from state $i \to j \ \forall \ i,j \in \{D, \overline{D}\}$. The transition probabilities in matrix $\underline{\mathrm{T}}_{EC}$ in (30) are defined as follows:

1) *Transition from deficit state to deficit state:*

$$\mathbb{P}_{DD} = \mathbb{P}\left(\sum_{b'}^{J} E^S(b',t) < \sum_{b}^{I} D(b,t) \,\middle|\, \sum_{b'}^{J} E^S(b',t-1) < \sum_{b}^{I} D(b,t-1) \right) \quad (31)$$

2) *Transition from deficit state to non-deficit state:*

$$\mathbb{P}_{D\overline{D}} = \mathbb{P}\left(\sum_{b'}^{J} E^S(b',t) \geq \sum_{b}^{I} D(b,t) \,\middle|\, \sum_{b'}^{J} E^S(b',t-1) < \sum_{b}^{I} D(b,t-1) \right) \quad (32)$$

3) *Transition from non-deficit state to deficit state:*

$$\mathbb{P}_{\overline{D}D} = \mathbb{P}\left(\sum_{b'}^{J} E^S(b',t) < \sum_{b}^{I} D(b,t) \,\middle|\, \sum_{b'}^{J} E^S(b',t-1) \geq \sum_{b}^{I} D(b,t-1) \right) \quad (33)$$

Algorithm 1: Transition probability computation in EC framework

Result: $\mathbb{P}_{DD}, \mathbb{P}_{D\overline{D}}, \mathbb{P}_{\overline{D}D}, \mathbb{P}_{\overline{D}\overline{D}}, \pi_D, \pi_{\overline{D}}$

1 **Input:** $\mathcal{B}, H(b,t), L(b,t), B_{cr}, B_{max}$
2 **Initialize:** $\mathbb{P}_{DD}=0, \mathbb{P}_{D\overline{D}}=0, \mathbb{P}_{\overline{D}D}=0, \mathbb{P}_{\overline{D}\overline{D}}=0$
3 Compute $B'(b,t)\ \forall b \in \mathcal{B}$ using (5)
4 **for** *b=1 to* $\mathcal{B}$ **do**
5   **for** *t=1 to* T **do**
6   Compute $E^S(b,t) = B'(b,t) - B_{cr}, \forall b$
7   Compute $D(b,t) = B_{cr} - B'(b,t), \forall b$
8   **if** *condition in* (31) **then**
9       $\mathbb{P}_{DD} \leftarrow \mathbb{P}_{DD} + 1$;
10   **else if** *condition in* (32) **then**
11       $\mathbb{P}_{D\overline{D}} \leftarrow \mathbb{P}_{D\overline{D}} + 1$;
12   **else if** *Condition in* (33) **then**
13       $\mathbb{P}_{\overline{D}D} \leftarrow \mathbb{P}_{\overline{D}D} + 1$;
14   **else**
15       $\mathbb{P}_{\overline{D}\overline{D}} \leftarrow \mathbb{P}_{\overline{D}\overline{D}} + 1$;
16   **end**
17 **end**
18 $\mathbb{P}_{DD} = \mathbb{P}_{DD}/T, \mathbb{P}_{D\overline{D}} = \mathbb{P}_{D\overline{D}}/T, \mathbb{P}_{\overline{D}D} = \mathbb{P}_{\overline{D}D}/T, \mathbb{P}_{\overline{D}\overline{D}} = \mathbb{P}_{\overline{D}\overline{D}}/T$
19 Compute $\underline{\pi}_{EC} \longleftarrow \underline{\pi}_{EC}\underline{\mathrm{T}}_{EC}$ such that $\sum \underline{\pi}_{EC} = 1$.

4) *Transition from non-deficit state to non-deficit state:*

$$\mathbb{P}_{\overline{D}\overline{D}} = \mathbb{P}\left(\sum_{b'}^{J} E^S(b',t) \geq \sum_{b}^{I} D(b,t) \,\middle|\, \sum_{b'}^{J} E^S(b',t-1) \geq \sum_{b}^{I} D(b,t-1)\right) \tag{34}$$

Below, we present the method used to compute these transition probabilities.

4.2 Probabilistic and complexity analysis

For the multi-BS EC model, the transition are computed as shown in Algorithm 1. The protocol takes as input the number of BSs, the energy harvest at each BS, the load at each BS depending on the degree of skewness [21], and the critical and upper limit of green energy storage. The transition probabilities are initially assigned with value zero (in Step 2). The amount of energy which can be shared by a energy sufficient BS is computed in Step 6, while the amount of deficit energy with an energy deficient BS is computed in Step 7. Steps 8 - 17 illustrate the computation of transition probabilities for the proposed EC model.

It can be inferred from Algorithm 1 that the complexity of the proposed EC model is $\mathbb{O}(\mathcal{B} \times T \times S^2)$, where, $\mathcal{B}, T, S$ represent the number of BSs, length of time horizon, and the number of states in the Markovian framework, respectively. Thus, the computation complexity is directly proportional to the number of states and the number of BSs.

The steady state probabilities can be computed for the EC model using the system of equations given below.

$$\begin{aligned} \underline{\pi}_{EC} &= \underline{\pi}_{EC}\underline{\mathrm{T}}_{EC} \\ \sum \pi_i &= 1. \end{aligned} \tag{35}$$

Here, $\underline{\pi}_{EC} = \{\pi_D, \pi_{\overline{D}}\}$ & $i \in \{D, \overline{D}\}$. In the upcoming subsection, we derive the probability of consecutive hour energy outage for a EC model.

Theorem 2. *The probability of k consecutive hour energy outage or blackout for the EC model is given as*

$$P_k = \pi_D \mathbb{P}_{\overline{D}D} \mathbb{P}_{DD}^{k-1} \mathbb{P}_{D\overline{D}} \tag{36}$$

Proof. The probability that the system will transit to the deficit state (D) from any state in the next time slot is

$$P_1 = \pi_D \mathbb{P}_{\overline{D}D} \mathbb{P}_{D\overline{D}}. \tag{37}$$

Similarly, the probability that the system will transit to state D in the next two and three consecutive time slots, respectively is

$$\begin{aligned} P_2 &= \pi_D \mathbb{P}_{\overline{D}D} \mathbb{P}_{DD} \mathbb{P}_{D\overline{D}} \\ P_3 &= \pi_D \mathbb{P}_{\overline{D}D} \mathbb{P}_{DD}^2 \mathbb{P}_{D\overline{D}} \end{aligned} \tag{38}$$

Thus, the probability that the EC system will transit to state D in the next k consecutive time slots is

$$P_k = \pi_D \mathbb{P}_{\overline{D}D} \mathbb{P}_{DD}^{k-1} \mathbb{P}_{D\overline{D}} \tag{39}$$

$\square$

4.3 Optimal EC cluster size and CAPEX planning for sustainability

In this subsection, we compute the optimal BS cluster size and the CAPEX required in a multi-BS cluster to achieve grid energy independence or self-sustainability. It may be noted that an energy-deficient BS can meet its energy deficit either by cooperative energy transfer from the energy-sufficient BSs $(S(b,t))$ or procure energy from the power grid $(G(b,t))$. Hence,

$$D(b,t) = S(b,t) + G(b,t). \tag{40}$$

The net energy which can be cooperatively shared among the grid connected solar powered BSs is

$$\begin{aligned} &\sum_{b}^{I} S(b,t) = \min\left(\sum_{b}^{I} D(b,t), \sum_{b'}^{J} E^S(b',t)\right), \\ &\text{with, } \sum_{b}^{I} G(b,t) = \sum_{b}^{I} D(b,t) - \sum_{b}^{I} S(b,t). \end{aligned} \tag{41}$$

To eliminate grid energy procurement, the net transferable green energy among the energy-sufficient BSs should be at least equal to the net deficit energy in the network. This condition can be mathematically written as,

$$\sum_{t=1}^{T}\sum_{b=1}^{I} D(b,t) \leq \sum_{t=1}^{T}\sum_{b'=1}^{J} E^S(b',t). \tag{42}$$

From an energy sustainable viewpoint, the joint optimal BS cluster and CAPEX computation problem is shown below.

$$\begin{aligned} P_1 :\ & \min_{\mathcal{B}, N_{PV}, N_B} \mathcal{B} \times (C_B N_B / L_B + C_{PV} N_{PV} / L_{PV}) \\ s.t., C1 :\ & N_B^O \geq N_B \geq 0 \in \mathbb{Z}^+, N_{PV}^O \geq N_{PV} \geq 0 \in \mathbb{Z}^+ \\ C2 :\ & \mathcal{B} = I + J \geq 2 \in \mathbb{Z}^+ \\ C3 :\ & \pi_D = 0. \end{aligned} \tag{43}$$

The optimization problem P_1 jointly optimizes the number of networked BSs $\mathcal{B}$ along with the solar provisioning required at each BS, for energy sustainability. Since all the variables being optimized in P_1 are integers $(\mathbb{Z}^+)$, P_1 is an integer programming problem. $C1$ constrains the number of number of PV panels and storage batteries, while $C2$ captures the minimum required BSs for EC. Constraint $C3$ represents the fulfillment of (42), i.e., grid energy independence achieved by the cluster of $\mathcal{B}$ BSs, with the steady state probability of deficit becoming zero. P_1 is solved using exhaustive search in MATLAB.

It may be noted that each BS is equipped with a finite number of storage batteries. Further, a BS is mandated to radiate up to P_{max} power as per the FCC guidelines, thereby limiting its coverage [3]. Thus the proposed EC framework is physically limited by two key physical system parameters, namely, battery storage capacity and BS power radiation limit. We perform the complexity analysis of the proposed framework in the upcoming subsection.

4.3.1 Complexity analysis

Referring to the CAPEX optimization problem in (43), Constraints $C1$ and $C2$ have a complexity of $\mathbb{O}(\mathcal{B} \times N_B^O \times N_{PV}^O)$, where N_B^O and N_{PV}^O denote the optimal bounds on solar provisioning derived in Section 3.3. Constraint $C3$ has a complexity of $\mathbb{O}(\mathcal{B} \times T \times S^2)$ as shown in Section 4.2. Thus the overall complexity of P_1 is $\mathbb{O}(\mathcal{B} \times (N_B^O \times N_{PV}^O + T \times S^2))$, that is the complexity is linear w.r.t. the number of BSs, time, and solar provisioning per BS, but is quadratic w.r.t. the number of Markovian states in the framework.

4.4 Operator revenue analysis

Operator cost profitability has been used as a basis to study network scalability [26]. In this subsection, we discuss the revenue aspects associated with operating a grid connected and energy harvesting enabled communication network. The key revenue components associated are:

1) Capital expenditure, CAPEX (C): As discussed in Section 3.3, CAPEX refers to the expenditure incurred by the operator in solar provisioning the networked BSs and is defined by (24).
2) Operational expenditure, OPEX: It refers to the expenditure incurred to the mobile operator in day to day operations of the network. It primarily comprises of revenue earned from selling energy back to the grid, cost incurred in energy transfer, and the cost incurred in procuring energy from the grid. In the current framework, since the network has been designed for sustainability (in Section 4.3), cost incurred in procuring energy from the grid does not arise to the operator.

    - Cost of energy transfer, $C^T = \sum_t \sum_b c_1 S(b,t)$, where c_1 refers to the price of transferring unit energy using the grid infrastructure.
    - Cost of energy purchase from grid, $C^B = \sum_t \sum_b c_2 G(b,t)$, where c_2 refers to the cost of purchasing from the grid. In the current analysis since $\pi_D = 0$, it implies that $G(b,t) = 0 \;\forall\; b \;\forall\; t$.
    - Revenue earned from selling energy back to the grid, $R^S(t) = c_3(\sum_{b'}^{J} E^S(b',t) - \sum_b^I D(b,t))$, where c_3 is the unit energy selling price. It denotes the surplus green energy sold back to the grid after performing energy transfer operation.

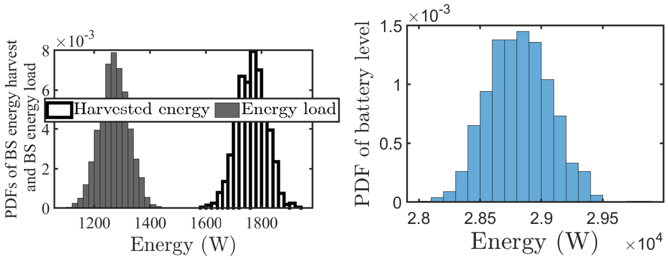
It may be noted that the energy transfer among the BSs through the power grid infrastructure is not free of cost. In other words, the mobile operator incurs some operational expenditure to transfer energy among the networked BSs towards grid maintenance. It is observed that the unit price of selling energy to the grid (c_3) is always much lesser than the price of buying energy (c_2) from the grid, i.e., $c_2 > c_3$ [27], [28]. Accordingly, the price of unit energy transfer among the BSs (c_1) is proposed to be greater than the unit energy selling price but lower than the unit energy procurement price i.e., $c_3 < c_1 < c_2$. Maintaining such relative pricing ensures that, instead of selling the energy at a cheaper price, the energy-sufficient BSs are incentivized to transfer surplus green energy to the needy BSs. Similarly, the energy-deficient BSs are also incentivized to procure energy from the networked BSs at a lower price, rather than procuring energy from the grid at a much higher price. Thus, the proposed energy transfer price ensures better green energy utilization in the network in addition to minimizing the carbon emission through grid energy procurement.

The total revenue of the operator is thus $R = R^S - C^B - C^T - C + K(\zeta)$. Here, $K(\zeta)$ refers to the revenue earned by the operator in serving network users as a function of the traffic-energy imbalance skewness factor [19]. In the upcoming section, we present the key results and inferences of our proposed framework.

5 RESULTS AND DISCUSSION

In this section, we discuss the simulation results along with the observations and inferences. The simulations have been performed in MATLAB R2020a, with the following processor specifications: 10^{th} generation core i9 having speed 3.7 GHz to 5.3 GHz, core count 10, and thread count 20. The mean of hourly varying energy harvest has been taken from the open source annual solar harvesting data available in [29], of Jaipur city in India. The parameter values used in simulations are, $N_{trx} = 6$ [17], $P_o = 118.7$ W [19], $P_{max} = 40$ W [3], $B_{cap} = 2460$ Wh [17], $\delta = 0.3$ [17], $C_{PV} = 1300$ USD [23], $C_B = 216$ USD [24], $\Delta = 4.7$ [3], $R_{PV} = 1$KW [17], $c_1 = 0.057$ USD, $c_2 = 0.079$ USD [28], $c_3 = 0.015$ USD [27], and $\eta = 0.5$ [17]. In the following, we study the WEC and EC modeling and system performance in terms of computation efficiency, outage performance, CAPEX, and operator profitability towards sustainable operation with green energy resource.

It may be noted that the cooperating BSs are assumed to be in the same local area or city. While the proposed framework is generalized and tractable, for simulation purpose the energy harvest at each BS is assumed to be equal. The traffic-energy imbalances arise in the network due to the traffic dynamics, affecting the green energy storage levels of the BSs. The traffic dynamics are captured and modeled through the skewness intensity factor ζ which is analytically modeled through (1). It represents the fraction



(a) (b)

Figure 4: PDFs of (a) BS energy harvest and load at a random time instant (4 PM); (b) battery level at a random time instant (4 PM).

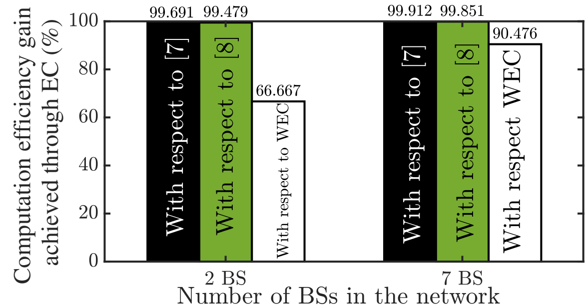
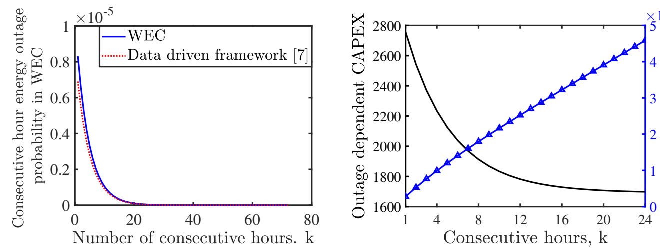


Figure 5: Computation efficiency gain in EC framework over state-of-art.

Table 2: Comparison of number of Markovian states

State of the art	Number of Markovian states, S
TCOMM 2016 [7]	For single BS: 3 (energy harvest) $\times$ 2 (BS load) $\times$ 36 (Battery level states) = 216
TSE 2015 [8]	For single BS: 4 (energy harvest) $\times$ 2 (BS load) $\times$ 24 (hour of day) = 192
Proposed WEC	For single BS: 3
Proposed EC	For the BS cluster: 2



(a) (b)

Figure 6: (a) Consecutive hour green energy outage probability in a standalone solar powered BS; (b) green energy outage dependent CAPEX and cumulative CAPEX for a standalone solar powered BS.

of traffic inhomogeneity experienced by a BS as compared to the homogeneous traffic scenario (i.e., when $\zeta = 0$). With increasing ζ, any random BS in the network experiences a higher skewed fraction of traffic. In this paper, we have simulated the system up to $\zeta = 2.0$, which corresponds to around 90% higher traffic with respect to the balanced homogeneous scenario. While ζ can take further higher values, we restricted our studies with up to 90% traffic imbalance as skewness levels higher than $\zeta = 2.0$ are not practical and have a low probability of occurrence in reality.

5.1 Computational overhead analysis

Through Figs. 4(a) and 4(b) we illustrate the PDFs of the energy harvest, BS load, and the corresponding battery level at an arbitrary time instant. It can be observed that all the individual PDFs are Gaussian in nature.

Table 2 captures the number of Markov states in our proposed approaches in contrast with the number of states in the state-of-art [7], [8]. The Markov modeling in [8] was aimed at computing the green energy outage occurring in standalone solar BS, wherein a day was characterized as good/bad depending on the solar harvest and a day was further quantized into four time windows. The study in [7] extended the work in [8] by additionally characterizing the BS load along with solar harvest, and battery storage was modeled by multiple Markov states. The total number of Markov states required in [8] was 192 for battery energy state characterization for a standalone BS, whereas in [7] it required 324 Markov states. In contrast, our proposed WEC framework characterizes a standalone solar powered BS by a three-state Markov model, whereas our multi-BS EC system (with BSs ≥ 2) characterizes the entire cluster of BSs into two states, to compute the desired green energy outage.

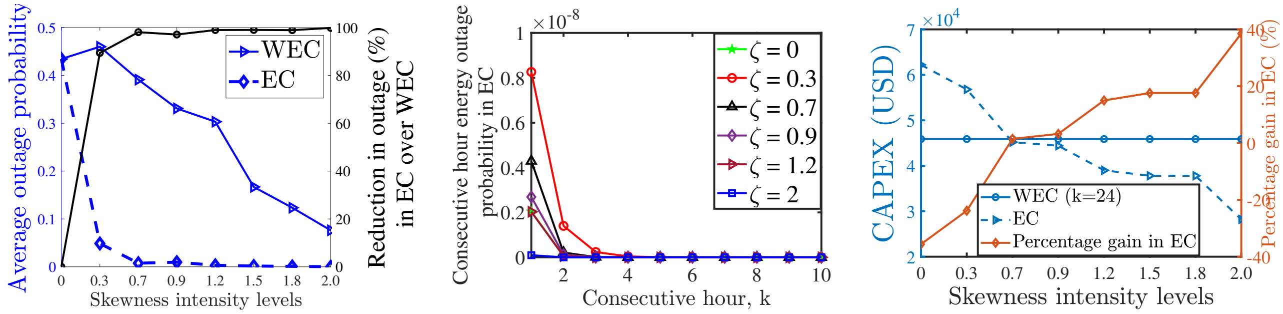
In Fig. 5, we illustrate the computational efficiency gains achieved at the OEMC for green energy outage estimation and resource provisioning in the proposed EC framework. It is noted that when the BSs do not have flexibility to share energy amongst each other, the proposed WEC modeling is computationally efficient in estimating green energy outages as compared to the state of art. In a 2-BS network, the proposed WEC modeling framework is about 30% more computationally efficient compared to the approaches in [7] and [8]. As the number of BSs in the network is increased to 7, the gain with the WEC model is about 10%.

Fig 5 further reveals that, for energy outage estimation in a cluster of BSs with EC, modeling the energy state of the distributed energy bank is significantly computationally efficient compared to modeling the individual BS battery state. The computational efficiency gain over the techniques in [7] and [8] is over 99%. The gain with respect to the proposed WEC model is also significant, respectively about 60% and 90% for a 2-BS cluster and a 7-BS cluster.

Remark 1. *To capture the battery state of a standalone solar powered BS three-state Markov model is sufficient. Individual modeling of energy harvest and BS load are not required, as these information are embedded in the battery level.*

Remark 2. *For standalone solar BSs, the proposed WEC model for outage estimation significantly reduces the computation complexity over the state of art non-energy cooperative frameworks.*

Remark 3. *In an EC system with a network of grid connected solar powered BSs, green energy storage in the cluster of BSs can be characterized together using a two-state model, which is also significantly computationally efficient.*



(a) (b) (c)

Figure 7: (a) Average outage probability and reduction in green energy outage in a cluster of 7 BSs operating through the WEC and EC frameworks, with $N_{PV} = 5, N_B = 5$ per BS; (b) consecutive hour green energy outage probability for various degrees of traffic skewness in a 7 BS EC framework with $N_{PV} = 5, N_B = 5$ per BS; (c) CAPEX required to achieve green energy sustainability in WEC and EC frameworks.

5.2 Outage performance and CAPEX analysis in WEC system

We now discuss the outage performance and CAPEX required in standalone solar powered BSs. Fig. 6(a) shows the variation of consecutive hour energy outage probability in the proposed WEC framework along with that in the data-driven framework in [7]. We show the variation of the number of consecutive hour k that the WEC framework transits in the deficit state, for 72 hours or 3 days. It is observed that the WEC modeled standalone BS outage performance closely matches with that in [7]. This also verifies the accuracy of the proposed three-state WEC model to characterize the energy outage. This observation along with the low computation overhead of WEC model, as discussed in Section 5.1, establishes the importance of this simplified energy characterization model.

Fig. 6(b) shows the CAPEX provisioning required in a standalone BS. Since Fig. 6(a) captures that the outage probability is close to zero after 24 hours, we show the energy outage dependent CAPEX along with the cumulative CAPEX in the WEC framework over 24 hours duration. The value of cumulative CAPEX at $k = 24$ represents the sustainable point of CAPEX at which the standalone BS can operate without procuring energy from the grid.

5.3 Relative performance of WEC and EC for sustainable operation with green energy

To compare and observe the benefits of the distributed energy bank based EC strategy over the WEC mode, we subject a cluster of 7 BSs, that are solar provisioned and grid connected, to varying levels of traffic skewness and operate the network through the two strategies. Through Fig. 7(a), we illustrate the variation of the long term average steady state energy outage probability when the system operates through both the strategies under the influence of skewed traffic. It can be observed that the WEC model consistently attains a significantly higher steady state outage probability as compared to the multi-BS EC model. The percentage reduction in outage probability achieved with the EC model over the WEC model is also depicted in Fig. 7(a). As a general trend, we infer that with increasing skewed nature of traffic, the percentage reduction in energy outage with the EC framework increases significantly over the WEC model, indicating the advantage of cooperative energy transfer.

Fig. 7(b) shows the variation of consecutive hour energy outage in an under-provisioned solar powered multi-BS EC system under different traffic skewness. We observe that in general, the probability for all skewed traffic levels tend to zero as k increases. Additionally it is inferred that at a moderate skewed traffic, $\zeta = 0.3$, the EC system experiences highest probability of consecutive hour green energy outage. As the system is subjected to more skewed traffic ($\zeta = 0.7, 0.9, 1.2, 2)$) the probability is relatively lesser. It is also inferred that when the system is subjected to homogeneous traffic ($\zeta = 0$), then the initial probability of consecutive hour energy outage is lower than moderately skewed traffic, but higher than extremely skewed traffic ($\zeta = 2$) . The nature of the plots in Fig. 7 for all ζ are inferred to be exponentially decreasing and converging in nature. Hence, P_k proposed through (36) in Theorem 2 can be inferred as convex and converging in nature. Since (36) is based on the transition and steady-state probabilities computed through Algorithm 1, hence, transition probabilities in $\underline{\mathrm{T}}_{EC}$ and π_D converge over long run, thus guaranteeing convergence of the proposed framework.

Figs. 7(c) and 7(d) show the optimal CAPEX required to attain sustainability in the WEC and EC models, respectively. Fig. 7(c) illustrates the variation of CAPEX required to achieve sustainability in the WEC and EC systems, when the network is subjected to skewed traffic of varying degrees. We observe that at a homogeneous traffic scenario, the EC obtains a negative gain over the WEC, but as the degree of skewness increases, the EC performs significantly better than the WEC, obtaining a CAPEX saving up to 40%. This is mainly due to the advantage that EC takes over WEC by improving the temporal network energy and exploiting the inherent imbalances.

Remark 4. *The proposed EC framework is able to exploit the traffic-energy imbalances occurring in a grid connected solar powered network to improve the temporal green energy utilization, thereby reducing the CAPEX incurred.*

Through Figs. 8(a) and (b) we show the effect of energy sharing in a clustered multi-BS EC sytem, towards attaining energy sustainability. It may be noted that a grid connected solar powered BS requires to procure energy from the power grid, if its energy harvest is unable to meet the load requirements. The proposed EC model provides flexibility to an

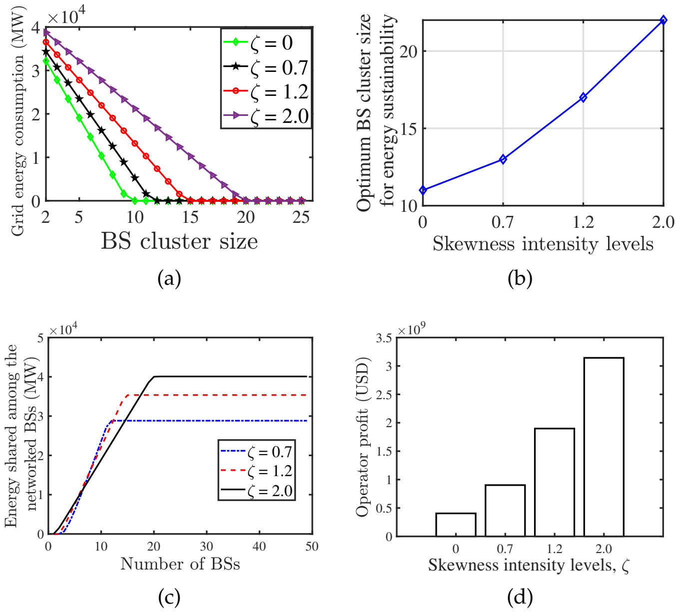


Figure 8: Green energy sustainability in EC framework: (a) required BS cluster size; (b) optimum BS cluster size as a function of traffic skewness; (c) quantum of energy shared among the networked BSs; (d) operator network profit variation with skewness intensity levels.

energy deficit BS to meet its deficit via the unused green energy present with energy-sufficient BSs, thus exploiting the space-time imbalance in green energy harvest and BS traffic. Once the networked BSs, through collaborative energy transfer achieve energy sustainability, then the grid infrastructure is used purely for sharing energy amongst the BSs and selling the excess energy to the power grid rather than energy procurement.

Fig. 8(a) illustrates that in general, the grid energy consumption reduces in the network as the BS cluster size keeps increasing. Further, it is inferred that higher levels of traffic inhomogeneity tend to require larger BS cluster size. It is observed from Fig. 8(b) that at a balanced/homogeneous load ($\zeta = 0$), around 10 BSs collaborate with each other through the proposed EC framework to achieve grid energy independence, whereas a much increased traffic inhomogeneity ($\zeta = 2.0$) requires a cooperative effort from around 22 BSs to achieve energy sustainability.

Through Fig. 8(c) and (d) we illustrate the convergence and scalability of the proposed EC framework. Fig. 8(c) depicts the energy sharing capability of a networked system of BSs. It is inferred that with increasing traffic inhomogeneity, a larger cluster of BSs are involved in attaining a energy sustainability. It is also observed that the energy transferring requirement of the networked BSs saturates after a certain number of BSs, indicating sustainable network operation point. Thus for a given skewness level, a finite number of BSs are involved in the proposed EC framework, illustrating convergence of the proposed framework. It can also be clearly inferred that the convergence is faster at lower skewness levels. Through Fig. 8(d), we illustrate the variation of operator revenue for varying levels of traffic inhomogeneity. It can be clearly seen that the operator achieves significant revenue gains (up to 87% at $\zeta = 2.0$) through the proposed EC framework with increasing inhomogeneity. Hence, indicating that the proposed EC framework is scalable to the network operator, as it is profitable in addition to realizing a carbon free green communication network.

Remark 5. *The proposed EC framework is very significant in facilitating cooperative green energy transfer in the network, resulting in energy sustainable solar provisioned BS clusters.*

Remark 6. *Subjecting the network to increasing levels of traffic inhomogeneity results in larger BS clustering in order to minimize the grid energy procurement.*

Remark 7. *The mobile service provider gains significant operator revenue in addition to achieving energy sustainability through the proposed EC framework, thereby indicating scalability and industrial applicability of the proposed framework.*

6 Conclusion

The paper has presented a cooperative energy transfer based distributed energy bank network operation strategy in grid connected and solar powered cellular networks. The proposed framework aimed at optimized green energy sharing ability among networked BS clusters towards attaining green energy sustainability under different traffic-energy imbalances. To this end, the battery energy availability of the standalone BSs (i.e., without energy cooperation or WEC) as well as networked BSs have been modeled using respectively 3-state and 2-state Markov models, which are shown to be significantly computationally efficient compared to the available techniques in the literature. Further, the proposed energy cooperative (EC) BS clustering has been demonstrated to be much higher CAPEX-efficient compared to the WEC mode of operation. Finally, this study has also captured the optimum required EC BS cluster size as a function of cellular traffic skewness for grid energy free operation. The study is expected to pave the way towards carbon free energy sustainable cellular networks, achieving significant savings in computational resource as well as CAPEX to the mobile service provider.

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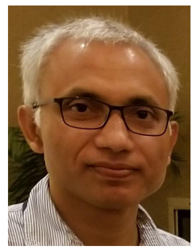

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